Estimating Spatial Measures of Roadway Network Usage from Remotely Sensed Data

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1 ABSTRACT

Roadway network usage is measured for purposes as diverse as design, planning, maintenance, operation, management and research. Traditionally these measurements are made using ground-based sensors. The sensors provide a temporally rich dataset, but an individual sensor lacks spatial coverage, limiting their use and application. High-resolution imagery remotely sensed from satellite or airborne platforms is an attractive alternative that can potentially supplement and enhance the existing traffic monitoring programs with a spatially rich dataset. This paper demonstrates spatial measurements of network usage as extracted from remotely sensed data.

Keywords: roadway traffic monitoring- average annual daily travel, vehicle density, remote sensing

2 INTRODUCTION

Roadway network usage is measured for purposes as diverse as design, planning, maintenance, operation, management and research. These data are collected both by public and private agencies using techniques developed over the last century. The results are distributed to many regional and local entities, e.g., metropolitan planning agencies and municipal transportation agencies; as well as federal agencies, e.g., US Department of Transportation (US DOT). The data are input to various applications such as transportation forecasting, model development, traffic signal timing, and allocating infrastructure investments on local and national levels.

The most common measurement of usage is vehicular traffic flow, the number of vehicles passing a specific location along a road during a unit of time. Flow is often expressed in terms of the annual average daily traffic (AADT), the traffic flow on a roadway segment on an average day during a year. The Traffic Monitoring Guide (TMG) provides precise definitions of AADT and how to collect the data [1]. These data collection programs were developed over the last century to balance cost with sufficient precision. Albright [2] provides a thorough history detailing the development of measuring roadway network usage, noting that the Bureau of Public Roads, in cooperation with several highway departments, published its *Guide for Traffic Volume Counting Manual* in 1965 and the conventional methods of organizing a traffic counting program have changed little since then.

In conventional practice, vehicular flow data are collected with ground-based sensors, most common of which are inductive loop detectors and pneumatic tube detectors. The sampling rate of a detector depends on the application and the operating agency, typically ranging from under a minute to an entire day. These data collection efforts can be costly in terms of both equipment and personnel to complete the job [3]. Detector installation often poses a hazard to the personnel involved and can cause delays to the traveling public due to the need to close traffic lanes.

Each state's department of transportation must collect roadway network usage data for the Federal Highway Administration (FHWA). Basic traffic flow data collection includes continuous counts from permanent automatic traffic recorders (PATR's) and short duration counts (typically 48 hours long) from movable automatic traffic recorders (MATR's). Both PATR and MATR data are used to estimate AADT. The continuous counts from the small number of PATR locations are used to estimate adjustment factors for MATR's within the same roadway classification and reduce the temporal effects from the short durations counts. The TMG, [1], recommends a periodic program of short duration count data collection over an entire state on a 6-year cycle. These counts ensure geographic diversity and coverage without continuous monitoring at a large number of locations.

To supplement the terrestrial measures, this paper presents a process to estimate roadway network usage from remotely sensed images (airborne or satellite). With the progress in image processing technologies, roads and vehicles can be identified from imagery automatically with a high level of accuracy, e.g., Shi and Zhu [4] and Moon et al. [5], respectively. Remotely sensed images provide a source of traffic data which is spatially very rich compared to a single PATR or

MATR location, e.g., within the state of Ohio there are approximately 188,000 km (117,000 mi) of roadways and 213 PATR's are used to monitor the whole system. Thus, on average, there is one PATR for every 880 km of roadway. Obviously this estimation process is rough, since different patterns of traffic flow exist for different types of roadways, and even different locations along a given roadway [6]. Under conventional practice, most roads either go without being measured or they are sampled at a very course level, e.g., the roadway is only observed for two days every six years and it is assumed that the conditions observed at the traffic recorder are representative of several km of roadway [1]. In contrast, a single satellite image can cover an area as large as 200 km^2, and the spatial traffic information could potentially be obtained for every link in the observed network. Unlike ground sensors, remotely sensed data are collected in a safe, off-the-road environment.

While other researchers are refining vehicle detection from imagery, most treating vehicle detection as the end goal, we have proceeded in parallel by examining various measures of network usage from remotely sensed images using manually extracted vehicles. Even before the automated vehicle detection becomes widely available this work could be used for smaller scale analysis, it is estimated that a trained professional could manually locate over 3,000 veh/hr in remotely sensed imagery. Of course an image only captures an instant in time and the spatial traffic information from remotely sensed images cannot be used to estimate temporal measures such as traffic flow or AADT without the trends obtained from ground-sensed data. McCord et al. [7] presents our current methodology to estimate AADT from a single remotely sensed image. Measured density (vehicles per km of roadway) is converted to a short-term flow via the fundamental equation of traffic flow theory (flow = density * velocity) with the assumption that imaged vehicles were traveling at the posted speed limit. Time-of-day conversion factors based on ground detectors located elsewhere [8] were then used to expand these flows to a daily estimate and the Ohio Department of Transportation's conversion factors for MATR stations were used to estimate AADT from the daily flow. Manually identifying vehicles in 14 different images taken over Ohio, each one including either a PATR or MATR station on a highway segment, the approach successfully estimated AADT within 31 percent of the corresponding ground counts for all 14 images, and within 15 percent for 12 of the images. These results represent the estimate based on a single instant in time while [9] showed that the accuracy could be improved by imaging the location on more than one occasion. When the assumption of free flow conditions is suspect, the short-term flow estimates can be improved further through the use of paired imagery. In such a case the trajectory of the imaging platform is known and two images are taken separated by a short delay of known duration. Such data collection is common both by airborne and satellite platforms for extracting topographical information, but the delay can also be used to measure velocity from the change in vehicle positions. Since the primary focus of this paper is measuring density, it does not consider paired imagery further.

Prior to estimating AADT and other measures of roadway usage, one must first identify the roads, and then identify the vehicles to measure density. As this paper will illustrate, rather than simply providing a new estimator of temporal roadway usage at discrete points on the network, these densities also enable new spatial measures of network usage.

The following section presents a brief review of various methods to automatically detect vehicles and roads in high-resolution imagery, the first step in an automated process. The next section discusses the process of measuring density from imagery, addressing issues of sampling distance and data aggregation. Finally, the paper closes with conclusions and a brief discussion of future research.

3 REVIEW OF VEHICLE DETECTION FROM DIGITAL IMAGERY

The first step in finding vehicles is typically that of finding the roadways. The simplest way to accomplish this objective is through a calibrated Geographic Information System (GIS) that includes an accurate representation of the roadway network. When such a GIS is not available, the roadway network can be identified in an image using pattern recognition techniques. Wang and Newkirk [10], for example, discussed algorithms for automated highway network extraction using image-processing approaches supported by artificial intelligence techniques. They defined the ratio of "number of highway pixels correctly identified" to "total number of highway pixels" as identification accuracy, and their methods yielded an average accuracy of 87.8 percent. Barzohar and Cooper [11] presented an automated approach to finding main roads in aerial images by building geometric probabilistic models. Their method could find all the long roads in the test images, but for short roads, the contexts of roads had to be used in order to distinguish them from long rectangular buildings or similar patterns. Geman and Jedynak [12] illustrated a general computational strategy for identifying one-dimensional structures, especially roads, from satellite imagery using computer vision tools. Given a starting point and starting direction, they were able to track highways over considerable distances without manual intervention, in one case up to 100 km. Shi and Zhu [4] presented an approach using a line segment matching method for extracting an urban roadway network from high-resolution satellite images. The method exploits the fact that roads are usually long narrow rectangles that are several pixels in width. They analyzed a 1-m resolution satellite image for an urban area in Valparaiso, Chile and found up to 92 percent of the roadways in their examples.

If vehicles can be detected from imagery, the traffic count on an imaged roadway segment can be used for measuring traffic density on this segment at the instant the image was captured. Many promising methods of automatic vehicle identification from remotely sensed data have been developed in recent years. Ruskone et al. [13] developed a vehicle recognition method for aerial images through line clustering, where a line is formed by two or more identically orientated vehicles. Vehicle recognition was made through a neural method. They detected approximately 87 percent of the vehicles while erroneously detecting approximately 5 percent non-vehicles. Parameswaran et al. [14] used parameter optimization strategies for algorithms employed on large image databases to detect and count vehicles. They chose the context based aerial image understanding (AIU) method, which was also known as "site model based image exploitation" and had been extensively studied by other researchers. A typical AIU task would be to detect changes in a newly acquired image of the site. They detected approximately 91 percent of the vehicles while erroneously detecting approximately 12 percent non-vehicles. Moon et al. [5] performed an analysis for a simple model-based vehicle detection algorithm for aerial images. They constructed a vehicle detection operator by combining four elongated edge operators

designed to collect edge responses from the sides of a vehicle. Their approach used Canny's formulation [15-16] of optimal edge detection, which addressed the natural trade-off between detection and localization performance with varying operator size. In this case, the algorithm was given information about the orientation of the vehicles, which would generally be in line with the roadway. They detected approximately 82 percent of the vehicles while erroneously detecting approximately 15 percent non-vehicles.

4 MEASURING DENSITY FROM IMAGERY DATA

One of the fundamental objectives of traffic engineering is to provide roadway capacity for travelers. Transportation professionals analyze the roadway usage data to balance the goals of supplying roadways and operating them efficiently. Traditional ground-based data are temporally rich compared with imagery data, which only captures an instant of time. However, an image can potentially capture an extensive roadway network, while a conventional detector collects data for only one link. This section illustrates how to measure density from a remotely sensed image. Specifically, we use a 1-m resolution IKONOS satellite image from Space Imaging, as shown in Figure 1A. The image was captured at 12:20pm on May 29, 2001 over southeast Columbus, Ohio. It covered an area of about 165 km^2 and several types of roadways were imaged, including freeways -- I-70, I-270 and SR104 between US23 and US33 -- and primary arterials -- US23, US33, Williams Rd., Parsons Ave., SR 317, and the remainder of SR104. Figure 1B shows a schematic of this network that was captured in the image. A PATR station was also visible in the image, as indicated with a star in this network. Zooming in to Figure 1A, Figures 1C-D show increasing levels of detail along a typical stretch of freeway. Traffic density was measured for a given segment by identifying vehicles, tallying their quantity, and dividing by the measured length of this segment. We manually located the roadways and vehicles from the image in a single coordinate system using the ERDAS Imagine software package and wrote a computer program using Matlab to display the roadway network. Traffic on the network of freeways and primary arterials were extracted.

A roadway segment between any two interchanges may be less than one km long or several km in length. If the segment is too short, transient fluctuations in demand are more likely to cause the instantaneous density to deviate from long-term trends of roadway usage. A longer sampling distance will generally reduce the influence of transient fluctuations provided there are no significant interchanges or other external factors that change demand. As discussed below, the sampling distance is essential in determining whether the traffic measurements are representative of roadway usage.

As a starting point in understanding the spatial density distribution, a single directional density value was measured along each road in this network. The results are shown in Figure 2A, where the magnitude of directional density is shown by the width of the band on the right-hand side of the roadway corresponding to the direction of travel. Densities of cars, trucks and the sum of the two groups are displayed by different shaded bands (as indicated in the legend) all originating at the centerline. SR317 is displayed in two pieces due to a change in the number of lanes. Except for I-270, a Columbus bypass, the truck densities are relatively low compared with car densities

on almost all of the roads. Normalizing these densities by the number of lanes yields Figure 2B. The scaling factor used to show the magnitude of normalized density is twice that used in Figure 2A. Figure 2B shows several features of network usage at the time of imaging:

- The average density by lane is similar on US23, US33, I-70 and I-270.
- Eastbound traffic is denser than westbound traffic on SR104.
- Williams, Parsons and the *lower portion* of SR317 exhibit relatively low density.
- The usage of SR317 changes dramatically between the *lower portion* and the *upper portion*, probably due to the fact that the two portions are primarily located in rural and urban areas, respectively, which likely explains the change in the number of lanes as well.

On a given roadway, an interchange can bring systematic patterns of spatial traffic distribution, e.g., freeway traffic downstream of an off-ramp is lighter than upstream due to exiting vehicles. As the sampling distance increases the likelihood of including an inhomogeneity increases, but the sensitivity to local fluctuation decreases. One must balance this tradeoff to seek an appropriate sampling distance. To this end, several sampling distances were considered. The graphs in Figure 3 show density on I-270 with various lengths of a *moving window*, whereby density is calculated for the traffic bounded by the moving window. Density is displayed at the midpoint of the moving window using a step distance of 100 m between each sample for all three of the graphs. Density above the horizontal axis represents the eastbound traffic, while that below the axis represents the westbound traffic. The two vertical lines in each of the graphs show the locations of interchanges, labeled A and B. Figure 3A shows the moving average density arising from a sampling distance of 0.5 km. The effects of platoons and gaps are clearly discernable in this plot, the most salient are the *spike* in the westbound density between the interchanges and the gap in the eastbound traffic at interchange B. When the sampling distance is increased to 1 km, as shown in Figure 3B, the density curve is much *smoother* but still exhibits local fluctuations. The result when using a sampling distance of 3 km is presented in Figure 3C. As expected, density with this larger averaging distance shows lower variability than the earlier plots.

Figure 4 shows the moving average density throughout the entire network when using a moving window width of 3 km, sampled every 100 m, without normalizing by the number of lanes. Freeways I-70 and I-270 exhibit a much smoother density than the arterials, such as Parsons and US23. The greater variability on the arterials is due to systematic spatial patterns arising from the effects of traffic control devices and the increased number of access points. The AADT estimates from the PATR were among the 14 reported in [7] and summarized in the Introduction, but as can be clearly seen in Figure 4, the local density at this PATR differ significantly from the rest of the roadway. Similar differences are most apparent on Parsons Ave at SR104. The conventional measurements of flow from the PATR, i.e., a discrete point in space, may not be sufficient to capture roadway usage, particularly at the large distance between detector locations necessary to keep costs manageable in a conventional monitoring program. The added spatial information from imagery should lead to better informed decision making for infrastructure management.

Furthermore, the spatial measures clearly show how drivers distribute themselves over the network, a feature that can facilitate applications such as signal timing and planning other network enhancements.

5 CONCLUSIONS AND FUTURE RESEARCH

The spatial richness of remotely sensed data has the potential to supplement and enhance existing traffic monitoring systems and this paper examined the potential of using remotely sensed data to measure roadway network usage. This new source of data can provide spatial information of traffic densities that cannot be measured directly from traditional detector data, e.g., Figure 4 shows that spatial traffic information could be obtained for every link in the observed network. The combination of spatial and temporal measures provides a more complete description of roadway network usage. In addition, the instruments required by remote sensing technologies are off-the-road, and the data collection neither disrupts traffic nor endangers ground crews.

Based on the fact that roads and vehicles can be identified from satellite images or aerial photos with a high level of accuracy, densities can be measured. The spatial distribution of vehicles requires care to be taken when choosing the appropriate sampling distance. As reported in [7], AADT estimates from these density measurements were very close to the ground counts collected by the Ohio Department of Transportation (ODOT).

This paper also illustrates the need for further research. Several questions remain, such as explicitly quantifying the impacts of inflow/outflow over larger sampling distances. It is possible that using discrete segments between major interchanges will prove to be more representative than moving averages. In any event, the benefits of measuring density from remotely sensed imagery are apparent, particularly when the required imagery are already being collected for other purposes (e.g., the ODOT Office of Aerial Engineering has an archive of over 500,000 aerial images). The manual data reduction process used in this paper is labor intensive and may not be practical for large-scale use. To this end, we are working to combine automated vehicle detection with our density measurement techniques to extract these measures automatically. In the mean time, there are numerous smaller scale applications where this manual technique could prove beneficial.

6 REFERENCES

[1] FHWA (2000). *Traffic Monitoring Guide*, U.S. DOT, Publication No. FHWA-PL-01-021.

[2] Albright, D., (1991) History of Estimating and Evaluating Annual Traffic Volume Statistics, *TRR 1305*, pp. 103-107

[3] Hartgen, D. T. and Lemmerman, J. H., (1983) Streamlining Collection and Processing of Traffic Count Statistics, *Transportation Research Record 928*, pp. 11-20

[4] Shi, W. and Zhu, C., (2002) The Line Segment Match Method for Extracting Road Network from High-Resolution Satellite Images, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 40, No. 2, pp. 511-514,

[5] Moon, H., R. Chellappa, A. Rosenfeld, A. (2002) Performance Analysis of a Simple Vehicle Detection Algorithm, *Image and Vision Computing*, Vol. 20, Issue 1, pp 1-13

[6] Petroff, B. B. and Blensly, R. C., (1954) Improving Traffic-Count Procedures by Application of Statistical Method, *Proc. of the Highway Research Board*, pp 362-375

[7] McCord, M., Yang, Y., Jiang, Z., Coifman, B., Goel, P., (2003) Estimating AADT from Satellite Imagery and Air Photos: Empirical Results, *Transportation Research Record 1855*, 2003, pp 136-142.

[8] California Department of Transportation - Highway Performance Monitoring System, http://pems.eecs.berkeley.edu

[9] Yang, Y., (2002) *Estimating Roadway Network Usage From Remotely Sensed Data*, Thesis, The Ohio State University.

[10] Wang, F. and Newkirk, R., A (1988) Knowledge-Based System for Highway Network Extraction, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 26, No. 5, pp. 525-531.

[11] Barzohar, M. and Cooper, D. B., (1996) Automatic Finding of Main Roads in Aerial Images by Using Geometric-Stochastic Models and Estimation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 7.

[12] Geman, D. and Jedynak, B., (1996) An Active Testing Model for Tracking Roads in Satellite Images, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 1, pp. 1-13

[13] Ruskone, R., Guigues, L., Airault, S., and Jamet, O., (1996) Vehicle, Detection on Aerial Images: A Structural Approach, *Proc. of ICPR*, Vol. 3, pp. 900-904

[14] Parameswaran, V., Burlina, P., and Chellappa, R., (1997) Performance Analysis and Learning Approaches for Vehicle Detection and Counting in Aerial Images, *Proc. IEEE International Conference on Acoustics, Speech, and Signal Processing*, Vol. 4, pp. 2753-2756

[15] Canny, J., (1983) *Finding Edges and Lines in Images*, MIT AI TR-720.

[16] Canny, J., (1986) A Computational Approach to Edge Detection, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol 8, No 6, pp. 679-698.

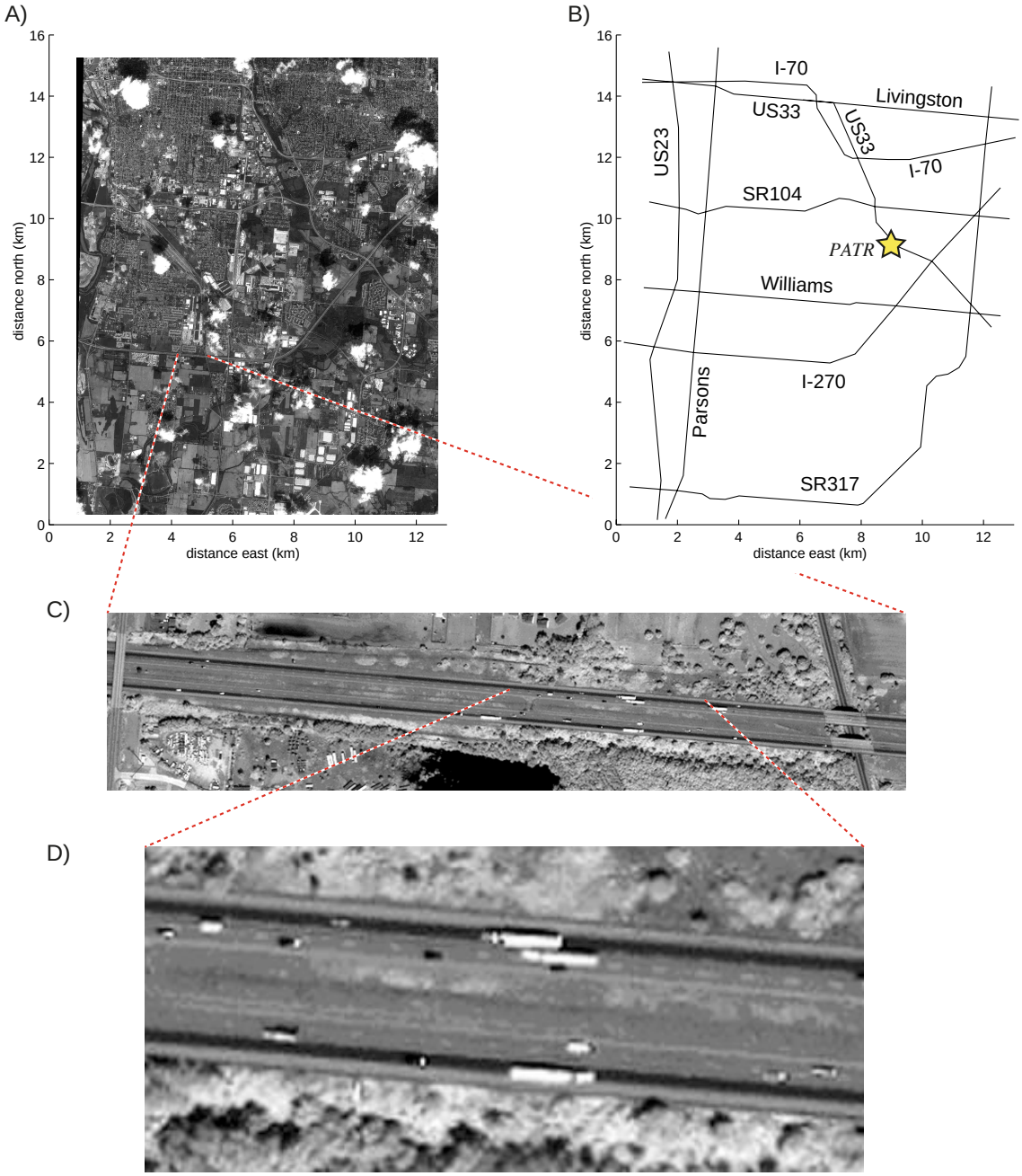

Figure 1 (A) a satellite image of Columbus, Ohio (B) the corresponding network of freeways and primary arterials, (C) zooming in on the image, (D) at the highest resolution, 14 vehicles are discernable in this sample.

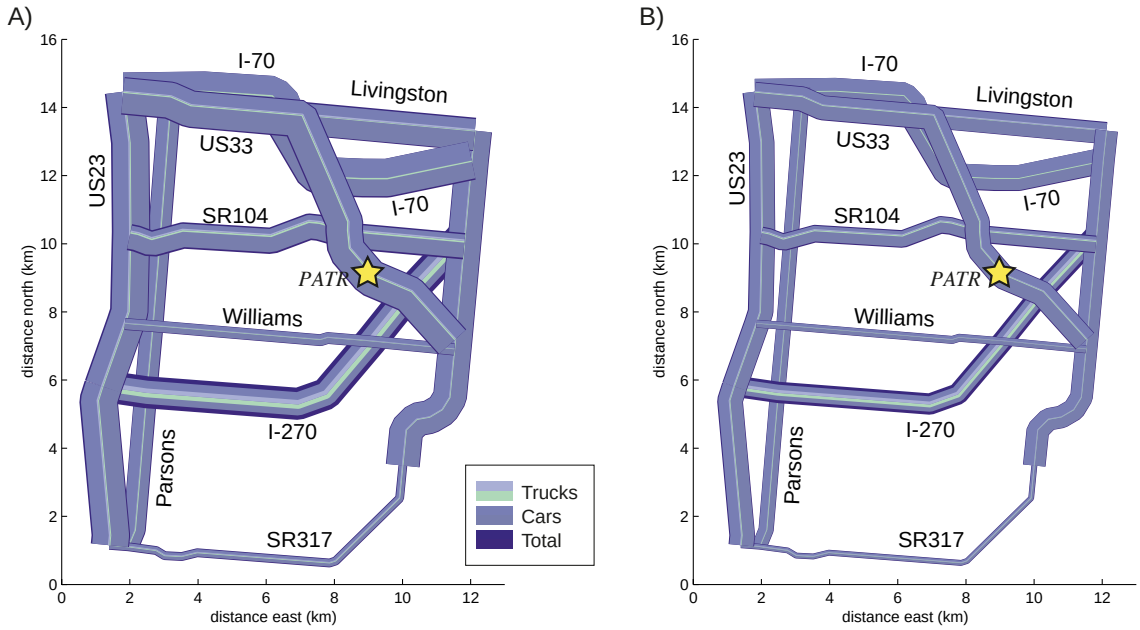

Figure 2 (A) measured density over the links of Figure 1B, (B) normalized by the number of lanes.

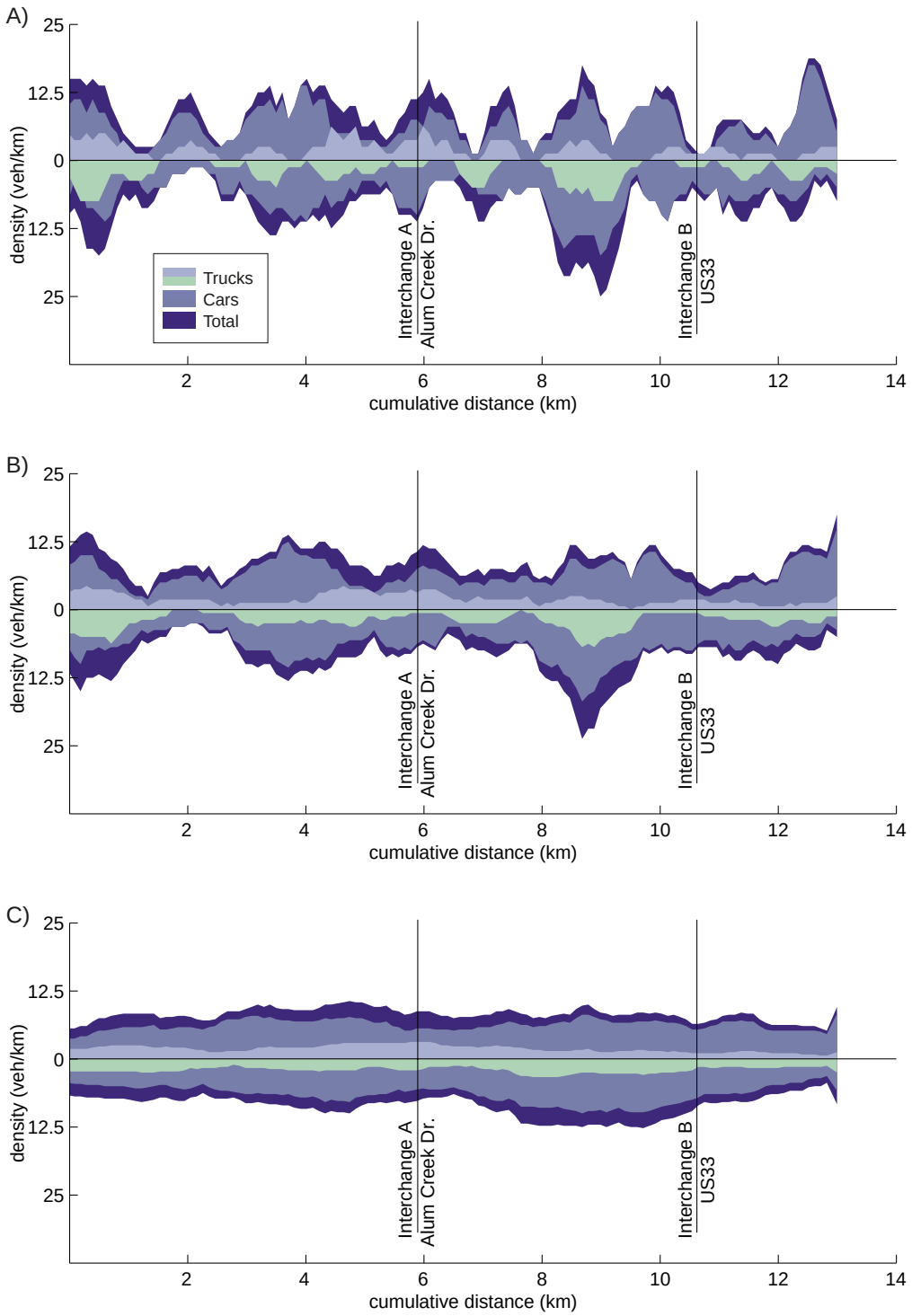

Figure 3 moving average density along I-270 from Figure 1A using a window of (A) 0.5 km, (B) 1 km, and (C) 3 km.

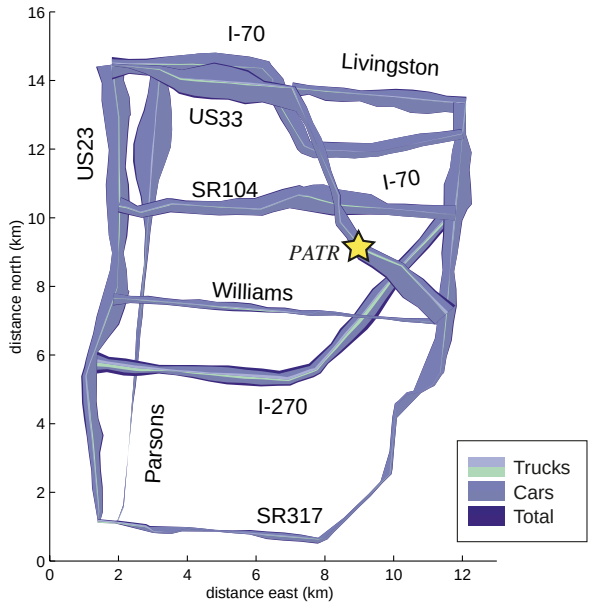

Figure 4 (A) moving average density throughout the network from Figure 1A-B using a moving window of 3 km.