TRAFFIC MANAGEMENT WITH STATE-OF-THE-ART AIRBORNE IMAGING SENSORS

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ABSTRACT:

In recent years remote sensing has made remarkable technological progress and has significantly expanded into several application fields. The rapid technological advances have come with the potential to widen the range of applications and to go beyond conventional mapping. Technical aspects of using high-resolution airborne imagery and LiDAR to support traffic flow monitoring and management are discussed in this paper. The primary objective of this ongoing research effort is to assess the feasibility and reliability of extracting moving objects over transportation corridors, and the accuracy of their velocity estimation. This investigation includes airborne LiDAR, video and high-performance digital camera imagery. A review on the potential of using CCD and airborne laser scanning technology for transportation applications, especially for identifying and tracking moving objects on the roads is provided.

1. INTRODUCTION

Unprecedented technological developments characterize the last five years in spatial data acquisition and processing, resulting in a paradigm shift in spatial information sciences and totally revolutionizing airborne surveying practice:

- New active imaging sensors were introduced, such as LiDAR, which almost immediately became the most important source of terrain data.
- GPS/IMU-based direct georeferencing, essential to several new sensors, including LiDAR and IfSAR, became the primary technique for sensor orientation.
- 1-meter commercial satellite imagery was introduced.
- Aerial photography experienced a major milestone, as digital cameras reached and in fact surpassed the performance of analog large format aerial cameras.

These advances in sensor technology lead to increased volumes of data along with more complex data types, which, in turn, demands higher automation of the data processing. In fact, the boundaries of spatial information sciences are becoming less defined as we enter the new age of telegeoinformatics (Grejner-Brzezinska *et. al.*, 2004a).

The rapidly increasing use of the new sensor data with rich information content presents a potential for new applications that could go beyond conventional mapping. Mapping of man-made objects with terrain features, such as urban mapping or corridor mapping of transmission and transportation lines, is probably the most common mapping task, which is primarily concerned with the static part of the object space. However, these are probably the most dynamic areas in terms of human activities. Most importantly the traffic, including a variety of vehicles and various dynamics presents a formidable challenge for the mapping processes, as moving objects should be identified and removed. Instead of throwing away the removed objects, it is very advantageous to use these data to derive valuable information for traffic monitoring and management. This paper is focused on detecting moving objects on the roads by using airborne remote sensing to support traffic flow information gathering.

The research described is supported by the National Consortium for Remote Sensing in Transportation-Flows (NCRST-F), sponsored by the U.S. DOT and NASA. NCRST-F was established in 2000 as a Consortium of three universities: The Ohio State University, George Mason University and the University of Arizona (http://www.ncrst.org/research/ncrst-f/ncrst-f_home.html).
The primary goal of the Consortium is to improve the efficiency of the transportation system at the national, state and local levels, by integrating remotely sensed traffic flow data obtained from airborne and/or satellite platforms with traditional data collected from the ground. It should be emphasized that the important features that are unique to remote sensing in traffic monitoring are: (1) sensors are not attached to just one location (for example, track dangerous cargo or incidents), (2) sensors can be deployed during special events (natural disasters, evacuation), (3) remote sensing can provide superior spatial resolution, and (4) can provide up-to-date traveler information, if applied in real-time.

This paper provides a review of research using state-of-the-art remote sensing sensors to support traffic flow extraction using LiDAR and digital camera sensors installed on airborne platforms. The results from LiDAR corridor mapping and helicopter-based road intersection monitoring are discussed. It is important to note that rapid developments of UAV technologies are expected to provide an additional platform that is not only extremely cost-effective, but very flexible to accommodate in terms of offering a wide variety of platform altitude and velocity.

2. LIDAR TECHNOLOGY

LiDAR (or airborne laser scanning) systems have become a dominant player in high-precision spatial data acquisition in the late 90's. Installed in aircraft and helicopters, these active sensor systems can deliver surface data at decimeter-level vertical accuracy in an almost totally automated way. In fact, this new technology has quickly established itself as the main source of surface information in commercial mapping. Despite the initial high price, these systems have made remarkable market penetration. Recent technical and algorithmic advances have further improved the capabilities of this remote sensing technology. In particular, intensity data became available, usually on all four multiple returns, and the laser repetition rate has approached 100 kHz. These developments provide an unprecedented point density on the ground, which, in turn, helps to accelerate the process of moving from simple surface extraction use of LiDAR to more sophisticated feature extraction, such as building or vehicle extraction (Vosselman and Dijkman, 2001).

Every indication is that transportation and other agencies will be deploying LiDAR systems over transportation corridors at an increasing rate in the future – mainly to support infrastructure mapping to create accurate surface information of highways and areas around highways. Primarily for engineering purposes, the road surface must be determined at sub-decimeter level accuracy. In general, the vehicles on the road represent obstructions to the LiDAR pulses sent to reflect off the pavement. Therefore, a substantial amount of processing must be devoted to "removing the vehicle signals." Rather than removing and discarding the signals, however, they can be turned into traffic flow information. This way, LiDAR surveys devoted to surface extraction will soon be able to provide a valuable byproduct with little or no additional effort. It was shown for the first time that civilian vehicles could be extracted from LiDAR data with good accuracy (Toth *et. al*., 2003c). As verified below, vehicles can be reliably classified into several categories such as cars, trucks, and multi-purpose vehicles, based on the pattern of the LiDAR returns. With the appropriate LiDAR point density, it is expected that vehicle velocities can be estimated more reliably in the future.

Figures 1 and 2 show representative LiDAR data, including range and intensity components over a highway segment in downtown Toronto, Canada. The data was acquired by a 70 kHz Optech 30/70 ALTM system.

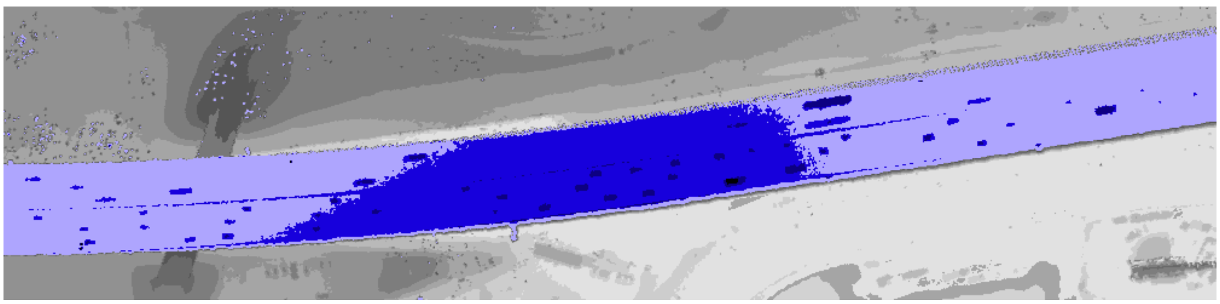


Figure 1. LiDAR elevation data of a freeway in Toronto downtown.

Figure 2. LiDAR intensity data of a freeway in Toronto downtown.

3. OPTICAL IMAGERY

Aerial photography was the main technology for airborne mapping for decades. As a proven tool, large format aerial cameras have provided an enormous amount of spatial data – estimates run as high as 95% of geospatial data were collected from aerial photography until the late 90's. Digital camera systems have been used on airborne platforms for a decade, but due to their limited resolution (ground coverage) they initially served only remote sensing applications – their good radiometric characteristics provide for excellent classification performance. As imaging sensor developments resulted in larger CCD chips, reaching the 16 Megapixel range, the feasibility of building photogrammetric quality aerial digital cameras became a reality. Currently, there are two main categories of these cameras: (1) medium format single sensor frame cameras, such as a 4K by 4K sensor based systems, and (2) high-performance large format aerial digital camera systems, such as the ADS40 scanner from Leica, which is based on linear sensors and multihead camera systems, for example, the DMC camera from Z/I Imaging or the UltraCam from Vexcel.

The digital camera systems are mostly different from their analog counterpart by the sensor characteristics. The complete description of this topic goes beyond the scope of this paper; see vendors specifications and, for example, the recently published Manual of Photogrammetry. In short, CCDs have linear transfer characteristics and, in general, can produce much better radiometric data than their analog predecessors (scanned imagery). 10-12 bit intensity data are quite common, and more importantly, the noise level can be as low as the least significant bit. To a great extent, this excellent radiometric performance can counterbalance a moderate spatial resolution in terms of processing efficiency. Earlier digital cameras had a rather low data cycling rate – it took seconds to read off the image from the CCD sensors. Newer systems, however, can acquire imagery at rates faster than one second, and thus multiple overlap can be easily obtained at literally no cost – a definite advantage to support highly automated processing. Finally, it must be noted that the large gap between the parameters of the images acquired from various sensor platforms is rapidly shrinking, as the resolution of the upcoming satellite systems continues to improve from the currently highest 62 cm GSD.

For the framework of the NCRST-F research, the focus was on using 4K by 4K cameras, as this category is frequently used as a companion digital camera for LiDAR systems. In addition, the availability as well as the cost prohibited the use of the high-end digital camera systems until recently. A representative 4K by 4K image, acquired by the DDS digital camera system simultaneously with the LiDAR data, is shown in Figure 3.

Figure 3. 4K by 4K digital camera ortho image of a freeway in Toronto downtown.

4. TRAFFIC FLOW

Vehicle traffic over the transportation infrastructure affects almost every facet of our life and has a primary impact on the economy. As vehicle traffic continues to grow while the resources to increase the road capacity are limited, the only answer to keep up with the ever-increasing traffic is better management. This, in turn, depends on the availability of better traffic data, i.e., timely information on almost every vehicle traveling on the transportation network.

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).

Short-term flow parameters, including daily or hourly parameters broken down to vehicle categories are also of high interest, but can be acquired only with a limited spatial extent with traditional techniques, as the density of ground-based sensors cannot be increased infinitely. The use of airborne imagery, however, offers an on-demand deployable tool with excellent temporal and spatial resolutions that can easily provide for sizeable area coverage at fast sampling rates. Therefore, the primary objective of this investigation was to research the feasibility of obtaining short-term flow data by using remote sensing technologies.

5. VEHICLE EXTRACTION, GROUPING AND TRACKING

The investigation of extracting flow data from airborne remote sensing has been carried out using two different sensor configurations: (1) to monitor the feasibility of obtaining traffic flow data over road segments, LiDAR data were acquired from several test flights, and in one case, 4K by 4K imagery was simultaneously captured and then used as the ground truth for the LiDAR data, and (2) to assess the potential of flow monitoring at intersections, a 4K by 4K digital camera and a standard video system were installed on a helicopter platform and several test flights were conducted.

5.1 Vehicle Extraction and Grouping From LiDAR Data

In the first step of the data processing, the input LiDAR data are filtered to reduce the point cloud to the road area. The approximate location of the road geometry is usually available from CAD or GIS databases, maintained by transportation agencies. Since the accuracy of the road location information is limited, or only the centerline data are available, it is mandatory to perform a road-matching step. During this process, the edge lines of the road are tracked from the LiDAR data. Once the road surface area has been identified, the vehicles can be extracted by a simple thresholding. During this process the road surface modeled and the surface normal are considered, thus, the resulting vehicle points are reduced to the height with respect to the modeled road surface (road invariant description of the vehicles).

The point cloud of a vehicle can contain a varying number of points, mainly depending on the laser point density and the relative speed between the vehicle and LiDAR sensor. The effect of the latter factor is more important and demands a parameterization of points that can, at least, partially reduce the effect of vehicle shortening and elongation (compare vehicles in Figures 1-2 to Figure 3). The selection of parameters has a major impact on the classification process, namely, how reliable can the different vehicle groups be separated. The basic model was formed from six parameters, including the length and width of the vehicle and four height values, representing an average height over four equal segments of the vehicle. Figure 4 shows the interpretation of the basic parameters.

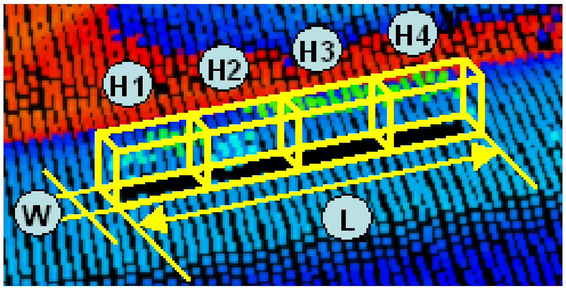


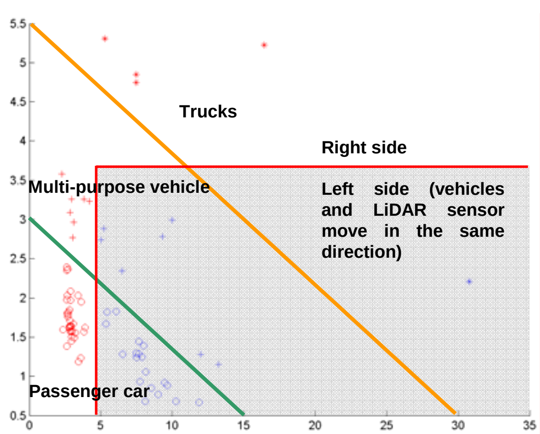
Figure 4. Vehicle close-up from LiDAR with parameters.

In subsequent tests, additional parameters were used, such as average intensity values of the four equal segments, or derived parameters, such as vehicle footprint size or vehicle volume. Since all these parameters were mostly generic, no physical modeling was used. The Principal Component Analysis (PCA) was selected as an obvious choice to identify significant correlation among the parameters describing the data, and ultimately, to use for the minimum and sufficient subset of parameters. There were two training sets used for PCA, one from Dayton, OH containing 72 vehicles and one from Toronto with 50 vehicles. Table 1 summarizes the PCA results for various parameter selections. Additional details can be found in (Toth and Brzezinska, 2004).

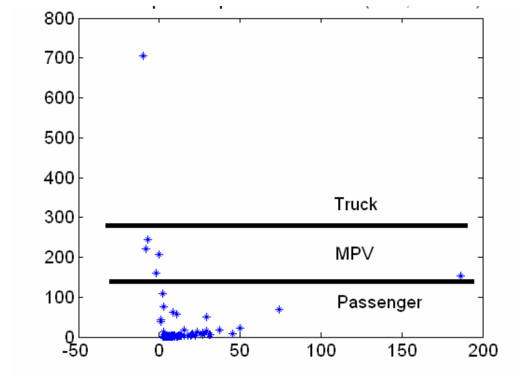
Parameters	**#**	**1st component**	**2nd component**
H1, H2, H3, H3	4	74.87	16.15
W, L, H1, H2, H3, H3	6	96.58	2.12
W, L, H1, H2, H3, H3, I1, I2, I3, I4	10	65.48	21.94
W, L, A (W*L), V (W*L*H)	4	99.43	0.49

Table 1. PCA performance for various parameter sets.

The vehicles of the two training sets were grouped into three categories: cars, MUVs (Multipurpose Utility Vehicles) and trucks. Using the two most significant eigenvalues as a classification space, the training set can be visualized as shown in Figure 5.



a)



b)

Figure 5. Vehicle distribution in the classification space defined by the 6 (a) and 4 (b) parameter spaces.

The classification performance was evaluated by using three widely used techniques (Toth *et. al.*, 2003a). The first method, a rule-based classifier, contains decision rules derived from the PCA transformed features. As depicted in Figure 4, a clear separation, in other words, a clustering of samples with identical labels, can be easily made between the groups by using straight lines. The second method was a fundamental statistical technique: the minimum distance method. This classifier is based on a class description involving the class centers, which are calculated by averaging feature components of each class. Finally, the third method in the vehicle recognition investigation was based on an artificial neural network classifier. A 3-layer feed-forward (back-propagation) neural network structure was implemented in our tests. The training method was the Levenberg-Marquard algorithm (Demuth, 1998), the maximal number of training steps (epochs) was 70, and the required error goal value was 0.1. The network error was calculated by the mean square error (MSE) method. The three studied vehicle classification techniques were tested on the first training data set of Ohio (1), on the data set containing vehicles from Ohio and Michigan (2), and on a combined dataset, including the Ontario data (3), provided by Optech. The first test (in-sample test) was only an internal check of the algorithms. Table 2 shows a performance comparison of the three techniques. Additional results can be found in (Toth *et. al.*, 2003a).

Data set (total number of vehicles)	**Rule-based**	**Minimum distance**	**Neural network**
Ohio (72)	0 (0%)	8 (11.1%)	2 (2.8%)
Ohio + Michigan (87)	2 (2.3%)	12 (13.8%)	8 (9.2%)
Ohio + Michigan + Ontario (102)	2 (2%)	17 (16.7%)	16 (15.7%)

Table 2. The comparison of the three classification techniques: vehicle count of misclassification errors.

5.2 Vehicle Extraction and Tracking from Helicopter Imagery

In cooperation with the University of Arizona (UoA), an experimental sensor configuration based on a 4K by 4K digital camera with a 50 mm focal distance and 15-µm pixel size, 60^2 mm^2 imaging area, a video, and a small resolution digital frame camera assembly was flown to acquire images over a busy intersection north of the UoA campus area (see details in Grejner-Brzezinska and Toth, 2003; Grejner-

Brzezinska *et. al*., 2003). A sample high-resolution and a video image are shown in Figure 6.

a)

b)

Figure 6. Sample images of the selected intersection: 4K by 4K CCD (a), video (b).

To support the vehicle matching and tracking in the image domain, the images were first orthorectified, i.e., all distortions due to surface and different camera pose have been removed. The processing, in general, benefits from the ortho domain; for instance, vehicle extraction can be done at true object scale and detection of moving objects can be easily obtained by simple image differencing, as shown in Figure 7. The vehicle extraction process includes edge extraction, intensity-based thresholding, profile analysis and morphological filtering (further details are in Paska and Toth, 2004; Toth *et. al.*, 2003b). The limitation of the 4K by 4K digital camera system, used in the Tucson, AZ flight, unfortunately allowed only for a 6-sec image acquisition rate, which was too low to obtain an adequate sampling of vehicle positions, and thus, resulted in unacceptable automated vehicle tracking performance. In contrast, the automation of video imagery resulted in excellent performance for small area tracking (see Mirchandani *et. al*., 2003).

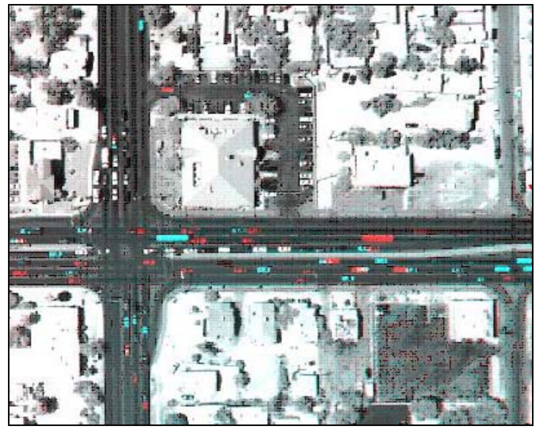


Figure 7. Detecting moving objects in the ortho domain.

5.3 Velocity Estimates

The information on the vehicle counts and locations represents only the density aspect of the traffic flow, as the velocity, at least the average velocity, is needed to obtain the true flow data. For the LiDAR data, the observed vehicle sizes compared to the actual sizes can provide a basis for the velocity estimation. However, the problem is that only the major vehicle categories can be identified, and thus, the true vehicle size is unknown, as only the size range is known for a given category. Nevertheless, the coarse estimates for individual vehicles can lead to an acceptable average velocity estimate. Table 3 shows the statistics of the road segment shown in Figure 1. The imagery, in general, can provide a better source for velocity estimates. In our test data, good velocity estimates were obtained from the video, while the slow image acquisition rate of the 4K by 4K camera could deliver only coarse average velocity estimates. Intersection flow volume of the test area in Figure 5 is shown in Figure 8.

Lane #	Spacing [m]	Velocity [km/h]	Density [vehicle/km]	Flow [vehicle/h]
1	32.8	81.6	30.5	2487
2	24.1	76.8	41.6	3187
3	23.7	75	42.2	3164
Average	**26.9**	**77.8**	**38.1**	**2946**

Table 3. Traffic data.

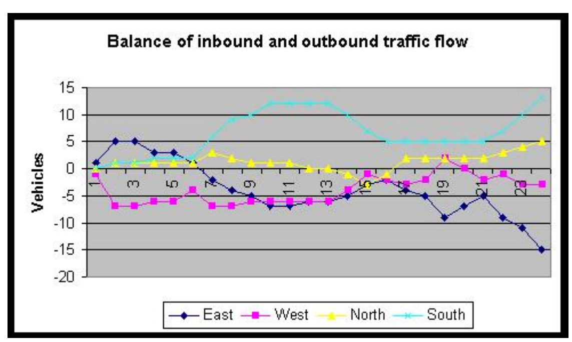


Figure 8. In bound and out-bound traffic flow of the selected intersection.

6. SUMMARY OF RESULTS

The experimental results obtained with the two data sets confirmed that LiDAR and optical imagery from airborne platforms can deliver valuable traffic flow data. In addition, the initial performance analyses of the representative data sample have shown a good potential for automated processing. Table 4 provides generic performance metrics, which compare the potential of various airborne remote sensing technologies to obtain traffic flow data.

Sensor	**LiDAR**	**Digital camera**		
Platform	**Airplane**	**Airplane**	**Helicopter**	**Satellite**
General characteristics				
Spatial extent	Good	Good	Limited	Excellent
Temporal extent	Moderate	Moderate	Excellent	Weak
Process				
Vehicle extraction	Simple	Difficult	Difficult	Complex
Vehicle classification	Simple	Feasible	Feasible	Limited
Vehicle tracking	Not feasible	Limited	Good	Not feasible
Velocity estimate	Moderate	Good	Excellent	Not feasible
Flow computation	Feasible	Good	Excellent	Not feasible

Table 4. Performance comparison metrics.

7. CONCLUSIONS

The feasibility and efficiency of using airborne remote sensing to traffic monitoring were demonstrated. Airborne sensors, LiDAR and frame imagery in particular, provide high spatial and temporal resolution data that can effectively support modeling and management of traffic flows. It should be mentioned that even though the cost per unit of traffic data for airborne platforms could be lower, as compared to the traditional ground based methods, the cost of the platform and the sensors might still be prohibitive. As a great amount of LiDAR data, as well as imagery, is collected for routine aerial mapping over transportation corridors and in urban areas with dense road networks, there is already an opportunity for obtaining such flow data at practically no extra effort. Similarly, digital sensor systems can be turned on to collect data during transit between mapping project areas. Thus, at almost no cost, a significant amount of data rich in traffic flow information can be acquired. To move from a prototype implementation to a turn-key system, further algorithmic developments are required to achieve a highly-automated processing plus more tests are needed with varying vehicle density and dynamics, as well as during various flight conditions/environment.

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