TRAFFIC FLOW ESTIMATION FROM AIRBORNE IMAGING SENSORS: A PERFORMANCE ANALYSIS

C. K. Toth[a], D. Grejner-Brzezinska [b]

[a]OSU, Center for Mapping, 1216 Kinnear Road, Columbus, OH 43212-1154, USA – toth@cfm.ohio-state.edu
[b]OSU, Department of Civil and Environmental Engineering and Geodetic Science, Columbus, USA

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ABSTRACT:

Recent developments in airborne sensor technologies have led to not only improved mapping performance, but have opened up a series of new applications. Enhanced spatial and temporal resolution can now allow for effectively detecting and describing moving objects for the first time. Vehicles, moving or standing, used to be problematic during the traditional mapping process; they needed to be detected and removed during the surface and/or object extraction process. From a traffic monitoring and management perspective, however, these objects are of high interest. The number of vehicles, their location and velocity as well as additional properties, such as vehicle type, size or weight, represents the essential base data for traffic flow description and modeling. Research has shown that vehicles can be extracted, counted and tracked from image sequences and that LiDAR data can provide an effective coarse categorization of vehicles in a highly automated way.

An analysis of the performance on the traffic flow estimation process for a typical state-of-the-art airborne sensor suite, composed of a LiDAR and a digital camera is presented. To assess the absolute performance, a dedicated test flight over a calibration range was conducted. The test area had specific ground targets that are equally identifiable and can be accurately positioned in both LiDAR data and imagery. In addition, a moving target was used to assess the size measuring performance of the moving object extraction process. The results confirmed that high-performance airborne sensors can provide quality data for traffic flow information extraction.

1. INTRODUCTION

Transportation represents a major segment of the world's economy, and as such must be carefully monitored and planned. This requires the most up-to-date, accurate and continuous methods for screening and mapping for effective modeling and management. Traditionally, permanent installations provide mostly real time information usually gathered from many diverse sources, such as electronic sensors in the pavement (loop detectors), road tubes, ramp meter sensors, and video and digital cameras. Data from these sensors are sent to the traffic management center at various times. Most of this information is only recorded; a small part of it is analyzed in real-time and used for immediate traffic control and decision-making. Furthermore, the installation and use of ground-based sensors disrupts traffic and endangers the crews. The major focus of this research effort, in general, is to improve the efficiency of the transportation system by the integration of remotely sensed data with the traditional ground data to monitor and manage traffic flows.

The National Consortium for Remote Sensing in Transportation-Flows (NCRST-F), led by The Ohio State University, and sponsored by the U.S. Department of Transportation and NASA, was established in 2001. Our partners in NCRST-F are the University of Arizona and George Mason University. As mentioned earlier, the major focus of the OSU research team is to improve the efficiency of the transportation system by the integration of remotely sensed data with traditional ground data to monitor and manage traffic flows. Our research team is concerned with the vehicle extraction and traffic pattern modeling based on airborne digital data that is collected by medium-format frame cameras and LiDAR systems. This paper is an extension of our earlier publications, where theoretical and practical studies on the feasibility of using LiDAR data and airborne imagery collected over the transportation corridors for estimation of traffic flow parameters, were presented.

The driving force behind this research effort is opportunity mapping. A fairly large percentage of geospatial data acquisition is done over urban areas with a substantial road network, where the vehicles become obstacles that need to be removed. In particular this is the case for road surface and/or road infrastructure mapping. This information should not be discarded, however, but rather the data should be directly converted to traffic flow data. Collecting data over the transportation corridors during regular surveys offers a unique opportunity to obtain important data for transportation planners and managers at practically no additional cost. Data can be acquired also in transit while the system is flown between various mapping jobs. Medium format cameras have become standard companion sensors for LiDAR, providing simultaneous visual image coverage and thus this imagery can be also used to support traffic flow extraction.

In this contribution the actual example of traffic flow estimation, along with performance validation obtained from high-accuracy datasets collected in late 2005 in Ohio, USA is presented. In particular, vehicle extraction, velocity estimation supported by fusion of LiDAR and image data, as primary parameters describing the traffic flow, are discussed and analyzed.

2. TRAFFIC FLOW

For highway planning and traffic management purposes, each road segment is characterized by its traffic flow. Flow can be defined as the number of vehicles passing a given point on a highway during a given period of time, such as vehicles per hour. Flow is one of the primary elements of traffic stream description besides density and speed. The three basic parameters of traffic stream are related to each other by the following relation: flow is the product of speed and density. The two basic types of mathematical models for describing traffic flow are the macroscopic and microscopic models. While macroscopic models are concerned with describing the flow-density relationship for a group of vehicles, microscopic models describe the flow by tracking individual vehicles using car-following logic. The relationship between flow and density is frequently used in freeway traffic management to control the density in an effort to optimize productivity (flow). The relationship between speed and flow could be used for design purposes, as it defines the trade-off between the level of service on a road facility (as expressed by the speed) and the productivity (as defined by the flow). Traffic control is aimed at managing and controlling the movement of traffic on streets, highways, and freeways in an attempt to optimize the use of such facilities. Traffic control service, in general, is responsible for collecting real-time traffic data from the field and then processing the data into useful information (Chowdhury and Sadek, 2003).

Traffic flow is a generic term used to describe vehicle movement and volume over a transportation network. Two of the most important traffic measures produced by state DOTs and other transportation agencies around the world are AADT and VMT (Pline Ed., 1992). Average annual daily traffic (AADT) is produced to represent the vehicle flow over a highway segment on an average day of the year. Vehicle miles traveled (VMT) indicates travel over the entire highway system and is used to indicate mobility patterns and travel trends. VMT is also used as an indicator for allocation of highway resources. Flow data are generally obtained by ground-based equipment, such as loop detectors or road tubes, which are fixed to a location and are deployable as needed. In the latter case, the sample data are collected from road tubes placed in the traveled portion of the road, disrupting traffic and endangering the crews when placing or collecting the tubes. Using satellites and air-based platforms, the survey/control crews can cover large areas, access remote highways, and carry sensors that can collect data from safe and non-disruptive off-the-road locations. The imagery collects “snapshots” of traffic over large areas at an instant of time or a sequence of snapshots over smaller areas, whereas traditional data collection observes vehicles at a point on the highway over much longer time intervals (McCord *et al*., 2003).

3. TRAFFIC FLOW FROM AIRBORNE SENSORS

The idea of using remote sensing for obtaining traffic flow data comes from two directions. First, a demand for finding new data sources to support and improve traffic flow monitoring and management inspired a research initiative on using remote sensed data in transportation. Second, the transition of the last few years from analog airborne imaging systems to fully digital multi-sensory imaging suites supported by high-performance direct georeferencing has provided the enabling technology needed for effective detection of moving targets.

Initial research focused on extracting traffic flow data from aerial and satellite imagery, see (Toth et al., 2003b; Merry *et. al*, 1999; Grejner-Brzezinska and Toth, 2002 and 2003b). Later, theoretical and practical studies were carried out on the feasibility of using LiDAR data to obtain traffic flow estimates, see (Toth *et. al*, 2003a and 2004; Ramprakash 2003; Grejner-Brzezinska and Toth, 2003a). These papers describe methods for vehicle detection, extraction, and tracking from both imagery and LiDAR, which form the basis for traffic flow parameter estimation, such as vehicle count, classification and vehicle velocity estimates.

3.1 Flow Data from LiDAR

A LiDAR point cloud offers explicit three-dimensional information of the object space and consequently provides an excellent basis for shape-based feature extraction. Furthermore, road surfaces have simple geometry and to some extent that applies to the vehicles; therefore, the vehicle extraction not only can be automated, but it can be done at a rather high performance level. Typically, a vegetation canopy over roads could pose some difficulty, although multiple returns from the LiDAR pulse can mitigate this problem. Obviously, the LiDAR point density plays a key role in the vehicle extraction performance and all the follow-on processing steps. Extended experiments proved that from 2-3 points/m^2 density, the vehicle extraction becomes robust and there is not much improvement beyond 5 points/m^2. A vehicle at 7 points/m^2 is shown in Figure 1. For vehicle classification, the situation is different, as the higher point density is essential to differentiate among vehicle categories. At the 2-5 points/m^2 density range, only major vehicle classes, such as cars, trucks and the remaining other vehicles could be classified at an acceptable success rate (Toth and Grejner-Brzezinska, 2004b). The 15-20 vehicle category based classification used by most transportation agencies requires substantially higher densities that is not routinely achieved in current airborne LiDAR practice (terrestrial laser scanning can easily provide that point density). The velocity of vehicles can be estimated from the motion artifact in LiDAR data due to the scanning pattern and the relative velocity of the sensor and the moving targets. The difficulty is that the true vehicle size is unknown and only the class mean or median data can be used, resulting in rather poor velocity estimates. The effect of the weak velocity data measures could be reduced, if the average velocity is computed for a larger group of vehicles (Toth *et al*, 2004b).

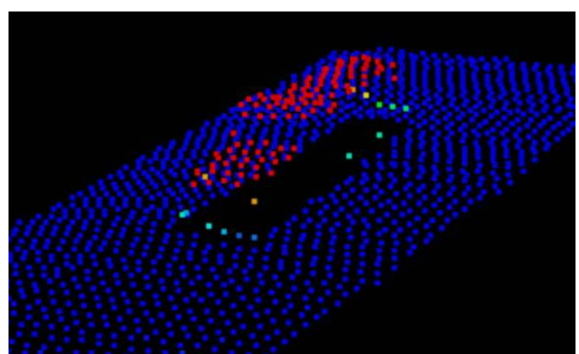

Figure 1. Vehicle close-up from LiDAR.

3.2 Flow From frame Imagery

Vehicle detection and tracking from reconnaissance and to a less extent conventional airborne surveying imagery has been a well-established research field for several decades. Developments have been mostly fueled by defense applications. Even a short overview of the available methods/techniques from this field would go beyond the size limitation of this paper. The approach we selected for our research is based on using orthorectified imagery. Furthermore, only medium format digital cameras, with a typical 4K by 4K sensor resolution were considered, such as the DSS system from Applanix. The image scale varied between 1:6,000 and 1:20,000 (in ground resolution terms, the GSD was in the 7-25 cm range). The creation of orthoimages imposes certain requirements, such as the availability of good surface data, either from a past mission or simultaneously acquired with the imagery and good direct sensor orientation data, but the benefits are irresistible. Most importantly, the vehicle shape in the horizontal footprint is preserved at true object scale. For overlapping images, the detection of moving vehicles (as well as any moving targets) can be accomplished by a simple image subtraction, as shown in Figure 2, while detection of non-moving vehicles is a much more complex task. Both processes can be supported by available road geometry data, such as road centerline or edge lines. Test images acquired from helicopter and fixed-winged aircraft were used to monitor traffic flow over road segments and to determine turning volume at intersections. Results showed good performance for extracting moving vehicles (Grejner-Brzezinska *et al*, 2004; Paska and Toth, 2004; Paska and Toth, 2005). Vehicle tracking, however, still needs more research, as the implemented solution produced unreliable results, which is partially due to the slow image acquisition rate (0.2-0.3 images/s) and/or lack of adequate overlap (Toth and Grejner-Brzezinska, 2004).

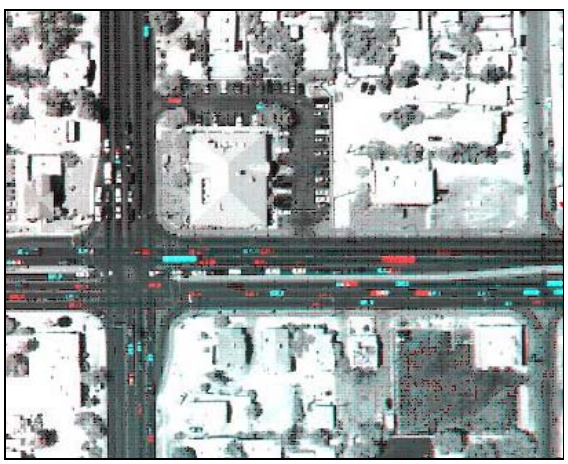

Figure 2. Detecting moving objects in the ortho domain.

3.3 Comparing Flow Data Obtained by LiDAR and Frame Imagery

The performance of LiDAR and image based traffic flow extraction depends on a variety of factors, such as sensor specification, sensor platform, data acquisition pattern, sensor calibration, sensor inter-calibration, direct georeferencing performance and feature extraction performance that could be further broken down into vehicle detection, vehicle parameterization/classification, and velocity estimation. Ignoring the common and non traffic flow specific aspects, a simple performance matrix is provided in Table I, where the parameters reflect the cumulative results from a wide spectrum of airborne tests within a time span of about three years. The sensor instrumentation included older 10 kHz and 33 kHz LiDAR systems and a new ALTM 30/70, a BigShot 4K by 4K digital camera and DSS systems. The direct georeferencing of the imaging sensors was supported by several geodetic grade IMUs and GPS receivers. Table 1 is intended only for orientation purposes, as it cannot account for several factors of various flight and sensor configurations, such as LiDAR point density or image data rate/overlap, processing and interpretation details, such as feature extraction performance, image artifacts, or absolute vs. relative accuracy performance. Nevertheless, Table I clearly shows the main trends, namely, that LiDAR is very effective at vehicle extraction and coarse classification, but is less adequate for velocity estimation. Imagery has just the opposite pattern; it is less effective for vehicle extraction, but once vehicles are extracted and tracked, the velocity estimation is rather good. Since flow is the product of vehicle counts and velocity, the end results are comparable for both sensors.

Sensor	**LiDAR**	**Digital Camera**	
Platform	**Airplane**	**Airplane**	**Helicopter**
Performance	**[%]**	**[%]**	**[%]**
Vehicle extraction			
Vehicles moving	95+	90+	95+
Vehicles not in motion	95+	80+	80+
Vehicle classification into three major classes	99+	60+	70+
Vehicle tracking	Not feasible	<50	60+
Error (typical)			
Velocity estimation	20-40	<20	<10
Flow computation	10-20	<10	< 5

Table 1. Performance of various traffic flow extraction tasks with respect to sensors and platforms.

4. COMBINING LIDAR AND IMAGERY

The recent trend in airborne surveying, the simultaneous data acquisition of LiDAR with medium format digital camera, allows for the fusion of both the sensor-level data and the results/features extracted from the two datasets. As discussed in the previous section, both sensors are capable of providing vehicle counts and velocity estimates, however, in varying quality. Since their limitations and strengths are complementary, they can support each other and their fusion could lead to better traffic flow estimation. Therefore, the next step in our research should be to combine the LiDAR outstanding vehicle extraction performance with the excellent velocity estimation of the optical imagery. Thus, the objective of this discussion is to assess how the velocity of moving objects extracted from LiDAR can be better estimated by using imagery.

To overcome the errors in the true vehicle length estimation in the LiDAR data due to generalization or possible misclassifications, the actual length of the vehicle must be determined from other sensory data, such as imagery collected simultaneously with the LiDAR data. Though a single image does not provide the absolute size information, the image may preserve the relative object size information, such as the width/height ratio of a vehicle. Although an extra effort, such as using an adequate matching technique, is required to identify the identical vehicles in the two datasets, the combination of the two datasets could eventually lead to an improved velocity estimation of the moving vehicles (Paska and Toth, 2005).

Figure 3 shows extracted vehicles from LiDAR data, as they are overlaid on an orthoimage formed from a simultaneously acquired image. LiDAR vehicle points are represented in green and red, corresponding to the motion along or against the flying direction, respectively. For referencing, some static objects, such as one point on the centerline and points at the guard rail, are also marked in the figure. This figure illustrates: (1) the elongated (when vehicles are moving along the flying direction) and shortened (when vehicles are moving against the flying direction) lengths of the moving objects, as sensed by the LiDAR, and (2) the relationship between corresponding vehicles on the imagery and in the LiDAR data. The matches of the corresponding vehicles in the two datasets are highlighted by rectangles with identical colors. Due to the different nature of the two data acquisition techniques, the continuous scanning mode of the LiDAR sensor and instantaneous capturing of frame imagery, the locations and also the shapes of the corresponding vehicles differ in the two datasets. The white triangle in Figure 1 shows the approximate location of the LiDAR beam when the image was taken.

Vehicles can be sorted into four categories based on their direction and the relation of their positions in the LiDAR and imagery data: (1) vehicles traveling along the flying direction and scanned before the image acquisition (in Figure 1 they are in the upper lanes and to the right from the triangle sign), (2) vehicles traveling along the flying direction and scanned after the image acquisition (in Figure 2 they are to the left from the triangle sign), (3) vehicles traveling against the flying direction and scanned before the image acquisition (in Figure 1 they are in the lower lanes and to the right of the triangle sign), and (4) vehicles traveling against the flying direction and scanned after the image acquisition (in Figure 1 they are to the left of the triangle sign).

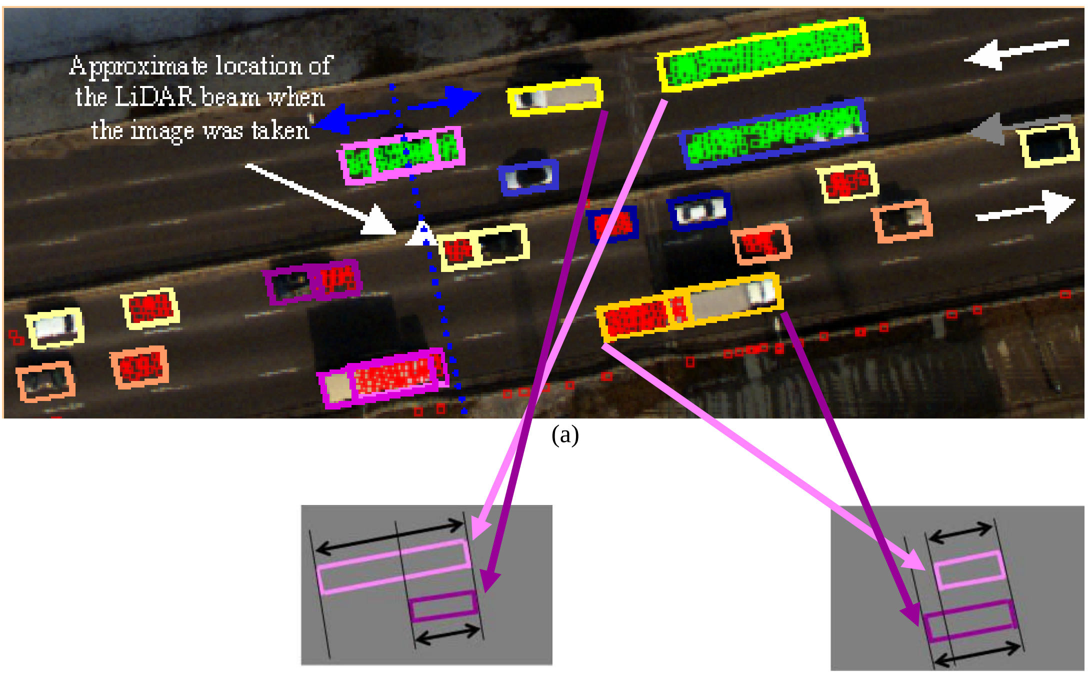

Figure 3. Vehicles extracted from the LiDAR data and overlaid on the orthoimage; (a) match of corresponding vehicles in the two datasets is marked with identical colors. Also shown are (b) vehicle elongation, and (c) vehicle shortening.

Note that the LiDAR point clouds of the vehicles fall in front of the corresponding vehicles on the left side of the blue dotted line and behind the corresponding vehicles on the right side of the line. This is because the LiDAR measured the vehicle either before or after the image was taken. Based on the known relative positions of corresponding vehicles, search areas for a matching procedure can be determined. The acquisition time of each LiDAR point, as well as the image capture time, is recorded in GPS seconds. The possible relative distance between the image and LiDAR vehicle positions could be calculated from the vehicle velocity and the acquisition time of the image and the LiDAR vehicle points (coarse vehicle velocity approximations could be obtained from vehicle velocity computation from image sequences or the minimum and maximum speed limits of the actual road and so on). Note in Figure 3 that the relative distance between corresponding vehicles is getting larger the farther from the triangle sign. Similarly, the difference between the data acquisition time of the LiDAR sensor and digital camera is also getting larger. The difficulty of matching can be substantially reduced with higher image acquisition rates that can be easily achieved with modern digital cameras. Since the road surface, as well as the image sensor plane on the airborne platform is usually horizontal, the width/height ratio of a vehicle is fairly accurate with respect to, for example, the LiDAR point horizontal positional accuracy. Thus, the LiDAR-sensed vehicle width can be used to determine the vehicle true length by using the width/height ratio obtained from the image.

5. PERFORMANCE EVALUATION

To check the performance of the combined LiDAR and image traffic flow extraction, as well as validate the LiDAR only or image only estimates, a dedicated test flight was organized in late 2004. The Madison County, Ohio, test range that includes a dense network of permanently installed signalized ground controls to support airborne surveys was temporarily extended by using LiDAR-specific targets, shown in Figure 4, that could be also used for image control (Csanyi *et al*., 2005). In addition, there was a "moving" target, the OSU Center for Mapping GPSVan (He *et al.*, 1994), a vehicle equipped with high performance GPS/IMU hardware. This vehicle, shown in Figure 4, was constantly moving in the test area and was mapped by both sensors several times under various sensor settings, such as the LiDAR system was operated at various pulse rates during repeated passes over the calibration range. This served several purposes. Most importantly, the impact of the point density for the vehicle extraction, classification and velocity estimation was assessed. This also provided valuable data to assess the impact of the various pulse rates on the overall accuracy of the system, with and without ground controls. The airborne sensor suite included an ALTM 30/70 LiDAR system and a DSS digital camera. The LiDAR system was operated at 33, 50 and 70 kHz pulse rates, resulting in point densities ranging from 3 to 8 points/m^2. The digital camera had a GSD range of 10-15 cm.

Figure 4. LiDAR target and the GPSVan.

Table 2 shows a representative set of measurements of the LiDAR sensor as it mapped the GPSVan at various pulse rates. As expected, the accuracy of the vehicle size, as measured by the smallest rectangle fitted to the vehicle points, depends on the point density, which, in turn, is basically a function of the pulse rate for a given flying height. Clearly, the vehicle width is fairly underestimated at lower point densities. The smaller size is a combined effect of the point density, laser pulse divergence and point pattern. The image measurements for the width/length ratios, however, show a good stability. The vehicle velocity estimates, shown in Table 3, illustrate that the larger error was introduced by the incorrect vehicle length. The GPSVan has a true length of 5.5 m but falls into the other vehicle category with a class length value of 4.7 m. This length could be effectively decreased by the vehicle length estimation from the LiDAR-measured width by using the image measured width/length ratio. The statistics, shown for the cases when the vehicle and the LiDAR traveled in the same direction (shaded area in Table 3) clearly indicate that accuracy of the true length-based velocity estimation can be achieved for the combined LiDAR and image solution. The opposite direction case has a smaller improvement, (with statistics of estimated bias and variance of 2.39 and 1.73, respectively). However, it is still important as it helps to obtain a better overall error in velocity when the average velocity of a group of vehicles is computed. Further discussion of the error characteristics of the LiDAR-based length and velocity estimation is in (Paska and Toth, 2005).

6. SUMMARY

Earlier research results demonstrated that airborne remote sensing based on state-of-the-art LiDAR and digital camera systems could provide valuable traffic flow data that can effectively support traffic monitoring and management. In particular, LiDAR has proven to be a good source of vehicle extraction and course classification, while digital imagery excels with better velocity estimation performance. In this paper, an initial analysis was provided to assess the overall performance gain in traffic flow estimation, if LiDAR and digital imagery were combined at the feature level.

Vehicle velocity estimation from LiDAR is based on the vehicle elongation and shortening of the moving objects due to the scanning mode of the data acquisition. The accuracy of vehicle velocity estimation depends on the vehicle's direction, true length, relative velocity between sensor and object, and on how accurately the true and LiDAR-sensed vehicle length could be estimated. The actual vehicle size is unknown in practice, and thus, the true length of the vehicles must be estimated from either the basic statistics of the vehicle categories, that can be determined after classifying the extracted vehicles, or by using additional information. To overcome the errors in the true vehicle length estimation due to generalization or possible misclassifications, the actual length of the vehicles was determined by using scale information from imagery collected simultaneously with the LiDAR. Initial results have shown that combining LiDAR with complementary sensor data, such as simultaneously collected imagery, can provide a better base for velocity estimation and thus allows for more reliable traffic flow parameter determination.

This discussion in a broader sense addresses the problem of mapping moving objects, which is an emerging field in geospatial science. Obviously, transportation, and in particular, traffic management needs this data, but rapid/emergency mapping also demand this type of geospatial data acquisition and processing. Our investigations provide an insight into the difficulty of mapping moving objects and clearly indicate that only multisensory systems can adequately solve the problem of collecting high spatial and temporal resolution geospatial data in a preferable highly redundant manner.

LiDAR sensor parameters						Vehicle measurements					Image-based correction	
Strip number	PRF [kHz]	Scan angle[°]	Spacing between profiles [m]	Point spacing in profiles [m]	Point density [pts/m^2]	Vehicle direction with respect to LiDAR platform	LiDAR-measured vehicle length [m]	LiDAR-measured vehicle width [m]	Ideal LiDAR vehicle length [m] (based on GPS)	Number of points per vehicle	Image-measured length/width ration	Vehicle length from image ratio and LiDAR width
5	33	10	0.52	0.50	2.9	+	8.37	1.81	8.87	51	2.95	5.34
12	33	10	0.48	0.50	4.0	+	10.52	2.01	10.52	81	2.83	5.69
9	33	20	0.71	0.70	1.8	-	3.40	1.59	4.02	15	2.85	4.53
11	50	10	0.40	0.40	6.1	+	9.40	1.99	9.48	95	2.83	5.63
13	50	20	0.55	0.65	3.2	+	9.70	1.86	10.33	51	2.91	5.41
14	50	20	0.58	0.60	2.8	-	3.68	1.85	4.13	22	2.85	5.27
10	50	20	0.55	0.55	3.1	0	5.25	1.72	5.55	27	2.97	5.11
4	70	10	0.35	0.35	8.2	+	7.85	1.90	7.95	120	2.89	5.49
8	70	20	0.50	0.50	4.1	-	3.89	1.88	4.10	31	2.84	5.34
											2.88	
											0.05	

Table 2. Vehicle length and width measurement from LiDAR and length estimation based on combined LiDAR and image data.

Strip number	Vehicle velocity computed from different vehicle length measurements [m/s]						GPS velocity
	Using vehicle class length (4.7 m)		Derived from LiDAR width using image ratio		True vehicle length (5.55 m)		Reference
	Velocity	Difference	Velocity	Difference	Velocity	Difference	
5	19.75	-3.90	21.22	0.59	25.71	2.06	21.81
12	23.85	-4.16	23.18	0.59	27.93	-0.08	23.77
9	33.31	-0.18	17.51	2.45	20.14	-13.35	19.96
11	21.94	-4.58	21.48	0.73	26.79	0.27	22.21
13	21.71	-2.77	22.45	0.94	26.16	1.68	23.39
14	26.85	3.37	22.83	-4.82	14.64	-8.84	18.01
10	2.85	-5.15	1.33	-1.26	5.22	-2.78	0.07
4	15.15	-5.28	15.55	-0.08	20.75	0.32	15.47
8	23.11	7.87	20.18	-1.03	11.28	-3.96	19.15
		4.14		**0.58**		**0.88**	
		0.93		**0.32**		**0.91**	

Table 3. Velocity estimation performance for various sensor settings for LiDAR-only and for combined LiDAR and image data.

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