Vehicle Reidentification and Travel Time Measurement on Congested Freeways

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ABSTRACT

The paper presents an algorithm for matching individual vehicles measured at a freeway detector with the vehicles' corresponding measurements taken earlier at another detector located upstream. Although this algorithm is potentially compatible with many vehicle detector technologies, the paper illustrates the method using existing dual-loop-detectors to measure vehicle lengths. This detector technology has seen widespread deployment for velocity measurement. Since the detectors were not developed to measure vehicle length, these measurements can include significant errors. To overcome this problem, the algorithm exploits drivers' tendencies to retain their positions within dense platoons. The otherwise complicated task of vehicle reidentification is carried-out by matching these platoons rather than individual vehicles. Of course once a vehicle has been matched across neighboring detector stations, the difference in its arrival time at each station defines the vehicle's travel time on the intervening segment.

Findings from an application of the algorithm over a 1/3 mile long segment are presented herein and they indicate that a sufficient number of vehicles can be matched for the purpose of traffic surveillance. As such, the algorithm extracts travel time data without requiring the deployment of new detector technologies. In addition to the immediate impacts on traffic monitoring, the work provides a means to quantify the potential benefits of emerging detector technologies that promise to extract more detailed information from individual vehicles.

Keywords: traffic surveillance, loop detectors, travel time measurement, vehicle reidentification

INTRODUCTION

This paper presents a vehicle reidentification algorithm for consecutive detector stations on a freeway, whereby a vehicle measurement made at a downstream detector station is matched with the vehicle's corresponding measurement at an upstream station. The work should be applicable to any detector technology capable of extracting a reproducible vehicle measurement, or *vehicle signature*. For the present research, the algorithm uses the effective vehicle lengths measured by conventional dual-loop-detectors.[1] As such, the algorithm can be deployed without requiring new detector hardware. The length measurements, however, may only be accurate to two feet (or worse) due to the resolution limitations of dual-loop-detector data.

For a given vehicle measurement at the downstream detector station, the algorithm uses arrival times and number of arrivals at the detector to identify the set of all upstream observations in the same lane that could have come from the same vehicle. The measurement resolution makes it difficult to identify which one of these measurements, if any of them, correspond to the downstream vehicle. To address this limitation, the algorithm takes the difference between the downstream measurement and each of the upstream measurements. It then identifies all pairs whose difference exceeds the measurement accuracy. These measurements presumably could not have come from the same vehicle, while all remaining pair-wise comparisons are treated as possible matches. Of course, with this simple test, the downstream vehicle will likely have many possible matches within the set. We term the collection of incorrect matches as false positives. Toward eliminating the false positives, the algorithm uses a remarkably simple yet very effective technique: it matches platooned vehicles whenever these pass both the upstream and downstream detector stations without altering their relative sequence. The sequence of a platoon's vehicle lengths provides more information than do the individual measurements, as is demonstrated herein.

For reasons that will be discussed in this paper, the accuracy of a dual-loop-detector's vehicle length measurement improves as vehicle velocity decreases. Consequently, for the existing detectors, the algorithm is limited to matching vehicles during congested traffic conditions, i.e., when the local velocity measured by the detectors is less than 45 mph at one or both of the stations. This limitation is not problematic, since freely flowing traffic is characterized by relatively constant velocities and thus, travel times can be estimated from the local conditions at the detector stations. If warranted, improved measurement accuracy could likely be achieved by deploying the algorithm

[1] The effective vehicle length is the length as "seen" by the detectors; i.e., the sum of the physical vehicle length and the length of the detection zone. Also note that dual-loop-detectors are quite common, often placed at half mile spacings or less on urban freeways.

with more sophisticated vehicle detector technologies, such as machine vision. Alternatively, Coifman (2001b) presents an algorithm for measuring travel time from dual-loop-detectors during free flow traffic conditions.

The travel time data recorded from the algorithm have a number of potential applications. For example, these data might improve traffic management tasks such as automatic incident detection, adaptive freeway ramp control, and traveler information systems. The data might also be used for routing vehicles over a network so as to reduce traveler delay, for calibrating traffic planning and simulation models, and for quantifying the potential benefits of emerging detector technologies that extract more detailed information from individual vehicles. Further discussion on potential applications can be found in Coifman (1998a).

The following section provides a brief review of previous work related to automatic vehicle reidentification and in emerging technologies that might enhance this task. Next, the vehicle reidentification algorithm is presented in detail, using field-measured freeway data to illustrate the various steps. The paper closes with a brief discussion regarding possible future work in this area.

PREVIOUS RESEARCH

Although at present, the proposed algorithm is used to match length measurements made by conventional dual-loop-detectors, the algorithm could be applied to vehicle signatures from other detector technologies. By providing improved measurement accuracy, these technologies might be used with our algorithm for improving the reidentification process. Examples of such signatures and their associated technologies include (1) inductive vehicle signatures collected from loop detectors using new sensor hardware (e.g., Kühne et al., 1997); (2) visual vehicle signatures from wayside cameras (e.g., MacCarley, 1998); (3) vehicle dimensions from laser based detectors (e.g., Larson et al., 1998). Notably, some of the above technologies have been designed to measure vehicle dimensions, such as length, with an error less than one inch even when the vehicles are traveling at free flow speeds.

These new detector technologies have been expressly developed for vehicle reidentification applications. Likewise, several algorithms have been proposed for measuring travel time directly using the improved vehicle signatures (e.g., Reijmers, 1979, Pfannerstill, 1984, Kühne and Immes, 1993, Huang and Russell, 1997). The implementation of the aforementioned algorithms, however, requires the deployment of new detector hardware, even before the benefits of measuring travel time can be quantified. Consequently, most installations of these systems have been limited to small test sites.

Of course, automatic vehicle identification (AVI) systems that rely on machine readable identification tags have also been deployed (e.g., Levine and McCasland, 1994, Balke et al., 1995, Cui and Huang, 1997). These systems provide reliable travel time measurements. However, the systems could potentially compromise personal privacy. Furthermore, the AVI systems do not monitor local conditions at the detector stations (such as flow, velocity and occupancy), this omission can impact traffic surveillance and control.

Other surveillance systems have been proposed for estimating vehicle travel time from aggregate traffic parameters like occupancy (e.g., Dailey, 1993, Petty et al., 1997). Although promising for free flow and lightly congested conditions, these systems currently perform poorly under heavy congestion. Another approach for estimating travel time is to match vehicles simply based on the cumulative arrivals at successive detector stations, i.e., the n-th vehicle at one station is matched to the n-th vehicle at the next station (e.g., Westerman and Immers, 1992, Westerman et al., 1996). To counter detector drift between stations, these systems use aggregate measurements to recalibrate during free flow conditions. Unfortunately, congestion can last several hours, leading to significant measurement drift between recalibrations. Finally, the vehicle reidentification algorithm discussed in this paper is an extension of simpler algorithms previously presented in Coifman (1998b).

THE PROPOSED ALGORITHM

The vehicle reidentification algorithm is described here via its application; i.e., it is applied to traffic data measured at two neighboring dual-loop-detector stations in a single travel lane along eastbound Interstate 80 in Berkeley, California. The site is shown in Figure 1. Video data were collected at each station and all vehicles that passed during the study period were visually matched between the two locations. Thus, the travel times extracted by the algorithm could be verified. Over 1,300 vehicles passed both stations in the subject lane during the videotaping, while another 200 vehicles entered or exited the subject lane between the stations.

We begin this section by briefly reviewing how a dual-loop-detector can be used to measure vehicle lengths. To this end, Figure 2A shows a time-space diagram depicting a vehicle passing over a dual-loop-detector. The controller normally records four transitions, i.e., the turn-on and turn-off times at each of the loops, as shown in Figure 2B. Occasionally a vehicle will change lanes over the dual-loop-detector or one of the loops malfunctions. In the event of such a detection error, only one loop will record the vehicle. These events are identified and discarded following the method presented in Coifman (1998a). To the algorithm, any discarded vehicle will simply appear to be a vehicle that entered or exited the lane between the stations. The algorithm addresses these *phantom lane change maneuvers* in the same fashion that it addresses actual lane change maneuvers, as presented in a subsequent section.

After accounting for detection errors, the following parameters are calculated for each vehicle: dual loop traversal time via the rising edges, TT_r, dual loop traversal time via the falling edges, TT_f, total on-time at the first loop, OT_1, and total on-time at the second loop, OT_2, as shown in Figure 2A. Obviously, the loop separation (20 ft in this case) divided by the traversal time yields the vehicle velocity. It is clear from Figure 2A that two measurements are available for the effective vehicle length,

$$\text{length measurement \#1:} \quad L_1 = 20 \cdot \frac{OT_1}{TT_r} \quad [\text{ft}] \tag{1}$$

$$\text{length measurement \#2:} \quad L_2 = 20 \cdot \frac{OT_2}{TT_f} \quad [\text{ft}]$$

and the algorithm uses the average of the two. Although the figure shows an example of a vehicle shorter than 20 ft, $off_1 < on_2$, Equation 1 also holds for longer vehicles, $off_1 > on_2$.

Notably, the controller samples the loops at 60 Hz, so at best, the traversal times and on-times in Equation 1 are accurate to 1/60 sec. To capture this resolution constraint, the measurement uncertainty is defined as the range spanned by L_1 and L_2 after including ±1/60 sec in OT_1, OT_2, TT_r and TT_f. By inspection of Equation 1 and Figure 2A, this measurement uncertainty range is inversely proportional both to velocity and to the true vehicle length. Misdetections will impact the calculation, e.g., if one of the on-times was too short due to a detection error. Depending on the severity, such errors might not impact the algorithm, but if they do, they will simply appear to be phantom lane change maneuvers. To ensure the accuracy of OT_1, OT_2, TT_r and TT_f, any hardware problems at each station, such as cross talk between detectors, were identified using Coifman (1999) and corrected.

Vehicle Arrival Numbers and Possible Matches

First, in the subject lane, vehicles are assigned consecutive arrival numbers as they pass each detector station and these numbers are assigned independently at each station. Next, a *set of feasible upstream measurements* is identified for each vehicle measured downstream. Assuming that the downstream vehicle did not change lanes between detector stations, the set should be chosen to ensure the true match for the vehicle falls within the set while not being so large as to preclude a computer from processing the data. For this paper, the set was defined as the most recent 100 measurements at the upstream detector prior to the downstream measurements. The size was chosen somewhat arbitrarily but subsequently verified to be adequate. In practice, a conservative set size could be estimated from the subject lane's jam density storage between the two detector stations.

Because a given vehicle length is not unique and because of the aforementioned measurement errors caused by the detector, it is not possible to match directly upstream and downstream measurements. To illustrate this point, Figure 3A shows a sequence of upstream length measurements with dark rectangles. The measurements are plotted in the order that the vehicles were observed at the upstream station. The vehicle lengths corresponding to each data point are shown by their positions along the ordinate, including the measurement uncertainty. For simplicity all of the vehicles are shown with the same uncertainty, but in practice, the range depends on the measurements and it varies from one vehicle to the next.

A single measurement made at the downstream station, along with its measurement uncertainty, is superimposed as a long, lightly shaded rectangle on Figure 3A. One observes a number of measurements from the upstream station that might correspond to the vehicle measured downstream; i.e., a number of lengths measured among the former coincide with the latter. These possible matches are indicated with open circles in Figure 3B. The algorithm eliminates from further consideration the upstream measurements that do not coincide with the downstream one.

Possible Matches and Sequences

A sequence of measured vehicle lengths (e.g., from a platoon) rapidly becomes distinct and the sequences measured at an upstream detector station can often be reidentified at a downstream station. Thus, the algorithm searches for sequences of measured vehicle lengths in the subject lane that exhibit strong correlation across the two detector stations. Since lane changes and measurement errors disrupt the sequences, the algorithm is specifically designed to match vehicles between these disruptions, as described below.

For each downstream measurement, the algorithm applies the resolution test illustrated in Figure 3 over the *set of feasible upstream measurements*, as defined above. The possible matches are stored in matrix format. Figure 4, for example, shows the possible matches for 100 vehicles measured at the downstream detector; these data were taken from the aforementioned sample of nearly 1,500 vehicles with corresponding video ground truth. The dots indicate possible matches and each row in Figure 4 represents the outcome from one resolution test. Note that the columns are indexed by the difference between the arrival numbers assigned to vehicles at the upstream and downstream detector stations. It is clear that numerous possible matches resulted from each resolution test since each vehicle can only have, at most, one true match.

The algorithm then proceeds through this matrix with the ultimate goal of selecting a set of final matches. If the algorithm is successful, the final matches will correspond to the true and correct matches for the downstream vehicles. In selecting the final match from the often large collection of possible matches, the algorithm exploits the fact that consecutive vehicles will often maintain their relative order within a platoon for long distances, (Windover, 1998). As such, the true but unknown matches will often reveal themselves as relatively long sequences of possible matches that appear in neighboring rows along the same column. To this end, the algorithm identifies all sequences of two or more possible matches in the matrix, as exemplified in Figure 5.

Empirical Evidence

We briefly consider all 1,500 vehicles in the sample to provide empirical motivation for the preceding steps. Calculating the number of possible matches divided by the number of pair-wise comparisons for each row, Figure 6A shows the cumulative distribution of the percentage of possible matches for all 1,500 vehicles. From this figure, it is clear, for example, that the frequency of false positives is less than 50 percent for seven out of 10 vehicles in this set. Because the algorithm looks for sequences, even the vehicles with a high frequency of false positives in Figure 6A are informative since the unlikely elements (i.e., the non-positive results) can break false sequences.

Next, using the true matches from the concurrent video, the solid line in Figure 6B shows the distribution of sequence lengths as measured by the algorithm for the true matches and the dashed line shows the distribution for all of the other possible matches, i.e., the false positives. The true sequences are, on average, over seven vehicles long, while the false sequences are, on average, about two vehicles long for this data set. The few long sequences of false positives are typically due to vehicles with common lengths and these sequences usually occur when there is a longer sequence of true matches.

Lane Changes and Disruptions

As previously noted, the algorithm is specifically designed to match vehicles between disruptions caused by lane changes and missed vehicle detections. After finding sequences of possible matches, the algorithm then searches for commonplace disruptions between the sequences to continue matching in the presence of these disturbances. Figures 7A-C show the specific disturbances searched for. Figure 7A illustrates the effects of a single vehicle exiting the lane between the two stations or not being detected at the downstream station. This vehicle would have been observed downstream between vehicles m-1 and m. In Figure 7B, a single vehicle, m-1, enters the lane between the two stations or is not detected at the upstream station. Finally, in Figure 7C, either one vehicle enters and another exits the lane between stations or the vehicle length is measured incorrectly at one of the stations for the pair-wise comparison in the center of the matrix.

For each new sequence of possible matches, the algorithm checks to see if it can be linked to an earlier sequence (i.e., a sequence starting with a lower vehicle number) via one of these disturbances. The procedure is demonstrated using the sequence starting with element (m,n) in Figure 7D. The algorithm checks to see if there are any earlier sequences passing through one of the three shaded elements, where each element corresponds to one of the disturbances in Figures 7A-C. When a possible disturbance occurs, the algorithm joins the two sequences in a *modified sequence*. A *modified sequence* contains at most two distinct sequences and the definition is necessary because the subject sequence starting at (m,n) may be joined to a later sequence without regard for the possible disturbances considered here. When the algorithm creates a *modified sequence,* it simultaneously subtracts one vehicle from the total number of possible matches in the *modified sequence*; as described shortly, this penalty influences how the algorithm selects the final matches.

By following the above logic, situations will arise whereby a particular sequence might be joined with more than one earlier sequence. In Figure 7E, for example, there are two possible disturbances that may have preceded the first possible match in the sequence starting at (m,n). In this hypothetical instance, the algorithm joins the two adjacent sequences in the manner shown in Figure 7F, since this union yields a *modified sequence* with the largest number of possible matches. Note that this union does not include the last two possible matches from the earlier sequence. The exact choice of when the disturbance occurred is based on convenience, since in this case, it is impossible to determine from the matrix whether the disturbance occurred as shown or after either of the two excluded matches.

At this juncture, a given possible match will be included in a sequence and it may be included in many *modified sequences*. The algorithm will select the longest *modified sequence* (or sequence) from this set and store the sequence's length in a new matrix with the indices corresponding to the pair-wise comparison. The algorithm uses the elements in this new matrix to eliminate many of the possible matches previously defined as false positives. For each row, the algorithm retains the element corresponding to the maximum value and discards all other possible matches in the row. The longest sequence containing the given downstream vehicle is thus retained. If more than one element contains the maximum, then the algorithm will discard all of the possible matches for that row. The remaining possible matches will henceforth be referred to as matches. Continuing the example from Figure 5, after applying the preceding steps to the 100 vehicles, the resulting matches are shown in Figure 8. Note how most matches fall near the same column in this plot. Those matches far from column 80 in this plot are likely false positives that still remain. Extending to the entire set of 1,500 vehicles with ground truth, the algorithm found a match for about 90 percent of the vehicles, which includes false positives that have not been eliminated yet. The corresponding travel times for the matches are shown in Figure 9. Clearly, some of the matches are due to false positives simply because the very large discontinuities between successive travel time measurements are not feasible.

Cleanup

To eliminate additional false positives, the algorithm follows three steps to "cleanup" the matches, as follows. The first step addresses the fact that a vehicle measured at the upstream station might be matched to multiple vehicles measured at the downstream station. As shown in Figure 10, the matches for an upstream vehicle fall on a diagonal at 45 degrees in the chosen coordinate system. It may take several minutes to observe all of the matches for a given upstream vehicle. Rather than waiting to observe the outcomes from all of the resolution tests, the algorithm uses as much information as possible immediately after identifying a match for a downstream vehicle. For the match at (m,n) in Figure 10, the match is discarded if its sequence length is less than that of an earlier match for the same upstream vehicle. Since the algorithm runs in real time, it can not consider the outcomes from subsequent downstream vehicles. So the upstream vehicle may still be matched to multiple downstream vehicles, but the later matches (with respect to downstream vehicle number) are stronger than any earlier ones.

Next, if several successive downstream vehicle measurements have a high frequency of false positives from the resolution test, there is a chance that the algorithm will select an incorrect sequence for these vehicles. In other words, the matrix previously shown in Figure 4 may not be very informative during these periods. The second step of the cleanup process recognizes that when the algorithm will select an incorrect sequence, its location will be uniformly distributed across the columns. Now recall the fact that for a given downstream vehicle the most recent upstream vehicle bounds the *set of feasible upstream matches* on the right hand side of the row. Several vehicles (and potentially a false positive associated with one of these vehicles) can usually be eliminated from the right hand side of this set simply because they would have to travel at excessive speeds to be a true match. For the current implementation, the algorithm discards any match that would require a link velocity in excess of 85 mph.

In the third step, the assumption that lane change maneuvers and missed vehicle detections are relatively infrequent is maintained. As such, a sequence of true but unknown matches in one column is presumed to be preceded by other sequences of true matches in nearby columns. To this end, the algorithm identifies *consecutive sequences* of matches, each consisting of all consecutive downstream vehicles whose matches have the same upstream offset. This calculation is necessary because the first two steps in the cleanup will likely disrupt the earlier sequences. The algorithm then compares the upstream offset of a given *consecutive sequence* against that of the preceding eight *consecutive sequences*. If at least three of these comparisons are within ±5 columns and the current *consecutive sequence* is more than one vehicle long, the matches in the *consecutive sequence* are retained as final matches. In any event, the *consecutive sequence* is kept for later comparisons at this step.

Results

After applying the cleanup steps to the entire set of 1,500 vehicles, approximately 25 percent of the matches were eliminated. Table 1 shows the number of matches retained after each step while the X's in Figure 11A indicate the travel times from the final matches. Superimposing the travel times from the ground truth matches, it is clear that the algorithm performed quite well. The algorithm followed the increasing and decreasing travel times as disturbances passed through the link, while the local velocity measured at the detector stations ranged between 0 and 40 mph. The algorithm matched approximately 65 percent of the vehicles that passed the upstream site. One false platoon of 12 vehicles and four false positives[2] remained, yielding an error rate of 1.6 percent for this example. It is important to note that the algorithm recovered after making these errors. Finally, the time between successive matches was typically on the order of a few seconds, as shown in Figure 11B, with 1.3 minutes being the longest period without a reidentification.

A LARGER EXAMPLE

No effort was made in this algorithm to match vehicles that changed lane changes. One could treat each lane as an independent process and integrate the results from all lanes for a more robust indicator. An obvious extension to this work would be to look across all upstream lanes rather than a single lane. Nonetheless, as demonstrated in this paper, the algorithm works using data from a single lane.

[2] These false positives fell at the start or end of sequences consisting mostly of true matches.

Figure 12 shows an example of vehicle reidentification over a much larger set. In this case, the algorithm was applied to all five lanes over an 1,800 foot segment of westbound Interstate 80 in Berkeley, California. The resulting travel times for matched vehicles are shown with dark points and the three hours shown in the figure include the onset of the morning peak. The algorithm matched between 40 and 55 percent of the passing vehicles in each lane during this period, even though the sample includes many free flow vehicles. Between 7:00 and 9:00, the most congested period, the algorithm found a match for 61 percent of the vehicles. Following Caltrans convention, the lanes are numbered from the inside out, and lane one is a high occupancy vehicle (HOV) lane.

The process of manually generating ground truth data would be prohibitively labor intensive for the 25,000 vehicles in this sample. Coifman (2001a) presents a methodology to estimate link travel times using data from a single detector station. Applying the estimation technique using data from the upstream detector, and then repeating the estimation using data from the downstream detector, yields the two lines in each of the plots. Except for a few transient errors, the pair of estimates bound the measured travel times in each of the lanes as disturbances propagate through the link. Unlike the measurement algorithm presented in this paper, the estimation technique can not accurately capture changes in travel time due to delay causing events within the link. Using the two procedures in conjunction, significant deviations between the two methods should be indicative of an incident or a recurring bottleneck within the link.

CONCLUSIONS

This paper has presented a new algorithm to match a vehicle's length measurement at a downstream detector station with that vehicle's corresponding measurement at an upstream station. The algorithm rules out unlikely matches, looks for sequences of possible matches between measurements at the two stations and then eliminates unlikely sequences of these matches.

The beauty of the approach is in its simplicity. Matching vehicles between detector stations is a difficult task. Preceding research efforts emphasized computationally intensive and/or hardware intensive strategies. By creating the solution space of possible matches, the algorithm facilitates vehicle reidentification using existing detector hardware and inexpensive computers. It is left to future research to determine the optimal parameters for the algorithm, as well as the relationship between station spacing and algorithm performance. To this end, work is underway to develop the Berkeley Highway Laboratory (BHL), which includes eight dual-loop-detector stations and machine vision vehicle tracking tools to ease the ground truth data collection (Coifman et al., 2000). The BHL already uses the algorithm presented above to measure travel time in real time.[3]

The contribution of this work to the field of traffic surveillance should prove to be significant since the vehicle reidentification algorithm will allow the study of travel time applications without deploying new hardware and thereby enable cost-benefit analysis before investing in a new detection system. If travel time measurement proves to be beneficial, the algorithm could be deployed using dual-loop-detectors[4], or it could be transferred to new detector technologies that have better measurement accuracy. The methodology should prove beneficial for research purposes as well; yielding better insight into vehicle dynamics between widely spaced detector stations without the host of assumptions necessary with simulation.

As illustrated in this paper, the algorithm will not match every vehicle; however, it will extract the trends exhibited by the majority of vehicles because the methodology matches platoons rather than individual vehicles. In this context, it is worth discussing the percentage of passing vehicles that must be matched for surveillance. For example, Origin-Destination studies would likely require near perfect performance from non-AVI vehicle reidentification systems. But travel time measurement is not as demanding, Van Aerde et al. (1993) estimated that matching 20 percent of the population is sufficient for such measurements while Holdener and Turner (1996) suggest that the percentage may even be smaller. Using dual-loop-detector data, the algorithm has already surpassed these guidelines for travel time measurement.

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

[4] It is worth noting that the additional hardware cost per station to deploy the algorithm across all lanes in the BHL is less than one percent of the cost to install a detector station for conventional traffic surveillance.

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FIGURE CAPTIONS

Figure 1, The segment of Interstate-80 in Berkeley, California used for this study.

Figure 2, One vehicle passing over a dual-loop-detector, (A) the two detection zones and the vehicle trajectory as shown in the time space plane. The height of the vehicle's trajectory reflects the non-zero vehicle length. (B) The associated turn-on and turn-off transitions at each detector.

Figure 3, (A) "Resolution test" between one downstream vehicle and a set of upstream vehicles. If the upstream measurement range does not intersect the downstream measurement range, the upstream vehicle can be dismissed as being an unlikely match for the downstream vehicle. (B) Everything that can not be eliminated are considered possible matches, as indicated with open circles. Note that each outcome is shown directly below the given comparison from part (A).

Figure 4, Consider a set of 100 downstream vehicles, applying the resolution test to each of these vehicles produces a set of possible matches, or one row in this matrix. Note that the columns are indexed by the upstream offset, so, if there were no lane changes in this coordinate system, all of the true matches would fall into a single column.

Figure 5, All sequences of two or more possible matches for the on-going example.

Figure 6, (A) The cumulative distribution of the percentage of possible matches for all 1495 downstream vehicles. (B) Using concurrent video to calculate the true matches, the solid line shows the cumulative distribution of sequence lengths measured by the algorithm for these matches. While the dashed line shows the cumulative distribution of sequence lengths for all other possible matches, i.e., the false positives.

Figure 7, A simple example illustrating the possible disruptions recognized by the Algorithm: (A) One vehicle exits the lane between stations or is not detected downstream, (B) One vehicle enters the lane between stations or is not detected upstream, (C) One vehicle enters and one vehicle exits the lane between stations or is measured incorrectly at one of the stations, (D) The search region for the sequence starting at element (m,n). (E) Three sample sequences, one in each column n-1 to n+1. (F) In this case, the sequence starting at (m,n) is joined via an entrance (part (B)) to a portion of an earlier sequence.

Figure 8, The resulting matches for the on-going example after allowing for lane changes. Each match corresponds to the longest modified sequence for the given downstream vehicle. Note how most matches fall near column 80 with small column shifts due to lane change maneuvers.

Figure 9, After applying the algorithm to 1495 vehicles, 1345 vehicles were matched by the algorithm. This figure shows the resulting travel times for the matches. Most of the travel times seem plausible; but clearly, there are a significant number of erroneous matches, manifest as random noise.

Figure 10, Each match is compared to any earlier matches for the upstream vehicle (i.e., the diagonal line for the match at (m,n)). The match is discarded if its sequence length is less than that of an earlier match for the same upstream vehicle. The comparison does not consider matches from later downstream vehicles since the algorithm runs in real time.

Figure 11, (A) Compare the travel times for the 1008 final matches against those from the ground truth matches. (B) The time between successive final matches.

Figure 12, A comparison between measured travel times and estimated travel times for three hours, across five lanes, over an 1,800 ft segment.

TABLE CAPTIONS

Table 1, Number of matches after each cleanup step for the on-going example.

Figure 1, The segment of Interstate-80 in Berkeley, California used for this study.

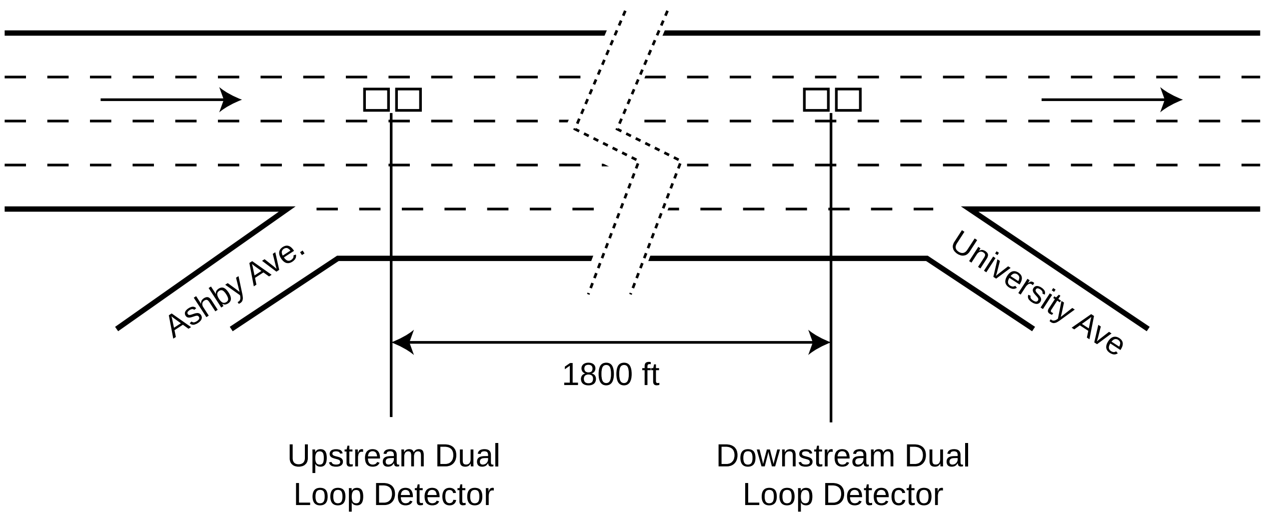


Figure 2, One vehicle passing over a dual-loop-detector, (A) the two detection zones and the vehicle trajectory as shown in the time space plane. The height of the vehicle's trajectory reflects the non-zero vehicle length. (B) The associated turn-on and turn-off transitions at each detector.

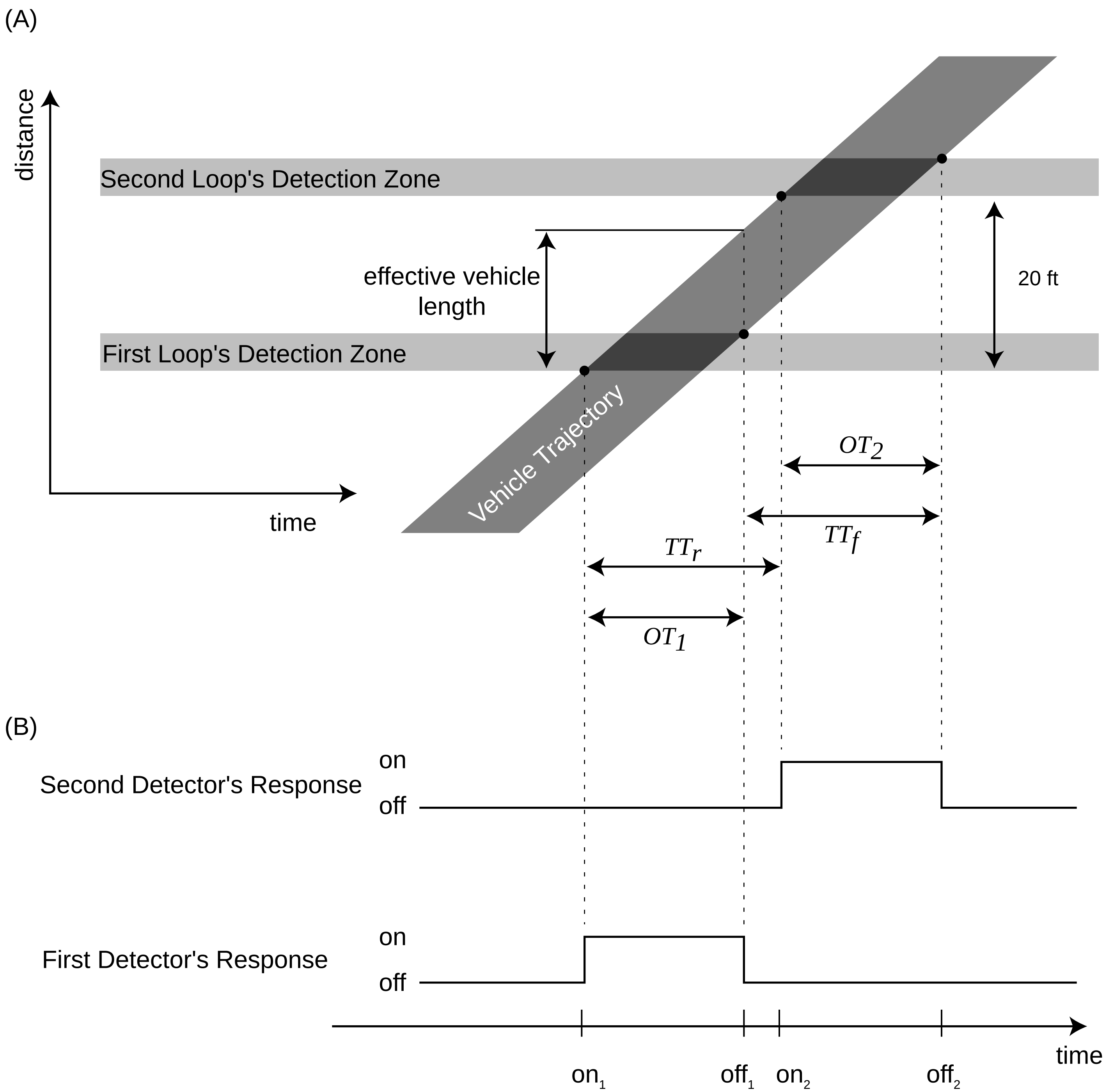
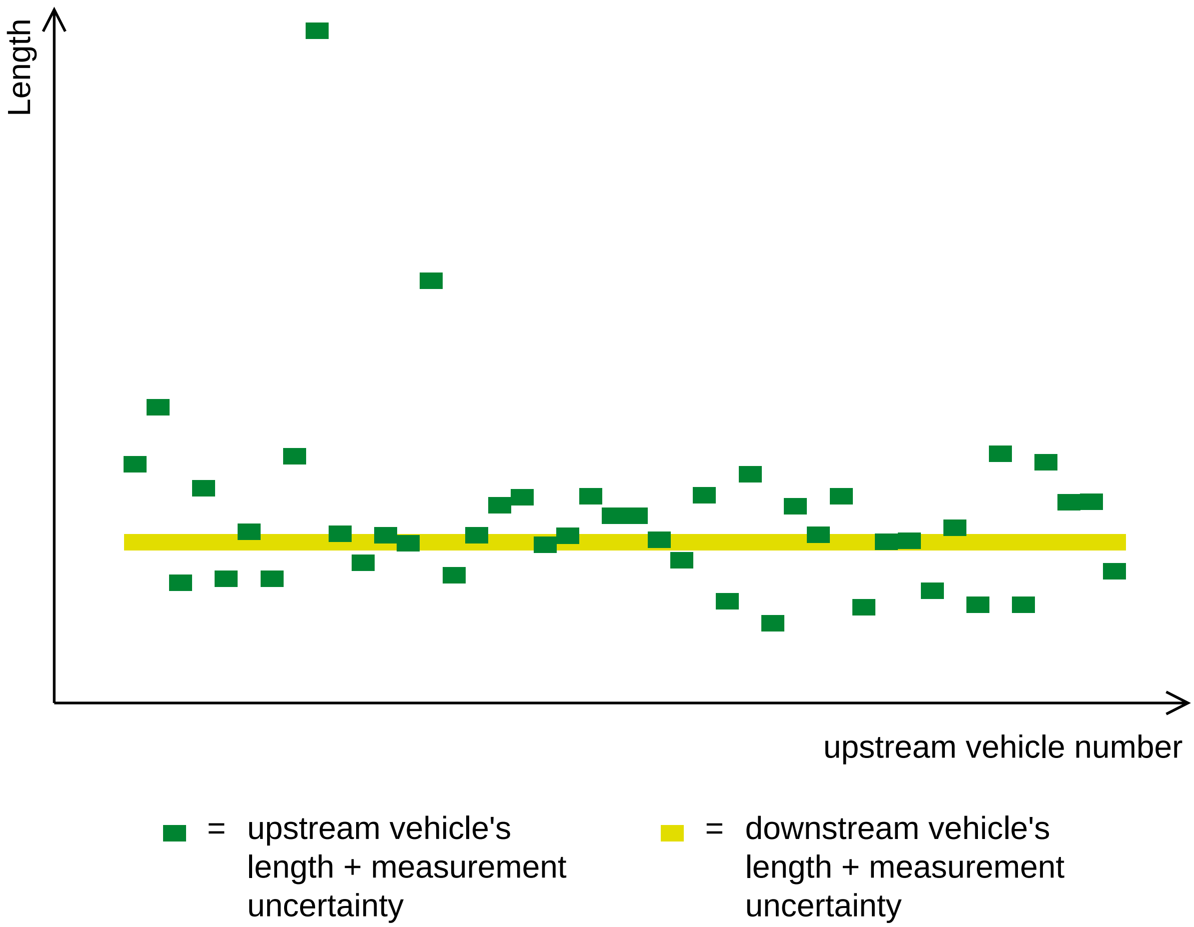


Figure 3, (A) "Resolution test" between one downstream vehicle and a set of upstream vehicles. If the upstream measurement range does not intersect the downstream measurement range, the upstream vehicle can be dismissed as being an unlikely match for the downstream vehicle. (B) Everything that can not be eliminated are considered possible matches, as indicated with open circles. Note that each outcome is shown directly below the given comparison from part (A).

(A)



(B)

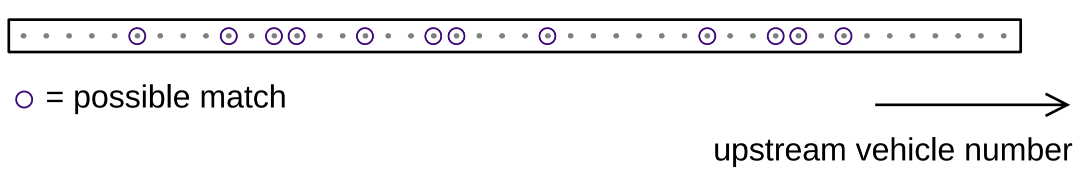


Figure 4, Consider a set of 100 downstream vehicles, applying the resolution test to each of these vehicles produces a set of possible matches, or one row in this matrix. Note that the columns are indexed by the upstream offset, so, if there were no lane changes in this coordinate system, all of the true matches would fall into a single column.

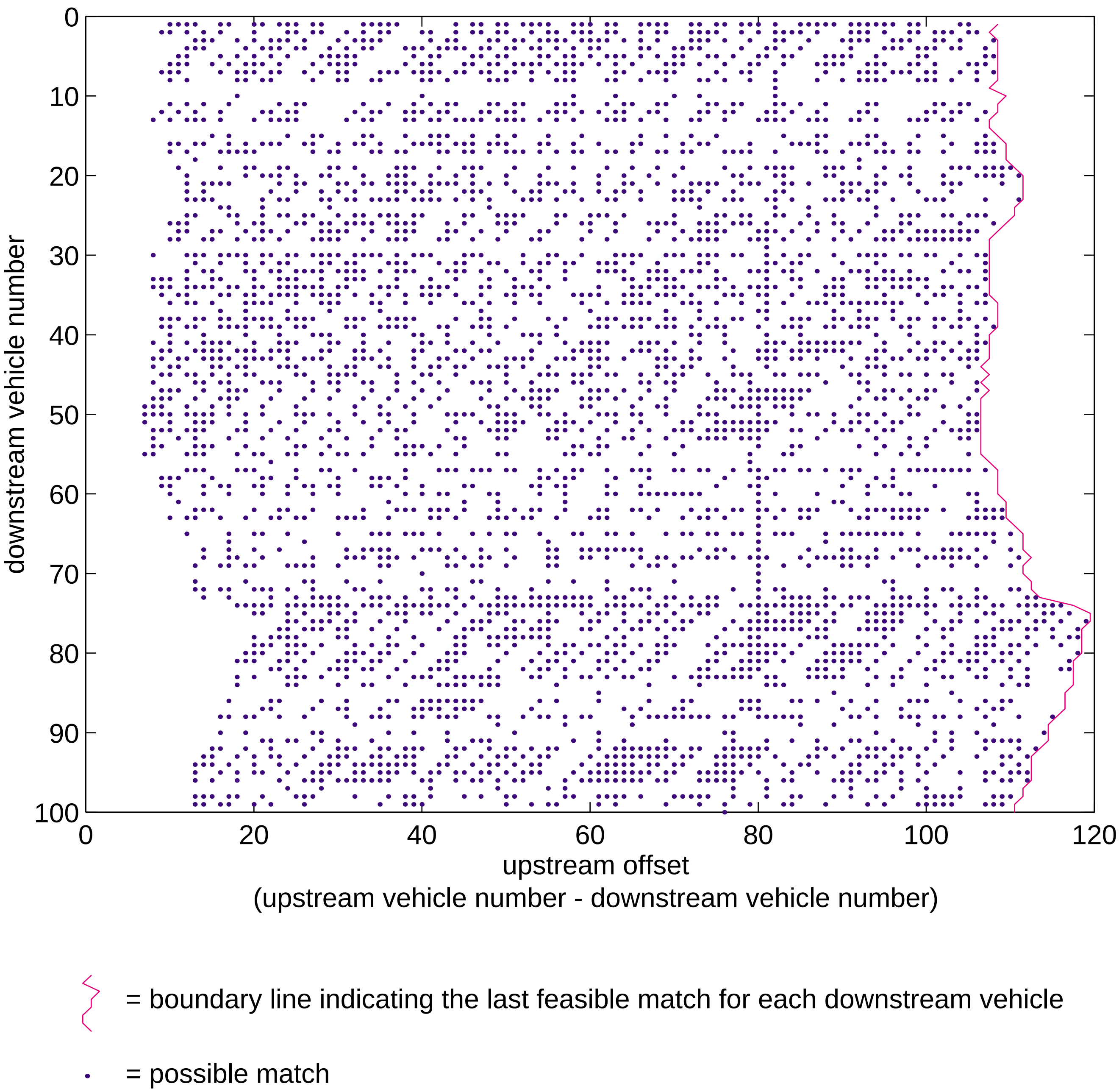


Figure 5, All sequences of two or more possible matches for the on-going example.

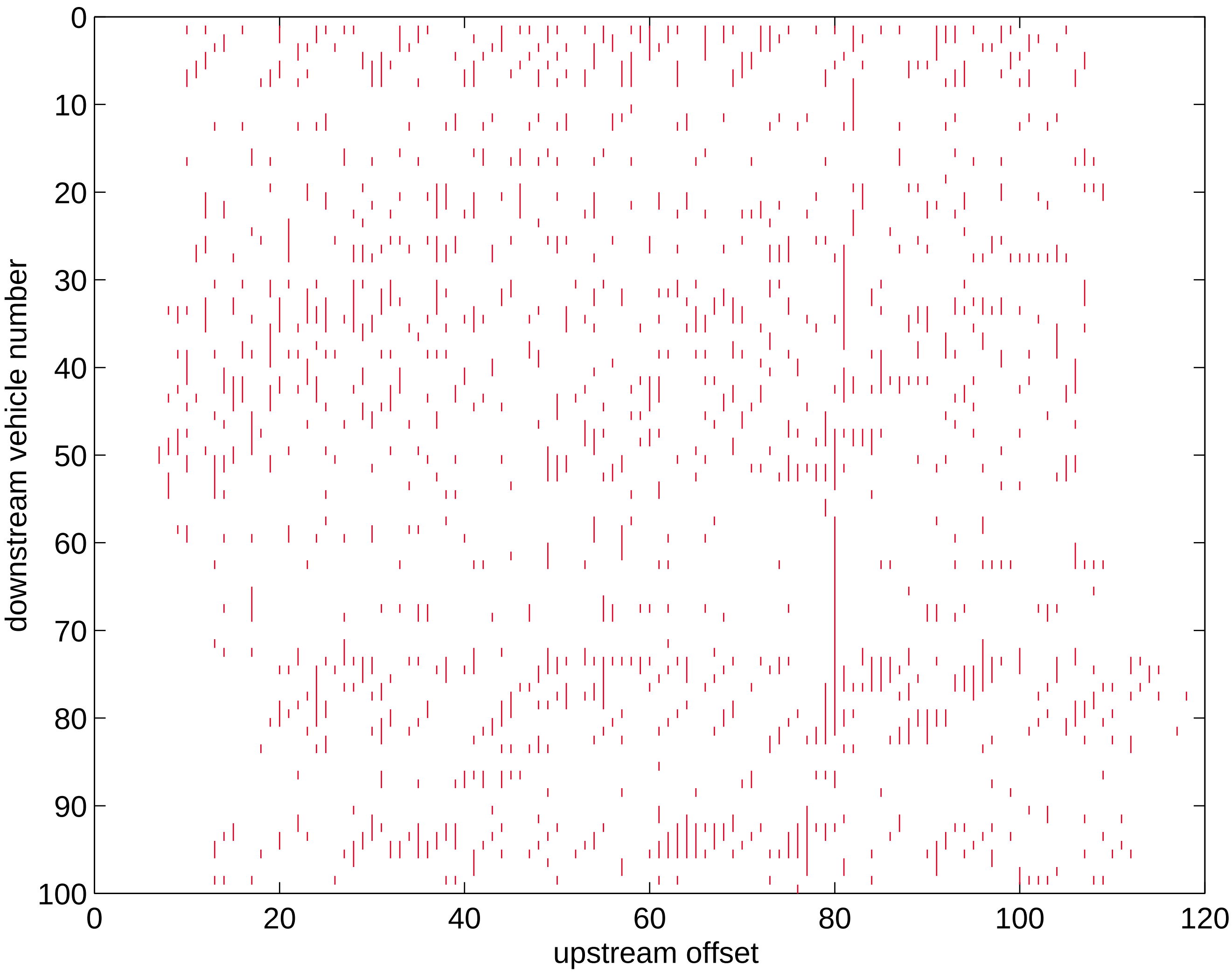
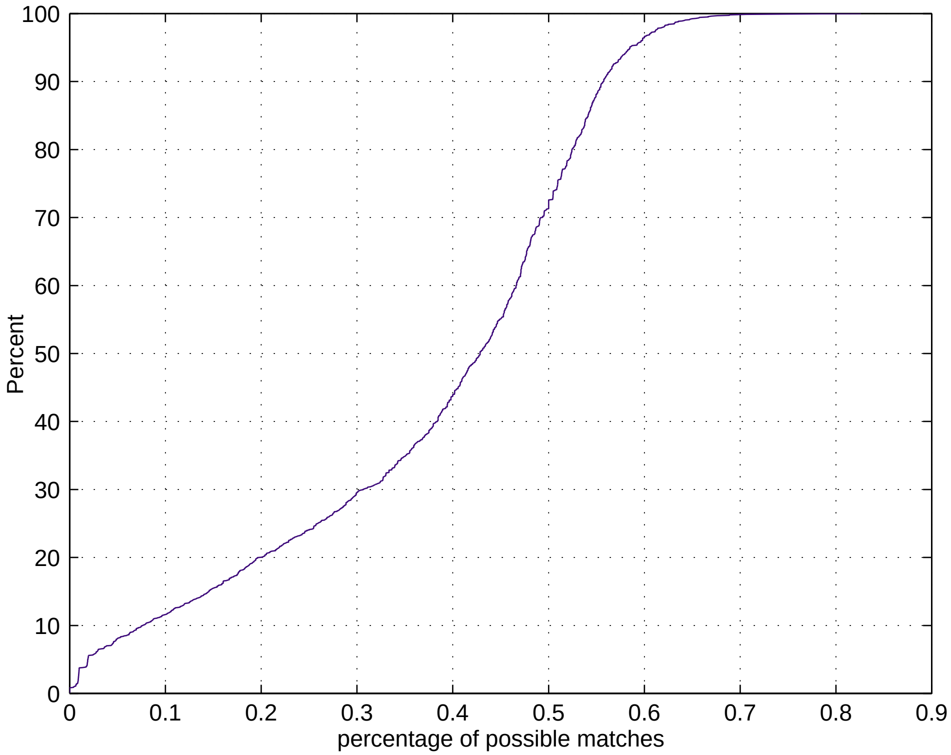
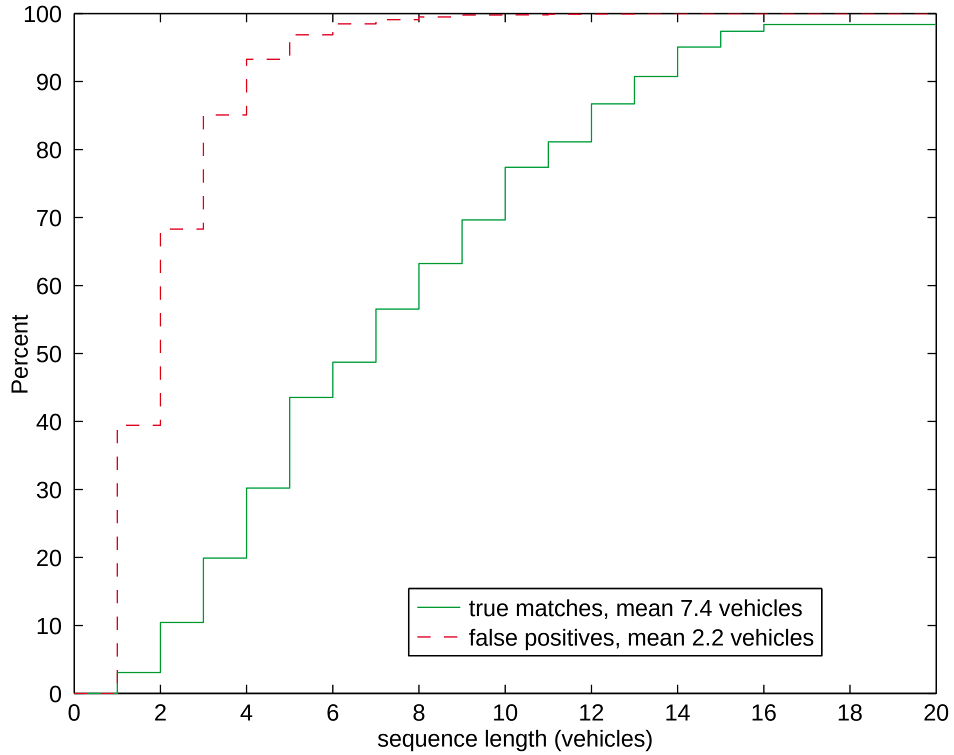


Figure 6, (A) The cumulative distribution of the percentage of possible matches for all 1495 downstream vehicles. (B) Using concurrent video to calculate the true matches, the solid line shows the cumulative distribution of sequence lengths measured by the algorithm for these matches. While the dashed line shows the cumulative distribution of sequence lengths for all other possible matches, i.e., the false positives.

(A)



(B)



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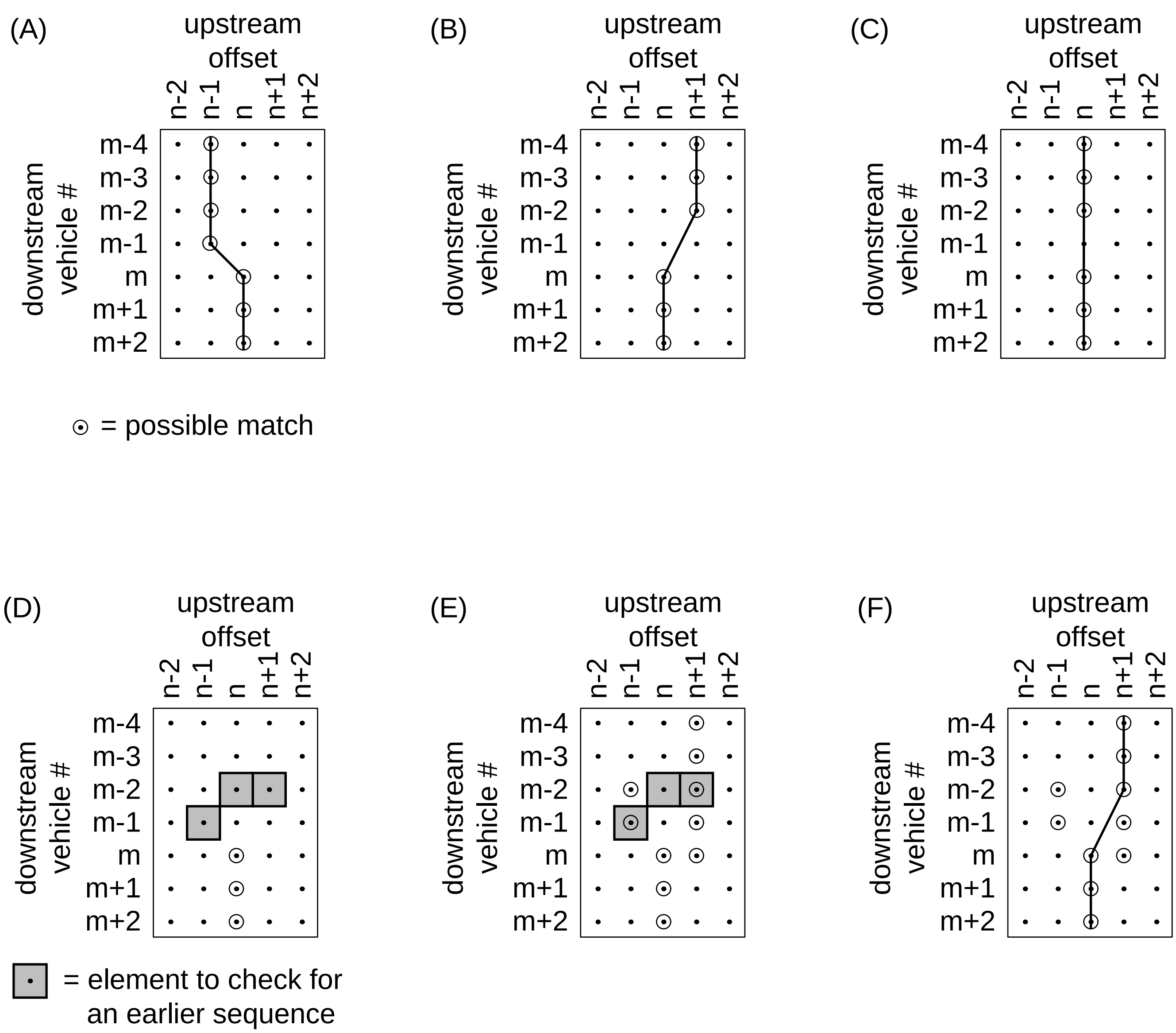

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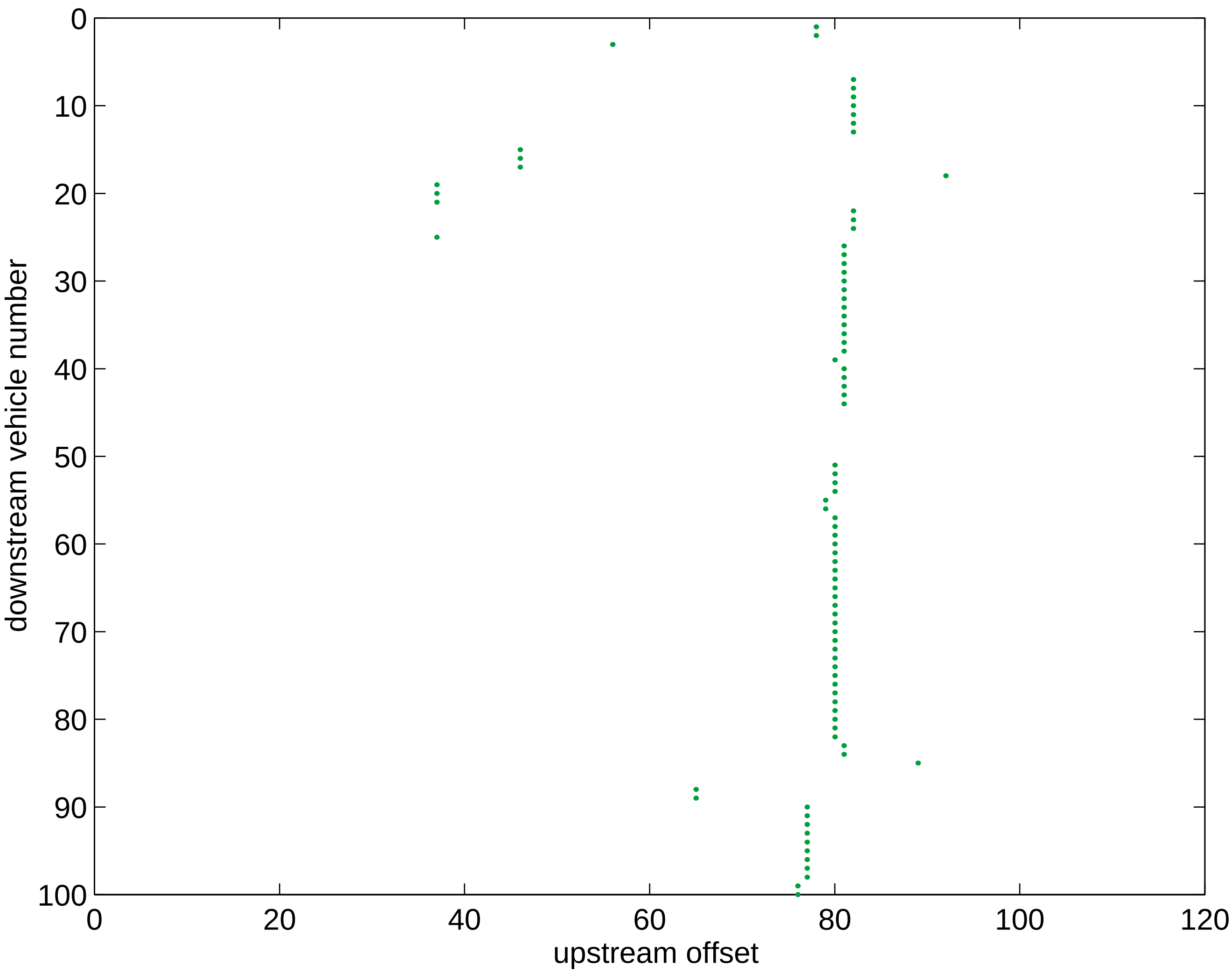

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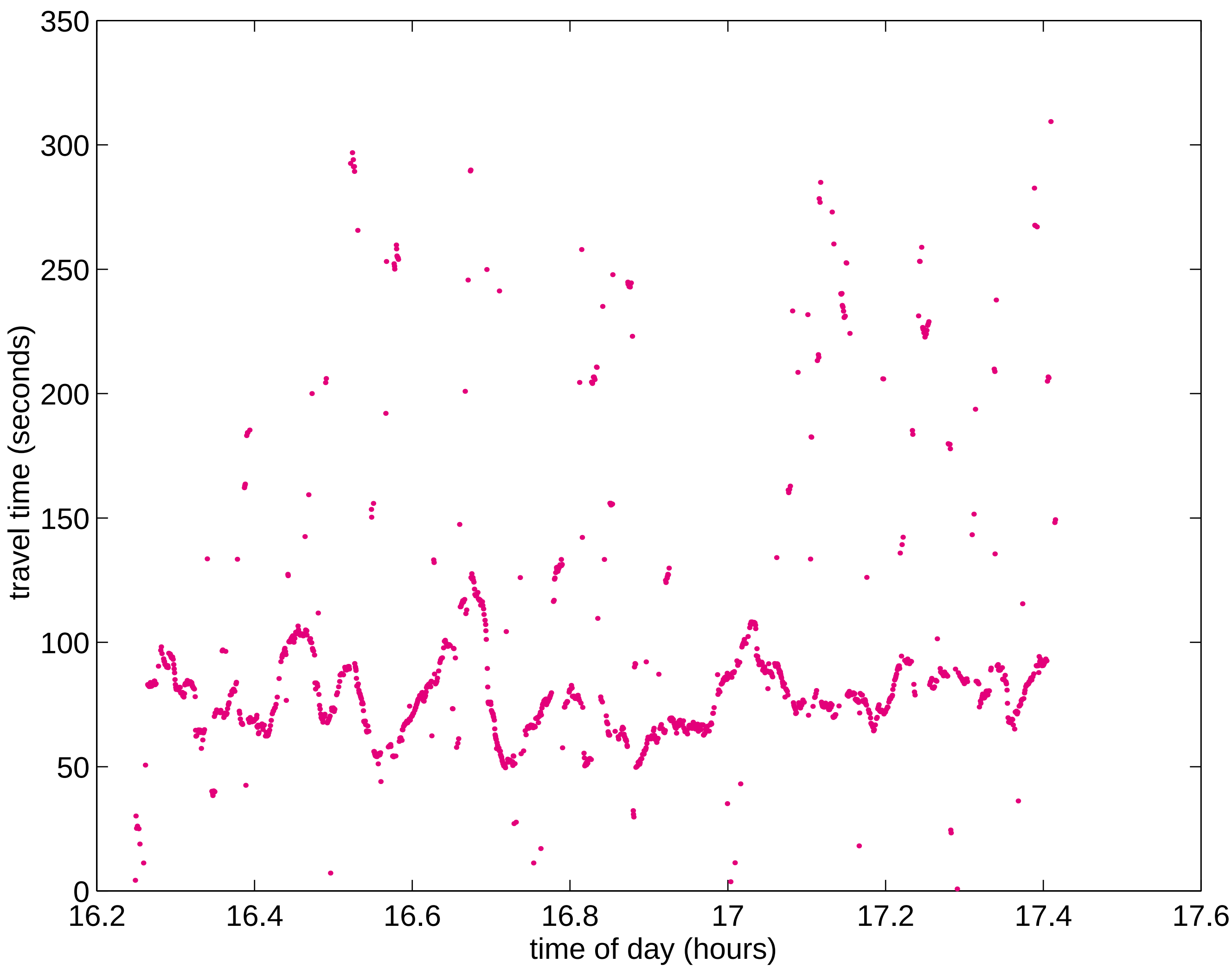

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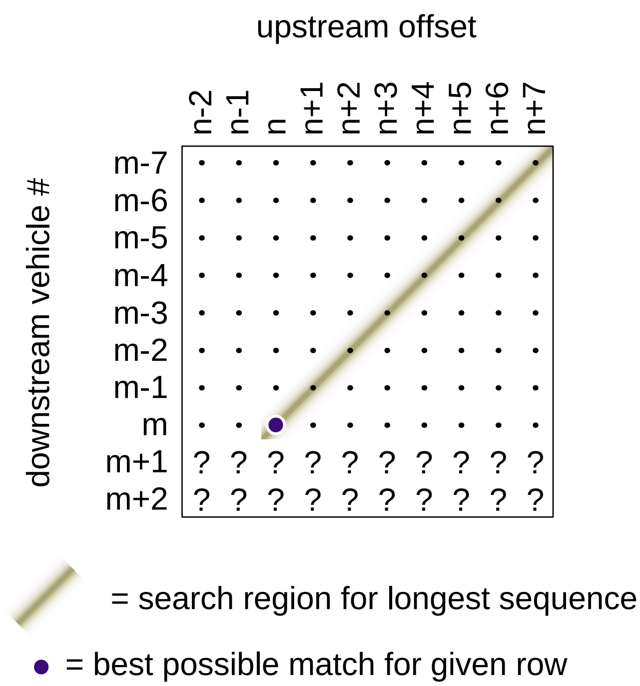

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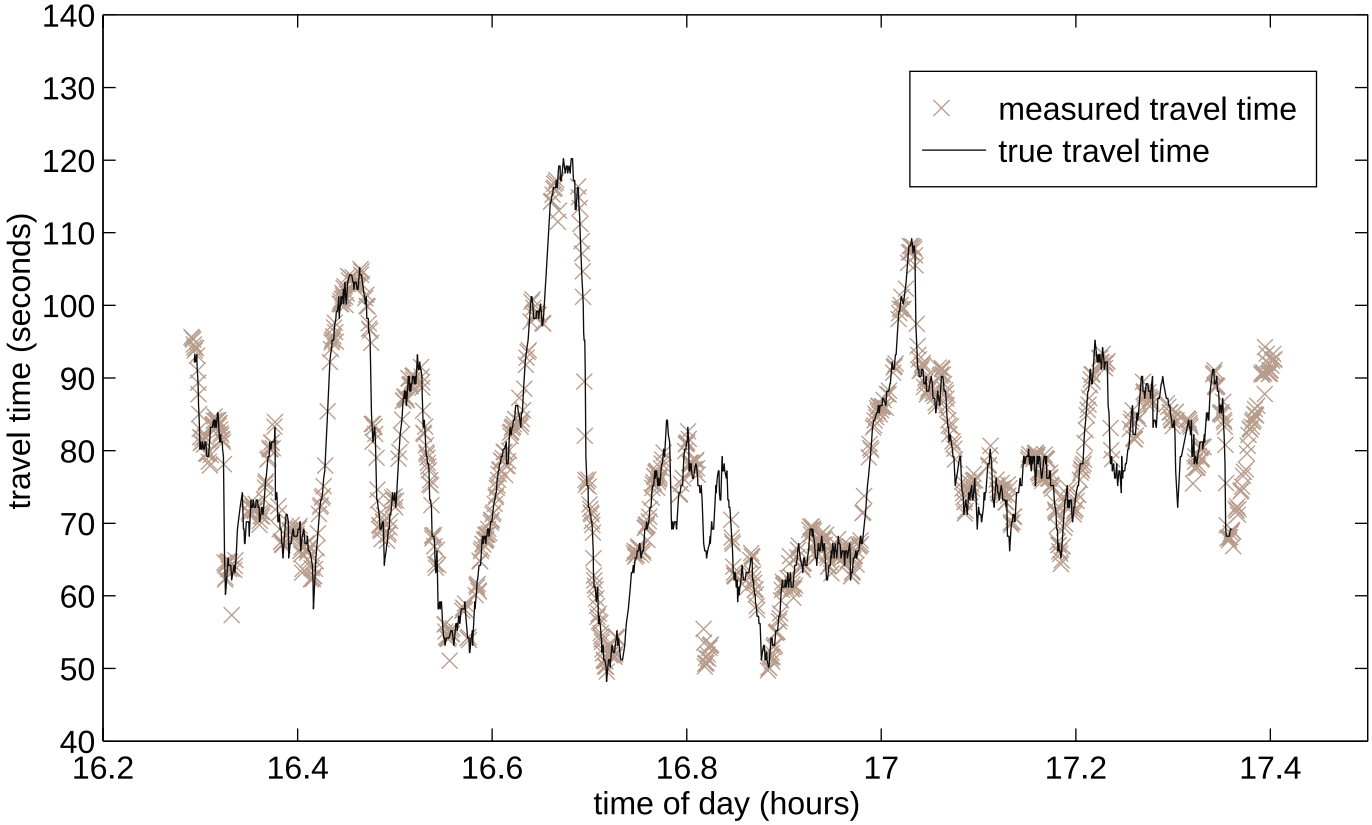
(A)



(B)

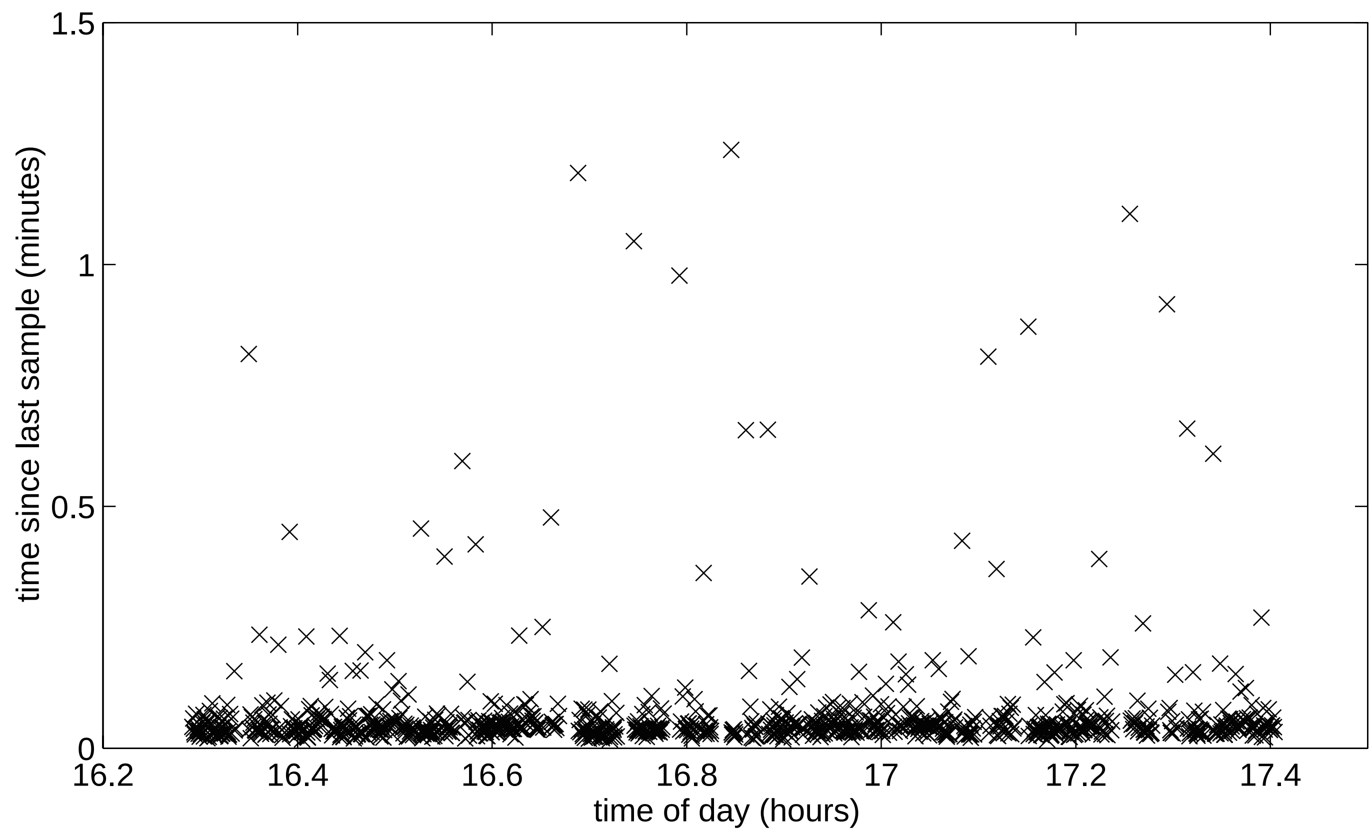


Figure 12, A comparison between measured travel times and estimated travel times for three hours, across five lanes, over an 1,800 ft segment.

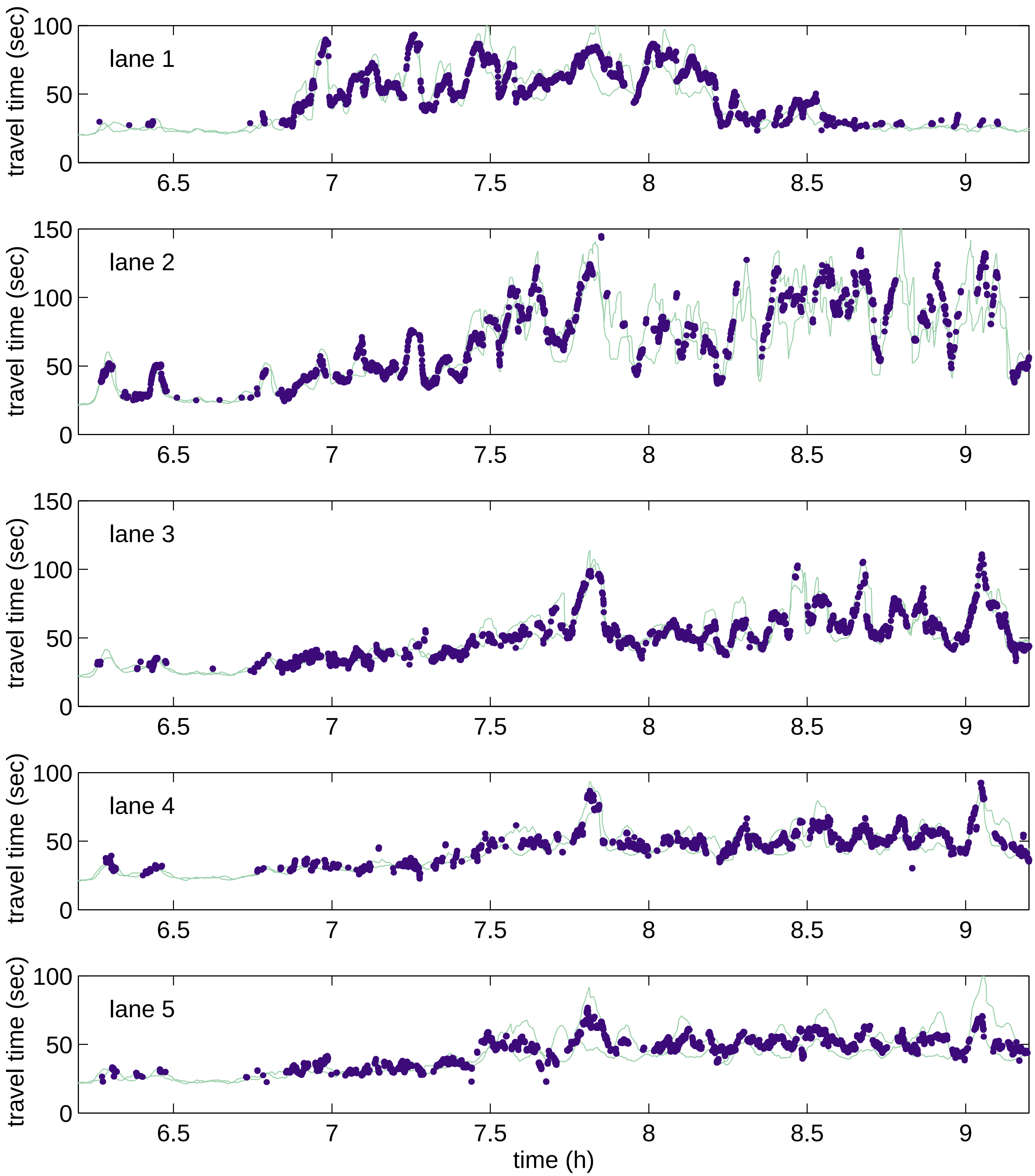


Table 1, Number of matches after each cleanup step for the on-going example.

Step	Number of Matches
pre-cleanup	1345
step 1	1212
step 2	1202
step 3, final matches	1008