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Automated Turning Movement Counts for Shared Lanes Using Existing Vehicle Detection Infrastructure

Final Report for
NCHRP IDEA Project 177

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Automated Turning Movement Counts for Shared Lanes Using Existing Vehicle Detection Infrastructure

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EXECUTIVE SUMMARY

Turning movement count data; that is, vehicle volumes broken down by movement, approach, and time period, are the foundation of signal performance evaluations and a crucial component of data-driven decision-making processes used by transportation agencies. Unfortunately, the availability of quality turning movement count data is arguably not the norm for agencies. In fact, the 2012 National Traffic Signal Report Card conducted by the National Transportation Operations Coalition identified traffic monitoring and data collection practices in the United States as weak by giving the practices an "F" grade. To this day, some of the current practices rely on manual procedures that limit the amount of data available. Automated methods can be temporarily installed at an intersection, but these are intended to improve on the traditional manual counts used and not to produce continuous count volumes. Permanent counting systems are unable to classify vehicles into their corresponding movements on shared lanes unless supplemental infrastructure is installed or additional count zones are defined.

As part of this NCHRP IDEA Stage 1 project the research team has shown that an algorithm that produces turning movement counts reports using vehicle trajectory data extracted from existing vehicle detection infrastructure can be created. The algorithm developed in this NCHRP IDEA project differs from existing approaches in that it does not rely on count zones on exit approaches or the use of time stamps of detection calls. As a proof of concept, the algorithm has shown significant promise in terms of performance at typical intersections. While changes to the algorithm are needed, results obtained are encouraging and can be used by those familiar with data analysis and collection techniques.

Innovation

Innovation as part of this project can be classified in two different areas. First, showing that exploiting the capabilities of existing infrastructure is possible and, second, developing an analysis procedure for vehicle trajectory data. The capability of existing devices was shown by extracting vehicle trajectory data from an existing, commercially available, radar-based vehicle detection system that was already installed at a signalized intersection as a replacement for inductive loops. Vehicle trajectory data extraction was possible through a custom software program that taps into the underlying data stream of the radar-based vehicle detection system without interfering with the primary function of vehicle detection. The trajectory data were then analyzed using an algorithm implemented in the R programming language to classify the vehicle movements into left, thru, and right. The combined data collection and analysis approach is built on top of open source technology, is independent of the controller type, and could be deployed in numerous hardware platforms, thus eliminating the need for proprietary solutions or significant capital investments that often are part of projects focused on monitoring performance measures.

Results

Performance obtained can be considered better than that of some of existing technologies and can be measured in two different areas. First, at intersections with simple geometry such as the main site used for data collection (three lanes per approach, no channelization, and a homogeneous stop bar location across all lanes of each approach). At the aforementioned type of intersection, performance of the algorithm was measured at the count period and movement level. A count period was defined as a 15-minute interval for a specific vehicle movement. Vehicle volumes by count period produced by the algorithm were compared with volumes from a manual count obtained from video of the intersection. Turning movement count volumes produced by the algorithm had an average error of -0.26 vehicles per 15-minute count period when compared with manual counts and an average absolute error of 2.31 vehicles.

The performance of the algorithm was evaluated at what could be considered a non-typical intersection (five lanes per approach, one bike lane, and a non-uniform stop bar position on each lane). The mechanics of the algorithm performed as expected. However, the nature of the intersection in terms of geometry and traffic resulted in a lower than expected algorithm performance, especially for the left-turn movement located the farthest away from the radar-based vehicle detection system. In the case of the left turn, accuracy dropped to less than 50%, due to occlusion. A review of the scenarios under which significant accuracy reductions by count period were experienced reveals the impact that non-typical intersections have on the performance of radar detection systems and consequently on the algorithm. Therefore, the need to improve it further in order to handle special circumstances related to geometry and traffic characteristics is highlighted.

As discussed, performance reported for the algorithm is measured not only every 15 minutes but also by individual movement. Therefore, the approach used by the team to report performance is one that goes beyond the standard practice of vehicle detection systems manufacturers in which performance is reported once a certain volume threshold is met and for entire approaches. This reporting approach was selected because it allows us to look at errors at a more detailed level and identify areas for future improvement.

Future Work

In order to successfully commercialize this innovation, the algorithm needs to be improved, a prototype data collection device developed that can be installed inside a signal cabinet, and a centralized software tool devised to manage multiple data collection devices. Although the results from the project are encouraging, algorithm improvements are needed in order to have a market-ready solution. Future work in terms of algorithm improvement should focus on making the algorithm capable of handling the following scenarios:

- Different intersection configurations; the algorithm developed as part of the project provides satisfactory performance on what could be considered a textbook intersection. For example, no testing has been done on intersections with channelized lanes and testing is required at intersections with a non-uniform stop bar location.

- Intersections with significant presence of heavy vehicles. Results from the second supplemental site show the need for further development in order to improve movement detection as a result of occlusion effects.

- Intersections with two detection devices per approach. For intersections with 5+ lanes per approach more than one radar device is desirable and will require changes to the algorithm in order to properly merge and analyze multiple data sources.

Modifications will require data collection across different locations in the country in order to obtain vehicle trajectory datasets from a wide array of geometric and traffic conditions. These modifications will in turn require further analysis and performance evaluations as part of an iterative development process. In terms of data collection, the system should be tested on a smaller hardware platform such as a development board and configured for an environment in which the data analysis algorithm and data collection system are on separate locations.

INTRODUCTION

Turning movement count data; that is, vehicle volumes broken down by movement, approach, and time period, are the foundation of signal performance evaluations and a crucial component of data-driven decision-making processes used by transportation agencies. Unfortunately, the availability of quality turning movement count data is arguably not the norm for agencies. The 2012 National Traffic Signal Report Card conducted by the National Transportation Operations Coalition identified traffic monitoring and data collection practices in the U.S. as weak by giving the practices an “F” grade. To this day, some of the currents methods used to collect turning movement count data are still based on manual procedures which limit the amount of data available. Automated methods can be temporarily installed by an intersection, but these are intended to improve on the traditional manual counts used and not to produce continuous count volumes.

And while existing vehicle detection systems (e.g., optical, thermal, and radar) can provide counts on a per-lane basis, breaking down the volume by movement type for lanes with more than one movement (shared lanes) is not a built-in feature of commercially available vehicle detection systems. The limitation of existing systems has not stopped researchers from collecting available data from vehicle detection systems and expanding its usability. As will be shown in the literature review section, data obtained from additional virtual and physical (inductive loop) detection zones on exit lanes has been used to estimate turning movement count volumes regardless of the lane configurations by analyzing the time stamp of detection zone actuations. Other attempts include estimation through statistical procedures that rely on main lane volumes. However, the aforementioned data analysis approaches can be fraught with errors and cannot be used at all locations, such as those that allow right turns on red. Furthermore, among the requirements for a valid location include a controller capable of logging high-resolution data, similar call monitoring functionality, or supplemental hardware. With the more prominent deployment of radar-based vehicle detection systems there is an opportunity to re-invent the way in which turning movement counts can be obtained from existing vehicle detection systems.

Radar-based vehicle detection systems continuously monitor vehicle trajectories. If a vehicle is within the range of the radar and is traveling toward the radar, the system will constantly keep track of the vehicle position, speed and length estimate. If the trajectory of each vehicle is known then each vehicle can be classified as going thru, left, or right and assigned to a specific time period. The objective of this report is to document a proof of concept that demonstrates how vehicle trajectory data produced by an existing radar-based vehicle detection system can be used for producing automated turning movement count reports. The concept presented eliminates the need for supplemental detection zones, a cornerstone of existing research. Furthermore, the concept presented does not rely on high-resolution data extracted from the traffic signal controller, thus making the approach a platform-independent one compatible with legacy controller systems such as the TS1 platform.

Vehicle trajectory data from a radar-based vehicle detection system was logged at three intersections using custom software developed by the team. An algorithm was created in the R programming language to analyze the trajectory data and produce vehicle turning movement counts in 15-minute intervals. The algorithm does not require the user to define detection zones or specify the intersection geometry. The proof-of-concept results are promising and demonstrate that a product developed based on this algorithm can eliminate the need for manual counts (or automated counts that rely on temporary hardware installations) at intersections with radar-based vehicle detection or any other detection system capable of monitoring vehicle trajectories.

LITERATURE REVIEW

Detailed turning movement count information from an intersection is key to understanding the performance of any signalized intersection. The required data, even with the technological advances available today, are too often not available to end users such as transportation engineers and planners that rely on the data to retime intersections, plan developments, and prioritize the installation of safety countermeasures. The limited availability of crucial volume data is well-known in the transportation community. In fact, the 2012 National Traffic Signal Report Card published by the National Transportation Operations Coalition identified traffic monitoring and data collection practices in the United States as the Achilles heel by giving it an “F” grade (NTOC 2012). The report highlights that even when data are available there are few quality checks performed that can lead to signals that operate without considering actual traffic conditions, therefore causing delays for roadway users. A review of the report suggests that a data collection system with a properly documented and auditable quality assurance process is one of the components key to supporting the needs of the transportation network such as the crucial retiming of signals.

The Need for Signal Retiming

Enabling signal retiming is the most direct application of detailed turning movement counts. Improper traffic signal timing is responsible for 5%–10% of traffic delay on major U.S. roadways (Chin et al. 2004). In fact, 75% of approximately 300,000 traffic signals in the United States could be improved through equipment updates and signal retiming. Retiming of traffic signals is one of the most cost-effective measures of improving traffic flow in urbanized areas (ITE 2015). Examples of signal timing benefits include decreased travel time by 13% and an average delay reduction of 23% in Anchorage, Alaska, after implementation of an inclement weather signal timing plan (Bernardin Lochmueller and Associates 1995). Similarly, in Minnesota a study revealed a 13% reduction in average delay along with a 6% reduction in average number of stops per vehicle (Maki 1999). In general, signal retiming can result in a benefit-cost ratio of 40:1 (Sunkari 2004). Consensus exists about the need to retime signals frequently and that different timing plans should be used to account for seasonal factors, weather conditions, and special events. However, maintaining optimized signal timing is a challenge for agencies because it requires turning movement volumes that are one of the most costly items in retiming signals (Robertson and Hummer 1994).

Although signal retiming is a key process that requires detailed turning movement count data, a review of commercially available vehicle detection systems manufactured by Autoscope, Iteris, FLIR, Peak, MsSedco, Wavetronix, and LeddarTech shows that for shared lanes their systems do not provide a vehicle volume by movement type breakdown. Based on the nature of existing systems it is not a surprise that researchers have been trying to find a solution to the problem. Existing approaches focus on the estimation of turning movement counts based on loop detector calls or from the use of virtual calls from video- or radar-based vehicle detection systems. The estimation approach is discussed ahead followed by a discussion of how data radar-based vehicle detection devices have been used in the past.

Approaches Relying on Video and Traditional Loop Detection

Attempts to automatically break down vehicle volume by movement type started more than three decades ago by the use of volume balancing (Hauer et al. 1981; Virkler and Kumar 1998) and continues to this day (Tian et al. 2004; Hu and Liou 2012). Most of the early attempts, along with some recent ones, focused on the estimation of counts from existing datasets instead of obtaining direct counts. Estimation attempts focus primarily on analyzing detection calls at the stop bar of the intersection along with detection calls on zones placed in exit lanes.

A problem with procedures that require the monitoring of calls on exit lanes is that the installation of loops to monitor vehicles on the exit lanes results in additional expenses. Additional expenses are not a problem when the procedure relies on the use of virtual loops defined using non-loop-based vehicle detection systems (Tian et al. 2004; Hu and Liou 2012; Kun et al. 2013). However, when virtual loops are used at intersections monitored by alternative detection the definition of the virtual count zones is not always possible. Situations that can make it impossible to define virtual loops on exit approaches include optical systems that need to be zoomed into a particular area of the primary approach, thus making the exit lanes invisible to the system.

Furthermore, the use of virtual loops makes the estimation methodology vulnerable to false and missed calls produced by the vehicle detection system (Tian et al. 2004). When the aforementioned limitation is combined with the possibility of right turns on red the limitations of methodologies that rely on monitoring exit lanes are clear. Limitations in the setup, along with uncertainty in the measurements, force the use of advanced statistical procedures to produce acceptable results such as the estimation of turning movement proportion through genetic algorithms (Jiao et al. 2005).

Potential of Data from Radar-Based Vehicle Detection Systems

Radar-based vehicle trajectory data from an intersection have been used in the past to push the boundaries of operational and safety evaluations at signalized intersections. Using the speed, position, and time stamp of vehicles logged from radar devices at a rate of 2 Hz, vehicle trajectories have been used to obtain direct stopped delay measurements at signalized intersections. The direct delay measurements show how vehicle trajectories can be used to replace delay estimates from analytical procedures (Santiago-Chaparro et al. 2012b). Existing work relies on custom software designed to monitor the underlying data stream produced by a radar-based vehicle detection system that goes unused once the purpose of detecting the presence of a vehicle over a virtual loop is fulfilled.

Vehicle trajectory data from radar-based devices has also been used to detect red light running at intersections by combining trajectories and signal status (Santiago et al. 2014), thus showing the application of vehicle trajectory for safety evaluations. More recently, the same type of trajectory data has been used to estimate vehicle emissions at intersections, thus showing applications beyond the realm of operations and safety (Zhixia et al. 2015). As shown, trajectory data obtained from radar-based vehicle detection provides researchers with a powerful and rich dataset that can be used for numerous applications. Since vehicle trajectory data show the actual path followed by vehicles on an intersection, a natural extension of existing work is to classify vehicles using an intersection approach into their corresponding movement.

DATA COLLECTION

Three data collection sites were used to develop and test performance of the classification and noise removal algorithms developed in this project. The main site from which data were extracted to guide the development of the algorithm presented in this report was the intersection of Wisconsin Avenue and Mead Street (Appleton, Wisconsin). The second location, used to test the performance of the algorithm, was the intersection of Wisconsin Avenue and Oneida Street (Appleton). Finally, a third intersection, Fish Hatchery Road and Greenway Cross (Madison, Wisconsin) was also used to test the algorithm performance. The details of the cabinet instrumentation used to log vehicle trajectories along with the characteristics of data obtained at the main site (Wisconsin and Mead intersection in Appleton) are discussed in the next section. The same procedures were used in the second and third data collection sites.

Main Data Collection Site

A top view of the main data collection site, Wisconsin Avenue and Mead Street, is shown in Figure 1. The intersection is four-legged with three lanes (one exclusive left and thru lane each and a shared right thru lane) on each approach. The estimated average daily vehicle volume of the intersection is 21,550. Each approach of the intersection is monitored by an Intersector system, a commercially available, radar-based (microwave technology) vehicle detection system manufactured by MsSedco.

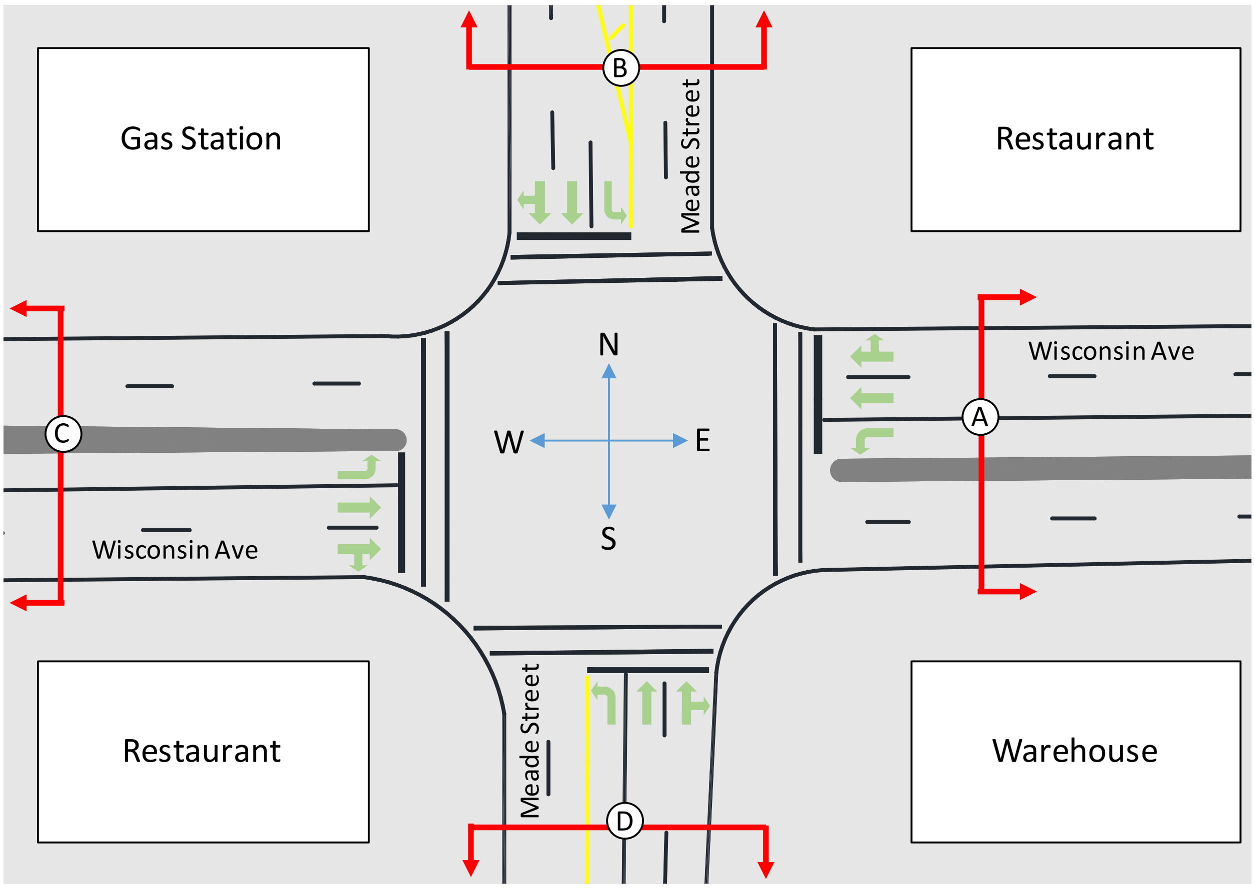


Figure 1. Schematic of data collection site.

Cross-sectional photos for each of the approaches of the intersection are shown in Figure 2. The main data collection site has business activity adjacent to the intersection. Due to the characteristics and range of the vehicle detection system vehicle activity in those adjacent businesses is often detected by the system. Pedestrians are also often detected by the radar. The non-intersection vehicle activity and pedestrian detection results in undesired noise from the device that needs to be accounted for during the data analysis process.

Figure 2. Photos of main data collection site (Wisconsin Avenue and Meade Street).

Instrumentation

In order to log vehicle trajectory data for all the four approaches, a laptop computer running custom data collection software was placed inside the signal cabinet. The software used for logging vehicle trajectory data from the radar devices relies on the technology previously developed by the authors (Santiago-Chaparro et al. 2012b). The data collection software monitors the underlying data stream of the radars without interfering with the main function of the vehicle detection system; that is, detecting vehicle presence over virtual detectors.

The data collection software was written in Python 3 and stored the underlying data stream into a SQLite database that was later converted to a MySQL database. Monitoring of the underlying radar data stream is possible because the radar devices expose their dataset via a web server accessible through the IP address assigned to each radar device. Network communication between the laptop computer running the data collection software and the radar devices is possible because the radars and the laptop computer are both connected to the same network via an Ethernet switch placed inside the signal cabinet. The connections between the switch, computer, and radar devices were made in accordance with the guidance provided in the radar device installation manual (MsSedco 2015) as shown in Figure 3.

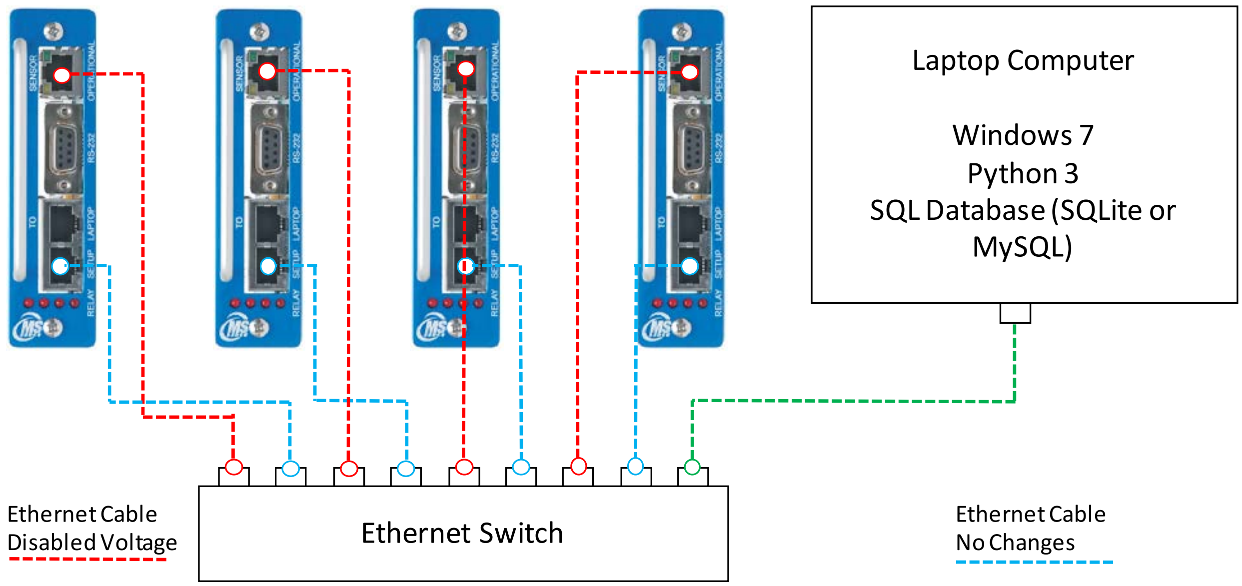


Figure 3. Connections made between switch, radars, and laptop computer.

Figure 4 shows the details of the instrumentation inside the signal cabinet. A solid state drive was used in the computer configuration to avoid any potential issues resulting from below freezing temperatures. No issues were experienced with the operation of the computer during the December 2014 to February 2015 period when the lowest monthly temperatures recorded in Appleton, Wisconsin, ranged from -19°C (-2°F) to -27°C (-16°F) (Weather Underground 2015). There was an instance in April 2015 when the computer turned off automatically because of overheating concerns; the situation will be discussed in the considerations section.

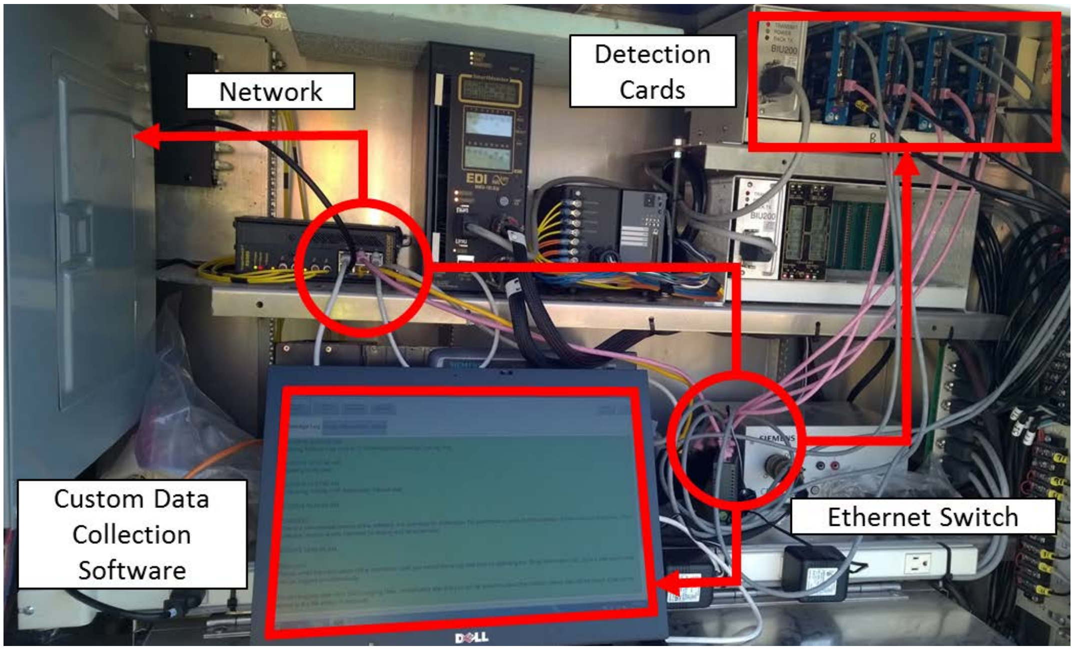


Figure 4. Cabinet instrumentation on main data collection site.

Trajectory Data

Figure 5 shows a visualization of the vehicle trajectory information (data points) that are obtained every 500 milliseconds using the cabinet instrumentation. Each of the dots in Figure 5 represents the position of a vehicle at an instance of time as detected by the radar devices. It should be noted that the image was transformed to make every approach align with the actual position on the intersection through rotations and position shits along the X and Y axes. Each data point is associated with a unique vehicle identifier, position, speed, and vehicle length estimate. Vehicle position is logged as Cartesian coordinates; that is, a pair of X and Y coordinates.

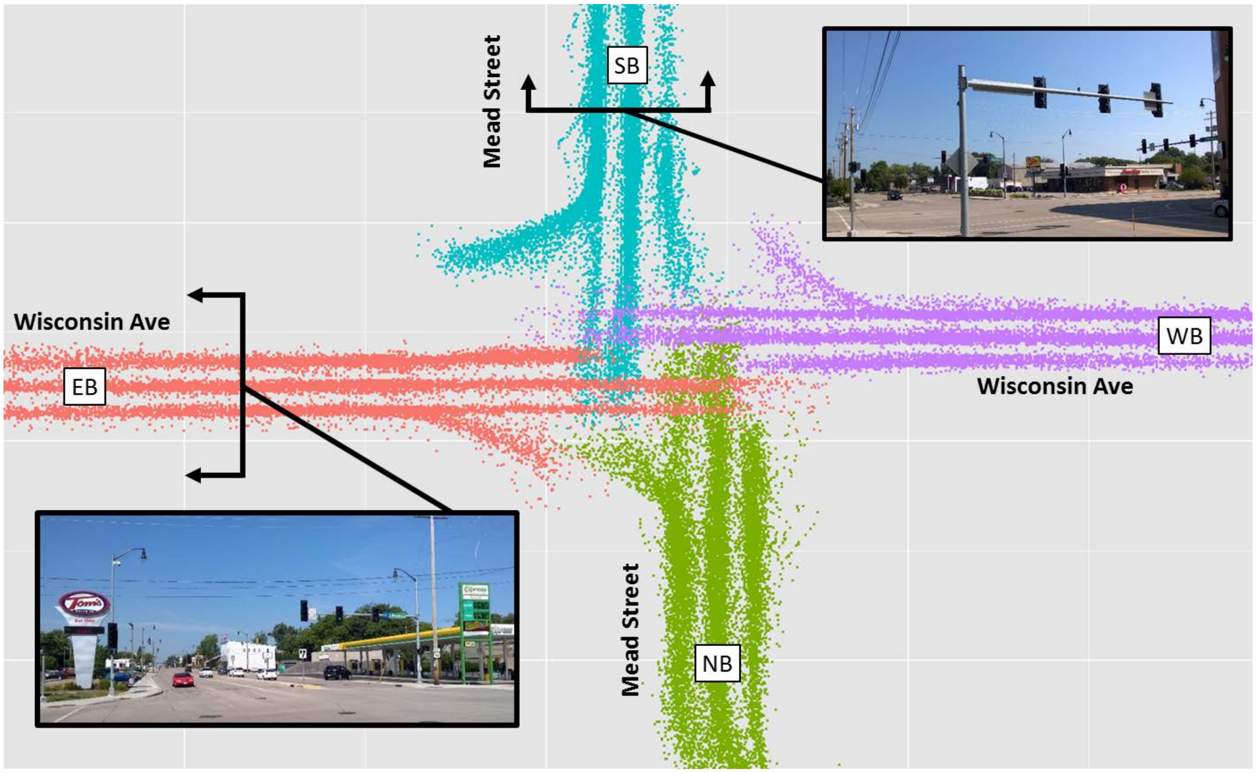
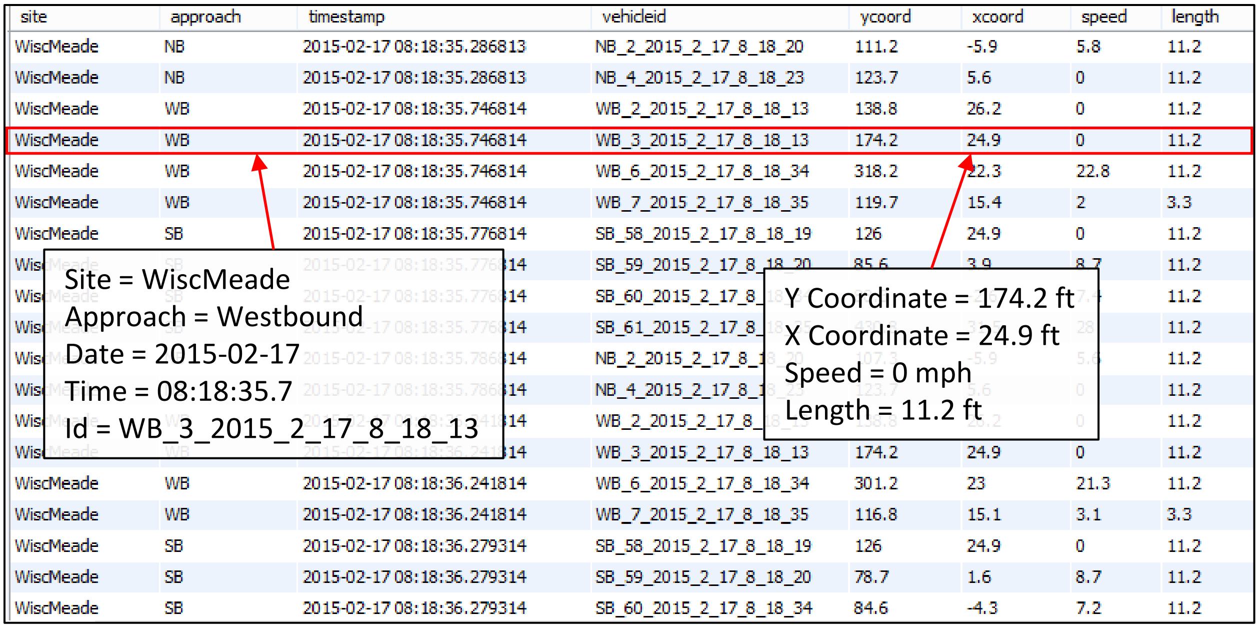


Figure 5. Visualization of data obtained using cabinet instrumentation.

All the data included in the visualization is stored in a MySQL server running on the laptop computer. As a result of the MySQL server the trajectory data are available from any other computer that is connected to the same network as the switch. Figure 6 shows a screenshot of the structure of the data included in the MySQL server. As the figure shows, all information associated with each data point is included in a table format that enables the data to be queried by approach, time period, and speed, among others. The data shown in Figure 6 is used by the algorithm developed in this research to generate the turning movement count reports.



site	approach	timestamp	vehicleid	ycoord	xcoord	speed	length
WiscMeade	NB	2015-02-17 08:18:35.286813	NB_2_2015_2_17_8_18_20	111.2	-5.9	5.8	11.2
WiscMeade	NB	2015-02-17 08:18:35.286813	NB_4_2015_2_17_8_18_23	123.7	5.6	0	11.2
WiscMeade	WB	2015-02-17 08:18:35.746814	WB_2_2015_2_17_8_18_13	138.8	26.2	0	11.2
WiscMeade	WB	2015-02-17 08:18:35.746814	WB_3_2015_2_17_8_18_13	174.2	24.9	0	11.2
WiscMeade	WB	2015-02-17 08:18:35.746814	WB_6_2015_2_17_8_18_34	318.2	22.3	22.8	11.2
WiscMeade	WB	2015-02-17 08:18:35.746814	WB_7_2015_2_17_8_18_35	119.7	15.4	2	3.3
WiscMeade	SB	2015-02-17 08:18:35.776814	SB_58_2015_2_17_8_18_19	126	24.9	0	11.2
WiscMeade	SB	2015-02-17 08:18:35.776814	SB_59_2015_2_17_8_18_20	85.6	3.9	8.7	11.2
WiscMeade	SB	2015-02-17 08:18:35.776814	SB_60_2015_2_17_8_18_[illegible]	[illegible]	[illegible]	7.4	11.2
WiscMeade	SB	2015-02-17 08:18:35.776814	SB_61_2015_2_17_8_18_25	[illegible]	[illegible]	28	11.2
WiscMeade	NB	2015-02-17 08:18:35.786814	NB_2_2015_2_17_8_18_20	107.3	-5.9	5.6	11.2
WiscMeade	NB	2015-02-17 08:18:35.786814	NB_4_2015_2_17_8_18_23	123.7	5.6	0	11.2
WiscMeade	WB	2015-02-17 08:18:36.241814	WB_2_2015_2_17_8_18_13	138.8	26.2	0	11.2
WiscMeade	WB	2015-02-17 08:18:36.241814	WB_3_2015_2_17_8_18_13	174.2	24.9	0	11.2
WiscMeade	WB	2015-02-17 08:18:36.241814	WB_6_2015_2_17_8_18_34	301.2	23	21.3	11.2
WiscMeade	WB	2015-02-17 08:18:36.241814	WB_7_2015_2_17_8_18_35	116.8	15.1	3.1	3.3
WiscMeade	SB	2015-02-17 08:18:36.279314	SB_58_2015_2_17_8_18_19	126	24.9	0	11.2
WiscMeade	SB	2015-02-17 08:18:36.279314	SB_59_2015_2_17_8_18_20	78.7	1.6	8.7	11.2
WiscMeade	SB	2015-02-17 08:18:36.279314	SB_60_2015_2_17_8_18_34	84.6	-4.3	7.2	11.2

Figure 6. Sample dataset included in the MySQL server database.

Supplemental Data Collection Sites

The instrumentation and data collection procedures discussed in the previous sections were implemented at two supplemental intersections. The first intersection, Wisconsin Avenue and Oneida Street, is located in Appleton, Wisconsin. The second intersection, Fish Hatchery Road and Greenway Crossing, is located in Madison, Wisconsin. The purpose of collecting data from the two supplemental sites is not for the development of the algorithm but for evaluating the performance. As the reader will see, the algorithm development is based on global concepts about the behavior of traffic on an intersection approach and not on characteristics of individual intersections. Therefore, data collected for the main site were sufficient for algorithm development and performance evaluation. The purpose of the two supplemental sites was to ensure that the algorithm performed adequately under different geometric conditions.

The first supplemental intersection contains a mix of shared lanes and dedicated lanes. On two of the approaches, northbound and southbound, left, thru, and right turning vehicles have a dedicated lane each. On the eastbound and westbound approaches there are three lanes for traffic. Of the three lanes, one is an exclusive left-turn lane, one is an exclusive thru lane, and one is a shared thru-right lane. Figure 7 shows a photograph of the Wisconsin Avenue and Oneida Street intersection. Each of the approaches of the intersection is monitored by a radar device.

The second supplemental site, Fish Hatchery Road and Greenway Cross, in Madison, is a much larger intersection (based on the number of lanes) than the main data collection site as well as the first supplemental site (Figure 8). The southbound approach of the intersection contains five dedicated movement lanes, one for the right turn, two for the thru movement, and two for left turns, as well a dedicated bicycle lane. On the northbound approach there are four lanes, one dedicated for left turns, two dedicated for the thru movement, and one shared lane for right and thru vehicles. The eastbound approach contains two shared lanes, one left-thru, and one thru-right. The westbound approach contains one exclusive left-turn lane, one dedicated thru, and a right-turn channelized lane. However, due to the configuration of the vehicle detection equipment, trajectory data were obtained only for the southbound approach of the intersection.

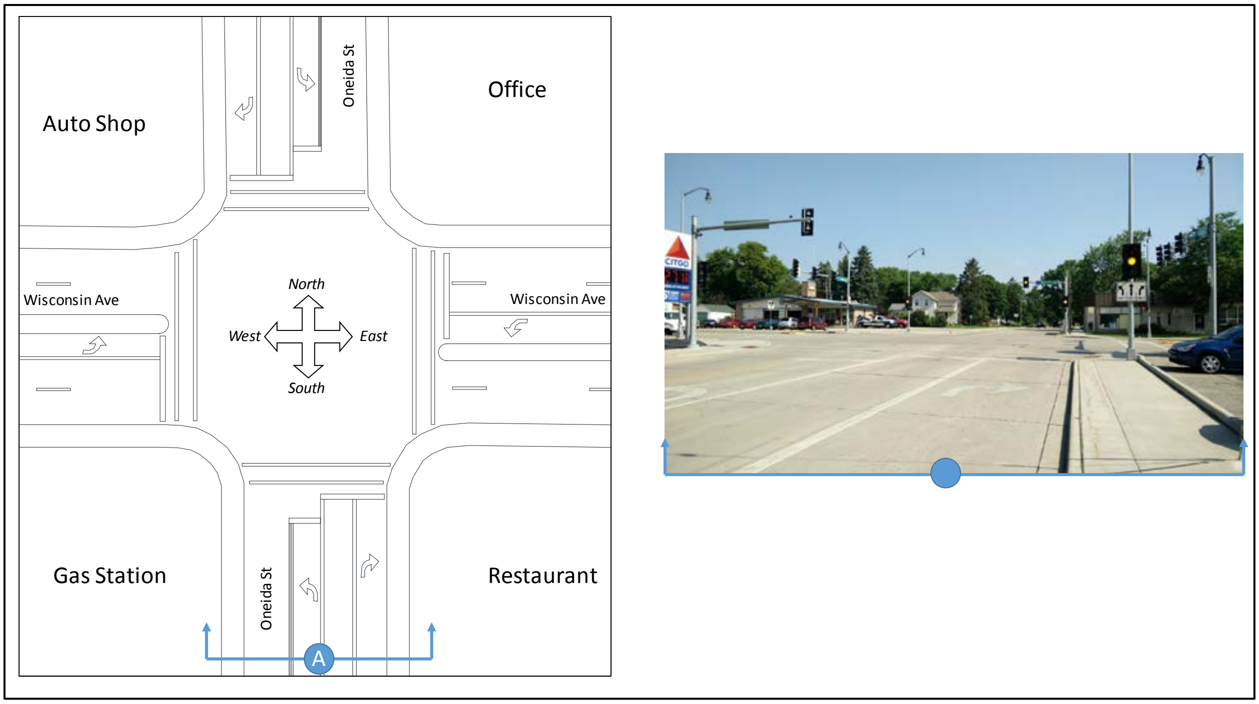


Figure 7. Wisconsin Avenue and Oneida Street (Supplemental Site 1).

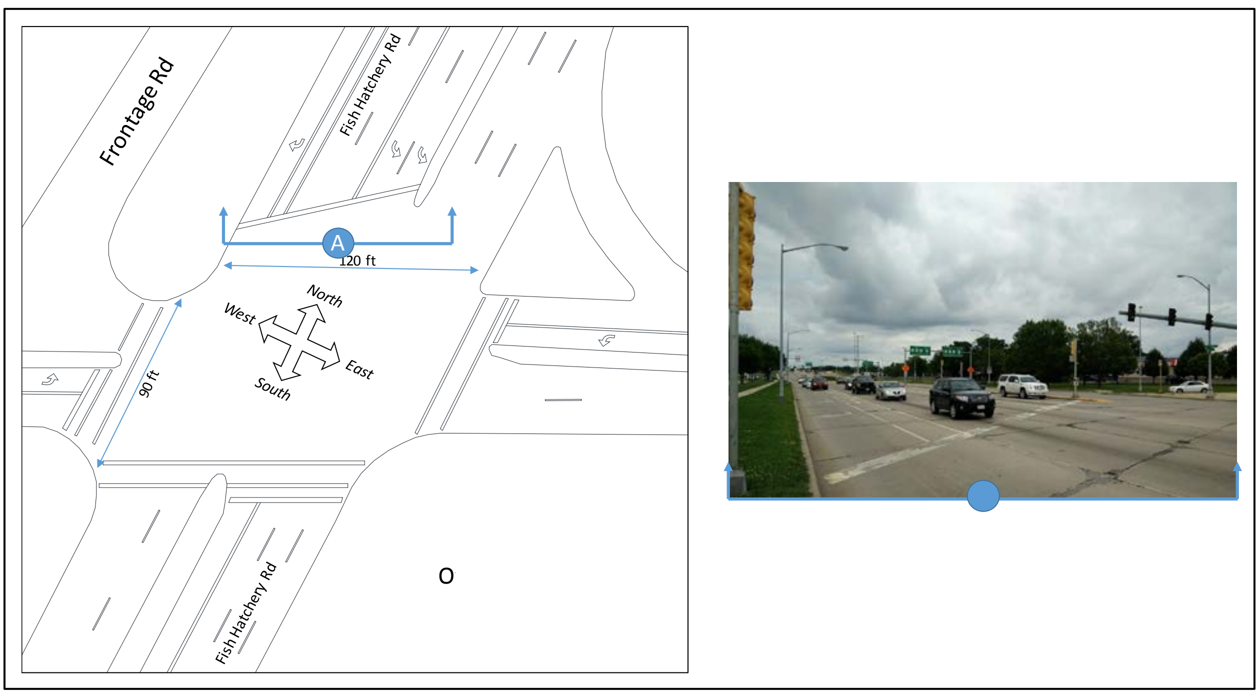


Figure 8. Fish Hatchery Road and Greenway Cross (Supplemental Site 2).

Video Recordings and Manual Vehicle Counts

Manual counts were conducted at each of the sites to compare the results of the algorithm. Manual counts were obtained from video recordings using a computer program to help streamline the count process. Figure 9 shows the computer program displaying video of the main data collection site, Wisconsin Avenue and Meade Street. A user counts vehicles by clicking on a button on the screen corresponding to the vehicle movement or through a series of shortcut keys on the keyboard. Every time that a vehicle movement is logged by the user a correct time stamp, based on the date and time of the video recording, is assigned to the observation. The data are post-processed to obtain counts aggregated over 15-minute intervals.

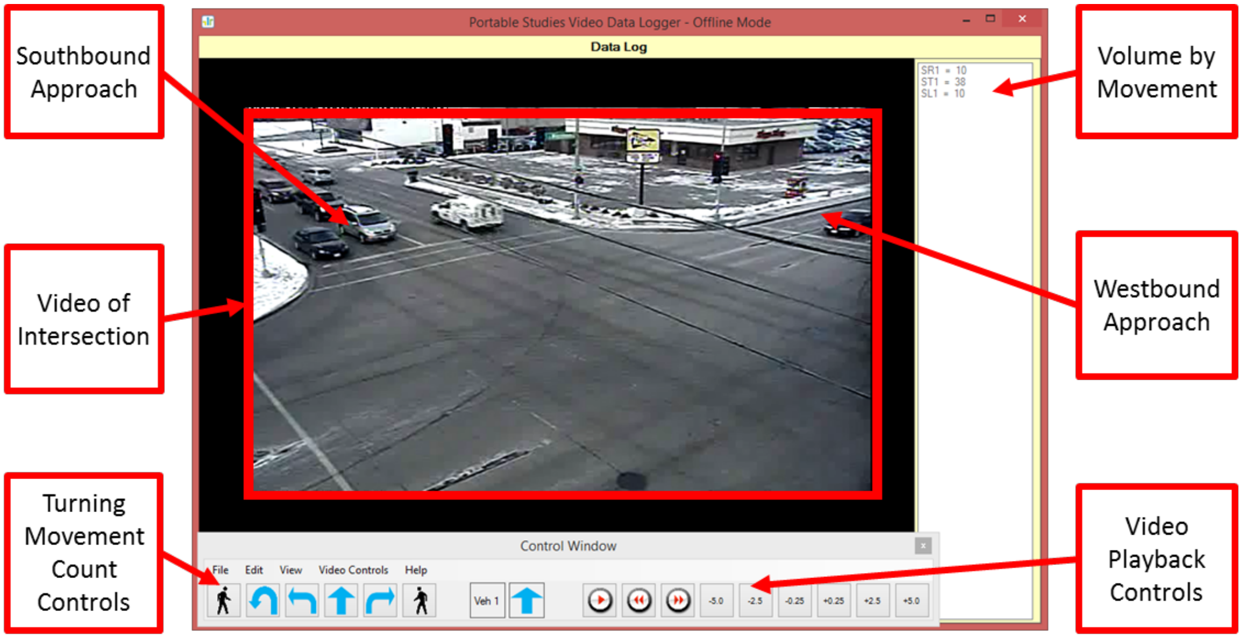


Figure 9. Software used to streamline the manual count process from video.

Using the software results in better quality of counts obtained from video than that from live manual counts conducted in the field. For example, the user of the program can slow down or speed up the video to make the count process more efficient based on traffic conditions. Furthermore, the user can also pause the count to avoid fatigue. The sources of video used for each of the data collection sites depend on what equipment was available at the intersection. At the Wisconsin Avenue and Meade Street intersection, video was obtained from a PTZ camera mounted on one of the intersection poles. At the supplemental data collection sites video was obtained from a video camera temporarily attached to a sign pole next to the intersection by the research team as shown in Figure 10.

The position of the cameras (PTZ and handheld) limit the approaches from which manual counts can be obtained and thus the movements that can be included to evaluate the performance of the algorithm. The section ahead details the manual count data periods available by approach and movement along with the characteristics of the raw data obtained using the cabinet instrumentation.

Figure 10. Camera mount used for video recording at supplemental data collection sites.

DATASET CHARACTERISTICS

Using the data collection procedures discussed in the previous section, vehicle trajectory data were obtained from the three data collection sites. The trajectory data collected played two important roles. First, to understand the nature of trajectory data in order to develop the algorithm for detecting vehicle movements regardless of lane configuration. Second, as a data source to verify the performance of the algorithm. A discussion of the characteristics of trajectory data is presented in the sections ahead.

Video recordings were also obtained for all data collection sites and manual turning movement counts performed. The results from the manual counts are also presented in the sections ahead as ground truth data by movement and approach. The ground truth data were used to test the performance of the classification algorithm developed in this research.

Raw Trajectory Data Characteristics

Vehicle trajectory data were collected at the three locations. Regardless of the location the characteristics of the data are similar. In Figure 11, sample trajectory data from the main data collection site are presented. The data shown in Figure 11 corresponds to a 1-hour period. While the data points in Figure 11 appear to resemble the shape of the approach, there are observations that do not appear to be constrained to the travel lanes. The out of boundary observations are primarily vehicles that were entering or exiting commercial establishments adjacent to the intersection and detected by the radar system. Other points outside the boundary of the travel lanes represent pedestrians and bicycles using the sidewalks. These points must be filtered out by the classification algorithm prior to computing the turning movement counts.

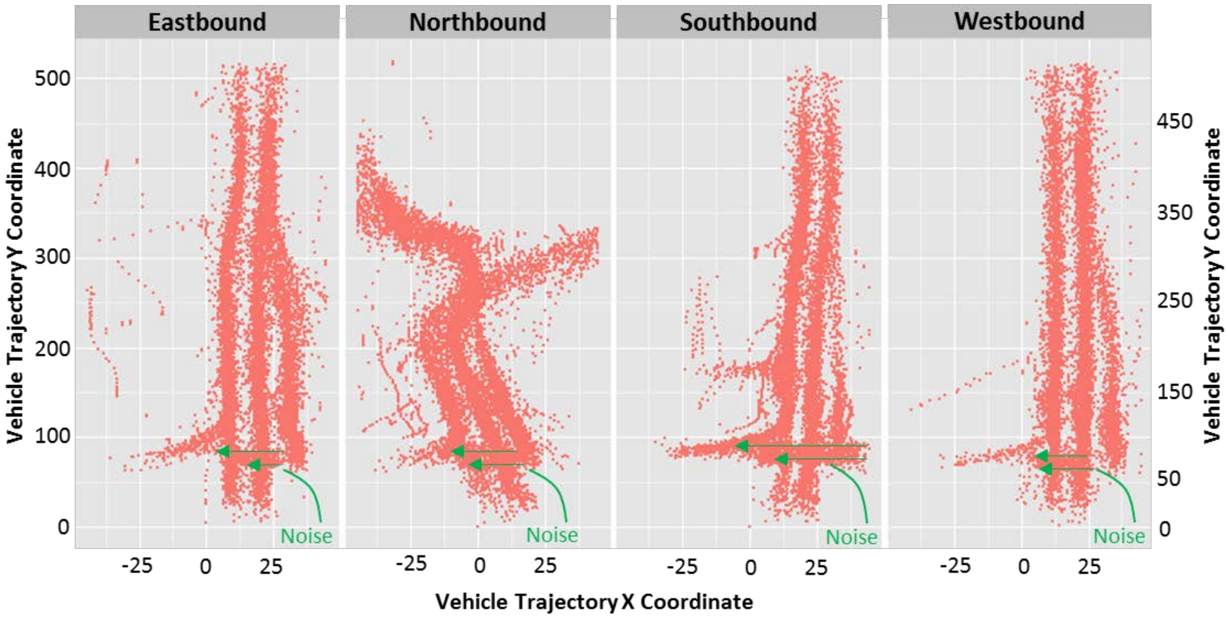


Figure 11. Nature of raw data obtained using the data collection process.

In the lower Y coordinates of each approach, shown in Figure 11, there are also points that appear to represent vehicles traveling perpendicular to the approach direction. These points are caused by cross traffic from other approaches briefly detected by the radar units monitoring the approach shown. For example, in the southbound approach some vehicles exiting the westbound approach are briefly captured by the radar system. These points also need to be filtered out by the classification algorithm. Each of the points in Figure 11 has an associated unique vehicle id. As a result, trajectories can be obtained for individual vehicles as they approach the stop bar as shown in Figure 12. As the figure shows, the nature of vehicle approach to the stop bar and eventual departure can be analyzed at the individual vehicle level.

Manual Count Data Characteristics

Using the data collection procedures described previously, manual turning movement counts were obtained for all data collection sites. As previously mentioned, due to the position of the video recording equipment it is not possible to obtain counts for all approaches and movements. Furthermore, because not all intersection approaches were equipped with radar devices, there was no need to obtain counts for all approaches and movements. The sections ahead summarize the manual count data available. The data are reported in terms of the number of count periods available for each data collection site. A count period is defined as a 15-minute period for a specific approach and movement. For example, a count period represents the number of vehicles turning left on the southbound approach between 13:00 and 13:15.

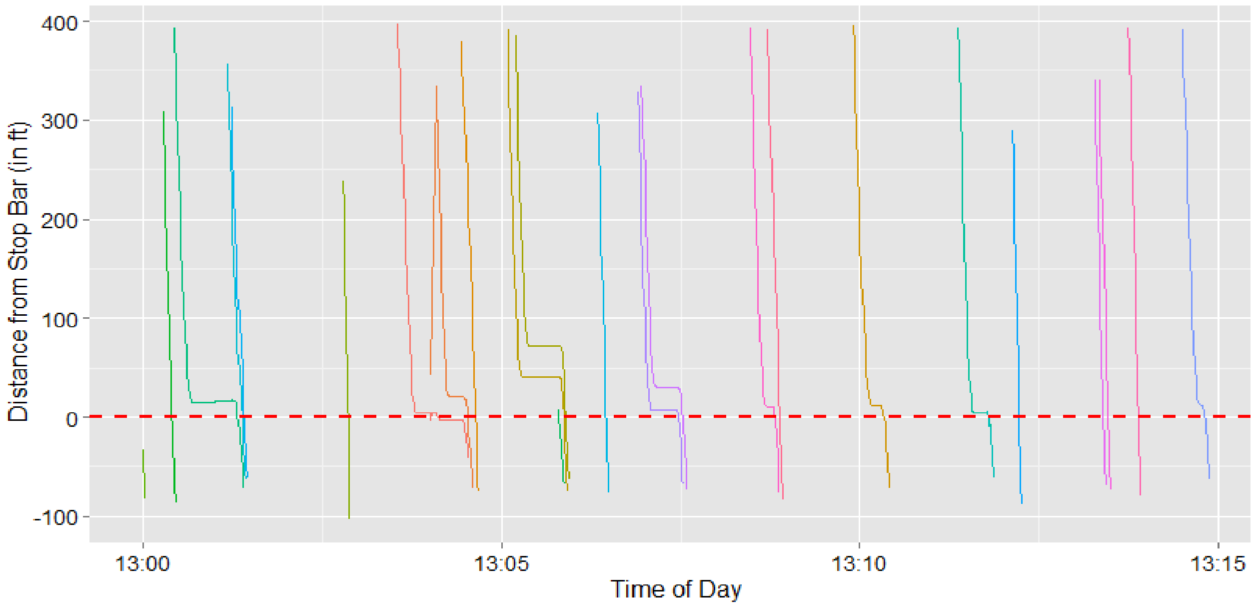


Figure 12. Sample individual vehicle trajectories.

Wisconsin Avenue and Meade Street (*Main Data Collection Site*)

At the main data collection site, video coverage was not available for all approaches simultaneously. The PTZ camera permanently mounted at the intersection provided coverage to adequately perform manual counts on the southbound approach and partial counts on the westbound approach (thru and right movements). Regardless of the limitation, the site was selected because it already had radar devices, access to video that could be recorded, and the engineer in charge of the system was willing to provide support and access to the cabinet when required. Table 1 shows a summary of the 190 count periods for which video and trajectory data are available. The count periods are summarized by approach and movement. The 190 count periods are the result of 9.5 hours of video recording available from the main data collection site. These 9.5 hours translate into a total of 19 approach-video hours. An approach-video hour is defined as an hour of video recording for a single approach.

Table 1. Manual Counts Summary (Wisconsin Avenue and Meade Street)

Approach	**Movement**	**Count Periods**	**Manual Vehicle Count**
Southbound	Left	38	307
	Thru	38	1,816
	Right	38	1,178
Westbound	Thru	38	2,364
	Right	38	325

Wisconsin Avenue and Oneida Street (*Supplemental Data Collection Site 1*)

At the first supplemental data collection site, video coverage for all approaches is available through the use of a handheld camera mounted on a sign pole next to the intersection. Table 2 shows a summary of the 48 count periods for which video and trajectory data are available. The count periods are summarized by approach and movement.

The 48 count periods are the result of 1 hour of video recording available from the supplemental data collection site 1. The 1 hour of video translates into a total of 4 approach-video hours.

Table 2. Manual Counts Summary (Wisconsin Avenue and Oneida Street)

Approach	**Movement**	**Count Periods**	**Manual Vehicle Count**
Eastbound	Left	4	36
	Thru	4	305
	Right	4	23
Northbound	Left	4	21
	Thru	4	92
	Right	4	28
Southbound	Left	4	30
	Thru	4	114
	Right	4	48
Westbound	Left	4	39
	Thru	4	360
	Right	4	24

Fish Hatchery Road and Greenway Cross (*Supplemental Data Collection Site 2*)
At the second supplemental data collection site, radar data were extracted from only the southbound approach. The limited radar data coverage was the result of the setup used by the city of Madison that prevented monitoring more than one radar at a time without the installation of an Ethernet switch. As a result, video was obtained only for the southbound approach using a handheld camera. Table 2 shows a summary of the 45 count periods for which video and trajectory data are available for this site. The 45 count periods are the result of 4.75 hours of video. At this site, the 4.75 hours of video translates into an equivalent 4.75 approach-video hours since video and data from only one approach are used.

Table 3. Manual Counts Summary (Fish Hatchery Road and Greenway Cross)

Approach	**Movement**	**Count Periods**	**Manual Vehicle Count**
Southbound	Left	15	1,218
	Thru	15	3,453
	Right	15	953

ALGORITHM DESCRIPTION

The turning movement count classification algorithm described in this section is applied to raw trajectory data from each approach. The algorithm steps are repeated for each approach of the intersection in order to produce a full turning movement count report. The approach raw data are referred to herein as Subset R_0. The classification algorithm is a two-stage process: Noise Removal and Movement Classification and is described here.

Noise Removal

The first step is removing noise from R_0. Noise is defined as observations detected by the radar-based vehicle detection system that do not correspond to vehicles using the monitored approach to either go right, thru, or left. Vehicles making U-turns are grouped into the left turns category since they are using the same left-turn lane. Figure 13a shows the type of data points included in R_0. As shown in Figure 13a, data points corresponding to vehicles entering or exiting access points next to the approach are included in the subset along with vehicles that are traveling on the crossing approach. Furthermore, pedestrians are occasionally detected by the radar-based vehicle detection system thus increasing the noise in R_0. It should be noted that Figure 13 contains observations used to illustrate the algorithm steps. While real steps of the classification process are shown, the periods of data included in each part of the figure are not the same. The use of different periods provides a visualization of the process given the limitations of a written document. The subsections ahead described the steps associated with the noise removal process. First, data adjustments are made if needed; second, the stop bar of the approach is identified; finally, trajectories representing potential pedestrians are removed.

Data Adjustments

The algorithm works under the assumption that vehicle trajectories on the thru lanes follow a path that is close to parallel to the Y axis of a Cartesian plane. Under certain conditions there is the possibility that the radar-based vehicle detection system for one or more of the approaches is configured in such a way that trajectories are angled. If this situation is present, then an adjustment to all trajectory coordinates is applied to all points defining the trajectory of vehicles of the approach. The adjustment is based on the angle between the path followed by thru vehicles and the Y axis. The transformation applied to the coordinates of the trajectories is based on Equations 1 and 2.

$$X' = X * \cos(-\beta) - Y * \sin(-\beta) \qquad \text{(Equation 1)}$$

$$Y' = X * \sin(-\beta) + Y * \cos(-\beta) \qquad \text{(Equation 2)}$$

Where,

X’ and Y ‘	= Transformed X and Y coordinates,
X and Y	= Original X and Y coordinates, and
β	= Adjustment angle.

Stop Bar Identification

The identification of the stop bar requires estimating the geometric boundaries of the approach. A subset of observations (A_0) that only includes those data points found in R_0 with a speed greater than zero is created. The lower 1 percentile of Y coordinate values in A_0 is then computed. The computed value is used to determine the position of the horizontal asymptote labeled as Bar 1 in Figure 13a.

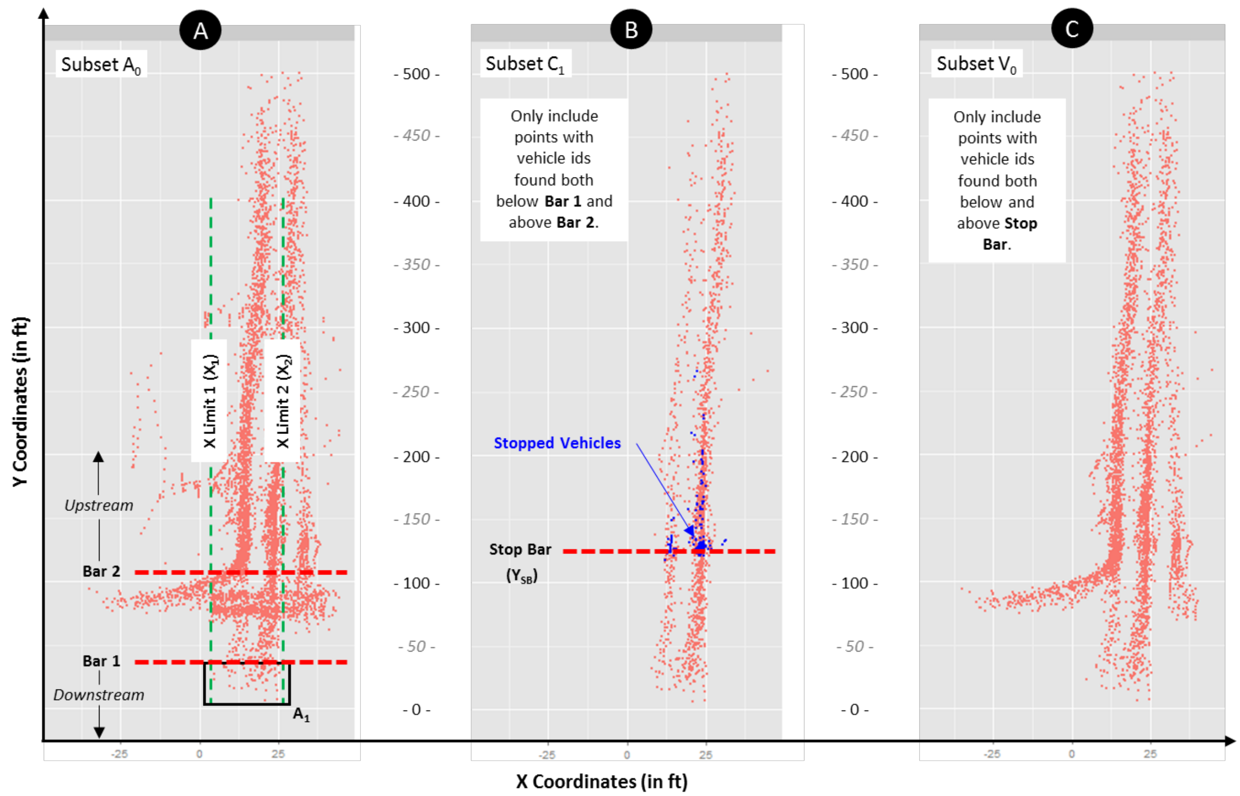


Figure 13. Algorithm Process Overview (Part 1).

Based on A_0, a new subset (A_1) is then created, which includes points from A_0 found downstream of Bar 1 and with a speed greater than 5 mph. The speed threshold is used to eliminate points corresponding to possible pedestrian observations. A_1 is used to determine the limits (measured along the X axis) of an area that defines lanes with thru movements. These limits are shown in Figure 13a as vertical asymptotes X Limit 1 (X_1) and X Limit 2 (X_2). The X_1 position is equal to the lower 1 percentile value of the trajectory points X coordinate while the X_2 value is equal to the upper 1 percentile value. The boundary computation is possible since in a typical installation vehicles going thru have a final Y coordinate lower than vehicles going left or right given that the radar will keep these vehicles in range for a longer period of time.

The next step in the stop bar identification process is selecting an arbitrary location for the position of Bar 2 shown in Figure 13a. The Y coordinate position of Bar 2 is determined by adding 75 feet to the position of Bar 1. The 75 feet is an arbitrary value used by the authors; however, any value larger than the width of a single lane of traffic will be sufficient since it is used to filter out noise from the crossing approach. Using the limits defined by the $[X_1, X_2]$ boundary along with the Bar 1 and Bar 2 positions two new subsets, B_1 and B_2, are defined based solely on coordinate values.

- B_1 includes points from R_0 with X coordinates in the $[X_1, X_2]$ range and Y coordinates are in the [Bar 2, ∞] range.
- B_2 includes points from R_0 with X coordinates are in the $[X_1, X_2]$ range and Y coordinates are in the [0, Bar 1] range.

B_1 and B_2 are used to identify points useful in computing the Y coordinate value of a horizontal asymptote (Y_{SB}) that defines the stop bar position. Useful points are identified by finding unique vehicle identifiers found both on B_1 and B_2. If a vehicle identifier is found in both B_1 and B_2 then trajectory points in R_0 with the same identifier are added to a new subset, C_1. A visual representation of the type of data points included in C_1 is shown in Figure

13b. Observations representing stopped vehicles are highlighted. The lowest 1 percentile value of Y coordinates corresponding to stop observations is assigned to Y_{SB}.

Identification of Valid Trajectories

Through the use of Y_{SB} a new subset of valid data points can be identified. Data part of R_0 can be grouped into two subsets, R_1 and R_2. R_1 includes data points with Y coordinates greater than Y_{SB} while R_2 includes observations with Y coordinates smaller than or equal to Y_{SB}. Unique identifiers found in both R_1 and R_2 are considered as identifiers of valid trajectories for analysis. Trajectory data points containing the aforementioned identifiers are copied from R_0 into a new subset V_0 (shown in Figure 13c). Therefore, subset V_0 contains possible vehicle trajectories found upstream and downstream of the stop bar (Y_{SB}), thus eliminating partial trajectories caused by the radar device dropping the tracking of a vehicle and picking it up again but with a different identifier. Furthermore, noise caused by vehicles on adjacent properties as well as vehicles on other approaches is eliminated. The risk of undercounting vehicles as a result of the filtering approach is minimal since the dropping and picking up of vehicles by the radar device is lower near the stop bar. A vehicle that is dropped will still be counted as long as it is picked up again by the radar upstream of the stop bar and if a vehicle is dropped past the stop bar it would still be counted.

Removing Pedestrian Observations

The potential for pedestrian observations exists in V_0. Potential pedestrian observations are removed from V_0 using a set of rules intended to identify trajectories that likely are not from vehicles. Vehicle trajectories are excluded from V_0 if:

- length of the vehicle is less than 6 feet, and
- average X coordinate value is less than X_1.

As a result of the exclusion process, V_0 ultimately contains the best possible estimate of trajectories that can be classified as a left, thru, or right movement. This pedestrian observations removal approach allows bicycle observations that are part of V_0 to remain in the dataset since these observations contributed to the computation of X_1 even if on an exclusive bicycle lane.

Movement Classification

The subset V_0 shown in Figure 14d (obtained after noise and pedestrian observations removal) contains vehicle trajectories that need to be classified into left, thru, and right movements. Classification into corresponding movements is achieved using count zones defined based on the values of X_1, X_2, and Y_{SB}. Two additional values Y_R and Y_L (defined later in this section) are also used. The count zones are automatically computed by the algorithm. Each vehicle trajectory in V_0 is then analyzed and classified by movement based on their position within the count zones using a two-step process designed to deal with two levels of uncertainty.

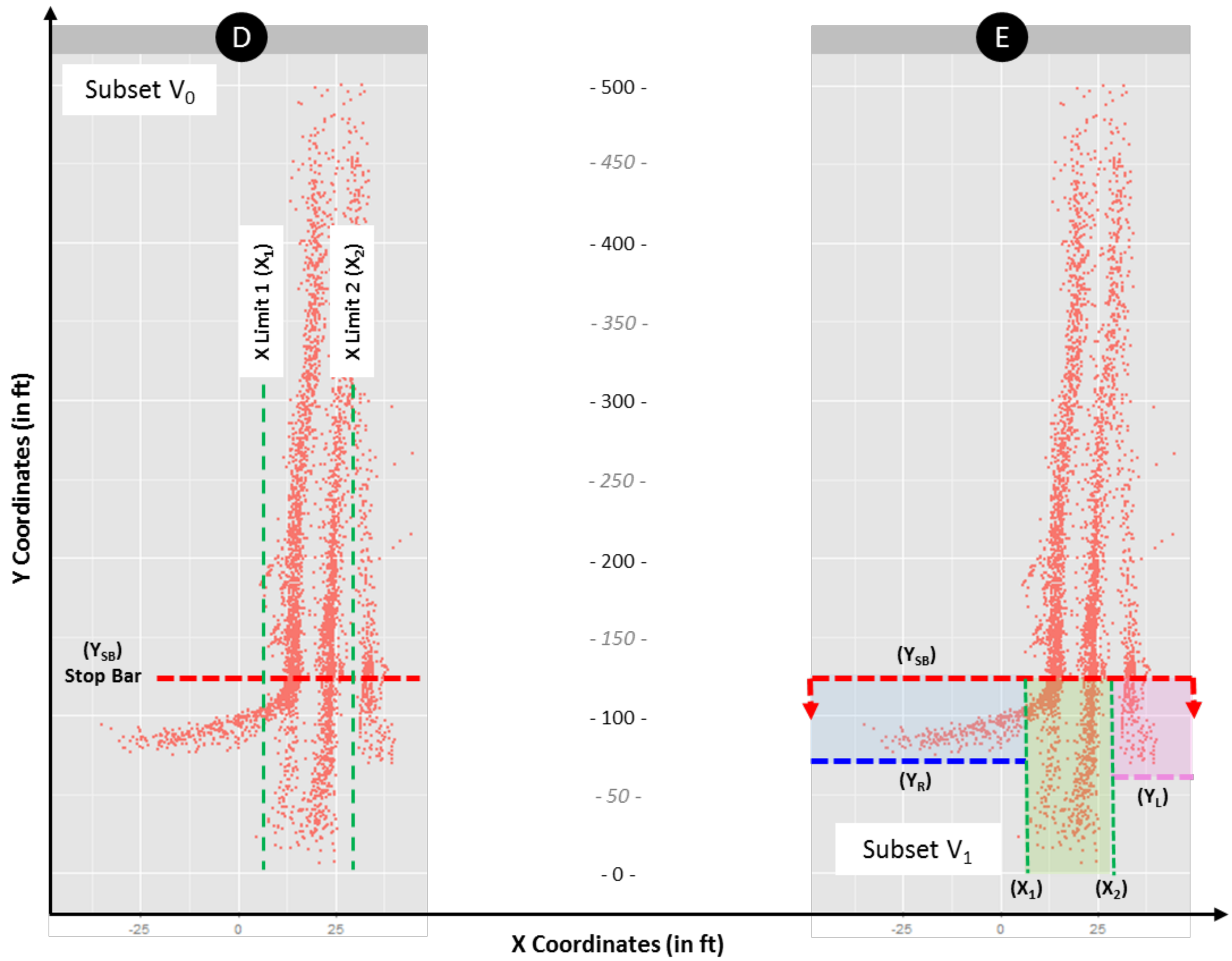


Figure 14. Algorithm Process Overview (Part 2).

Count Zones Definition

Three count zones are defined for each approach (left, thru, and right) using limits defined in Cartesian coordinates as shown in Figure14e. The limits rely on stop bar position (Y_{SB}), vertical asymptotes X_1 and X_2, as well as Y_R and Y_L values. Y_R is defined as the lowest 1 percentile value of the Y coordinate of trajectory points with an X coordinate less than X_1. Y_L is defined as the lowest 1 percentile value of the Y coordinate of trajectory points with an X coordinate greater than X_2. Each of the aforementioned count zones can be defined as follows:

- Thru movement count zone limits on the Y axis are $[0, S_B]$ and $[X_1, X_2]$ on the X axis.
- Right movement count zone limits on the Y axis are $[Y_R, Y_{SB}]$ and $[-\infty, X_1]$ on the X axis.
- Left movement count zone limits on the Y axis are $[Y_L, S_B]$ and $[X_2, \infty]$ on the X axis.

Classification by Movement: Level 1

As part of the Level 1 classification, vehicle observations with a high degree of certainty (in terms of belonging to a specific movement) are identified. Points part of V_0 and with a Y coordinate value lower than Y_{SB} are copied into a new subset V_1. Points part of V_1 are assigned an “Unknown” movement value. The following steps are then taken on V_1 points:

- Points inside the right-turn count zone that are at least 5 feet from the X_1 asymptote are copied into subset T_0.

- Points inside the left-turn count zone that are at least 5 feet from the X_2 asymptote are copied into subset T_1.
- Points inside the thru count zone that are at least 3 feet from X_1 and 3 feet from X_2 are copied into Subset T_2.

The 5 and 3 feet values were determined by the authors after observing the characteristics of the data. The 5 feet value was selected based on the typical width a bicycle lane. The 3 feet value was selected based on the 1/4 to 1/3 of the typical width of a highway lane. Tests conducted by the authors revealed limited sensitivity in the vicinity of these values, but do contribute to an improved accuracy.

As a result of the aforementioned steps subsets T_0, T_1, and T_2 contain points belonging to vehicles going right (T_0), left (T_1), and thru (T_2). Unique vehicle identifiers found in T_0, T_1, and T_2 are used to change the movement value assigned to points part of V_1. For example, a list of unique identifiers found in T_0 is generated; the list of identifiers is then used to change the movement value of all trajectory points part of V_1 to "right."

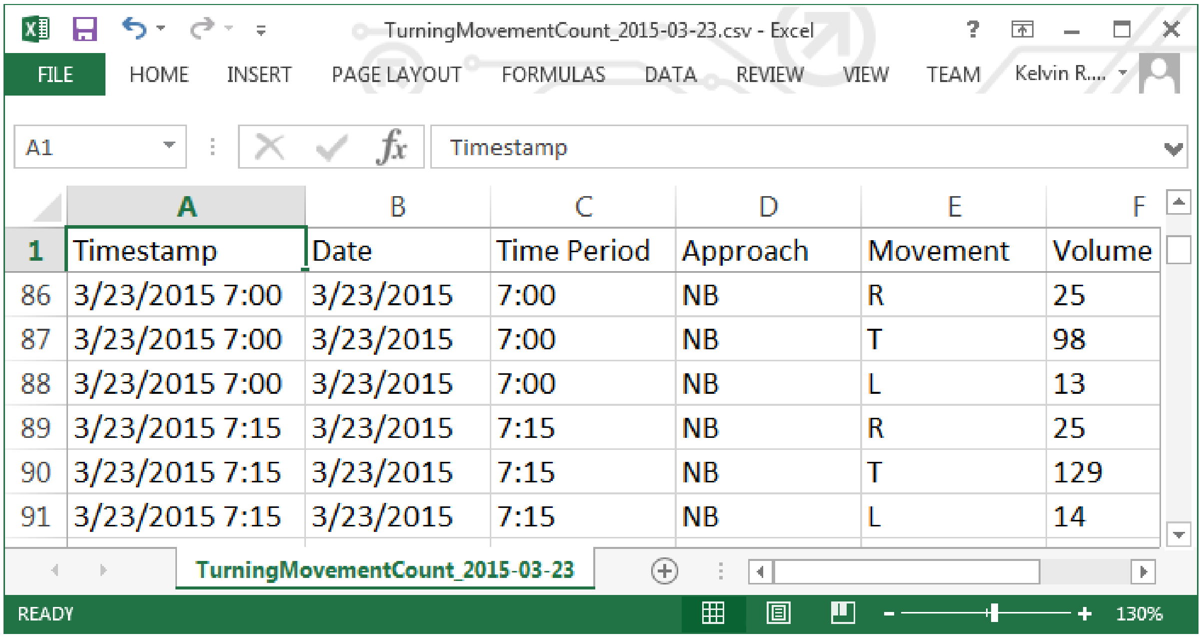
Classification by Movement: Level 2

After the completion of the Level 1 classification, V_1 contains points with movement values equal to unknown, right, thru, and left. Points with an unknown movement value were those points not classified as part of the Level 1 classification. A list (L_1) of unique vehicle identifiers in V_1 with an "unknown" movement value is created. L_1 is used to classify each remaining vehicle trajectory as right, thru, or left. The classification is achieved by tallying the number of points found by trajectory on each count zone. The steps are summarized here:

- For each identifier part of L1, points in V1 with the same identifier are extracted as P1.
- Percentage of P1 points on the left, thru, and right count zone is computed.
- The count zone with the highest percentage of points determines the vehicle movement.
- If more than one count zone contains an equal percentage of points the movement is defined based on the position of the last (in terms of time) point observation.
- The steps are repeated for each identifier part of L1.

Presentation of Results

Once all vehicle trajectories are classified into the corresponding movement, the trajectories (vehicle observations) are then filtered by approach and time period. To simplify the analysis of the data and make it compatible with a wide range of software the summarized data are exported as a CSV file with content similar to the one shown in Figure 15. The format used enables the computation of peak hour periods of volume during the day as well as the peak hour factors for each movement of the intersection. Furthermore, when multiple CSV files are combined an analysis of volume fluctuations over different days and months can be performed, thus enabling the computation of seasonal adjustment factors that are key to understanding yearly traffic fluctuations when only limited volume observations are available.



	A	B	C	D	E	F
1	Timestamp	Date	Time Period	Approach	Movement	Volume
86	3/23/2015 7:00	3/23/2015	7:00	NB	R	25
87	3/23/2015 7:00	3/23/2015	7:00	NB	T	98
88	3/23/2015 7:00	3/23/2015	7:00	NB	L	13
89	3/23/2015 7:15	3/23/2015	7:15	NB	R	25
90	3/23/2015 7:15	3/23/2015	7:15	NB	T	129
91	3/23/2015 7:15	3/23/2015	7:15	NB	L	14

Figure 15. Algorithm output.

RESULTS

The counts produced by the classification algorithm were grouped into 15-minute counts periods. As previously mentioned, a count period is defined as a 15-minute period for a specific approach and a movement. For example, a count period represents the number of vehicles turning left on the southbound approach between 13:00 and 13:15. Results from each count period from the algorithm; that is, volume for a specific movement on an approach, will be compared with the corresponding manual count data to evaluate the performance of the algorithm.

Performance results are presented individually for each of the data collection sites. However, it should be noted that the site for which the largest comparison dataset is available is the main data collection. Therefore, any discussions about the performance of the algorithm outside of this results section will be based on the main data collection site performance. The performances on the supplemental sites were computed as a confirmation value to make sure that performance values were comparable across different locations.

Performance values for the algorithm at the count period level will be reported using average error as well as average absolute error. The error of the algorithm for a single count period is measured based on the ground truth data as shown in Equation 3. The average error is computed by adding all error values and dividing the result by the number of count periods. The average absolute error is computed by adding absolute values of all errors and dividing the result by the number of count periods.

$$E = V_A - V_M \qquad \text{(Equation 3)}$$

Where,

E = Error of algorithm for count period,

V_A = Algorithm reported by algorithm for count period, and

V_M = Volume for count period (from manual count).

Performance reporting will focus on the count period level because the authors believe that reporting the performance by aggregating observations into periods of time larger than 15 minutes is misleading to end users. The idea behind the reporting interval is that transportation engineers traditionally use 15-minute volume periods when making design and operational decisions.

Wisconsin Avenue and Meade Street (Main Data Collection Site)

Over the 190 count periods included in the main data collection site, a total of 5,941 vehicles were counted and classified by the algorithm, whereas 5,990 vehicles were manually classified and counted. The 49 vehicle difference between manual and algorithm results is equivalent to an average error of -0.26 vehicles per count period (-0.81%). A breakdown of the algorithm and manual count differences by count period is shown as a histogram in Figure 16 and grouped by approach. As shown in the figure, a significant portion (62.3%) of the count periods experienced either no error or a difference of at most one or two vehicles.

A general view of the performance of the algorithm reveals that the average error for a count period in the southbound (SB) approach was -0.24 vehicles per count period, whereas for the westbound (WB) approach was -0.27 vehicles per count period, thus making the results similar across two different approaches. Average absolute error values for the southbound and westbound approach were 2.26 and 2.38 vehicles, respectively. Across all approaches included in the comparison dataset (southbound and westbound) the average absolute error was 2.31 vehicles. Therefore, the results suggest similar performance across different approaches.

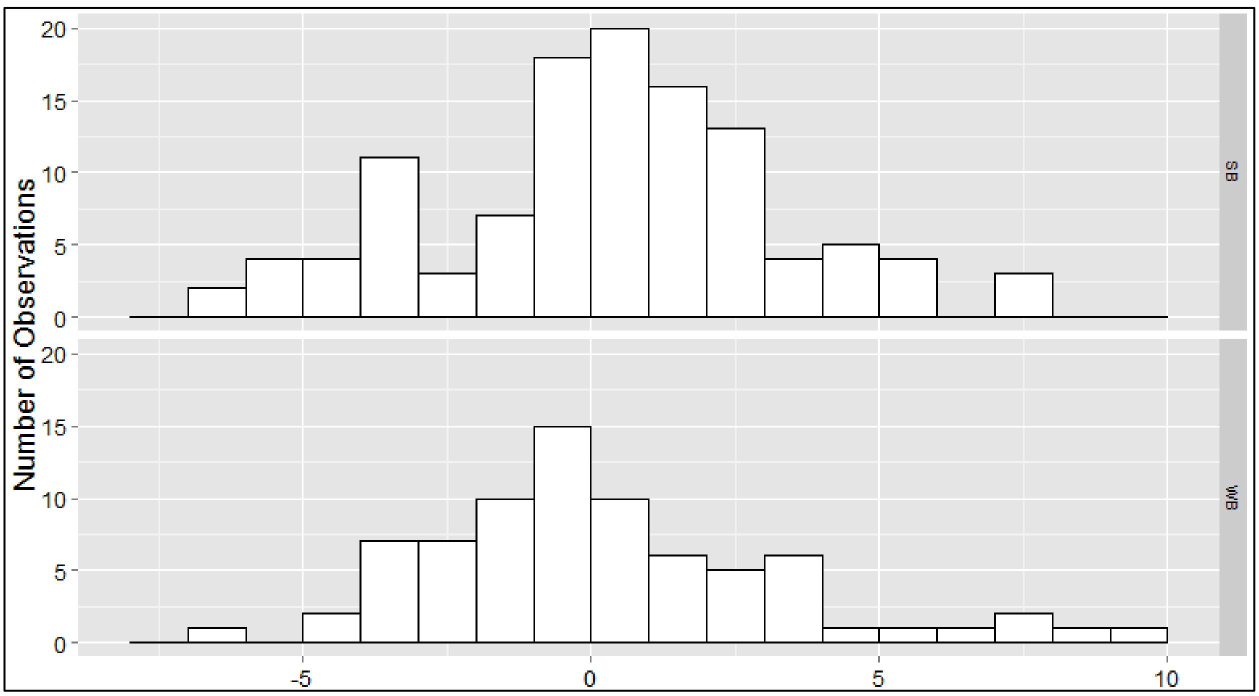


Figure 16. Distribution of error.

When data from the 190 count periods is analyzed, 62.3% of the count periods have an absolute error of at most two vehicles between the algorithm and the manual count as shown in the cumulative distribution presented in Figure 17. In other words, for approximately 62% of the count periods absolute error will be two vehicles or less.

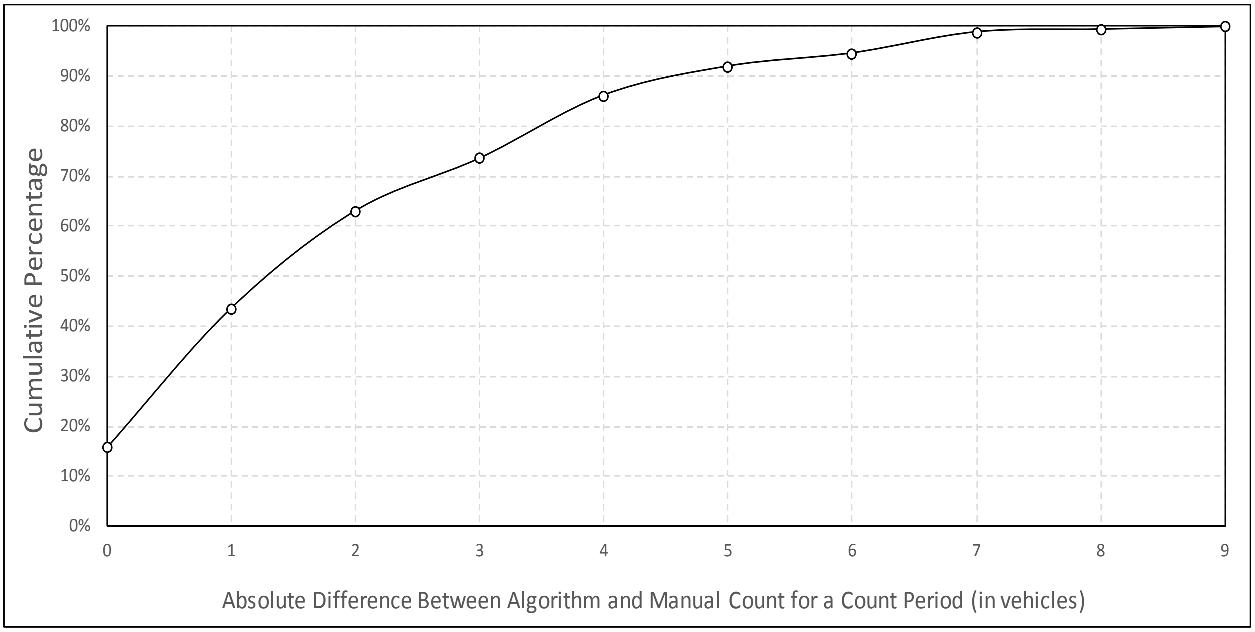


Figure 17. Absolute error cumulative distribution.

Until now, absolute errors have been discussed as a number of vehicles instead of a percentage. Error percentages can be a misleading indicator especially when the ground truth values are low. Figure 18 shows the absolute error values for individual count periods as a percentage of the ground truth count period volume. As the figure shows, high percentage errors are observed when the volumes of a count period are low. In other words, the 100% error shown in Figure 18 is the result of the algorithm counting four vehicles while the manual count indicated two. From a traffic engineering perspective, counting four vehicles on an approach when there were in fact two vehicles will likely have a negligible effect on analyses. However, when higher volume count periods are considered, a trend toward lower percentage errors is shown in Figure 18.

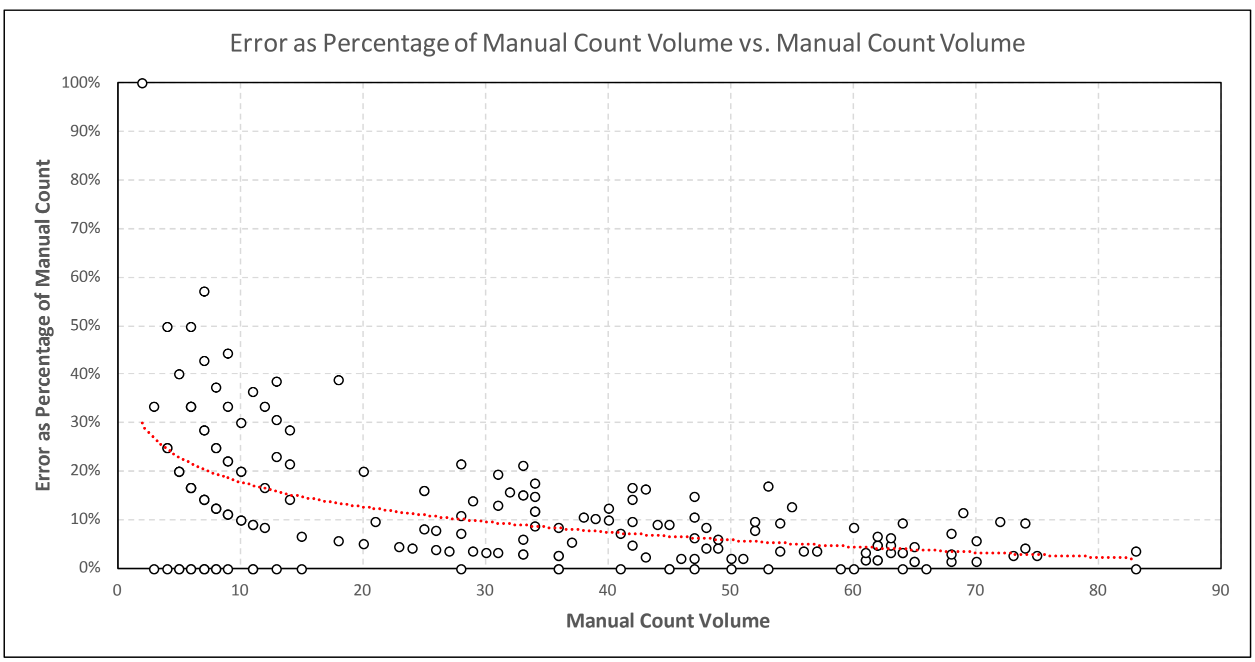


Figure 18. Absolute error as percentage of manual count volume.

Sources of Error

As Figure 16 shows the nature of the errors is close to evenly distributed in the sense that sometimes the difference between the algorithm count and the manual counts is either negative or positive. Based on previous work by the authors, the likely source of this error is not the result of missed calls by the radar-based detection system (Santiago-Chaparro et al. 2012a). Also, the same work suggests that weather and illumination conditions are not likely to impact the performance of the radar-based vehicle detection system. However, as with other vehicle detection systems, when volumes are high and vehicle composition includes larger vehicles there is a chance for occlusion as well as for double tracking.

Occlusion can result in the radar not being able to constantly track a vehicle throughout the approach (i.e., upstream and downstream of the stop bar) if a larger vehicle blocks the line of sight between the vehicle and the radar. Based on the algorithm design, if a vehicle is not seen both upstream and downstream of the stop bar it is not considered a valid trajectory, thus resulting in the algorithm computing a lower volume for a movement than a manual count. Double tracking is another source of error present for vehicles with an attached trailer. Double tracking can happen when a vehicle with an attached trailer is tracked throughout the approach as two separate vehicles. As a result, count periods with vehicle volume higher than those obtained through a manual count can be the result of a vehicle being tracked as two by the radar.

Wisconsin Avenue and Oneida Street (First Supplemental Data Collection Site)

Manual count and algorithm volumes were available for a total of 48 count periods for the first supplemental data collection site. Over the 48 count periods, a total of 1,129 vehicles were manually counted while the algorithm counted 1,120 vehicles. The nine vehicles over the entire period represents a difference of 0.80%. When analyzed at the count period level the average error for the algorithm is equal to -0.19 vehicles, while average absolute error equals 1.56 vehicles. Figure 19 shows a histogram of the algorithm error for each of the count periods. As shown in the figure, the error values with the highest frequency of observations are 0, -1, and 1. In fact, 77% of the count periods reported have an absolute difference between the manual count and algorithm results of two vehicles or less. The error values reported for this site suggest that the algorithm is capable of producing similar results (in terms of performance) across multiple sites.

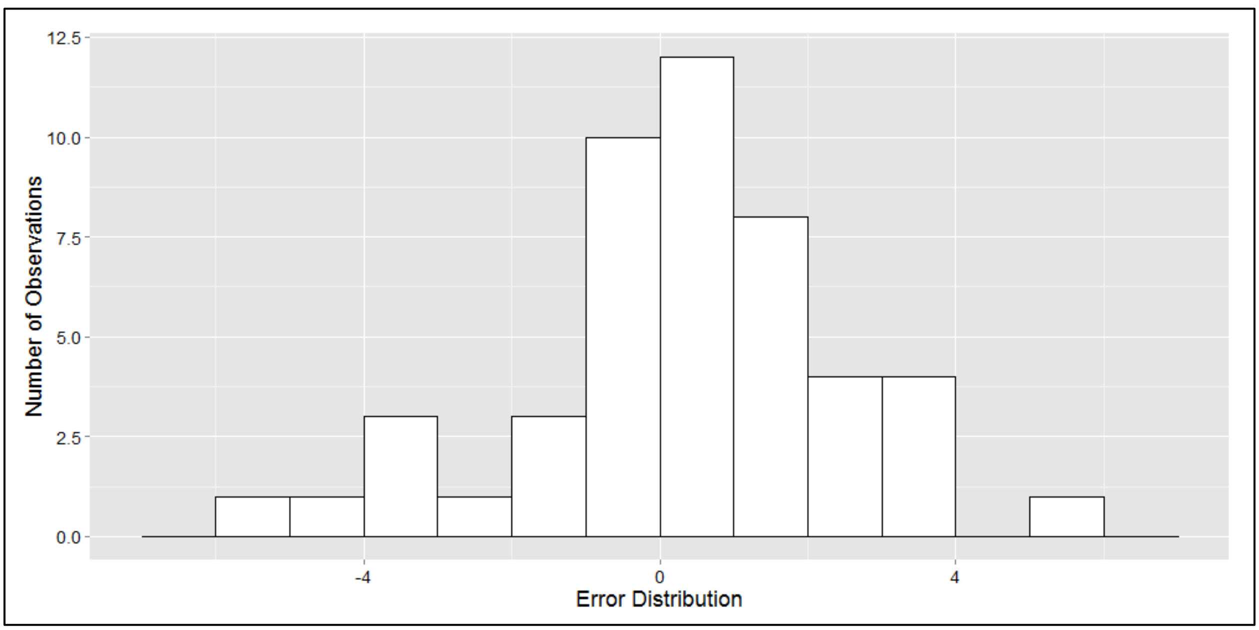


Figure 19. Distribution of error (Supplemental Data Collection Site 1).

Fish Hatchery Roads and Greenway Cross (Supplemental Data Collection Site 2)

The intersection of Fish Hatchery Road and Greenway Cross is significantly different when compared with that of the main data collection site and the first supplemental data collection site. In terms of volume, the intersection more than doubles the volume of the main data collection site (estimated average weekly traffic = 52,100 vehicles). The geometry is also significantly different. For example, on the studied approach there are a total of five lanes for traffic and one bicycle lane. Due to the geometry of the intersection each lane has a different stop bar location. There is also a significant presence of large vehicles at the intersection in all movements as a result of the area characteristics, which include three auto dealerships that continuously receive shipments in car trailers that can block the line of sight between the detection system and other vehicles. An example of the heavy vehicle presence is shown for the right-turn movement in Figure 20, which took place in a period of less than 30 minutes.

Figure 20. Potential line of sight obstructions.

Manual count and algorithm volumes were available for a total of 15 count periods for the second supplemental data collection site. Over the 48 count periods, a total of 5,624 vehicles were manually counted, while the algorithm counted 4,787 vehicles. Figure 21 shows a distribution of the efforts by count period. The accuracy of the algorithm decreased on this intersection and this was expected by the research team due to the nature of the vehicle detection configuration at the location. For example, the size of the intersection and placement of the detection warrants the use of two detection units per approach, but only one was used. This is the result of the radar-based system acting as supplemental detection and not as the primary source.

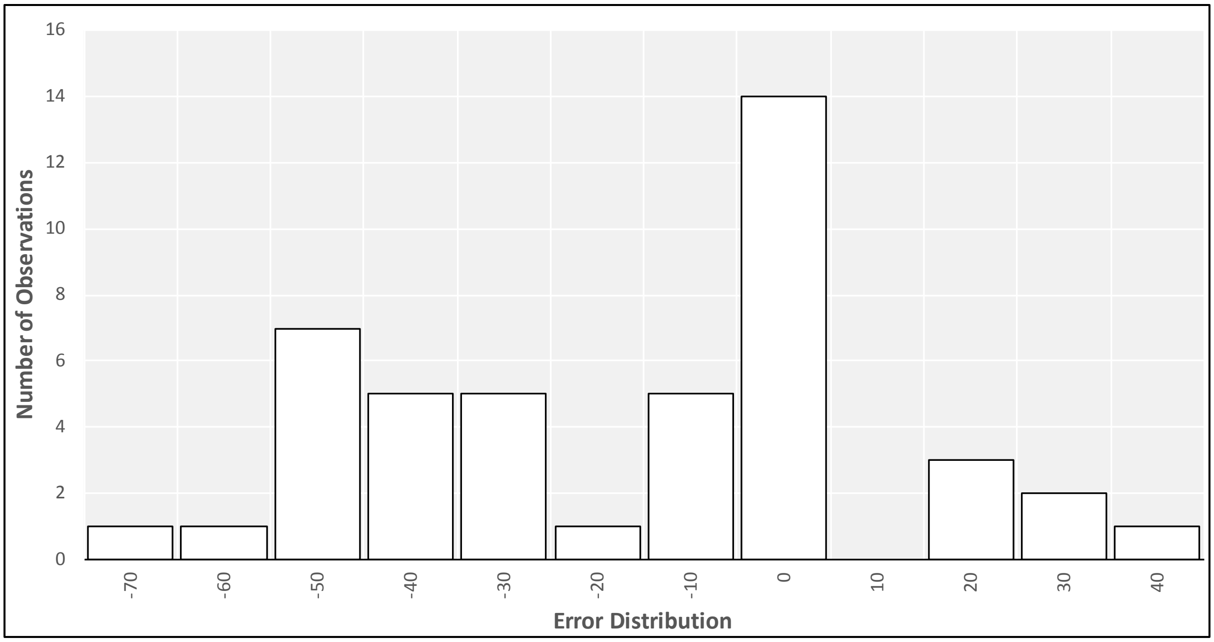


Figure 21. Distribution of error (Supplemental Data Collection Site 2).

However, the findings at the intersection are still encouraging. For instance, the procedures for automatic zone detection worked as expected, which is a critical part of the automated turning movement count process. The sources of error shown in Figure 21 are primarily the result of two undercounting situations.

A review of the data and intersection characteristics suggests that undercounting on the left turn can be the result of occlusion, larger vehicles on one of the left-turn lanes blocking other left turning vehicles, and that the stop bar of the left-turn lanes is further upstream than the other lanes. The further upstream stop bar position could increase the occlusion effects since large vehicles on the adjacent through lanes can block the line of sight between the detection system and vehicles.

Undercounting of vehicles on the right turn movement has been primarily attributed to large vehicles on the right-turn lane such as the ones shown in Figure 20 blocking the line of sight between the radar and smaller vehicles behind the larger one. Furthermore, due to the non-uniform location of the stop bar the temporary stop bar identified by the algorithm will be detected further upstream, thus increasing the chance of vehicles on the right-turn lane being dropped and considered upstream noise. These situations suggest the need to improve the nature of the algorithm and highlight the need for further testing in order to handle non-typical intersections such as the ones on the main data collection site and the first supplemental data collection site.

POTENTIAL IMPLEMENTATION PATH (CONCEPTUAL PROCESS)

The current version of the algorithm has been implemented and packaged as a group of Python and R data collection and analysis scripts. Furthermore, trajectory data were stored using a relational database. Existing code enables the deployment of a proof-of-concept version of the algorithm. However, while the results are encouraging, further refinement of the algorithm is required to handle a wider array of intersection scenarios and traffic conditions. Once these improvements are made the project presented will be able to move into a market-ready solution by wrapping the analysis and data collection process into a user-ready solution. The following are a set of recommendations by the authors to implement a more refined version of the trajectory classification algorithm. There recommendations are conceptual and intended to provide guidance, but do not represent a blue print for the process.

Data Collection Process

The procedures used by the authors to log vehicle trajectory data from the radar-based vehicle detection system rely on a consumer grade laptop running inside the signal cabinet of the intersection. The computer runs Windows 7 and includes a Python interpreter. Furthermore, the computer also runs a MySQL server where data collected via the Python program are stored and made available to any computer located on the same network. The data collection is made possible because the computer is connected to the same network (via an Ethernet switch) as the radar-based vehicle detection system through an Ethernet cable.

The data analysis happens on a different machine; therefore, the computer placed inside the signal cabinet is technically acting simply as a data storage device capable of serving on-demand vehicle trajectory data. With the rapid growth experienced in the field of single board computers, the possibility of replacing the laptop computer used by the research team with a credit card size device is a real possibility. Figure 22 shows a potential device and approach that can be used to replace the vehicle trajectory data collection process.

Figure 22 shows a Raspberry Pi single board computer the size of a credit card that runs a version of the Linux operating system (OS). The computer is capable of running Python as well as a MySQL server and includes an Ethernet port. Therefore, the single board computer can be used a replacement to the Windows 7 laptop used by the research team to collect the vehicle trajectory data. The single board computer is powered through the use of a USB port similar to that of a phone, which makes concerns about power availability inside the signal cabinet a non-issue.

Because the single board runs a version of the Linux operating system there are some changes that will be required in the data collection scripts and the database structure used. For example, the Python program used to log vehicle trajectory relies on libraries that enable communication with the servers running on the radar devices needs to be modified and configured to work on a computer running a Linux OS. Other platform changes such as error recovery and performance monitoring would also need to be added. Finally, given the lack of a display on the device a web-based management interface will need to be created in order to allow the configuration of the data collection unit prior to installation in the field. The management interface should rely on a lightweight web server that can be accessed by any device with a web browser and an Ethernet port; for example, a laptop computer or tablet with the proper adapter.

Figure 22. Potential data collection unit.

The Windows version is able to handle time stamp values that contain millisecond precision; a capability that is not currently available on the corresponding Linux version of the software. Therefore, the structure of the database needs to account for this limitation of the Linux version and include supplemental fields that can store millisecond values given that the millisecond-level accuracy is valuable when analyzing vehicle trajectory data. The changes in the structure of the database, while trivial, do open doors for potential applications of the data collection methodology to areas such as surrogate safety evaluations and highlight the need for understanding how every small change in the process can impact the long-term potential of a system.

Analysis Process

For purposes of this NCHRP IDEA Stage 1 project, when the data analysis algorithm is executed it will communicate with the MySQL server containing the vehicle trajectory data and generate a data file containing vehicle trajectory information for the previous day. In other words, if the program is executed at 3 a.m. on July 15, a turning movement count report will be produced for the period of July 14 (12:00 a.m.) to July 15 (12:00 a.m.), a 24-hour period. This process can be automated through the use of the task scheduler included in virtually all versions of the Windows operating system. Figure 23 shows a concept of how the analysis process can be automated.

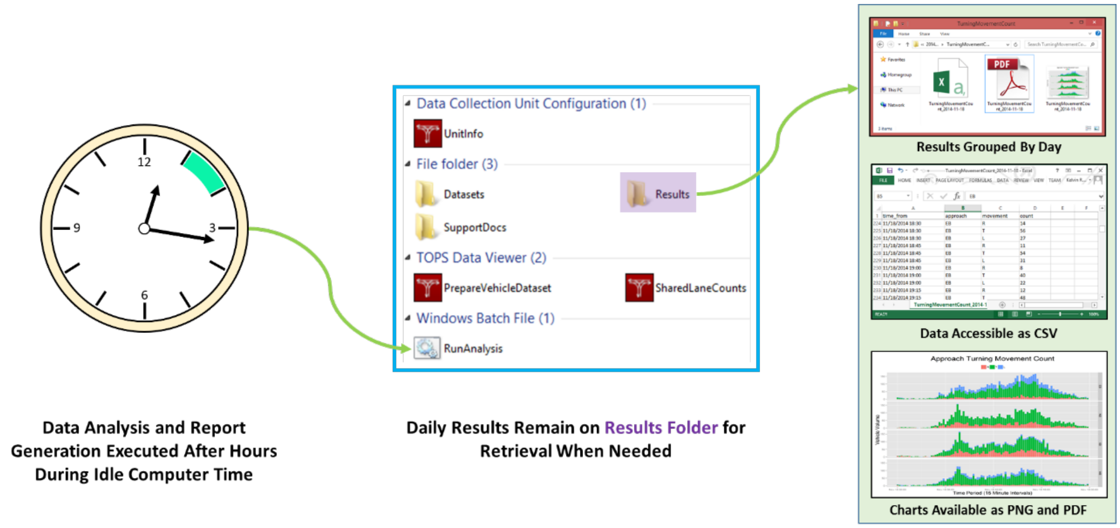


Figure 23. Conceptual data analysis implementation process flow.

The idea behind the workflow show in Figure 23 is the use of idle computer time to produce and archive turning movement count reports daily without the need for user interaction. A dedicated folder can be established on a computer for every intersection for which a turning movement count report is desired. The Windows Task Scheduler will then execute a script that will make the computer establish a connection with the server containing the vehicle trajectory, create a vehicle trajectory file on the computer for the previous day, and launch a process that analyzes the trajectory data using the algorithm described in this report. A folder structure for each intersection that includes a place to store the raw data and reports can be created. The reports folder should include graphs and data summaries that are sorted by date.

The aforementioned procedure can be achieved manually, but will require knowledge about computer programming. The data analysis algorithm code needs to be established as a template that relies on supplemental information passed as arguments at run time pointing to a correct intersection on the network from which vehicle trajectory data will be extracted. Furthermore, end users will have to configure how the operating system handles the execution of code written in R to analyze the trajectory data. R will also need to be installed on the computer of the end user. Therefore, a computer program that wraps the data retrieval, data analysis, and scheduling task needs to be created. The program will also need to include an embedded version of the R programming language in order to be functional. The final goal of the program should be to make the data analysis process configuration as simple as opening a text file and changing the IP address of the intersections from which data is required.

CONCLUSIONS

Through this NCHRP IDEA Stage 1 project the research team demonstrated a proof of concept of an algorithm that produces turning movement counts reports using vehicle trajectory data extracted from existing vehicle detection infrastructure. At the heart of this concept is a previously developed data collection methodology that continuously extracts vehicle trajectories from radar-based vehicle detection systems, without the need for specialized hardware or changes to the vehicle detection system configuration. The algorithm developed in this NCHRP IDEA project differs from existing approaches in that it does not rely on the definition of count zones on exit approaches or the use of time stamps of detection calls. As a proof of concept, the algorithm has shown significant promise in terms of performance.

The performance of the classification algorithm was evaluated by comparing count period volumes from manual counts with volumes produced by the algorithm at three intersections with varying characteristics. A count period was defined as a 15-minute period for a specific approach and movement. The average difference between manual counts and algorithm results was -0.26 vehicles (-0.81%). The average absolute difference was 2.31 vehicles. Furthermore, for 62.3% of the count periods reported the difference between manual and counts from the algorithm was at most two vehicles. Similar results were obtained at a supplemental data collection site, thus suggesting that the algorithm performance is stable when geometric conditions are not significantly different from those of the main data collection site, which arguably correspond to those of a typical signalized intersection.

Considering the errors in manual counts, which arguably provide the most accurate turning movement count data, for a typical intersection the performance of the algorithm is deemed satisfactory. The algorithm is capable of handling noise in the data produced by adjacent businesses and pedestrian traffic as demonstrated by the results. Furthermore, because the methodology presented can be used for long-term data collection efforts (weeks and months) the daily fluctuations of traffic volumes by count period at a location will make the absolute error a negligible factor. The performance of the algorithm is expected to improve when used at rural locations because traditionally the volume is lower and the noise from adjacent business and pedestrians will be lower or non-existent.

The performance of the algorithm was tested at a wide, non-typical signalized intersection in Madison, Wisconsin. The algorithm performed as expected; however, it was found that detection limitations, traffic characteristics, and large geometry contributed to the reduced accuracy. As a result, performance at the Madison site revealed the need to make adjustments to the algorithm in order to support non-typical and larger intersections. The required changes should focus on triggering different classification procedures based on detected intersection characteristics. Furthermore, the findings highlight that the algorithm is only as good as the configuration and placement of the detection systems.

In addition to describing the characteristics of the algorithm and performance experienced, a potential implementation path has also been presented. If the implementation path is followed, the process of generating turning movement count reports for intersections could be made as simple as opening a text file on a computer and typing IP addresses of radar detection systems at intersection. If the procedures presented are refined and packaged into a market ready solution through further development and testing, performance measures reporting for signalized intersections could be simplified and made accessible to small agencies without the need for significant capital investments.

FUTURE WORK

As an NCHRP IDEA Stage 1 project, the goal of the work presented was to show a proof of concept that can evolve into a tool from which transportation agencies can benefit. The algorithm presented by the authors has shown that, in fact, turning movement count reports can be produced for a signalized intersection regardless of the lane configuration. To successfully commercialize this innovation, the algorithm needs to be improved, a prototype data collection device that can be installed inside a signal cabinet constructed, and a centralized software tool to manage multiple data collection devices needs to be developed. The goal of the centralized software would be to run the classification algorithm on data collected across multiple field data collection units.

While the results from the project are encouraging, there are still improvements to the data analysis algorithm that need to be performed in order to have a market-ready solution. Future work should focus on making improvements to the algorithm in order to handle the following scenarios:

- Different intersection configurations. the algorithm developed as part of the project provides satisfactory performance on what could be considered a textbook intersection. For example, no testing has been done on intersections with channelized lanes and testing is required at intersections with a non-uniform stop bar location.
- Intersections with significant presence of heavy vehicles. Results from the second supplemental site show the need for further development in order to improve movement detection as a result of occlusion effects.
- Intersections with two detection devices per approach. For intersections with 5+ lanes per approach more than one radar device is desirable and will require changes to the algorithm in order to properly merge and analyze multiple data sources.

The aforementioned modifications and requirements will require data collection across different locations in the country in order to obtain vehicle trajectory datasets from a wide array of geometric and traffic conditions. These modifications will in turn require further analysis and performance evaluations that will trigger an iterative development process. The iterative process will not only extend to the underlying data analysis procedures, but also to the reporting process and data collection procedures.

In terms of data collection, the system should be tested on a smaller hardware platform such as a development board. Furthermore, it should be configured for an environment in which the data analysis algorithm and data collection system are on two separate locations. The configuration of the data collection system, and corresponding analysis environment, will require gathering feedback from different transportation agencies across the country in order to identify a reporting and analysis procedure that serves end users. As with the algorithm changes, the feedback received will trigger the need for an iterative development process and testing in order to produce a market-ready solution.

The centralized software tool will also manage the execution of the code for the improved version of the algorithm across multiple intersections to produce and store daily turning movement count reports for a group of intersections. The report will be available on demand, thus eliminating the need for constant user interaction and allowing end users of the data to access the reports when needed without the need for daily interaction with the system.

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