Municipal Vehicles as Sensor Platforms to Monitor Roadway Traffic

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Abstract

Urban traffic monitoring is important for applications ranging from real time traffic responsive signal control to long-term estimations for planning and infrastructure health. Current urban roadway traffic monitoring suffers from two problems: generally the monitoring locations are at discrete locations that are spatially sparse, and in many cases the collection only lasts a few days during a multi-year interval. As a result, most of the network goes unmonitored.

In an effort to supplement conventional traffic monitoring this study explores the possibility of using municipal or public vehicles as moving sensor platforms to monitor the surrounding roadway traffic, thereby extending data collection to a large portion of the currently unmonitored network. This work uses many hours of empirical sensor data collected from a prototype instrumented vehicle to identify and count passing vehicles, measure their speed, and classify the target vehicles based on the measured shape and size. The instrumented vehicle is equipped with DGPS for localization and side-view, vertically scanning planar LiDAR sensors for perception. This paper presents the process of extracting vehicles from the LiDAR data, validates the results using several experiments, and ultimately demonstrates that such a system could be used to collect meaningful traffic measurements.

Introduction

Traffic information on urban roads, as currently collected, suffers from two significant problems: generally, the detector locations are spatially sparse, and in many cases the collection is also temporally sparse, collected for a few days at a time over three to five year intervals. Typically, the data are collected from fixed locations using either permanent sensors (e.g., inductive loop detectors), temporary sensors (e.g., pneumatic tube detectors), or manually by human observers. Thus, most of the roadway network goes for years without being monitored due to the labor and resources required for the conventional traffic monitoring tools. We seek to collect information about the unobserved links on the network. At the base of this work are probe vehicles collecting *floating car* data, whereby individual vehicles equipped with position and velocity sensing (e.g., GPS) serve as traffic probes, measuring velocity or travel time as experienced by that vehicle. Conventional probe vehicle and floating car studies have been a common tool for collecting journey time, delay and the number of stops [1-5], and they are becoming an increasingly common tool for real time travel time measurement [6-11]. However, these data do not provide vehicle counts or flow rates for the non-equipped vehicles. On the other hand, the moving observer method [12] uses a floating car with a dedicated person to count the number of vehicles passed by the floating car. A significant impediment to the widespread adoption of moving observer methods is the simple fact that, as originally proposed, the methodology requires a vehicle and two people dedicated to do the traffic-study: a driver and a counter.

Rather than attempting to estimate flows from travel time data or use the labor intensive moving observer method, this study investigates the possibility of developing a system that uses an instrumented vehicle as a *sensor platform* with perception sensors that directly monitor the ambient vehicles and surrounding traffic flows, e.g., to automate the moving observer method. Municipal vehicles (or other public vehicles like buses) are a logical choice for the host vehicles since they already spend a significant fraction of the day traveling urban roadways. They may be driven on fixed but complex routes (e.g., transit busses or refuse collection vehicles) that offer repeated observations of a given route or variable and non-recurring routes (e.g., police or road maintenance vehicles). In either case, a fleet of such vehicles may traverse a significant percentage of main urban thoroughfares repeatedly and over a fairly short period of time. Already these municipal vehicles are being used as GPS equipped probe vehicles to collect general information regarding velocities and areas of congestion [6-8], but it is difficult to distinguish actual traffic conditions from the effects of primary operational activities, for example stopping at a bus stop to serve passenger can knock these vehicles out of the signal progression experienced by private automobiles [13]. Hence our focus on automating the moving observer method instead of the conventional reliance on travel time alone. In this fashion the municipal vehicle becomes a moving platform for the traffic monitoring sensors. While we envision monitoring both directions of traffic on the road, the host vehicle's operations will definitely have minimal impact on traffic in the opposing direction, and thus, the opposing direction is our initial focus. Henceforth a vehicle serving a sensor platform will be referred to as an instrumented probe vehicle, or IPV for short.

This paper describes a prototype implementation of a sensor and data analysis system that could potentially be deployed on municipal vehicles. It consists of a data collection system equipped with GPS and inertial measurement for positioning as well as multiple LiDAR sensors

to monitor the ambient traffic. The IPV also has several video cameras to collect validation data. The sensor data are presently analyzed offline, after collection. This system has been tested in and around The Ohio State University (OSU) campus for more than a year. This paper demonstrates that the system is capable of detecting vehicles over multiple lanes, measuring the speed of each vehicle, and providing geometric information used for vehicle classification. We also present the results of several validation experiments, comparing the detection system against concurrent ground truth data. While the focus of this paper is the detection of individual vehicles in the traffic stream surrounding the IPV, the ultimate objective of our team's research is to measure traffic stream variables such as link flows by aggregating individual vehicle measurements and collecting repeated observations of a given link [14].

Methodology

To facilitate the research this study used a dedicated minivan rather than a municipal vehicle to serve as the mobile sensor platform, i.e., the IPV. The study's IPV was equipped with a Trimble GPS receiver using the Omnistar wide-area differential corrections and providing 5 Hz sample rates with sufficient accuracy to identify the IPV's lane of travel under nominal operating conditions, a fiber optic yaw rate gyroscope to measure turning motions, and access to the vehicle's onboard data bus to collect available vehicle state measurements. As shown in Figure 1, pairs of LiDAR sensor units acting as vertical planar scanners, were mounted high on the driver and passenger sides of the vehicle (approximately 2.2 m above ground) in order to observe multiple adjacent lanes of traffic while minimizing occlusions. The LiDAR sensors were mounted with a separation of 1.4 m, and each one scans 180° of a vertical plane with 0.5° resolution at an update rate of approximately 37 Hz. The vehicle is also equipped with forward, reverse, and side looking cameras, which record compressed video for manual observations and ground truth extraction. Data are collected and stored onboard the IPV with all measurements accurately timestamped since temporal correlation of the multiple sensors is required to properly match objects seen in each sensor, to estimate target vehicle relative velocities, and to accurately identify target vehicle locations on the roadway. Another aspect of the experiment was the selection of an appropriate route over which the IPV should be repeatedly driven at different times of the day over a period of many months. The route selected was motivated by a desire to follow an OSU campus transit system route for part of the tour (*Campus Loop South*, [15]) that members of our team have studied extensively [16-19] while also collecting a diverse sampling of various arteries in the campus region.

Vehicle Detection and Extraction

The basic procedure for extracting objects from the raw scan data from an individual LiDAR sensor is as follows. First, the range and azimuth data are converted to lateral distance and height relative to the mounting point of the LiDAR sensor (2.2 m) on the IPV. To eliminate possible ground features all LiDAR returns below 1.65 m are ignored at this stage. Likewise, all LiDAR returns above 20 m are discarded. All remaining LiDAR returns that are *close* in time and horizontal distance are extracted. The LiDAR returns are clustered using Equation 1, a distance measure between points or sets of points defined in terms of lateral distance, Y, height, Z, and time, T, where the weighting factor of 900 was heuristically established to balance impacts over time and space.

$$dist = (\Delta Y^2 + \Delta Z^2 + 900 * \Delta T^2)^{\frac{1}{2}} \quad (1)$$

For each initial cluster found, all original LiDAR points that are below the 1.65 m threshold and physically close (within 2 m of height and 4 m of lateral or longitudinal distance) to the growing cluster are added to it. A ground plane for the cluster is identified using a Random Sample Consensus (RANSAC) search of 4000 iterations. For each iteration 3 points are randomly selected from the cluster, creating a candidate plane, and the support for the candidate is determined by counting the number of points in the cluster lying within 0.15 m of the plane. Candidate planes that are pitched too far from horizontal are discarded. The candidate plane with the most supporting points is taken to be the ground plane for the cluster. A refined ground plane is generated by computing a least squares *optimal plane* from all the points of the cluster that lie within 0.2 m of the RANSAC plane. Finally, each point in the cluster that is within 0.07 m of the refined ground plane is marked as "ground". An example of an extracted object, a pickup truck, is shown in Figure 2. At this stage, each initial cluster has been expanded to include all nearby LiDAR points, some of which are marked as ground. The point cloud for each expanded initial cluster is divided into sub-clusters of points within 0.9 of each other (via Equation 1). The collection of all sub-clusters forms the final cluster list.

To match clusters of each individual vehicle from the paired forward and rearward LiDAR sensors, a linear assignment problem is solved using [20]. The generally rectangular cost matrix is formed for each pair of clusters selected from the forward and rearward lists (again via Equation 1). At this point a complete set of matched target clusters exists and at this stage it includes both vehicles and non-vehicle objects. We then generate a side profile for each cluster. Generally, the side profile thus obtained is fairly complete due to the height and observation angle of the sensor. Profiles of each cluster from the front and rear LiDAR sensors can then be correlated in time using both the profile shape and the timestamps associated with the data. Using horizontal cut-lines to match particular points on the front and rear of each profile, the time difference between the detection of these points are extracted and used to estimate the velocity of the target cluster relative to the IPV. It is possible that due to partial occlusions only the front or the rear of the target cluster is sufficiently visible, as evidenced by differing side profile shapes. One can still extract a relative velocity in this case from the non-occluded end, although with reduced accuracy because of the single measurement. If the occlusion is too severe, it might not be possible to extract a velocity, but the cluster can still be counted.

Each extracted cluster is then categorized as a vehicle or non-vehicle as follows. With a measurement of relative velocity, we compute the length of the target object. The first test is to ensure that the length and height of the target object are consistent with a reasonable range of dimensions for a road vehicle. Then the lateral position as well as the depth of the target object are checked to ensure that the object is on the road. For this study the "on-road" test was done using a detailed map, but it can also be done using curb detection, e.g., [21], or using other techniques to find the road boundaries. As a final check, the relative velocity measurement of each cluster must be within an acceptable range for that cluster to be retained as a vehicle.

Potential sources of velocity measurement error include calibration errors affecting the separation distance of two LiDAR sensor vertical planes (primarily an angle offset such that the actual planes are not perfectly parallel), jitter, and time stamping errors. In fact the calibration errors proved to be an unanticipated challenge in this project, whereby a very small angular offset yielded large errors in the velocity measurements. Because of the design of the LiDAR sensors, the difficulty of observing the infrared laser planes, and the mounting mechanisms it

proved impossible to produce a perfectly parallel alignment of the front and rear LiDAR sensors on a given side of the IPV. While this challenge could be addressed at the design stage of future sensor systems, for the current work, after a large number of observations and validation experiments, it was found that the relative velocities being computed from the LiDAR sensor data were too low, and that this systematic error became more pronounced at greater longitudinal distances from the mobile platform. The distance between the two LiDAR sensor planes is given by Equation 2, assuming that the only error is an angular offset, θ, where the effective separation of the two LiDAR scanning planes is D_{sep}, at a longitudinal distance, D_{long}, away from the mobile platform and the original sensor separation is 1.4 m.

$$D_{sep} = 1.4m + D_{long} * \tan(\theta) \tag{2}$$

A series of data collection experiments were undertaken to calibrate θ with the IPV passing parked vehicles at various longitudinal distances. In this manner, the parked vehicles were passed with known relative velocity (simply the negative of the IPV's ego speed) that was then used to evaluate the measured speed from the paired LiDAR sensors. Using approximately 100 detected vehicles, the optimal angle θ was found to be 2.79°. This manual calibration procedure could easily be automated and incorporated into a production system, e.g., by tracking many stationary, non-vehicle objects, the system could be programmed to auto-calibrate.

Although there was no evidence of the following errors, in principle, velocity measurement errors may also arise from violations of various geometric assumptions including: that the mobile platform and target vehicle are traveling in the same plane, that the ground is flat, and that there is no pitching or rolling of either vehicle due to decelerations, potholes, high velocity turn rates, or similar disturbances.

After segmenting the vehicles, they can be classified according to extracted shape measurements. A simple vehicle classification algorithm was derived by inspection of the empirical data [22]. The critical parameters for vehicle classification were found to be vehicle length L, the height of the front of the vehicle, H_1, and the height of the rear of the vehicle, H_2. The following heuristic classification rubric was developed:

1. Motorcycle/Bicycle: $L < 2.3$ m
2. Passenger Car: $H_1 < 1.5$ m
$H_2 < 1.4$ m
$2.3 \text{ m} < L < 7.4$ m
3. SUV/Small Van: $H_1 < H_2 + 0.1$ m
$1.4 \text{ m} < H_2 < 1.95$ m
$2.3 \text{ m} < L < 7.4$ m
4. Pickup Truck: $H_1 > 1.5$ m
$H_1 > H_2 + 0.1$ m
$2.3 \text{ m} < L < 7.4$ m
5. Small Bus/Large Van/Single Unit Truck: $H_1 < H_2 + 0.1$ m
$H_2 > 1.95$ m
$2.3 \text{ m} < L < 7.4$ m
6. Bus/Large Truck: $L > 7.4$m

Other FHWA-defined vehicle types were not considered in this study because of a lack of representative samples in the collected data, but the methodology has been extended by [23-24].

Evaluation

A key element of the validation carried out in this study is the observation of ground truth from concurrent video. Video was collected by side-facing cameras mounted interior to the vehicle at the top of the side door windows, roughly centered longitudinally between the forward and rearward LiDAR sensors. A timestamp is superimposed on the upper left corner of the recorded video image by the data collection system, e.g., as seen in Figure 2b. Manual extraction of video ground truth requires a human operator to record the timestamp at which an observed vehicle is approximately centered in the image, ascertain the lane, ascertain the direction of travel, and note the vehicle classification. We have developed software tools to assist this process in a semi-automated manner, so that the data reduction time is only a few seconds per vehicle (see [22] and [24] for more details).

The initial validation of relative velocity estimates was performed using the same approach to calibrate the angle between the paired LiDAR sensors, i.e., by driving the IPV along an extended stretch of roadway with parallel parked cars. From the perspective of the LiDAR sensor, the relative velocity is independent of which vehicle is moving, so we are able to exploit the fact that the parked cars had a true velocity of zero for validation, i.e., the true relative velocity of the target clusters was exactly the negative value of the IPV's velocity when the target cluster was observed. The IPV's velocity is known accurately both from the GPS velocity measurement and the vehicle's odometer measurement. Typical results are shown in Figure 3. Notice the proximity of the plotted points to the 45° line, indicating the measured velocities were close to the true velocities throughout the range of observations.

Vehicle detection performance was validated by comparing extracted data with data manually extracted from the recorded video. Table 1 shows validation results for 5 passes of the IPV in a single morning through 3 distinct homogeneous links. The IPV passed westbound (WB) twice and eastbound (EB) three times through each of the links. The links are two lanes each direction, with the IPV usually traveling in the right-most lane. The table shows the number of vehicles seen traveling in the opposite direction via the driver's side LiDAR sensors. The number of vehicles observed by a human viewer in the collected video appears in the columns labeled Video. If there were occluded vehicles in the driver's side video for the given pass, the video column includes a second number in parenthesis indicating the number of non-occluded vehicles seen by the human (the non-occluded vehicles are also included in the total number of vehicles). The number of vehicles automatically extracted from the LiDAR sensor data is shown in the columns labeled LiDAR. One can see from the table that for the most part the LiDAR derived counts are close to the ground truth, especially when only non-occluded vehicles are considered. Nevertheless, some discrepancies are evident. Notably, when the IPV is traversing link 3 the LiDAR identifies fewer vehicles than are observed in the video extraction, in the worst case (pass WB 1) only identifying 8 of the 15 vehicles seen in the recorded video. This discrepancy is due to the presence of several large columns in the center median supporting a freeway overpass and many trees along the median between the IPV and the vehicles being monitored. These fixed obstructions prevent the LiDAR sensors from capturing the front and rear of the vehicles (disrupting the speed and length measurements), and the portions of the target vehicles that are captured are often so short that they wind up being discarded as non-vehicle targets. In the short

term this problem could be addressed by redefining the links to exclude the overpass. In the longer term, they highlight the need for future refinements to the vehicle segmentation.

This process was repeated on a larger scale only now using six longer sub-routes that span several intersections. As enumerated in the right hand side of Table 2, these sub-routes ranged from 0.37 km to 2.1 km long, containing between two and eight signalized intersections (including the two intersections bounding the given sub-route), all but one had four lanes (two each direction), all but one had speed limits between 40 to 56 km/h, and all but one had no median divider [22]. Using data from seven tours all of the passing vehicles on the given sub-routes were manually identified in the video and matched to the concurrent LiDAR returns. The IPV traveled in the right-most lane and vehicles are counted in both directions (with far more vehicles seen in the opposing direction due to the higher relative velocities). Table 2 compares the manual ground truth against the LiDAR results on a per vehicle basis. The table shows that across 2,415 vehicles on average 96.7% were correctly identified by the automated vehicle detection and there were 3.3% of non-vehicles erroneously classified as vehicles. The largest errors were in sub-route 4, the only one to have a raised median for a portion of the sub-route. This sub-route included link 3 discussed above, with several trees and bridge supports in it. Excluding sub-route 4 the overall results improve to 97.1% of the ground truth vehicles correctly identified and only 2.4% of the LiDAR detections were non-vehicle that were erroneously classified as vehicles. This performance is similar to or better than many conventional vehicle classification systems, see, e.g., [24-25].

Validation experiments were also conducted to determine the accuracy of the vehicle classification using the rubrics described in the previous section. Table 3 compares the number of vehicles of a given class as identified by the automatic classification algorithm with those manually extracted from the recorded video. Notice that most classifications are correct (the entries on the diagonal in Table 3) and when they are not, most misclassifications are off by one class (as evident by the distribution of the off-diagonal entries in Table 3).

Conclusions

This study investigated the possibility of using an instrumented probe vehicle (IPV) as a sensor platform to monitor the ambient vehicles and surrounding traffic while the IPV traverses the network. In practice it is envisioned that the IPV's would be municipal vehicles because they are already on the network, eliminating the need for a dedicated vehicle for the monitoring task. This work uses many hours of empirical sensor data collected from a prototype IPV to identify and count passing vehicles, measure their speed, and classify the target vehicles based on the measured shape and size. The IPV is equipped with DGPS for localization and side-view, vertically scanning planar LiDAR sensors for perception. This system has been tested in and around The Ohio State University (OSU) campus for more than a year. The prototype system is designed for research and development. Future research will focus on identifying the key measures needed, what sensors to use to collect those measures in the most cost effective manner, and how to harden the system so that it is low cost and can operate long term without any manual intervention.

This paper presents the process of extracting vehicles from the LiDAR data and validates the results using several experiments, and ultimately demonstrates that it could be done for the purpose of using such a system for collecting meaningful traffic measurements. We also present the results of several validation experiments, comparing the detection system against concurrent

ground truth data. It was found that the system is capable of detecting vehicles over multiple lanes, measuring the speed of each vehicle, and providing geometric information used for vehicle classification. In one of the real world tests involving 2,415 ambient vehicles the system exhibited vehicle detection rates on the order of 97% and erroneous non-vehicle detections on the order of 3%. In this individual vehicle comparison case the errors happen to roughly cancel one another, underscoring the importance to look deeper than simple aggregate counts. Meanwhile, the vehicle classification scheme exhibited almost 93% accuracy over 927 vehicles.

This approach is meant to supplement rather than supplant conventional traffic monitoring, extending data collection to the large portion of the network that is currently unmonitored. While the focus of this paper is the detection of individual vehicles in the traffic stream surrounding the IPV, the ultimate objective of our team's research is to measure traffic stream variables such as link flows by aggregating individual vehicle measurements and collecting repeated observations of a given link [14].

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Table 1, Validation of LiDAR vehicle extraction - concurrent video-extracted and LiDAR-extracted vehicle counts

IPV Travel Dir	Link 1		Link 2		Link 3	
	Video	LiDAR	Video	LiDAR	Video	LiDAR
EB 1	11(10)	10	1(0)	1	9(7)	5
EB 2	5	6	4	3	17	15
EB 3	14(13)	12	5	4	4(3)	3
WB 1	30	28	3	2	16(15)	8
WB 2	28	28	7	6	13	9

Table 2, Validation of LiDAR vehicle extraction over six sub-routes across seven tours

sub-route	Veh in ground truth	Correctly detected veh		Missed vehicles		Non-vehicles detected		Length (km)	Signalized intersections	lanes
		#	%	#	%	#	%			
1[a]	343	335	97.7%	8	2.3%	14	4.1%	1.7	3	4
2	235	230	97.9%	5	2.1%	0	0.0%	0.37	2	4
3	879	842	95.8%	37	4.2%	20	2.3%	1.6	8	4
4[b]	439	417	95.0%	22	5.0%	40	9.1%	1.2	4	4
5	144	138	95.8%	6	4.2%	3	2.1%	2.1	7	4
6	375	374	99.7%	1	0.3%	10	2.7%	0.41	2	2
total	2,415	2,336	96.7%	79	3.3%	87	3.6%			
excluding #4	1,976	1,919	97.1%	57	2.9%	47	2.4%			

notes:

a: this sub-route had a 72 km/h speed limit

b: this sub-route had a tree lined dividing median for roughly 1/4th of its distance

Table 3, Validation of extracted vehicle classification

		True Classification (from video)						
		1	2	3	4	5	6	Total Assigned
Assigned Class (from method)	1	**11**	5	1	-	-	-	17
	2	-	**548**	11	9	-	-	568
	3	-	28	**190**	-	-	-	218
	4	-	1	11	**42**	-	-	54
	5	-	-	-	3	**36**	-	39
	6	-	-	-	-	-	**31**	31
	Total (Truth)	11	582	213	54	36	31	
	% Correctly Assigned	100%	94.16%	89.62%	77.78%	100%	100%	

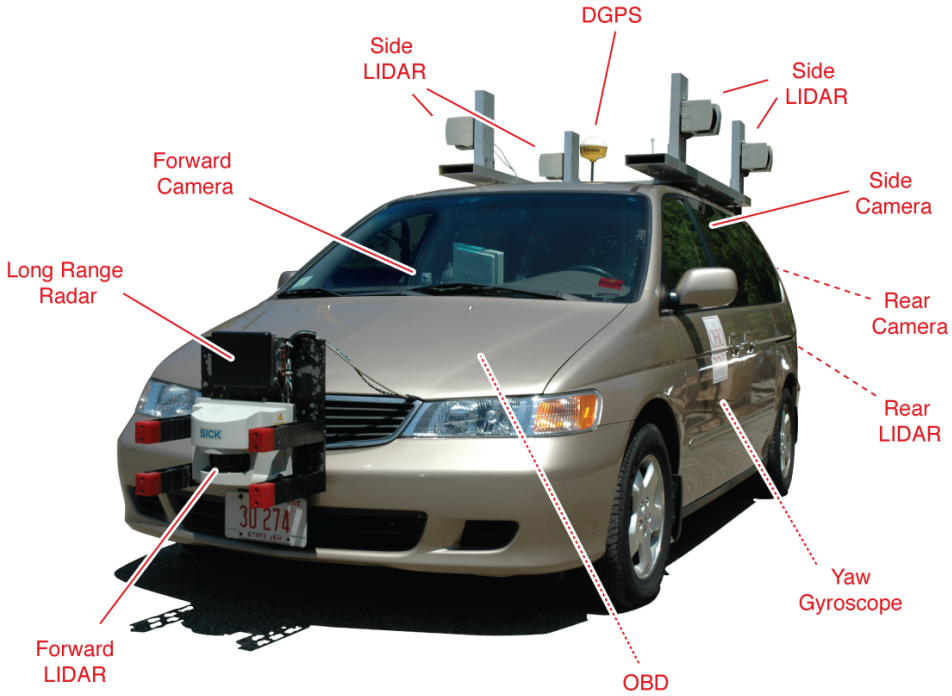
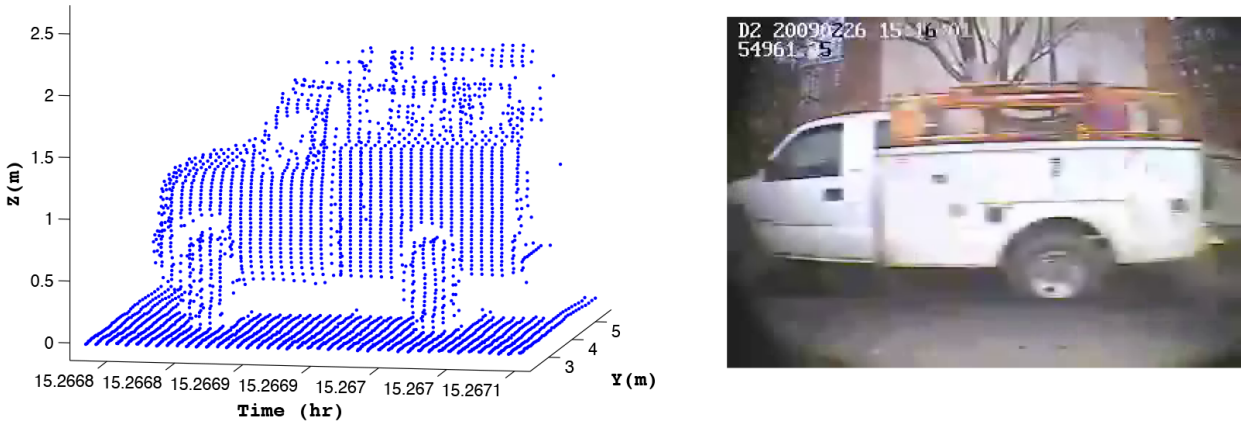


Figure 1, Illustration of the various sensors on the instrumented probe vehicle (not all of the sensors shown are used in this study)



(a) (b)

Figure 2, (a) An example of a vehicle extracted from the LiDAR data, and (b) the corresponding view of that vehicle in the driver's side validation video.

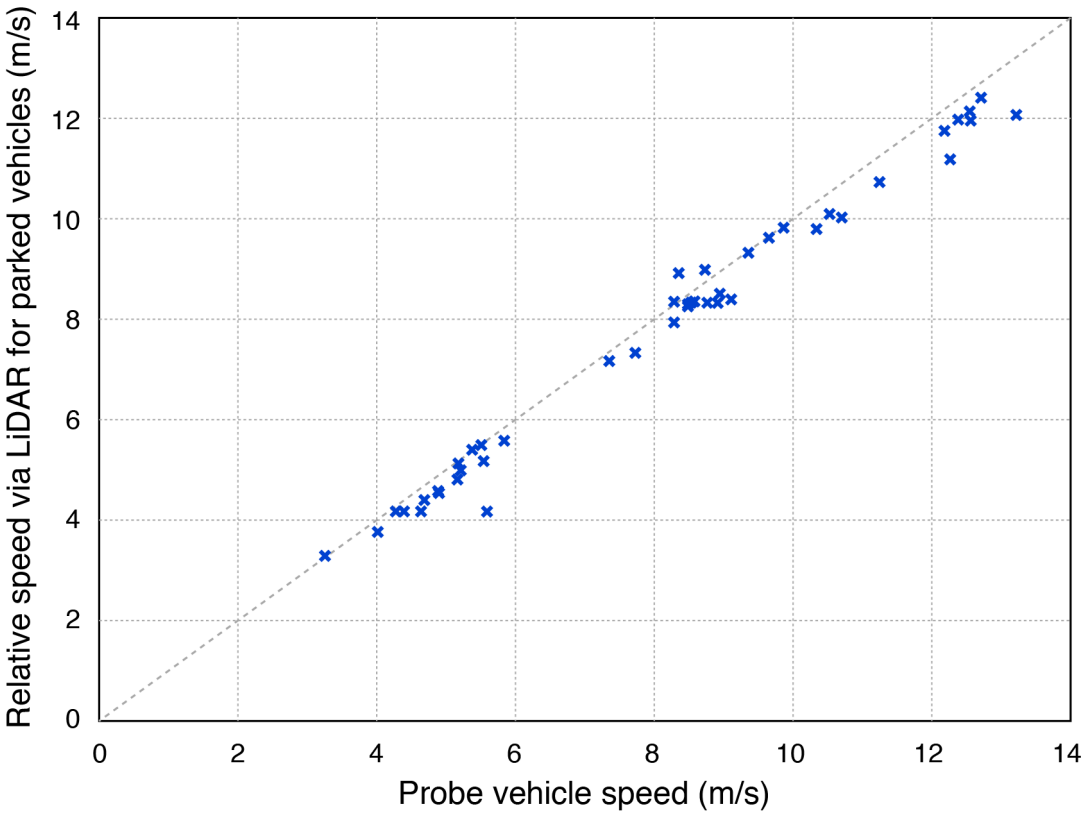


Figure 3, Observed relative velocities of parked vehicles versus the IPV speed