USDOT Region V Regional University Transportation Center Final Report

TECHNICAL SUMMARY

NEXTRANS Project No. 176OSU2.2

ROADWAY TRAFFIC DATA COLLECTION
FROM MOBILE PLATFORMS

by

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1. Introduction

Traffic flow estimates are typically derived from vehicle counts collected at fixed locations using either permanent sensors (e.g., inductive loop detectors), temporary sensors (e.g., pneumatic tube detectors), or manual human observers. It is infeasible to deploy fixed-location sensors or human observers on every segment of spatially extensive networks, and most road segments are either unmonitored or are monitored on a very infrequent basis. In contrast, transit buses regularly and repeatedly traverse a large portion of the urban roadway network. If traffic data could be collected using buses as sensor platforms at low marginal cost and processed to produce reasonable traffic flow estimates, the extensive and repetitive coverage of roadway segments by transit buses could potentially be exploited to determine traffic flows in urban areas with much greater spatial coverage and update rates than are presently available.

This project empirically investigates the traffic flow estimations from different types of data collected from two types of mobile platforms – transit buses in service operations and a van driven to emulate bus coverage – that repeatedly traverse roadway segments. At the root of this approach are probe vehicle-based studies and, in particular, the moving observer method. Conventional probe vehicle and floating car studies have been commonly used to collect travel time, delays, and stops, and they are becoming increasingly common for real time travel time measurement (*1*-*6*). Within the probe vehicle literature is the moving observer method, which can be traced back at least as far as (*7*). A good review of subsequent efforts can be found in (*8*), although some later publications present minor variations of the method. As originally conceived, the moving observer method suffers from two major limitations. First, it requires a dedicated vehicle and two people – someone to drive and someone to count vehicles. Second, a single pass of the moving observer over a roadway segment will be brief and result in a short-duration observation that is subject to high variability in flow conditions from, for example, nature of travel demand, signal phasing, major or minor incidents, and behavior of drivers of detected vehicles.

Using transit buses as sensing platforms can mitigate these limitations. The transit vehicle is already in service; therefore, a dedicated vehicle and driver are not required. If sensors are mounted on the platform, the need for a data collector is also eliminated. Transit companies are increasingly installing inward and outwork looking video cameras on their buses, primarily for safety, security, and liability reasons. If the video data can be used for traffic flow estimation, as is investigated in this study, the need for additional sensors is also eliminated. Each individual pass of the platform will still result in a short-duration observation, but the repeated (many times per day, days per week, weeks per year) traversal of the same road segments by sensor-equipped buses can lead to multiple, independent observations that can be aggregated to reduce the effects of the single pass, short-duration observations and potentially yield meaningful traffic flow estimates, as was demonstrated in a different context in (*9*).

A modification of the moving observer method is needed to estimate the flow rate from data that would be obtained from a bus platform on a transit route. This method is described in the next section. In the third section the various data sets collected from transit buses in regular operations and from a sensor-equipped van that was driven over segments traversed by the buses are presented. The implementation issues used to process the different data sets into input data for use with the modified moving observer method are also presented in this section. In the fourth section empirical results are presented. Comparisons among the estimated flows obtained from different types of data, different time-of-day periods, and different periods of the year support the reasonableness of the estimated results and, therefore, of the ability to estimate reasonable flow rates by using the modified moving observer method with data obtained from a mobile platform that repeatedly covers road segments. In the final section, it is argued that further investigation of the present results is warranted, as are additional empirical studies, but that the results obtained in this study and the potential of using available video from transit bus fleets also motivate pursuing issues involved with operational implementation of the ideas developed in this project.

2. Estimation Methodology

Traditionally, traffic flow data are collected by recording vehicles passing a fixed location over an interval of time. To estimate the traffic flows from the mobile platform, a variant of the moving observer estimation method is used (*10*). In the traditional method, e.g., (*7*,*8*), the moving observer method is used to estimate traffic flow in one direction (say "Direction 1") on a segment when the observes makes a "loop" consisting of two "legs": one leg that involves observing Direction 1 traffic while the observer travels on the segment in "Direction 2" (in the opposite direction across the centerline), and a second leg that involves observing Direction 1 traffic (specifically, vehicles that overtake and are overtaken by the moving observer) while the observer travels in the other direction ("Direction 1"). The two legs should be traversed closely enough in time that the Direction 1 flow can be considered homogeneous when the observer is traveling on both legs.

If only a few buses are equipped with sensors, many hours may pass between traversal of the two legs of the segment. Or, the bus route may be such that the bus only traverses the first leg. Therefore, a modification of the moving observer method was developed (*10*) to estimate traffic flows from the first leg (estimating Direction 1 traffic while the platform travels only in Direction 2). This modification is illustrated in the time-space diagram of Figure 2.1. The schematic on the left depicts the segment of interest between locations x_o and x_e, the vehicles to be detected travelling in the left lane from top to bottom ("Direction 1"), and the mobile platform traveling in the right lane from bottom to top ("Direction 2"). The time-space diagram is presented on the right, with distance from x_o increasing from bottom to top. Therefore, the trajectory of the mobile platform has positive slope, while the trajectories of the vehicles to be detected have negative slopes. An intersection of the platform and vehicle trajectories indicates that the platform and vehicle are at the same location (in different lanes) at the same time. This is when the vehicle traveling in Direction 1 would be detected by the moving observer traveling in Direction 2. The platform trajectory indicates that the platform entered the segment ($x = x_o$) at time t_o and existed the segment ($x = x_e$) at time t_p. Of interest is the time $t_1 = t_p - t_o$ the platform took to traverse the segment. In the illustration, the platform detects four vehicles during this time. (The platform trajectory intersects four vehicle trajectories.)

To estimate a flow rate, a hypothetical "virtual observer" is considered to be stationed at the downstream (relative to the traffic to be detected) end of the segment. (The virtual observer is indicated in Figure 2.1 by the "eyeball" located at x_o to the left of the roadway schematic.). Any detected vehicle would pass this virtual observer after the moving observer detects the vehicle (after the trajectory intersection). Specifically, a detected vehicle would pass the virtual observer when its trajectory intersects the $x = x_o$ line. Therefore, the time between the instant when the mobile platform detects the last vehicle and the instant when its trajectory reaches the virtual observer must be considered when determining the time interval during which the virtual observer would observe the vehicles detected by the moving observer. (Only the time when a vehicle trajectory intersects the location x_o, and not the shape of the trajectory, is important.)

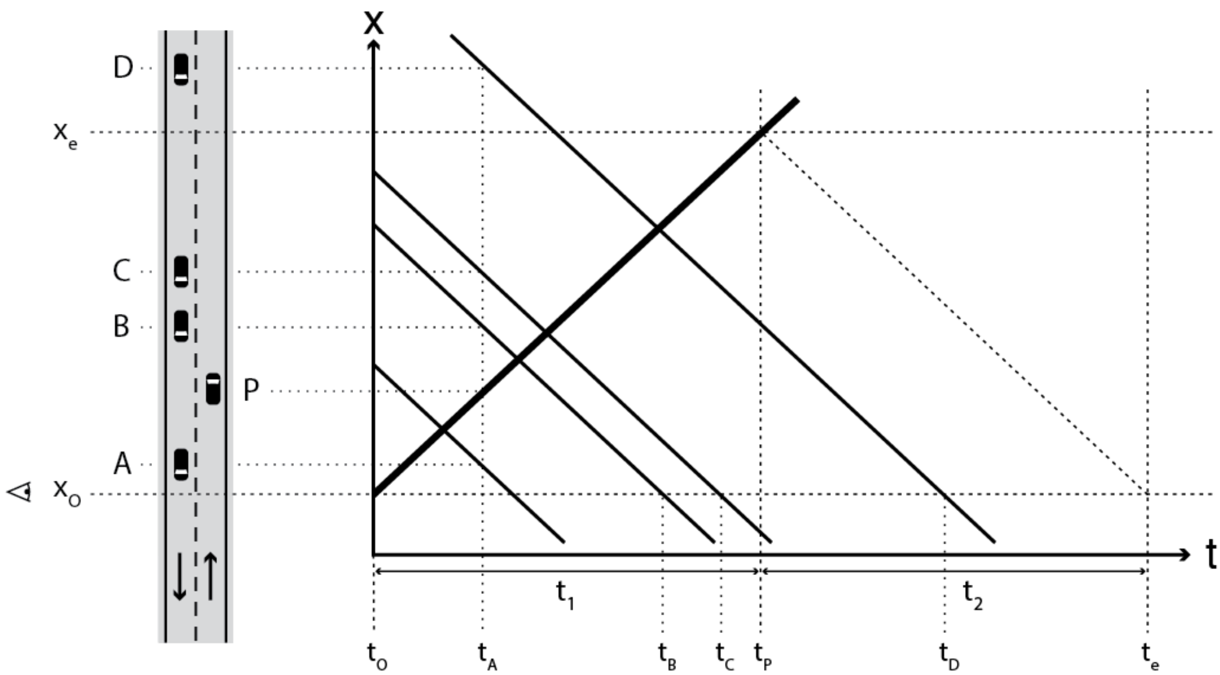


Figure 2.1: Illustration of the modified moving observer method used to estimate traffic flow from a mobile platform traveling in only one direction

As illustrated, after detecting the last vehicle, the moving observer can continue on the segment while observing no vehicles. Not observing vehicles provides additional information on the flow rate. To account for the sub-interval during which the mobile platform traverses the segment without observing additional vehicles, a "virtual vehicle" is considered to enter the segment at the instant the mobile platform exits the segment. The (hypothetical) trajectory of this virtual vehicle is depicted with dashes as the rightmost trajectory. Of interest is the time $t_2 = t_e - t_p$ required for this virtual vehicle to traverse the length of the segment and reach the virtual observer. The interval during which the virtual observer would observe what was detected by the mobile platform – no vehicles detected until detecting the first vehicle, detecting four vehicles on the segment, and detecting no vehicles while completing traversal of the segment after detecting the last vehicle – would be $t_1 + t_2$. In general, then, the flow rate q corresponding to the traversal of the mobile platform on a segment would be:

$$q = n^{veh} / (t_1 + t_2) \tag{2.1}$$

where n^{veh} is the number of vehicles detected by the platform while it is traversing the segment (in "Direction 2"), t_1 is the time taken by the mobile platform to traverse the segment in its direction of travel, and t_2 is the time it would take a "virtual vehicle" to traverse the segment in the direction of the vehicles being detected ("Direction 1").

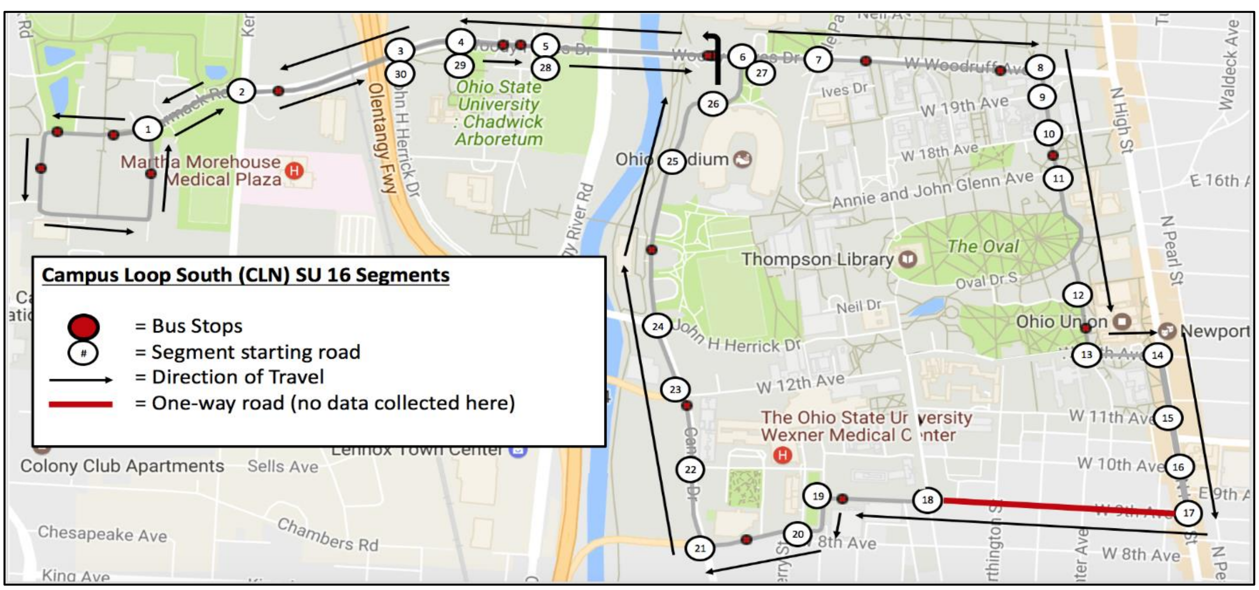
The virtual vehicle time t_2 could be determined in several ways. For example, one could use the length of the segment and some estimate of average vehicle speed, which could depend on the speed limit or the number of vehicles detected (reflecting the effect of congestion). In this study, t_2 was determined in slightly different ways, depending on the nature of the data collected, as described in the next section.

3. Data Collection and Determination of Input Values

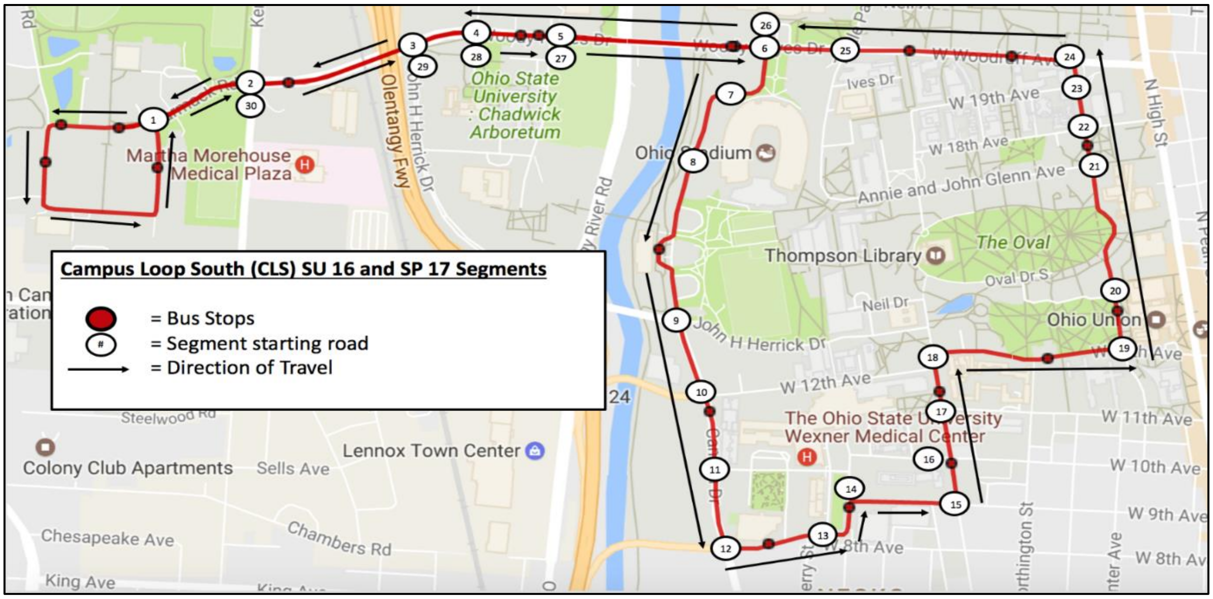
Three types of data were collected from mobile platforms and processed to provide estimates of vehicle flows using the modified moving observer method: manually collected data, LiDAR data, and video data. Data of the first type are collected using transit buses as mobile platforms, while the data of the second and third types are collected using the van as a mobile platform. The ways in which the values of the variables needed to estimate flow rates were determined varied slightly, depending on the type of data collection, and are described in this section.

3.1 Manually Collected Data from Transit Buses

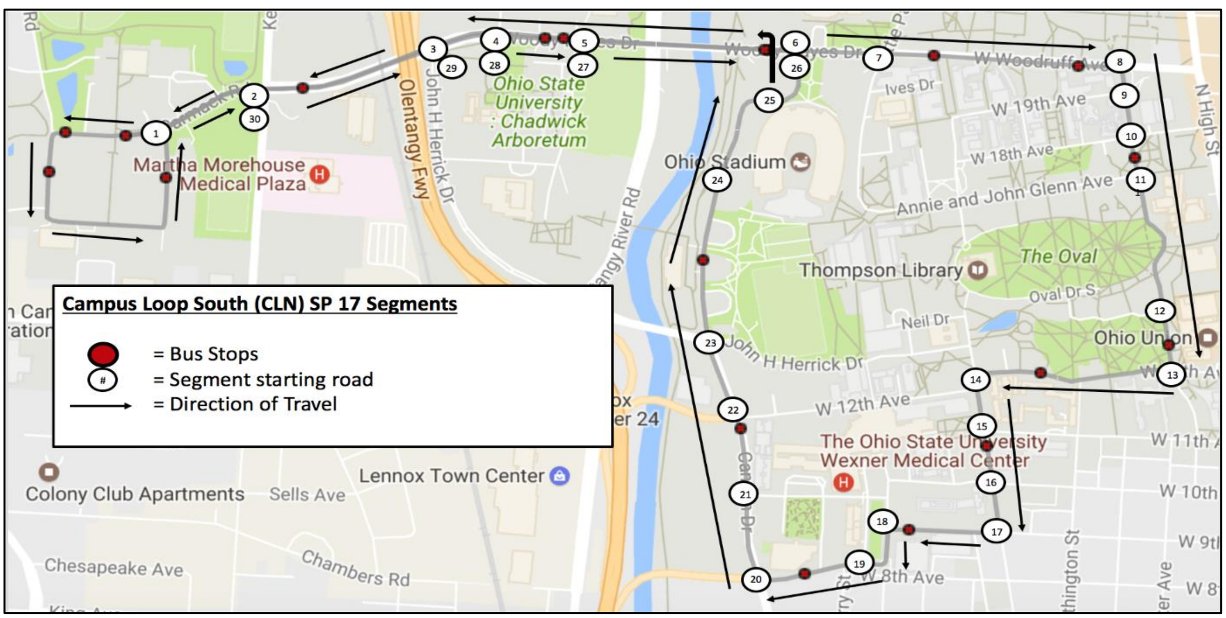
Data collectors rode The Ohio State University (OSU) Campus Area Bus Service (CABS) buses during periods of operation and manually recorded clock times at time-points that marked the beginnings and ends of pre-specified roadway segments and the number of vehicles the bus passed on the segments travelling in the direction opposite that of the bus direction. These manually collected, bus-based data were collected when riding Campus Loop North (CLN) and Campus Loop South (CLS) routes during the Summer 2016 academic term and the CLN route during the Spring 2017 academic term. The CLN Summer 2016, CLS Summer 2016, and CLN Spring 2017 routes and segments are indicated in Figures 3.1a-c, respectively, where the numbered circles represent time-points and the arrows indicate direction of bus travel. Descriptions of the segments are provided in Tables 3.1-a-c. (Construction during Summer 2016 led to differences in route alignment between Summer 2016 and Spring 2017.) The Summer 2016 data collections were scheduled to correspond to morning, noon, and afternoon flows. The Spring 2017 data collections occurred at times that correspond to the noon period.



3.1a: Campus Loop North (CLN) route, Summer 2016



3.1b: Campus Loop South (CLS) route, Summer 2016



3.1c: Campus Loop North (CLN) route, Spring 2017

Figure 3.1: Indication of time-points (numbered circles) determining roadway data collection segments and direction of bus mobile platform for manual data collection

Table 3.1: Description of segments for manual data collection

3.1a: Campus Loop North (CLN) route, Summer 2016

Segment Number	Starting Road	End Road
1	i/c following Carmack	Woody & Kenny
2	Woody & Kenny	Woody & John Herrrick
3	Woody & John Herrrick	Woody & Fyffe
4	Woody & Fyffe	Woody & Coffey
5	Woody & Coffey	Woody & Cannon
6	Woody & Cannon	Woody & Tuttle Park
7	Woody & Tuttle Park	Woodruff & College
8	Woodruff & College	19th & Collge
9	19th & Collge	18th & Collge
10	18th & Collge	Annie/John & Collge
11	Annie/John & Collge	Hagerty & College
12	Hagerty & College	12th & College
13	12th & Cllge	12th & High
14	12th & High	Chittndn & High
15	Chittndn & High	E 11th & High
16	E 11th & High	W 9th & High
17	W 9th & Neil	Med & 9th
18	Med & 9th	Med & Westpark
19	Med & Westpark	Med & Cannon
20	Med & Cannon	Cannon & 10th
21	Cannon & 10th	Cannon & 12th
22	Cannon & 12th	Cannon & John Herrick
23	Cannon & John Herrick	Middle Stadium Entrance
24	Middle Stadium Entrance	NW Stdium Lot
25	NW Stadium Lot	Cannon & Woody
26	Cannon & Woody	Woody & Coffey
27	Woody & Coffey	Woody & Fyffe
28	Woody & Fyffe	Woody & John Herrick
29	Woody & John Herrick	Woody & Kenny
30	Woody & Kenny	"constantly changing"

3.1b: Campus Loop South (CLS) route, Summer 2016

Segment Number	Starting Road	End Road
1	i/c following Carmack	Woody & Kenny
2	Woody & Kenny	Woody & John Herrick
3	Woody & John Herrick	Woody & Fyffe
4	Woody & Fyffe	Woody & Coffey
5	Woody & Coffey	Woody & Cannon
6	Woody & Cannon	NW Stadium Lot
7	NW Stadium Lot	Middle Stadium Entrance
8	Middle Stadium Entrance	John Herrick & Cannon
9	John Herrick & Cannon	12th & Cannon
10	12th & Cannon	10th & Cannon
11	10th & Cannon	Med & Cannon
12	Med & Cannon	Med & Westpark
13	Med & Westpark	9th & Med
14	9th & Med	9th & Neil
15	9th & Neil	10th & Neil
16	10th & Neil	11th & Neil
17	11th & Neil	12th & Neil
18	12th & Neil	12th & College
19	12th & College	Hagerty & College
20	Hagerty & College	Annie/John & College
21	Annie/John & College	18th & College
22	18th & College	19th & College
23	19th & College	Woodruff & College
24	Woodruff & College	Woodruff & Tuttle Park
25	Woodruff & Tuttle Park	Woody & Cannon
26	Woody & Cannon	Woody & Coffey
27	Woody & Coffey	Woody & Fyffe
28	Woody & Fyffe	Woody & John Herrick
29	Woody & John Herrick	Woody & Kenny
30	Woody & Kenny	"constantly changing"

3.1c: Campus Loop North (CLN) route, Spring 2017

Segment Number	Starting Road	End Road
1	i/c following Carmack	Woody & Kenny
2	Woody & Kenny	Woody & John Herrrick
3	Woody & John Herrrick	Woody & Fyffe
4	Woody & Fyffe	Woody & Coffey
5	Woody & Coffey	Woody & Cannon
6	Woody & Cannon	Woody & Tuttle Park
7	Woody & Tuttle Park	Woodruff & College
8	Woodruff & College	19th & Collge
9	19th & Collge	18th & Collge
10	18th & Collge	Annie/John & Collge
11	Annie/John & Collge	Hagerty & College
12	Hagerty & College	12th & College
13	12th & College	12th & Neil
14	12th & Neil	11th & Neil
15	11th & Neil	10th & Neil
16	10th & Neil	W 9th & Neil
17	W 9th & Neil	Med & 9th
18	Med & 9th	Med & Westpark
19	Med & Westpark	Med & Cannon
20	Med & Cannon	Cannon & 10th
21	Cannon & 10th	Cannon & 12th
22	Cannon & 12th	Cannon & John Herrick
23	Cannon & John Herrick	Middle Stadium Entrance
24	Middle Stadium Entrance	NW Stadium Lot
25	NW Stadium Lot	Cannon & Woody
26	Cannon & Woody	Woody & Coffey
27	Woody & Coffey	Woody & Fyffe
28	Woody & Fyffe	Woody & John Herrick
29	Woody & John Herrick	Woody & Kenny
30	Woody & Kenny	Before Carmack

The number of vehicles manually counted on a segment corresponds to n^{veh} in Equation (2.1) used to estimate flows in the modified moving observer method. The difference between the times at time-points denoting the beginning and ends of the segment correspond to $t_{1.}$

As discussed above, the time t_2 for a virtual vehicle to traverse the segment for which flow was being estimated in the direction of traffic flow could be determined in several ways. In the empirical study conducted, if time-points were manually recorded from a bus (on either route) when traversing the segment in the direction of flow being estimated during the same time-of-day period (morning, noon, afternoon) and academic term (Summer 2016, Spring 2017), the traversal times determined from the times at the time-points are used to determine what is called a *raw* t_2 value for the segment. Specifically, all the traversal times corresponding to the time-of-day period and academic term are averaged to determine the *raw* t_2 value. The loop nature of the CLN and CLS bus routes results in some segments being traversed in only one direction by the buses on that route (see Figure 3.1). However, buses on the other route traversed the same segments in the other direction. In Summer 2016, data were collected on both CLN and CLS during all the time periods. Therefore, the *raw* t_2 values on segments where data were collected from CLN (CLS) buses that were only traversed in one direction are obtained from the traversal times of CLS (CLN) buses on the segment in the other direction. Specifically, the average traversal times in the corresponding time-of-day period are used as the *raw* t_2 value. In Spring 2017, data were only collected from CLN buses. For these bus-based estimates, the average t_1 values are used as the *raw* t_2 values for the segments that were only traversed in one direction.

As discussed above, the t_2 value is intended to represent the time a virtual vehicle in the traffic stream would take to traverse the segment in the direction where the flow is being estimated. If there is a bus stop on the segment for which traffic flow was being estimated and the time for the bus to traverse the segment is used to represent the *raw* t_2 value, the bus dwell time would be included in the *raw* t_2 value. If the bus stop is on a street with only one directional lane of traffic with no bus stop pullout, the time the bus spent dwelling at the stop would affect travel times of all vehicles on the segment. Therefore, in these cases the *raw* t_2 value is assumed to be representative of the virtual vehicle time, and the *raw* t_2 value is used as the t_2 value. However, in the cases where there is more than one lane of directional traffic or where there is a bus stop pullout, the bus dwelling at the stop is assumed not to affect the virtual vehicle time. In these cases an estimate of dwell time is subtracted from the *raw* t_2 value to determine the value of t_2. In this study, dwell times at the stop on the segment are determined from CABS automatic vehicle location (AVL) data (which, in the case of CABS data, are easily computed from AVL information incorporated in the automatic passenger count (APC) dataset) for the respective time-of-day periods and academic terms. The dwell time determined is subtracted from the *raw* t_2 value to determine the t_2 value. At first the median (50^{th}-percentile) dwell time of all buses serving the stop during each of the time-of-day periods (Morning, Noon, or Afternoon) for each of the academic terms (Summer 2016 or Spring 2017) was used as the value of the dwell time to be subtracted. However, in some cases the median is larger than the *raw* t_2 value (due to recurrent bus holding or high boarding and alighting volumes at the served stops at times other than when the *raw* t_2 values are collected), which leads to a negative t_2 value. Therefore, the 5^{th}-percentile value of the dwell times for the time-of-day period and academic term is used as a possible alternative. Results are presented below both when subtracting the median dwell time and when subtracting the 5^{th}-percentile dwell time from the *raw* t_2 value.

3.2 LiDAR Data from Sensor-Equipped Van

Similar to what is described in (*11*), a 2000 Honda Odyssey minivan was equipped with LiDAR and GPS sensors and repeatedly driven on a pre-specified route. The LiDAR sensors were mounted to point perpendicular to the direction of travel to sense traffic traveling in lanes across the centerline from the van. The LiDAR data were automatically processed – see (*11*) – to identify distinct vehicles the van passed traveling in the direction opposite that of the van direction. The times of the LiDAR and GPS data were synchronized. Therefore, these time stamps allow a determination of the time when each vehicle is identified. From the GPS information as to when the van was on the segment (see below), the time the vehicle is identified in the LiDAR data allows a unique determination of the segment on which the vehicle was sensed. The value of n^{veh} is then determined by aggregating all identified vehicles on the segment during a pass of the van.

The GPS data allow a determination of the times when the van entered and exited pre-specified roadway segments and, hence, a calculated value of t_1, the time the van spent on the segment. In this study, the times the van entered and exited segments were determined as described in Section 3.2.

In this project the flow estimates determined from LiDAR data were only calculated on segments where the van traveled the segment in both directions on a given data collection tour. Therefore, the *raw* t_2 value discussed when presenting the processing of the manually collected, bus-based data are calculated by averaging all the van traversal times when traveling on the segment in the direction of flow being estimated for a given time-of-day period. (In this project, the van was only operated in Summer 2016, so there was only one academic term to consider.) Since the van did not dwell at bus stops and travelled with traffic, the *raw* t_2 value is used as the value of t_2 to estimate flow using Equation (2.1).

3.3 Video Data from Sensor-Equipped Van

The van was also equipped with forward-, side-, and back-facing video cameras. Software was developed that allows an individual watching a video recording in a playback mode to click when observing a vehicle. The forward-facing camera was used for this project, and the individuals observing the video recordings were instructed to click when the vehicle appeared to be at the front of the van. The clicks are saved in an output file along with the video frame numbers and the synchronized GPS times at which the clicks occurred.

The software was also written so that the frame number and GPS time are portrayed on the computer screen. In addition to clicking when a vehicle was seen in the video, the software user also recorded the frame number and GPS time when the van arrived at time-points. The arrival at time-points was apparent by watching the video and watching a graphical representation of the vehicle location on the van's tour alignment, which was programmed to appear on the computer screen simultaneously with the video image. In this way, the clicks indicating a vehicle passing in the opposite direction that occurred between the times or frame numbers associated with the time-points defining a segment are aggregated to determine n^{veh} to estimate flows from the video data. (Similarly, the number of vehicles identified from the LiDAR data (see above) at the times occurring between the times corresponding to the van's arrival at the appropriate time-points are aggregated to determine n^{veh} to estimate flows from the LiDAR data.) The times corresponding to the clicks indicating arrival at time-points are used to determine t_1 values for use when estimating flows from the video data. The same times are used to determine t_1 values for use with the LiDAR data.

As mentioned above, the van traversed the segments of interest in both directions on each data collection tour. Therefore, the times at time-points defining the segment in the opposite direction of van travel (i.e., in the direction of flow to be estimated) were averaged to determine the t_2 value for the time-of-day period.

4. Empirical Results

As discussed above, manually collected data were obtained from transit buses, whereas LiDAR and video data were collected together from the sensor-equipped van. Flow estimates were determined separately for each of the datasets and for each pass of the mobile platform past the segment whose flow was being estimated. Summary statistics of the estimated flows are presented in this section.

Summary statistics of the flow estimates determined from the data manually collected from Campus Loop North (CLN) buses during the Noon time-of-day period of the Summer 2016 academic term are presented in Table 4.1. Corresponding results for Summer 2016 data collected from Campus Loop South (CLS) buses and for Spring 2017 data collected from the CLN buses are presented in Tables A1.1 and A1.2, respectively, in Appendix 1. As discussed above, when there was a bus stop that did not block all directional flow on the segment whose flow is being estimated, a dwell time value (referred to as DT in the table) was subtracted from the *raw* t_2 values to determine the t_2 value for use in Equation (2.1). Results are presented in Table 4.1 using both the 5^{th}-percentile and 50^{th}-percentile (median) dwell times as the value of the subtracted dwell time. (Naturally, the segments for which the statistics shown under each of the 5^{th}-percentile and 50^{th}-percentile columns are identical for the segments where dwell times are not subtracted from *raw* t_2.)

As expected, on those segments where dwell times are subtracted from the *raw* t_2 values, the flows estimated when subtracting the median dwell times are greater than those when subtracting the 5^{th}-percentile dwell times because of the resulting lower t_2 value in the denominator of Equation (2.1). The differences between the mean, median, and standard deviation of the flows when using the different percentiles appear relatively small compared to differences across segments. Because large values of dwell times led to negative values of t_2 in some cases and low values in other cases, the 5^{th}-percentile value is used when determining results presented in the remainder of this section.

Table 4.1: Summary statistics of flow estimates determined from data manually collected from CLN buses during Noon time-of-day period in Summer 2016 using 5th- and 50th-percentile dwell times (DTs) to determine t_2 values when dwell times are subtracted from *raw* t_2

Seg. No.	N*	Flows (veh/hr) using 5th-percentile DT**					Flows (veh/hr) using 50th-percentile DT**				
		Mean	Median	S.D	Min	Max	Mean	Median	S.D	Min	Max
1	28	104	99	114	0	561	104	99	114	0	561
2	28	251	222	116	56	485	251	222	116	56	485
3	28	209	208	148	0	567	209	208	148	0	567
4	28	150	135	90	33	329	159	141	95	36	351
5	28	189	156	95	44	398	190	157	96	44	401
6	28	326	301	173	0	681	326	301	173	0	681
7	22	124	115	53	50	257	124	115	53	50	257
8	22	187	130	159	0	430	207	145	176	0	457
9	22	177	192	154	0	528	177	192	154	0	528
10	22	133	114	95	0	425	140	120	101	0	458
11	28	127	139	54	33	253	127	139	54	33	253
12	28	140	127	91	0	406	n/a***				
13	24	92	95	46	0	180	92	95	46	0	180
14	14	804	811	390	58	1452	804	811	390	58	1452
15	14	740	705	446	56	1567	740	705	446	56	1567
16	14	508	537	289	55	1021	508	537	289	55	1021
17	25	116	101	54	52	251	116	101	54	52	251
18	25	n/a***									
19	25	241	231	99	55	461	241	231	99	55	461
20	27	216	217	112	0	391	216	217	112	0	391
21	27	197	183	111	43	518	204	187	116	45	539
22	27	440	379	254	49	1085	440	379	254	49	1085
23	27	107	104	60	35	310	111	106	63	36	325
24	27	220	209	128	0	476	220	209	128	0	476
25	27	163	134	119	0	415	163	134	119	0	415
26	27	191	189	101	51	429	193	191	103	52	435
27	27	113	117	56	0	238	118	121	58	0	247
28	27	171	105	173	0	613	171	105	173	0	613
29	27	226	235	139	15	547	228	237	140	15	553
30	Construction-related route alignment changes do not allow stable estimates										

* Number of individual flow values determined (one for each bus passage).

** In Summer 2016 data, to determine t_2 values for segments 4, 5, 7, 10, 12, 18, 19, 21, 23, 26, 27, and 29 dwell time values (either 50th- or 5th-percentile value) are subtracted from *raw* t_2 value.

*** Calculated values of t_2 on these segments were negative because dwell the time value is greater than the corresponding *raw* t_2 value.

Summary statistics of the flow estimates determined from the data manually collected from the CLN buses during Summer 2016 academic term are presented in Table 4.2 by time-of-day period (Morning, Noon, Afternoon). The corresponding table for flows estimated from CLS Summer 2016 buses is presented in Table A1.3 in Appendix 1.

The differences in flows by time-of-day periods are apparent, as would be expected because of time-of-day traffic flow patterns. The estimated flows also appear reasonable in that they correspond to *a priori* understanding of traffic patterns around campus. For example, the heavy commuter pattern results in heavier inbound flows on Segment 27 (flow toward north campus) in the morning than later in the day, and on Segment 5 (flow away from north campus) in the afternoon (evening) than at other times of day. (As presented above, the segments are defined in terms of the direction of travel of the bus platform, which is opposite the direction of the flows being estimated.) Similarly, the flows being estimated from Segment 27 and Segment 5 correspond to the same roadway segment, but in the opposite direction (see Figure 3.1a or Table 3.1a). The estimated morning flow rate is markedly larger in the Morning period for (bus platform) Segment 27 than for (bus platform) 5, which corresponds to greater inbound flows in the morning than in the afternoon, as expected. The opposite pattern is seen in the Afternoon period, which corresponds to greater outbound flow in the afternoon than in the morning, as expected.

Table 4.2: Summary statistics of flow estimates determined from data manually collected from CLN buses during Summer 2016 by time-of-day period using 5th-percentile dwell times to determine t_2 value when dwell time is subtracted from *raw* t_2 value

Seg	AM Flows (veh/hr)				Noon Flows (veh/hr)				PM Flows (veh/hr)			
No.	N*	Mean	Median	S.D	N*	Mean	Median	S.D	N*	Mean	Median	S.D
1	20	314	277	222	28	104	99	114	8	47	31	56
2	20	256	234	88	28	251	222	116	8	356	323	176
3	20	282	267	160	28	209	208	148	8	211	208	153
4	20	101	77	76	28	150	135	90	8	297	295	129
5	20	137	139	62	28	189	156	95	8	313	333	137
6	20	288	273	168	28	326	301	173	6	273	261	96
7	16	103	79	66	22	124	115	53	6	188	185	82
8	16	86	99	73	22	187	130	159	6	234	261	121
9	16	129	104	119	22	177	192	154	6	242	223	182
10	16	80	53	67	22	133	114	95	6	124	121	42
11	20	90	73	54	28	127	139	54	8	123	131	67
12	20	129	117	75	28	140	127	91	8	76	73	46
13	16	111	79	79	24	92	95	46	7	70	46	62
14	12	485	422	290	14	804	811	390	6	437	400	389
15	12	423	424	261	14	740	705	446	5	453	341	458
16	12	420	435	181	14	508	537	289	5	745	654	640
17	18	177	155	83	25	116	101	54	4	129	137	62
18	18	n/a**			25	n/a**			6	539	570	299
19	18	435	469	158	25	241	231	99	6	150	141	61
20	20	183	217	76	27	216	217	112	8	443	447	168
21	20	226	234	124	27	197	183	111	8	198	187	75
22	20	433	423	184	27	440	379	254	8	563	570	201
23	20	87	89	53	27	107	104	60	8	156	130	80
24	20	120	85	123	27	220	209	128	8	197	187	119
25	20	202	196	120	27	163	134	119	8	195	203	83
26	20	277	273	112	27	191	189	101	8	199	174	78
27	20	282	262	123	27	113	117	56	8	116	84	123
28	20	241	238	211	27	171	105	173	8	221	193	188
29	20	244	194	142	27	226	235	139	8	179	185	60
30	Construction-related route alignment changes do not allow stable estimates											

* Number of individual flow values determined (one for each bus passage).
** Calculated values of t_2 on these segments were negative because dwell time value was greater than *raw* t_2 value.

To quantify differences for subsequent comparisons, relative differences between the Morning and Noon flows on the same segment collected from CLN buses in Summer 2016 are quantified. These relative differences are presented in Table 4.3.

Table 4.3 Comparison between Morning and Noon Summer 2016 flows estimated from data manually collected from CLN buses

	AM Flows (veh/hr)			Noon Flows (veh/hr)			Relative Difference*		
Seg No	Mean	Median	S.D	Mean	Median	S.D	Mean	Median	S.D
1	314	277	222	104	99	114	1.00	0.95	0.64
2	256	234	88	251	222	116	0.02	0.05	-0.27
3	282	267	160	209	208	148	0.30	0.25	0.08
4	101	77	76	150	135	90	-0.39	-0.55	-0.17
5	137	139	62	189	156	95	-0.32	-0.12	-0.42
6	288	273	168	326	301	173	-0.12	-0.10	-0.03
7	103	79	66	124	115	53	-0.19	-0.37	0.22
8	86	99	73	187	130	159	-0.74	-0.27	-0.74
9	129	104	119	177	192	154	-0.31	-0.59	-0.26
10	80	53	67	133	114	95	-0.50	-0.73	-0.35
11	90	73	54	127	139	54	-0.34	-0.62	0.00
12	129	117	75	140	127	91	-0.08	-0.08	-0.19
13	111	79	79	92	95	46	0.19	-0.18	0.53
14	485	422	290	804	811	390	-0.49	-0.63	-0.29
15	423	424	261	740	705	446	-0.55	-0.50	-0.52
16	420	435	181	508	537	289	-0.19	-0.21	-0.46
17	177	155	83	116	101	54	0.42	0.42	0.42
18	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]
19	435	469	158	241	231	99	0.57	0.68	0.46
20	183	217	76	216	217	112	-0.17	0.00	-0.38
21	226	234	124	197	183	111	0.14	0.24	0.11
22	433	423	184	440	379	254	-0.02	0.11	-0.32
23	87	89	53	107	104	60	-0.21	-0.16	-0.12
24	120	85	123	220	209	128	-0.59	-0.84	-0.04
25	202	196	120	163	134	119	0.21	0.38	0.01
26	277	273	112	191	189	101	0.37	0.36	0.10
27	282	262	123	113	117	56	0.86	0.77	0.75
28	241	238	211	171	105	173	0.34	0.78	0.20
29	244	194	142	226	235	139	0.08	-0.19	0.02
						Average	-0.03	-0.04	-0.04
						Standard Deviation	0.43	0.49	0.37
						Average of absolute values	0.35	0.40	0.29
						Standard Deviation of absolute values	0.25	0.27	0.22

*Relative Difference = (AM Value – Noon Value)/Average of AM and Noon Values.

One would also expect differences between the flows estimated for the same time-of-day period in Summer 2016 and Spring 2017 periods. There is much more activity during the Spring academic term than during the Summer term, which would lead to heavier traffic in the Spring term. Manual data were collected in both terms only from CLN buses during the Noon time-of-day period. Because of construction related realignments, some CLN segments differed between the two terms (see Figures 3.1a and 3.1c and Tables 3.1a and 3.1c). Summary statistics of the estimated flows on CLN segments that are common in the two periods and the relative differences between them are presented in Table 4.4.

Table 4.4 Comparison between Spring 2017 and Summer 2016 Noon flows on common segments estimated from data manually collected from CLN buses

Seg	SP 2017 Flows (veh/hr)			SU 2016 Flows (veh/hr)			Relative Difference**		
No.	Mean	Median	S.D	Mean	Median	S.D	Mean	Median	S.D
1	42	39	31	104	99	114	-0.85	-0.87	-1.14
2	313	258	163	251	222	116	0.22	0.15	0.34
3	237	243	183	209	208	148	0.13	0.16	0.21
4	307	283	128	150	135	90	0.69	0.71	0.35
5	260	244	105	189	156	95	0.32	0.44	0.10
6	296	265	168	326	301	173	-0.10	-0.13	-0.03
7	193	157	94	124	115	53	0.44	0.31	0.56
8	314	247	358	187	130	159	0.51	0.62	0.77
9	93	82	85	177	192	154	-0.62	-0.80	-0.58
10	159	143	79	133	114	95	0.18	0.23	-0.18
11	141	142	75	127	139	54	0.10	0.02	0.33
12	110	99	62	140	127	91	-0.24	-0.25	-0.38
17	104	92	63	116	101	54	-0.11	-0.09	0.15
18	130	86	108	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]	n/a[4]
19	201	195	102	241	231	99	-0.18	-0.17	0.03
20	298	271	150	216	217	112	0.32	0.22	0.29
21	249	234	147	197	183	111	0.23	0.24	0.28
22	394	382	231	440	379	254	-0.11	0.01	-0.09
23	353	343	158	107	104	60	1.07	1.07	0.90
24	222	159	183	220	209	128	0.01	-0.27	0.35
25	147	140	86	163	134	119	-0.10	0.04	-0.32
26	224	238	72	191	189	101	0.16	0.23	-0.34
27	253	235	84	113	117	56	0.77	0.67	0.40
28	260	184	195	171	105	173	0.41	0.55	0.12
29	206	213	133	226	235	139	-0.09	-0.10	-0.04
		Average					0.13	0.12	0.09
		Standard Deviation					0.42	0.45	0.44
		Average of absolute values					0.33	0.35	0.35
		Standard Deviation of absolute values					0.28	0.30	0.28

*Relative Difference = (Spring 2017 Value – Summer 2016 Value)/Average of SP17 and SU16 Values.

The large number of positive differences and the positive average of the Mean and Median relative differences in Table 4.4, especially when comparing to those of Table 4.3, imply that the Spring 2017 flows are generally higher than the Summer 2016 flows. This result corresponds to the expectation of higher flows in the Spring academic term, when there is more activity, than in the Summer academic period. That is, the flows estimated from data collected from the mobile platform using the modified moving observer method produce reasonable results.

Several segments were identical in the Summer 2016 CLN and CLS manual data collections (see Figures 3.1a and b and Tables 3.1a and b). Since the manual data collectors rode the buses on different days and at different times in a given time-of-day period, estimated vehicle flows would not be expected to correspond exactly to each other. However, the motivation for use of buses as a mobile platform is that the repeated passes of a fixed-route transit bus could be exploited to determine a stable estimate of hourly flow for a time-of-day period. Therefore, to assess the stability of the estimates, the differences between common segments are determined and presented in Table 4.5.

Table 4.5: Comparison of flows estimated on common segments estimated from CLN and CLS buses in Summer 2016

Segment Number	AM Flows (veh/hr)								
	Data from CLN buses			Data from CLS buses			Relative Difference*		
	Mean	Median	S.D	Mean	Median	S.D	Mean	Median	S.D
1	314	277	222	185	143	154	0.52	0.64	0.36
2	256	234	88	208	174	101	0.21	0.29	-0.14
3	282	267	160	233	227	155	0.19	0.16	0.03
4	101	77	76	103	100	71	-0.02	-0.26	0.07
5	137	139	62	149	127	86	-0.08	0.09	-0.32
26	277	273	112	298	318	106	-0.07	-0.15	0.06
27	282	262	123	341	378	120	-0.19	-0.36	0.02
28	241	238	211	193	193	145	0.22	0.21	0.37
29	244	194	142	262	248	114	-0.07	-0.24	0.22
	Noon Flows (veh/hr)								
1	104	99	114	102	85	79	0.02	0.15	0.36
2	251	222	116	255	255	83	-0.02	-0.14	0.33
3	209	208	148	279	225	246	-0.29	-0.08	-0.50
4	150	135	90	207	197	97	-0.32	-0.37	-0.07
5	189	156	95	218	191	111	-0.14	-0.20	-0.16
26	191	189	101	180	175	53	0.06	0.08	0.62
27	113	117	56	129	128	81	-0.13	-0.09	-0.36
28	171	105	173	188	193	141	-0.09	-0.59	0.20
29	226	235	139	199	199	98	0.13	0.17	0.35
		Average					0.00	-0.04	0.08
		Standard Deviation					0.20	0.29	0.30
		Average of absolute values					0.15	0.24	0.25
		Standard Deviation of absolute values					0.13	0.16	0.17

*Relative Difference = (CLN Value – CLS Value)/Average of CLN and CLS Values.

The average relative difference of the mean flows is zero (to two decimal places), indicating no systematic differences between estimates determined using data collected from CLN buses and data collected from CLS buses. Moreover, the averages of the absolute values of the relative differences of mean and median flows are much smaller than the corresponding averages of absolute values for the comparisons presented in Tables 4.3 and 4.4, where larger differences were expected. Again, the flow estimates obtained using data from the mobile bus platforms appear reasonable.

As discussed above, flows were estimated from LiDAR and video data simultaneously collected when operating the sensor-equipped van in Summer 2016. A flow estimate was determined for each pass of the van. Two of three different individuals independently processed the video data for each pass of the van so that two flow estimates on a segment were determined for each pass of the van. (On one segment and one tour of the van all three individuals collaborated on processing the video data. One of the individuals processed the same video data independently at a later time, so that there were again two estimates for each van pass of a segment.)

Considering the procedure for processing the video data explained above, different individuals could conceivably make different errors when clicking to indicate a vehicle observations or differ in determining the time or frame number when the van arrived at various time-points. As a result, different flow estimates could be determined from the data processed by different individuals. The numbers of vehicles recorded and the times the van arrived at the time-points for the different individuals are presented in Table B.1 in Appendix B. More detailed analysis of the reliability of the flow estimates across individuals is left for future study, but there appears to be mostly small differences, if any, in the numbers of vehicles and times recorded by the different individuals for the same raw video data. For this study, the flow estimates determined from the data processed by different individuals for the same van pass are averaged to produce a single flow estimate for each van pass.

Summary statistics of the flow estimates obtained from the LiDAR data and from the video data are presented in Tables 4.6 and 4.7, respectively. Unlike the comparisons of the various estimates determined from the bus-based data presented above, the LiDAR and video sensors were sensing the same vehicles. Therefore, the flow estimates from these two types of data obtained from each van pass would differ only because of the differences in detected vehicles determined from the automatically processed LiDAR data and from the human- processed video data. (The same t_1 and t_2 times were used for the two datasets.) Relative differences between the summary statistics of the flows estimated from the LiDAR and video data are presented in Table 4.8.

Table 4.6: Summary statistics of flows estimated from LiDAR data collected in Summer 2016 by time-of-day period

Seg. No.*	AM Flows (veh/hr)						Noon Flows (veh/hr)					
	N**	Mean	Median	S.D	Min	Max	N**	Mean	Median	S.D	Min	Max
2	10	246	223	127	120	582	12	304	295	186	72	637
3	10	148	110	135	0	425	12	196	203	78	35	301
4	10	179	215	146	0	395	12	320	277	156	144	643
5	10	153	176	86	0	254	12	239	211	96	123	409
6	10	179	195	135	0	383	12	360	217	327	96	1274
25	10	497	522	243	89	844	12	281	267	142	0	514
26	10	318	325	133	129	508	12	253	252	67	102	396
27	10	478	417	263	132	800	12	274	276	150	0	496
28	10	225	156	223	0	648	12	192	171	97	64	358
29	10	521	417	333	109	1214	12	255	235	134	56	454

*Seg. No: Number corresponds to CLN Summer 2016 and Spring 2017 segment numbers (see Figures 3.1a or 3.1c or Tables 3.1a or 3.1c.

** Number of individual flow values determined (one for each van pass).

Table 4.7: Summary statistics of flows estimated from video data collected in Summer 2016 by time-of-day period

Seg. No.*	AM Flows (veh/hr)						Noon Flows (veh/hr)					
	N**	Mean	Median	S.D	Min	Max	N**	Mean	Median	S.D	Min	Max
2	10	218	181	111	102	451	12	268	256	167	57	584
3	10	125	106	125	0	425	12	163	154	113	0	369
4	10	122	135	114	0	263	12	275	221	197	70	681
5	10	105	103	61	0	190	12	226	213	94	82	393
6	10	199	171	160	0	460	12	327	242	307	68	1206
25	10	456	383	332	22	985	12	313	254	182	64	656
26	10	318	290	150	129	617	12	254	266	93	102	396
27	10	375	293	232	66	711	12	240	259	122	0	396
28	10	186	131	228	0	721	12	149	146	58	64	233
29	10	414	427	216	57	722	12	234	272	112	56	366

*Seg. No: Number corresponds to CLN Summer 2016 and Spring 2017 segment numbers (see Figures 3.1a or 3.1c or Tables 3.1a or 3.1c.

** Number of individual flow values determined (one for each averaged pair of video-based estimates on a van pass).

Table 4.8: Comparison of flows estimated from LiDAR and video data collected from sensor-equipped van in Summer 2016

Seg. No.*	LiDAR Data Flows (veh/hr)			Video Data Flows (veh/hr)			Relative Difference**		
	Mean	Median	S.D	Mean	Median	S.D	Mean	Median	S.D
	Morning Flows								
2	246	223	127	218	181	111	0.12	0.21	0.14
3	148	110	135	125	106	125	0.17	0.04	0.08
4	179	215	146	122	135	114	0.38	0.46	0.25
5	153	176	86	105	103	61	0.37	0.52	0.33
6	179	195	135	199	171	160	-0.11	0.13	-0.17
25	497	522	243	456	383	332	0.09	0.31	-0.31
26	318	325	133	318	290	150	0.00	0.11	-0.12
27	478	417	263	375	293	232	0.24	0.35	0.13
28	225	156	223	186	131	228	0.19	0.17	-0.02
29	521	417	333	414	427	216	0.23	-0.02	0.43
	Noon Flows								
2	304	295	186	268	256	167	0.13	0.14	0.11
3	196	203	78	163	154	113	0.18	0.27	-0.37
4	320	277	156	275	221	197	0.15	0.22	-0.23
5	239	211	96	226	213	94	0.06	-0.01	0.02
6	360	217	327	327	242	307	0.10	-0.11	0.06
25	281	267	142	313	254	182	-0.11	0.05	-0.25
26	253	252	67	254	266	93	0.00	-0.05	-0.33
27	274	276	150	240	259	122	0.13	0.06	0.21
28	192	171	97	149	146	58	0.25	0.16	0.50
29	255	235	134	234	272	112	0.09	-0.15	0.18
			Average				0.13	0.14	0.03
			Standard Deviation				0.13	0.18	0.25
			Average of absolute values				0.15	0.18	0.21
			Standard Deviation of absolute values				0.10	0.14	0.13

*Seg. No: Number corresponds to CLN Summer 2016 and Spring 2017 segment numbers (see Figures 3.1a or 3.1c or Tables 3.1a or 3.1c)

**Relative Difference = (LiDAR value – Video value)/Average of LiDAR and Video values

As expected, the averages of the relative differences of the mean and median flows are much smaller than those obtained when comparing estimates from bus-based data for different time-of-day periods (Table 4.3) and for different academic terms (Table 4.4), again supporting the reasonableness of the data. It is surprising, however, that the average relative differences are approximately the same as those obtained when comparing estimates for the same time-of-day period and academic term but obtained from different buses, i.e., at different times during the period (Table 4.5). The expectation is that the differences between the LiDAR and video data, where the same vehicles were being detected, would be smaller than the differences between estimates obtained when traffic conditions could be different. The large number of positive relative differences in Table 4.8, and the resulting positive average relative difference, indicates that the LiDAR-based flow estimates were generally larger than the video-based flow estimates. Further investigations of these differences is left for future work. However, one present hypothesis is that the automatic vehicle detection algorithms used with the LiDAR data may occasionally break up individual vehicles into multiple vehicles. Another hypothesis is that human error in processing the video data is prone to not noticing some vehicles due to poor ambient natural light conditions, which do not affect LiDAR data.

5. Conclusions

The empirical results support the potential of estimating average flow rates for time-of-day periods using the modified moving observer method presented with vehicle counts obtained from a mobile platform that repeatedly covers roadway segments. Any individual pass of the mobile platform past a roadway segment would provide a very noisy estimate of the traffic flow, but repeatedly covering the same segment during the time-of-day period allows averaging the multiple noisy estimates so that a valid estimate of the average time-of-day period flow could be determined. Transit buses are proposed as attractive mobile platforms because of their repeated coverage of a large number of roadway segments in urban areas that are infrequently sampled with traditional methods. In addition, many transit agencies are implementing outward looking videos on their bus fleets for other reasons. Therefore, these transit buses will be collecting repeated vehicle observations across the urban network that can conceivably be used with the modified moving observer method to provide traffic flow estimates with unprecedented spatial coverage and to update these estimates with unprecedented temporal frequency.

In this project data were manually collected from The Ohio State University transit buses in regular operation. The average flow rates estimated for the same roadway segments determined from data manually collected from buses operating on different bus routes for the same time-of-day period are found to be much more similar than the estimates for the same roadway segments determined from data collected in different time-of-day periods or different academic terms. Moreover, the differences in the estimates for the different time-of-day periods correspond to known commuting traffic patterns (greater inbound flows in the morning, larger outbound flows in the afternoon), and the differences for the different academic terms correspond to known traffic activity (less traffic in the Summer term than in the Spring term)

Flows were also collected from LiDAR and video sensors mounted on a van that traversed several of the same segments traversed by the transit buses. The LiDAR data were automatically transformed into vehicle counts and times. Software was developed to allow individuals watching the video recordings in a playback mode to click to record locations and times of vehicle detections. These data were then transformed to input values for use with the modified moving observer method to estimate traffic flows. Since the raw LiDAR and video data are recorded simultaneously from the van, they record the same vehicles. Therefore, the differences in flows estimated from the LiDAR and video data would be expected to be smaller than the differences in flows estimated from data manually collected from the buses. The magnitudes of the relative differences between average flows estimated from the LiDAR and video data are, indeed, much smaller than the magnitudes of the relative differences between flows estimated from buses in different time-of-day periods and different academic terms.

Contrary to expectations, however, the magnitudes of relative differences between flows estimated from LiDAR and video data are similar to the magnitudes of the relative differences between flows estimated from data collected from buses serving different routes traversing the same segments during the same time-of-day period. Investigating this surprising result is left for future study. However, the differences appear to be attributable to errors in the algorithms that transform LiDAR data into vehicle identifications or to human errors in processing the video data, and not to a deficiency in the concept of using repeated data collected from a mobile platform with the modified moving observer method to estimate average time-of-day traffic flows. Future research is also warranted to understand the traffic and infrastructure conditions that would lead to better or worse estimates of traffic flows from a transit bus platform and to determine the number of bus passes required to provide sufficiently accurate estimates.

Despite the need for future research, promising results obtained in many of the empirical comparisons support the potential of obtaining accurate estimates of traffic flows from transit buses with spatial coverage of the urban area that is presently not available and to update these estimates with temporal frequency that is also presently not available. The present tendency of transit agencies to install cameras on their fleets for other purpose increases the motivation for operational development of this concept.

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Appendix A: Empirical Results for Data Sets Complementary to those Presented in Empirical Results Section

Table A1.1: Summary statistics of flow estimates determined from data manually collected from CLS buses Noon time-of-day period in Summer 2016 using 5th- and 50th-percentile dwell Times (DTs) to determine t_2 values when dwell times are subtracted from *raw* t_2

Seg. No.	N*	Flows (veh/hr) with 5th Percentile DT**					Flows (veh/hr) with 50th Percentile DT**				
		Mean	Median	S.D	Min	Max	Mean	Median	S.D	Min	Max
1	18	102	85	79	0	230	102	85	79	0	230
2	18	255	255	83	100	406	255	255	83	100	406
3	18	279	225	246	0	913	279	225	246	0	913
4	18	207	197	97	39	434	219	208	103	41	459
5	18	218	191	111	79	469	221	194	113	80	476
6	18	151	124	115	0	384	151	124	115	0	384
7	18	210	205	126	0	456	210	205	126	0	456
8	18	137	134	44	69	211	140	136	45	70	216
9	18	436	427	208	70	778	436	427	208	70	778
10	18	335	329	152	0	602	354	343	161	0	637
11	17	434	445	189	91	801	434	445	189	91	801
12	14	205	213	88	39	345	205	213	88	39	345
13	14	79	64	73	0	281	79	64	73	0	281
14	14	131	133	67	0	258	135	137	69	0	266
15	17	122	101	77	0	303	122	101	77	0	303
16	16	83	94	77	0	237	83	94	77	0	237
17	16	43	0	63	0	168	43	0	63	0	168
18	17	61	46	55	0	176	61	46	55	0	176
19	17	176	164	80	65	340	n/a***	n/a***	n/a***	n/a***	n/a***
20	17	149	128	71	60	296	149	128	71	60	296
21	13	97	73	106	0	341	102	79	110	0	357
22	13	63	0	79	0	223	63	0	79	0	223
23	13	150	139	134	0	460	150	139	134	0	460
24	14	159	145	47	105	277	159	145	47	105	277
25	18	251	227	133	0	469	251	227	133	0	469
26	18	180	175	53	79	256	182	178	54	80	260
27	18	129	128	81	0	280	136	134	85	0	293
28	18	188	193	141	0	497	188	193	141	0	497
29	18	199	199	98	77	452	201	200	99	77	457
30	Construction-related route alignment changes do not allow stable estimates										

* Number of individual flow values determined (one for each bus passage).

** In Summer 2016 data, to determine t_2 values for segments 4, 5, 8, 10, 12, 14, 19, 21, 26, and 27 dwell time values (either 50th- or 5th-percentile value) are subtracted from *raw* t_2 value.

*** Calculated values of t_2 on these segments were negative because dwell time value was greater than *raw* t_2 value.

Table A1.2: Summary statistics of flow estimates determined from data manually collected from CLN buses during Noon time-of-day period in Spring 2017 using 5th- and 50th-percentile dwell times (DTs) to determine t_2 values when dwell times are subtracted from *raw* t_2

Seg. No.	N*	Flows (veh/hr) using 5th Percentile DT**					Flows (veh/hr) using 50th Percentile DT**				
		Mean	Median	S.D.	Min	Max	Mean	Median	S.D.	Min	Max
1	35	42	39	31	0	103	42	39	31	0	103
2	35	313	258	163	87	728	313	258	163	87	728
3	35	237	243	183	0	682	237	243	183	0	682
4	35	307	283	128	68	717	345	310	146	77	818
5	35	260	244	105	81	486	265	248	107	84	497
6	35	296	265	168	94	787	296	265	168	94	787
7	35	193	157	94	30	421	219	180	107	33	494
8	35	314	247	358	0	1848	314	247	358	0	1848
9	35	93	82	85	0	345	93	82	85	0	345
10	35	159	143	79	40	389	185	168	93	47	450
11	35	141	142	75	32	434	141	142	75	32	434
12	35	110	99	62	15	251	176	164	100	22	442
13	35	131	128	43	54	259	129	127	42	53	253
14	35	220	194	142	0	534	220	194	142	0	534
15	35	100	79	115	0	707	112	88	129	0	799
16	35	222	169	216	0	767	222	169	216	0	767
17	35	104	92	63	0	363	109	96	67	0	382
18	35	130	86	108	0	491	130	86	108	0	491
19	35	201	195	102	57	558	205	199	104	59	573
20	35	298	271	150	44	755	298	271	150	44	755
21	35	249	234	147	0	791	262	245	156	0	849
22	35	394	382	231	26	1038	394	382	231	26	1038
23	35	353	343	158	73	872	379	369	175	80	963
24	35	222	159	183	0	781	222	159	183	0	781
25	35	147	140	86	0	338	147	140	86	0	338
26	35	224	238	72	19	328	230	244	74	20	339
27	35	253	235	84	145	512	272	252	91	158	561
28	35	260	184	195	0	759	260	184	195	0	759
29	35	206	213	133	0	547	212	220	137	0	562
30	35	145	127	115	20	486	145	127	115	20	486

* Number of individual flow values determined (one for each bus passage).

** In Spring 2017 data, to determine t_2 values for segments 4, 5, 7, 10, 12, 13,14, 15, 16 17, 18, 19, 21, 23, 26, 27, and 29 dwell time values (either 50th- or 5th-percentile value) are subtracted from *raw* t_2 value.

Table A1.3: Summary statistics of flow estimates determined from data manually collected from CLS buses during Summer 2016 by time-of-day period using 5th percentile dwell times (DTs) to determine t_2 value when dwell time is subtracted from *raw* t_2 value

Sg. No.	AM Flows (veh/hr)				Noon Flows (veh/hr)				PM Flows (veh/hr)			
	N*	Mean	Median	S.D	N*	Mean	Median	S.D	N*	Mean	Median	S.D
1	22	185	143	154	18	102	85	79	14	84	34	187
2	22	208	174	101	18	255	255	83	14	307	320	146
3	22	233	227	155	18	279	225	246	14	238	242	204
4	22	103	100	71	18	207	197	97	14	333	280	181
5	22	149	127	86	18	218	191	111	14	251	205	116
6	22	167	162	143	18	151	124	115	14	301	222	490
7	22	269	203	229	18	210	205	126	14	248	221	129
8	22	181	180	55	18	137	134	44	14	192	180	95
9	22	409	332	228	18	436	427	208	14	563	540	224
10	22	439	405	196	18	335	329	152	14	624	592	170
11	22	642	583	258	17	434	445	189	14	527	471	208
12	20	77	78	40	14	205	213	88	14	305	304	149
13	20	73	69	72	14	79	64	73	14	205	213	111
14	20	121	115	53	14	131	133	67	14	201	207	67
15	22	77	52	80	17	122	101	77	14	143	146	57
16	22	91	66	108	16	83	94	77	14	18	0	47
17	22	40	0	55	16	43	0	63	14	0	0	0
18	22	42	27	40	17	61	46	55	14	17	16	15
19	22	54	44	33	17	176	164	80	14	194	211	99
20	22	104	96	55	17	149	128	71	13	111	99	73
21	18	44	33	47	13	97	73	106	13	45	48	39
22	18	110	101	138	13	63	0	79	14	62	0	94
23	18	179	119	182	13	150	139	134	14	95	55	116
24	18	134	141	41	14	159	145	47	14	144	148	58
25	22	359	383	186	18	251	227	133	14	319	307	186
26	22	298	318	106	18	180	175	53	14	222	183	145
27	22	341	378	120	18	129	128	81	14	132	112	108
28	22	193	193	145	18	188	193	141	14	211	205	194
29	22	262	248	114	18	199	199	98	14	186	189	69
30	Construction-related route alignment changes do not allow stable estimates											

* N: Number of individual flow values determined (one for each bus passage).

Appendix B: Video data across individuals

Table B.1: Vehicle counts on segments and times t_1 (in seconds) for vehicle to traverse segments from processed video data for different individuals; data obtained from van platform in Summer 2016

			Segments																			
			Trip 1										Trip 2									
No.	Var.	Proc.	2	3	4	5	6	25	26	27	28	29	2	3	4	5	6	25	26	27	28	29
1	Veh Ct	A,B,C	6	1	0	3	0	8	5	8	1	10	4	1	0	1	5	2	12	1	0	11
		A	5	1	0	2	0	7	7	6	1	11	3	0	0	1	7	1	11	1	1	10
	Time	A,B,C	28	21	16	50	21	17	41	39	16	25	31	37	23	59	22	31	41	25	27	53
		A	27	24	16	51	18	17	42	37	18	36	31	37	39	43	24	30	39	26	28	51
2	Veh Ct	B	10	3	1	7	1	4	5	2	2	4	10	1	1	5	14	6	9	2	1	9
		C	8	4	1	8	1	4	6	3	2	5	7	2	2	6	14	7	9	2	1	8
	Time	B	30	14	13	44	19	11	51	5	42	28	61	12	12	35	27	38	43	12	12	48
		C	29	11	13	44	19	20	44	15	15	46	38	35	13	42	17	30	44	13	10	47
3	Veh Ct	B	4	2	5	0	1	6	4	15	0	12	2	1	1	2	1	4	10	1	0	11
		A	4	2	6	0	1	5	4	16	0	10	3	2	2	2	1	4	11	1	0	11
	Time	B	30	47	24	39	17	22	40	59	14	34	59	13	13	39	18	19	54	14	16	32
		A	29	46	25	40	17	14	40	59	14	33	59	12	13	39	19	19	55	15	16	29
4	Veh Ct	C	7	2	2	5	2	7	8	1	1	2	4	1	5	6	2	5	4	4	4	9
		B	9	2	2	5	1	7	6	2	2	2	11	1	2	7	2	5	4	5	2	10
	Time	C	48	34	13	52	25	18	46	16	12	29	61	20	25	42	19	20	48	17	32	11
		B	49	36	18	48	19	20	43	17	11	26	33	27	13	43	17	19	46	36	13	99
5	Veh Ct	A	6	2	1	8	1	1	7	5	2	6	2	1	3	4	4	3	8	1	2	9
		B	7	2	1	11	1	1	6	6	2	9	3	0	3	3	5	3	8	1	2	9
	Time	A	58	29	18	50	23	28	42	32	11	32	28	31	17	40	18	24	43	15	10	69
		B	58	29	17	42	31	28	42	33	12	31	32	28	17	39	19	23	44	14	12	70
6	Veh Ct	C	1	4	4	3	2	10	3	7	11	17	4	4	0	4	3	4	16	1	8	0
		B	6	0	3	4	2	8	3	11	2	17	8	1	0	4	2	4	14	6	2	5
	Time	C	29	44	17	41	20	19	38	25	39	43	31	49	19	41	18	25	55	25	36	31
		B	60	14	14	45	19	19	44	44	14	44	71	20	17	40	18	39	40	42	12	87
7	Veh Ct	C	2	6	2	4	4	10	4	8	8	10	5	0	3	1	0	7	10	2	6	2
		B	6	4	1	1	2	8	5	8	4	10	4	0	3	2	0	7	9	5	5	3
	Time	C	31	93	15	43	16	17	41	19	30	50	29	5	21	37	16	26	67	19	26	31
		B	62	59	19	42	16	16	42	31	33	36	29	12	12	36	16	44	42	33	13	32
8	Veh Ct	B	13	2	1	4	6	4	4	1	1	5	2	2	9	10	3	5	7	3	0	9
		C	8	7	2	4	5	5	4	1	2	3	1	2	9	8	4	5	7	3	1	11
	Time	B	60	32	14	43	21	15	44	15	16	38	29	22	32	44	17	45	41	16	28	60
		C	93	47	24	42	21	18	44	13	15	35	29	21	34	43	18	43	46	13	8	78
9	Veh Ct	B	2	0	4	5	2	2	8	3	3	5	5	1	5	3	3	2	4	0	1	4
		A	2	0	4	5	1	2	7	3	2	4	4	1	5	3	3	2	4	0	2	3
	Time	B	40	12	7	56	17	22	41	30	39	67	27	12	12	46	14	17	38	18	11	75
		A	28	11	19	46	16	16	47	30	39	65	28	10	14	45	21	17	39	15	13	71
10	Veh Ct	B	11	1	1	2	2	6	2	3	1	4	3	3	0	7	2	1	8	3	1	1
		C	11	0	1	2	3	5	3	2	2	7	4	4	2	5	2	1	13	2	1	1
	Time	B	32	27	13	44	17	38	42	15	17	58	32	38	13	42	17	44	40	15	21	31
		C	28	21	21	46	16	33	43	9	29	26	26	18	38	42	18	11	70	13	16	40
11	Veh Ct	B	4	5	0	2	2	4	6	4	2	6	8	0	2	4	3	0	8	2	0	5