Estimating Density and Lane Inflow on a Freeway Segment

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ABSTRACT

This paper illustrates a methodology for estimating density in a freeway lane between detector stations and measuring the net number of vehicles to enter (or leave) the lane, i.e., the lane inflow. The work uses vehicle arrivals at each detector station and information from a sparse vehicle reidentification system, one that may match the measurements from as few as five percent of the vehicles that pass both detector stations. Such reidentification systems have already been documented and deployed for dual loop detectors and they will be used for illustration. Of course this work is also applicable to other vehicle reidentification systems, which may be based on other detection technologies, that may have a higher rate of reidentification.

Keywords: traffic surveillance, loop detectors, vehicle reidentification, traffic density, lane change maneuvers

1. INTRODUCTION

Virtually all traffic flow models are based on the relationships between flow, q, density, k, and velocity (space mean speed), v. This fact is due to the spatial and temporal nature of traffic flow and has been reflected all the way back to the seminal works on traffic flow theory, e.g., Greenshields (1935), Lighthill and Whitham (1955) and Richards (1956). One can easily measure q and v at a point in space with conventional traffic detectors, but k is more difficult to measure. Although in theory, density could be measured between detector stations using simple input-output models, vehicle detectors are imperfect and detector drift precludes such simple measurement. Most traffic flow theory has been developed using point measurements and in some cases, resource-intensive data collection efforts to capture spatial information. The latter were typically short-term studies, often consisting only of a few minutes or a few hours of data, and were usually based on photogrammetric tools dating back to Greenshields (1934). In addition to the difficulties of capturing simple spatial measurements such as k, it has long been recognized that lane change maneuvers can influence the relationships underlying traffic flow theory or even disrupt the relationships if lane change maneuvers are not accounted for. While density can be measured from a single image, quantifying lane change maneuvers requires both spatial and temporal coverage.

Considerable efforts have been made to estimate and model density: Gazis and Knapp (1971), Nahi and Trivedi (1973), Gazis and Szeto (1974); lane changing frequency: Worrall and Bullen (1970), Worrall, Bullen and Gur (1970), Phal (1972), Munjal and Hsu (1973), Gang and Kao (1991); as well as the combination of density and lane changing behavior: Chang and Gazis (1975), Sheu (1999). The density models must accept a large uncertainty range due to conventional operation of vehicle detectors, while many of the lane change models assume accurate measurement of density. All of the models are limited by the small amount of available spatial data for validation. For example, in most cases lane changing was modeled as a function of flow, but it is likely that excluded factors such as location, time of day, and vehicle mix are significant.

Recent advances in traffic surveillance could solve this data deficiency. Video image processing and vehicle tracking tools may soon be accurate enough to extract density and lane changes within a limited field of view. However, occlusion and oblique viewing angles limit the distance that one camera can be used to automatically extract such data and a vehicle traveling at free flow speeds will likely be out of (trackable) view within a few seconds.

In the mean time, Reijmers (1979) presented new vehicle detection hardware that is compatible with existing loop detectors and is capable of extracting detailed magnetic vehicle signatures. Kuhne and Immes (1993) and others have since used these signatures to match a vehicle's measurements between one location and another, so-called *vehicle reidentification*. By matching almost every vehicle, these new loop based systems could provide direct measurement of true density and lane change frequency. So far, the new detectors have seen limited deployment because they require additional hardware and considerably higher communication bandwidth compared to conventional loop detectors.

Recent work by our group has produced an alternative to the hardware intensive vehicle reidentification tools. Our approach uses the existing vehicle detection hardware and communication infrastructure. Unlike the detailed magnetic signatures, the approach uses the standard bivalent loop detector output to measure effective vehicle lengths at dual loop detectors. These vehicle measurements are assigned sequential arrival numbers in each lane at each detector station, denoted $N_u(t)$ and $N_d(t)$ for the upstream and downstream stations, respectively. Two complementary algorithms use these length measurements, arrival numbers and arrival times to reidentify vehicles between detector stations. The first algorithm attempts to find a match for every vehicle during congestion (Coifman and Cassidy, 2002). Although an individual length measurement is not unique, a sequence of measurements rapidly becomes identifiable and this first algorithm uses the sequence of length measurements at each station to match platoons of vehicles that pass both detector stations without changing their order. Unfortunately, the dual loop detector measurement resolution degrades as vehicle speed increases. At free flow speeds most cars become indistinguishable from one another, but because of the large range of feasible lengths, it is still possible to distinguish between the long vehicles at these speeds. So the second algorithm only attempts to match the long vehicles during free flow conditions (Coifman, forthcoming). The operating regions of the two algorithms overlap, allowing for uninterrupted vehicle reidentification. The algorithms are not able to match every vehicle under the limited resolution of the loop detector length measurements. Experimental results found that the congestion algorithm can match up to 75 percent of the passing vehicles while the free flow algorithm can match up to seven percent. These reidentification rates are sufficient for travel time measurement (Van Aerde et al., 1993, Holdener and Turner, 1996) and the algorithms have been running continuously in the Berkeley Highway Laboratory (BHL) for several years[1] on Interstate 80, north of Oakland, California (Coifman, Lyddy and Skabardonis, 2000). This paper will show how the resulting matches can be used to estimate density in a freeway lane between detector stations and measure lane inflow, the difference between the number of lane change maneuvers that enter and the number that exit the lane.

These new measurements have many potential applications. First, they could help verify and calibrate earlier density and lane changing models, allowing data collection over an extended period at a large number of locations. Such tools could be used to model the lane changing patterns in a weaving section. Second, the new traffic parameters should improve incident detection and assessment, e.g., identifying increased lane change maneuvers that deviate from historical lane inflow patterns. Third, lane inflow can lead to better detector diagnostics because the net inflow summed over all lanes should be zero if there are detectors at all entrances and exits. Similarly, as will be shown in this paper, lane inflow can be used to estimate ramp flow using only the mainline detectors. This point is important because, depending on the ramp geometry, drivers may ignore striping and make it difficult to place ramp detectors to ensure accurate detection of all vehicles. The remainder of this paper presents the density estimation and lane inflow measurement techniques given a vehicle reidentification methodology that only matches a portion of the passing vehicles.

2. DENSITY ESTIMATION

The vehicle reidentification algorithms developed by our group provide data on a small percentage of the vehicles passing on the segment between detector stations. Figure 1 shows an example of the matches from Coifman and Cassidy (2002) for 100 consecutive vehicles at the

[1] The real time system can be viewed at: http://www.its.berkeley.edu/projects/freewaydata.

downstream detector in one lane on an 1,800 ft freeway link in the BHL. The downstream vehicle number, N_d, is shown on the horizontal axis and offset between the vehicle numbers, N_d-N_u, for each match on the vertical axis. Notice that approximately 40 percent of the vehicles do not have matches in this figure. Although the reidentification rate from the two vehicle reidentification algorithms can be significantly lower then shown in this example, the measurements capture valuable spatial information about the traffic conditions between the stations. In contrast to the spatial measurements from the subgroup of matched vehicles, conventional loop detector data contain information on the entire vehicle population passing a single point. Combining the point data with the matched vehicle data, assuming few detector errors, it is possible to estimate link density at two instants for each reidentified vehicle. Consider the case where downstream vehicle measurement $N_d(t_2)$ is matched to upstream vehicle measurement $N_u(t_1)$. The travel time for this vehicle is simply t_2-t_1. If no vehicles change lanes, then all vehicles that passed the upstream station while the matched vehicle traversed the link must still be in the lane at time t_2 and no other vehicles will be in the lane. Similarly, all vehicles that were in the lane at time t_1 will have passed the downstream detector by t_2 and no other vehicles will have exited during the period that the matched vehicle traversed the link. Of course the assumption that no vehicles change lanes is unreasonable. Relaxing the assumption such that most vehicles do not change lanes, the following two estimates of lane density are available each occurrence that a vehicle is matched between the two stations:

$$\hat{k}_u(t_2) = \frac{N_u(t_2) - N_u(t_1)}{\text{distance}} \tag{1}$$

$$\hat{k}_d(t_1) = \frac{N_d(t_2) - N_d(t_1)}{\text{distance}} \tag{2}$$

Where $\hat{k}_u$ and $\hat{k}_d$ are based on the upstream and downstream arrivals, respectively, as illustrated in Figure 2.

The points in figure 3A-B show the resulting density estimates after applying Equations 1-2 to just over an hour of dual loop data from the same 1,800 ft freeway segment used in Figure 1. For comparison sake, the density estimates from the upstream station are shifted to the right by the measured travel times, so that both of the plots are presented relative to the times that matched vehicles passed the downstream station. In this case, measured speeds at the dual loop detectors were on the order of 20 mph and approximately 1,400 vehicles passed the downstream detector during the sample period. Concurrent video data were collected at both stations and all vehicles in the lane were manually matched during the same time period. The resulting density estimates from the manually matched vehicles are shown with solid lines in Figure 3A-B. Figure 3C compares the two manual density estimates. If there were no lane change maneuvers the two density curves should fall on top of one another. Although the curves do not show a perfect match, they are within seven percent of one another on average, with a few transients out to 30 percent. These differences are due to the fact that some vehicles do change lanes. The benefit of making two density estimates per matched vehicle is not the increased sampling frequency, since $\hat{k}_d(t_1)$ cannot be made until after the matched vehicle leaves the link at t_2. Rather, the redundancy between the two independent estimates can be used to highlight periods in which the accuracy of the estimates may be reduced due to lane change maneuvers, as illustrated by the comparison in Figure 3C. If the inflow and outflow are balanced, it will not degrade the density estimation, but if they are unbalanced, the two estimates will drift apart. The next section addresses this inflow measurement.

3. LANE INFLOW ESTIMATION

Assuming few detector errors, most of the drift in $N_d(t_2)$-$N_u(t_1)$ for the set of matched vehicles will be due to lane inflow. The lane inflow can be measured even with a low frequency of vehicle reidentification. The two vehicle reidentification algorithms mentioned previously only match vehicles when they can, but more importantly, these matches are made relative to the local arrival numbers at each detector station, N_u and N_d. The lane inflow is simply the change in offset and the lane flux is defined as the time derivative of the inflow. Both values can be calculated whenever a new match is found. Consider the hypothetical example shown in Figure 4 in which two vehicles are reidentified and many more vehicles pass without being matched. The trajectories for the reidentified vehicles are shown for reference, but are unknown to the algorithm. The algorithm knows the passage times for all vehicles at each station and that the two vehicles are matched from one station to the next, e.g., that the vehicle that passed upstream at t_1 is the same vehicle that passed downstream at t_3. Each reidentified vehicle allows for a measurement of the offset and in this example the two offset measurements are,

$$offset(t_3) = N_d(t_3) - N_u(t_1) \quad (3)$$

$$offset(t_4) = N_d(t_4) - N_u(t_2) \quad (4)$$

Given two offset measurements, the inflow and lane flux can be measured,

$$inflow(t_3, t_4) = offset(t_4) - offset(t_3) \quad (5)$$

$$flux(t_3, t_4) = \frac{offset(t_4) - offset(t_3)}{t_4 - t_3} \quad (6)$$

In the example from Figure 4, there is a net inflow of -1 between t_3 and t_4, e.g., one vehicle left the lane between the two reidentified vehicles, but it is not known which of the unmatched vehicles left the lane. Using real data, Figure 1 shows that no matches were found for downstream vehicles numbered 55 to 78. The difference in the upstream offset before and after the gap indicates a net inflow of -4 vehicles (although not shown on the plot, the times each vehicle passed the detectors were recorded).

As noted previously, the lane inflow captures the difference between the number of lane change maneuvers that enter and the number that exit the lane. If there are no ramps between the detector stations, the net inflow summed across all lanes should be zero because a vehicle leaving one lane will enter another. If there are on or off ramps, the net inflow should equal the sum of the ramp flows.

Using data from the I-880 Field Experiment (Skabardonis et al., 1996), both vehicle reidentification algorithms were applied independently to each lane of a five lane freeway segment south of Oakland, California. The segment is 1,500 ft long with an on-ramp near the upstream detector station (see inset Figure 5A for schematic). Three hours of data were used and no attempt was made to explicitly account for lane change maneuvers or entering vehicles while reidentifying vehicles. The number of vehicles and percentage that were matched for this example are presented in Table 1. For each match in a given lane, the upstream offset versus downstream arrival time is shown in Figure 5A. The slope of each curve is the lane flux, quantifying the net number of vehicles that enter (positive slope) or exit (negative slope) the given lane per unit time, over the distance that spans the two stations. Lane 5 (the outside lane) had a net inflow of 856 vehicles (22 percent) and lane 4 had a net inflow of 405 vehicles (almost 10 percent) during the three hour period. The remaining lanes saw a smaller net inflow during the same period. Summing the inflow across all five lanes yields the gray line in Figure 5B and a net inflow of 1,360 vehicles. During the same period, 1,384 vehicles passed a detector on the on-ramp and these arrivals are shown with a black line in Figure 5B, while the difference between the two curves is shown in Figure 5C.

Although the vehicle reidentification algorithms were applied to each of the mainline lanes independently -- ignoring both the other lanes and the presence of the ramp -- and only 11 percent of the vehicles were matched, the net lane inflow and on-ramp flow are within two percent of one another. The fact that the net inflow corresponds with the ramp flow validates the accuracy of the individual lane inflow measurements and provides an estimate of the ramp flow in the absence of a detector on the ramp. Figure 5D shows the time series velocity at the downstream station for reference and it is clear that the matches come from free flow conditions prior to 8:00 and congested conditions thereafter.

Returning to the BHL for a larger example,[2] the process is repeated over 24 hours on a five lane, 1,800 ft long segment without ramps. Once more, the reidentification algorithms were applied to each lane independently. The number of vehicles and percentage that were matched for this example are presented in Table 2. Figure 6A shows the time series evolution of the inflow for all of the lanes on the segment and the inset shows a schematic of the location. The lane changing patterns are due to the split of I-80, I-580 and I-880 less than two miles downstream of the study segment. Lane 1 is a high occupancy vehicle lane and on most days lane 2 experiences the heaviest congestion due to traffic backed up from the left-hand branch of the diverge downstream of the segment. This plot shows three transient periods of high lane flux in lanes 2 and 5, as enumerated in Table 3 and normalized for distance. Obviously, vehicles can not move directly between non-adjacent lanes, so these data indicate movement through all of the intervening lanes. The additional lane change maneuvers in lanes 3 and 4 are roughly balanced, i.e., after removing the long-term trend, one vehicle leaves lane 4 between the stations for each vehicle that enters the lane. This example illustrates the fact that the net inflow differs from the total number of lane change maneuvers. For reference, Figure 6B-C show the time series velocity at the upstream and downstream stations, respectively. As shown with dashed lines on these plots, the periods of high lane flux listed in Table 3 correspond to mixed traffic conditions on the link: free flow at the upstream station and congested at the downstream station. Apparently, when the tail of the queue is within the link, drivers exhibit different lane changing patterns. Quantifying this behavior will be the subject of further research.

Summing the inflow across all five lanes yields the curve in Figure 6D. Simply employing vehicle conservation, one would expect that the total inflow should be constant since there are no ramps in the link. Considering the fact that over 100,000 vehicles pass during the day, indeed the total inflow is nearly constant. Most of the drift in this curve is likely due to infrequent detection errors. However, there are two distinct periods in which the drift can be explained

[2] Unlike the I-880 Field Experiment, the BHL provides 24 hour a day coverage but lacks functional ramp detectors.

readily. First, at 9:35 a sharp spike is evident and is due to a brief error in the vehicle reidentification algorithm applied to lane 4 (the error is also evident in Figure 6A). Then, a broader spike is evident for approximately half an hour, centered on 10:15. This event is due to an extended period without any matched vehicles in lane 2 coincident with the upstream detector returning to free flow conditions, as shown in Figure 6B. As discussed in Coifman (forthcoming), the free flow vehicle reidentification algorithm can continue matching vehicles after the onset of congestion and into the range of the congestion algorithm. However, once a link becomes completely congested, the free flow algorithm does not resume matching vehicles until the entire link returns to free flow conditions. So as seen here, when a queue recedes over a link, travel times may leave the effective range of the congestion algorithm before they return to the range of the free flow algorithm and lead to a brief period without any matches from either algorithm. As discussed in the next section, the broader spike is simply due to a lack of information from one of the lanes and does not represent an inflow estimation error.

4. IMPACTS OF TEMPORAL GAPS IN VEHICLE REIDENTIFICATION

Changes in density do not impact the inflow measurements in a single lane because inflow is the difference in offset since the last match in that lane. Lane inflow and changes in offset do not depend on q, k or v. But changes in density can impact the instantaneous net inflow summed across all lanes. Lane inflow can only be measured when a vehicle is reidentified and as shown at 10:15 in lane 2 of Figure 6A, time between matches in a lane can occasionally be large. During these gaps, vehicles may leave (enter) the lane and be reflected in the inflow (outflow) from adjacent lanes. Summing across all lanes during one of these large gaps will capture the vehicles that enter (leave) the other lanes without including corresponding impact of those vehicles when they leave (enter) the subject lane with a large temporal gap in vehicle reidentification, e.g., the broader spike in Figure 6D. The impact of these maneuvers in the subject lane can not be quantified until another vehicle is reidentified in that lane, at which point the gap in reidentification will no longer impact the net inflow across all lanes. Similarly, if adjacent lanes have significantly different travel times, the resulting inflow (outflow) from one lane may be observed at the downstream station before the corresponding outflow (inflow) from the other.

The temporal gaps in reidentification also complicate the task of estimating the instantaneous net density across all lanes. Equations 1 and 2 can only be applied when a vehicle is reidentified, and it is unlikely that this will occur in all lanes simultaneously. Given a sufficiently accurate travel time estimation methodology, however, the density estimation equations can be extended to apply in cases without vehicle reidentification. For example, Coifman (2002) presents an algorithm to estimate travel time using data from a single detector station and one could apply these equations with the modification that t_1 is estimated in Equation 1 and t_2 is estimated in Equation 2. This extension allows density estimation in all lanes at the same instant.

5. CONCLUSIONS

This paper presents a methodology to estimate density and lane inflow on a freeway segment between two detector stations. The work uses vehicle arrival times at each detector station and information about a small percentage of the vehicles from a vehicle reidentification system. The methodology does not need a high frequency of matches, just accurate ones. For those vehicles that are reidentified, their travel time is simply the difference between their arrival times at each station. Although the methodology is based on the basic principle of conservation of vehicles, it is the measured travel time that allows for density estimation and upstream offset that allows for lane inflow measurement. Equations 1-2 provide two independent density estimates assuming the inflow is near zero; the redundancy between the estimates can be used to identify periods in which their accuracy may be reduced due to lane change maneuvers. For the example presented herein, the two estimates were within seven percent of one another on average, with a few transients out to 30 percent. These differences are due to non-zero inflow. Equation 5 shows the inflow measurement and it was applied to each lane independent of the other lanes. In the one example, over 20,000 vehicles passed during a three hour period and the net inflow summed across all lanes was within two percent of the on-ramp flow that entered the link during the same period. As expected by conservation of vehicles, the net inflow was very close to the ramp flow. In the second example there were no ramps, over 100,000 vehicles passed during 24 hours and the net inflow summed over all lanes did not drift by more than 20 vehicles.

The paper has shown that it is possible to capture the net effect of vehicle maneuvers in space using loop detectors at fixed points. The new measurements have many potential applications. For example, although the inflow only captures the difference between the number of vehicles to enter and leave a lane, it can be used to verify and calibrate earlier lane changing models by calculating the inflow or lane flux that would arise from the model. Other examples include real time incident detection and off line correlation between accident frequency and lane inflow. The measures can also be used to verify the performance of detectors, any unexplained drift in inflow would likely be due to faulty detectors. The reader should be cautioned though, the fundamental equation, $q=kv$, does not hold unless care is taken to estimate q and k over the same region of the time-space plane, e.g., Edie (1963). Finally, although the methodology was demonstrated using loop detectors, it is potentially applicable to other detector technologies as well.

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8. TABLE CAPTIONS

Table 1 Vehicle statistics for the three hour long I-880 lane inflow example in Figure 5.

Table 2 Vehicle statistics for the 24 hour long I-80 lane inflow example in Figure 6.

Table 3 Transient periods of high lane inflow in lanes 2 and 5 from Figure 6.

9. FIGURE CAPTIONS

Figure 1, A sample showing the downstream vehicle number and offset for reidentified vehicles.

Figure 2, An example illustrating the two density estimates that are available after reidentifying a vehicle. In this example the matched vehicle is shown as number zero at both stations.

Figure 3, Density estimated from automated vehicle reidentification compared against those from manual reidentification (A) using upstream arrivals, (B) using downstream arrivals, (C) comparing upstream and downstream manual estimates.

Figure 4, A hypothetical example showing two true but unknown vehicle trajectories for matched vehicles in a single lane and many other unmatched vehicles in the same lane.

Figure 5, (A) Estimated lane inflow between two detector stations (inset) 1500 ft apart, (B) comparing the net lane inflow across all lanes to on-ramp arrivals, (C) difference between curves in part B, (D) 30 sec average velocity by lane during study period.

Figure 6, (A) Estimated lane inflow between two detector stations (inset) 1800 ft apart during 24 hrs, (B) five min average velocity by upstream lane, (C) five min average velocity by downstream lane, (D) change in net lane inflow across all lanes during the day.

Table 1 Vehicle statistics for the three hour long I-880 lane inflow example in Figure 5.

	lane 1	lane 2	lane 3	lane 4	lane 5	total
Number of vehicles	2,052	5,593	4,298	4,210	3,885	20,038
Number of matched vehicles	203	439	611	554	342	2,149
Percent of vehicles matched	9.9	7.9	14.2	13.2	8.8	10.7
Net inflow	55	18	26	405	856	1,360
Inflow as percent of flow	2.7	0.3	0.6	9.6	22.0	6.8

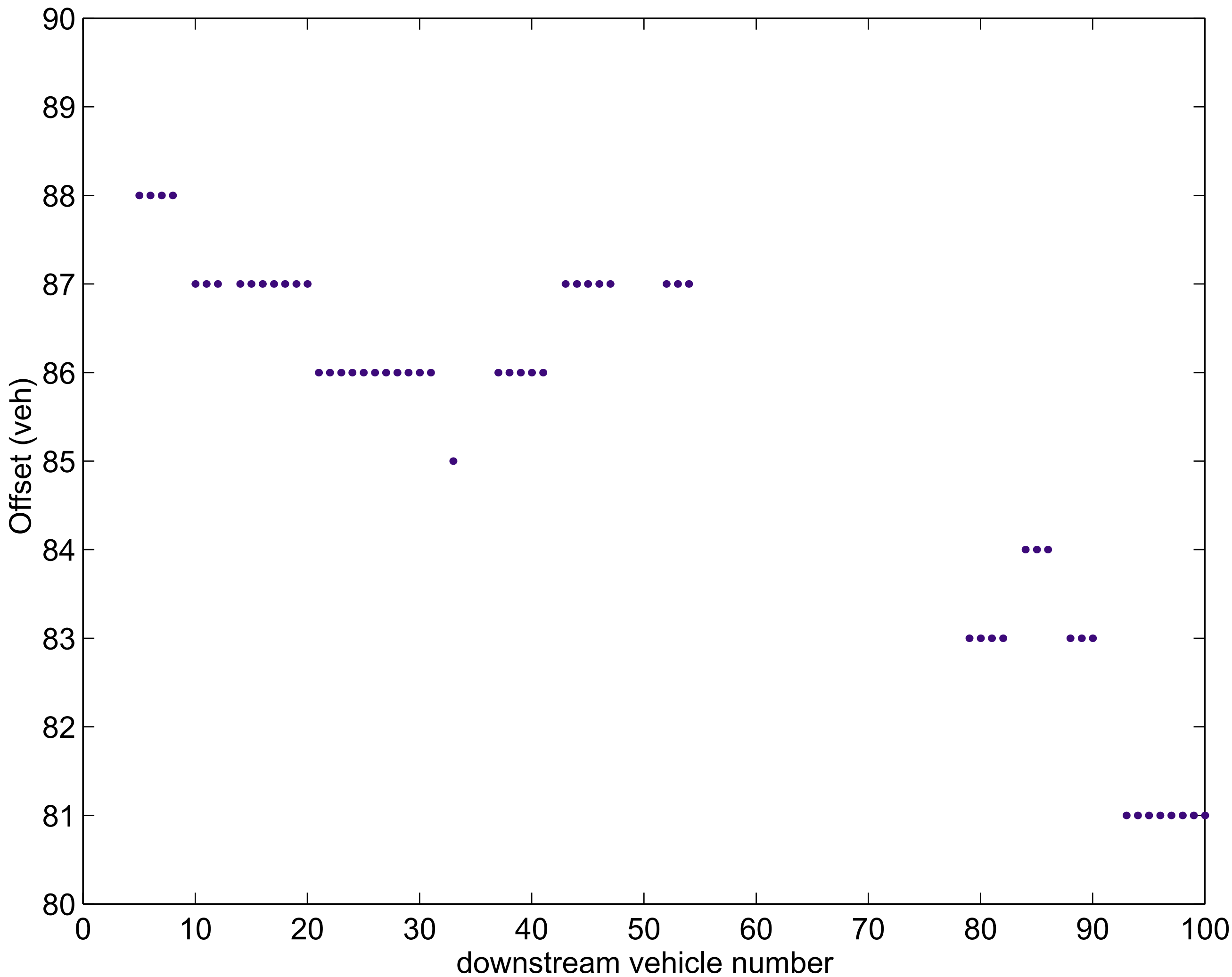
Table 2 Vehicle statistics for the 24 hour long I-80 lane inflow example in Figure 6.

	lane 1	lane 2	lane 3	lane 4	lane 5	total
Number of vehicles	16,256	27,268	23,312	24,596	25,173	116,605
Number of matched vehicles	2,968	3,904	5,136	4,496	4,854	21,358
Percent of vehicles matched	18.3	14.3	22.0	18.3	19.3	18.3
Net inflow	584	-891	-979	-415	1,708	7
Inflow as percent of flow	3.6	-3.3	-4.2	-1.7	6.8	0.0

Table 3 Transient periods of high lane inflow in lanes 2 and 5 from Figure 6.

	Lane 2			Lane 5		
Approximate time of day (hr)	inflow (veh)	duration (hr)	lane flux per mile (veh/hr/mi)	inflow (veh)	duration (hr)	lane flux per mile (veh/hr/mi)
10:00	-170	0.6	-830	100	0.2	1,467
15:00	-240	0.8	-880	250	0.8	917
17:20	-130	0.5	-762	150	0.4	1,100

Figure 1, A sample showing the downstream vehicle number and offset for reidentified vehicles.



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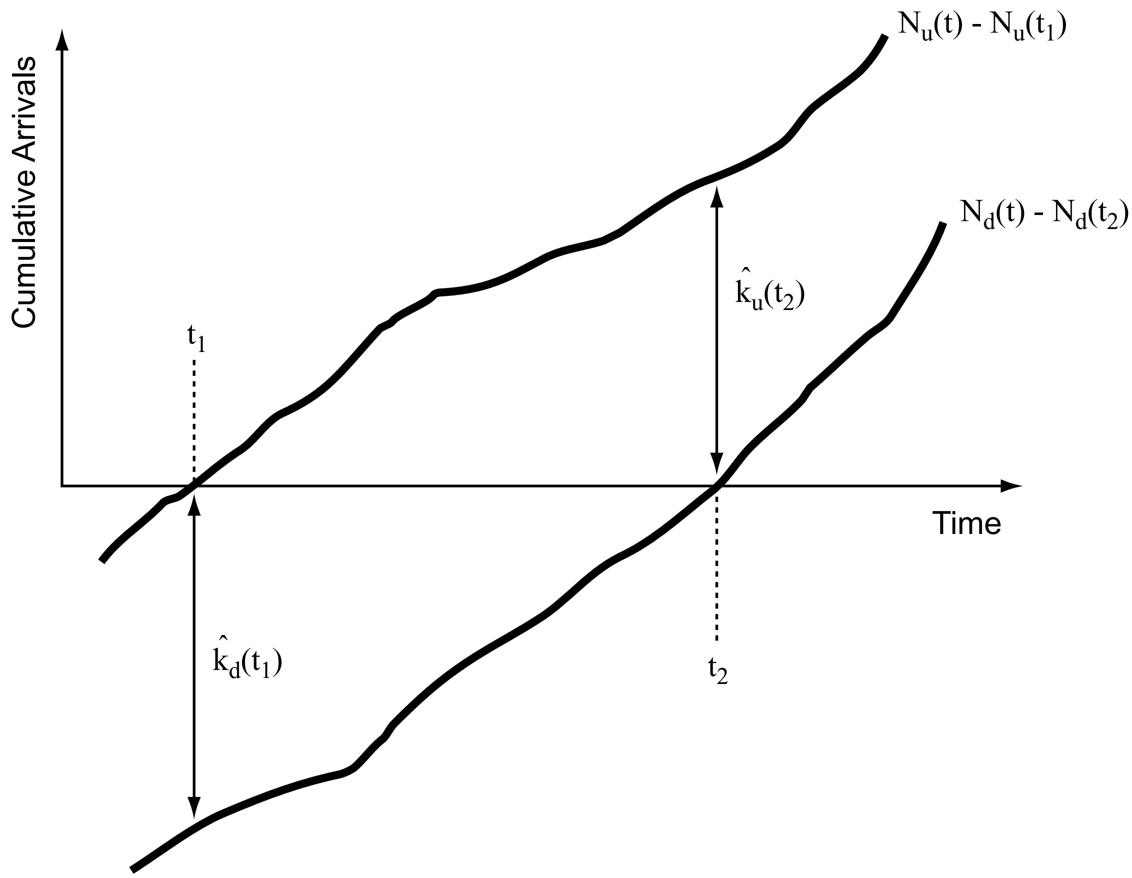

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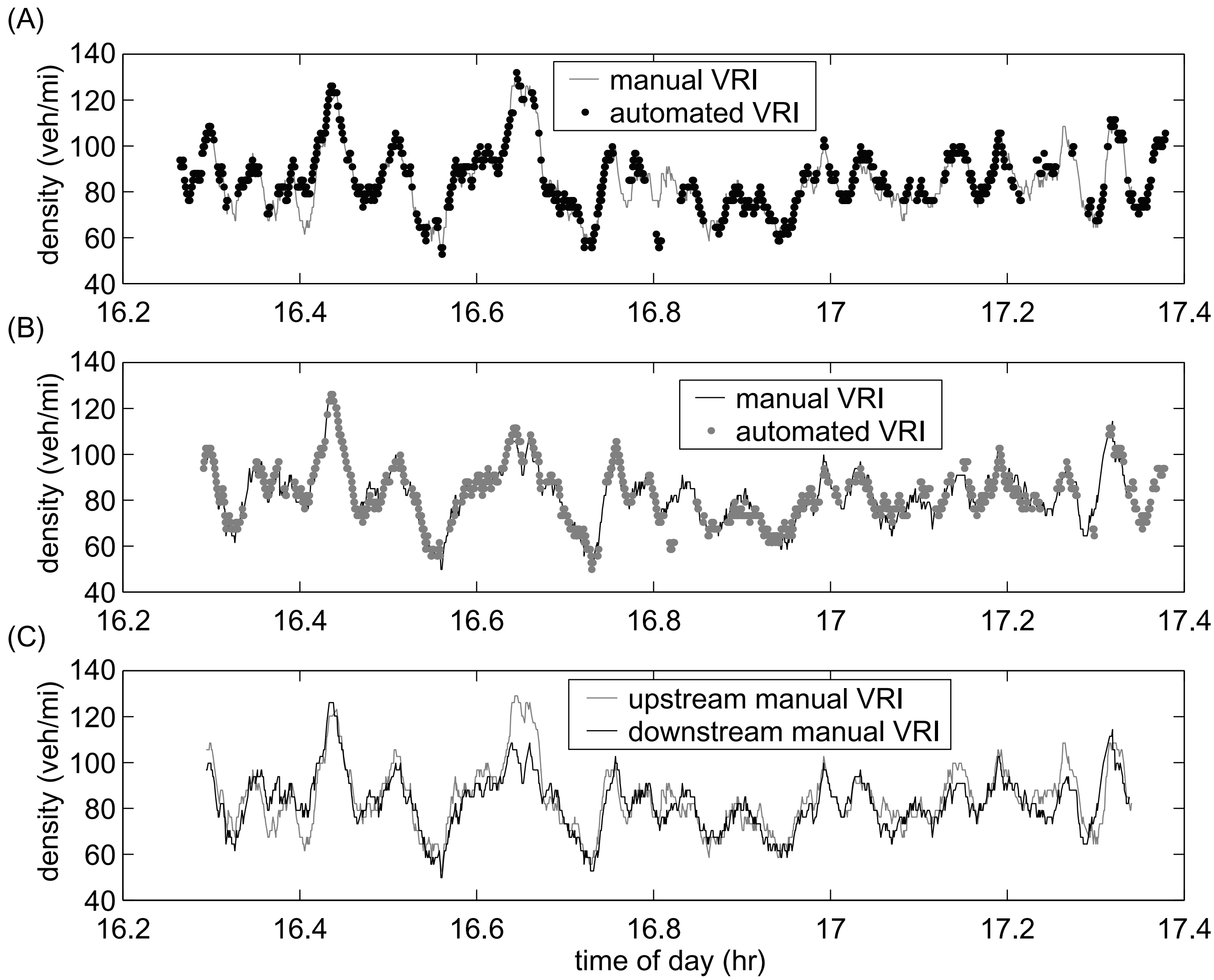

Figure 4, A hypothetical example showing two true but unknown vehicle trajectories for matched vehicles in a single lane and many other unmatched vehicles in the same lane.

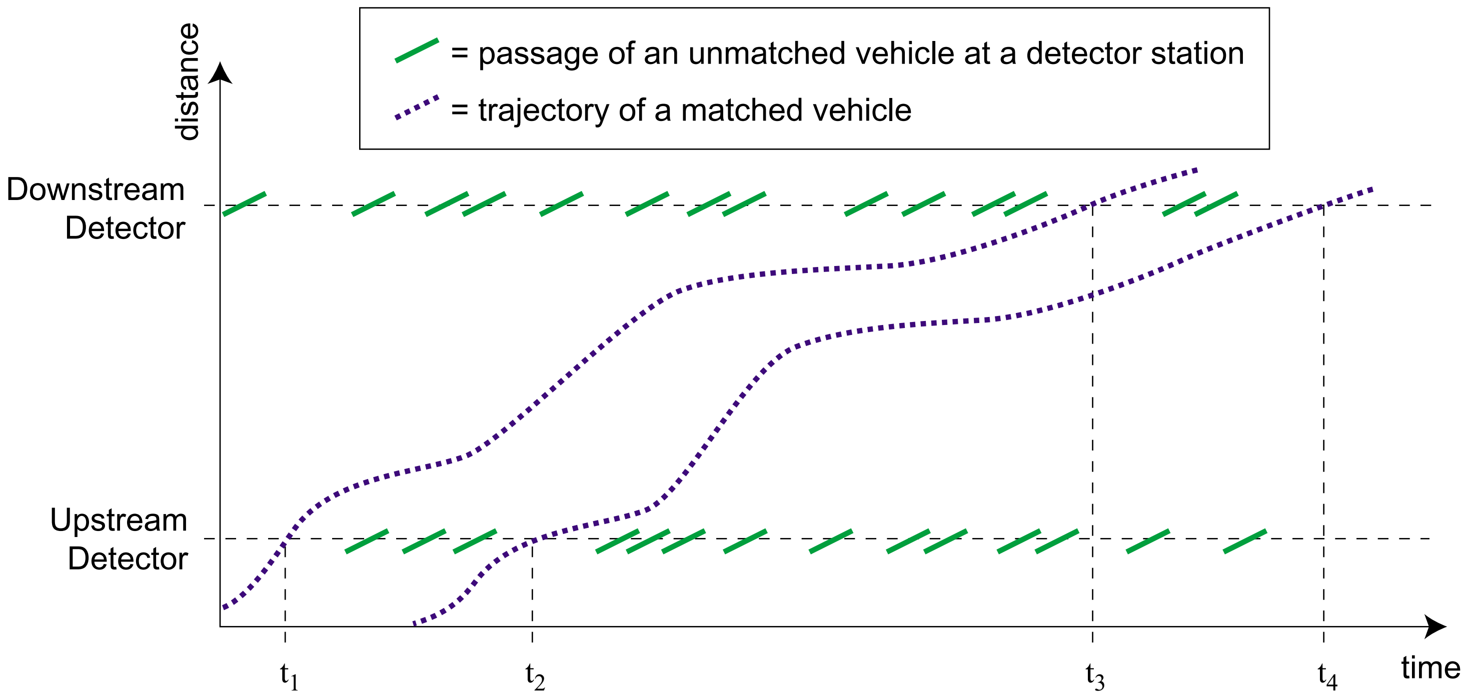

Figure 5, (A) Estimated lane inflow between two detector stations (inset) 1500 ft apart, (B) comparing the net lane inflow across all lanes to on-ramp arrivals, (C) difference between curves in part B, (D) 30 sec average velocity by lane during study period.

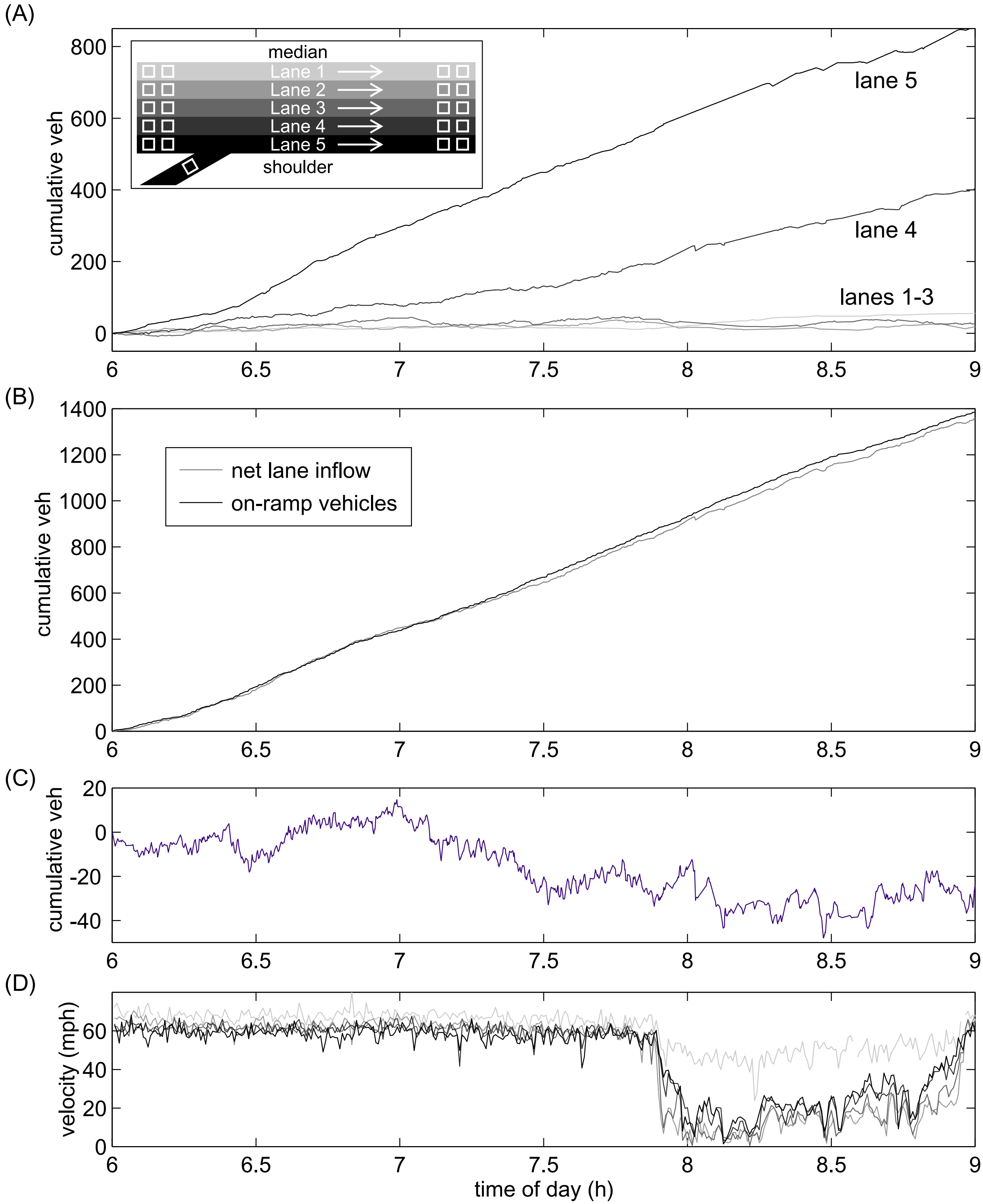

Figure 6, (A) Estimated lane inflow between two detector stations (inset) 1800 ft apart during 24 hrs, (B) five min average velocity by upstream lane, (C) five min average velocity by downstream lane, (D) change in net lane inflow across all lanes during the day.