Techniques for Mining Truck Data to Improve Freight Operations and Planning

Robert L. Bertini
Department of Civil and Environmental Engineering
Portland State University
P.O. Box 751
Portland, OR 97207-0751
Phone: 503-725-4249, Fax: 503-725-5950
Email: bertini@pdx.edu

Zachary Horowitz
Department of Civil and Environmental Engineering
Portland State University
P.O. Box 751
Portland, OR 97207-0751
Phone: 503-725-4285, Fax: 503-725-5950
Email: horowitz@cecs.pdx.edu

Kristin Tufte
Department of Computer Science
Portland State University
P.O. Box 751
Portland, OR 97207-0751
Phone: 503-725-4285, Fax: 503-725-5950
Email: tufte@cs.pdx.edu

Spicer Matthews
Department of Computer Science
Portland State University
P.O. Box 751
Portland, OR 97207-0751
Phone: 503-725-4285, Fax: 503-725-5950
Email: spicer@pdx.edu

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Abstract. Freight plays an increasingly valuable role in the national economy, and a growing percentage of freight—measured by both total volume and market value—is being moved along the highway system by truck. An important part of the research process to fully understand the impacts of these increased truck volumes on the transportation network is fueled by collecting and analyzing freight data. With the adoption of just-in-time supply chain management solutions, and increasing congestion on urban, rural, and intercity motorways, better knowledge of freight movements can serve to improve highway operations. The real-time data generated by the development of travel time algorithms can be provided to commercial vehicle operators to enable them to minimize the delay associated with goods movement, and assist in streamlining the logistics planning process. Increased knowledge of truck travel patterns has the potential to increase overall highway safety, lead to better-managed maintenance operations, provide cost savings to public agencies, validate investments in intelligent transportation systems (ITS), and improve long-range planning and forecasting. This paper explores techniques that use current ITS technologies such as video image processing and loop detector data algorithms to collect and verify short and long vehicle count and length data. Three sets of traffic data for each time interval were created, and then compared using statistical analyses to produce results that that reveal some new information about the freight transportation system in the Portland metropolitan region.

INTRODUCTION

The growing volume of freight that is increasingly moved by trucks on the nation's transportation network makes it more important than ever to develop a better understanding of the freight system's overall operational characteristics. This project attempts to establish a base level of knowledge regarding the characteristics of the movement of freight in the Portland region through the analysis of long vehicle (LV) volumes and speeds. A body of knowledge about the technical aspects of freight data collection has been established through experimentation with ITS subsystems such as the CCTV network, video image processing technologies, inductive loop detectors, the traffic data storage networks, and data processing algorithms.

This project had several objectives. First, the ability of researchers and public agencies to collect freight data using the existing Oregon Department of Transportation (ODOT) CCTV camera network was tested. This was accomplished by coordinating camera positioning with the ODOT traffic management operation center and the successful connection of the fiber optic data feed to the Intelligent Transportation Systems (ITS) Laboratory at Portland State University. Second, it was demonstrated that traffic recorded on DVDs could be processed with a video image processing system (Autoscope RackVision), and done such that a methodology was established that can be used for future data collection experiments. Third, the robustness of the Nihan-Wang algorithm (*1*) was established for data collected in the Portland metropolitan region. Other literature was also reviewed (*3-7*), and discussed more fully in a related research report. (*8*)

This research has shown that it is possible to use the existing ODOT CCTV surveillance network to collect freight data in the Portland metropolitan region. The Nihan-Wang algorithm can be used to derive volume data for short and long vehicles using ODOT's existing loop detector infrastructure and the PORTAL data archive at Portland State University. Over 45 hours of traffic video data has been archived, processed and can be used for future research projects, transportation coursework or further instructional use such as training for students, faculty and members of public agencies or private firms. The viability of video image processing using Portland data has been tested and the results can be applied when considering or evaluating future applications for either research or practical use. Several students have been exposed to the technical, practical and theoretical aspects of current intelligent transportation system technologies, research project methodologies, modern traffic engineering practices and have gained knowledge in the fields of computer systems, report writing, statistical data analysis. In summary, the project has provided multiple stakeholders with verified data, technical knowledge, and learning opportunities. The project has also helped to raise additional research questions, has created room for future exploration in the field, and created additional partnerships with local agencies.

DATA SOURCES

Site Selection

Three locations were chosen to collect data for the project. It was important to select locations that had high volumes of truck traffic, and were able to be recorded by ODOT's CCTV network in a manner that allowed the recorded video to be processed using the Autoscope RackVision and accompanying software package. Furthermore, it was necessary that the CCTV cameras could be positioned in such a manner that enabled the field of vision to include the location of the inductive loop detectors that are located in each highway lane. The data fidelity of each loop detector was an important consideration in site selection, since high quality data was needed as an input into the

Nihan-Wang algorithm. This was necessary so that the robustness of vehicle classification estimations produced by the algorithm could be adequately tested versus ground truth data.

FIGURE 1 Site map.

Four sites (see Figure 1) were selected to begin recording video and collecting data using manual counting techniques and the Autoscope video image processing system:

- I-5 and Marine Drive in North Portland.
- I-84 and Sandy Blvd in Northeast Portland.
- SW Lower Boones Ferry Rd. and Interstate 5 in southwest suburban Washington County.
- ORE-217 and Hall Blvd. in Washington County

The ODOT CCTV cameras were designed to maximize the amount of high volume or high crash freeway locations that can be monitored for incident verification and response. All cameras have pan, tilt and zoom (PTZ) functionality so dispatchers can see both travel directions. The camera network functions well for its purpose, but poses some difficulties when used for video image processing. For collecting data using the Autoscope Rackvision, the cameras should be mounted at least 35 feet above the freeway and positioned directly over the center lane of traffic. This would allow between 200-250 feet of pavement to be seen, and the camera can be pointed downward to reduce sun glare and occlusion. Small deviations from the ideal camera position produce large errors in the processed speed and length data. Through coordination with ODOT Traffic Management Operations Center (TMOC) staff, cameras were placed in fixed positions during data collection periods, though occasionally cameras had to be moved as part of an incident verification and response effort.

Manual Data Collection

Data were collected manually by viewing the recorded traffic video and using an executable keystroke recorder. As vehicles passed a point on the freeway, a student recorded the passage by pressing a key. Four keys were used to denote different vehicle types and lane. The students made informed judgments about each vehicle's length. Vehicles were classified as either short (SV < 39 feet) or long (LV > 39 feet). The manual counting method was not free from error. Future research should include efforts to examine the magnitude of this error rate, and to compare it to the error rates of other methods. In addition, further segregation of the data by vehicle type (e.g., domestic trailer, 20-foot marine trailer, etc.) could further illuminate error rates.

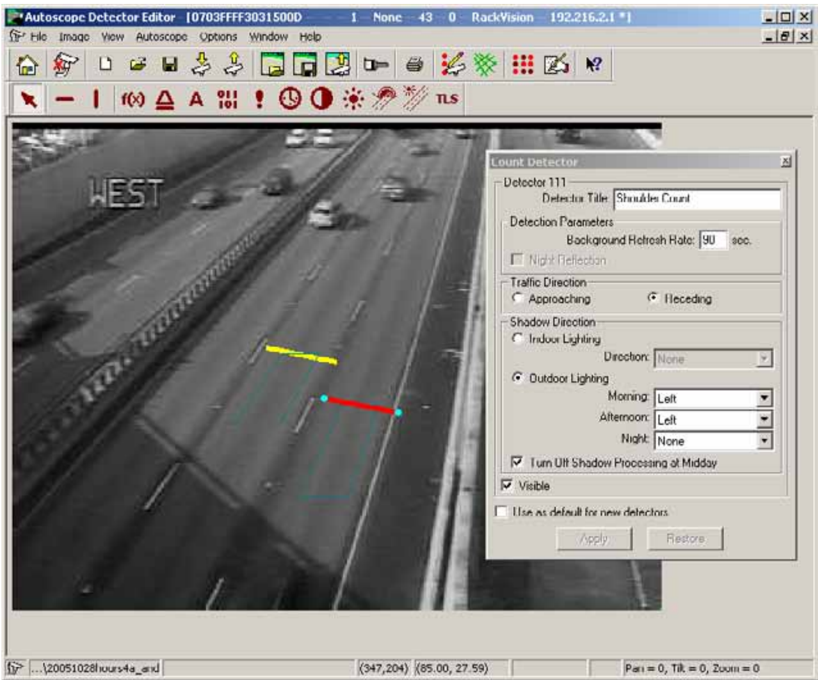

FIGURE 2 Video image processor detector layout.

Video Image Processing

The recorded video was processed by the Autoscope Rackvision hardware and software. The ODOT fiber optic video feed from their TMOC was dampened by a hardware device because it was, unexpectedly, too strong and produced a snowy feed. After loading a freeway image, it is necessary to calibrate the field of vision, including the dimensions of the image, and camera height. Virtual detectors were created, a data collection poll was set up and executed. The speed detectors (that also count) that were used for this project collect: vehicle presence, speed, and length. The speed detectors were placed so they could capture the front part of the hood of a vehicle, to produce the most accurate measurements of speed and length.

Speed detectors are the rectangular section seen in the center and right hand shoulder lane in Figure 2. The larger lines at the end of each speed detector represent the count detectors. The count detector portion of a speed detector is the on the downstream side of the speed detector. When vehicles travel over a detector during video image processing, a detector will change its status to 'on.' When vehicles leave the influence area of a detector, it turns 'off.' Speed and length are calculated when the vehicle leaves the detector zone of the speed detector. The presence of the vehicle is noted at this time by both the speed and count detectors. Once the detectors are set up, as the traffic video plays, the Rackvision processes the data and outputs it to both the data collector window and to a text file that can be easily manipulated.

ITS Data Archive

The Portland Oregon Regional Transportation Archive Listing (PORTAL) has been archiving speed, volume, and occupancy data from 485 loop detectors on the Portland metropolitan freeway system since July 2004. The system also produces performance metrics derived from the archived data, such as hours of delay, travel time, and vehicle miles traveled, are available to individuals and agencies such as transportation planners, metropolitan planning organizations, state transportation planners, traffic management operators, transit operators, and transportation researchers. For this study, PORTAL has been used to generate truck counts using an algorithm designed by Wang and Nihan (*1*).

ANALYSIS TOOLS

Wang-Nihan Algorithm

The Wang-Nihan algorithm (*1*) generates speed and vehicle-classification from single-loop data. The algorithm assumes constant speeds within a 5-min period, estimates a speed for the period, and calculates the LV volume. The speed is calculated based on Athol (*2*) (Equation 1), where $\bar{s}(i)$ is estimated average speed, $N(i)$ is volume, $O(i)$ is occupancy for time period i, T is the interval length, and g is the speed estimation parameter (g-factor), based on effective vehicle length (EVL).

$$\bar{s}(i) = \frac{N(i)}{T \cdot O(i) \cdot g} \tag{1}$$

The g-factor is dynamic between time intervals that LVs skew the mean EVL, so intervals with LVs are sorted from those without to create a more accurate speed estimate. In each 5-min period, the 20-sec intervals are sorted into those with SVs (less than 11.89 m) and intervals with LVs.

$$g(i) \frac{1}{\bar{l}(i)} \tag{2}$$

To separate intervals with LVs from intervals without, the algorithm assumes that there are at least two 20-sec intervals with only SVs in a 5-min period, based on empirical evidence. Using the SV-only intervals and the occupancy proportion, the EVL is calculated, and is used to calculate the 5-min speed by taking the summed SV volume and occupancy:

$$\bar{s}(j) = \frac{N_{SV}(j)}{O_{SV}(j) \cdot g} \tag{3}$$

where $\bar{s}(j)$ is average speed for a period, $N_{sv}(j)$ and $O_{sv}(j)$ are total volume and occupancy for the two short-vehicles only intervals. The algorithm also uses a correction coefficient (β) for each detector:

$$g = \frac{1}{\beta \, \bar{l}_{SV}} \tag{4}$$

This study has used β=1, which was reasonable based on volume-occupancy graphs from PORTAL. With a known period speed the interval counts can be divided into SV and LV counts. To calculate an estimated EVL for any interval:

$$\bar{l}_k(j) = \frac{O_k(j) \cdot \bar{s}(j)}{N_k(j) \cdot \beta} \tag{5}$$

where $\bar{l}_k(j)$ is the interval EVL, $O_k(j)$, $N_k(j)$ $s(j)$ and are the measured occupancy and count and estimated speed for the interval.

There can be no more than 7 LVs in a 20-sec interval (empirical evidence), so if the volume is over 7 it is assumed that there were no LVs. The volume plus one indicates how many possible SV-LV categorizations there can be for one interval. For example, a count of 3 vehicles gives the possibility of 3 short; 2 short and 1 long; 1 short and 2 long; or 3 long. A statistical process is used to determine the most likely distribution of vehicles (SV/LV) in each interval, so the estimated truck volume can be determined for each interval:

$$d_{kx}(j) = \left| \frac{\bar{l}_k(j) - l_{loop} - \mu_{kx}(j)}{\sigma_{kx}(j)} \right| \text{ for } x = 0, 1, \ldots\ldots, \min(N_k(j), 7) \tag{6}$$

Implementation in PORTAL

The Wang-Nihan algorithm was implemented in the PORTAL system which enabled this project to easily extract data in a convenient format. A user can log in and choose a day, a time, and a duration, and the website will query the archived data and produce a graph, a table or a comma separated value (CSV) file. Currently, PORTAL displays seven columns in its table output including start time, volume, occupancy, truck count, car count, ODOT speed, and estimated speed. The data displayed in the table output is at a 20-sec resolution; no aggregation is implemented for the table output. The Volume and Occupancy columns display the measured volume and occupancy reported by the ODOT loop detector systems. Note that Volume is the total measured volume for an interval. The Truck Count and Car Count columns provide the estimated number of LVs and SVs in the interval, respectively. Truck Count and Car Count are based on the Wang-Nihan algorithm calculations. The Estimated Speed column reports the estimated speed for a 5-min period based on the Wang-Nihan algorithm. This estimated speed is used as input to the truck count algorithm. The ODOT Speed column reports the average of the speeds reported from the ODOT system over the 5-min period. The current ODOT speeds tend to be underestimated due to the added occupancy contributed by the LVs in each period. This has been a problem that is exacerbated during low traffic flow periods (for example, over night) when a single truck in an interval can result in a very low speed being reported.

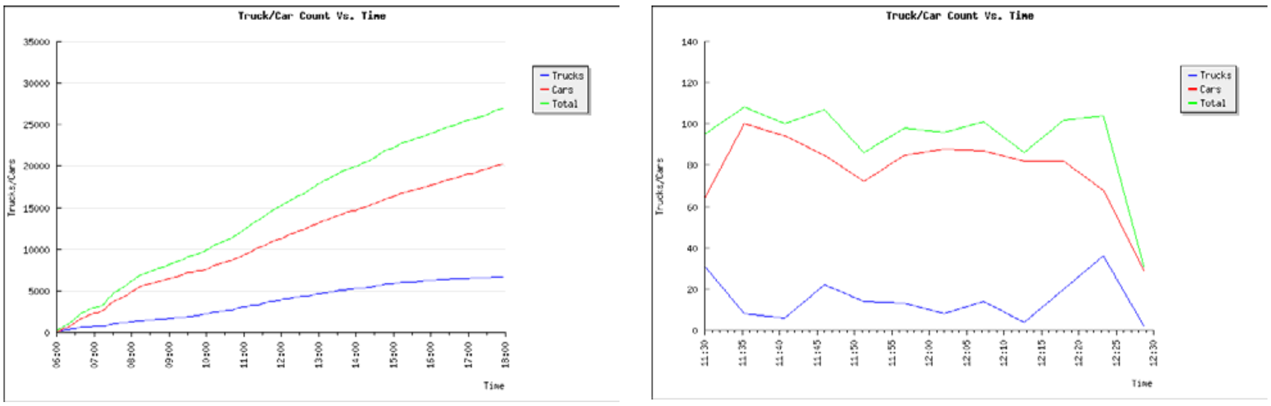

FIGURE 3 Examples of line plot and cumulative plot output.

PORTAL contains several automated plotting features. For example, the plots shown in Figure 3 contain cumulative and time series count totals for each 5-min period. For example, in the period 11:30-11:35 there were approximately 30 trucks, 65 cars, and 95 total vehicles. Based on these data, Figure 4 provides a contour plot of truck volume percentage for the I-5 Northbound corridor on Dec 15, 2005; the plot uses data at a 5-min aggregation level. For I-5 Northbound on Dec 15, 2005, the average percent trucks in a 5-min period was 14.35%, with a standard deviation of 12.57%. The volume-weighted average truck percentage for 5-min periods for the entire day was 18%, with a standard deviation of 13.09%.

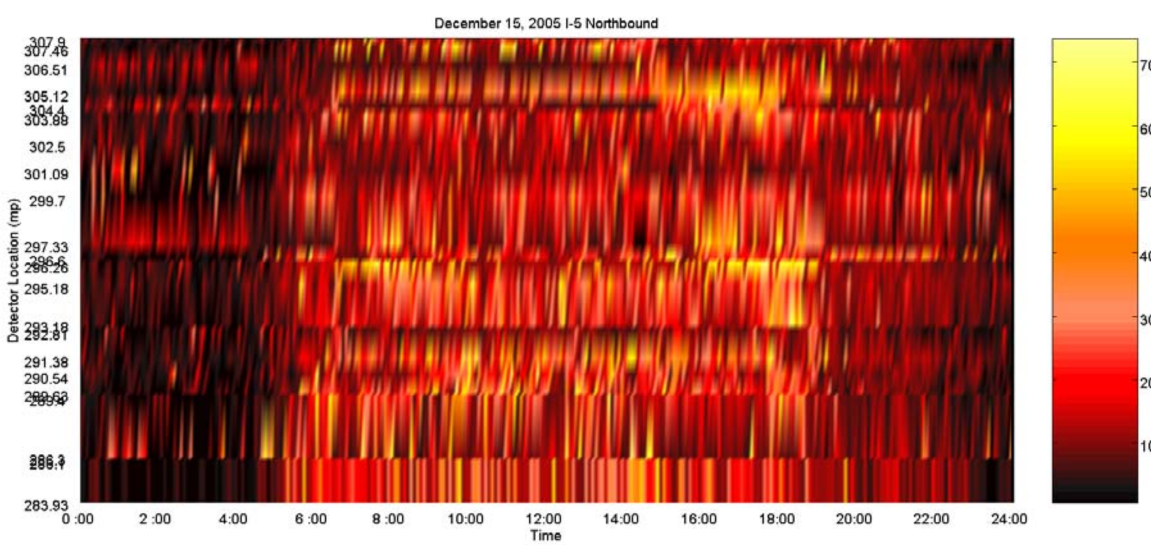

FIGURE 4 Truck percent contour plot I-5 northbound, Dec 15, 2005.

SUMMARY OF RESULTS

Data from a total of 47 video segments (totaling 43 hours) were collected from the three study sites during October and December 2005 and February 2006. The length of the time periods for each data unit ranged between 30 min and one hour. A total of 65,256 vehicles were manually counted (3,986 trucks) as the "ground truth." Autoscope count data included total and LV counts using the count and speed detectors. PORTAL also provided total and LV counts using the Wang-Nihan algorithm. Prevailing flow and speed data (including variability) were also available through PORTAL and are used below for additional analysis. For each of the 47 data periods, a number of comparisons were made among the following sources:

- Manual (ground truth) total and truck counts.
- Autoscope count detector.
- Autoscope speed detector total and truck counts.
- PORTAL-Wang total and truck counts.

The average absolute percent difference between the Autoscope count detector and the ground truth for all vehicles was 3.5%, with a standard deviation of 3.5%. The absolute percent difference between the Autoscope speed detector counts for all vehicles and ground truth was 2.6% (standard deviation 2.3%). The absolute percent difference between the Autoscope truck counts and ground truth was 4.4% (standard deviation of 6.7%). For the data periods that had good freeway detector data, the average absolute difference between PORTAL-Wang and ground truth for all vehicles was 2.7% (standard deviation of 13.3%). In the area of truck counting, the average absolute difference between the PORTAL-Wang count and ground truth for trucks was 54.6% (standard deviation 64.1%).

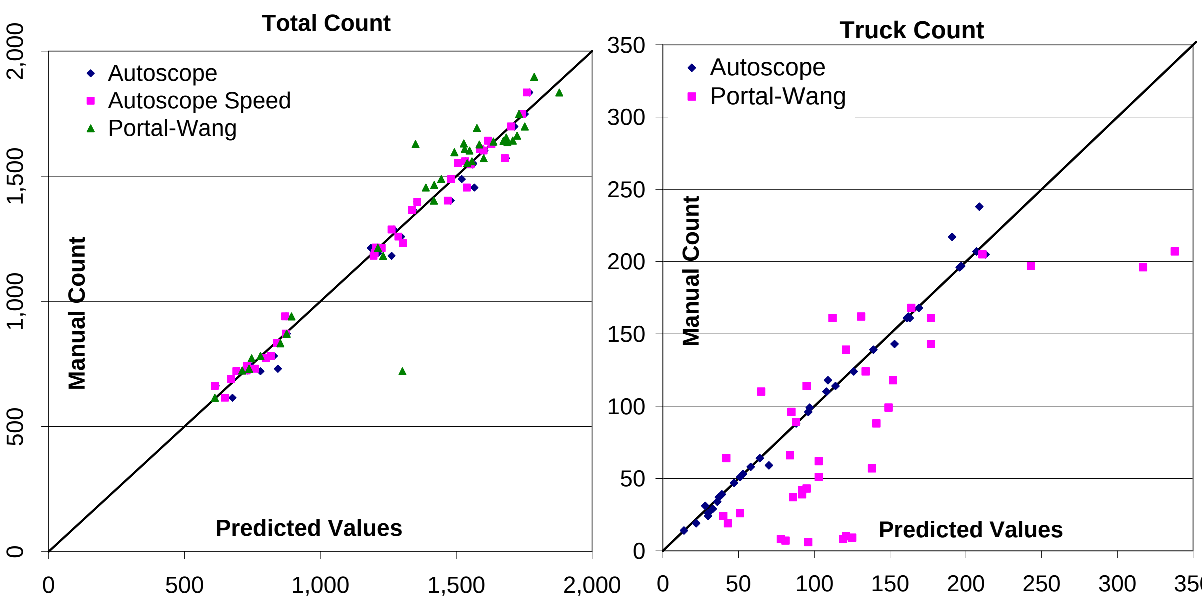

FIGURE 5 Comparison of total and truck count mechanisms to ground truth.

In order to illustrate some of the relationships between the differences found in this empirical analysis, a number of graphical illustrations have been prepared. Figure 5 shows the three total count mechanisms (Autoscope, Autoscope Speed and PORTAL-Wang) on the *x*-axis versus the manual count ground truth on the *y*-axis. As shown, except for two outliers, the counts obtained from the three sources do not deviate dramatically from the diagonal line, indicating that most of the total count predictions were within a few percentage points of the ground truth.

Figure 5 also shows the predicted truck count values using Autoscope and PORTAL-Wang on the *x*-axis against the manual counts on the *y*-axis. As shown on the figure, it appears that the Autoscope truck counts hover closer to the diagonal line than do the counts predicted by PORTAL-Wang.

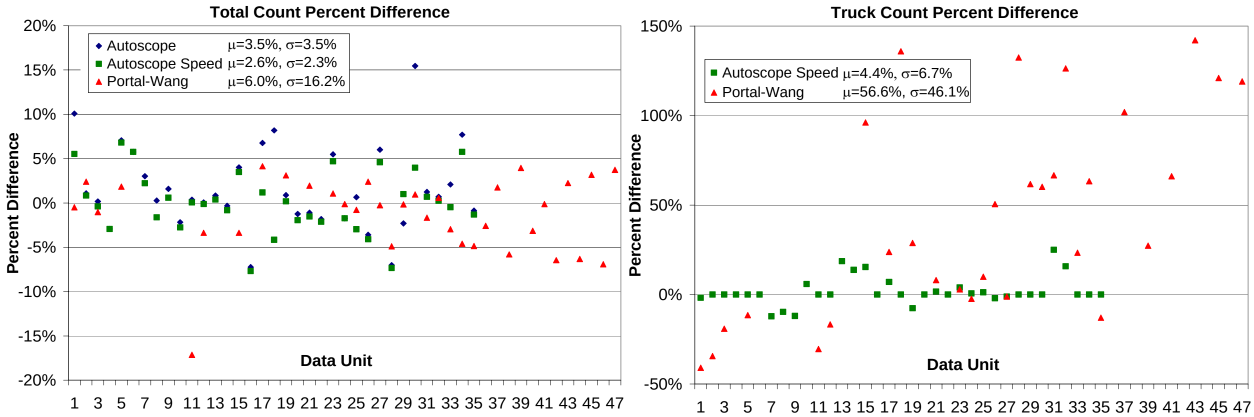

FIGURE 6 Total and truck count percent difference.

In order to gain further insights into the level of vehicle and truck count capabilities from the considered methods, Figure 6 shows the percent difference for the three methods across all 47 data units (the *x*-axis in the figure refers to the 47 data units). As shown in the figure, there is a tight band of points within the +/- 5% range, with a few outliers above and below these values. The Autoscope Speed method appears to perform the best with an average error of 2.6%. The Autoscope method exhibits a 3.5% error on average while the PORTAL-Wang method had an average of 2.7% error.

The primary interest in this research was to determine whether there are potential systematic means for estimating truck traffic flows on the freeway network of the Portland metropolitan region. Toward this end, Figure 6 also shows the percent difference for the two truck counting mechanisms as compared to ground truth for all 47 data periods (where data were available). As shown, the Autoscope Speed method displayed an average of 4.4% error with most points near the zero *x*-axis. The PORTAL-Wang method exhibited truck counts that were more scattered.

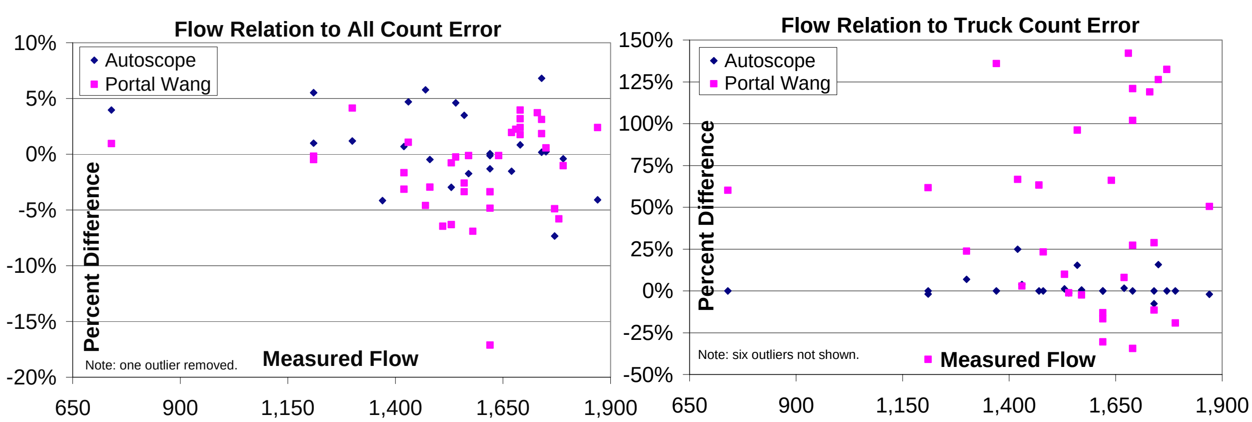

FIGURE 7 Flow relation to all count and truck count error.

Most flow values measured were between 1,400 and 1,800 vehicles per hour per lane (average 1,560 vph), Figure 7 now makes it possible to determine whether there is a relationship between the prevailing flow during a particular measurement period and the level of error for the total counts using the Autoscope and PORTAL-Wang methods (when data were available). From the figure, without need for any statistical tests at this point, it appears possible that there is a slight spreading of the percent difference as the flow exceeded about 1,600 vehicles per hour. This should be the topic of further research before firm conclusions can be drawn. The quantitative relationship would be important for data collection and usability issues.

Similar to the previous graphic, Figure 7 also shows the relation between measured prevailing flow and the truck count accuracy. Here it is more difficult to draw any conclusions due to the wide range of errors in the PORTAL-Wang implementation using the Portland data.

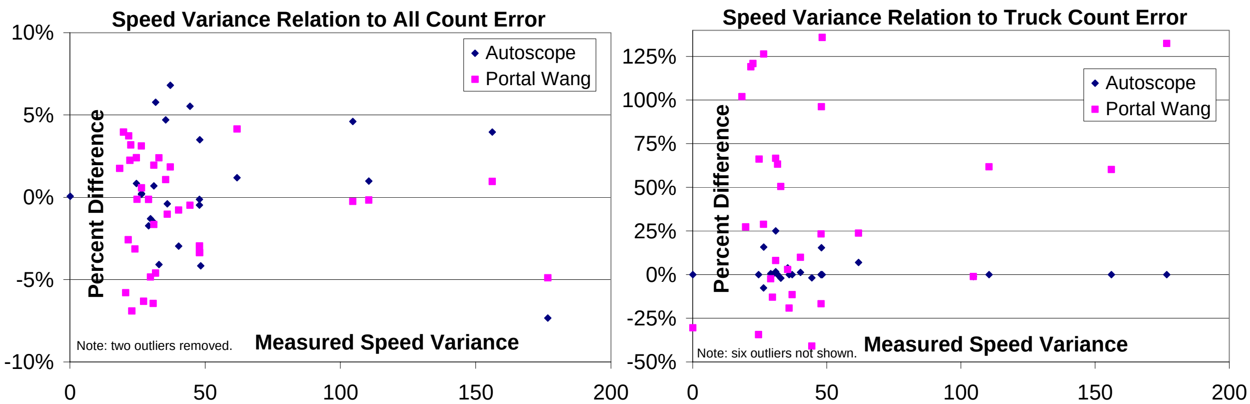

FIGURE 8 Measured speed variance relation to all count and truck count error.

The Wang-Nihan algorithm requires constant speed during the 5-min calculation intervals in order to make accurate LV estimates. It was thought that if this assumption were not valid in this project, that the prediction accuracy would be negatively impacted. Therefore, the effect of the prevailing speed variance on count error was analyzed as shown in Figure 8. Here the measured speed variance is shown on the *x*-axis while the percent difference for total vehicle count using the Autoscope and PORTAL-Wang methods is shown on the *y*-axis. There were several measurements with high variance (and five measurements with variance to mean ratios greater than one) which could indicate that the violation of the constant speed assumption contributed to the wide ranging errors found in this research. Figure 8 also shows a similar image, with the measured speed variance (when data were available from PORTAL) against the percent truck count difference for both Autoscope and PORTAL-Wang methods. Due to the many outliers, the picture here is less clear.

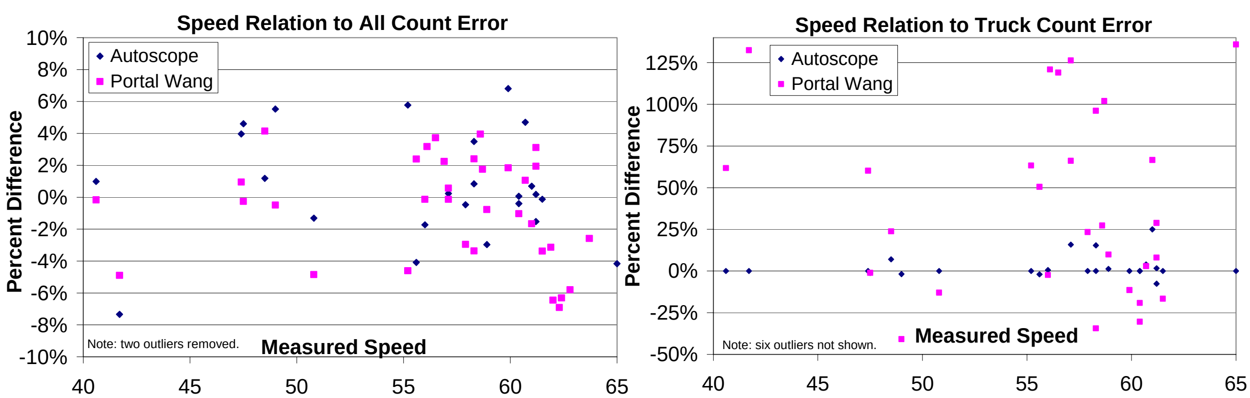

FIGURE 9 Measured average speed relation to all count and truck count error.

The question also arose whether the speeds of traffic during the data collection were appropriate for the use of Autoscope and the Wang-Nihan algorithm. Thus, Figure 9 was constructed to examine the measured average speed during each of the 47 data periods where data were available against the percent error in total count. Most of the observations were during periods with traffic flowing between 55 and 65 mph as measured by ODOT (average of 57 mph). The figure does not show a clear relation between the two. Figure 9 also illustrates a similar relation between measured speed and percent error in truck counts for both the Autoscope and PORTAL-Wang methods. Here it appears that the scatter widens with increasing speed, particularly for the PORTAL-Wang method.

The three sites presented different opportunities for obtaining good Autoscope readings as well as varying in other ways. This analysis considers the four sites (Boones, Marine, Sandy, and Hall) separately across the five classifications. The total count using Autoscope, Autoscope Speed and PORTAL-Wang is compared against ground truth in absolute percent difference. As shown in Figure 10, the Marine Drive site appeared to perform worse than the other three sites. For the PORTAL-Wang method, the Hall site is the worst of the four. Turning to the truck counts the Marine site also performs less well than the Boones, Sandy and Hall locations.

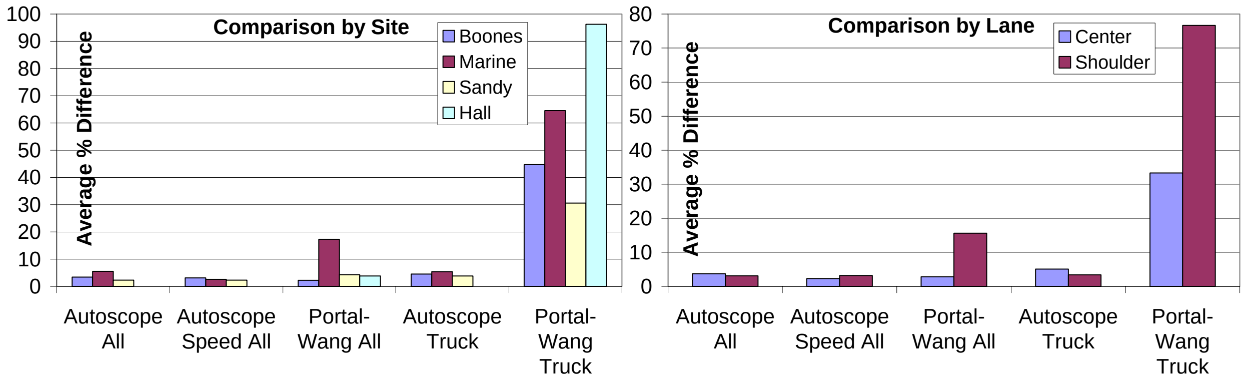

FIGURE 10 Percent count differences by freeway site and by lane.

The final consideration in this analysis was whether the lane used mattered in terms of the accuracy of the total or truck count. From Figure 10, it appears that the counts taken in the shoulder lane worked less well in the PORTAL-Wang method. This does not necessarily imply that there is anything wrong with using video or detector counts from the shoulder lane, but it could imply a need for detector tuning at the particular locations studies.

CONCLUSIONS

This project has illustrated that video image processing can be an effective tool for determining truck and passenger vehicle volume counts. In addition, it can produce good estimates of individual vehicle speeds. This experiment has shown that when used under the available CCTV camera conditions (the various positions, locations, and heights of highway cameras located in the Portland region) the image processor did not produce accurate vehicle length measurements. While vehicle lengths were overall incorrect, in many circumstances the distribution of vehicle lengths measured during a time period conformed closely to a generalized distribution of manual observations.

The Wang-Nihan algorithm results were less clear. In certain situations, the algorithm did a good job of predicting LV volumes. In others, the algorithm over- or under-estimated truck volumes. The analysis of the estimation error patterns was inconclusive—there were inconsistencies during periods of heavy and light traffic, both when the volume of trucks was low, and when trucks constituted a larger percentage of the traffic stream. Sources of error may lie in the choice of study locations when they correspond to areas with poor detector performance. Further research needs to be undertaken in order to understand where the errors are coming from and if it is possible to improve detector performance to result in more accurate truck counts. Work on this is ongoing.

In general, this project exhibited mixed results. There were some unforeseen loop detector malfunctions that resulted in limited data availability. Reliability of loop detectors is a known problem—in this case some of the preferred CCTV camera locations were associated with particularly poor loop detector performance. The PORTAL-Wang algorithm as implemented within the PORTAL database did not perform as well as was hoped, presumably due to loop detector tuning, loop sensitivity and low occupancy data resolution issues that need to be resolved. The image processing methods performed surprisingly well in total count and truck count, but were labor intensive and depended upon the surveillance cameras remaining in stationary positions for extended periods. In the case of these particular datasets, it appears that the Wang-Nihan algorithm was over-estimating truck counts more so than under-estimating. There are under-estimates, but the most notable misses are all over-estimates. Performing further sensitivity analysis using different/improved values of the correction coefficient (β) may help in this area.

There were numerous opportunities for error to enter into this research, despite the care taken in the experimental design, implementation, and analysis. The camera position/height may have contributed to some of the errors found with the image processing methods. Generally, Autoscope is known to work better with high camera positions, since suboptimal camera angles lead to incorrect vehicle lengths, speeds and vehicle counts due to occlusion. Also, as expected, the research relied on traffic conditions and ODOT TMOC staff.

It is clear from the original research (*1*) that the Wang-Nihan algorithm is not expected to perform as reliably in congested conditions. In this project, none of the traffic conditions were congested since measured speeds were almost all above 40 mph and most were above 50 mph. The two primary assumptions in are that 1) speed should be constant over a 5-min period and 2) there are at least two 20-sec intervals in a 5-min period without LVs. (*1*) If either is violated there can be an accuracy problem. Clearly both can be violated in very congested conditions, but it is not clear that the conditions in this research violated those assumptions. If condition 1) is violated then both speed and long-vehicle volume will be over-estimated (large occupancies from low speeds are incorrectly attributed to LVs). If condition 2) is violated then speed and long-vehicle volume will be under-estimated.

One further issue involved artificially high speeds on I-84 at Sandy that may have been caused by the artificially low occupancies reported by those detectors. High speeds were a likely result of low occupancies. It is interesting that the truck counts for I-84 at Sandy were reasonable even though the speeds were not. Also, the PORTAL-Wang speed estimates were highly variable and unreasonably high in some cases. It is possible that detector problems led to these unusual readings. Also in some cases, such as on I-84 at Sandy, where the detector was reporting artificially low occupancies, the ODOT reported speeds appeared reasonable. The PORTAL implementation of the Wang-Nihan algorithm did not take into account detector calibration—it assumed the detectors were properly calibrated. This will need to be corrected for future research, and work in this regard is ongoing.

There is no question that there is a current need for collecting freight data. One method for doing so is by using the existing ITS infrastructure readily available in metropolitan regions around the country—inductive loop detectors, surveillance cameras, data processing algorithms and software programs, communication networks and data archiving and retrieval technologies. These technologies can produce favorable results—good, useable data—when care is taken to design data collection experiments and implement methodologies that produce verifiable data. Coordination and cooperation between researchers, state and local DOTs, and other stakeholders helps to speed the data collection process and to enable worthwhile data to be collected. Overall, the technologies used in this project show some promise in terms of their long-range abilities to produce freight data in an automated way.

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