COLLECTION OF VEHICLE ACTIVITY DATA BY VIDEO DETECTION FOR USE IN TRANSPORTATION PLANNING

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ABSTRACT

Advanced traffic management systems allow video image detection to supplement and improve data inputs in transportation modeling efforts. Video detection systems use machine vision technology, the interaction of video cameras, and specialty computer hardware and software to measure traffic. Traffic parameters such as hourly flows, density, vehicle speed, level of service, and other parameters derived from measured and default values are automatically computed. However, the accuracy of video image detection systems is dependent upon factors such as the camera height, location, and angle above the roadway. Environmental factors such as rain, sun intensity, and day/night also affect vehicle detection accuracy.

Existing transportation models can benefit from video image detection technology and improved travel demand models can be developed from such data, providing video detection is accurate. This paper examines how transportation models can benefit from video data. A commercially available system is used to collect data from freeway segments in Atlanta, Georgia. The detected vehicle counts, classifications, and average speeds are compared to true counts obtained over the same interval. Differences in these traffic parameters are determined as a function of camera location and site conditions that constrain the accuracy of video detection. The analytical results lead to recommendations on use of video detected traffic parameters in model improvement.

KEYWORDS

Advanced Traffic Management Systems, Vehicle Activity, Video Detection, Machine Vision, Autoscope, Motor Vehicle Emissions

INTRODUCTION

The Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and the Clean Air Act Amendments (CAAA) of 1990 have made transportation planning analyses more relevant to national policy issues and concerns. Growing traffic congestion and environmental awareness have resulted in increased emphasis on management of traffic systems and development of capabilities to forecast accurate traffic characteristics as well as demand on the future transportation system. Estimates of capacity and service volumes from transportation models are no longer adequate. Air quality and conformity analyses (using current models) require the ability to predict vehicle speeds under different scenarios, and different scales of modeling. Analyses that employ future emissions models will require even more detail about traffic conditions [Guensler, et al., 1997]. Video detection may provide the improved data necessary for input into transportation models, depending upon the accuracy of counts, computed speeds, and formulae used to compute traffic parameters.

Operational deployment of advanced traffic management systems (ATMS) has demonstrated that video image detection systems (VIDS) are practical alternatives to conventional sensors for signalized intersection and ramp meter control. VIDS can be a low cost addition to existing traffic management centers [Courage, et al., 1996]. Freeway imaging sensors have been employed to successfully perform automated incident detection and have shown increased accuracy in detecting occurrences [Michalopoulos, 1993]. Improvement of imaging systems and collection of more accurate vehicle activity data allow engineers and planners to move beyond traffic management, allowing the detailed data to be used in making general transportation demand and motor vehicle emissions model improvements. VIDS data can be used for calibration and validation of models. However, these new uses of the video data may require accuracy levels that exceed that necessary for uses in current traffic management activities.

This paper describes the current capabilities of the VIDS implemented in Atlanta, Georgia and identifies potential planning uses of the monitored data. The authors undertook a study of the monitoring accuracy for traffic counts, average speeds, and vehicle classification and the quality of the data currently available from the advanced traffic management system has been assessed. Data benefits and limitations are discussed within the context of planning activities and preliminary quality assurance guidelines for collection and use of VIDS data are outlined.

VIDEO IMAGE DETECTION SYSTEMS

The Georgia Department of Transportation (GDOT) operates the Advanced Traffic Management System (ATMS) in the Atlanta area. The Atlanta system utilizes VIDS technology and provides GDOT with the ability to manage traffic along more than 60 miles (96 km) of freeway. Flow of traffic is monitored along Interstates 75 and 85, that run through the middle of the Atlanta central business district and out to the surrounding suburbs. Small monochrome or color electronic cameras mounted on poles or bridges record traffic conditions for each section of the highway. More than 300 cameras feed real-time video images of traffic data to the traffic management center (TMC) via fiber optic cable. The video images from these cameras can be processed and analyzed with the Autoscope 2004 video imaging system. Automated incident detection algorithms are used to program changeable message signs and to dispatch freeway service patrols.

Field-of-View Calibration

To estimate vehicle length and vehicle speeds, the camera field-of-view must be calibrated. Calibration establishes ground distances relative to the view of the camera, providing a three-dimensional measurable perspective to a two-dimensional video image. Calibration lines are placed parallel and perpendicular to the travel lanes by viewing the camera image on the computer screen and using the mouse to draw the lines at the appropriate locations. Each calibration line has a measurement representing the distance from the “base” calibration line. The height of camera is also entered in the calibration process. Proper calibration allows the program to estimate vehicle lengths and travel distances, which are used to calculate speeds. Precise calibration requires knowledge of lane widths, downlane distances, and camera height [Image Sensing Systems, Inc., 1996]. Figure 1 illustrates the creation of calibration lines on a video image, with crosslane and downlane calibration lines.

Creation of Detector Files

After calibration of the field-of-view, traffic detectors are placed on the video image using the manufacturer’s software. These detectors can determine the number of actuations, vehicle length, and vehicle speed. The techniques used in developing detector files can play an integral part in the accuracy of machine vision counts. The image view should be examined to determine if environmental or traffic stream variables are likely to cause false vehicle detection. Factors that must be examined include: background anomalies, relative vehicle position, areas of occlusion, and presence of weaving areas (areas where vehicles are undertaking lane changes). Detector placement will vary for each freeway, ramp, and intersection layout [Image Sensing

Systems, Inc., 1996]. Figure 2 illustrates the placement of count and speed detectors on a video image.

Ideally, detectors are made as wide as their travel lanes to employ as much of the image as possible and avoid missing detection of vehicles not centered in the lane. However, angled camera views can restrict detector width considerably, and vehicles in one lane may actuate detectors in the adjacent lane. To prevent this occurrence, detectors may cover only a percentage of the entire lane width.

Time of day must also be considered in detector file development. For example, a detector created during daylight could be placed in a given lane near a streetlight. When the streetlight is lit at night, it could create a glare and affect the detector's performance. Proper consideration of image quality during all times of day should be given during detector file creation.

Measurement of Traffic Parameters

With tripline-based systems, count and speed detectors are used to measure traffic volumes, vehicle speeds, and vehicle classification. These counters are placed on the video image using specially designed software to graphically overlay “detectors” on the video image.

Speed detectors (Figure 2) are placed longitudinally in a travel lane and measure vehicle speeds and vehicle lengths by computing the time a vehicle travels within a speed trap of known length. Classification of vehicles is solely based on vehicle length, as opposed to the typical FHWA Scheme F classification which uses axles and number of units. Vehicle lengths are aggregated into classes by predetermined length. Count detectors record instances when vehicles cross the detector. Volume data can be collected for individual travel lanes, or at multiple locations in a travel lane to detect queue formation.

Given the vehicle count, speed, and classification information, the internal software estimates other traffic data parameters including, but not limited to: vehicle flow, time headway, time occupancy, time service, level of service, space mean speed, space occupancy, and density. These estimates are based on the common formulae established in traffic engineering and the Highway Capacity Manual [Transportation Research Board, 1994].

TRAFFIC VARIABLES FROM VIDEO DETECTION

Video image detection allows collection of supplemental traffic information from multiple locations for use in validation/calibration of models. Continuous monitoring of traffic activity through automated software allows collection of local/regional traffic variables for use as model inputs. VIDS technologies allow for collection of supplemental data that can be used to improve the travel demand and air quality modeling processes.

Recent surveys of local, regional, and state agencies show that published standards, such as the Highway Capacity Manual (HCM), the Urban Transportation Planning System (UTPS) tables, state DOT tables, and the Bureau of Public Roads (BPR) curves are used frequently in the transportation planning process [Dowling, et al., 1997]. While the sources are credible for planning purposes, utilizing locally available data can complete more accurate and locally realistic modeling of the transportation network.

Observed VIDS activity can provide more realistic inputs into travel demand and emission models. In fact, data can be used directly in estimating vehicle activity and emissions for a specific monitored event. Yet, the basic purpose of travel demand and emissions modeling efforts is to predict future vehicle activity and emissions impacts. Data available from VIDS can be used in the validation and calibration of current and developing models so that our ability to predict future vehicle activity and emissions is enhanced.

Average vehicle speed is a critical component in the current emissions modeling process. A small change in average speed of vehicles could dramatically change the emission rates that the MOBILE5a emission rate model assigns to the fleet (dependent on base speed and pollutant). Current modeling of average speed is at best (under current practices through 4-step travel demand modeling approaches) estimated at ±5 mph (±8 kph). More likely, the average speeds are estimated at ±15 mph (±24.1 kph) [Chatterjee, et al., 1997]. These errors can significantly alter emissions estimation for some operations. Table I shows errors in speed input that would cause a 10% change in the modeled emission rate (composite values of whole fleet) for different pollutants.

In emissions analyses, most agencies input free-flow speed from the HCM, UTPS-type models, posted speed limits, or design speeds. Some areas conduct field studies to provide better estimates of average vehicle speeds. Congested speed estimation techniques range from HCM methods, to field measurements, to local and BPR curves [Dowling, et al., 1997; Chatterjee, et al., 1997]. Prediction of speed is based on the free-flow speed, capacity, and volume, which can be obtained through continuous video detection. This means that calibration of roadway speed-flow relationships can be developed using VIDS data rather than using assumed relationships.

Transportation models generate link-specific estimates of traffic volume and average speed which have been used with MOBILE5a emission rates to generate link-specific emissions estimates. New facility-specific inventory cycles have recently been developed for use in the MOBILE6 emissions model. These cycles will better represent actual fleet driving and move away from use of average speed, as well as including more aggressive real-world driving. With MOBILE6, emission rates will be associated with different facilities (freeways, arterials/collectors, local roads) under different levels of service [Carlson and Austin, 1997; USEPA, 1997]. Video detection data will allow computation of level of service for roadways based on volume/capacity measurements or average speed of vehicles.

Table II provides a list of additional potential uses of VIDS data in the transportation planning process based on the ability of the video detector to accurately measure comprehensive traffic activity on a continuous basis for a corridor.

COMPARISON OF VOLUMES, CLASSIFICATION, AND SPEED

To assess whether VIDS output will be useful for planning purposes, a comparative analysis of VIDS data output accuracy was undertaken for actual data from Atlanta freeway segments. The accuracy of vehicle counts, classification, and speeds are examined by comparing detected counts with true counts obtained over the same interval. Graduate students reviewed each tape repeatedly in the laboratory to compare to VIDS output developed classifications to develop the "true" volume counts. Random speeds were sampled in the field at the same time of video recording of traffic to develop the distribution and confidence limits. Differences in total volume, types of vehicles, speeds based on camera are linked to geometric and traffic conditions which constrain accuracy. The results of count comparisons are used to formulate recommendations for use of video detected traffic parameters in the modeling process.

Video from the cameras was recorded along the freeways during a period from late July to August 1996. Video signals were transmitted to the TMC by fiber optic cable and recorded on VCRs. Approximately 190 8-hour tapes were recorded over a three-week period. Post-processing of the data included cataloging of the camera location, traffic conditions, view changes, and environmental conditions.

Traffic for speed comparisons was recorded by cameras located on tripods along overpasses of freeways rather than by ATMS cameras. This way, spot speeds collected simultaneously by laser rangefinders (LRF) and video calculated speeds could be compared directly to the same vehicles using simultaneous LRF speed and video recording.

The vendor-supplied Autoscope software computes volume, average speed, and number of vehicles by length over operator-specified specified time intervals. This interval can range from ten seconds to one hour and allows the user to specify the level of data aggregation required [Image Sensing Systems, Inc., 1996]. In the analyses that follows, the video data were aggregated at one minute intervals, manual count data aggregated to one minute intervals, and spot speeds computed for a random selection of vehicles.

The traffic count and speed data were compared for each lane to highlight accuracy at each site and the degradation/improvement in quality of data across lanes of traffic. Lane by lane analysis is important due to differences in vehicle activity (speeds, LOS, classifications, etc.) and impact in modeling activity and emissions. However, in segment analysis, accuracy may improve due to offset of false readings in one lane and omissions in another.

Factors Influencing Accuracy

In evaluating traffic data, the conditions leading to possible inaccuracies include motion of the camera image, slanted camera views, poor lighting conditions, heavy traffic volumes, inclement weather, and sensitivity of equipment used to record the video:

Camera image motion. Movement of the camera image may be caused by motion of the camera itself, or by motion of the videotape image during playback. The cameras of the Atlanta ATMS remain quite still, except for cameras mounted on bridges which shake as vehicles travel across the bridge. As the pavement surface shakes and shifts the image on the video screen, VIDS may record some of the vibrations as vehicles traveling over the detectors. Disruption occurs when the count and/or presence detectors remain on for extended periods (up to several seconds) because they read the vibrations as vehicles continuously crossing. A stabilizer function is included with the software, which detects the movement of the background from camera movement and corrects the image to reduce false readings.

Slanted camera views. Ideally, cameras should be placed directly above a roadway. Often this camera angle is not possible. While cameras placed to the immediate side of a roadway provide reasonable views, cameras located further from the roadway yield slanted views. With slanted views, vehicles can appear to travel partially or even fully over adjacent lanes. Such vehicles can trigger detectors in adjacent lanes, resulting in these vehicles being double counted. This problem is more readily noticeable with taller vehicles, such as tractor-trailers.

Poor lighting conditions. Whenever vehicle lights are on, the headlight beams disperse into adjacent lanes. The detectors in adjacent lanes may record the passing light beams as a vehicle, resulting in double or triple counting of single vehicles. In addition, speed detectors may read the headlight rays as part of the vehicle, recording such vehicles as having inaccurately long lengths.

Heavy traffic volumes. Count detectors may have trouble holding the presence detection of vehicles that rest on the detectors during heavy traffic congestion. The count detectors may flash on and off, resulting in multiple counting of a single vehicle. Also, two vehicles in the same lane may travel or rest on the same speed detector. The speed detector may not be able to distinguish that there are two vehicles.

Inclement weather. Inclement weather can be in the form of wind, which may cause cameras to sway, or in the form of rain or snow, which may disrupt the traffic detectors. Rain and snow can also require drivers to turn headlights on, which in turn can cause the aforementioned problems.

Media used in collecting data. When traffic data are post-processed, the equipment used to store traffic data can play a considerable role in the accuracy of the data recorded. Both the VCR type (standard VHS, SVHS, BETA professional, etc.) and the recording speed may affect the quality of the image offered to the VIDS. Different types of VCRs provide varying degrees of resolution, and different recording times (e.g., 8 hours, 6 hours, 2 hours).

Volume Counts

Volume data were collected from different camera views across multiple lanes of traffic to determine the difference in count quality based on the site geometry, traffic levels, and environmental conditions. Thirty-three different volume counts were made over ten different camera views to compare VIDS to manual counts. The traffic counts were converted to hourly flows from the VIDS and plotted against measured flows from manual counts in Figure 3, where perfect counts would fall on the 1:1 line. Points falling above the 1:1 line represent locations where VIDS counted more vehicles than were in the lane (false detections), while points below the line are those which in which the VIDS missed vehicles. Distribution of errors is shown in Figure 4, where positive values represent over-counting of volume by the VIDS.

The majority of the sites (20 out of 33) achieved counts that were ±5% of the true counts. Viewing tapes as the image processor counts vehicles reveals which counters are missing vehicles, counting vehicles in other lanes, or counting vehicles due to external effects such as rain or shaking camera. Variation in counts are extreme, with maximum error of 74.2% (in “More” column), a site condition at night in which vehicles in the adjacent lanes were activating the counter with headlights. Other less accurate count locations suffered from poor camera views, where the count location was counting vehicles from adjacent lanes for a portion of the time. Accuracy at locations distant from the camera is reduced further when a large percentage of heavy-duty vehicles are present.

Deviation from hand counts increased with each lane moving away from the camera location. If the camera was located between the two directions of traffic, the most accurate counts were in the fast lane and least accurate in the slower lanes and vice-versa for cameras located on the shoulder of the slow lane. Accuracy did not degrade beyond 5% until the third or fourth lane from traffic (where lane 1 is the closest to the camera position), as shown in Table III. The decrease in accuracy is the result of false detection of vehicles in adjacent lanes. The deviations reduce in the furthest lanes due to a second counteracting error as the view of vehicles are blocked by trucks and not counted by VIDS. This is especially true for site 1, where lane 6 was congested and vehicles in lane 7 were moving without being detected.

The placement of detectors in a particular lane also affects count accuracy. Several of the locations were run with count detectors spaced at equal intervals down the lane (i.e. each lane had five or more consecutive counters). Data showed a general degradation in count quality as the count station increased in distance from the camera location. Figure 5 shows one site with selected lanes and the error of each count as the distance increased from the camera. Lane 1 is the lane closest to the camera and the detector is unobstructed from other traffic. More vehicles were missed at count locations farther downstream from the camera. This likely occurred because the gap in following vehicles was indiscernible by the software and two or more following vehicles were counted as a single vehicle. In lanes 3 and 5, false detection associated with camera angle increased, more than offsetting the undercounting errors associated with closely spaced vehicles.

Vehicle Classification

Camera locations are situated along the length of Interstates 75 and 85 in the central business district, within the Interstate 285 perimeter loop. These two freeways are the heaviest traveled corridor, and represent the locations where the highest marginal improvements can be made through video monitoring. However, vehicles with more than three axles are restricted from using this corridor unless delivering to the area within the perimeter Interstate 285. Thus, heavy-duty vehicle activities along these routes are low.

Labeling each vehicle that passed as a vehicle (light-duty auto), a single unit truck, or a double unit truck completed manual classification counts. The number of sites for classification comparison is a subset of the volume counts, with 15 locations classified for vehicles and trucks. Comparing counts for the trucks will have some intrinsic errors associated with different classification schemes. VIDS classifies vehicles based on length, and certain assumptions have to be made to determine numbers of trucks detected. A car pulling a trailer would be classified as a truck using VIDS because of the length, while some smaller single unit trucks could be classified as vehicles.

At every location sampled, VIDS estimated significantly more heavy-duty vehicles in the traffic stream than were present. Figure 6 shows a plot of the VIDS versus manual counts for trucks. Given the small number of trucks noted at sample the locations, the absolute number of trucks counted by VIDS was off by orders of magnitude. Estimates of truck volume fractions (percent of total traffic volume) show a maximum difference of 12%, with the median difference of 4%. Similar to total volume counts, the accuracy of classification decreases as the distance of the count location from the camera increases. At longer distances, the VIDS was unable to distinguish a space between following vehicles and counts two (or more) vehicles as one long vehicle, reducing the overall volume and increasing truck counts. Camera angle affects counts in adjacent lanes due to the height of trucks tripping counts in other lanes. On a six-lane segment, the lane closest to the camera only varied 4.8%, while the other lanes had discrepancies in truck counts of 55% to 84%.

Vehicle Speeds

Average speed comparisons were completed at different locations than were used for the count and classification studies. The sites for the speed studies were locations where comparable data could be collected using video and laser rangefinders (LRF). Measurement of sites for distance calibration was completed using the LRF to record distances from objects to the camera. Locations were varied to provide sites for higher percentage of trucks and traffic.

The tripod camera height is much lower than ATMS cameras and the view is more profile than plan, potentially affecting computed speeds. A higher camera looking directly down on traffic in plan view is able to distinguish gaps in vehicles and eliminates errors associated with heights of vehicles. With the camera focused down the lanes of traffic (Figure 2), the height of the vehicle trips the speed counts earlier. Thus, the software computes the vehicle moving through the fixed speed trap distance in a shorter time (i.e. at a higher speed).

Average spot speeds are compared to VIDS average speeds at seven different locations, across twenty-nine total lanes. Two of the locations were under congested conditions. Spot speeds were measured using laser rangefinders on a random sample of vehicles. Two lanes were simultaneously sampled for a period up to 45 minutes, before moving equipment to different lanes. Speeds were corrected for the height of the instrument above the roadway and confidence bounds were developed based upon the number of vehicles monitored and the variance in observed speeds.

The maximum difference in computed average speeds from the two sources is -8.3 mph (-13.4 kph), with the median difference in average speed for all the samples falling at 2.1 mph (3.4 kph). More than 40% of the locations produced VIDS average speeds that were less than the spot speeds, with 69% of the locations having a VIDS computed average speed within 5 mph (8 kph) of the spot speeds.

A plot of average speeds for each location is shown in Figure 7, where points would fall on the 1:1 line for a perfect match. Two sets of points are plotted. The first set provides data for the roadways where the VIDS average speed *does not* fall within the 95 confidence interval surrounding the laser rangefinder average speed. The second set is VIDS average speed, which *do* fall within the 95% confidence interval of the laser rangefinder spot speeds. Of the sampled sites, only 17% (5 out of 29) of the VIDS-estimated average speeds exhibited means that did not fall within the 95% confidence level of the measured spot speeds. However, it is important to note that approximately 70% of the sites showed average speeds within 5 mph (8 kph) of the measured average speed.

CONCLUSIONS

The accuracy of vehicle counts, classification, and speeds were examined by comparing detected counts with manual counts obtained over the same interval. In this study, distinct differences in accuracy of volume counts were related to the geometric layout of the site. Distance of the count location from the camera, number of lanes of adjacent traffic, and heavy-duty vehicles all impact volume accuracy. The largest errors occurred when detectors were placed at the greatest distances from the camera. Where distances and number of lanes are great, alternative methods of volume estimation should be used.

Vehicle speed computation using VIDS can significantly improve current techniques of estimation of free-flow and congested speeds. Even though the VIDS analyses yielded average travel speeds that were significantly different (statistically) than measured speeds on the freeways, approximately 70% of the sites showed average speeds within 5 mph (8 kph) of the measured average speed. For emissions modeling purposes, using today's average speed modeling regime in MOBILE5a, the emission rate prediction associated with ±5 mph (±8 kph) in average speed is well within the confidence bounds of the uncertain speed-emissions relationship [Chatterjee, et al., 1997]. This indicates that VIDS data can likely be employed in emissions modeling studies. A measurement of the degradation of speed accuracy was not completed as distance of speed detector increases from camera location, but is likely similar to volume counts. Hence, caution must still be exercised in using average speed data.

The ability of video detection to classify trucks was poor, and improvement in detector and camera location will have to be made to improve counts. More likely, coordinated studies of trucks can be made to determine percentage of trucks in the traffic stream. It is unclear at this time if VIDS data can be reliably used to estimate travel fractions by vehicle class. However, future studies will examine the coupling of VIDS and weigh-in-motion data streams to improve vehicle classification algorithms.

All of the data in this study came from freeways. Several studies still need to be completed on video detection, including using data from on-ramps, arterials, collectors, and local roads. Activity on different facility types could affect measured volumes and speeds differently. In addition, a similar speed study should also be completed comparing actual speeds to VIDS speeds on the ATMS cameras.

Video image detection outputs can be useful for planning purposes with results improving data input into existing and developing models. The impacts of a variety of infrastructure, environment, and traffic flow characteristics are being evaluated by the Georgia Tech research team to determine their impact on VIDS performance. Use of the video-detected data in models requires quality control over collection of the data. Significant errors can be created from blindly using VIDS data without understanding where, when, and how the data were obtained. Data use requires development of site sampling plans for sampling across facilities (temporally and spatially) to provide reasonable and realistic measurement values.

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Table I - Sensitivity of MOBILE5a Emission Factors to Changes in Average Speed

Pollutant	Speed, mph (kph)	Emission Factor, g/mi (g/km)	Slope, g/mi/mph (g/km/kph)	Speed Change Causing ±10% Change in Emission Factor, mph (kph)
CO	20 (32.2)	23.12 (14.37)	1.0 (0.39)	2.3 (3.7)
CO	40 (64.4)	13.00 (8.08)	0.23 (0.089)	5.6 (9.0)
CO	60 (96.6)	19.80 (12.30)	1.7 (0.66)	1.2 (1.9)
VOC	20 (32.2)	2.56 (1.59)	0.095 (0.037)	2.7 (4.3)
VOC	40 (64.4)	1.62 (1.01)	0.025 (0.0097)	6.5 (10.5)
VOC	60 (96.6)	1.64 (1.02)	0.042 (0.016)	3.9 (6.3)
NO_X	20 (32.2)	2.56 (1.59)	0.025 (0.0097)	10 (16.1)
NO_X	40 (64.4)	2.63 (1.63)	0.012 (0.0046)	22 (35.4)
NO_X	60 (96.6)	3.91 (2.43)	0.113 (0.044)	3.5 (5.6)

Source: *NCHRP 25-7*

Table II - Potential Uses of VIDS Data

Local factor development
Peak hour factors
Directional factors
Seasonal adjustment factors
Traffic distributions
15 minute to 24 hour aggregation
Vehicle speeds validation
Temporal distribution
Individual link
By link aggregation
VMT validation
Individual link
By link aggregation
Capacity restraint analysis
Development of local speed/flow curves
Vehicle classification
Congestion mitigation analysis
Episodic modeling of special events
Weekend travel forecasting

Table III - Accuracy of Counts as Distance from Camera Increases (camera located alongside lane 1 at both sites)

Lane	*Site 1*	*Site 2*
1	1.7%	-1.6%
2	2.3%	0.7%
3	6.3%	-2.7%
4	12.9%	9.0%
5	33.3%	7.8%
6	20.7%	7.1%
7	-6.2%	
Total	*8.6%*	*3.2%*

Figure 1 - Calibration of Camera Field of View

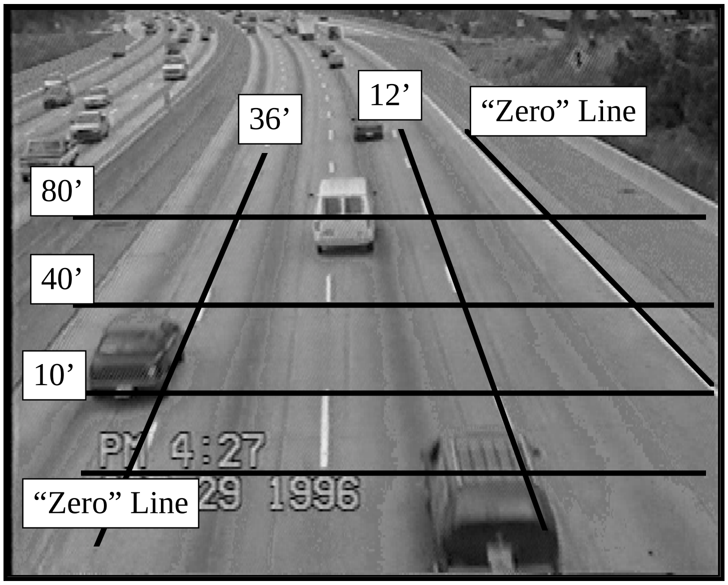


Figure 2 - Example Layout of Count and Speed Detectors in Detector File

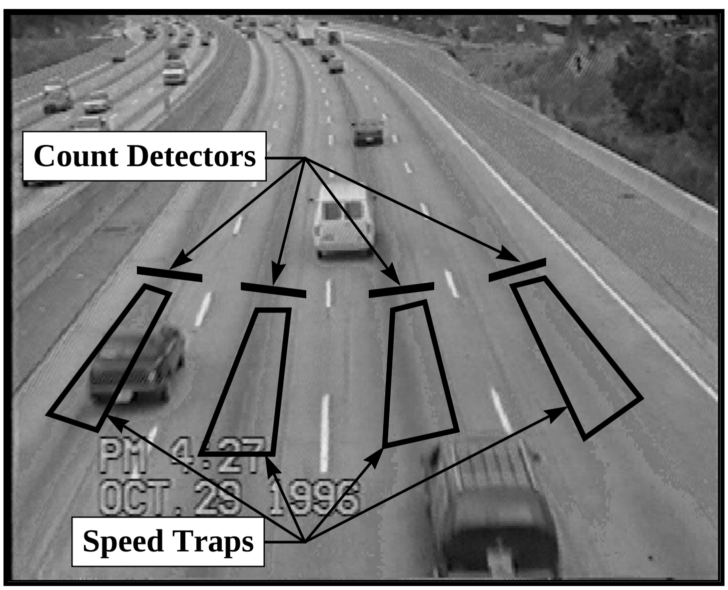


Figure 3 - Comparison of Volume Counts, Video Detected vs. Manual Counts

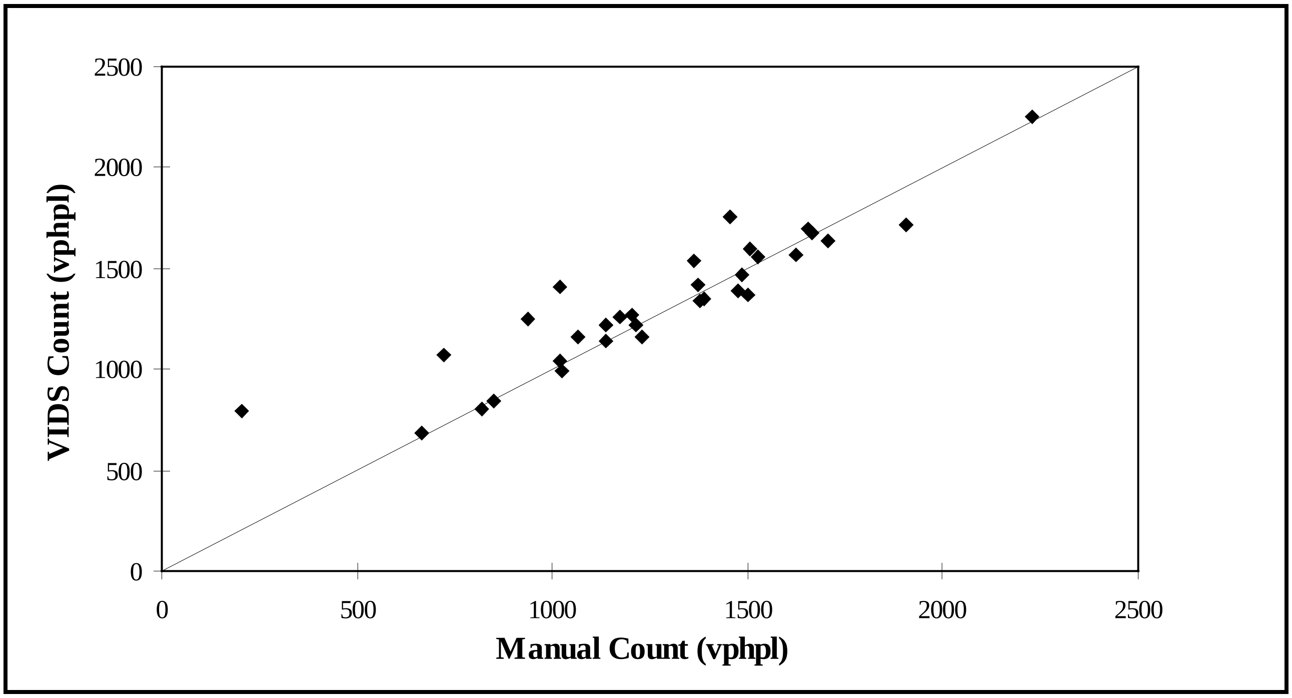


Figure 4 - Percent Difference of VIDS Counts from Manual Counts

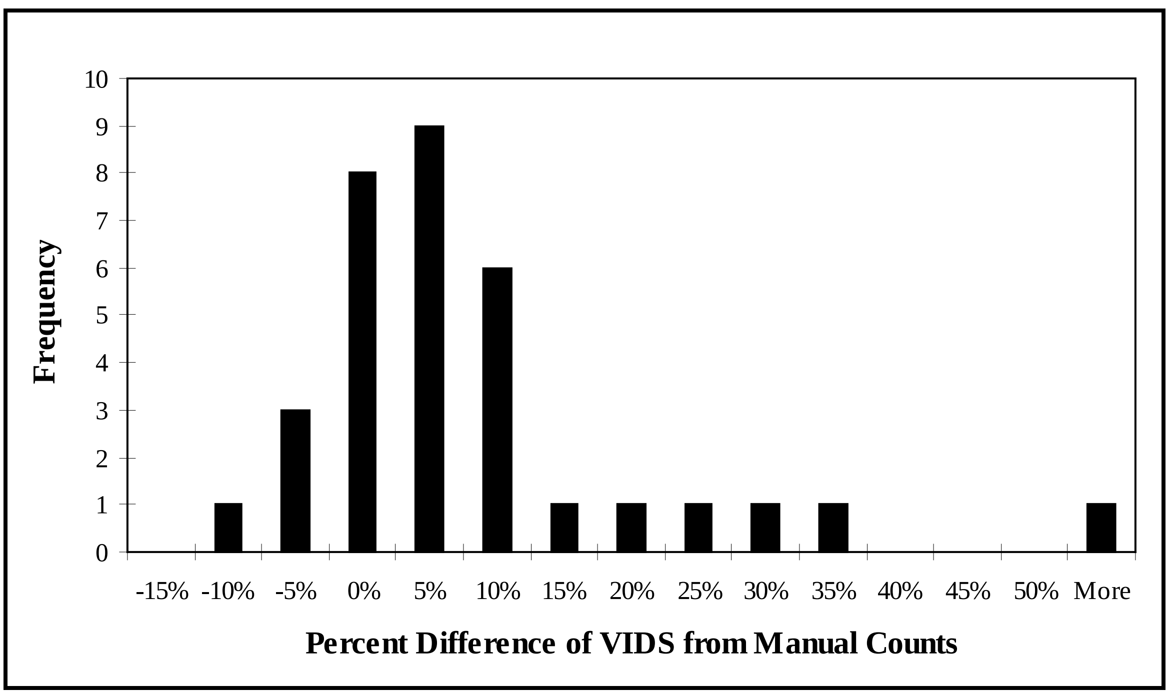


Figure 5 - Accuracy of Counts as Count Location (Distance from Camera) Increases

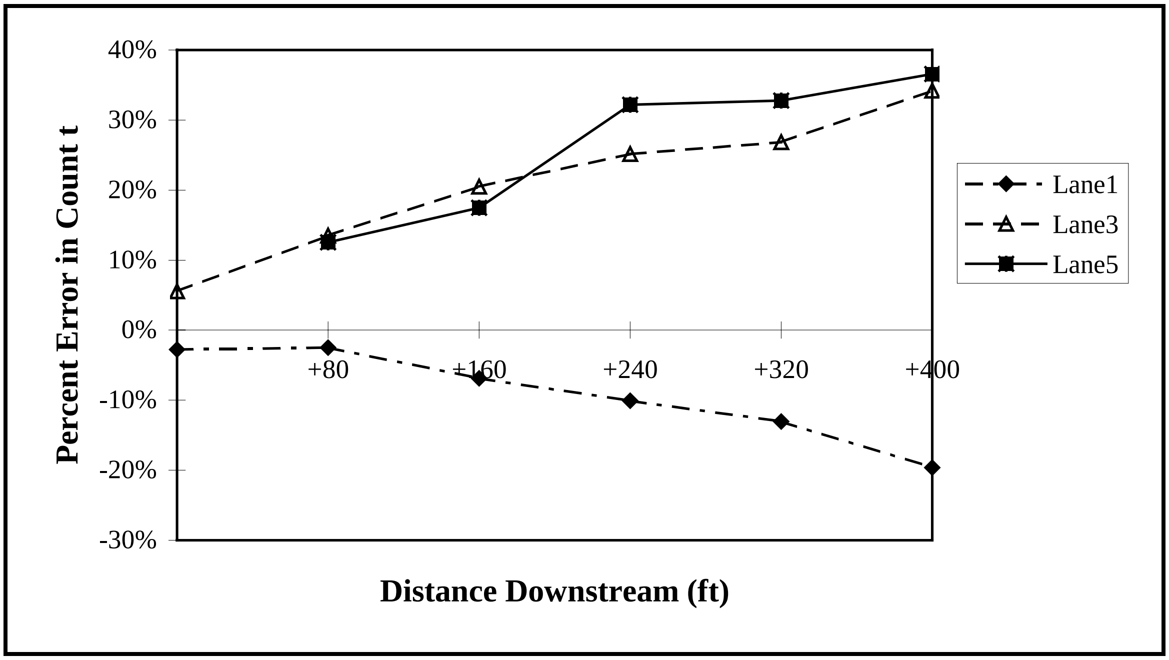


Figure 6 - Comparison of Heavy-duty Vehicle Counts, Video Detected vs. Manual Counts

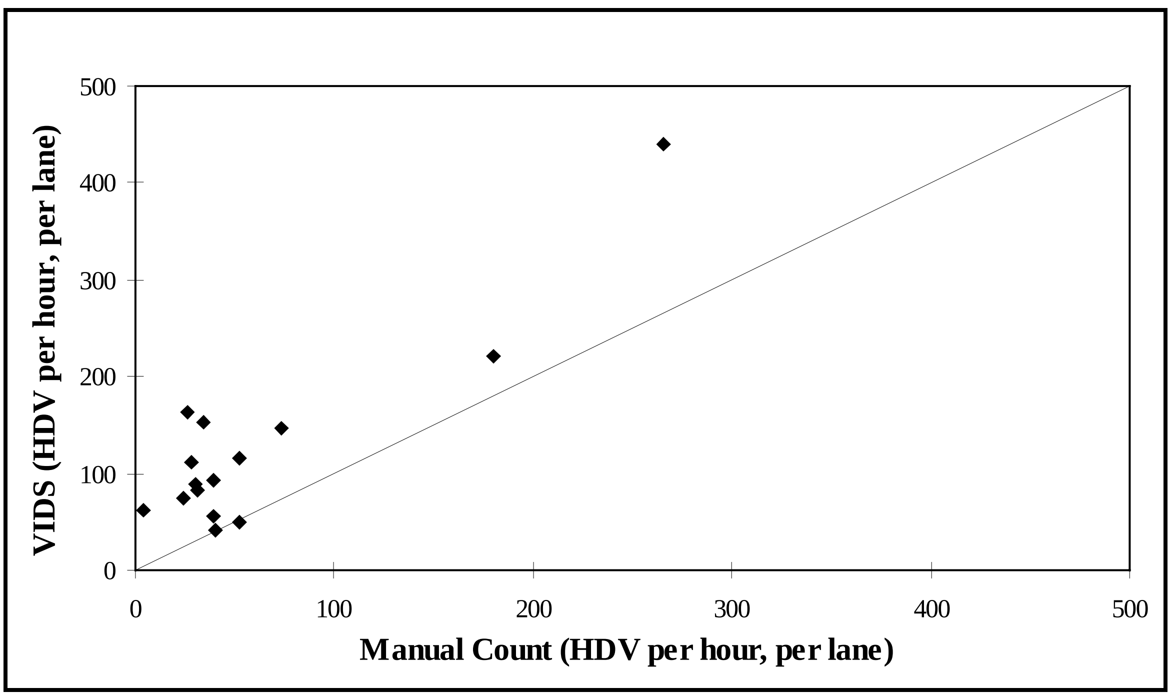
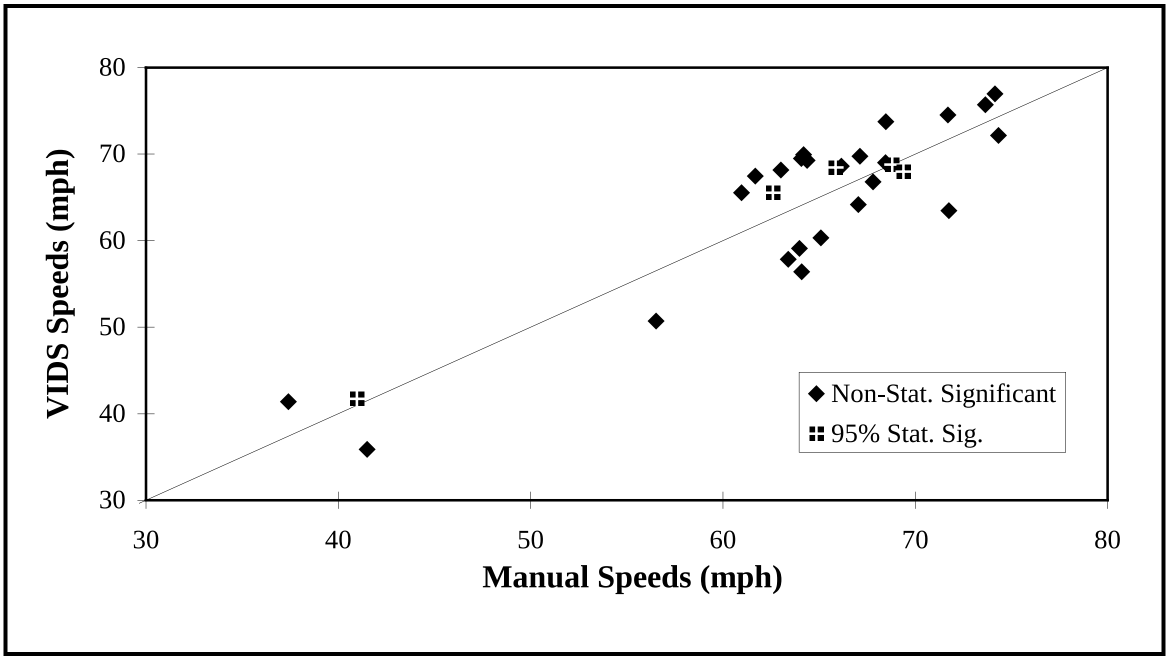


Figure 7 - Scatterplot of Video Detected Average Speeds vs. Measured Spot Speeds



BIOGRAPHIES

Dr. Christopher Grant is an assistant professor of Civil Engineering at Embry-Riddle Aeronautical University. Dr. Grant received his Ph.D. in Civil Engineering from the Georgia Institute of Technology in 1998, with a focus on transportation engineering, mobile source emissions, and vehicle modal activity. He received his Masters of Engineering degree and B.S. degree from the University of Louisville and previously worked for HNTB Corporation. Mr. Grant is a member of Institute of Transportation Engineers, American Society of Civil Engineers, and Transportation Research Board.

Dr. Randall Guensler is an associate professor in Georgia Tech's School of Civil and Environmental Engineering and an adjunct professor in the School of Public Policy. Dr. Guensler received his M.S. in Environmental Engineering in 1989, and his Ph.D. in Civil Engineering in 1993. Dr. Guensler is currently a member of the USEPA Office of Mobile Sources Technical Advisory Committee, a sub-committee of the Clean Air Act Advisory Committee. Dr. Guensler is the Chairman of the Transportation Research Board (TRB) committee on Transportation and Air Quality (A1F03).

Bret Gillis is a currently a transportation engineer with TransCore in Atlanta, Georgia. Mr. Gillis received his M.S. in Civil Engineering from the Georgia Institute of Technology in 1997. While obtaining his degree, Mr. Gillis performed research on the accuracy and precision of machine vision. He collected and statistically evaluated VIDS data for Atlanta summer 1996 and summer 1997 traffic conditions, to demonstrate the linkage between the changes in traffic conditions and

Atlanta's air quality. Mr. Gillis is a member of the Institute of Transportation Engineers and the American Society of Civil Engineers.