

Event Data Based Traffic Detector Validation Tests

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ABSTRACT

The accuracy of detector data is paramount for traffic surveillance, control and information systems, yet little has been published on identifying or correcting errors in the data. This paper presents eight detector validation tests for freeway surveillance using individual vehicle data collected from loop detectors. Five of these tests can be applied to single loop detectors, while all of them can be applied to dual loop detectors. The tests are used to contrast the performance between different sensor models and most of the tests are presented using 24 hr blocks of data. In practice, they can also be used to identify permanent and transient hardware problems in other components of the detection system, e.g., cross talk between loops or a short in the lead wires. For operational implementation, the tests could be modified so that they are applied hourly or after a fixed number of vehicles pass. Some of the tests can even be used to "clean up" erroneous measurements.

Keywords: traffic surveillance, loop detectors, freeway traffic, error detection

INTRODUCTION

All traffic control systems depend on the quality of detector data, yet little research has been conducted to assure the performance of the detection and communication system. Traffic surveillance systems will have occasional transient errors, such as when a vehicle changes lanes over a detector. Although their presence is expected, if these errors go undetected they will degrade the performance of traffic controls and driver information systems. If the errors are chronic, such as when a component consistently fails to provide accurate measurements, the impacts can be more severe. The conventional solution to these problems appears to be the allowance of large error margins in aggregate parameter measurements. Of course this strategy will degrade the fidelity of any control that depends on the data.

Inductive loop detectors are the preeminent vehicle detection technology. Many operating agencies use specialized loop testers to assess the quality of the wiring (Kell et al, 1990, Ingram, 1976), but these tools bypass the controller and loop sensor units; thus, they do not analyze the entire detector circuit, nor do they analyze the circuit in operation. To this end, most operating agencies employ simple heuristics such as, "Do the loop sensor indicator lights come on as a vehicle passes?" or simply, "Do the time series 30 second average flow and occupancy seem reasonable to the eye?" Such tests are typically employed when the loops are installed or when the quality of data coming from the detector station is questionable. These heuristics will catch severe errors and help diagnose them, but other problems can easily go unnoticed.

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Many practitioners and some researchers have worked to automate the latter heuristic by rephrasing the question, "Are the time series 30 second average flow and occupancy within statistical tolerance?" (Jacobson et al, 1990, Cleghorn et al, 1991, Nihan, 1997) These systems often go undocumented in the literature because they are either designed in-house by an operating agency¹ or were developed by a consulting firm using proprietary information. Because these automated systems only use aggregated data, they must accept a large sample variance and potentially miss problems altogether. For example, the systems have to tolerate a variable percentage of long vehicles in the sample population. As the percentage of long vehicles increases, the occupancy/flow ratio should increase simply because a long vehicle *occupies* the detector for more time compared to a shorter vehicle traveling at the same velocity, see Coifman (2001) for examples.

Chen and May (1987) developed a new approach for verifying detector data using event data, i.e., individual vehicle actuations. Their methodology examines the distribution of vehicles' *on-time*, i.e., the time the detector is occupied by a vehicle. Unlike conventional aggregate measures, their approach is sensitive to errors such as "pulse breakups", where a single vehicle registers multiple actuations because the sensor output flickers off and back on.

Coifman (1999) went a step further and compared the measured on-times from each loop in a dual loop detector on a vehicle by vehicle basis. At free flow velocities the on-times from the two loops should be virtually identical regardless of vehicle length, even allowing for hard decelerations. Many hardware and software errors will cause the two on-times to differ. At

¹ See Chen and May (1987) for examples.

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lower velocities, vehicle acceleration can cause the two on-times to differ even though both loops are functioning properly and thus, congested periods were excluded from the earlier analysis.

This paper presents several new detector validation tests that employ event data to identify detector errors both at single loops and dual loop detectors. The tests are presented in terms of evaluating loop sensor units and detector validation, e.g., "if the data pass the test then the sensor can be trusted." The data are analyzed off-line, but the tests are simple enough that they could be implemented in real-time to identify detector errors in real time and many of them could be used to actively *clean* incoming data from a traffic surveillance system.

After presenting the basic data collection and measurement, this paper presents eight different detector validation tests. Five of these tests can be applied to single loop detectors or non-invasive sensors that aggregate data using similar techniques, while all of the tests can be applied to dual loop detectors.

THE DATA

This work uses event data collected from dual loop detector stations in the Berkeley Highway Laboratory along Interstate-80, north of Oakland, CA (Coifman et al, 2000) to demonstrate the tests. This site was chosen to control for as many factors as possible that may cause detection errors. The one factor that was varied was the sensor unit used to collect data. The following five sensor units are evaluated in this study,

Peek GP5 revision E (GP5-E),

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Peek GP5 revision G (GP5-G),

Peek GP6 revision C (GP6),

Eberle Design Inc. LM222 (EDI),

Intersection Development Corporation Model 222 (IDC).

Except where noted, the study uses 24 hours of data from one dual loop detector for each sensor unit. The date and detector were chosen at random, but all of the loop detector stations were evaluated thoroughly to identify and exclude any preexisting hardware problems. Table 1 summarizes the number of vehicles observed in each of these data sets, aggregated into three velocity ranges. The performances of these different sensor units have been studied previously (Coifman, 1999) and this knowledge will be used to verify that the tests are performing as expected. The earlier research found that two of the models are problematic, in the first case, for random vehicles the GP5-G sensor frequently stays on an extra fraction of a second after the vehicle passes. In the second case, the EDI sensor is prone to flicker, turning on and off multiple times as a vehicle passes. The remaining three sensor units did not exhibit any systematic errors in the earlier study. Although all of the sensor units are supposed to meet the same design specifications, they exhibited a large variability from one model to the next. In the case of the GP5 sensor, there is even a significant change in performance between two revisions of the same unit.

It is envisioned that in practice these tests would be deployed over a large number of detector stations, without accounting for sensor model a priori. The results could be used to

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identify the most problematic detectors, allowing an operating agency to focus resources on these locations, identify trends, and improve the performance of the surveillance system in a cost effective manner.

Vehicle measurements

This research used conventional model 170 controllers to collect the bivalent event data at 60 Hz (Coifman et al, 2000). Obviously the sampling frequency will limit the resolution of the tests. To place this study in context, the authors are familiar with deployed systems that have sampling frequencies between 30 Hz and 240 Hz. There are several emerging loop detector units that actually sample a vehicle's inductive signature,² but these systems have not entered standard practice and they are beyond the scope of this study.

The process of measuring bivalent data is illustrated in Figure 1. Figure 1A shows a time-space diagram of 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 1B. Integral to these measurements is the process of matching pulses between the paired loops. For this study, each pulse at the second loop is matched to the most recent pulse at the first loop that preceded it. When the dual loop detector is operating properly, two successive pulses rarely come from one loop without an intervening pulse on the other loop (the loops are typically spaced close enough to ensure that one vehicle will actuate both loops before the next vehicle

² IST, PEEK and 3M are just a few of the manufacturers producing sensors that can provide inductive vehicle signatures.

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actuates the upstream loop). The error detection strategies presented below for dual loops are sensitive to unmatched pulses and they will respond when this assumption breaks down.

After matching pulses between loops, as indicated in Figure 1, 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 . These data yield two measurements of individual vehicle velocity:

$$V_r = (\text{loop separation}) / TT_r \quad (1)$$

$$V_f = (\text{loop separation}) / TT_f \quad (2)$$

and these measurements are used calculate two measurements of effective vehicle length,

$$L_1 = OT_1 * V_r \quad (3)$$

$$L_2 = OT_2 * V_f \quad (4)$$

In the case of single loop detector tests, this paper uses the second loop in the dual loop detector and estimates velocity. Conventional velocity estimation from single loops uses the equation,

$$V_{est_conventional} = L_A * \text{flow} / \text{occupancy} \quad (5)$$

where L_A is the assumed average effective vehicle length at the detector. This equation is inversely proportional to average on-time. Coifman et al (in press) demonstrated that,

$$V_{est} = L_A / \text{median}(OT_2) \quad (6)$$

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is less sensitive to outlying OT_2 measurements. Provided the sample size is large enough, the accuracy of Equation 6 approaches that of the average velocity measured from a dual loop detector. The present work uses a median of 11 OT_2 measurements centered on the given vehicle, based on the fact that Coifman (in press) found that for the subject data, a sample size of 10 yields an average absolute error under 4 km/h. These estimated velocities can be used to estimate individual vehicles' effective vehicle length,

$$L_{est} = OT_2 * V_{est} \quad (7)$$

Finally, whether using both loops or a single loop, the vehicle headway, H , is measured from the difference between on_2 , as defined in Figure 1B, from two consecutive vehicles.

TRAFFIC DETECTOR VALIDATION TESTS

Examination of Figure 1B reveals that there are only seven different errors that may occur in bivalent loop detector data. Two errors will extend the OT measurement: *premature rising edge* and *delayed falling edge*. Three errors will shorten the OT measurement: *delayed rising edge*, *premature falling edge*, and *flicker* (turning off and back on in the middle of a vehicle). A *missed vehicle* will result in no OT measurement when one should have occurred and a *detection in the absence of a vehicle* will lead to the opposite problem. Of course the true OT depends both on L , which varies from vehicle to vehicle, and V which is a function of traffic conditions.

The redundancy of measuring twice every vehicle that passes a dual loop detector can be used to identify the presence of any of these errors, provided the occurrence of an error at one of the loops is independent of an error at the other. Even in the absence of this independence or in

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the case of single loop detectors, the time series data can also be used to identify most of the errors. Any analysis either has to control for L and V , or allow sufficient tolerance for a reasonable range of L and V . Using these basic principles, the following eight tests are developed to identify the seven different errors in bivalent loop detector data.

Individual vehicle velocity versus moving median velocity test

As the title suggests, this test compares individual vehicle velocity against the median of 11 velocity measurements centered on the given vehicle. If the velocity of the vehicle deviates from the median by more than a preset threshold, (set to 32 km/h in this analysis), the individual velocity measurement is considered erroneous. Based on the aforementioned results in Coifman (in press), the range of 11 vehicles was selected to be large enough so that transient errors should rarely impact the median but small enough so that traffic conditions usually will not change significantly during the sample. This test will identify errors due to either the rising or falling edge being premature or delayed. It will also identify situations in which one detector is actuated and the other is not, either due to an omitted detection or an actuation in the absence of a vehicle.

When these errors are encountered, it could result in the vehicle being classified in an incorrect velocity range. So the moving median of V_r is used to select the velocity range in all of the tables. To illustrate the power of this filter, Figure 2 compares the measured velocities and the moving median velocities from the GP5-G sensor, the worst case observed in our data sets. As can be seen from the figure, the median velocities filter out much of the noise from the raw data. In real-time analysis, one may not be able to afford the lag time necessary to observe all of

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the following vehicles, so the research also considered a moving median restricted to observations that preceded the current vehicle. As expected, performance was not as good as the results presented here, but it still proved beneficial.

Tables 2-3 present the statistics after applying this test to each day of data from the different sensor units using velocity from the rising and falling edge, respectively. The falling edge from the GP5-G sensor unit stands out as clearly being poorer than the other sensors. These results are consistent with the fact that the GP5-G randomly stays on a fraction of a second too long. As noted in Coifman et al (in press), Equation 6 is an estimate of median velocity, so the comparison can be repeated using the measured velocity across loops and the estimated velocity from a single loop, i.e., the test checks whether the on-times are consistent with the measured velocities. These results are presented in Tables 4-5, for the subject data sets and they are similar to Tables 2-3. One notable difference is that the EDI sensor shows slightly diminished performance when using the estimates and this result is consistent with the flicker observed with these sensors. Finally, although not shown here, the test can be repeated using estimated data from the other detector.

Headway versus on-time test

There are certain combinations of H and OT that can only be observed during free flow conditions if the detector is working properly, likewise, there are other combinations that can only be observed during congested conditions. When these measurements conflict with measured or estimated velocity, it would be indicative of a detection error.

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To illustrate, Figure 3A-B shows the measured H versus OT_2 from the day of GP6 data. These data were grouped into free flow and congested groups based on $V_r > 72$ km/h (45 mph). Relatively short on-times and occasional long headways characterize the free flow data, while occasional long on-times characterize the congested data. We defined two regions of the headway on-time plane that should contain strictly free flow observations or strictly congested observations, as shown in Figure 3C. The free flow region is bounded by $OT_2 < 0.3$ sec and $H > 8$ sec. The former constraint was chosen because a car traveling at free flow speeds should have an OT_2 on the order of 0.2 sec. Any valid OT_2 measurement over this value must either be due to a long vehicle or low velocity. Using several weeks of data from GP5-E and GP6 sensor units, the headway constraint ensured that fewer than 0.01 percent of the congested vehicle measurements would fall in this region. While the congested region is bounded by a single constraint, $OT_2 > 1.3$ sec. This bound ensures that any long vehicle at free flow speeds should not fall in the range if measured correctly. The same data set was used to ensure that fewer than 0.01 percent of the free flow vehicle measurements fell in this region. Of course most observations under either condition will fall somewhere between these two regions. For each sensor unit in this study, fewer than 10 percent of the observations fell in the two pre-defined regions.

This traffic flow characterization can be utilized in detecting certain errors at single loop detectors, e.g., if a measurement falls in the free flow region but $V_{est} < 72$ km/h or conversely if a measurement falls in the congested region but $V_{est} > 72$ km/h. Table 6 summarizes the results of this test applied to each of the data sets. Very few errors were found for these sets, but as noted

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previously, the detector hardware was verified to be in full functioning order before the tests were applied. Perhaps more importantly, one would expect to find some measurements in the free flow region after a day and in the congested region if those conditions existed at the detector. These expected results were demonstrated by each of the sensor units. Finally, one could modify this test to use measured velocity at dual loop detectors rather than V_{est} .

Feasible range of vehicle lengths test

There exists some finite range of feasible vehicle lengths and this research assumes feasible effective vehicle lengths to range between 3 m and 27 m (10 ft and 90 ft). If a measured vehicle length falls outside of this range, it would indicate a detector error. Obviously, the range should be modified to reflect local restrictions on vehicle sizes and the resulting effective vehicle lengths. The test can be applied to estimated or measured lengths, thereby providing a test for both single and dual loop detectors. If the individual length is too short, it may be indicative of pulse break-ups, a sensor set to pulse mode rather than presence mode, or similar errors. On the other hand, if the individual length is too long, it may be due to the detector sticking on after the passing of the vehicle.

Tables 7-9 present the results after applying this test to each data set using L_1 , L_2 , and L_{est} , respectively. As with the previous test, very few errors were found in these sets, but they should be able to identify chronic errors. As with Tables 4-5, the EDI performance is slightly worse than the other sensors.

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Feasible range of headway and on-time tests

As with vehicle length, there are physical limits on feasible headways and on-times. These parameters can be used to detect chronic errors at single and dual loop detectors. This research assumes a minimum feasible headway of 0.75 sec and based on Equations 3-4, a minimum on-time of 0.16 sec. During free flow conditions, one can also apply a maximum feasible on-time, a 24 m (80 ft) vehicle (the longest vehicle observed at the test site) traveling at 72 km/h should have an on-time of approximately 1.2 sec. Adding an error margin of 0.1 sec, a detector observing many free flow vehicles with on-times greater than 1.3 sec would be suspect.

Tables 10-13 present the statistics after applying these tests to each data set. Consistent with the known flicker problem, the EDI has more short headways and on-times than the other sensors.

Length differences and ratios at dual loop detectors

Earlier research by our group used the difference between OT_1 and OT_2 to assess the performance of a dual loop detector during free flow conditions (Coifman, 1999). These tests were constrained by the fact that at lower velocities, acceleration can cause an on-time difference even though the loop detectors are functioning properly. Unfortunately, this constraint precludes the earlier test from identifying errors that only occur during congested conditions. In response to this limitation, this new test uses the difference between L_1 and L_2 to control for velocity and extend the test into congested conditions. Of course some errors may be correlated to vehicle length as well, so a second version of the test is used to normalize for length, i.e.,

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$$(L_1 - L_2) / (L_1 + L_2). \tag{8}$$

If the sensors are functioning properly, these differences should be close to zero.

Table 14 summarizes the results for $L_1 - L_2$. To facilitate collection and analysis, the data were aggregated into bins by 15 cm (0.5 ft), so the central bin represents a range of +/- 8 cm (3 in), and the central three bins span +/- 23 cm (9 in). Similarly, Table 15 summarizes the results for $(L_1 - L_2) / (L_1 + L_2)$ aggregated into bins of size 0.003. Thus, the central bin represents a range of +/- 0.0015 and the central three bins span +/- 0.0045. In both tables and all velocity ranges, the GP5-G performs the worst out of all of the sensors. These results are consistent with the results during free flow found in (Coifman, 1999). Also note that the EDI sensor performs almost as bad as the GP5-G in the second test but not the first, indicating a vehicle length bias in the EDI's errors.

Cumulative distribution of vehicle lengths

The cumulative distribution function (CDF) of measured or estimated lengths provides information on detector performance. Of course the CDF will capture site specific phenomena, such as the percentage of large trucks, so it is not feasible to specify a universally "good" range for this distribution. But it is possible to compare the CDF measured one day with that measured during the same time period on the next day. Thereby allowing an operating agency to detect sudden changes in detector performance. It is also possible to compare the CDF from one detector station to that at the next detector station on the roadway to control for day to day variance. Figure 4A illustrates such a comparison using L_1 . This plot shows the daily CDF of L_1

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in a single lane, over five days at one detector station and seven days in the same lane at a second detector station, 550 km away. All of these data were recorded with a GP5-E sensor unit except for one of the days at the second station, which were recorded using an EDI sensor unit. Aside from some variability in the percentage of long vehicles, all of the curves from the GP5-E sensors fall on top of each other. The curve from the EDI sensor is distinct from the other curves and indicates that the sensor is recording many more "short vehicles". As mentioned previously, these sensors tend to flicker and the short length measurements are simply due to detector errors. This plot shows that one can compare across days and nearby locations reliably. The process is repeated using the corresponding estimated lengths in Figure 4B. This time, however, the curves only show the deciles to reduce the required data storage. Unfortunately, the problem with the EDI sensor units impact both the on-time and the median on-time. Since the estimate is proportional to the former and inversely proportional to the latter, the problem is less pronounced in this plot, but it is still evident.

Loss of a loop in a dual loop detector

One loop in a dual loop detector may stick on or stick off while the other loop continues working. It is a simple test to count the number of pulses at one loop since the last pulse at the other loop and quickly identify when these errors occur. For example, if the controller sees five pulses at the second loop since the last pulse at the first loop, it could respond by resetting the sensor card, sending an alarm, and/or treating the remaining loop in the dual loop as a single loop detector.

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Counting the number of consecutive congested samples

A freeway segment usually does not fluctuate rapidly between free flow and congested conditions. If the detector data indicate otherwise, it may be due to a detection error. This test is intended both for single and dual loop detectors and explicitly tracks the frequency of switching between the two traffic regimes. It takes samples of 10 consecutive vehicles and applies Equation 6 to estimate the velocity, e.g., Figure 5A. The test assumes that traffic becomes congested whenever this estimate drops below 64 km/h for four consecutive samples, the last of which is explicitly marked as being congested. The four samples are used to exclude occasional transient errors due to an unusually large number of long vehicles during free flow conditions and to reduce the sensitivity when the true velocity is close to 64 km/h. The test then assumes that traffic remains congested until it sees a single sample of 80 km/h. The higher threshold is used to further prevent frequent transitions when the true velocity is near the threshold velocity. Continuing the example, the individual sample results are shown in Figure 5B. The test keeps track of how many congested samples precede each free flow sample. Based on the criteria, one would expect that most free flow samples would be preceded by another free flow sample, i.e., zero congested samples, but some will be preceded by many congested samples. To quantify this test, the distribution is calculated, e.g., Figure 5C. There should be few free flow samples that are preceded by few congested samples, if this is not the case, then it would suggest a detector error.

CONCLUSIONS

The accuracy of detector data is paramount for traffic control and information systems, yet little has been published on identifying or correcting errors in the data. This paper has demonstrated the information available in high resolution detector data (60 Hz) and the potential benefits of microscopic data validation. To identify errors, the paper developed eight detector validation tests using event data. Five of these tests can be applied to single loop detectors. Some of the tests are quite simple, such as the loss of a loop in a dual loop detector, while other tests are more involved, such as the length differences at dual loops, which extends our earlier work with dual loop detectors to non-free flow conditions. Almost all of the tests are applicable to any traffic conditions, ranging from low demand to heavy congestion. Although most of the tests exploit freeway traffic dynamics, three of the tests could also be applied to arterial loop detectors: Headway versus on-time test, Feasible range of vehicle lengths test, Feasible range of headway and on-time tests.

In most cases, the tests were presented without explicit criteria to distinguish between good and bad sensor units. This deliberate omission is due both to the fact that such parameters depend on the required accuracy from the loop detectors, and because the event data used in this study are uncommon. The authors know of only a few locations where such data have been collected, making it difficult to provide universal guidelines for deploying such tests. The research can be deployed with little additional effort to make relative comparisons between different locations. The paper also provides enough guidance to assist a practitioner in assessing

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the usefulness of a given test and the first steps toward implementing it if it appears promising. As such, additional calibration may be necessary, but it should not be difficult to conduct.

The tests were used to contrast the performance of five different sensor models and most of the tests have been presented using 24 hr blocks of data. To control for variability, all of the loop detector stations used in this study were evaluated thoroughly to identify and exclude any preexisting hardware problems. Then, the research exploited several known problems in the different sensor units to verify the performance of the validation tests. It is envisioned that in practice these tests would be deployed over a large number of detector stations, without accounting for sensor model a priori. The results could be used to identify the most problematic detectors, allowing an operating agency to focus resources on these locations, identify trends, and improve the performance of the surveillance system in a cost effective manner. In other words, the tests could be used to identify permanent and transient hardware problems in other components of the detection system, e.g., cross talk between loops or a short in the lead wires that only materializes after a rain storm.

The analysis presented in this paper was conducted off-line using Matlab, a mathematical analysis software package. The tests could be applied in a similar manner by an operating agency, or they could be incorporated into the controller software for continuous monitoring. For operational implementation, the tests could be applied hourly or after a fixed number of vehicles pass. Some of the tests can even be used to clean up erroneous measurements, such as the individual vehicle velocity versus moving median test, which was used in this study to classify properly all measurements in the presence of transient errors. Other tests, such as the

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feasible length test, could be used to exclude individual vehicle measurement errors from aggregate parameter calculations such as flow and occupancy. Finally, we hope that the paper will encourage the collection of more high resolution data for further research.

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REFERENCES

Chen, L., and May, A. (1987). "Traffic Detector Errors and Diagnostics," *Transportation Research Record 1132*, TRB, Washington, DC, pp 82-93.

Cleghorn, D., Hall, F., and Garbuio, D. (1991). "Improved Data Screening Techniques for Freeway Traffic Management Systems," *Transportation Research Record 1320*, TRB, Washington, DC, pp 17-31.

Coifman, B. and Dhoorjaty, S.

Coifman, B. (1999) "Using Dual Loop Speed Traps to Identify Detector Errors," *Transportation Research Record no. 1683*, Transportation Research Board, pp 47-58.

Coifman, B., Lyddy, D., and Skabardonis, A. (2000). "The Berkeley Highway Laboratory-Building on the I-880 Field Experiment," *Proc. IEEE ITS Council Annual Meeting*, pp 5-10.

Coifman, B. (2001). "Improved Velocity Estimation Using Single Loop Detectors," *Transportation Research: Part A*, vol 35, no 10, pp. 863-880.

Coifman, B., Dhoorjaty, S., Lee, Z. (in press). "Estimating Median Velocity Instead of Mean Velocity at Single Loop Detectors," *Transportation Research: Part C*. (draft available at: <http://www-ceg.eng.ohio-state.edu/~coifman/documents>)

Ingram, J. (1976). *The Inductive Loop Vehicle Detector: Installation Acceptance Criteria and Maintenance Techniques*, California Department of Transportation, Sacramento, CA.

Jacobson, L, Nihan, N., and Bender, J. (1990). "Detecting Erroneous Loop Detector Data in a Freeway Traffic Management System," *Transportation Research Record 1287*, TRB, Washington, DC, pp 151-166.

Kell, J., Fullerton, I., and Mills, M. (1990). *Traffic Detector Handbook, Second Edition*, Federal Highway Administration, Washington, DC.

Nihan, N. (1997). "Aid to Determining Freeway Metering Rates and Detecting Loop Errors," *Journal of Transportation Engineering*, Vol 123, No 6, ASCE, pp 454-458.

TABLE CAPTIONS

Table 1	Number of vehicles in each sample
Table 2	Percentage of vehicles passing the median velocity test using V_r versus $\text{moving_median}(V_r)$
Table 3	Percentage of vehicles passing the median velocity test using V_f versus $\text{moving_median}(V_f)$. Italicized entries indicate poor performance on the test.
Table 4	Percentage of vehicles passing the median velocity test using V_r versus V_{est} . Italicized entries indicate poor performance on the test.
Table 5	Percentage of vehicles passing the median velocity test using V_f versus V_{est} . Italicized entries indicate poor performance on the test.
Table 6	Percentage of vehicles passing the headway on-time test
Table 7	Percentage of vehicles passing the feasible length test using L_1
Table 8	Percentage of vehicles passing the feasible length test using L_2
Table 9	Percentage of vehicles passing the feasible length test using L_{est}
Table 10	Percentage of vehicles with $H > 0.75$ sec. Italicized entries indicate poor performance on the test.

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Table 11 Percentage of vehicles with $OT_2 > 0.16$ sec. Italicized entries indicate poor performance on the test.

Table 12 Percentage of vehicles with $H > 0.75$ sec and $OT_2 > 0.16$ sec. Italicized entries indicate poor performance on the test.

Table 13 Percentage of free flow vehicles with $OT_2 < 1.3$ sec.

Table 14 Percentage of vehicles passing the $L_1 - L_2$ test. Italicized entries indicate poor performance on the test.

Table 15 Percentage of vehicles passing the $(L_1 - L_2) / (L_1 + L_2)$ test. Italicized entries indicate poor performance on the test.

FIGURE CAPTIONS

- Figure 1 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 2 (A) Individual V_f from the GP5-G, (B) moving median of the data from part A.
- Figure 3 (A) Measured H versus OT_2 from the GP6 data using $V_r > 72$ km/h to identify the free flow data from over 24,000 vehicle measurements, (B) repeating the process for $V_r < 72$ km/h (C) regions of the headway on-time plane in which measurements should all be free flow or all congested.
- Figure 4 Five days of data from one detector station and six days of data from another station 0.54 km away, both using GP5-E sensor units. Also one day from the second station an EDI sensor unit, (A) Cumulative Distribution of L_I , (B) deciles of L_{est}
- Figure 5 (A) Measured velocity, (B) traffic state from estimated velocity (high = free flow, low = congested), (C) distribution showing the number of congested samples preceding each free flow sample.

Table 1 Number of vehicles in each sample

Data File	# veh > 72 km/h	# veh 32-72 km/h	# veh < 32 km/h	Total # veh
GP5-E	18825	5083	2147	26055
GP5-G	19802	2254	292	22348
GP6	20362	1320	2636	24318
EDI	20251	4697	2309	27257
IDC	20711	3096	2155	25962

Table 2 Percentage of vehicles passing the median velocity test using V_r versus moving_median(V_r)

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.9%	100.0%	100.0%	99.9%
GP5-G	99.8%	99.8%	100.0%	99.8%
GP6	99.9%	100.0%	100.0%	99.9%
EDI	99.8%	100.0%	99.9%	99.8%
IDC	99.9%	100.0%	100.0%	99.9%

Table 3 Percentage of vehicles passing the median velocity test using V_f versus moving_median(V_f). Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.2%	99.9%	100.0%	99.4%
GP5-G	78.7%	95.1%	100.0%	80.6%
GP6	99.9%	100.0%	100.0%	99.9%
EDI	98.7%	99.7%	99.8%	99.0%
IDC	99.7%	100.0%	100.0%	99.8%

Table 4 Percentage of vehicles passing the median velocity test using V_r versus V_{est} . Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.6%	96.8%	99.7%	99.1%
GP5-G	99.0%	98.2%	99.7%	98.9%
GP6	99.6%	94.6%	100.0%	99.3%
EDI	92.7%	100.0%	99.8%	94.6%
IDC	99.7%	98.3%	99.8%	99.5%

Table 5 Percentage of vehicles passing the median velocity test using V_f versus V_{est} . Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.4%	97.0%	99.7%	99.0%
GP5-G	78.2%	90.4%	99.7%	79.7%
GP6	99.6%	94.9%	100.0%	99.4%
EDI	95.1%	99.7%	99.7%	96.3%
IDC	99.1%	98.5%	99.8%	99.1%

Table 6 Percentage of vehicles passing the headway on-time test

Data File	% FF median_vel & FF region in h-o plane	% FF median_vel & Cong. Region in h-o plane	% Cong. Median_vel & FF region in h-o plane	% Cong. Median_vel & Cong region in h-o plane
GP5-E	5.1%	0.0%	0.0%	2.1%
GP5-G	6.9%	0.0%	0.0%	0.5%
GP6	5.4%	0.0%	0.0%	2.2%
EDI	5.1%	0.0%	0.0%	0.9%
IDC	5.4%	0.0%	0.0%	1.6%

Table 7 Percentage of vehicles passing the feasible length test using L_1

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.7%	99.7%	99.8%	99.7%
GP5-G	99.9%	99.9%	99.3%	99.9%
GP6	99.7%	99.7%	100.0%	99.7%
EDI	98.1%	98.7%	98.1%	98.2%
IDC	99.8%	99.7%	99.9%	99.8%

Table 8 Percentage of vehicles passing the feasible length test using L_2

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.6%	99.8%	99.9%	99.7%
GP5-G	98.8%	99.2%	99.7%	98.9%
GP6	99.7%	99.7%	100.0%	99.7%
EDI	97.4%	98.2%	98.0%	97.6%
IDC	99.8%	99.8%	99.9%	99.8%

Table 9 Percentage of vehicles passing the feasible length test using L_{est}

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	99.5%	99.5%	99.3%	99.5%
GP5-G	99.6%	99.6%	99.0%	99.6%
GP6	99.6%	99.6%	99.5%	99.6%
EDI	99.1%	99.3%	98.0%	99.0%
IDC	99.5%	99.7%	98.6%	99.4%

Table 10 Percentage of vehicles with $H > 0.75$ sec. Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	96.2%	99.5%	100.0%	97.2%
GP5-G	96.3%	99.0%	100.0%	96.6%
GP6	96.6%	98.6%	100.0%	97.1%
EDI	92.1%	99.2%	100.0%	94.0%
IDC	94.9%	99.6%	100.0%	95.9%

Table 11 Percentage of vehicles with $OT_2 > 0.16$ sec. Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	93.6%	99.7%	100.0%	95.3%
GP5-G	95.4%	99.9%	100.0%	95.9%
GP6	97.6%	99.7%	100.0%	98.0%
EDI	74.8%	99.5%	99.7%	81.2%
IDC	96.8%	99.9%	100.0%	97.4%

Table 12 Percentage of vehicles with $H > 0.75$ sec and $OT_2 > 0.16$ sec. Italicized entries indicate poor performance on the test.

Data File	% acceptable (> 72 km/h)	% acceptable (32-72 km/h)	% acceptable (< 32 km/h)	% acceptable all vehs.
GP5-E	90.2%	99.3%	100.0%	92.8%
GP5-G	91.9%	98.9%	100.0%	92.7%
GP6	94.3%	98.4%	100.0%	95.1%
EDI	68.0%	98.7%	99.7%	76.0%
IDC	91.9%	99.5%	100.0%	93.5%

Table 13 Percentage of free flow vehicles with $OT_2 < 1.3$ sec.

Data File	% acceptable (> 72 km/h)
GP5-E	100.0%
GP5-G	99.9%
GP6	100.0%
EDI	100.0%
IDC	100.0%

Table 14 Percentage of vehicles passing the $L_1 - L_2$ test. Italicized entries indicate poor performance on the test.

Data File	% central bin			% central 3 bins			% central bin all vehs	% central 3 bins all vehs
	> 72 km/h	32-72 km/h	< 32 km/h	> 72 km/h	32-72 km/h	< 32 km/h		
GP5-E	85.4%	90.2%	83.9%	92.1%	94.2%	92.9%	86.2%	92.6%
GP5-G	62.1%	50.7%	63.5%	72.5%	69.2%	87.2%	61.0%	72.4%
GP6	89.9%	93.1%	87.8%	94.4%	95.5%	93.2%	89.8%	94.3%
EDI	70.7%	84.5%	66.9%	92.7%	95.8%	88.4%	72.8%	92.9%
IDC	88.6%	92.6%	85.4%	94.0%	95.5%	93.1%	88.8%	94.1%

Table 15 Percentage of vehicles passing the $(L_1 - L_2) / (L_1 + L_2)$ test. Italicized entries indicate poor performance on the test.

Data File	% central bin			% central 3 bins			% central bin all vehs	% central 3 bins all vehs
	> 72 km/h	32-72 km/h	< 32 km/h	> 72 km/h	32-72 km/h	< 32 km/h		
GP5-E	58.4%	62.5%	51.2%	78.6%	86.6%	78.2%	58.6%	80.1%
GP5-G	40.3%	27.8%	28.8%	56.1%	45.0%	56.9%	38.9%	55.0%
GP6	72.7%	77.8%	67.7%	87.9%	92.0%	85.4%	72.4%	87.9%
EDI	51.9%	36.4%	22.1%	60.2%	67.6%	51.8%	46.7%	60.8%
IDC	71.1%	75.4%	63.2%	86.2%	91.3%	83.2%	71.0%	86.6%

Figure 1 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.

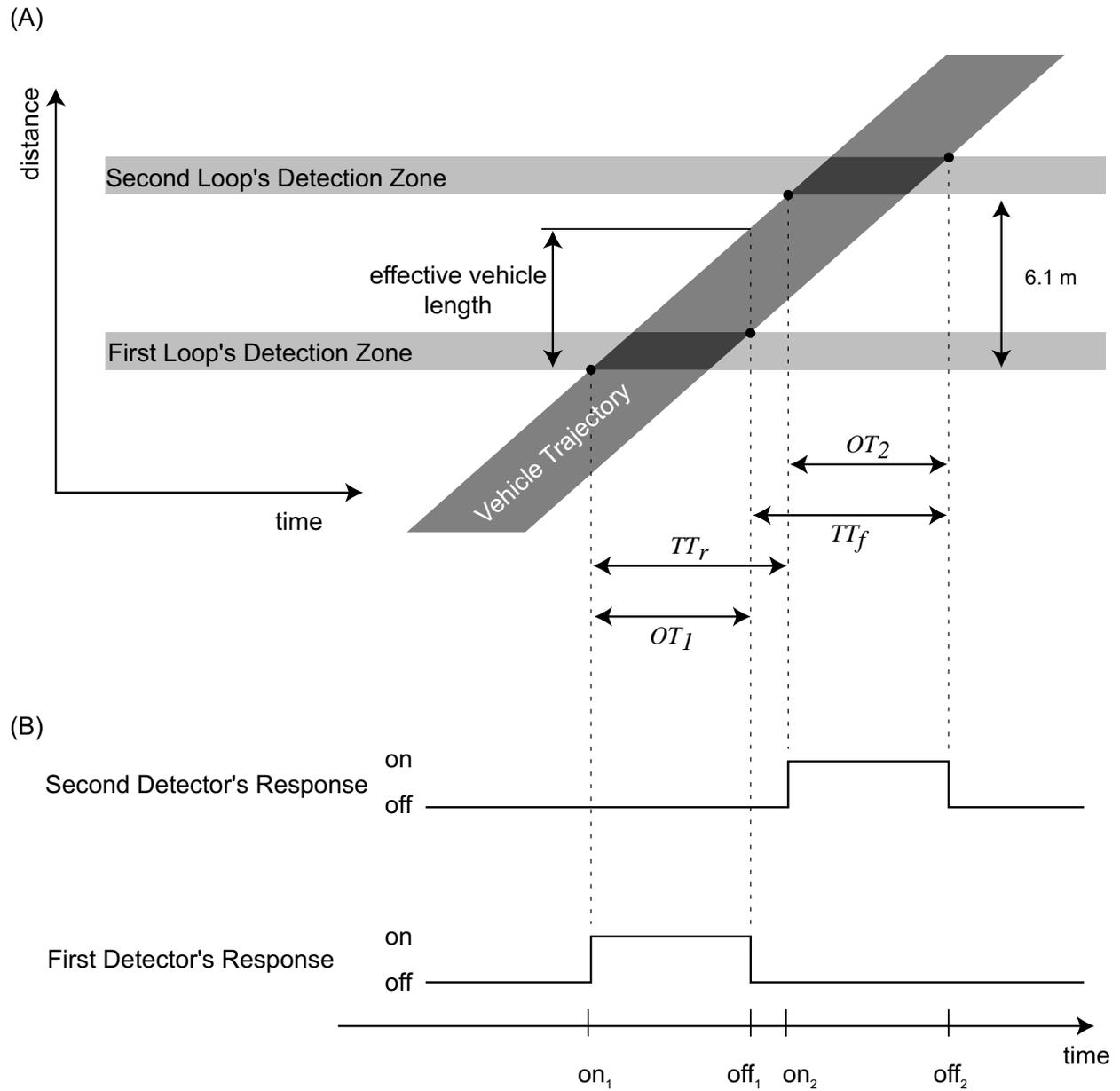


Figure 2 (A) Individual V_f from the GP5-G, (B) moving median of the data from part A.

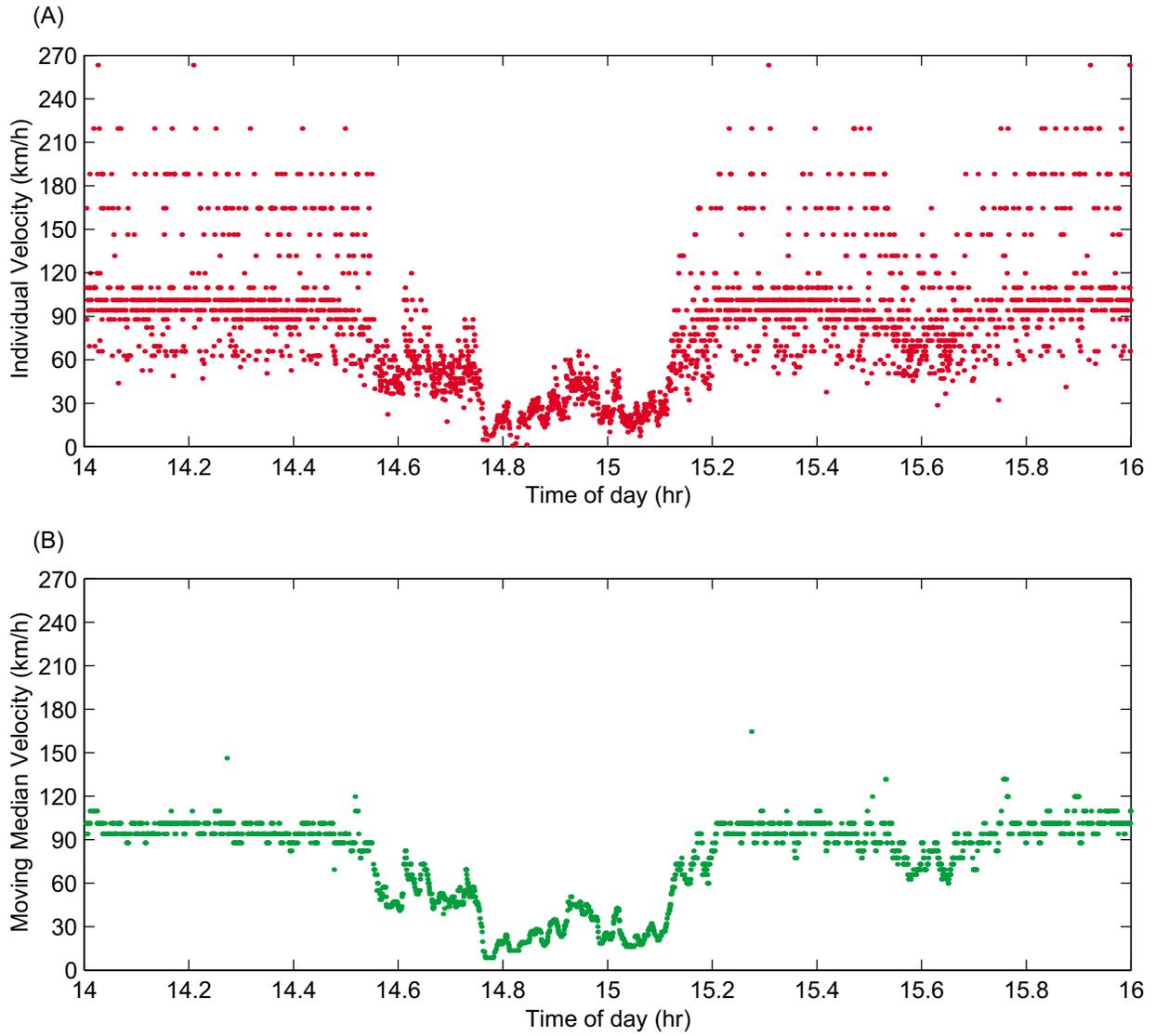


Figure 3 (A) Measured H versus OT_2 from the GP6 data using $V_r > 72$ km/h to identify the free flow data from over 24,000 vehicle measurements, (B) repeating the process for $V_r < 72$ km/h (C) regions of the headway on-time plane in which measurements should all be free flow or all congested.

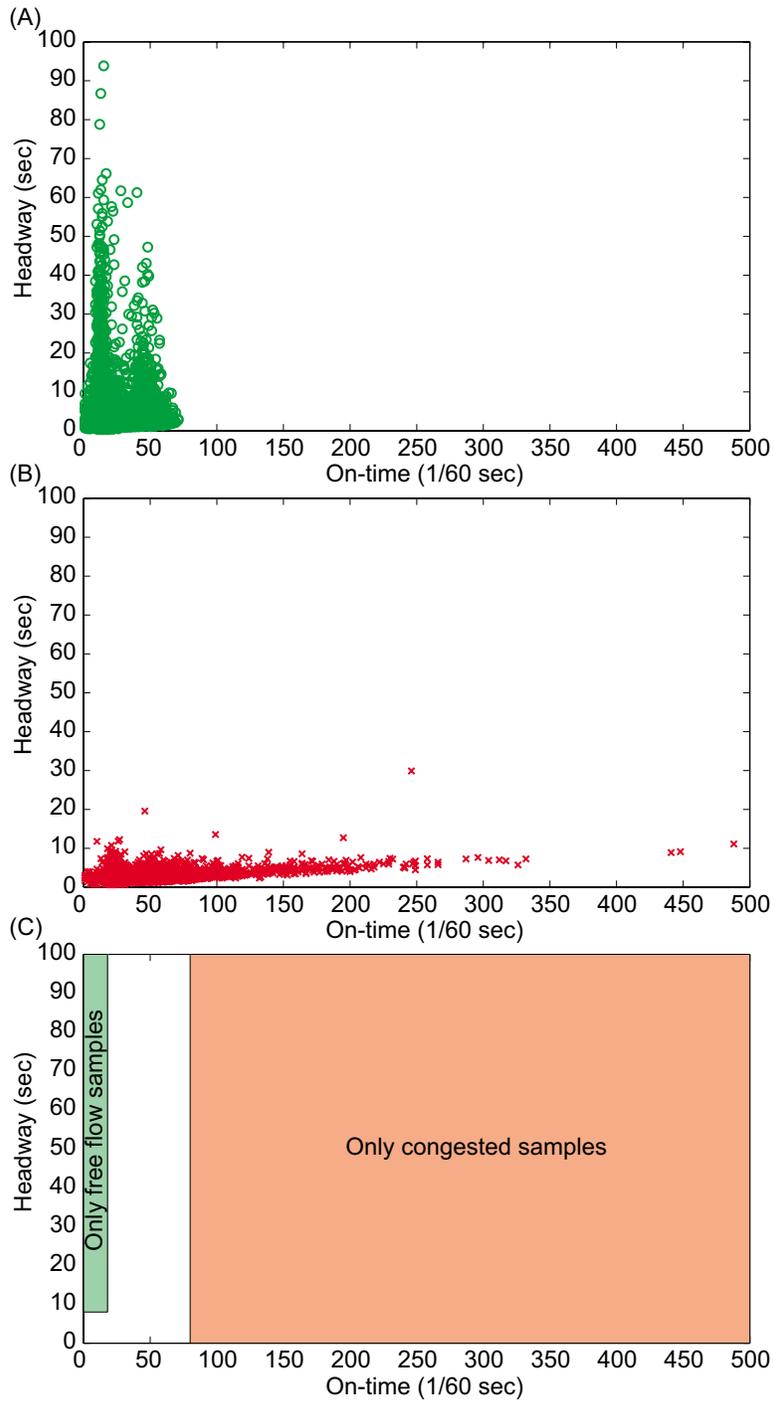


Figure 4 Five days of data from one detector station and six days of data from another station 0.54 km away, both using GP5-E sensor units. Also one day from the second station an EDI sensor unit, (A) Cumulative Distribution of L_I , (B) deciles of L_{est}

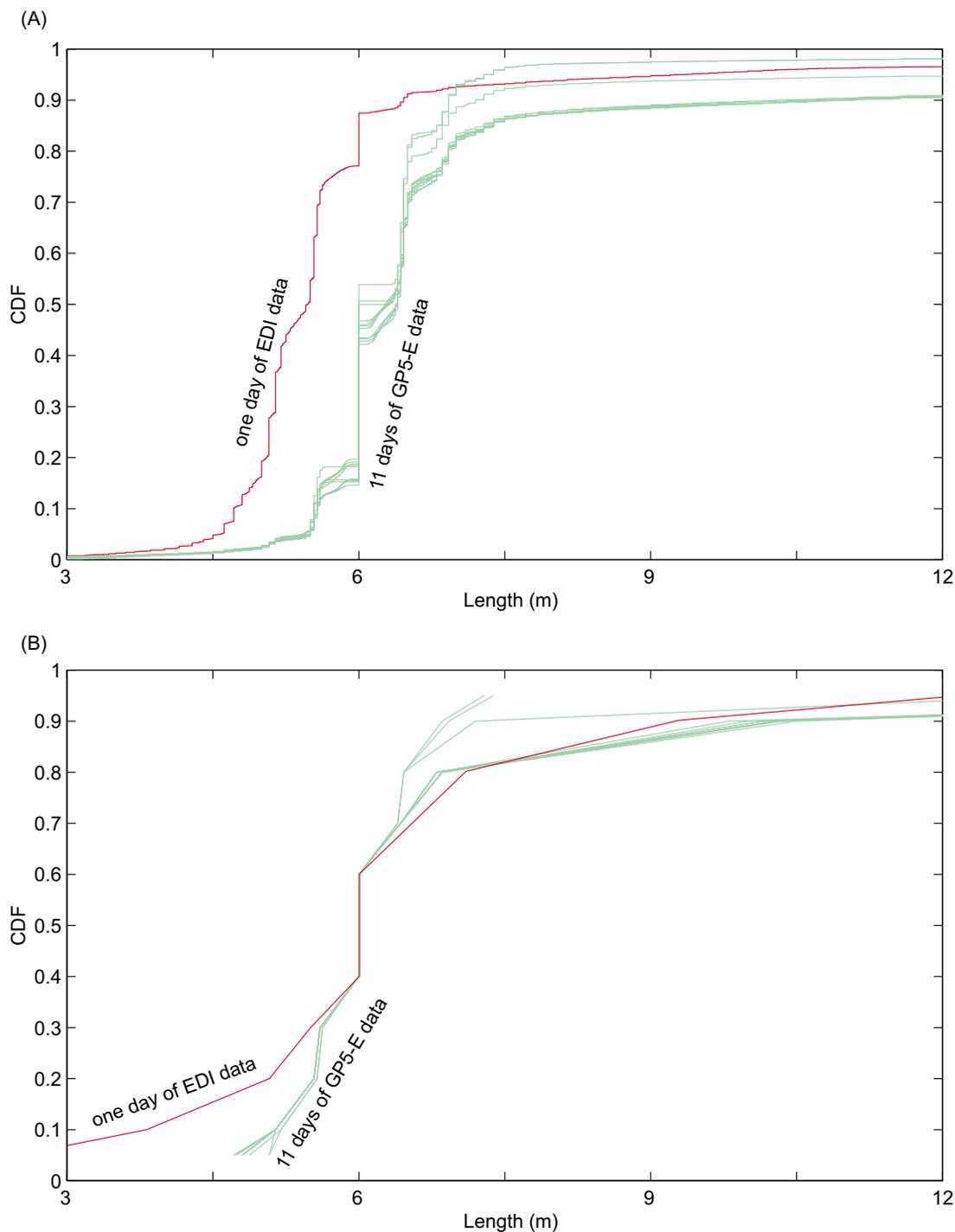


Figure 5 (A) Measured velocity, (B) traffic state from estimated velocity (high = free flow, low = congested), (C) distribution showing the number of congested samples preceding each free flow sample.

