VEHICLE CLASSIFICATION FROM SINGLE LOOP DETECTORS

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16. Abstract

Vehicle classification data are important inputs for pavement maintenance, traffic modeling, and emission evaluation. Various technologies including weight-in-motion (WIM), axle counting with piezo-electric sensors or length measurement from dual loop detectors have been used for vehicle classification. This research extends length based vehicle classification to single loop detectors. It promises a lower cost alternative as well as the potential to use existing detectors already deployed for freeway management. Of course the single loop based estimates could also be easily incorporated in a more sophisticated classification station as an independent validation of its measurements.

The main challenge with single loop detector based length based classification comes from accurately estimating speed and thus, length. In this study we develop a methodology to make such accurate speed and length estimates and then use the latter to classify vehicles based on length. Performance is validated against two sources of independent ground truth data with results that approach the accuracy of dual loop detectors. In the process of generating ground truth data a few previously unknown, sight specific problems with existing vehicle classification and detection stations were found and diagnosed, e.g., pulse break-up, as discussed herein.

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1 EXECUTIVE SUMMARY

1.1 Project Summary

This project developed a means for vehicle classification from single loop detectors, which are effectively metal detectors embedded in the pavement and they are among the simplest vehicle detectors in common use. Vehicle classification data are important for pavement maintenance, traffic modeling, and emission evaluation. This first of its kind work promises a lower cost alternative to conventional vehicle classification stations as well as the potential to use existing detectors already deployed for freeway management.

The Federal Government mandates that states collect classification data, in part because these data are among the most important inputs when forecasting pavement lifespan and condition. But most classification technologies are expensive to install and maintain. Perhaps the simplest (and least expensive) of these technologies in use are dual loop detectors, which consist of two single loop detectors per lane, spaced about 20 ft apart. The dual loop detector allows for direct speed measurement from the traversal time between the two loops. Multiply this speed by the time that a vehicle "occupies" one of the detectors and you get the vehicle's length. Vehicles can then be classified based on length. To date, single loops have not been used for vehicle classification because there is no traversal time to measure, and so speed can only be estimated. In conventional practice the speed estimate is very noisy and it would be impossible to get accurate vehicle lengths.

Researchers at the Ohio State University developed algorithms for processing single loop data to produce speed estimates that approach the accuracy of speed measurements from dual loop detectors. This research applied the algorithms to measure speed and vehicle length at single loop detectors, and then classify vehicles. It starts by refining our existing speed estimation algorithms to accurately estimate speed under a wide range of traffic conditions. Vehicle length is then estimated from the product of speed and the time that a vehicle "occupies" the detector. This study examined performance under a wide range of traffic conditions: free flow to congested, as well as from low to high truck volumes. A process of generating synthetic data was developed to capture higher truck volumes than observed. Following the Ohio Department of Transportation (ODOT) length based classification scheme for dual loop detectors, the lengths are then used to classify vehicles into three bins. This classification is evaluated against concurrent measurements from video and dual loop detectors.

The goal of this research is to mainstream the advances in speed and length estimation from single loop detectors and then develop a vehicle classification methodology for these detectors. It is envisioned that the classification work will feedback and improve length-based classification at dual loop detectors as well. As noted in a draft research statement from the TRB Committee on Highway Traffic Monitoring, "Classification based solely on vehicle length is an alternative to axle-based classification but there has been no systematic study of how well it works -- or how it should work." The present research had to address many of these issues in the course of verifying the performance of single loop detector based classification.

The first task was to meet with ODOT engineers to establish the properties of existing classification systems and desired properties of the proposed classification system, e.g., number of bins and length thresholds between bins.

The second task was to collect additional detector data from several locations. Particular emphasis was placed on stations with significant truck flows. Each location had to have an external measure for verification (concurrent video and/or dual loop detectors). Fortunately, most of the ODOT classification stations incorporate at least one loop detector per lane. We worked with ODOT to log individual vehicle data from several detector stations. In addition, we collected concurrent video at several stations to manually verify the vehicle class.

The third task used these data to develop and test the single loop detector classification against the ODOT classification. Ultimately we chose to adapt the length based classification scheme used by ODOT at dual loop detector stations and refined the classification methodology to single loop length estimates. The basic scheme employed by ODOT uses three classes: under 22 ft, between 22 ft and 40 ft, and above 40 ft. In parallel, we further improved the length estimation techniques from single loop detectors. We also employed vehicle level data from hundreds of detectors in the Columbus Metropolitan Freeway Management System (CMFMS) (see Coifman, 2006 for details). Only a few of these detectors experience significant truck demand so ultimately a scheme was devised to simulate the higher truck flows.

The fourth task used the manually extracted vehicle class from video to verify the performance of the new single loop classification methodology as well as the existing loops and classification station. This task was included because none of the existing detector technologies are perfect. Several errors were found in the existing systems and where possible, we systematically diagnosed the cause, reported the findings to the sponsors, and incorporated the lessons in our research.

While the cost of a single loop detector station is only a few thousand dollars less than a dual loop detector station, there are several applications of this research

1) Extend vehicle classification to existing detector stations used for real-time traffic management. Most large cities in the US have instrumented freeways that provide current conditions on the network, but most stop short of classifying vehicles. Most of these systems have single loop detectors or sensors that emulate single loop detectors. By extending classification to these real-time systems, more information will be available for planners, e.g., helping to track freight movements within the metropolitan areas.

2) New, out-of-pavement detectors seek to replace loop detectors using wayside mounted sensors, e.g., the Remote Traffic Microwave Sensor (RTMS), but most of these detectors emulate the operation of single loop detectors. The single loop detector developments will transfer to these emerging technologies.

3) More sophisticated classification stations could benefit from this research in two ways. First, the single loop detector classifications could be used to verify the measurements from the classification station. If the two classification schemes differ too frequently, the station could request a technician visit. Secondly, most of the classification stations use some form of the traversal time employed by dual loop detectors. When one detector fails, presently it would eliminate monitoring in that lane. The present work provides a software based treatment that could keep that lane operational until the agency is able to schedule a maintenance crew, close the lane(s) and undertake the repair.

4) Finally, develop methods for working with length based classification data, no matter what type of detector was used

1.2 Findings and Conclusions

Performance is validated against two sources of independent ground truth data with results that approach the accuracy of dual loop detectors. The validation data included concurrent measurements from video and dual loop detectors. In the process of generating ground truth data a few previously unknown, sight specific problems with existing vehicle classification and detection stations were found and diagnosed. The ultimate goal of this research is to mainstream the advances in speed and length estimation from single loop detectors. It is envisioned that the classification work will feedback and improve length-based classification at dual loop detectors as well.

The research compared the estimation results (speed, length, and class) against concurrent measurements from dual loops, axle based classification, and manually extracted ground truth from concurrent video. The 90th percentile speed estimation error was 10 mph, and 90th percentile length estimation error was 4 ft. Length estimation and classification showed sensitivity to congested conditions, and improving vehicle classification during congestion should be the topic of further research. Single loop detector classification accuracy was over 95% during free flow periods, and was comparable to the dual loop detector results. Performance degraded at one test site due to a chronic detector error (the detectors would "drop out" in the middle of many semi-trailer trucks). While beyond the initial scope of this research, a pilot study is included in this report to demonstrate the proof of concept that many such errors could be caught, though catching such errors should be the topic of further research. In any event, these errors impacted single and dual loops alike. More stations, a wide range of conditions, and simply more ground truth data need to be generated.

Finally, classification performance drops to about 85% accuracy during congestion due to the fact that we estimate a "typical" speed within a sample of many vehicles but a given vehicle may have a speed that is far from typical within a congested sample. In the meantime, the algorithms can be used to reliably detect congested conditions, so results during such periods can at least be identified by the current methodology and weighted appropriately. There is likely room for further improvement in estimating individual vehicle speed from single loop detectors during heavy congestion.

1.3 Recommendations for Further Action

Two issues remain and need following up: (1) collect additional ground truth data at more locations and under different traffic conditions for further validation and development. (2) Address conditions that still challenge length based classification from single and dual loop detectors, specifically, (a) poorly tuned loops and detector errors, (b) performance under heavily congested conditions.

2 INTRODUCTION

Roadway usage, particularly by large vehicles, is one of the fundamental factors determining the lifespan of highway infrastructure. The importance of road usage is evidenced by the federally mandated Highway Performance Monitoring System (HPMS) and the significance of large vehicles is reflected in the Weigh in Motion (WIM) data collected for the Long Term Pavement Performance (LTPP) program. Interest in the movement of these large vehicles has also increased from the transportation planning perspective, as freight shipments are finally entering the planning process. Ultimately the planning process feeds back into infrastructure needs, allowing better forecasts of future demands.

Each state typically has several dozen WIM stations to monitor large vehicle usage. These stations are expensive to install and maintain, so they are usually supplemented with many more vehicle classification stations. Some of the classification stations employ axle counters, but the simplest of these stations use dual loop detectors to measure vehicle length from the product of measured speed and detector on-time, and classify vehicles based on this measurement. The state of Ohio currently has 216 permanent count stations, roughly half of which provide WIM or axle based classification. Of the remaining 99 count stations, 50 provide length based classification from dual loop detectors and the other 49 only provide volume data from single loop detectors. The classification data are used in a wide variety of applications, including, but not limited to: Modeling and Forecasting, Planning, Roadway Engineering, and Pavement Design.

Meanwhile, single loop detectors are the most common vehicle detector in use to monitor traffic, both for real time operations and for collecting census data such as Annual Average Daily Travel (AADT) used in the HPMS. New, out-of-pavement detectors seek to replace loop detectors using wayside mounted sensors, e.g., the Remote Traffic Microwave Sensor (RTMS), but most of these detectors emulate the operation of single loop detectors. In either case, collecting reliable length data from these detectors has been considered impossible due to the noisy speed estimates provided by conventional data aggregation at single loop detectors[1]. As discussed herein, our research group has developed new techniques for estimating speed at a single loop detector, yielding estimates that approach the accuracy of a dual loop detector's measurements. This research investigates the feasibility of taking these advances in speed estimation to extend length based vehicle classification to single loop detectors, as well as many of the emerging wayside based, out-of-pavement detectors that emulate single loop detectors. The research promises to extend vehicle classification to the single loop detector count stations and offers a viable treatment in the event that one of the loops in a dual loop detector classification station fails. In addition to the aforementioned count stations, there are many single loop detector stations used for real time traffic management. Thus, the research promises to provide a lower cost means of collecting vehicle classification data, provide a software based solution when one of the detectors in more sophisticated classification station fails, and extend classification to traffic monitoring stations in urban areas. In fact the classification work could allow these urban traffic management systems to better monitor freight traffic within the metropolitan areas.

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[1] See Coifman (2001) for a detailed discussion of this problem.

The present study develops a length based classification methodology from single loop detectors. It starts by refining our existing speed estimation algorithms to accurately estimate speed under a wide range of traffic conditions. Vehicle length is then estimated from the product of speed and measured on-time. This study examines performance under a wide range of traffic conditions: free flow to congested, as well as ranging from low to high truck volumes. To capture higher truck volumes than empirically observed, a process of generating synthetic on-times is also developed. Following the Ohio Department of Transportation (ODOT) length based classification scheme for dual loop detectors, the lengths are then used to classify vehicles into three bins. This classification is evaluated against concurrent measurements from video and dual loop detectors.

2.1 Overview

The remainder of this section reviews the research objectives, provides general background on loop detector based vehicle classification, as well as specific background on speed and length estimation at single loop detectors. Section 3 then provides details on the improved speed estimation methodologies for single loop detectors and the data sources used in this study. Section 4 evaluates the speed estimation performance using measured and synthetic data. Section 5 evaluates detector performance at two test sites using concurrent video and provides further details about the data sets used throughout the remainder of this report. Section 6 evaluates the performance of length based classification. Finally, Section 7 closes this report with a summary, conclusions, and future work.

2.2 Research Objectives

The goal of this research is to mainstream the advances in speed and length estimation from single loop detectors and then develop a vehicle classification methodology for these detectors. It is envisioned that the classification work will feedback and improve length-based classification at dual loop detectors as well. As noted in a draft research statement from the TRB Committee on Highway Traffic Monitoring, "Classification based solely on vehicle length is an alternative to axle-based classification but there has been no systematic study of how well it works -- or how it should work." The present research had to address many of these issues in the course of verifying the performance of single loop detector based classification.

The first task was to meet with ODOT engineers to establish the properties of existing classification systems and desired properties of the proposed classification system, e.g., number of bins and length thresholds between bins.

The second task was to collect additional detector data from several locations. Particular emphasis was placed on stations with significant truck flows. Each location had to have an external measure for verification (concurrent video and/or dual loop detectors). Fortunately, most of the ODOT classification stations incorporate at least one loop detector per lane. We worked with ODOT to log individual vehicle data from several detector stations. In addition, we collected concurrent video at several stations to manually verify the vehicle class.

The third task used these data to develop and test the single loop detector classification against the ODOT classification. Ultimately we chose to adapt the length based classification scheme used by ODOT at dual loop detector stations and refined the classification methodology to single loop length estimates. The basic scheme employed by ODOT uses three classes: under 22 ft, between 22 ft and 40 ft, and above 40 ft.[2] In parallel, we further improved the length estimation techniques from single loop detectors. We also employed vehicle level data from hundreds of detectors in the Columbus Metropolitan Freeway Management System (CMFMS) (see Coifman, 2006 for details). Only a few of these detectors experience significant truck demand so ultimately a scheme was devised to simulate the higher truck flows.

The fourth task used the manually extracted vehicle class from video to verify the performance of the new single loop classification methodology as well as the existing loops and classification station. This task was included because none of the existing detector technologies are perfect. Several errors were found in the existing systems and where possible, we systematically diagnosed the cause, reported the findings to the sponsors, and incorporated the lessons in our research.

2.3 Background

There has been considerable research on vehicle classification leading to the conventional technologies as well as on-going work in emerging technologies. Needless to say, the body of work is broad and this report does not seek to review all of the different means used to classify vehicles. Loop detectors are the preeminent vehicle detector for freeway traffic management. Limiting the scope to loop detector based speed estimation, length estimation, and vehicle classification, this section reviews the related literature.

For length-based classification from loop detectors, there are three interrelated parameters that can be measured or estimated for each passing vehicle, namely length (l), speed (v) and the amount of time the detector is "on", i.e., the *on-time* (on). These parameters are related by the following equation,

$$l = v \cdot on \tag{1}$$

At a single loop detector, only the on-time can be measured directly, while a dual loop detector can measure the speed from the quotient of the detector spacing and the difference in actuation times at the two loops. Given two of the three parameters, obviously the third is defined by Equation 1. In the absence of accurate speed estimation from single loops, these detectors generally have not been used to estimate vehicle length or classify vehicles.

In fact, although single loop detectors have been used for decades, debate continues on how to interpret the measurements. Many researchers have sought better estimates of speed from single loop detectors. The preceding research has emphasized techniques that use many samples of aggregate flow (q) and occupancy (occ) to reduce the estimation error (e.g., Mikhalkin et al., 1972, Pushkar et al., 1994, Dailey, 1999, Wang and Nihan, 2000, and Coifman, 2001). Although rarely explicitly noted, these techniques effectively seek to reduce the bias due to long vehicles in measured occupancy. Rather than manipulating aggregate data, we developed new aggregation methods to reduce the estimation errors.

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[2] The two threshold vehicle lengths of 22 ft and 40 ft are in terms of physical vehicle length, after correcting for effective vehicle length "seen" by the detector.

Provided that vehicle lengths and vehicle speeds are uncorrelated, as shown in Coifman (2001) and elsewhere, harmonic mean speed (mean v) and arithmetic mean vehicle length (L) for a given sample are related by the following equation:

$$mean\ v \approx \frac{q \cdot L}{occ} \tag{2}$$

This equation is an extension of Equation 1, since q/occ is simply the reciprocal of average on-time and as with Equation 1, average length and average speed cannot be measured independently at a single loop detector. Typically, an operating agency will set L to a constant value and use Equation 2 to estimate speed from single loop measurements. But this approach fails to account for the fact that the percentage of long vehicles may change during the day or the simple fact that a sample may not include "typical" vehicle lengths. Particularly during low flow, when the number of vehicles in a sample is small, a long vehicle can skew occupancy simply because it takes more time for that vehicle to pass the detector. For example, at one detector station Coifman (2001) found that approximately 85 percent of the individual vehicle lengths observed were between 15 and 22 feet, but some vehicles were as long as 85 feet, or roughly four times the median length.

In accordance with the law of large numbers, the sample distribution should become more representative of the entire population as the sample size increases, which in turn, increases with flow. Figure 1 demonstrates this phenomena in real data using two common sampling periods (T) at a dual loop detector to plot the true L as a function of flow. In part A, T=30 sec and the maximum number of vehicles per sample is so small that the observations fall into distinct columns, i.e., the first column contains observations with only one vehicle, the second column contains observations with only two vehicles, and so on. Notice that for both values of T, the range of L is inversely proportional to q.

This large range of average vehicle lengths arises due to the small number of vehicles with lengths far from the center of the distribution. The median of a sample is much less sensitive to these outliers, and

$$median\ v \approx \frac{L}{median\ on\ time} \tag{3}$$

provides an alternative estimate of speed[3]. As shown in Coifman et al. (2003), Equation 3 performs significantly better than Equation 2, and in fact it approaches the accuracy of dual loop detector measurements for the study data.

2.4 Estimating Vehicle Lengths

There have been several efforts to estimate the percentage of vehicles passing a single loop detector that are long based on time-series trends in flow and occupancy. Yinhai and Nihan (2004) developed an algorithm that estimates truck volume dynamically from single loop detector using pattern discrimination and nearest-neighbor methods. They used dual loop measurements to verify the performance. Kwon et al. (2003) also introduced an algorithm to

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[3] Note that the optimal value of L for Equation 3 may differ from Equation 2.

estimate truck volume, defined to include any vehicles longer than 50 ft, from single loop detectors. They developed the estimation algorithm using the fundamental relationship among flow, occupancy, and speed, taking in to account the impacts of effective vehicle length, and then evaluated the mean effective vehicle length produced as a "by-product" from speed estimation. Both of these studies are built on assumptions that may not apply to all traffic conditions. In both cases, the algorithms use aggregate data, were only validated in urban freeways with limited truck volume (under 10%) and the fleet composition was assumed to remain static. Significant changes in the proportion of trucks and simply high truck volumes were beyond the scope of the earlier work. Other studies have looked specifically at conventional dual loop based classification on a vehicle by vehicle basis, e.g., Cheevarunothai et al (2007) and Nihan et a (2002). There have also been efforts to use new loop detector sensors to measure the inductive vehicle signature for vehicle classification, e.g., Reijmers (1979) and Gajda et al (2001). While these inductive signature based efforts are promising, they have not yet seen widespread deployment, and the conventional loop detectors with a binary output (occupied or empty) remain the dominant configuration.

Returning the focus to conventional single loop detectors, the present research seeks to estimate vehicle lengths and classify vehicles. Assuming the loop detector is functioning properly, Equation 1 shows that a given on-time measurement is simply a function of the vehicle's length and speed. During free flow conditions the vehicle speeds typically fall in a small range and during congested conditions the difference between successive vehicles' speeds is usually small. If one assumes that all of the vehicles in a sample are traveling near the median speed, one can use Equation 3 in conjunction with measured on-times to estimate individual vehicle lengths with the following equation,

$$\hat{l}_j = \hat{v}_i \cdot on_j \tag{4}$$

where

$\hat{l}_j$ = estimated vehicle length for the j-th vehicle in the i-th sample

$\hat{v}_i$ = estimated speed for the i-th sample

on_j = measured on-time for the j-th vehicle in the i-th sample.

Of course the number of vehicles per sample must be small enough for the speed assumption to hold and one must control for low speed conditions, when acceleration becomes non-negligible during the sample. Using samples of ten consecutive vehicles and restricting the analysis to samples with $\hat{v}_i$>20 mph (from Equation 3), Coifman et al. (2003) found the average absolute error in $\hat{l}_j$ is less than six percent for 210,000 vehicles in the sample data set that satisfy the speed constraint[4]. The length estimates can be improved further by calculating the median speed for the N vehicles centered on the subject vehicle.

[4] This error is on the order of the measurement resolution of a dual loop detector sampling at 60 Hz, measuring passenger vehicles at free flow speeds.

2.5 The Impact of Heavy Truck Traffic

In the presence of heavy truck traffic, e.g., 40-60 percent of the flow, the improvements from Equation 3 degrade because of the high variability in sample median vehicle length. Using data from a detector with heavy truck traffic, Nellisetty and Coifman (2004) developed a methodology to address this problem. As demonstrated in the paper, two consecutive vehicles usually have similar speed, even during congestion, and thus, from Equation 1, the ratio of the on-times is a good approximation of the ratio of their lengths. The extension explicitly recalibrates speed estimates by looking for two consecutive vehicle measurements possessing the longest feasible vehicle length and the shortest feasible length, roughly 80 ft and 18 ft, respectively or a ratio of 4:1 in successive on-times. When this ratio is observed in the on-times, one then knows the vehicle lengths in addition to the on-times and can use Equation 1 to estimate speed. Further checks are then made to eliminate transient detection errors that would otherwise disrupt this speed estimation. In the end, the speed estimation methodology had an average absolute percent error under six percent for a detector with heavy truck traffic.

3 IMPROVED SPEED ESTIMATION FROM SINGLE LOOP DETECTORS

This research set out to estimate speed using a combination of the moving median method (Equation 3, from Coifman et al., 2003) and the sequence method (from Nellisetty and Coifman, 2004). In the course of the research, some shortcomings were encountered and a third technique was devised that examines the on-time distribution within a sample (henceforth called the distribution method). The research also considered the conventional speed estimates from Equation 2. After reviewing the development data, specific details of the three non-conventional speed estimation methods will be presented.

3.1 Development Data

The detector stations deployed as Phase I of the CMFMS in Columbus, OH served as the primary data source for development (see Coifman, 2006, for more details). Phase I covered I71 from the central business district (CBD) to the northern suburbs, as highlighted in Figure 2. The deployment covered roughly 14 miles, with dual loop detector stations every mile and an average of two single loop detector stations between each successive pair of dual loop detector stations. The detector stations report individual transition data for each vehicle that passes, i.e., the times when the given detector becomes occupied or empty, sampled at 240 Hz. From these data, it is possible to measure arrival time, on-time, and off-time for each vehicle at the given detector. If it is a dual loop detector, one can also measure speed and vehicle length for each vehicle.

As with the earlier speed estimation studies, the dual loop detectors provided a ready source of ground truth for vehicle speeds and lengths. Also like the earlier studies, except for a few detectors, these urban data are characterized by relatively low truck volumes and those detectors with high truck volume rarely see any congestion. Figure 3A shows a typical distribution of individual vehicle lengths observed in this corridor over a 24 hr period. As with most stations, this bimodal distribution is characterized by a tall, narrow peak around 20 ft due to passenger vehicles and a shorter and broader peak around 70 ft due to longer vehicles. Figure 3B shows the corresponding on-times from known free flow periods, as would be observable from a single loop detector. As long as speed is stable, e.g.., due to being in a known free flow period, the two distributions should exhibit similar trends via Equation 1.

But one of the objectives of this research is to extend single loop based length classification to detectors with high truck volumes. Such data were synthesized by combining measured speed and arrival times from a dual loop detector station that experiences recurring congestion with synthetic vehicle lengths for the vehicles and then calculating a new set of on-times that would result from Equation 1. Each vehicle length was determined via a two step process, first randomly determine whether the vehicle was long (LV) or short (SV) based on the desired percentages of each type of vehicle, then for the given vehicle type, randomly sample a synthetic vehicle length from an empirically observed distribution of either long or short vehicles at a dual loop detector station. The details of this process are presented in the following subsection.

3.2 Synthetic Data

Synthetic data generation focused on generating single loop output under various proportions of truck volume. Individual vehicle arrival times and speeds were measured at station 1 northbound, a dual loop detector station that experiences recurring congestion. The actual lengths and on-times are discarded. Each vehicle is randomly assigned to be either SV or LV in accordance with the desired percentages. Based on the empirical distributions and their bimodal nature, e.g., Figure 3A, the threshold between the two groups is set at 50 ft. The cumulative distribution function (CDF) for vehicles below this threshold and separately for vehicles above this threshold are then used to randomly generate a specific vehicle length for the given SV or LV, respectively. This new length is assigned to the vehicle and the corresponding on-time is calculated via Equation 1 from the measured speed and synthetic length. Figure 4A-B show the underlying length distributions for the two groups, while Figure 4C-D show the resulting length distribution given 10 percent LV and 90 percent LV, respectively. The individual vehicle speed and synthetic length are stored for validation purposes.

By preserving the arrival times and changing the on-times (typically extending them), this process will disturb the occupancy because the off-times between vehicles are no longer representative of what drivers would actually do, e.g., as illustrated in Figure 5. While the new speed and length estimation techniques do not use occupancy and are not impacted by the changed off-times, we still calculate a corrected occupancy to evaluate the performance of conventional speed estimation from Equation 2. So when calculating occupancy, after generating the synthetic on-times, we retain the original off-times between vehicles. Equation 5 illustrates this calculation for the pulses in Figure 5

$$occ' = \frac{on'_i + on'_{i+1}}{on'_i + on'_{i+1} + off_i + off_{i+1} + off_{i+2}} \times 100\% \qquad (5)$$

where the primes are used to denote metrics that are changed as a result of the synthetic on-times. In effect, this correction extends the sample period but the expansion does not affect the speed estimation provided the flow is adjusted in a similar manner, thus when we apply Equation 2, we directly calculate average on-time.

3.3 Moving Median Method

For this study, the median on-time was used to estimate speed via Equation 3. The median is taken from a fixed window of 33 vehicles centered on the current vehicle. The window moves by one vehicle each sample, hence "moving median". This same window is used when applying the conventional speed estimate from Equation 2. In either case, the fixed number of vehicles ensures that there will be many vehicles in the sample, even during periods of low flow.

3.4 ***Sequence Method***

If the percentage of long can fluctuate from sample to sample, then the true value of L in Equation 2 will vary as well. If the fluctuation is large enough, the true value of L in Equation 3 will also vary. Following Nellisetty and Coifman (2004), generally the speed of two successive vehicles is close to one another and their on-time ratio from a single loop detector should be proportional to their length, even during congestion. For most pairs of successive vehicles this fact does not help, for example an on-time ratio of 1:1 just means the two vehicles have the same length. However, when the two successive vehicles are the longest and shortest vehicles, one can deduce their lengths directly from the on-times. From Figure 3A, the longest vehicles are about 70 ft and the shortest are about 20 ft, i.e., a ratio of 3.5:1. In the absence of detector errors, this length ratio can only be observed from such a pair of LV and SV. Provided their speeds are similar, the on-times will exhibit the same ratio. There are two possible sequences one can expect to recognize: a SV followed by a LV; and a LV followed by a SV. To accommodate the fact that these two populations have some variability in lengths and that the speeds might not be exactly equal, the method looks for ratios between successive on-times that fall in a range rather than a fixed value, namely from 3.0 to 4.5. When this ratio is observed in the on-times, Equation 1 is used to estimate the speed of the two vehicles given l_{SV}=20 ft for the SV and l_{LV}=70 ft for the LV, i.e.,

$$\hat{v}_{SV} = \frac{l_{SV}}{Ontime_{SV}} \tag{6A}$$

$$\hat{v}_{LV} = \frac{l_{LV}}{Ontime_{LV}} \tag{6B}$$

If there are multiple sequences within sample, the algorithm keeps estimating speed for each sequence and then assigns the median speed from all of the individual estimates to all vehicles within the sample. On the other hand, when there are no such sequences within the sample, the algorithm falls back to the moving median method.

After working with the sequence method, particularly when using the synthetic data, it was found that it fails too frequently during congestion. The assumption that two successive vehicles have the same speed simply does not hold at low speeds when acceleration is non-negligible (e.g., stop-and-go traffic).

3.5 ***Distribution Method***

The limitations of the Sequence method in congestion lead to the development of a new method that considers the entire distribution of on-times observed in a sample. As with the moving median, vehicles are sampled in fixed numbers of 33 vehicles. If this window exhibits a clear bimodal distribution, e.g., as seen in Figure 3B, then the two peaks can be localized and the speeds estimated using Equation 6. If the resulting distribution is not bimodal, a series of steps are taken to estimate the speed. The details of the process are as follows.

First check to see if the sample exhibits the expected bimodal distribution, i.e., establish whether there two peaks. If so, following the same logic used in the Sequence Method, check to see if the ratio between the two mode on-times in the neighborhood of 3-4.5. Explicitly enumerating the steps,

Step 1: find the dominant mode on-time, i.e., the largest peak

Step 2: search for observations within 3 to 4.5 times larger than the dominant mode

Step 3: search for observations within 3 to 4.5 times smaller than the dominant mode

Step 4: compare the number of observations on both sides of the dominant mode and decide which one has more observations

Step 5: if the secondary peak from Step 4 includes three (just under 10% of the sample) or more vehicles, the sample is considered bimodal and analysis continues to Step 6, otherwise, the sample is considered unimodal and treated using one of the techniques that follow

Step 6: assign assumed average vehicle length to the dominant mode based on the location of the secondary peak with more observations from step 4 (l_{SV} or l_{LV}) and estimate speed from Equation 6

With the threshold of 10% of the vehicles having to fall in the secondary peak before the distribution is considered bimodal, one would frequently expect samples to be classified as unimodal, e.g., in practice most of vehicles passing through the I71 corridor are passenger vehicles and it is not uncommon to find that all 33 vehicles within a sample are passenger vehicles yielding a unimodal on-time distribution.

For these unimodal distributions, taking 45 mph as a conservative lower bound to free flow conditions, using Equation 1 one can calculate the feasible on-times for SV and LV under different traffic conditions. The on-time of 20ft vehicle at 85 mph should be 9.6 [1/60 sec] and at 45 mph should be 18.2 [1/60 sec]. Similarly the on-time of 70 ft vehicle at 85 mph should be 35.8 [1/60 sec] and at 45 mph should be 63.7 [1/60 sec]. Figure 6 plots these thresholds versus on-time and denotes four regions,

Region 1- 20 ft vehicle traveling above 45 mph (free flow)

Region 2- 20 ft vehicle traveling below 45 mph (congestion)

Region 3- Either 20 ft traveling below 45 mph or 70 ft vehicle traveling above 45 mph (uncertain)

Region 4- Either 20 ft or 70 ft vehicle traveling below 45 mph (congestion)

The dominant mode will fall in one of these four regions. If the dominant mode falls within Region 1 or 2, it can be deduced directly that the mode corresponds to a SV and speed can be estimated from Equation 6. In region 4 it is not clear what the dominant vehicle is, but it is clearly congested. The largest ambiguity arises in region 3, it is either due to free flowing LV or congested SV. To identify the traffic condition of a unimodal sample falling in region 3, we apply the following three tests: an occupancy filter, on-time variance within sample, and estimated speed from previous sample.

Occupancy filter: Empirically, low occupancy corresponds to freely flowing traffic with low flow (Jain and Coifman, 2005). Therefore, a sample can be considered as free flowing one if its occupancy is less than a certain threshold. In this study when occupancy is below 15%, the sample is considered free flowing and speed is estimated from Equation 6 assuming the mode corresponds to a LV. Otherwise, analysis continues with the next two steps in parallel,

On-time variance: In general speed during free flow is more stable than during congestion because a common feature of congested traffic is the acceleration and deceleration waves. Furthermore, the relative impact to on-time of a given small speed fluctuation, e.g., 1 mph, increases as the traffic speed decreases. For the same level of speed fluctuations the variation of on-time during free flow is less than congestion. An on-time sample variance of 1/9 [sec^2] is used as the threshold between free flow and congested. The particular threshold value was derived from empirical analysis of dual loop data.

Estimated speed from previous sample: Two successive samples will typically have similar speeds, i.e., the transitions between free flow and congestion are only observed a few times a day (if at all). So if a unimodal distribution is found with the mode in Region 3 in one sample, the estimated speed from preceding sample is used as a proxy for the traffic condition of the current sample.

If the sample is deemed congested by the on-time variance and this result is consistent with the previous sample, speed is estimated from Equation 6 assuming the mode corresponds to a SV. Likewise, if both tests indicate that conditions are free flowing, speed is estimated from Equation 6 assuming the mode corresponds to a LV. If none of the above cases are met, then the sample is treated as an exception, as discussed below.

Before considering the exceptions, however, consider the performance of these three tests. Using data from a dual loop detector station one can collect both the measured speed from the two loops and concurrent estimated speed from just one of the loops. Specifically, using an entire month of data (April 2005) from lane 3[5] northbound at station 1 (a dual loop detector that regularly experiences congestion) to illustrate, all unimodal samples that fall in Region 3 are extracted and put through these three tests. Because the I-71 corridor typically has only about 10% truck flow, few unimodal free flow samples fell in Region 3. So the same time series data were used to generate synthetic observations with 80% truck flow, and all the resulting unimodal samples that fall in Region 3 were added to those from the measured data. Figure 7 shows the CDF of dual loop speeds for the samples classified as free flow from the occupancy filter applied to the single loop on-times. The remaining samples are run concurrently through the on-time variance test and the estimated speed from the previous sample is considered. Those samples exceeding the variance threshold and preceded by a congested sample are also considered congested, while those samples below the threshold and preceded by a free flow sample are considered free flow. Figure 8 shows the CDF of dual loop speeds for samples classified as congested (solid curve) and free flow (dashed curve) by the pair of filters. As can be seen in the two figures, most of the samples are assigned to the correct traffic condition.

[5] Following the convention of the CMFMS, lanes are numbered from left to right, starting at the median.

When the mode falls in Region 4, traffic has to be congested, whether the dominant vehicle is long or short. But differentiating between the possible vehicle lengths is necessary to get an accurate speed estimate. Given a unimodal distribution, one cannot differentiate between the two situations. The algorithm increases the sample size to 51 vehicles and examines whether the distribution has changed to a bimodal distribution or still remains a unimodal distribution. If it turns out to be a bimodal distribution then speed is then estimated in the same fashion as a normal bimodal distribution. Otherwise, the sample is an exception and handled as follows.

There are three exceptions where the above methodology is not applied to estimate speed for a given sample, namely,

- Samples whose distributions have more than two peaks
- Unimodal samples falling in Region 3 that are not filtered from the three tests
- Samples falling in Region 4 that still have unimodal distribution after expanding the sample size

For those exceptional cases, the second shortest on-time measurement within each sample is taken and assumed to come from a passenger vehicle, as it is not likely to observe 33 successive long vehicles in a lane, so the shortest on-times likely come from passenger vehicles. Taking the second shortest reduces sensitivity to detector errors that might cause erroneously short on-times. Speed is then estimated from this on-time using SV in Equation 6. Thereby estimating speed for one of the faster passenger vehicles in the sample and assuming it applies to all of the vehicles in the sample. Finally, note that these exceptions are relatively uncommon, only 0.66% of the samples from the month used to generate Figures 7 and 8 were classified as exceptions.

4 SPEED ESTIMATION PERFORMANCE

The four methods of estimating speed: conventional, moving median, sequence, and distribution, were evaluated in two ways. First in terms of the actual measured on-times (upstream loop) and speeds from dual loop detectors on I-71, and then in terms of the synthetic data with various percentages of trucks.

4.1 *Performance Evaluation Using Measured Data*

The analysis begins with data from northbound dual loop station 1, which as noted earlier, sees recurring congestion. Then the analysis is extended to all operational, northbound dual loop detector stations. Figure 9 compares the time series speed estimates from the four methods against one another as well as against the measured speed for one day in one lane. The conventional method exhibits the most noise, with several hours of under-estimation during the early morning low flow periods, while the distribution method the least noise. All three of the new estimation methods appear to yield satisfactory performance for this lane. Extending the analysis to the entire month of April, 2005, and all operational dual loop detectors, the results are similar to those shown in Figure 9. Figure 10 tabulates the 90th percentile of the absolute difference between the given estimate and the measured speed over the month for each lane at each station. Once more, all three of the new estimation methods yield similar performance, and this performance is generally better than the conventional method. Among the three new methods, the sequence method yields slightly poorer results.

Using the on-times and speed estimates to estimate vehicle lengths (via Equation 1), Figure 11 compares the individual estimated vehicle lengths against the corresponding measured lengths for the same data used in Figure 9. Each row shows a different method. The first column shows all of the data, middle shows the data from the periods when speeds were above 20 mph, and last column shows the data from the periods when speeds were below 20 mph. The conventional method tends to underestimate vehicle length for some long vehicles due to underestimating speed in the early morning hours. The last column shows that all four methods had problems during heavy congestion, over estimating vehicle lengths for passenger vehicles when speeds were below 20 mph. This problem arises for several reasons, first, even with samples of just 33 vehicles, the chosen speed for the sample may not be representative of a specific vehicle's speed. Second, at these low speeds, acceleration becomes non-negligible, impacting both the measurements and the estimates. When measured speeds are above 20 mph, all three of the new estimation methods yield good results. Figure 12 tabulates the 90th percentile of the absolute difference between the given individual vehicle length estimation and the corresponding measured length over the month for each lane at each station. Once more, all three of the new estimation methods yield similar performance (with the sequence method being slightly poorer), and this performance is generally better than the conventional method.

4.2 Performance Evaluation Using Synthetic Data

When using the data measured directly from I71, all three of the new estimation methods yield similar performance. But this urban corridor is characterized by relatively low truck volumes, which masks the difference between the three methods. Synthesizing on-times for various truck volumes, the analysis revisits the resulting speed estimates from the four methods from the April 2005 time series data at station 1 northbound. Figures 13-16 show the CDF of the absolute difference between the given estimate and the measured speed for the four methods when the percentage of trucks varies between 10% and 90%. Each figure compares the four methods within a single lane. The conventional method and moving median performance degrades significantly as the percentage of trucks increases. This degradation arises due to the fact that L in Equations 2 and 3 is no longer representative of the vehicle fleet. As the fleet becomes more homogeneous at higher truck flows, conceivably the errors could be countered at least in part by actively selecting a new value for L. But when the percentage of trucks and cars are roughly equal, even such a recalibration will fall to solve all of the problems. In contrast, the sequence method and distribution method show little change in performance as the percentage of long vehicles increases. In other words, for these two methods there is no need to recalibrate L in the presence of different percentages of trucks. Close inspection of the four figures reveals that the distribution method has smaller errors. The difference between the two methods becomes more apparent in Figure 17, which tabulates the average absolute difference between the given estimate and the measured speed over the month, across all lanes at station 1, as the percentage of trucks varies between 10% and 90%. The figure presents separately the results during free flow and congestion, using a measured speed of 45 mph as the threshold. The sequence method has a higher absolute average error because the method typically only uses a small number of the on-times observed in a given sample, and thus, is more sensitive to detector errors. As a result, the distribution method will be used throughout the remainder of this work.

Figures 18-22 repeat the comparisons, using individual vehicle lengths rather than speed. The trends are similar to those seen in speed. One notable exception is evident in Figure 22, the performance of the sequence and distribution methods are much more similar. While reviewing this figure, note that the average absolute errors should be expected to increase as the truck flows increase because the average vehicle length increases. Consistent with the results observed using measured data in Figure 11, comparing the two parts of Figure 22, the length estimation errors increase significantly during congestion, almost by a factor of five.

5 MANUALLY VALIDATED DATA

In the course of this research, detector data and concurrent video data were collected at two locations to test the performance of single loop detector estimated length based vehicle classification. The concurrent video allowed us to also find any detector errors as well. The first test location is an axle based classification station on I70, just east of Brice Rd. The second test location is station 9 on I71, a single loop detector station just south of Hudson St. Both locations are shown on the map of Figure 2.

5.1 I70 Test Site, East of Brice Rd.

The first test site is an ODOT classification station on I70, just east of Brice Rd. The station is equipped with dual loop detectors and a piezo electric axle detector in each of the three eastbound lanes. Figure 23 shows a schematic of the location and Figure 24 shows the camera truck used to collect the video. Note that at this location the lane numbering is reversed from the CMFMS stations, starting on the right and increasing towards the median. In normal operation the station uses the dual loop detectors to measure speed and length, and then uses the speed in conjunction with the times the piezo electric sensor is activated to estimate axle spacing. From these axle spacings vehicles are classified into the 13 FHWA vehicle classes (see, e.g., FHWA, 2001). Normally the vehicles are binned by the 13 classes and the counts are taken over relatively long periods (ranging between 15 min and 24 hrs). For this study, deviating from normal operation, the per-vehicle records were recorded, consisting of: passage time, measured speed, measured vehicle length, axle count, axle spacing, and vehicle classification. Notably absent from the per-vehicle record are the vehicle on-times. For this station the on-times were calculated from the measured length and speed via Equation 1.

The performance of the classification station was unknown at the time of the data collection, so the first step in the analysis was to evaluate whether the station was correctly measuring and classifying vehicles. To this end a software tool was developed to semi-automate the extraction of ground truth data from the video.[6] The tool allows the user to measure vehicle length (in pixels) and record the FHWA class after synchronizing the detector and digitized video data. Figure 25 shows a screen shot of this tool. The top shows the current video frame while the bottom shows the time series detector data across all lanes. The user specifies length by clicking on the image while the right hand side provides several buttons for the user to input other information and control the display (e.g., step forward or back one frame). The tool is triggered by the detector data, so as soon as the user finishes inputting the data for a vehicle, it jumps to the next detector actuation recorded in that lane.

Because the ground truth tool triggers off of the detector data, if care is not taken, a vehicle not seen by the detector will also be absent in the ground truth. So to address this fact, an image

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[6] This tool was inspired in part by Caltran's VideoSync, http://www.dot.ca.gov/research/operations/videosync/index.htm

processing "trip-wire" was used to independently monitor when a vehicle occupied the detection zone, thereby providing a second time series for each lane. The original detector data were compared to the trip-wire data. Any discrepancy was examined and classified by the user. The most common problem was a tall vehicle being seen by the trip-wire for a further lane and the user dismissed these errors as they arose from the viewing angle and did not indicate any detector problems. The second most common error was a time offset between the trip-wire and the detector data, impacting about two percent of the observations. After investigating the problem, it appears that most of these vehicles were measured correctly by the detectors, but the arrival time was incorrectly recorded. This offset is not likely to impact the normal classification operation and we hypothesize that the controller's decision tree was waiting to see if a rear axle of higher-class vehicle passes before recording the observation; then, when the tree times out, the controller records the observation with the current time. If this hypothesis is correct, it is possible that the controller might be filtering out other loop detector errors as well. The remaining errors that the controller is not filtering out are tabulated below.

The station was observed midday, under clear weather and free flow conditions from 10:12:44 to 14:00:01, on June 20, 2006. All told, almost four hours of data were recorded. As enumerated in Table 1, 9,746 vehicles were seen in the video and the detectors recorded 9,807 vehicles. The difference between the two totals is due in part to the fact that the recording time from the detectors included short periods when the video was stopped to change DVDs. After eliminating periods that were only recorded by the loops, 9,372 vehicles were ground truthed from the video and an additional 374 vehicles were seen but were obscured by other vehicles and no ground truth was generated for these vehicles. Among the 9,372 vehicles, 104 were found to be missing from the loop detector data.

Finally, the detectors measure vehicle length in feet, but the user measures the length in pixels. So a conversion factor is needed, and different conversion factors are necessary for each lane because no two lanes are the same distance from the camera. The saw cuts for the loop detectors were plainly visible in the video and the leading edge of the upstream loop to the trailing edge of the downstream loop is known to be 22 ft. So the user separately measured this distance in each lane using the same tool used to measure vehicle lengths. The resulting conversion factors are: 8.5 pixels/ft in lane 1, 7.0 pixels/ft in lane 2 and 6.2 pixels/ft in lane 3.

5.2 FHWA Classification at the I70 Test Site

As enumerated below, several FHWA classes are very similar, both visually and in terms of the number of axles. When classifying, vehicles in these similar classes can be difficult to differentiate; as a result the manual vehicle classifications could differ from the axle-based classifications due to very small deviations. Table 2 enumerates the 13 classes and expected axle based misclassifications due to similarities between various classes (which is by no means an exhaustive record of possible misclassifications). The reasons for misclassification vary according to the situation. The classification station uses length and number of axles to determine vehicle classes. Ranges of different classes overlap, so several misclassifications can occur due to this reason. Class 2 and 3 vehicles are the most common vehicles on most roadways, as was the case at the test sites of this study, and it was found that the lengths of these vehicles were very similar, resulting in classification errors. FHWA classes 3 and 5 both have two axles, and may have very similar lengths. Some trucks are class 5 due to the six tires while others are class 3 due to four tires. This difference cannot always be verified by video ground-truthing, and an estimate of the number of tires was used for these cases. It is also evident that classes 1 through 5 can all have two axles, providing an opportunity for axle based misclassifications. According to FHWA regulations, recreational trailers, when pulled by Class 2 or 3 vehicles, should not be included in the number of axles of that vehicle. But the classification station may not be able to correctly verify the presence of a recreational trailer every time; therefore, an incorrect vehicle class may be assigned in these cases. Some trucks are difficult to manually classify, specifically those that have one or more floating axles that can be raised and lowered to the surface depending on the weight of the load that they are carrying, e.g., as shown in Figure 26. Given the camera angle it was sometimes difficult to differentiate between raised or lowered axles on these trucks.

All vehicles from the I70 video at Brice Road that could be manually classified were classified according to the 13 FHWA classifications. The manual classifications for each vehicle were compared to the classifications reported by the detector station. The number of vehicles manually classified using the 13 FHWA classifications are compared to the axle-based classifications in Table 3. The shaded cells in the table denote the correct classifications and the expected errors from Table 2. Table 4 summarizes the totals from Table 3. Again, the expected errors were the vehicles misclassified by the detector station that fell into the "expected" cells of Table 2. In all, there was a 27.8% misclassification rate, but only 1.1% of the misclassifications fell outside of the expected cells. It was found that roughly 4 percent of class 6 and 7 vehicles were misclassified due to floating axles. As a result, the vehicles can change what FHWA class they belong in. Unfortunately, as already noted, the camera angles did not allow for better manual vehicle classification of the floating axles.

Figure 27 plots the manually extracted FHWA vehicle class versus the manually extracted vehicle length for the 9,372 ground truthed vehicles. Figure 28 shows the same data grouped in to 5ft bins, where each subplot shows a different FHWA class. Figure 29 shows the histogram of the number of axles seen for each axle-based FHWA classification and indicates the expected number of axles. This matching was done to verify that the axle classifications matched the expected number of axles for each vehicle. The majority of the vehicles appeared to have the expected number of axles, according to FHWA classifications. Unexpected axle counts are evident in class 1, 2, 3, and 13. Axle bin classes 1, 2, and 3 have vehicles with more than 2 axles. When analyzing these vehicles, it was found that all vehicles with additional axles were due to recreational trailers. For axle bin class 13 vehicles with abnormal number of axles, it was established that the vehicles with less than 7 axles are classified in error. The class 13 vehicles with 3 axles should be axle class 5 vehicles with a recreational trailer, and the vehicle with 6 axles should be axle class 7.

All of the unexpected errors in Table 3 were examined in detail and the following provides a representative finding of the results. For vehicles manually classified as FHWA class 2, two different problems occurred. Two vehicles were misclassified due to a vehicle in the adjacent lane that had tires touching the lane line, as illustrated in Figure 30A. The tires appeared to trigger the axle sensor in both lanes, which erroneously added those two axles to the vehicle actually in that lane. As a result, the class 2 vehicle in the outside lane was erroneously classified as a class 7, a four or more axle single truck. In one case, a class 2 vehicle was making a lane changing maneuver. When analyzing the controller's per-vehicle record, no error message was made, but sensors were activated for both lanes. For this lane changing vehicle, in one lane the classification and lane was correct, but in the other lane the sensors recorded the wrong classification and speed. This resulted in another sensor error that caused this vehicle to be recorded as an FHWA class 13. Furthermore, a more basic error arose in this case by virtue of the vehicle being counted separately in two lanes. For vehicles manually classified as FHWA class 3, there were several discrepancies in the axle-based classification. The majority of the errors were due to the axle-based classification recording the axles of the recreational trailers that were pulled behind the class 3 vehicles, e.g., as shown in Figure 30B. Once again, according to the FHWA standards, the axles of recreational trailers should not to be included in classifying procedures. Figure 30C shows an example where a manually classified class 5 vehicle was classified as a class 13 by the classification station. The classification station recorded 3 axles with the inclusion of the trailer, so it should have correctly classified this vehicle as an FHWA class 5 if the trailer is not included, or an axle-class 6 if the trailer is inadvertently included in classifying. After analyzing all vehicles that were classified as FHWA class 13 by the classification station, it is suspected that the classification station algorithm is written to match all vehicles to both axle count and axle spacing for a particular axle class; and those vehicles that do not match both specifications for classes 1 through 12 are placed in class 13 by default. In other words, it is suspected that the controller's decision tree defaults "unclassifiable vehicles" as class 13, though we do not have access to the source code and were not able to prove this supposition.

5.3 Sensor Miss (SnMis) and Missing Vehicles at the I70 Test Site

The controller at the I70 test site recorded 185 sensor misses, SnMis, in the per-vehicle record, as enumerated in Table 1. These SnMis reportedly arise when one of the three detectors in a single lane gives a result inconsistent with the other two detectors, e.g., two detectors detect a vehicle while the third does not. Figure 31 shows a sample of the per-vehicle record with data for three vehicles. Usually each vehicle results in the recording of four rows in this data file. The first column indicates the lane, while the remaining columns present either individual sensor data (e.g., the first three rows show the length measurements from the two loops and the axle spacing from the piezo electric sensor) or the net measurement as calculated by the controller (e.g., the fourth row). If one or more of the sensors have a fault, then the per-vehicle record stores a "SnMis". Sometimes the controller is able to calculate some of the measurements and these are recorded in addition to the SnMis, other times, the controller is only able to identify the presence of the fault, and just records the SnMis with a time stamp, (e.g., the fifth row of Figure 31). The causes of the SnMis events are not readily apparent in the per-vehicle record, so we manually examined both the record itself and the concurrent video whenever a SnMis occurred. Table 5 shows the apparent source of the 185 SnMis events. Almost all of these events appear to be correlated either with specific vehicle types or vehicle maneuvers.

The analysis revealed that some of the SnMis events were isolated, though many others resulted in the controller missing several following vehicles in the lane. It appears that sometimes the controller or detectors lock up in a given lane after a SnMis and during this short time period none of the vehicles passing on the detector are detected. Out of the 104 missed vehicles listed in Table 1, 93 appear to arise from this SnMis problem. While not all SnMis resulted in missing vehicles, the largest number of missing vehicles due to a single SnMis in the data set was six.

5.4 I71 Test Site, South of Hudson St.

The second test site is an ODOT detector station used for real-time management in the CMFMS on I71, just south of Hudson St. The station is equipped with single loop detectors in each of the three lanes, in each direction. Figure 32 shows a schematic for the location. This station reports individual detector transitions by lane and time to the traffic management center. Normally the transition data are aggregated to conventional traffic measures (flow, occupancy, and average speed). The transitions can be used to measure individual vehicle on-times, then estimate individual vehicle speed and length as discussed earlier. This particular station was chosen because out of all of the stations in the CMFMS it is closest to an existing close circuit television (CCTV) camera. Detector data and concurrent video were collected for two hours between 12:20:00 and 14:20:00, on June 5, 2006. The station was observed midday, under clear weather and free flow conditions. Figure 33 shows a screen shot from the video, the controller cabinet is visible in the top left corner behind the guardrail, and the loop detectors were roughly parallel with the cabinet.

As enumerated in Table 6, 15,251 vehicles were recorded by the detectors. The same ground truthing tool presented above was used to associate the loop and video data together and then manually generate vehicle lengths. Unlike the I70 test site, vehicles were not counted separately in the video, and the trip-wire video image processing tool was not used to catch vehicles missed by the detectors. For a vehicle entry to be ground-truthed it was detected by the loop and the length was manually measured from the video. There were three notable differences from the I70 location, first, the I71 test site does not have any visual references for which length is known. So after measuring visual length and estimating vehicle length, we calculated pixels/ft for each vehicle, then within each lane the conversion factor was found by taking the median of the individual vehicle conversion factors. The resulting conversion factors ranged between 0.8 pixels/ft for the furthest lane to 8.2 pixels/ft for the closest lane. Second, the controller does not report SnMis at this station. Third, 441 detector actuations were recorded that do not correspond uniquely to a passing vehicle in the video. Most of these extra pulses arose due to the detector "dropping-out" in the middle of a long vehicle and causing "pulse break-up," i.e., semi-trailer trucks frequently resulted in two pulses (one for the tractor and one for the trailer) or more when these trucks should have only been recorded as a single pulse.

6 LENGTH BASED CLASSIFICATION

In the broadest sense, length based vehicle classification simply calls for estimating vehicle length and using this length to place the vehicle in to one of several classes based on a predetermined classification scheme. This study adapts the length based classification scheme used by ODOT at dual loop detector stations. The basic scheme places vehicles into one of three classes, as enumerated in Table 7. The middle column shows the thresholds relative to the physical vehicle length and the right hand column shows the thresholds relative to the effective vehicle length as "seen" by the detector (i.e., including the length of the detection zone).

6.1 *Length Based Classification at the I70 Test Site*

Figures 27-28 compared the measured FHWA class against measured length. These figures also show the thresholds between the length classes at 22 ft and 40 ft. Presenting the data in a slightly different fashion, Figure 34 uses the measured length to plot the histogram of the length class for each of the 13 FHWA classes. Figure 35 repeats the exercise using the estimated vehicle length. From these figures it is evident that FHWA classes 1-3 roughly correspond to length class 1, FHWA classes 4-7 roughly correspond to length class 2, and FHWA classes 8-13 roughly correspond to length class 3. This reduction in classes eliminates many of the errors seen in the

FHWA classification, e.g., from Table 3 almost 2,280 FHWA class 3 vehicles were misclassified as being FHWA class 2 but both of these FHWA classes fall predominantly in to length class 1.

For the 9,268 vehicles from Table 1 that were ground-truthed and were not missed by the detector, the scatter plots in Figure 36 compares the estimated length from on-times versus manually measured length by lane and across all lanes. Most of the points fall close to the diagonal, indicating the estimates are generally close to the measurements. Figure 37 clusters these points based on the resulting length class from the estimated and measured length. The correctly classified vehicles fall in the three cells on the diagonal, while the other six cells tally the various misclassifications. For reference, Figures 38-39 repeat the exercise using the original reported lengths from the classification station (i.e., measured from dual loop detectors). Comparing Figure 36 to 38, the plots show the reported lengths are closer to the measured lengths than the estimated lengths are. However, Table 8 summarizes the classification results from Figures 37 and 39 and as evident, the classification performance is very similar whether using estimated or reported length. This result arises from the fact that the classification scheme is tolerant to large length estimation errors provided the true length is far from the boundary between two classes.

6.2 <u>Length Based Classification at the I71 Test Site</u>

After accounting for the pulse break-ups, 6,998 vehicles are ground truthed in the southbound lanes and 6,648 vehicles in the northbound lane. Figures 40-41 compare the estimated length against the manually measured length for all of the vehicles, southbound and northbound, respectively. In both figures, part A shows the results with the pulse break-ups included[7], while part B shows the results excluding those due to pulse break-ups. Figure 42-43 cluster these points based on the resulting length class from the estimated and measured length and again, show the results with and without the vehicles impacted by pulse break-up. As before, the correctly classified vehicles fall on the diagonal and the totals are summarized in Table 9.

From Tables 8-9, for the two test sites, given correct on-times (i.e., after excluding pulse break-ups at the I71 test site) the methodology had an accuracy of over 99% for class 1 and over 93% for class 3, while performance was over 74% accurate for class 2. Of course these results are mid-day, without congestion, and in the case of the I71 test site it excludes the pulse break-up data. The lower performance in class 2 appears to be due in part to the fact that most of the class 2 vehicles are close to the lower boundary and are frequently misclassified as class 1. A similar error rate was observed for class 2 when using the reported vehicle length (last column of Table 8).

Most misclassified long vehicles at the I71 test site were due to pulse break-up. When the pulse break-ups are included, the on-times for long vehicles are too short and many class 3 vehicles are misclassified, as evident in Table 9. Even including these errors, from Figures 41A and 42A, very few of the errors were more than one class away from true.

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[7] As a pulse break up results in two or more pulses for a single vehicle, only the first pulse is shown in the plot, the remaining pulses are considered extra and are suppressed from the plot.

6.3 *A Pilot Study to Catch Pulse Break-up*

The detectors on I71 were deployed primarily to measure speed, and to our knowledge, have not been tuned to count vehicles accurately. But presumably the observed performance is not atypical of what one might find at other detector stations deployed for real-time traffic management. After diagnosing the problem, we devised a pilot scheme to differentiate between broken pulses and complete vehicles, as follows,

- Condition 1: Short off-time
  If an off-time < 0.3 sec, this gap is so short that it is unlikely to be observed between two vehicles. So the preceding on-time is considered to have arisen from a possible broken pulse and analysis continues to the next condition. Otherwise, the preceding pulse is accepted as a vehicle.
- Condition 2: Estimated length from pulses
  If the short off-time occurs in the middle of a vehicle, then the bounding on-times should be much shorter than the on-time arising from the maximum vehicle length. In particular, most of the observed pulse break-ups occurred with semi-trailer trucks. The tractor has a large mass of ferrous metal, followed by the front of the trailer which is high off the pavement and has a much smaller loop detector response (potentially dropping out), followed by the axles of the trailer that are closer to the pavement and are more likely to be detected. Or formalizing the process, if a short off-time is seen, it remains suspect of arising from a broken pulse if the preceding on-time results in an estimated length between 18 ft - 40 ft, and the following on-time results in an estimated length between 4 ft and 17 ft (both via Equation 1 and the current speed estimate). If these two conditions are met, then the analysis continues to the next condition, otherwise, the preceding pulse is accepted as a vehicle.
- Condition 3: New estimated length
  If the detector dropped out in the middle of a vehicle, the true on-time should be at least as long as the combination of the off-time and its two bounding on-times, preceding and following it. Combining these times into a net-on-time, a new vehicle length is estimated. If this new estimated length is between 40 ft - 100 ft, the combined pulse is long enough to be a truck and short enough that it can be a vehicle and then the analysis continues to the next condition. Otherwise, the preceding pulse is accepted as a vehicle.
- Condition 4: On-time ratio
  If the preceding on-time is more than 50% larger than the following on-time, the off-time is considered to have arisen from a broken pulse, is classified as such, and the combined pulse from Condition 3 is stored. Otherwise, it is considered a valid off-time (albeit short) and the preceding pulse is accepted as a vehicle.

Figure 44 shows the resulting decision tree and the results at each stage when applied to the two hours of data from both directions at the I71 test site. At each state the (number of vehicles)/(number of extra, broken pulses) is shown. An off-time must meet all four conditions to be considered pulse break-up. The decision tree caught 331 of the pulse break-ups and erroneously accepted 105 of them. Meanwhile, 14,812 vehicles are correctly classified while only three are erroneously labeled as broken pulses. Figure 45 reviews these results in the context of the detector measurements and estimates for (A) southbound and (B) northbound across all lanes. In each direction the top left plot repeats the original length comparison across all lanes, simply repeating the lower right hand plot in 40A or 41A. The top right hand plot shows the pulses caught by the decision tree for the given direction (i.e., meeting all four conditions)[8]. When a broken pulse is found the net on-times from the successive broken pulses (including the intervening off-time) can be calculated directly, as per Condition 3. Thereby allowing for an improved on-time measurement for these vehicles, and thus, length estimate. Doing just this, the lower left hand plot for each direction shows the revised length estimates against the length measurements, and the plot includes all of the undetected pulse break-ups. The lower right hand plot clusters these points based on the resulting length class from the estimated and measured length (compare to the lower right hand plot in Figures 42A and 43A). An additional 98 southbound and 229 northbound class 3 vehicles are now classified correctly (92 errors remain in the two directions among the class 3 vehicles).

This method was developed using data from both directions at the I71 test site. The reader is cautioned that more work is needed, we believe performance can be improved even beyond what is reported here. Furthermore, the analysis should be extended to more detector stations, data from congested traffic conditions, and of course more ground truth data. Although such data cleaning is beyond the original scope of the present study, this section is presented here to provide proof of concept for further research.

6.4 <u>Length Based Classification at all I71 Dual Loop Detector Stations</u>

Now extending the analysis to all of the northbound dual loop detector stations in the I71 corridor, in this section length based vehicle classification from single loop detectors is contrasted against the corresponding classification from dual loop detectors for the same vehicle, using one month of data (April, 2005). We use the on-time data from the upstream loop to estimate individual vehicle speeds and lengths, then measure these parameters from the corresponding dual loop. The vehicles are then classified based on the estimated and measured lengths. Performance during free flow and congestion are examined separately (again, using 45 mph as the threshold). No effort is made to correct for pulse break-up in this analysis. Examining the time series detector data at the dual loop detectors, it would appear that the pulse break-up problem observed at the I71 test site is not uncommon at the detector stations in this corridor. This assessment is based on free flow conditions and is made without independent ground truth at the other stations. If the supposition holds, based on our observations, when pulse break-up occurs in a dual loop it will usually occur in both of the loops for a given vehicle.

Using the estimated length and repeating with the measured length, each vehicle is sorted into one of the three classes. The vehicle's measured speed is used to determine whether it is free flowing or not. Then the two classifications per vehicle are compared one with another. If the two classes are identical, it is considered a correctly classified vehicle. Otherwise, it is considered as either an over-classified vehicle (estimated class is higher than the measured class) or an under-classified vehicle (estimated class is lower than the measured class). This process is repeated for all free flowing vehicles in a given day and the daily proportions of correctly classified, over-classified, and under-classified vehicles are calculated for that day. Figure 46 summarizes the results across all northbound lanes for each of the 13 dual loop detector stations

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[8] Again, as a pulse break up results in two or more pulses for a single vehicle, only the first pulse is shown in the plot, the extra pulses are suppressed from the plot at this stage.

in the study segment. Each station is presented in a different column in the subplots, while the same column is used for the given station in all three subplots. Each column has 60-120 points, one point per lane per day in the month. The left hand plot shows the percentage of vehicles correctly classified each day, the middle plot shows the percentage over-classified each day, and the right hand plot shows the percentage under-classified each day. Over 97% of the vehicles are correctly classified at each station. Between the two errors, over-classification is dominant, this result is due to the fact that vast majority of vehicles passing through the I71 corridor are passenger vehicles, falling in class 1 and cannot be under-classified.

As when evaluating the various methods to estimate speed, here too, this analysis relies on synthetic data to emulate detector measurements under different percentages of long vehicles. Once more the analysis is limited to station 1 northbound and the same data set used to generate Figure 17A is used here. Rather than simply showing the daily results, Figure 47 shows a box plot of the monthly data for each percentage of long vehicles. As with Figure 46, one point is generated per lane per day, for a total of 120 points underlying each column at this station with four lanes. In each box plot, the top and bottom edge of a box show the first and third quartiles and the horizontal line within the box shows the median value of the observations. The top and bottom edges denoted with "T" are boundaries of the maximum and minimum values of the observations, while a plus shape denotes an outlier (defined to be $1.5\times$interquartile beyond the nearest quartile). The figure shows that the median performance is roughly constant across the different percentages of long vehicles, falling above 99% in each case, indicating that the classification methodology is not sensitive to the percentage of long vehicles.

Moving to congested conditions, Figure 48 repeats the empirical analysis from Figure 46, while Figure 49 repeats the synthetic analysis from Figure 47. Now the monthly median of the correctly classified vehicles falls between 80% and 90%. Although the performance is worse than under free flow conditions, it is still roughly consistent across the different % of long vehicles even during congestion. Of course the percentage of over-classified vehicles drops and under-classified vehicles increases as the percentage of long vehicles increase, simply because class 1 vehicles can not be under-classified and class 3 vehicles can not be over-classified.

6.5 <u>Why Performance Degrades in Congestion</u>

As mentioned previously, during congestion the range of speed within a sample is typically larger than during free flow due to the instability of speed typically seen in freeway queues. The distribution speed estimation method seeks to estimate a "typical" speed for the sample, while due to the larger range of speed, any given vehicle within the sample may have a speed far away from this typical speed. Figure 50 illustrates this phenomenon, by comparing estimated speed against the individual vehicle's measured speed and then against the median measured speed over the sample. The average absolute errors are 5.7 mph and 2.6 mph, respectively. Therefore, speed and length can be over-estimated and under-estimated for several vehicles within a sample, resulting in a higher occurrence of misclassification.

7 CONCLUSIONS

Roadway usage, particularly by large vehicles, is one of the fundamental factors determining the lifespan of highway infrastructure. Each state typically has several dozen vehicle-classification stations to monitor large vehicle usage, the simplest of these stations use dual loop detectors to measure vehicle length. Meanwhile, single loop detectors are the most common vehicle detector in use to monitor traffic, both for real time operations and for collecting census data such as Annual Average Daily Travel (AADT). Collecting reliable length data from these detectors has been considered impossible due to the noisy speed estimates provided by conventional data aggregation at single loop detectors. This research has questioned those assumptions, demonstrating length based vehicle classification on freeways from single loop detectors under a wide range of traffic conditions, yielding estimates that approach the accuracy of a dual loop detector's measurements. The research promises to provide a lower cost means of collecting vehicle classification data, provide a software based solution when one of the detectors in more sophisticated classification station fails, and extend classification to traffic monitoring stations in urban areas. In fact the classification work could allow these urban traffic management systems to better monitor freight traffic within the metropolitan areas.

The present study developed a length based classification methodology from single loop detectors. In the process, it lead to improved speed and length estimates from single loop detectors. The work started by refining our existing speed estimation algorithms to accurately estimate speed under a wide range of traffic conditions: free flow to congested, as well as ranging from low to high truck volumes. To capture higher truck volumes than empirically observed, a process of generating synthetic on-times is also developed. Following the ODOT length based classification scheme for dual loop detectors, the lengths are then used to classify vehicles into three bins. This classification is evaluated against concurrent measurements from video and dual loop detectors.

The ultimate goal of this research is to mainstream the advances in speed and length estimation from single loop detectors. It is envisioned that the classification work will feedback and improve length-based classification at dual loop detectors as well. The research compared the estimation results (speed, length, and class) against concurrent measurements from dual loops, axle based classification, and manually extracted ground truth from concurrent video. Figure 10 shows that the 90th percentile of the absolute error in speed estimation was less than 10 mph, while Figure 12 shows that the 90th percentile of the absolute error in length estimation was on the order of 4 ft. Length estimation and classification showed sensitivity to congested conditions, and improving vehicle classification during congestion should be the topic of further research. Performance degrades during congestion due to the fact that we estimate a "typical" speed within a sample of many vehicles but a given vehicle may have a speed that is far from typical within a congested sample. The methods can be used to reliably detect congested conditions, so results during such periods can at least be identified by the current methodology and weighted appropriately. There is likely room for further improvement in estimating individual vehicle speed from single loop detectors during heavy congestion.

Table 8 shows that the length based single loop detector estimation classification results are very close to the dual loop detector measured length based classification results for the I70 test site, both class 1 and 3 had over 97 percent correct classifications. At the I71 test site, Table 9 shows that performance for class 3 drops significantly, which after investigation proved to be due to pulse break-up. Excluding the pulse break-ups the classification performance is comparable to the I70 test site. But one cannot summarily exclude pulse break-ups and the fact remains that stations installed to measure speed might not count vehicles as well as a station deployed and tuned primarily to classify vehicles. So a pilot study was conducted to investigate the feasibility to catch these errors, and as shown in Figure 44, was able to catch over 75% of the pulse break-ups. But such error detection remains a topic of future research, the pilot study only considered a single station over two hours of free flow traffic. More stations, a wide range of conditions, and simply more ground truth data need to be generated. Several smaller detection errors were found in the existing systems, e.g., errors made by the axle based classification station on I70. Where possible, we systematically diagnosed the cause, reported the findings to the sponsors, and incorporated the lessons in our research.

8 ACKNOWLEDGEMENTS

This report includes significant contributions from two students: Seoungbum Kim and Justin Ahmann. Many other students in the Traffic Monitoring Laboratory made smaller contributions to this work. We are also indebted to ODOT for the in kind help, particularly in regard to collecting field data. At various points in this research invaluable help came from the following ODOT employees: Dave Gardner, Tony Manch, David Stewart, Kevin Calovini, Farouk Aboukar, Matt Graf, and Nick Hegemier.

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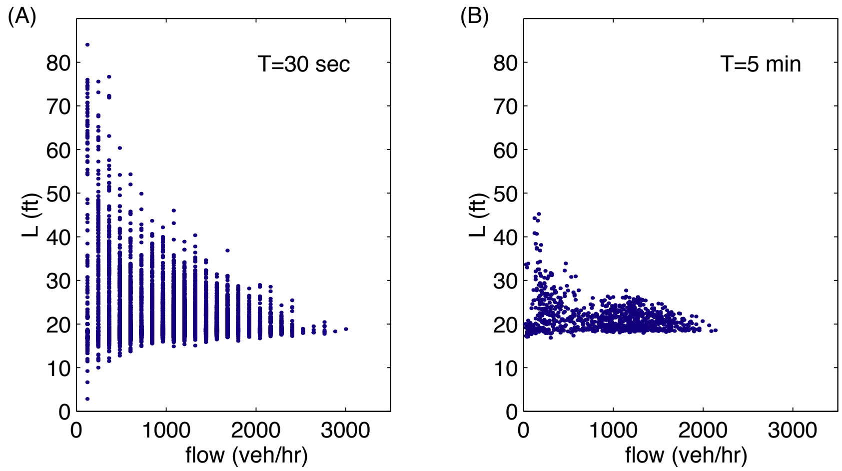


Figure 1, Observed average effective length versus flow for five lanes at one detector station, over one day, sampled at (A) T = 30 sec, (B) T = 5 min. (repeated from Coifman, et al, 2003)

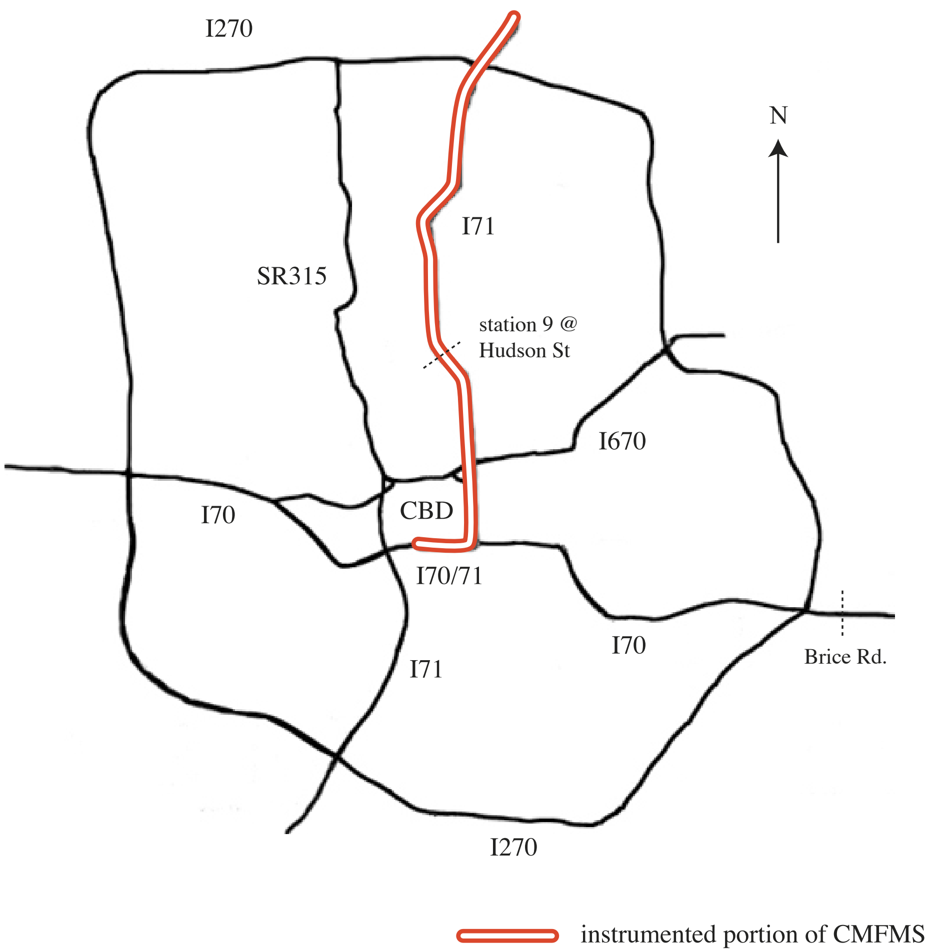


Figure 2, Freeway network in Columbus Ohio, highlighting the instrumented portion of the CMFMS.

A) B)

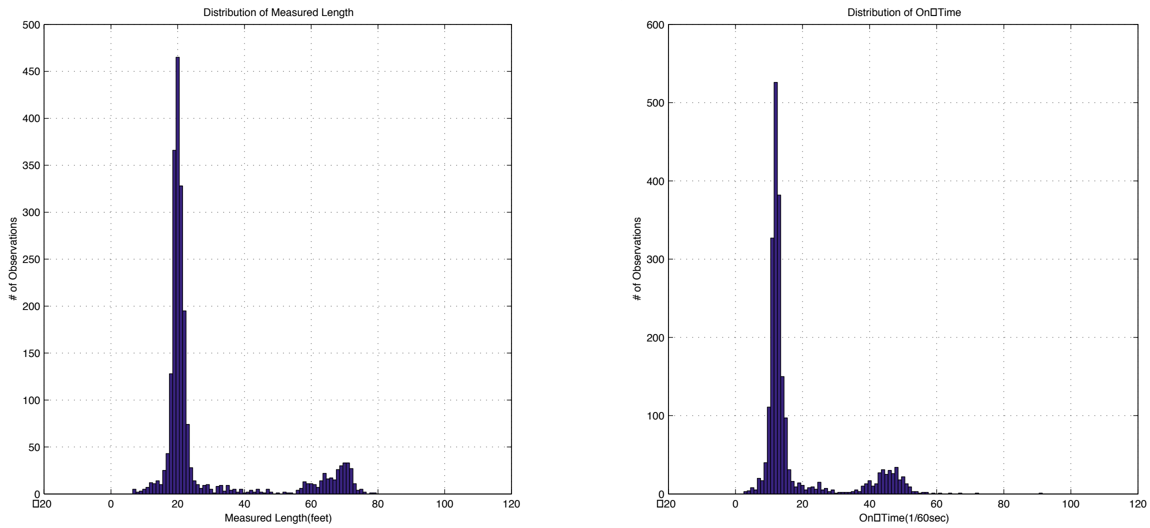


Figure 3, (A) Example of bimodal distribution of measured length, and (B) the corresponding bimodal distribution of on-times from the upstream detector (April 1, 2005, lane 3, station 1)

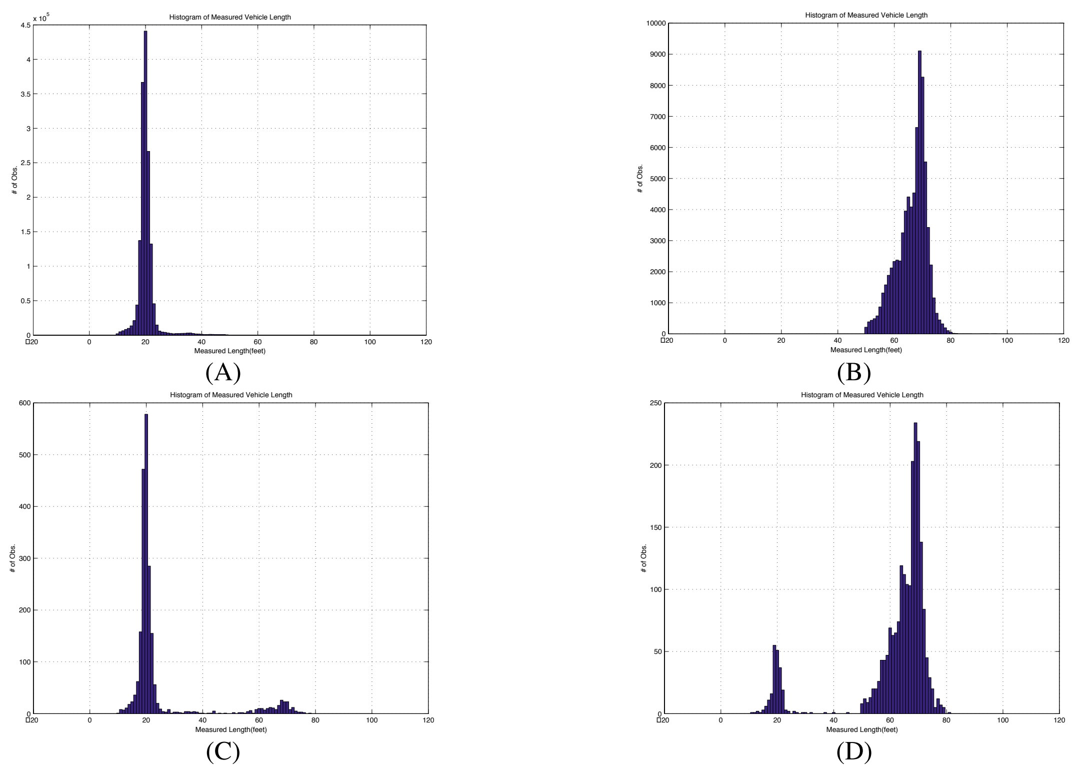


Figure 4, (A) Distribution of measured length for short vehicles, (B) Distribution of measured length for long vehicles, (C) Distribution of replaced measured length for synthetic data with 10% of long vehicles, (D) Distribution of replaced measured length for synthetic data with 90% of long vehicles

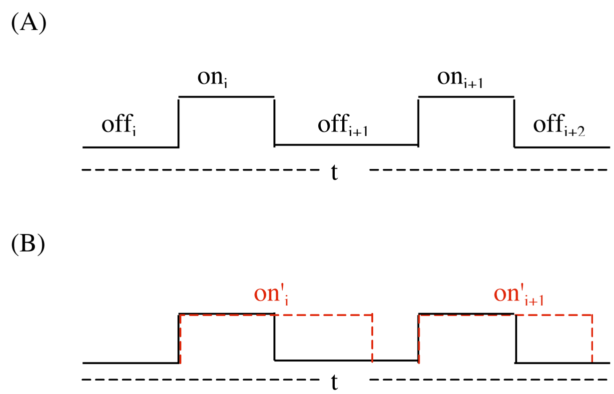


Figure 5, (A) Occupancy calculation before generating synthetic on-times, and (B) after.

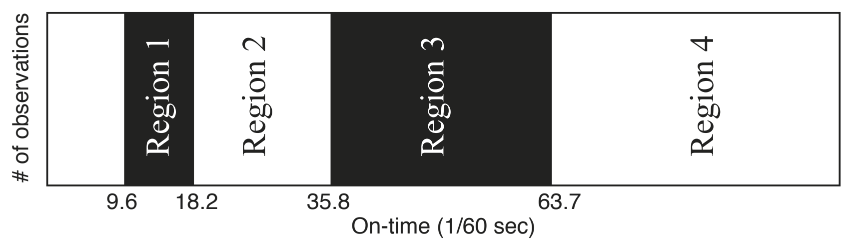


Figure 6, On-time regions used for unimodal speed estimation

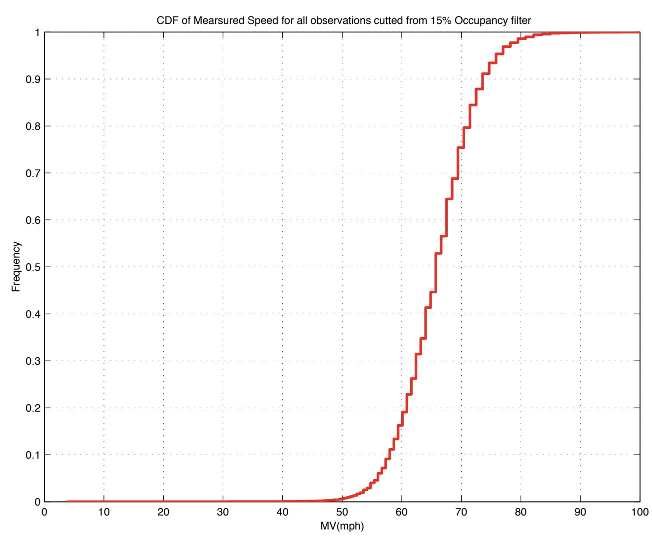


Figure 7, CDF of median measured speed for data filtered by the occupancy filter

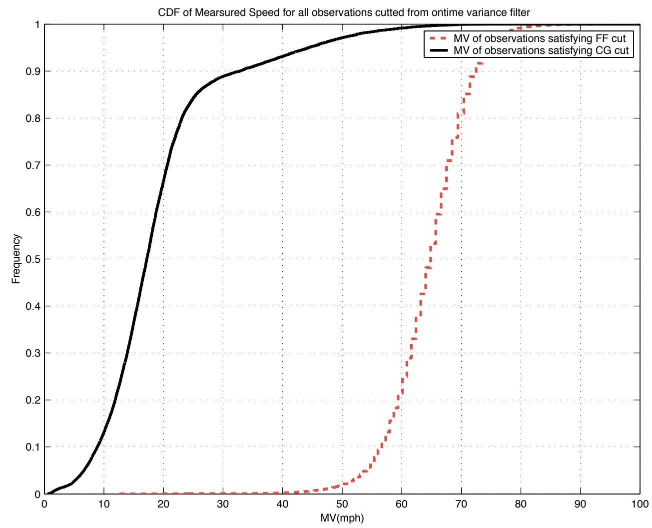


Figure 8, CDF of median measured speed for samples classified as free flow and as congested from the on-time variance and previous estimated speed filters

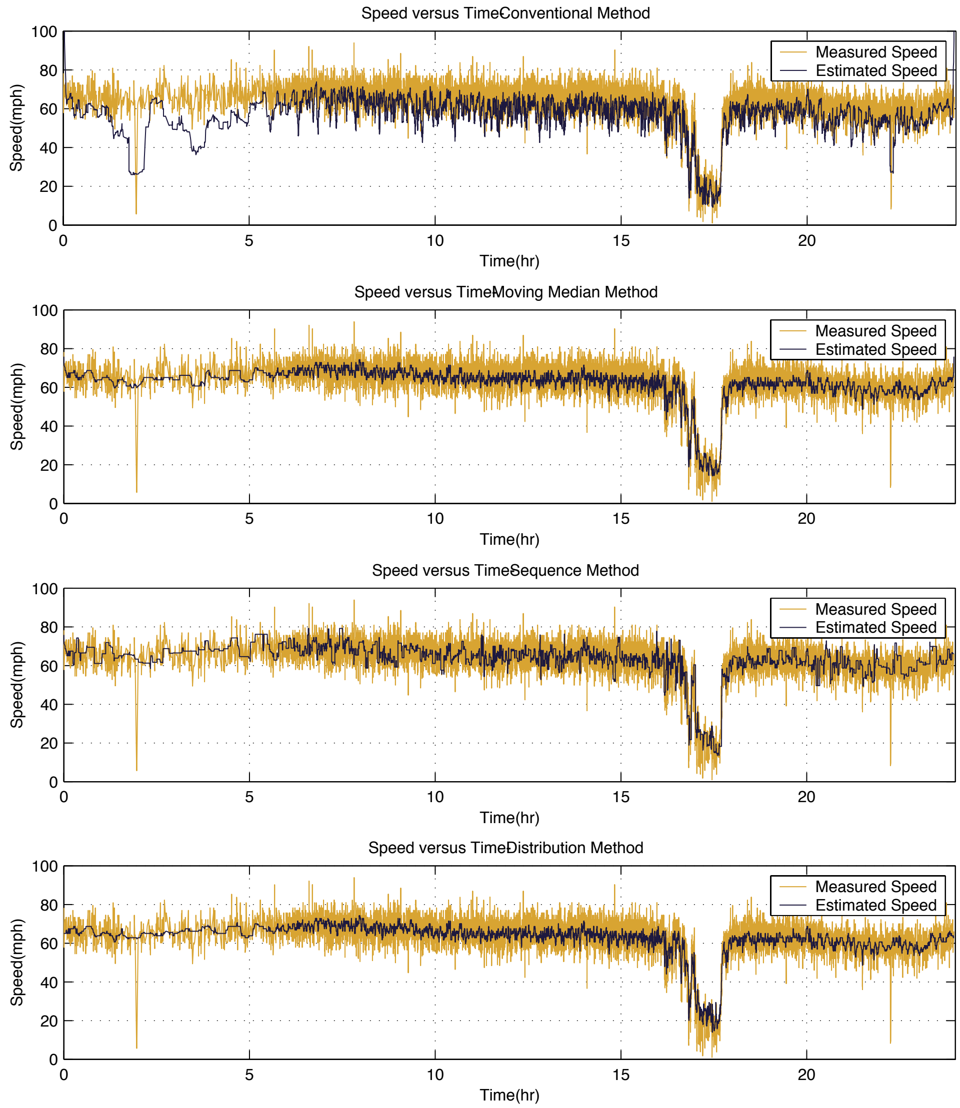


Figure 9, Time series speed estimates from the four methods (top to bottom: conventional, moving median, sequence, and distribution) shown with a darker curve, superimposed on the measured speed shown with a lighter curve, lane 1, station 1, April 1, 2005.

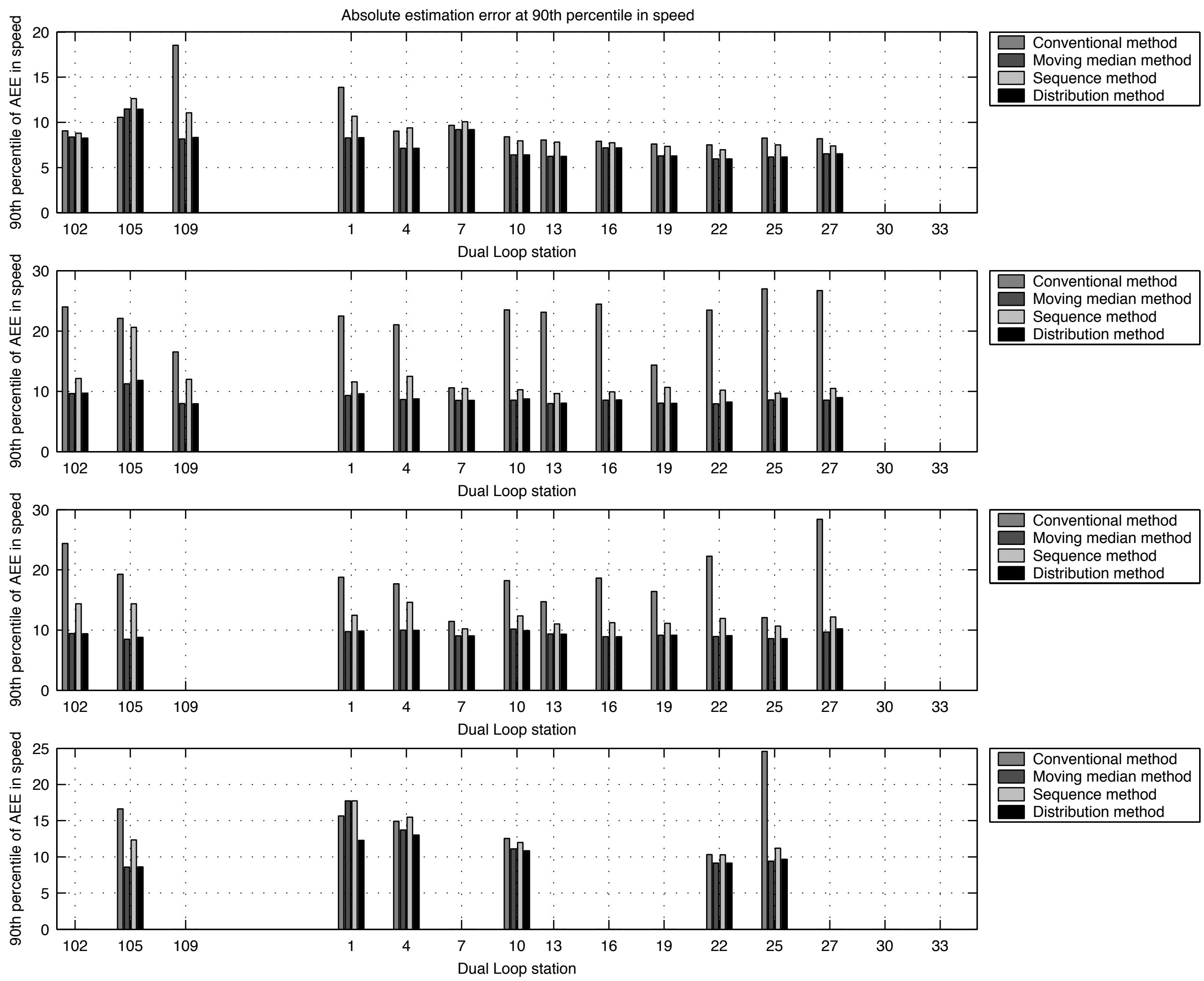


Figure 10, The 90th percentile of the absolute error from the speed estimation over one month (April, 2005) for each lane at each dual loop detector station (top to bottom: lane 1 to lane 4)

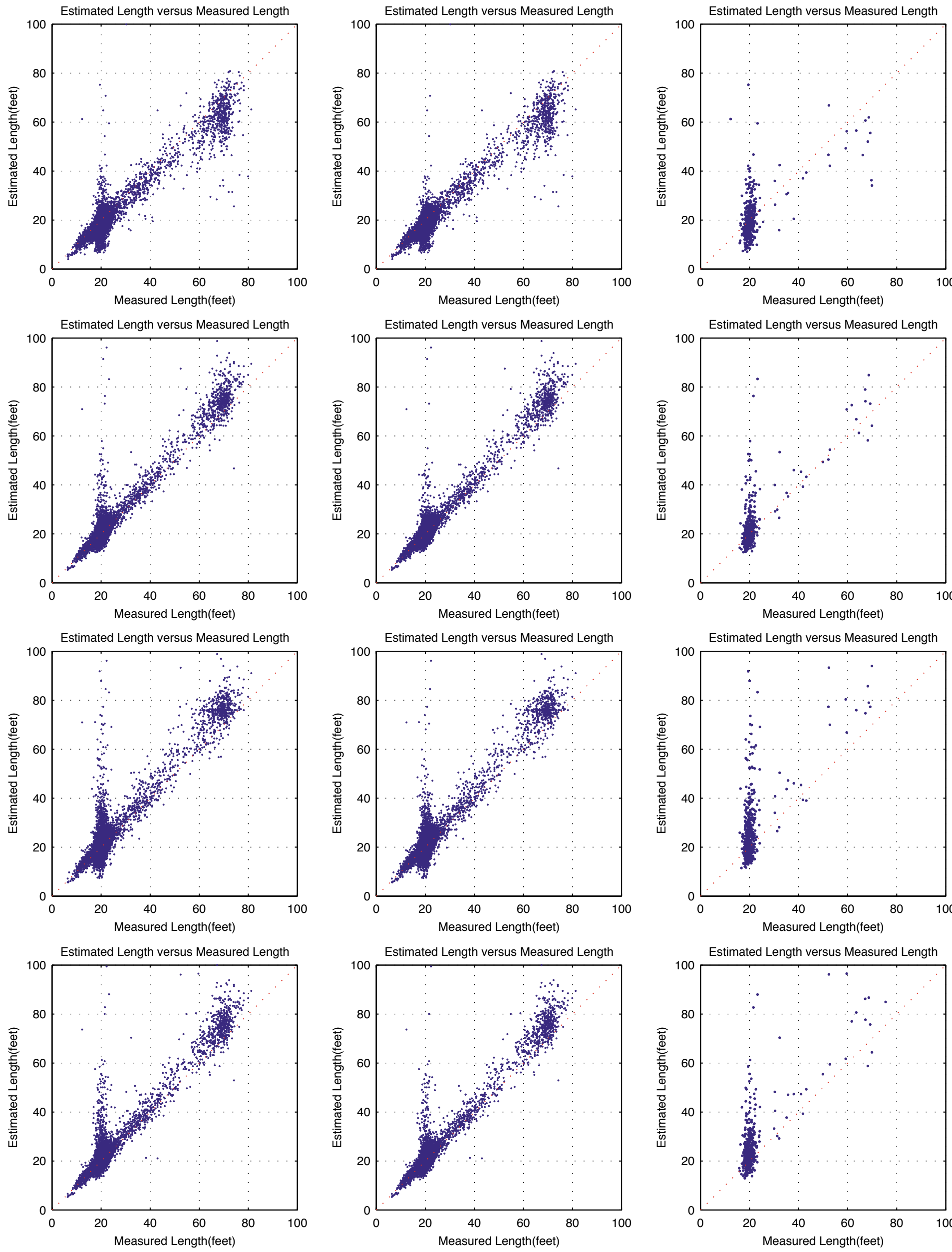


Figure 11, Estimated length versus measured length for each method (top to bottom: conventional, moving median, sequence, and distribution; left to right: all data, only when speed is above 20 mph, only when speed is below 20 mph), lane 1, station 1, April 1, 2005.

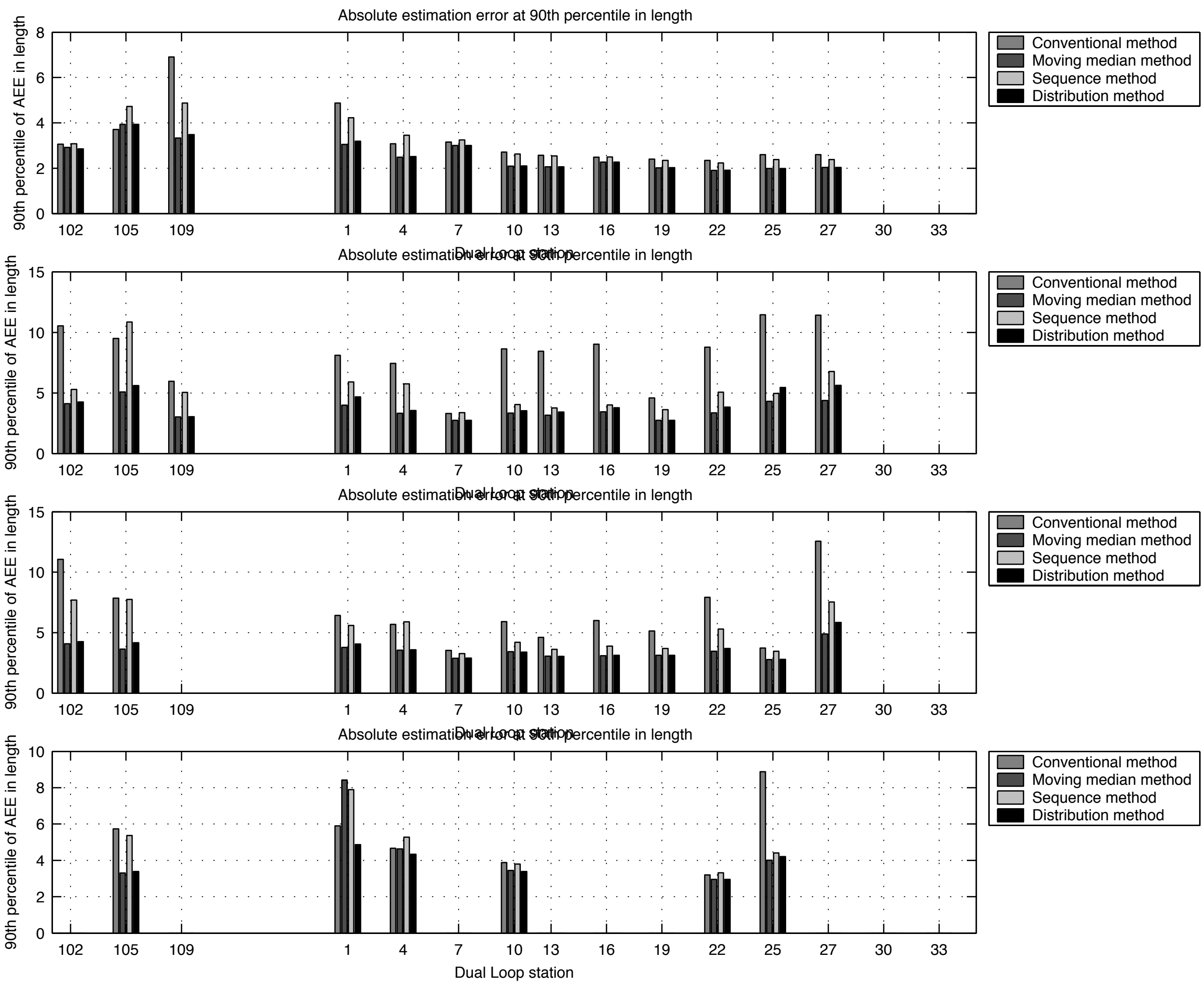


Figure 12, The 90th percentile of the absolute error from the individual vehicle length estimation over one month (April, 2005) for each lane at each dual loop detector station (top to bottom: lane 1 to lane 4)

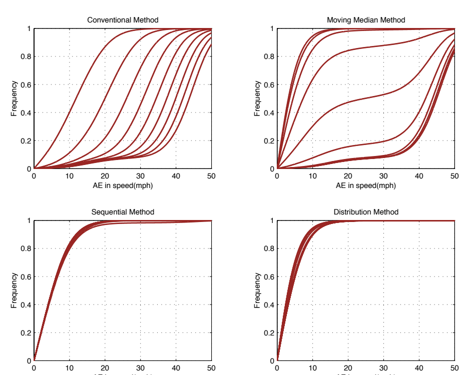


Figure 13, CDF of the absolute error from the speed estimation over one month (April, 2005) for lane 1, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

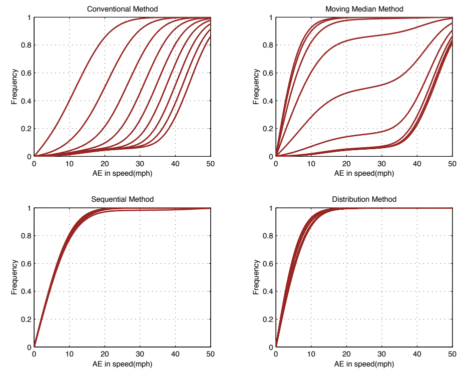


Figure 14, CDF of the absolute error from the speed estimation over one month (April, 2005) for lane 2, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

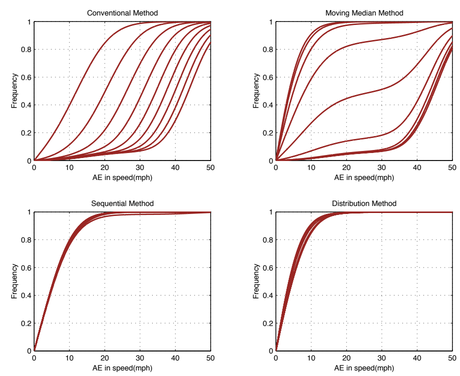


Figure 15, CDF of the absolute error from the speed estimation over one month (April, 2005) for lane 3, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

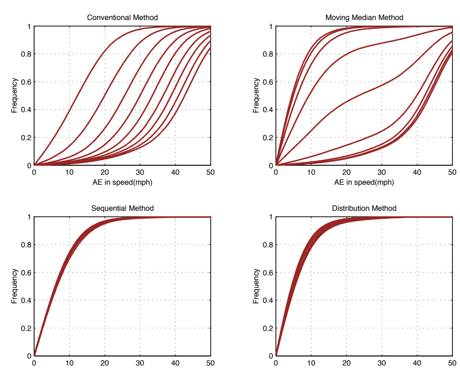


Figure 16, CDF of the absolute error from the speed estimation over one month (April, 2005) for lane 4, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

A) B)

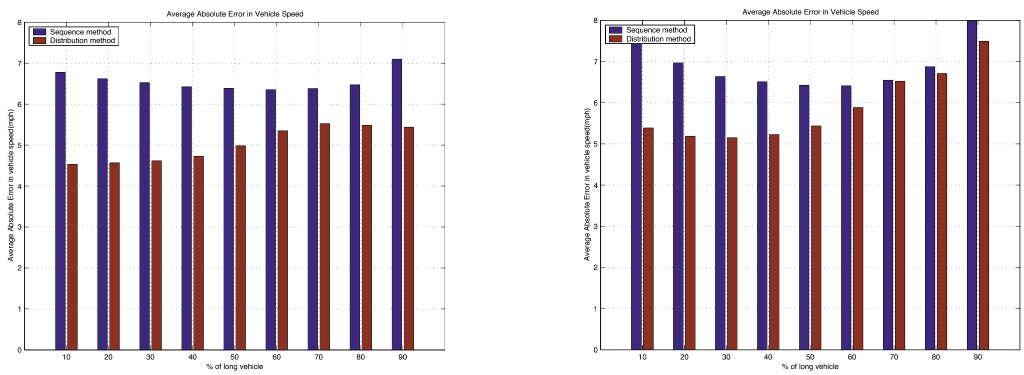


Figure 17, Average absolute error in speed across all lanes from sequence and distribution estimation methods over one month (April, 2005), station 1 when the percentage of trucks varies between 10% and 90%. (A) When measured speeds are above 45 mph. (B) When measured speeds are below 45 mph.

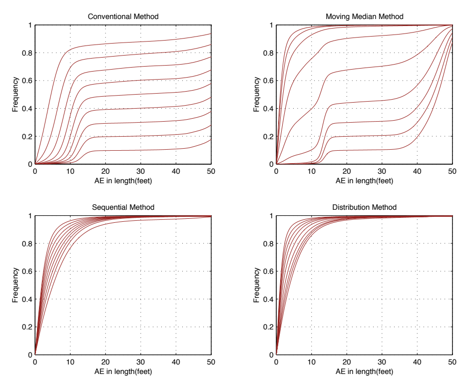


Figure 18, CDF of the absolute error from the length estimation over one month (April, 2005) for lane 1, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

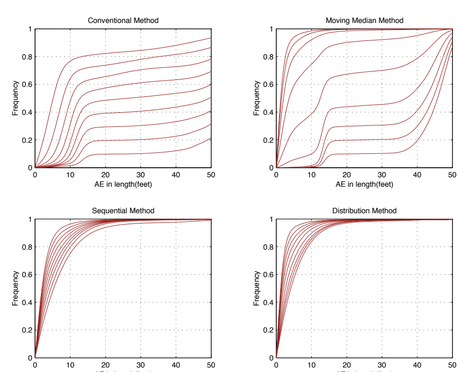


Figure 19, CDF of the absolute error from the length estimation over one month (April, 2005) for lane 2, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

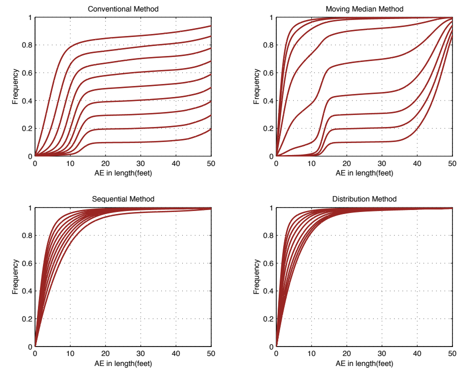


Figure 20, CDF of the absolute error from the length estimation over one month (April, 2005) for lane 3, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

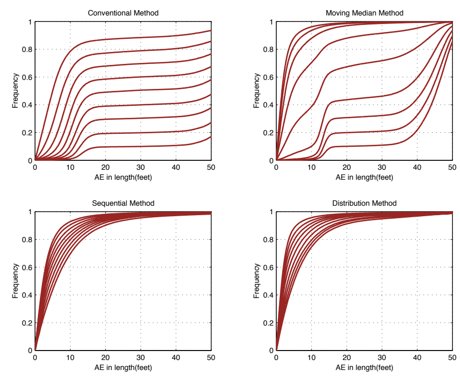


Figure 21, CDF of the absolute error from the length estimation over one month (April, 2005) for lane 4, station 1 when the percentage of trucks varies between 10% and 90% (top row: conventional, moving median; bottom row: sequence, distribution)

A) B)

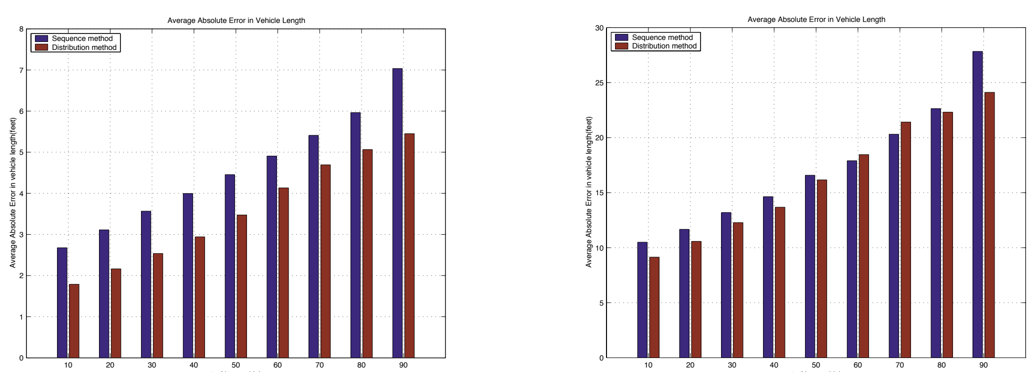


Figure 22, Average absolute error in individual vehicle lengths across all lanes from sequence and distribution estimation methods over one month (April, 2005), station 1 when the percentage of trucks varies between 10% and 90%. (A) When measured speeds are above 45 mph. (B) When measured speeds are below 45 mph.

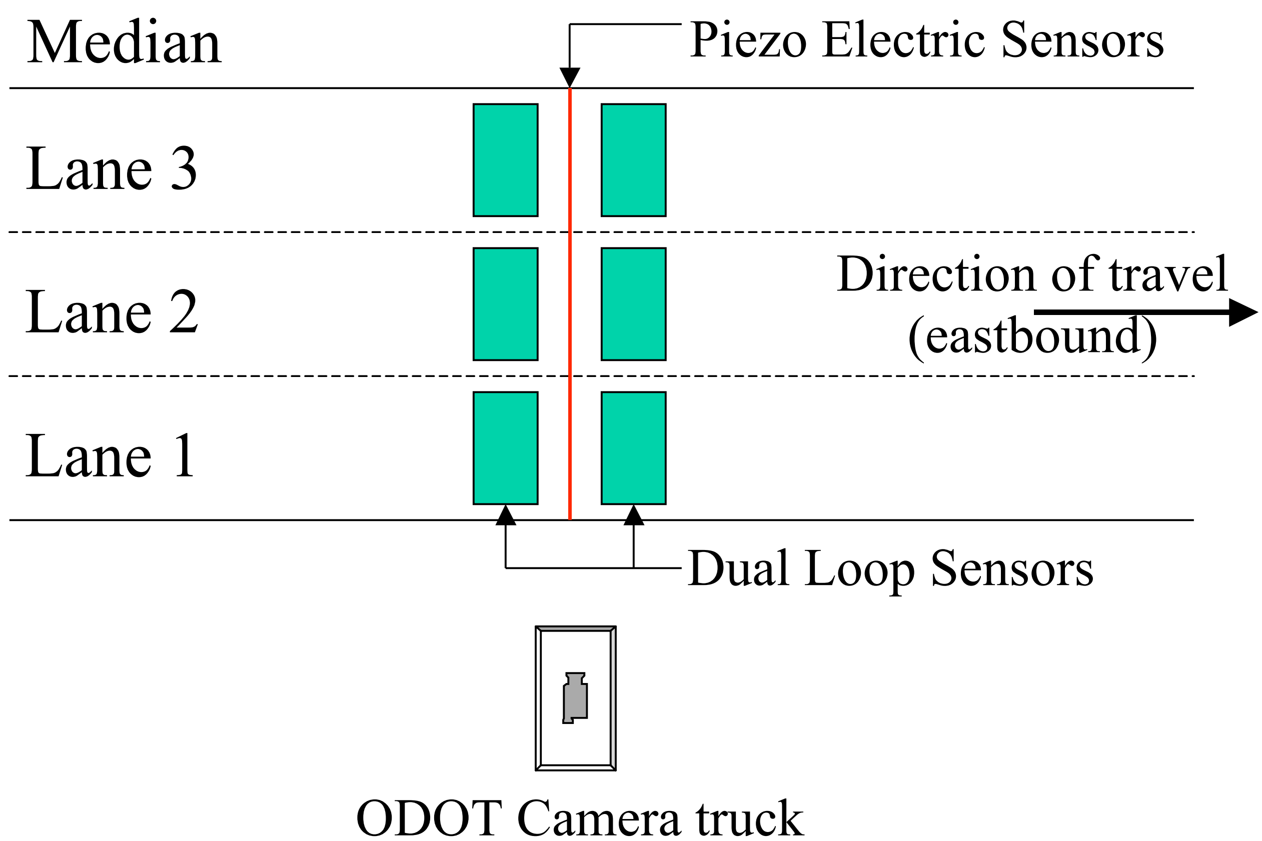


Figure 23, Schematic of the I70 test site, east of Brice road.

Figure 24, I70 test site, east of Brice road. The left image shows the ODOT camera truck used to monitor the detectors and the right image shows one frame from the video.

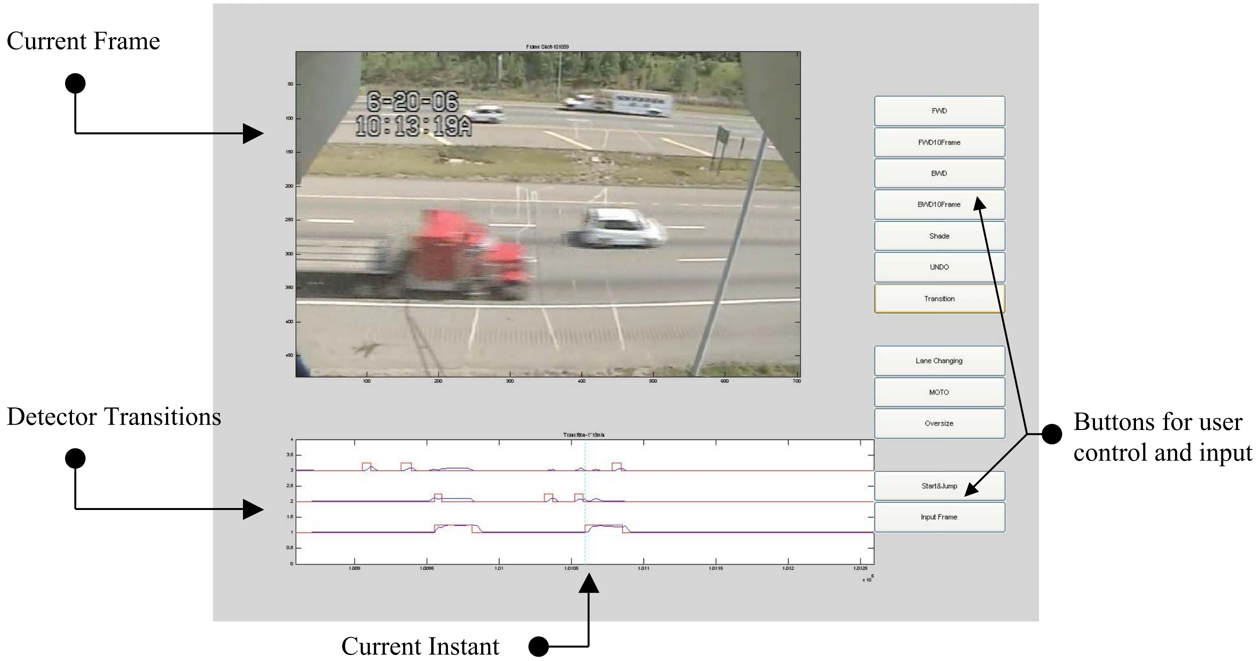


Figure 25, Ground truth tool for extracting length and class from video.

Table 1, Number of observations at the I70 test site.

	Brice Rd.
Direction	**Eastbound**
# of vehicle entries seen in video	**9746**
# of vehicle entries ground-truthed	**9372**
# of vehicles not ground-truthed	**374**
# of missing vehicles found	**104**
# of vehicle entries recorded by detectors	**9807**
# of extra pulses due to pulse breakup	**0**
# of SnMis	**185**

Table 2, Expected axle-based misclassifications and the reasons.

13 manual FHWA	Definition	ODOT axle-based Class 1	2	3	4	5	6	7	8	9	10	11	12	13
1	motorcycles	X												
2	passenger cars		X	A/B										
3	other 2-axle, 4-tire single unit vehicles		A/B	X		A/C			E					
4	buses				X	A/D	A/B/D							
5	2-axle, 6-tire, single unit trucks			A/C	A/D	X			E					
6	3-axle single-unit trucks				A/B/D		X	F						
7	4 or more axle single-unit trucks						F	X	A/B	A/B	A/B			
8	4 or fewer axle single-trailer trucks			E		E		A/B	X			A/B		
9	5-axle single-trailer trucks							A/B		X		A/B		
10	6 or more axle single-trailer trucks							A/B			X		A/B	A/B
11	5 or fewer axle multi-trailer trucks								A/B	A/B		X		
12	6-axle multi-trailer trucks										A/B		X	
13	7 or more axle multi-trailer trucks										A/B			X
Total														

Legend

(dark grey)	= Expected errors due to similar classes
(light grey)	= Correct classifications
A	similar lengths
B	may have same number of axles
C	extra tires can't be verified
D	may have similar axle spacing
E	class 3 or 5 may have recreational trailer length and axles
F	construction vehicles may have floating axles

Figure 26, An example of a truck with floating axles

Table 3, Number of observations: 13 FHWA manual classifications versus automated axle-based classifications

		ODOT axle-based Class													
		1	2	3	4	5	6	7	8	9	10	11	12	13	Total
13 manual FHWA	**Definition**														
1	motorcycles	**31**													31
2	passenger cars		**3663**	22				2						1	3688
3	other 2-axle, 4-tire single unit vehicles	1	2278	**1497**		3			29						3808
4	buses			1	**2**	11									14
5	2-axle, 6-tire, single unit trucks			116	3	**135**	1	1	12					1	269
6	3-axle single-unit trucks		1	2	1		**93**	4	5	6	32				144
7	4 or more axle single-unit trucks						2	**1**	1	4	7				15
8	4 or fewer axle single-trailer trucks						1		**35**	3		1			40
9	5-axle single-trailer trucks		3	1			15		10	**1230**	6				1265
10	6 or more axle single-trailer trucks						1		1	6	**23**				31
11	5 or fewer axle multi-trailer trucks					1			2	2		**45**	3		53
12	6-axle multi-trailer trucks										1		**11**		12
13	7 or more axle multi-trailer trucks											1		**1**	2
Total															9372

Legend

= Expected errors due to similar classes

= Correct classifications

Table 4, Summary statistics for the 13 FHWA manual classifications versus automated axle-based classifications

Total # of vehicles	Total correct	Total incorrect	# incorrect	
			expected	not expected
9372	6767	2605	2499	106
100.0%	72.2%	27.8%	26.7%	1.1%

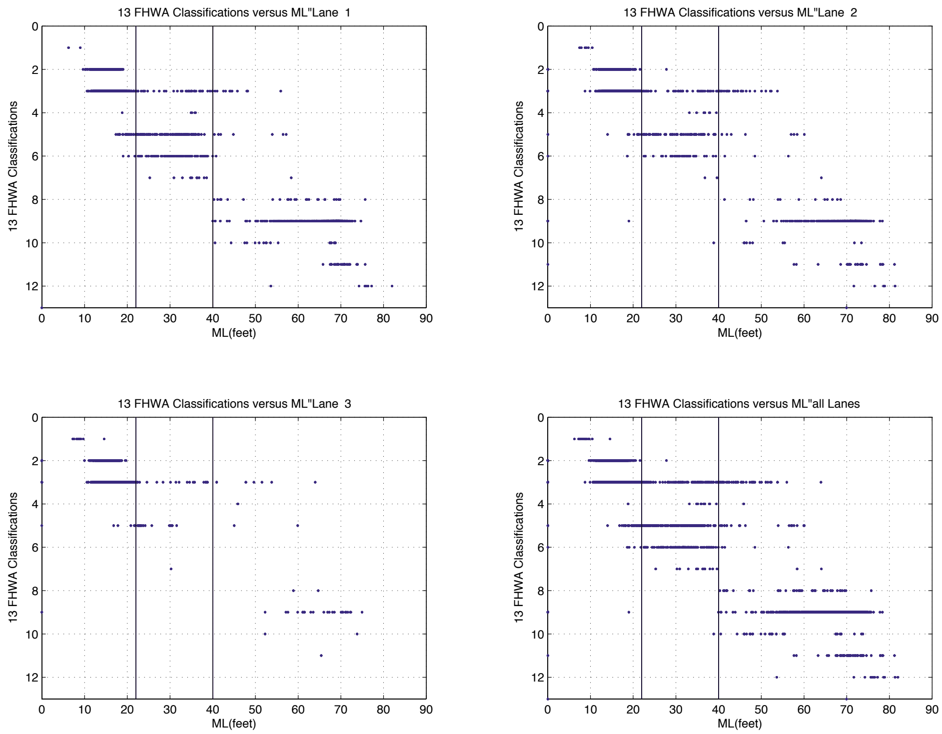


Figure 27, Manual FHWA classifications versus measured length (ML) (top: lane 1, lane 2; bottom: lane 3, all 3 lanes combined)

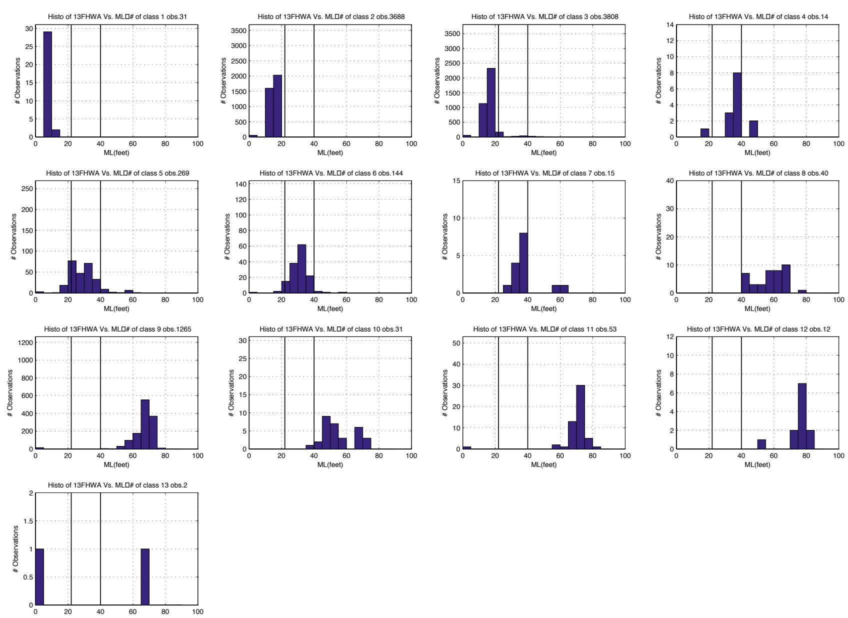


Figure 28, Histograms of FHWA classifications versus measured lengths, 5 ft bins (top row: class 1-4, second row: class 5-8, third row: class 9-12, bottom row: class 13)

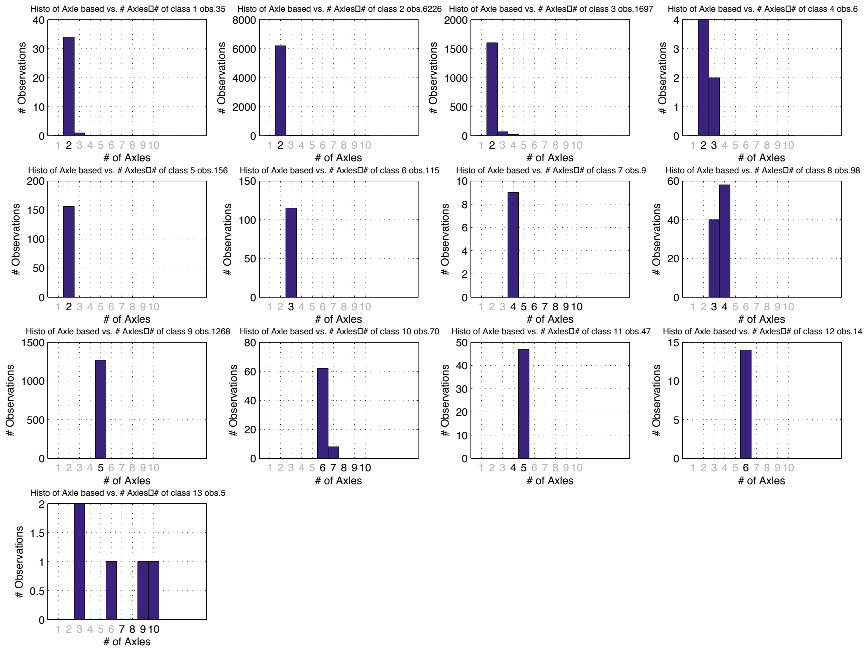


Figure 29, Histograms of FHWA classifications versus number of axles, expected number(s) shown in dark (top row: class 1-4, second row: class 5-8, third row: class 9-12, bottom row: class 13).

A)

B)

C)

Figure 30, Examples of axle based FHWA classification errors (a) class 2 recorded as class 7, (b) class 3 recorded as class 8, (c) class 5 recorded as class 13

```
1: Pres Sensor #1=(2), 76.2'
1: Axle Sensor #1=(5), 17.7'  4.1' 35.4'  3.9'
1: Pres Sensor #2=(2), 76.2'
1: 09:27:07.63  64.0mph,  5 Axles, Length= 70.2', A#9  S#6  L#3  G#1
                         H#1 , 17.7'  4.1' 35.4'  3.9'
1: 09:27:12.38 SnMis #0
2: Pres Sensor #1=(2), 75.5'
2: Axle Sensor #1=(5), 17.4'  4.3' 35.2'  4.0'
2: Pres Sensor #2=(2), 75.0'
2: 09:27:12.81  60.6mph,  5 Axles, Length= 69.2', A#9  S#6  L#3  G#4
                         H#4 , 17.4'  4.3' 35.2'  4.0'
```
Figure 31, Example of SnMis in the per-vehicle record

Table 5, Apparent reasons for SnMis events

Reason	# of Observations(All Lanes)
Lane Changing Maneuver	141
Passing of long vehicle	25
Passing of motorcycle	13
Tailgating vehicles	4
No vehicle present	1
Obscured vehicle	1
Total	185

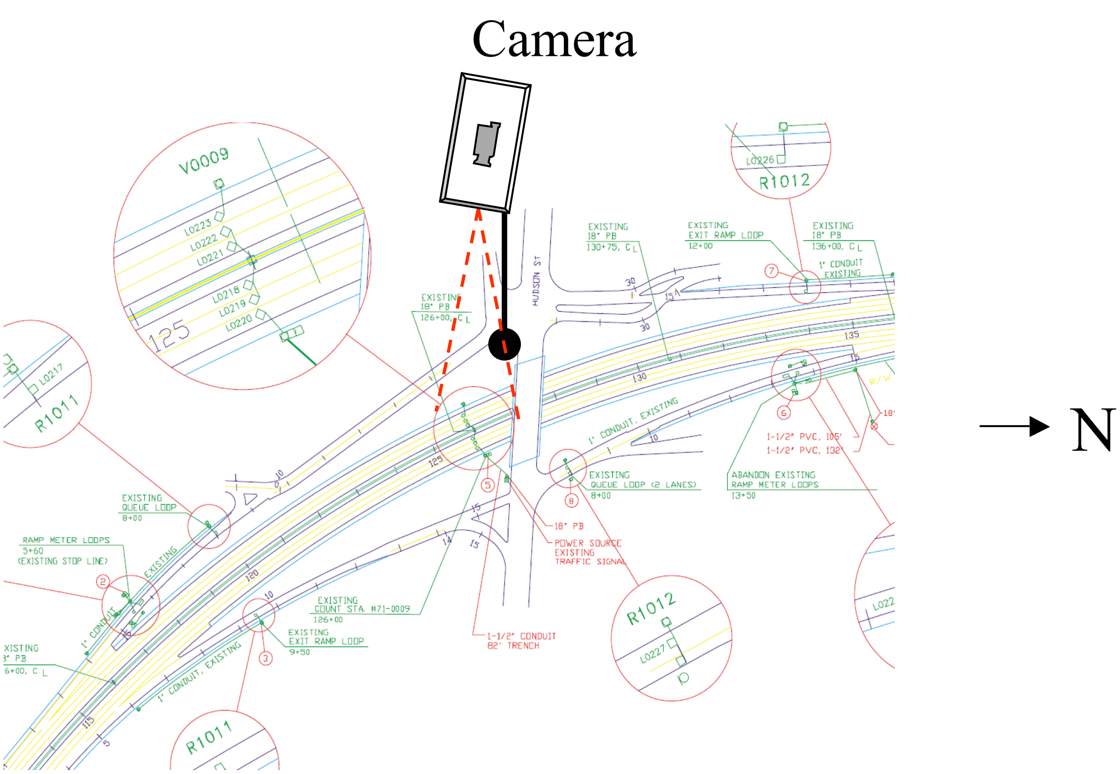


Figure 32, Schematic of the I71 test site, south of Hudson Street (adapted from Coifman, B., 2006).

Figure 33, one frame of the video captured at the I71 test site, south of Hudson Street.

Table 6, Number of observations at the I71 test site.

	Hudson St.	
Direction	**Southbound**	**Northbound**
# of vehicle entries seen in video	**n/a**	**n/a**
# of vehicle entries ground-truthed	**7128**	**6951**
# of vehicles not ground-truthed	**428**	**303**
# of missing vehicles found	**n/a**	**n/a**
# of vehicle entries recorded by detectors	**7686**	**7565**
# of extra pulses due to pulse breakup	**130**	**311**
# of SnMis	**n/a**	**n/a**

Table 7, Length based classes.

Class	Physical vehicle length (L_p) range	Effective vehicle length (L_e) range
1	$L_p \le 22ft$	$L_e \le 28ft$
2	$22ft < L_p \le 40ft$	$28ft < L_e \le 46ft$
3	$40ft < L_p$	$46ft < L_e$

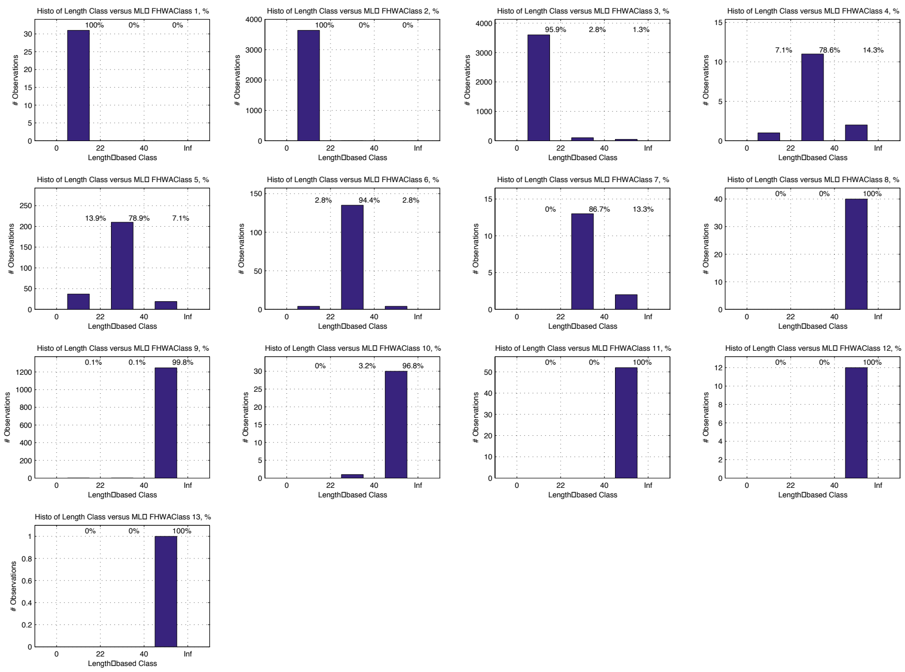


Figure 34, Histograms of FHWA classifications versus resulting length class from <u>measured</u> lengths (top row: FHWA class 1-4, second row: FHWA class 5-8, third row: FHWA class 9-12, bottom row: FHWA class 13)

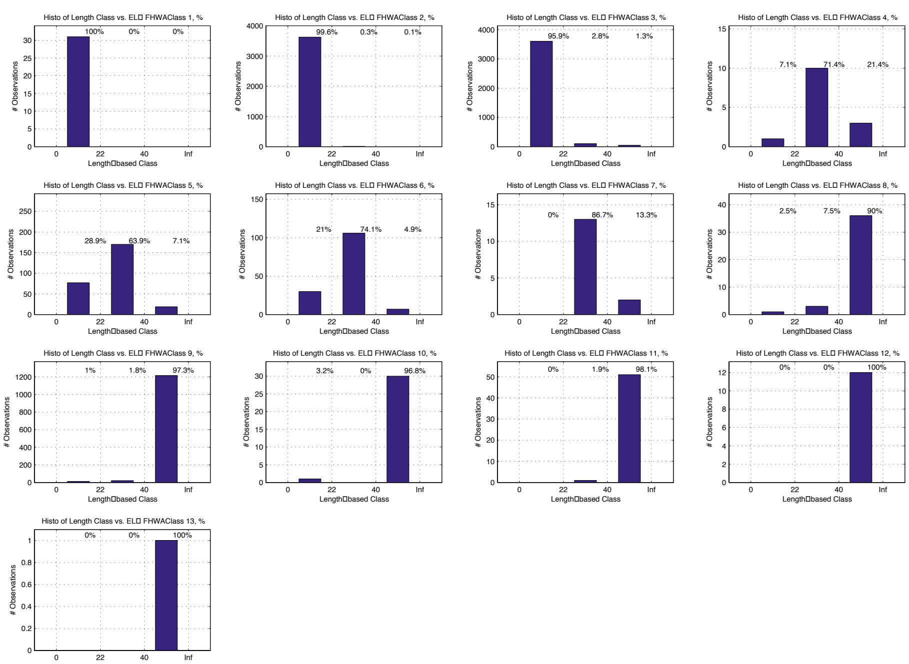


Figure 35, Histograms of FHWA classifications versus resulting length class from <u>estimated</u> lengths (top row: FHWA class 1-4, second row: FHWA class 5-8, third row: FHWA class 9-12, bottom row: FHWA class 13)

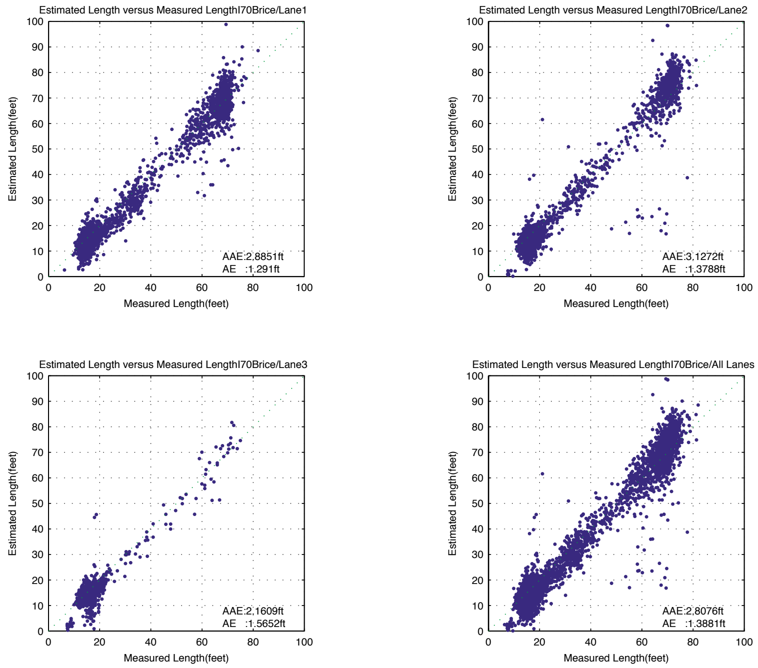


Figure 36, Estimated length from on-times versus manually measured length, I70 test site (top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

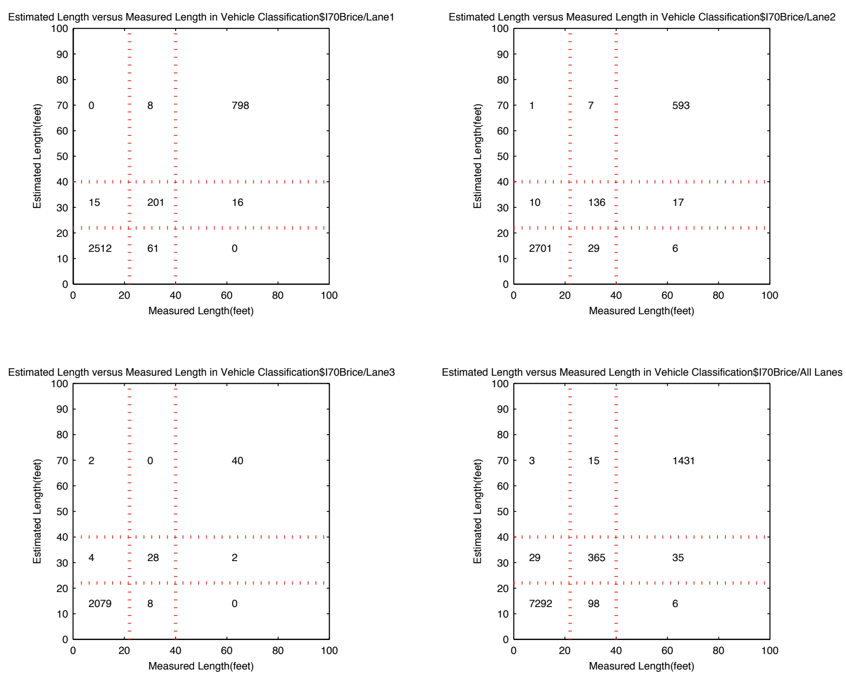


Figure 37, Length based class from estimated length from on-times versus length based class from manually measured length, I70 test site (top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

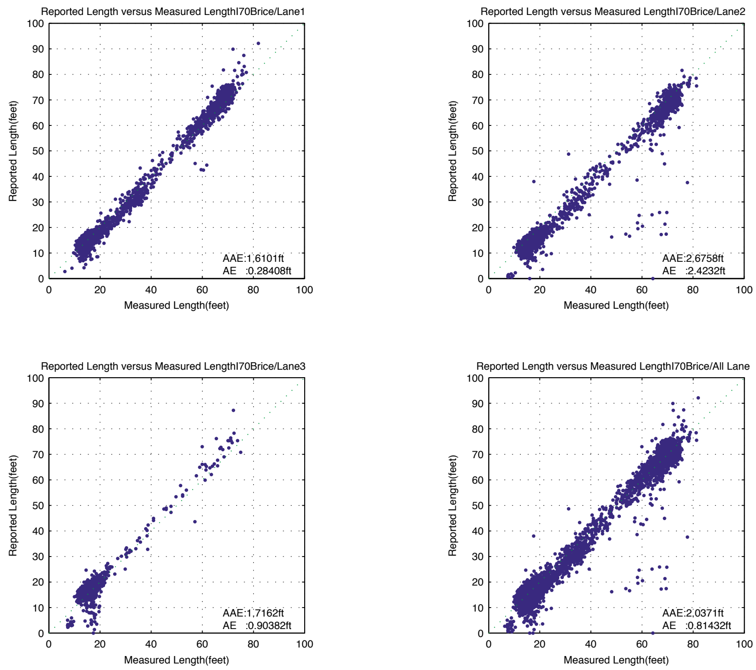


Figure 38, Reported length versus manually measured length, I70 test site (top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

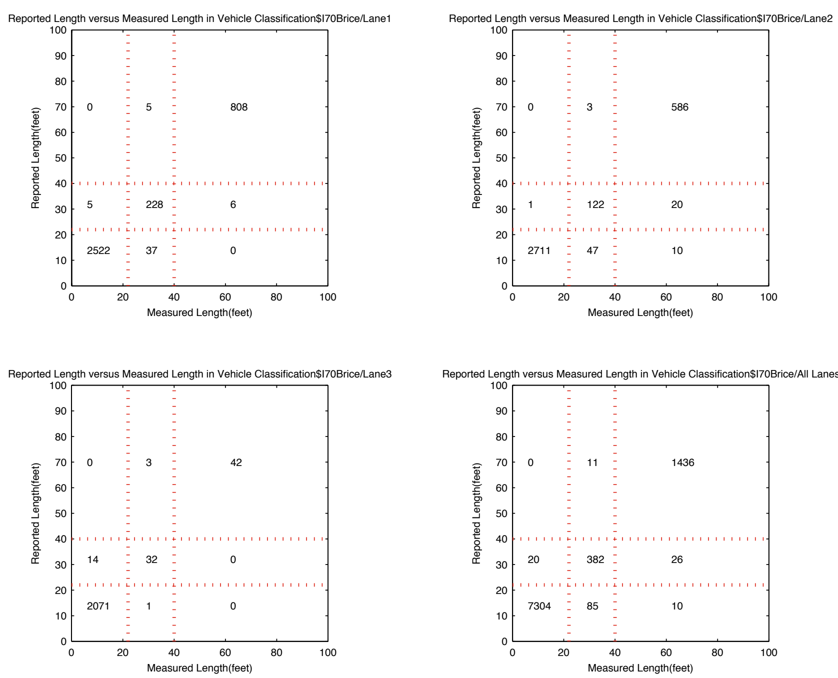
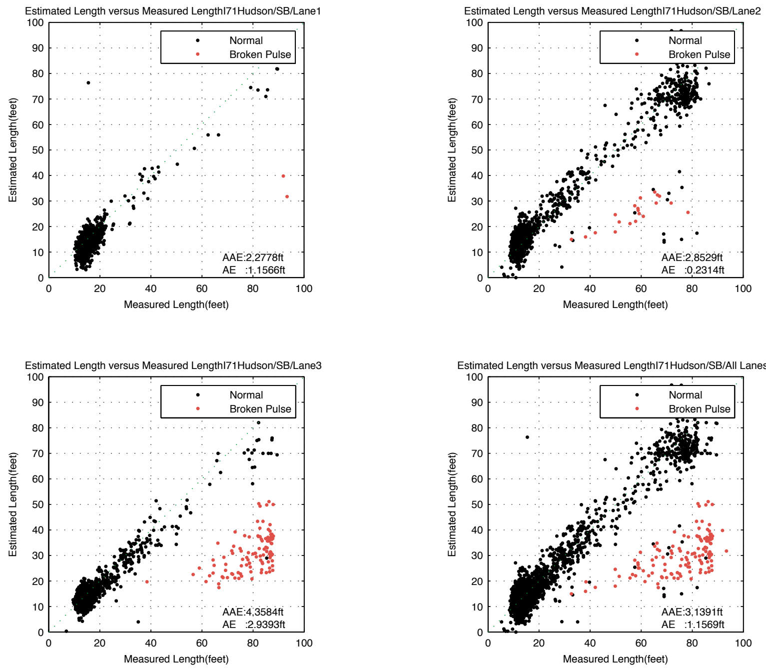


Figure 39, Length based class from reported length versus length based class from manually measured length, I70 test site (top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

A)



B)

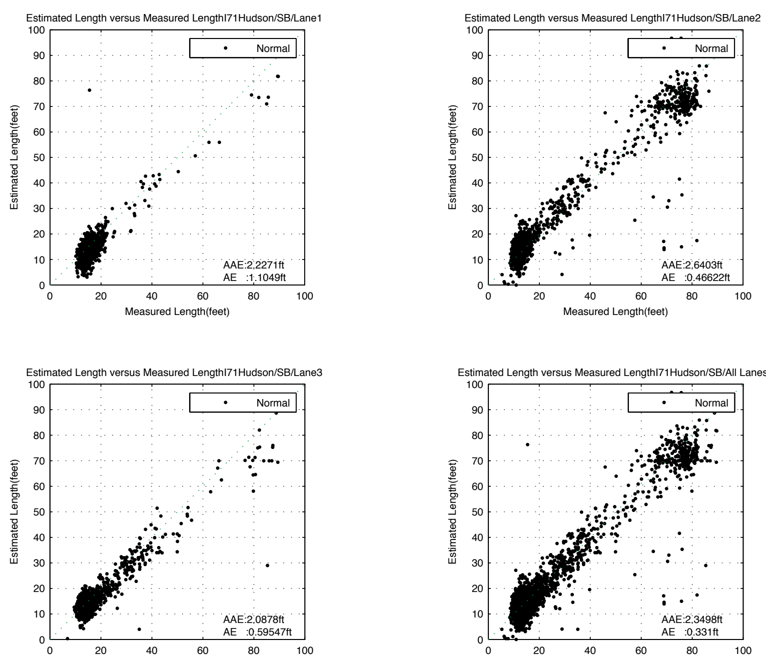
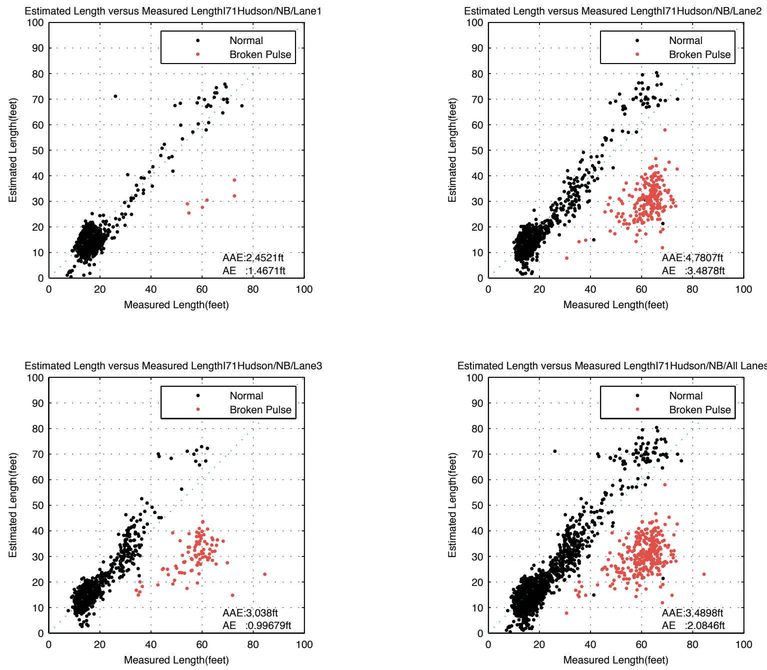


Figure 40, Estimated length versus manually measured length, I71 test site, southbound lanes (A) including pulse break-ups, (B) excluding pulse break-ups, (within each figure top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

A)



B)

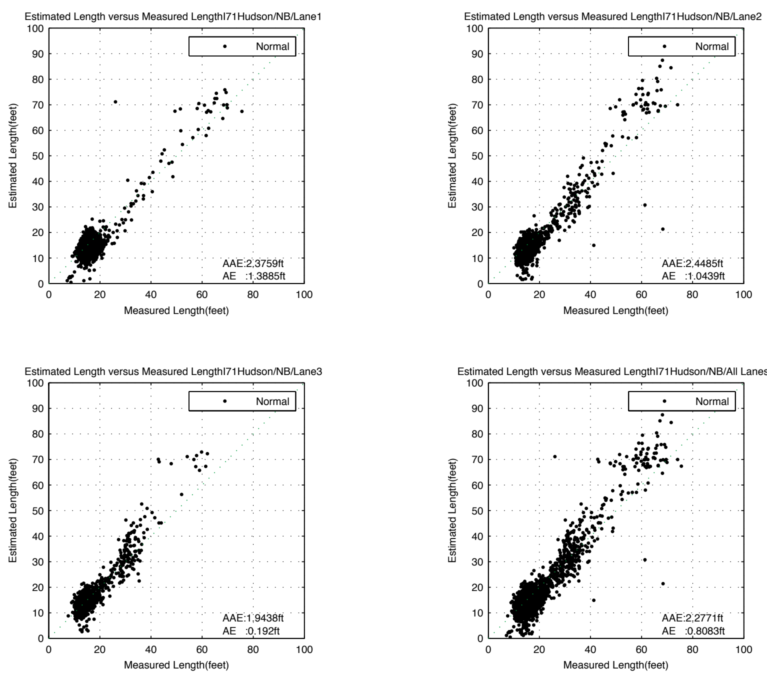
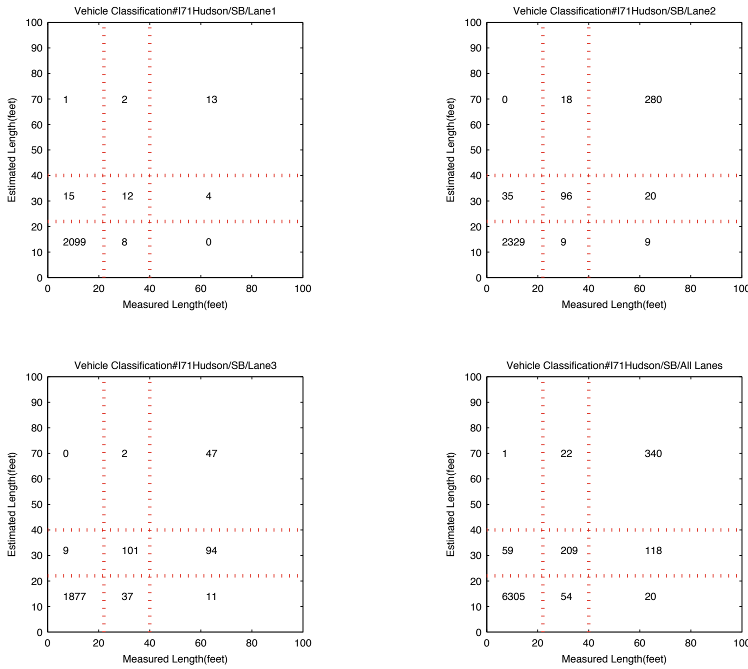


Figure 41, Estimated length versus manually measured length, I71 test site, northbound lanes (A) including pulse break-ups, (B) excluding pulse break-ups, (within each figure top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

A)



B)

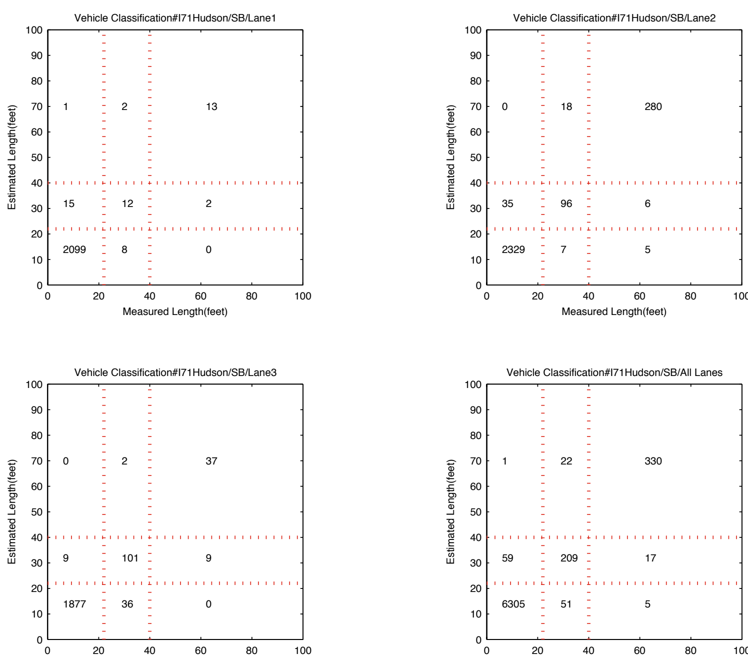
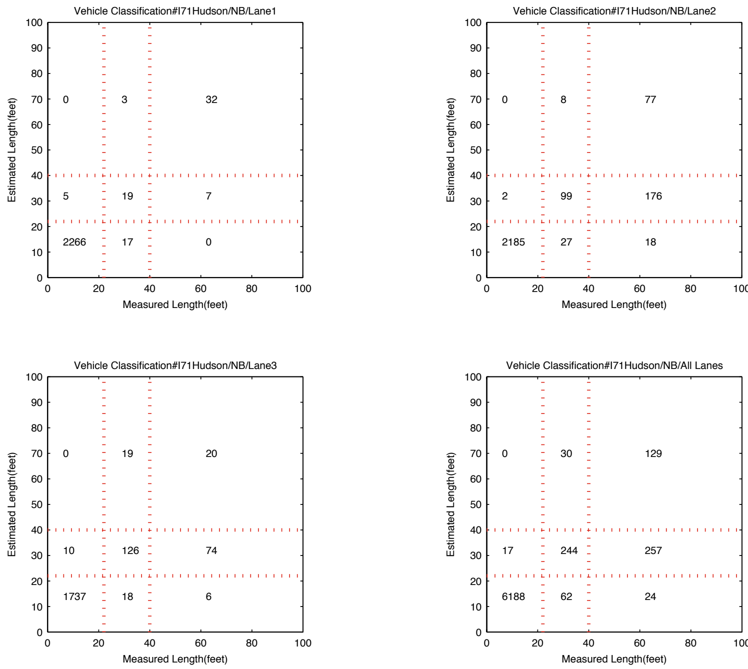


Figure 42, Length based class from estimated length versus length based class from manually measured length, I71 test site, southbound lanes (A) including pulse break-ups, (B) excluding pulse break-ups, (within each figure top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

A)



B)

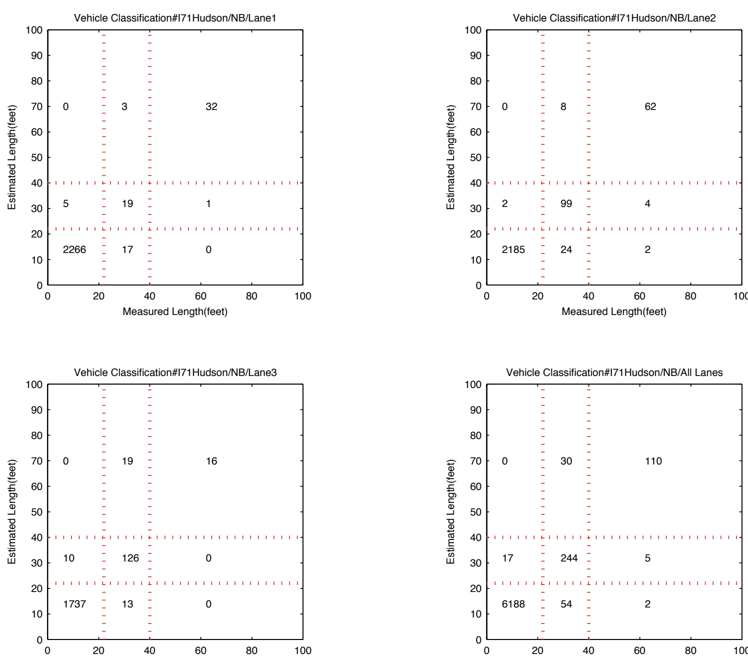


Figure 43, Length based class from estimated length versus length based class from manually measured length, I71 test site, northbound lanes (A) including pulse break-ups, (B) excluding pulse break-ups, (within each figure top row: lane 1, lane 2; bottom row: lane 3, all lanes combined).

Table 8, Percent of correctly classified vehicles in each length class at the I70 test site.

	Estimated length compared to measured length	Reported length compared to measured length
Class 1	99.6%	99.7%
Class 2	76.4%	79.9%
Class 3	97.2%	97.6%

Table 9, Percent of correctly classified vehicles in each length class at the I71 test site.

	Estimated length compared to measured length			
	Including pulse break-ups		Excluding pulse break-ups	
	Southbound	Northbound	Southbound	Northbound
Class 1	99.1%	99.7%	99.1%	99.6%
Class 2	73.3%	72.6%	74.1%	77.1%
Class 3	71.1%	31.5%	93.8%	97.9%

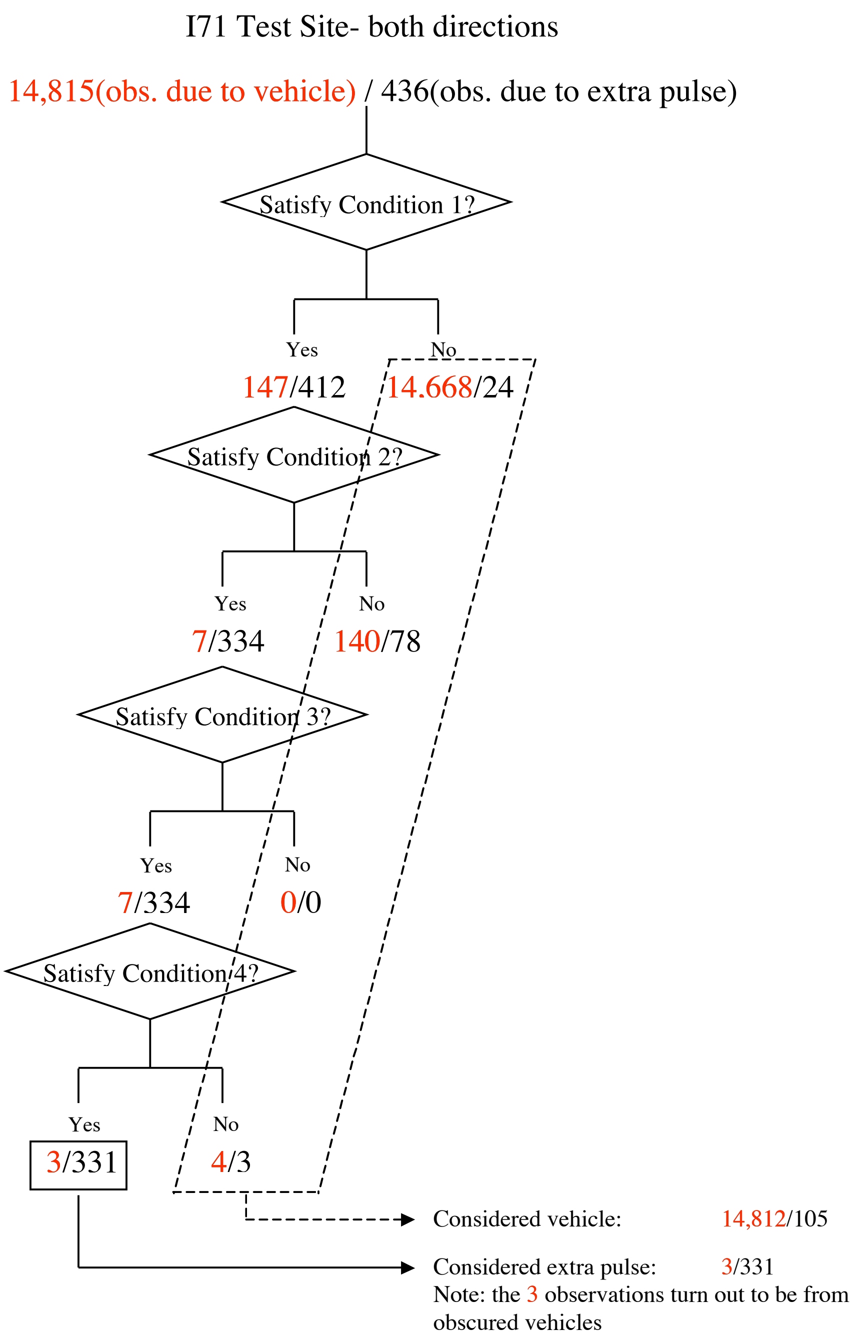
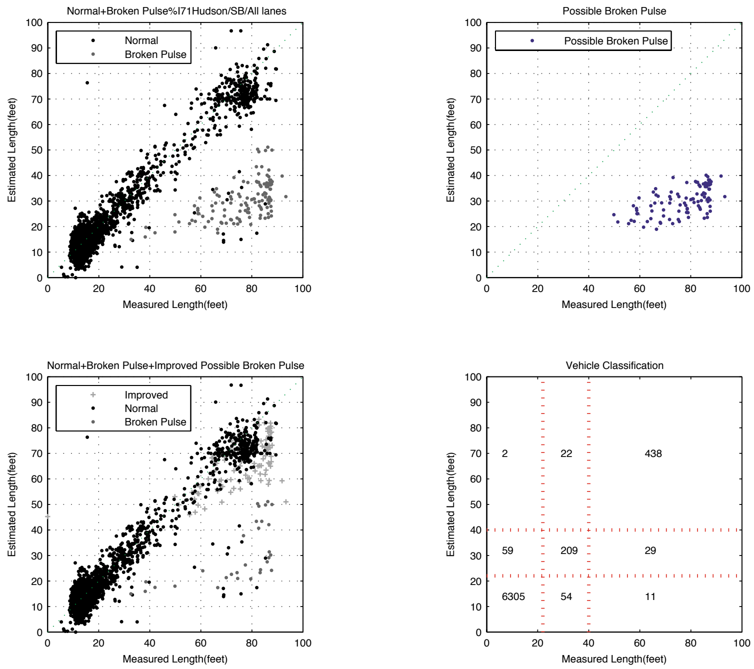


Figure 44, Proof of concept decision tree for detecting pulse break-ups applied to the I71 test site data. At each state the (number of vehicles)/(number of extra, broken pulses) is shown. As shown on the bottom, this tree caught 331 of the pulse break-ups and erroneously accepted 105 of them.

A)



B)

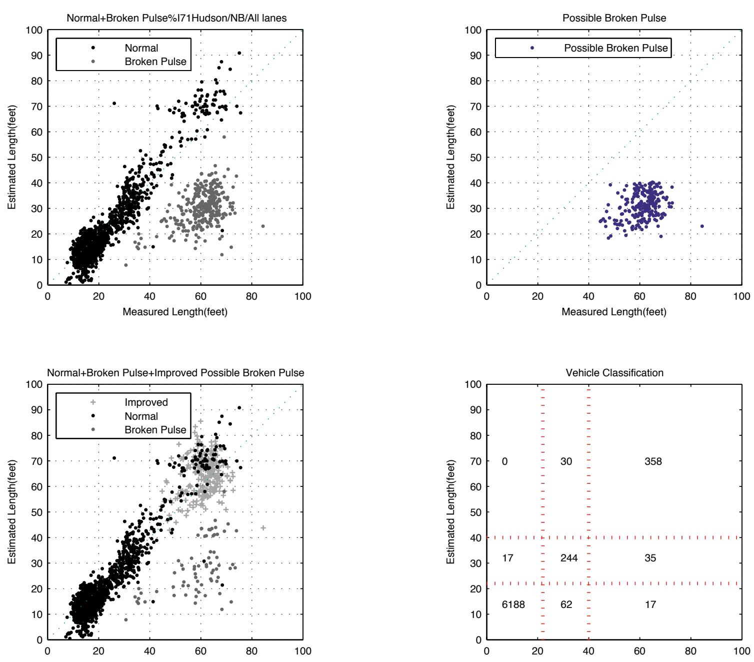


Figure 45, Repeating the classification after considering pulse break-ups (A) southbound (B) northbound across all lanes (within each figure top row: raw data, detected broken pulses; bottom row: repeating raw data after merging broken pulses, resulting classification statistics).

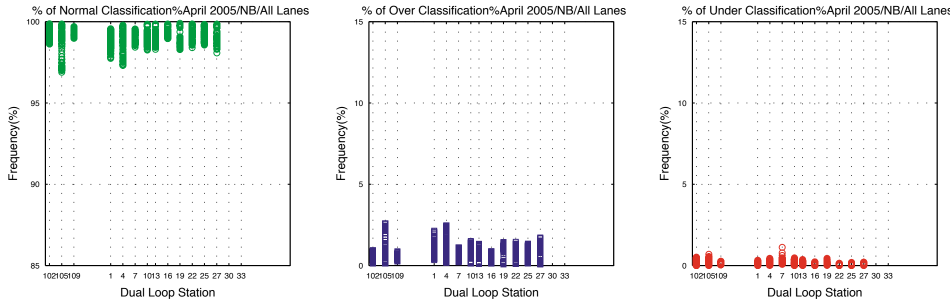


Figure 46, Monthly summary plot for vehicle classification during free flow conditions, all lanes (one point per lane per day). Left: % of correctly classified vehicles, middle: % of over-classified vehicles, and right: % of under-classified vehicles.

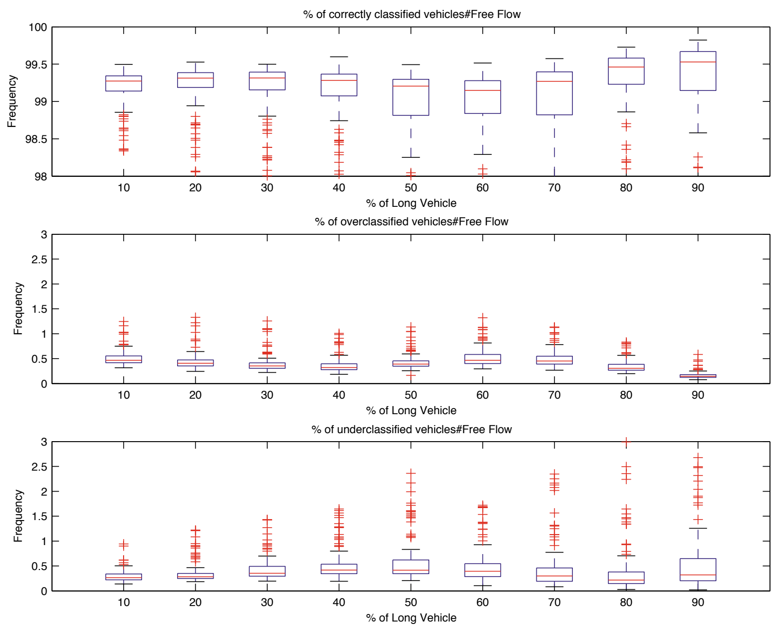


Figure 47, Box plot for vehicle classification during free flow conditions at station 1 northbound over one month (April, 2005), when the percentage of trucks varies between 10% and 90%. Top: % of correctly classified vehicles, middle: % of over-classified vehicles, and bottom: % of under-classified vehicles.

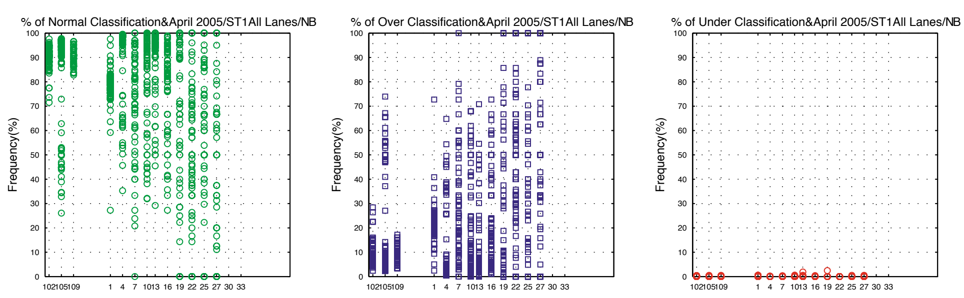


Figure 48, Monthly summary plot for vehicle classification during congested conditions, all lanes (one point per lane per day). Left: % of correctly classified vehicles, middle: % of over-classified vehicles, and right: % of under-classified vehicles.

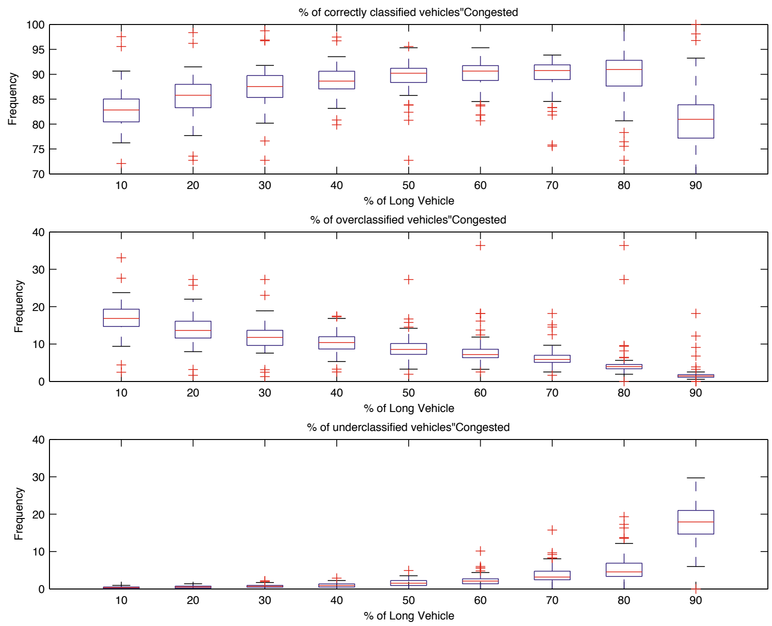
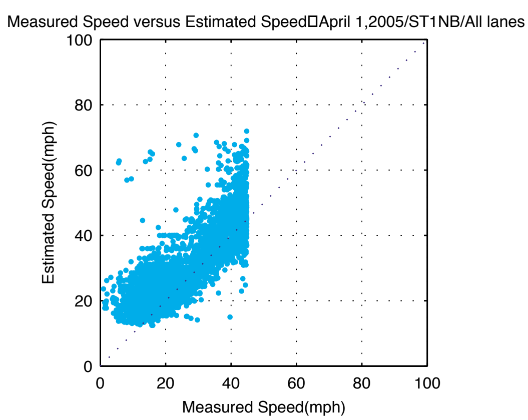


Figure 49, Box plot for vehicle classification during congested conditions at station 1 northbound over one month (April, 2005), when the percentage of trucks varies between 10% and 90%. Top: % of correctly classified vehicles, middle: % of over-classified vehicles, and bottom: % of under-classified vehicles.

A)



B)

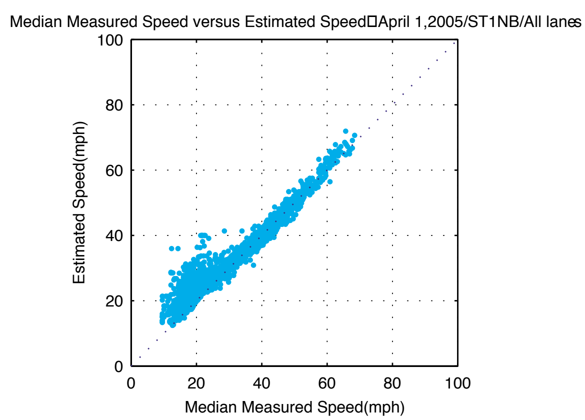


Figure 50, (A) Estimated speed versus the individual vehicle's measured speed. (B) Estimated speed versus the median measured speed for the sample (April 1, 2005, northbound station 1, all lanes).