Potential Applications of Video Technology for Traffic Management and Safety in Alabama

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16. Abstract

Video technology applications for traffic management and safety are being implemented by state and local government agencies in Alabama. This technology offers both tangible and intangible benefits. Although video technology provides many benefits, it requires substantial up-front costs for purchasing and installing the equipment and training staff. Due to the complexity of video systems and the rapid pace of change related to this technology, agencies may overlook some applications while using resources to implement less valuable applications.

This study compiled a detailed review of current capabilities of video technology. This research applied and tested new, low cost video applications for traffic management and safety in Alabama on pilot scale projects to help agencies employ video technology to its fullest potential. Several video systems, like digital video cameras, conventional video recorders, surveillance cameras, and Autoscope were implemented and tested at various locations within the state. This research project demonstrated applications of low cost video technology that can be implemented to improve safety and reduce crashes and violations.

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Executive Summary

Video technology applications for traffic management and safety are being implemented by state and local government agencies in Alabama. This technology offers both tangible and intangible benefits. Video technology requires a substantial up-front investment costs for the purchase and installation of equipment and training of staff. Due to the complexity of video systems and the rapid pace of change related to this technology, agencies may overlook some applications while using resources to implement less valuable applications. This research applied and tested new, low cost video applications for traffic management and safety in Alabama on pilot scale projects to help agencies employ video technology to its fullest potential. Several video systems, like digital video cameras, conventional video recorders, surveillance cameras, and Autoscope were implemented and tested at various locations within the state. This research project demonstrated applications of low cost video technology that can be implemented to improve safety and reduce crashes and violations.

Section 1
Introduction

Video technology applications for traffic management and safety are being implemented by state and local government agencies in Alabama. This technology offers both tangible and intangible benefits related to safety and management of traffic. A comprehensive review of current and potential uses of video technology for traffic management and safety in Alabama was performed by the University Transportation Center for Alabama (UTCA). Preliminary results from this research indicate several specific applications of video technology that may be implemented in the State of Alabama to improve traffic management and safety (McFadden and Graettinger, 2000).

Although video technology provides many benefits, it requires substantial up-front costs for purchasing and installing the equipment, and for training staff. Due to the complexity of video systems and the rapid pace of change related to this technology, agencies may overlook some applications while using resources to implement less valuable applications.

The goal of this research was to apply and test new video applications for traffic management and safety in Alabama on pilot scale projects to help agencies employ video technology to its fullest potential. This research provides a review of the current capabilities of video applications, their implementation, and where in Alabama these systems can most improve traffic management and safety.

This research first identified the specific areas of concern (red-light running, speeding, and railroad grade crossing safety) and then found specific locations in Alabama where video technology can be potentially employed to improve traffic management and safety. Several video systems, like digital video cameras, conventional video recorders, surveillance cameras, and Autoscope were implemented and tested.

Several organizations such as the City of Birmingham (Traffic Engineering Division), the Tuscaloosa Department of Transportation (TDOT), the Alabama Department of Transportation (ALDOT), the Alabama Department of Public Safety (DPS), and the Alabama Emergency Management Agency (EMA) were involved in executing the tasks associated with this project.

This report is organized to reflect the research tasks accomplished during this project:

Section 2.0: CARE® Analysis for Identification of Video Surveillance Locations
Section 3.0: Compositional Traffic Counting Using Video Technology
Section 4.0: 15th Street Corridor Modeling
Section 5.0: Railroad-grade Crossing Automated Video Enforcement Analysis

Section 6.0: Variable Message Signs for Violation Notification
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Section 8.0: Video for Emergency Response Management
Section 9.0: Conclusions and Recommendations

Section 2
CARE Analysis for Identification of Video Surveillance Locations

Introduction

Video surveillance is beneficial if the surveillance occurs at the same location as traffic incidents. To develop appropriate countermeasure for locations with high incidents of traffic crashes, a study is required to identify these locations. The necessary data for this purpose can be obtained from the Critical Analysis Reporting Environment (CARE®) database, which provides a comprehensive record of traffic crash information in the State of Alabama. This data is distributed to traffic safety professionals who perform investigations and select countermeasures.

To gauge the potential impact of video technology applications, three specific types of crashes were examined related to red-light running (RLR), speeding, and railroad-grade crossings for the years 1994-2000 in Alabama. This section of the report includes an overview of the CARE® software, the method of data acquisition, and analyses of information for the purpose of the intended study.

CARE® Overview

CARE® is one of the most sophisticated systems designed for crash problem identification. It is a software system that provides accident information to decision-makers involved with traffic safety. These individuals then analyze the potential crash causes and develop solutions to combat specific types of traffic crashes. CARE® was developed at The University of Alabama to provide a simple tool to access the vast database associated with accident information, and it exists on two platforms: desktop and Internet (http://care.cs.ua.edu).

Some of the CARE® capabilities are listed below:

- CARE® gives information on high-accident location (by frequency) with a graphical display for major roadways.
- CARE® is designed for problem identification and countermeasure development for crashes associated with alcohol, speed, RLR, railroad crossings, etc.
- CARE® produces statistics that allow visualization of statistically significant results.
- CARE® acts as a “front end” to many statistical processors, and is fully compatible with existing data-oriented software packages such as MS-Access and MS-Excel (Keith and Brown, 2002).
- CARE® automatically prioritizes counties, cities, and even intersections or road segments by the number of crashes for a particular query.

CARE® can be divided into three components: 1) a dataset, 2) a filter, and 3) an analysis process. The system is query-based, which means to run CARE® and analyze information, a dataset and a filter are needed. The complete dataset consists of accident and occupant data from the years 1994 to the present for the State of Alabama. To make the data more manageable a subset can be generated and employed in subsequent queries through a filter. A filter is a specification used to restrict processing of a particular query. Various types of CARE® analyses can be performed with a selected filter. Two analyses reported in this work were: 1) Frequency Analysis, a simple count and percentage provider and 2) Cross-tabulation, a simultaneous summary of two different variables that includes counts and percentages.

Apart from these two analyses, CARE also provides advanced features like an IMPACT analysis, HOTSPOT locations, Intersection Magic, ACT, and DataGen. IMPACT provides outputs in a worst-first order for each variable and identifies scenarios where appropriate counter measures may reduce maximum incidents. HOTSPOT can be employed to list details of intersections with the highest numbers of crashes. A description of these preprogrammed analyses can be found in Brown and Turner, 2002.

CARE® Analysis for Video Location Identification

CARE® was used to develop a criteria for determining high accident locations in Alabama focusing on RLR, speeding, and railroad related crashes. These crash types were selected because they were the subject of ongoing research focused on employing video technology as a countermeasure (McFadden and Graettinger, 2000). The analysis was performed for the entire State of Alabama, for counties with the highest crash rates, and for the City of Tuscaloosa. Variables such as month, day of the week, time, primary contributing circumstances, number of injuries and fatalities, age of the driver, gender, traffic control unit, direction of travel, speed limit, traffic lanes, accident severity, and weather conditions assisted in refining the data retrieval for the most probable causes for the accidents.

As an example, the following steps describe the procedure to retrieve accident data for the City of Tuscaloosa for the three categories of crashes:

Step 1: The 1994-2000 Alabama accident dataset was selected.
Step 2: Using the "create filter" option in CARE®, new filters T-City (City of Tuscaloosa), RLR (red-light running - fail to heed to signal/sign with a traffic signal), Speeding (speeding), and RR (railroad grade crossings-related) were generated.
Step 3: Using the filter combination option in CARE®, the generated filters were then combined as T-City-RLR, T-City-speeding, and T-City-RR.
Step 4: To select the most critical scenario, specific analyses like frequency, cross tabulation, IMPACT, and HOTSPOT were performed for crash variables.

The retrieved information was summarized in the form of tables and bar charts. Based on the results obtained from the CARE® system, general crash trends for Alabama and the City of Tuscaloosa were analyzed and reported.

It should be noted that CARE® retrieved the accident data by number of crashes only, and did not consider total vehicular volume or number of violations at or near the crash location. Another limitation of using CARE® is the potential legal repercussions associated with the release of the specific locations of high crash incidents. Therefore, this report uses cities as the smallest geographic area although specific high incident intersections can be identified in a similar manner. IMPACT and HOTSPOT were beneficial in identifying intersections for video surveillance, although the results are not reported herein. In many cases, due to the infrequency of some types of crashes, there was no statistical significance for choosing one intersection over another. However, when used in appropriate situations with appropriate data, CARE® yields extremely useful safety information, which can be employed to help locate video surveillance units.

General crash trends in Alabama

Crash data related to Alabama RLR, speeding, and railroad grade crossings is summarized in Table 2-1. It can be seen from Table 2-1 that the total number of railroad related crashes in the State is quite small (946) when compared to speed (51,231) and RLR (31,750) related crashes. This indicates that employing video surveillance to capture a railroad related crash would be difficult, but traffic behavior at a railroad grade crossing could be analyzed with the help of video.

Table 2-1. Summary of 1994-2000 Alabama accident data

	Red-light running	Speeding	Railroad
Property damage	22145	25974	484
Injuries	9533	23271	390
Fatal	72	1986	72
Total crashes	**31750**	**51231**	**946**
High accident rate:			
Month	December	May	June
Day of week	Friday	Saturday	Thursday
Time	3:00 PM - 4:00 PM	3:00 PM - 4:00 PM	4:00 PM - 5:00 PM
Speed limit	31 – 35 mph	41 – 45 mph	21 – 25 mph
Number of lanes	4	2	2
Weather	Clear	Clear	Clear

Although there were more speed related crashes in the State than railroad or RLR related crashes, these crashes typically occur on two-lane roads with posted speed limits between 41 – 45 mph. This indicates a rural area where it would be difficult to capture a crash or even evaluate traffic behavior with video because the area to be covered is very large. If one rural location produced a high crash rate, this could be a location for video surveillance.

RLR is ideal for video surveillance. First, there is a high rate of this type of crash. Second, these crashes occur at specific locations, which are small enough to be captured on a single video system. Lastly, RLR crashes occur in an urban development, which lends itself to permanent video systems like the system in Tuscaloosa.

The annual statistics of Alabama-specific crash severity for the years 1994-2000 are reported in Tables 2-2, 2-3, and 2-4.

Table 2-2. Annual Alabama red-light running crash data

Year	Property damage only	Injuries	Fatalities	Total
1994	3142	1398	9	4549
1995	3175	1365	9	4549
1996	3223	1350	10	4583
1997	3061	1420	12	4493
1998	3248	1384	15	4647
1999	3224	1395	9	4628
2000	3072	1221	8	4301

Table 2-3. Annual Alabama speed-related crash data

Year	Property damage only	Injuries	Fatalities	Total
1994	3075	2905	224	6204
1995	3433	3104	297	6834
1996	3705	3183	297	7185
1997	4006	3667	302	7975
1998	4024	3610	299	7933
1999	3946	3542	290	7778
2000	3785	3260	277	7322

Table 2-4. Annual Alabama railroad grade crossing crash data

Year	Property damage only	Injuries	Fatalities	Total
1994	86	85	8	179
1995	84	67	11	162
1996	77	60	13	150
1997	59	53	13	125
1998	62	50	10	122
1999	60	44	9	113
2000	56	31	8	95

The City of Tuscaloosa specific crash statistics for variables like time, day of the week, month, age of the driver, condition of the driver, gender, speed limit, number of traffic lanes, and weather conditions are summarized in Table 2-5.

Table 2-5. Summary of 1994-2000 Tuscaloosa accident data

High accident rate:	Red-light running	Speeding	Railroad grade crossings
Month	October	August	August
Day of week	Friday	Friday	Wednesday
Time	5:00 PM - 6:00 PM	3:00 PM - 4:00 PM	8:00 - 9:00 (AM and PM)
Speed limit	41 – 45 mph	21 – 25 mph	21 – 25 mph
Number of lanes	6 or more	2	2
Weather	Clear	Clear	Clear
Number of occupants	1	1	1
Light conditions	Daylight	Daylight	Daylight
Age of the driver	25 - 34 years	25 - 34 years	25 - 34 years

Red-light running crashes and trends

Red-light running crash data is reported in Table 2-6 for the counties with the most crashes, and in Table 2-7 for cities with the most crashes. Table 2-8 and column two of Table 2-5 present detailed findings of RLR-related crashes in the City of Tuscaloosa for the years 1994-2000.

Table 2-6. Selected county red-light running crash data

Year	Jefferson	Mobile	Montgomery	Madison	Tuscaloosa	Calhoun
1994	1058	633	460	405	202	176
1995	1082	622	458	391	229	154
1996	1072	624	477	376	231	166
1997	946	704	423	406	213	136
1998	1010	676	453	424	258	117
1999	930	621	470	470	266	119
2000	889	625	407	427	229	117
Total	**6987**	**4505**	**3148**	**2899**	**1628**	**985**

Table 2-7. Selected city 1994-2000 RLR related crashes

Ranking	City name	No. of crashes
1	Birmingham	4008
2	Mobile	3353
3	Montgomery	3129
4	Huntsville	2717
5	Tuscaloosa	1417
6	Florence	857
7	Dothan	816
8	Gadsden	692
9	Decatur	665
10	Mobile Rural	663
11	Auburn	636
12	Anniston	621

Table 2-7 shows that the City of Tuscaloosa stands fifth in the state with 1417 RLR-related crashes out of a total of 31,750 RLR crashes in Alabama. It should be noted that these numbers are not per capita; therefore, one would expect larger cities to have a larger total number of crashes. Table 2-8 shows RLR crashes in each of the severity categories (property damage, injuries, and fatalities), which remained approximately the same in Tuscaloosa between the years 1994 - 2000.

Table 2-8. Tuscaloosa red-light running crash data

Year	Property damage only	Injuries	Fatalities	Total
1994	118	56	0	174
1995	133	65	1	199
1996	144	62	2	208
1997	128	56	0	184
1998	152	75	2	229
1999	152	80	0	232
2000	134	57	0	191

About 36% of these crashes in Tuscaloosa happened on roads of six or more lanes, and about 38% happened on roads with a speed limit between 41-45 mph (city major roads). Friday experienced relatively more crashes than any other day in a week, and 5:00 PM-6:00 PM was the most crash prone time of the day.

Speed related crashes and trends

Speed-related crashes for the counties with the most accidents are presented in Table 2-9, while Table 2-10 reports the cities with the most accidents. Table 2-11 and column three of Table 2-5 present detailed findings of speed-related crashes in the City of Tuscaloosa for the years 1994-2000.

Table 2-9. Selected county speed-related crash data

Year	Jefferson	Mobile	Tuscaloosa	Madison	Calhoun	Baldwin
1994	915	351	272	254	243	198
1995	899	361	279	300	244	179
1996	839	378	273	289	233	224
1997	800	430	339	309	246	216
1998	721	403	357	311	282	312
1999	730	401	362	332	301	179
2000	672	369	333	332	290	236
Total	**5576**	**2693**	**2215**	**2127**	**1839**	**1544**

Tuscaloosa County had the third highest number of speed-related accidents from 1994 through 2000. And, speed-related crashes were more severe than general crashes. Speed related crashes in the City of Tuscaloosa occurred on Friday more frequently than any other day and almost 50%

happened on roads with a speed limit of 21-25 mph (mostly residential areas). The frequency of crashes was observed to be higher between 3:00 PM - 4:00 PM.

Table 2-10. Selected city 1994-2000 speed-related crashes

Ranking	City name	No. of crashes
1	Jefferson Rural	2108
2	Birmingham	1495
3	Mobile Rural	1314
4	Tuscaloosa Rural	1291
5	Baldwin Rural	1212
6	Madison Rural	1193
7	Calhou Rural	1081
8	Talladega Rural	1050
9	Mobile	989
10	Walker Rural	797
11	Montgomery	774
12	Tuscaloosa	708

Table 2-11. Tuscaloosa speed-related crash data

Year	Property damage only	Injuries	Fatalities	Total
1994	67	30	2	99
1995	65	35	1	101
1996	67	47	2	116
1997	67	33	3	103
1998	70	37	1	108
1999	56	41	1	98
2000	50	32	1	83

Railroad (RR) related crashes and trends

Selected county and city crash data related to railroad grade crossing accidents are summarized in Tables 2-12 and 2-13. Detailed accident information for the City of Tuscaloosa during the years 1994 - 2000 is summarized in Table 2-14 and in column four of Table 2-5. Due to the small number of crashes in Tuscaloosa, almost no conclusions can be drawn from the CARE® data. From the data, the highest rate of railroad related crashes occurred on Wednesdays between 8:00 - 9:00 AM and PM. Although there were no fatalities, each railroad accident caused property damage and the possibility of the accident being fatal was very high. It should be noted that due to the small number of railroad-related crashes, any spike or hotspot in the data is most likely random and do not indicate a trend in these crashes.

Table 2-12. Selected county railroad grade crossing crash data

Year	Jefferson	Mobile	Tuscaloosa	Escambia	Talladega	Dallas	Lee
1994	32	16	6	17	5	3	5
1995	31	6	10	4	12	3	2
1996	21	20	7	6	2	7	0
1997	16	16	8	5	5	9	6
1998	17	11	15	4	3	4	6
1999	23	5	4	7	3	2	4
2000	9	7	4	1	5	4	9
Total	**149**	**81**	**54**	**44**	**35**	**32**	**32**

Table 2-13. Selected city 1994-2000 railroad related crashes

Ranking	City name	No. of crashes
1	Brimingham	95
2	Tuscaloosa	36
2	Mobile	36
3	Montgomery	27
3	Mobile Rural	27
4	Colber Rural	25
5	Bessemer	21
5	Selma	21
6	Jefferson rural	18
6	Atmore	18
7	Auburn	17
7	Morgan Rural	17

Table 2-14. Tuscaloosa railroad grade crossings accident data

Year	Property damage only	Injuries	Fatalities	Total
1994	4	0	0	4
1995	4	3	0	7
1996	4	2	0	6
1997	3	3	0	6
1998	7	1	0	8
1999	2	0	0	2
2000	3	0	0	3

Video technology locations based on CARE® data

Crash related information generated by CARE® can be useful in understanding crash scenarios. The dataset employed by CARE® has location information down to the intersection level, although in this report City was the smallest geographic area reported. CARE® retrieves crash details of intersections that have the most incidences, which on occasion may list intersections that had only one accident of a specific type. An example of this is railroad-related crashes where there may only be one occurrence in an entire City or County. Hence, it is recommended to analyze other parameters like history of violations, traffic volume, and neighborhood characteristics to select locations for installing video equipment. Data acquisition from CARE® can be used to summarize the crash statistics at four different levels – state, county, city, and location (intersection or road link). This compilation allows decision makers to select locations with the highest numbers of specific types of crashes for further study. The use of parameters like speed limit and traffic lanes for choosing video locations further refines potential video locations.

It can be concluded that CARE® can aid, but cannot be the sole basis for development of the criteria to select locations for the deployment of a video-based technology.

Section 3
Compositional Traffic Counting Using Video Technology

Introduction

To assess highway system performance, states are required to submit numerous annual compositional traffic count reports to the Federal Highway Administration (FHWA). Compositional counts represent the volume by type (trucks, trailers, buses, recreational vehicle, automobiles, motorcycles, etc.). These classifications are based on axle arrangement, number of trailers, and other vehicle characteristics. This data is typically collected manually or by automatic counters.

The primary objective of this portion of the research was to evaluate the use of video-based technology for vehicle classification, and to develop a methodology for obtaining compositional vehicle counts solely using video.

Background

The FHWA's Office of Highway Information Management conducts a national program that assembles traffic reports furnished by individual state highway agencies into a national database entitled Highway Performance Monitoring System (HPMS). These compositional traffic counts are important traffic data used to support decision-making and design processes. These counts can be used for a variety of purposes, some of which are mentioned below (TMG, 2001):

1. planning and programming of transportation facilities,
2. pavement design and rehabilitation,
3. apportionment of pavement damage,
4. compliance with vehicle weight regulations,
5. development of geometric design standards,
6. compliance and regulatory policy development of truck dimensions,
7. safety analysis,
8. traffic operation and control,
9. analysis related to highway bridges,
10. estimating truck traffic for highway cost allocation studies,
11. predicting traffic volumes for roadways, and
12. aiding in the formulation of air quality models.

HPMS reporting requirements suggest that States are to submit vehicle classification data by 14 categories (13 vehicle categories and 1 unknown category) under each of the 12 roadway functional classes as shown in Table 3-1. There is a growing controversy over this procedure because the vehicle classification data collectors prefer to report fewer classes while the users of the data prefer more classes.

Table 3-1. Vehicle classification data by roadway functional class as reported to HPMS

Functional System		1	2	3	4	5	6	7	8	9	10	11	12	13	14
		Motor Cycle	Passenger car	Light truck	Bus	Single Unit Truck			Single Trailer Truck			Multi-Trailer Truck			Un-known
			2 axle, 4 tires	Other 2 axle, 4 tires		2 axle 6 tire	3 axle	4 axle or less	4 axle or more	5 axle	6 axle or more	5 axle or less	6 axle	7 axle or more	
RURAL															
1	Interstate														
2	Other Principal Arterial														
3	Minor Arterial														
4	Major Collector														
5	Minor Collector														
6	Local														
URBAN															
7	Interstate														
8	Other Principal Arterial														
9	Minor Arterial														
10	Major Collector														
11	Minor Collector														
12	Local														

Until the development of non-intrusive technologies (video-based, microwave radar, and infrared sensors), the methods for collecting traffic volume and vehicle classification counts were limited to manual counts, road tubes, and inductive loops. These conventional methods had limitations such as traffic disruption, staff safety, and efficiency of data collection. Recently developed technologies including video and radar can be mounted overhead or to the side of the roadway. They do not disrupt traffic, and they increase staff safety.

The advent of video with image processing created several options for traffic data collection. Advantages of video vehicle detectors are: multi-lane data collection by one detector, collection of a large variety of traffic data, and visual traffic surveillance. Video systems have disadvantages such as a drop in performance under certain environmental conditions. In addition to environmental issues, video technology classifies vehicles in fewer groups than the 14 FHWA classes. Hence, there is a need for a methodology that can take video data and produce the 14 FHWA classes. This was the focus of this research section.

Video Cameras and Image Processor

Video image processors employ machine vision technology to automatically analyze video images. A video image processor system consists of one or more cameras, whose data is processed and digitized either in the camera unit itself or is fed to a computer. Application-specific software for interpreting the images to extract information for traffic surveillance and control is available (Sami Mohamed, 1996). Similar to inductive loops, video places "virtual loops" in the area of interest to detect changes as a vehicle passes. The image processing algorithms analyze the variation of gray levels in the group of pixels contained in the video image plane. Traffic flow parameters such as volume, flow rate, speed, presence, occupancy, density, queue length, headway, dwell time, and classification based on length can be calculated by analyzing successive video frames (FHWA-PL-97-018, 1997).

Image processing technology does not require color for the detection process and hence can use monochrome cameras. These cameras can provide continuous live coverage of traffic, and the software allows placement of virtual loop detectors and detection boxes on the TV or computer screen without disrupting traffic. As in inductive loops, a signal is generated when a car passes through a virtual detector and a single video unit can manage multiple detectors placed in multiple lanes (Hani, 1999). Advantages include the ability to cover a wide area, along with the ability to rapidly extract a variety of traffic parameters. Some limitations of video include occlusion, shadowing, salt grime, icicles, cobwebs, and inability to perform well in adverse weather conditions.

Some of the systems that are available in the market are Video Trak-900, Autoscope Solo Pro used in this work and shown in Figure 3-1, TraFicon VIP 3.1, and Vantage One video detection systems. Since these systems are much safer and easier to use than loops or tubes, research is being conducted to minimize the drawbacks associated with these systems.

Figure 3-1. Autoscope Solo Pro camera

Although the permanent installation costs of video systems are expensive, their flexibility and low maintenance costs make them a cost-effective means of obtaining traffic data. In addition, these systems are portable and can be set up inexpensively for short-term analyses.

All video image systems collect classification information based on vehicle length, which classifies vehicles into fewer and more general categories than the 14 FHWA classes (TMG, 2001). This is because:

- broad vehicle length categories reduce the amount of error associated with misclassification, as video classifiers are not accurate enough in measuring small differences in vehicle length.
- video cannot differentiate between long vehicles (trucks) and small vehicles with trailers (boat trailers) of equal lengths.
- small differences in truck lengths are difficult to identify and hence it is advisable to group all trucks together.

According to the Traffic Monitoring Guide (TMG), four vehicle length categories are sufficient for most analytical purposes, which primarily require data on heavy trucks and light vehicles. These four traditional classes reflect passenger cars, single unit trucks, single-trailer combination trucks, and multi-trailer trucks. As suggested in the TMG, Table 3-2 shows the vehicle length boundaries typically used to estimate the four vehicle classes (TMG, 2001).

Table 3-2. Vehicle classification based on length given by Traffic Monitoring Guide

Vehicle Class	Boundaries
Passenger vehicles	0 - 13 ft
Single unit trucks	13 - 35 ft
Combination trucks	35 - 61 ft
Multi-trailer trucks	61 - 120 ft

Advanced video cameras with machine vision processors (MVP), such as Autoscope, can process and store up to five vehicle classes based on length. This is insufficient for FHWA classification, hence, a methodology was developed at the University of Alabama during this project to generate the 14 FHWA vehicle classes from Autoscope classes.

Experimental Design

A vehicle classification disaggregation (VCD) model was developed based on a disaggregation process, which was introduced in stochastic hydrology by Valencia and Schaake (1973) for generating (or disaggregating) seasonal, monthly, weekly, daily, and even hourly variations in rainfall using a series of historical annual rainfall data. This method is very popular as it conserves all linear relationships between variables at successive levels, and preserves the long and short-term variance and covariance properties, including seasonal variations (Valencia and Schaake, 1973). Using the principle of disaggregation, a model was developed at The University of Alabama for estimating the 14 FHWA vehicle classes from as few as two Autoscope length-based classifications. The next section contains a detailed description of the equipment used, site selection process, procedures adopted, and problems encountered, to perform the traffic data collection needed to develop the disaggregation methodology.

Equipment and cost

For the purpose of this research, the Autoscope Solo Pro MVP was chosen because of its enhanced features such as color imaging; integrated zoom lens; and ability to detect, count, and store five vehicle categories based on length (Econolite, 2001). The portable Autoscope Solo Pro MVP setup used to perform the data collection consisted of the following components.

1. Autoscope Solo Pro MVP camera ($8000)
2. Interface panel and Minihub ($1000)
3. Laptop or PC to store the data ($1400)
4. Solo MVP 30 foot cable ($350)
5. Gas generator to supply power to the above equipment ($400)

The total cost of the portable setup was approximately $11,000. Figure 3-2 shows the Autoscope installation in the field. It should be noted that an Autoscope field setup takes very little space and can be established in 15 minutes.

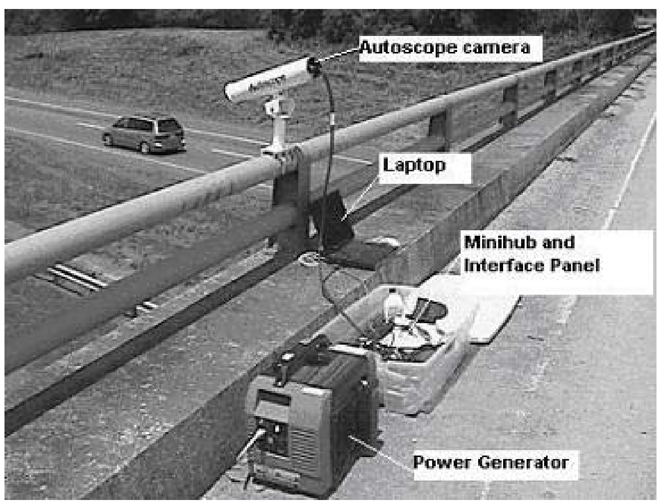

Figure 3-2. Autoscope field setup

Site Selection

For the purpose of selecting a site, ALDOT officials were contacted and a list of locations was obtained where ALDOT maintains axle counters. As shown in Figure 3-3, a site on Interstate 65 at milepost 210 in the City of Clanton was selected for two reasons.

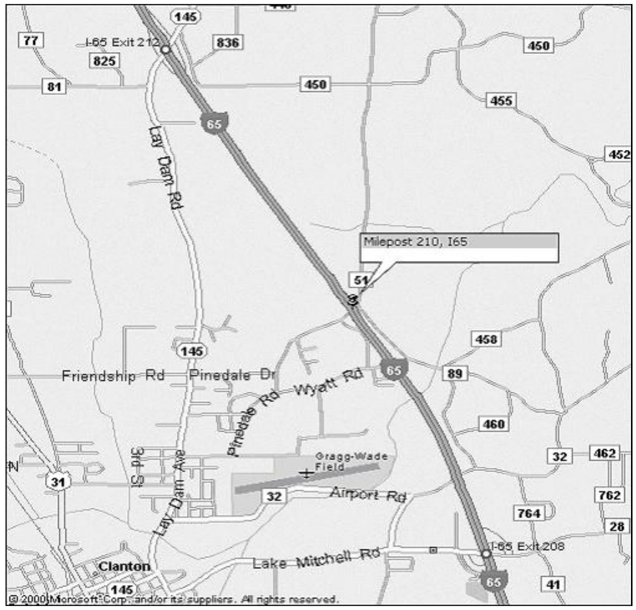

Figure 3-3. Location of Autoscope at milepost 210 on I-65 (courtesy: Microsoft Streets & Trips 2001)

First, an ALDOT axle counter is located there. Second, the presence of an overhead bridge just above the axle counters provided a location for temporary installation of an Autoscope camera. The camera was placed on the bridge railing above the southbound lanes at a height of 23 feet. The axle counters were functional for both northbound and southbound traffic on I-65, which allowed data collection in either direction. The field setup at the Clanton site is shown in Figure 3-2.

Period of I-65 data collection

Video data was collected eight hours per day on three weekdays (Monday, Wednesday, and Friday) for two weeks. A total of 28 hours of useful data was obtained for this research. The majority of the data (25 hours) was used to develop the vehicle classification disaggregation (VCD) model while the remaining portion (3 hours) was used to evaluate the performance of the model.

Procedure for data collection by Autoscope

Video detection requires a clear view of the area in which detection is desired. The video image must be calibrated to establish a relationship between the ground and the camera's field of view. For this purpose, lane widths, down lane distances, and the camera height were measured. Calibration lines representing the ground measurements were digitally placed on the video image parallel and perpendicular to the traffic lanes. By placing the calibration lines on the image in the same location as the ground measurements, the image was calibrated to the ground.

After calibrating the field of view, detector files were created using the Autoscope software. These detectors were placed on the video image and treated as "virtual" loops. Detector files play an integral part in the accuracy of machine vision counts for volume, speed, classification, and other parameters. While creating detector files, care should be taken with areas of occlusion, areas of weaving traffic, and relative vehicle position in the lane to avoid missing detection. Typical detectors types are presence, count, speed, and station detectors, which can be combined to create a "detector function" to provide customized output.

Once detectors were in place and the detector configuration had been downloaded into Autoscope, polling (recording) of data begun. Vehicle detection was carried out with a superimposed image of the traffic on the computer screen. Autoscope continuously provided detector outputs and stored traffic data in its internal non-volatile memory to protect against power failure. The collected traffic and detection data was made available in a readily accessible ASCII (text) format. The computer software provided file management routines for efficiently filing, retrieving, and reporting of the collected traffic data.

Autoscope Length Classifications

Autoscope has the capability to classify vehicles into a maximum of five categories based on length. These categories are: vehicles less than 23 feet (class A), vehicles between 23 and 40 feet (class B), vehicles between 40 and 75 feet (class C), vehicles between 75 and 80 feet (class D), and vehicles greater than 80 feet (class E). A list of the 14 FHWA classes, the corresponding aggregated five Autoscope classes, and their length boundaries are summarized in Table 3-3. The table also shows two additional Autoscope classifications (Autoscope 3 classes and Autoscope 2 classes) that were evaluated at the site. When comparing Autoscope and FHWA data where more Autoscope classes were used, the Autoscope count data became less accurate. Therefore, the disaggregation model was developed on the Autoscope two-class grouping where vehicles were classified as less than 23 feet (class A) and greater than 23 feet (class B), as shown in the last column of Table 3-3.

Table 3-3. Grouped FHWA and Autoscope classes used in VCD model development

Class No	FHWA Class	Autoscope 5 classes	Autoscope 3 classes	Autoscope 2 classes
1	Motorcycles			
2	Passenger cars	A: 0 - 23 feet	A: 0 - 23 feet	A: 0 - 23 feet
3	Other 2-axle 4-tire			
4	Buses			
5	Single Unit Trucks 2-axle, 6-tire	B: 23 - 40 feet		
6	Single Unit Trucks 3-axle			
7	Single Unit Trucks 4-axle or more		B: 23 - 80 feet	B: > 23 feet
8	Single Trailer Truck 4-axle or less			
9	Single Trailer Truck 5-axle	C: 40 - 75 feet		
10	Single Trailer Truck 6-axle or more			
11	Multi Trailer Truck 5-axle or less			
12	Multi Trailer Truck 6-axle	D: 75 - 80 feet		
13	Multi Trailer Truck 7-axle or more			
14	Unknown	E: > 80 feet	C: > 80 feet	

In the two-class grouping, class A corresponds to FHWA classes one to three, and class B corresponds to FHWA classes four to 14. Table 3-4 illustrates the comparison of data collected by Autoscope and the FHWA axle count data.

Columns one and two of Table 3-4 are Autoscope counts for Class A and B denoted by X1 and X2. Columns three and four are a summation of the FHWA axle count data for class one to three and class four-14 respectively. Columns five and six show the difference between the two Autoscope classes and the corresponding aggregated FHWA classes. A difference in the total hourly volume counts is shown in column seven, which ranges from –81 to +114, with a negligible average difference of –6 vehicles. The mean and standard deviations of the corresponding columns shown in the last two rows indicates the range of differences in Autoscope and FHWA values for which the VCD model is developed. The differences can be attributed to calibration errors, bad triggers caused by shadowing of vehicles, occlusion, time setting differences, and lane changing of vehicles near the axle counters. These values were obtained from 28 hourly volume datasets gathered and analyzed for this research.

Table 3-4. Comparison between Autoscope and FHWA data

S.No	Autoscope Data		FHWA Data		Difference		Net Difference
	X1	X2	sum (Y1 - Y3)	sum (Y4 - Y14)	col 1 – col 3	col 2 – col 4	col 5 + col 6
Hours	**col 1**	**col 2**	**col 3**	**col 4**	**col 5**	**col 6**	**col 7**
1	672	163	713	159	-41	4	-37
2	696	193	674	150	22	43	65
3	743	200	813	187	-70	13	-57
4	700	195	796	180	-96	15	**-81 (min)**
5	764	182	783	161	-19	21	2
6	848	211	847	166	1	45	46
7	891	161	896	140	-5	21	16
8	724	161	672	146	52	15	67
9	731	220	746	207	-15	13	-2
10	798	191	819	196	-21	-5	-26
11	811	206	848	188	-37	18	-19
12	905	244	932	171	-27	73	46
13	944	181	962	144	-18	37	19
14	816	162	722	142	94	20	**114 (max)**
15	1130	201	1147	173	-17	28	11
16	1454	214	1526	178	-72	36	-36
17	1638	218	1722	194	-84	24	-60
18	1824	216	1911	185	-87	31	-56
19	1721	221	1834	159	-113	62	-51
20	1634	193	1620	148	14	45	59
21	692	174	742	166	-50	8	-42
22	798	198	861	196	-63	2	-61
23	757	193	817	191	-60	2	-58
24	781	220	844	218	-63	2	-61
25	789	177	804	163	-15	14	-1
26	847	192	869	163	-22	29	7
27	847	158	855	137	-8	21	13
28	829	142	826	140	3	2	5
				Mean =	**-29.18**	**22.82**	**-6.36**
				Standard Deviation =	**45.27**	**18.73**	**48.95**

Vehicle Classification Disaggregation Model (VCD Model)

The disaggregation process was introduced in stochastic hydrology for generating (or disaggregating) seasonal, monthly, weekly, daily, and even hourly variations in rainfall using a series of annual rainfall data. This method is very popular as it conserves all linear relationships between variables at successive levels, and preserves the long and short-term variance and covariance properties, including seasonal variations. The process has been successfully used for disaggregating rainfall data in Puerto Rico, streamflow data for the Colorado River the United States, and for the generation of hourly water demands in the Boston water distribution system (Valencia and Schaake, 1973).

A similar model was developed at The University of Alabama during this research for estimating (disaggregating) the 14 FHWA classes (similar to 12 months in a year) from the aggregated Autoscope classes (similar to a aggregated seasonal or annual rainfall or stream flow data). The goal was to develop a relationship between the two Autoscope classes and the 14 FHWA classes by taking into account the variance and covariance properties of the data. Using these relations, the model would use Autoscope data for any hour as input information to generate FHWA data for that particular hour.

The disaggregation model takes a simple mathematical form

$$Y = AX + BW \quad \text{...(3.1)}$$

where, Y is a $(n \times 1)$ vector of disaggregated values representing the 14 FHWA classes resulting from disaggregation process, X is a $(m \times 1)$ vector of values obtained from Autoscope classes, A is a $(n \times m)$ parameter matrix calculated to preserve covariance between aggregated (X) and disaggregated (Y) vectors, B is a $(n \times n)$ coefficient matrix calculated to preserve the proper covariance structure, and W is a $(n \times 1)$ vector of independently distributed standard normal deviates, which are randomly generated and normally distributed elements with a mean of $\mu = 0$ and variance of $\sigma^2 = 1$. In the model developed in this research, n = 14 represent the 14 FHWA classes and m = 2 represent the two Autoscope classes. The approach assumes that all the data used to develop the model follow a normal distribution and that the system maintains consistency of the cumulative relation. In other words, the sum of the generated disaggregated values should be equal to the given Autoscope values. Practically, all these assumptions cannot be satisfied (Valencia and Schaake, 1973). For example, the data used for this model need not follow a normal distribution.

Parameter matrices A and B are obtained from the following equations:

$$A = S_{yx}S_{xx}^{-1} \quad \text{...(3.2)}$$

$$BB^{T} = S_{yy} - S_{yx}S_{xx}^{-1}S_{xy} \quad \text{...(3.3)}$$

where, S_{xx} is the generated sample variances and covariances of the Autoscope classes, S_{yy} is the generated sample variances and covariances of the 14 FHWA classes, and S_{yx} is the generated sample variances and covariances between the Autoscope and FHWA classes. The resulting BB^T matrix is always a positive semidefinite and should be decomposed to obtain matrix B (Valencia and Schaake, 1973). A mathematical description of the disaggregation model, including a detailed discussion of parameter estimation procedures and decomposition of the BB^T matrix is available in Rodriguez-Iturbe (1993). Since the parameters for this calculation are determined from both Autoscope and FHWA data, the model will have properties that preserve:

- the mean of FHWA data,
- the variance and covariance of elements of S_{yy},
- the variances and covariances between Y and X, S_{yx}, and
- the cumulative relations of disaggregated FHWA values that add up to the aggregated Autoscope values.

After estimating the parameter matrices A and B, W matrix can be randomly generated. Finally, using the X-values obtained from Autoscope data, new set of Y-values can be estimated, which resemble the historical data values of Y (14 FHWA classes) used to develop the model. A flowchart representing the overview of the VCD model is shown in Figure 3-4.

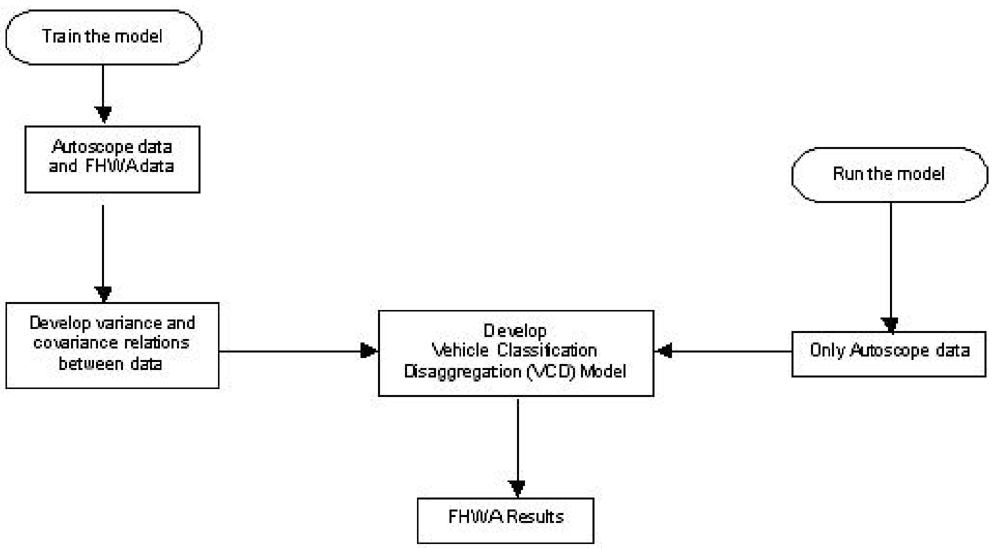

Figure 3-4. Flowchart representing an overview of VCD model

VCD model development

This section discusses the procedure used to develop the VCD model for estimating the parameter matrices A and B. The model was developed using weekday data on Interstate I-65 and can be retrained for other locations and times. For training purposes, the 14 FHWA classes (Y's) were obtained from axle counters and the aggregated values (X's) were obtained from Autoscope. The VCD model was developed using two Autoscope classes, where the first

Autoscope class represented the aggregation of the first three FHWA classes, and the second Autoscope class combind the rest of the FHWA classes.

The data collected from the FHWA axle counters and Autoscope were compiled and are presented in Table 3-5, wherein column headings Y1 to Y14 are the 14 FHWA classes. Column headings X1 and X2 at the far right of the table are Autoscope classes.

The rows numbered one through 28 contain the hourly volume in each vehicle class. Below the 28 hours of data are the minimum and maximum number (or range) of vehicles in each class used in the development of the VCD model. The last two rows of the table are the calculated mean number of vehicles and standard deviation in each of the FHWA and Autoscope classes. The disaggregation model operates on aggregated values, regardless of their origin. To evaluate the performance of the VCD model, it was first trained and validated using only FHWA data.

Table 3-5. Compilation of FHWA data and Autoscope data (28 datasets)

S.No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14	X1	X2
1	7	560	146	9	27	4	2	2	105	2	0	1	0	7	672	163
2	7	545	122	16	26	3	3	3	89	1	1	1	0	7	696	193
3	8	680	125	5	28	8	1	1	119	2	3	1	0	19	743	200
4	4	672	120	12	21	6	1	1	128	0	0	0	0	11	700	195
5	6	642	135	5	15	4	1	3	128	0	0	0	0	5	764	182
6	9	694	144	2	21	9	0	1	119	6	1	0	0	7	848	211
7	11	737	148	2	18	5	0	2	99	4	1	1	0	8	891	161
8	9	594	69	5	21	5	0	2	106	0	2	0	0	5	724	161
9	8	624	114	7	21	8	0	3	156	5	1	0	0	6	731	220
10	7	676	136	8	26	7	0	2	137	1	0	0	0	15	798	191
11	7	713	128	4	22	5	0	2	146	3	0	0	0	6	811	206
12	7	752	173	3	22	4	1	3	126	3	1	0	0	8	905	244
13	8	785	169	5	15	1	0	3	109	1	3	0	0	7	944	181
14	8	585	129	3	16	5	0	0	107	2	3	1	0	5	816	162
15	15	950	182	10	28	6	0	2	109	5	2	0	0	11	1130	201
16	11	1299	216	8	33	9	0	2	102	1	5	2	0	16	1454	214
17	15	1471	236	7	37	5	0	6	119	1	3	2	0	14	1638	218
18	10	1583	318	8	33	14	0	2	115	0	0	0	0	13	1824	216
19	16	1550	268	5	23	3	0	0	111	1	1	0	0	15	1721	221
20	7	1388	225	4	23	8	0	0	103	1	1	0	0	8	1634	193
21	12	603	127	8	32	7	0	2	106	1	1	3	0	6	692	174
22	7	664	190	13	38	10	0	1	113	6	0	2	0	13	798	198
23	9	671	137	4	36	14	2	2	117	1	2	1	0	12	757	193
24	4	707	133	12	29	3	1	3	150	4	2	0	0	14	781	220
25	12	666	126	5	25	4	0	4	115	4	0	0	0	6	789	177
26	10	719	140	2	22	5	1	2	116	4	1	0	1	9	847	192
27	11	674	170	4	19	2	1	1	90	6	2	2	0	10	847	158
28	9	673	144	3	15	7	0	0	101	2	1	1	0	10	829	142
Min	4	545	69	2	15	1	0	0	89	0	0	0	0	5	672	142
Max	16	1583	318	16	38	14	3	6	156	6	5	3	1	19	1824	244
Mean	**9.29**	**853.57**	**163.89**	**6.14**	**24.71**	**6.39**	**0.43**	**2.00**	**117.57**	**2.50**	**1.46**	**0.68**	**0.07**	**10.11**	**996.86**	**193.46**
SD	**3.005**	**316.97**	**52.39**	**3.63**	**6.705**	**3.14**	**0.79**	**1.319**	**16.478**	**1.97**	**1.249**	**0.87**	**0.189**	**3.893**	**347.429**	**24.102**

Training and validating the model using only FHWA data: For this purpose, instead of using Autoscope data, the values of X1 and X2 were obtained by summing the FHWA classes one to three and FHWA classes four to 14. This was performed to comply with the underlying assumption of the cumulative relation. The eight-step procedure explained below was followed to train and validate the VCD model.

The disaggregation process was developed and can be verified with the following steps:

1. To develop the model, the data is transformed to have a zero mean using the following equations 3.4 and 3.5.
$$Y_{ijt} = Y_{ij} - \mathbf{Y}'_j \qquad (3.4)$$
$$X_{ikt} = X_{ik} - \mathbf{X}'_k \qquad (3.5)$$
where i = 1 to 28 and is the hourly datasets, j = 1 to 14 and is the FHWA classes, k = 1 and 2 and is the aggregated values from FHWA data representing Autoscope data, t is the transformed data, $\mathbf{Y}'_j$ is the mean number of vehicles in each of the FHWA classes, and $\mathbf{X}'_k$ is the average number of vehicles in each of the aggregated FHWA classes.
2. The transformed data was used to compute the basic statistics of each column, which included mean, standard deviation, variance, and covariance.
3. All variances and covariances were determined to construct the S_{xx}, S_{yy}, and S_{yx} matrices, which were stored and used to obtain the parameter matrices A and B. It should be noted that the matrices remained constant throughout the model development process.
4. A MATLAB program was designed to perform the matrix operations associated with equations 3.2 and 3.3 to determine the parameter matrices A and B.
5. The MATLAB program used the calculated parameter matrices A, B, a dataset of transformed X-values, and a generated normally distributed random number array (W matrix) to perform the calculations associated with equation 3.1 to produce a set of Y-values.
6. To minimize bias in the VCD model due to the randomness of the W matrix, the model was run 10,000 times for one dataset of transformed X-values by generating the W matrix 10,000 times. This lead to the generation of a set of fourteen Y-values that were the averages over each 10,000 runs.
7. The generated Y-values (average over 10,000 runs) were re-transformed by adding the actual means, $\mathbf{Y}'_j$ to obtain a new set of final Y-values.
8. Likewise, the remaining datasets of transformed X-values were used to generate a total of 28 new sets of final Y-values. Statistics of these 28 new datasets were obtained and compared with the statistics of the input data to evaluate the performance of the model. If the VCD model output exhibited similar statistical properties, it was assumed to be viable.

The VCD model output is shown in Table 3-6 where the first 28 rows are the generated Y-values, and the next two rows are the mean number of vehicles and standard deviation observed in each of the 14 FHWA classes. The differences between actual and generated values are shown in Table 3-7. It can be seen in Table 3-7 that the average of the differences for all 28 sets for each of the 14 FHWA classes is almost zero, indicating a negligible average difference between the true and predicted values. To determine the proximity of VCD model generated values to the true values, confidence intervals were estimated for the generated data. The procedure adopted for determining the confidence intervals is described in the following section.

Table 3-6. Output of VCD model (28 datasets)

S. No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14
1	8.41	542.70	117.72	5.65	20.95	5.15	0.63	1.52	107.34	2.46	1.14	0.90	0.04	7.52
2	7.73	587.43	124.32	6.95	24.15	5.73	0.78	2.13	121.71	2.93	1.12	0.59	0.05	8.97
3	7.73	634.26	131.29	7.17	24.91	5.92	0.75	2.25	124.50	2.93	1.14	0.50	0.05	9.40
4	7.57	592.53	124.90	6.99	24.21	5.79	0.78	2.13	122.85	2.94	1.10	0.54	0.05	9.02
5	8.35	638.63	132.17	6.32	23.14	5.64	0.63	1.87	114.94	2.62	1.18	0.71	0.05	8.65
6	7.97	735.74	146.96	7.45	26.31	6.26	0.71	2.41	127.64	2.91	1.19	0.42	0.05	10.22
7	9.60	734.57	147.68	5.16	21.45	5.47	0.42	1.38	101.38	1.99	1.32	0.98	0.04	8.14
8	8.72	587.05	124.62	5.53	20.95	5.20	0.57	1.46	105.31	2.31	1.19	0.93	0.04	7.61
9	7.09	639.46	131.59	8.00	26.86	6.27	0.87	2.65	134.82	3.34	1.08	0.27	0.06	10.25
10	8.26	676.62	137.98	6.71	24.21	5.83	0.67	2.03	118.47	2.68	1.20	0.62	0.04	9.28
11	7.87	699.05	141.54	7.23	25.59	6.11	0.72	2.30	125.96	2.92	1.16	0.45	0.05	9.90
12	7.31	811.91	158.18	8.72	29.70	6.92	0.83	3.02	142.73	3.39	1.20	0.08	0.05	11.87
13	9.30	796.76	156.86	5.86	23.53	5.94	0.44	1.71	110.52	2.25	1.33	0.75	0.04	9.23
14	9.18	668.51	137.72	5.40	21.35	5.41	0.47	1.42	103.64	2.18	1.24	0.95	0.04	7.93
15	9.78	976.80	183.71	6.41	26.04	6.53	0.37	2.04	116.21	2.19	1.46	0.59	0.03	10.72
16	11.11	1273.00	229.00	6.33	28.16	7.22	0.10	2.11	115.37	1.75	1.69	0.51	0.02	12.28
17	11.95	1439.00	254.69	6.20	29.18	7.62	-0.07	2.07	113.36	1.45	1.85	0.51	0.02	13.14
18	13.01	1601.90	279.83	5.73	29.50	7.89	-0.27	1.92	108.02	1.03	2.02	0.60	0.01	13.66
19	12.31	1514.90	266.57	6.09	29.76	7.83	-0.14	2.09	113.12	1.34	1.91	0.52	0.02	13.55
20	12.65	1415.70	251.81	5.12	26.66	7.22	-0.20	1.55	100.80	1.07	1.89	0.80	0.01	12.07
21	8.18	568.72	121.68	6.10	22.20	5.40	0.67	1.76	112.47	2.58	1.15	0.78	0.05	8.04
22	8.06	681.15	138.66	6.96	24.87	5.94	0.71	2.16	122.03	2.81	1.19	0.55	0.05	9.51
23	8.02	641.42	132.64	6.79	24.24	5.77	0.72	2.11	120.27	2.80	1.18	0.60	0.05	9.17
24	7.33	683.90	138.27	7.90	27.04	6.33	0.83	2.62	133.64	3.22	1.14	0.30	0.06	10.43
25	8.65	657.02	135.33	6.03	22.63	5.58	0.58	1.72	111.69	2.45	1.20	0.77	0.04	8.51
26	8.52	719.71	144.79	6.57	24.46	5.97	0.60	2.02	118.13	2.62	1.24	0.62	0.04	9.39
27	9.48	692.46	141.14	5.11	20.91	5.34	0.42	1.32	100.76	2.05	1.28	1.00	0.04	7.76
28	9.85	664.15	136.86	4.45	19.24	4.98	0.35	1.01	93.26	1.81	1.30	1.16	0.03	7.07
Mean	**9.07**	**816.97**	**159.59**	**6.39**	**24.72**	**6.12**	**0.50**	**1.96**	**115.75**	**2.39**	**1.32**	**0.64**	**0.04**	**9.76**
SD	**1.68**	**315.17**	**48.27**	**0.98**	**2.95**	**0.81**	**0.33**	**0.45**	**11.40**	**0.65**	**0.28**	**0.24**	**0.01**	**1.87**

Table 3-7. Summary of differences between FHWA data and Autoscope data (28 datasets)

S. No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14
1	-1.41	17.30	28.28	3.35	6.05	-1.15	1.37	0.48	-2.34	-0.46	-1.14	0.10	-0.04	-0.52
2	-0.73	-42.43	-2.32	9.05	1.85	-2.73	2.22	0.87	-32.71	-1.93	-0.12	0.41	-0.05	-1.97
3	0.27	45.74	-6.29	-2.17	3.09	2.08	0.25	-1.25	-5.50	-0.93	1.86	0.50	-0.05	9.60
4	-3.57	79.47	-4.90	5.01	-3.21	0.21	0.22	-1.13	5.15	-2.94	-1.10	-0.54	-0.05	1.98
5	-2.35	3.37	2.83	-1.32	-8.14	-1.64	0.37	1.13	13.06	-2.62	-1.18	-0.71	-0.05	-3.65
6	1.03	-41.74	-2.96	-5.45	-5.31	2.74	-0.71	-1.41	-8.64	3.09	-0.19	-0.42	-0.05	-3.22
7	1.40	2.43	0.32	-3.16	-3.45	-0.47	-0.42	0.62	-2.38	2.01	-0.32	0.02	-0.04	-0.14
8	0.28	6.95	-55.62	-0.53	0.05	-0.20	-0.57	0.54	0.69	-2.31	0.81	-0.93	-0.04	-2.61
9	0.91	-15.46	-17.59	-1.00	-5.86	1.73	-0.87	0.35	21.18	1.66	-0.08	-0.27	-0.06	-4.25
10	-1.26	-0.62	-1.98	1.29	1.79	1.17	-0.67	-0.03	18.53	-1.68	-1.20	-0.62	-0.04	5.72
11	-0.87	13.95	-13.54	-3.23	-3.59	-1.11	-0.72	-0.30	20.04	0.08	-1.16	-0.45	-0.05	-3.90
12	-0.31	-59.91	14.82	-5.72	-7.70	-2.92	0.17	-0.02	-16.73	-0.39	-0.20	-0.08	-0.05	-3.87
13	-1.30	-11.76	12.14	-0.86	-8.53	-4.94	-0.44	1.29	-1.52	-1.25	1.67	-0.75	-0.04	-2.23
14	-1.18	-83.51	-8.72	-2.40	-5.35	-0.41	-0.47	-1.42	3.36	-0.18	1.76	0.05	-0.04	-2.93
15	5.22	-26.80	-1.71	3.59	1.96	-0.53	-0.37	-0.04	-7.21	2.81	0.54	-0.59	-0.03	0.28
16	-0.11	26.00	-13.00	1.67	4.84	1.78	-0.10	-0.11	-13.37	-0.75	3.31	1.49	-0.02	3.72
17	3.05	32.00	-18.69	0.80	7.83	-2.62	0.07	3.93	5.64	-0.45	1.15	1.49	-0.02	0.86
18	-3.01	-18.90	38.17	2.27	3.50	6.11	0.27	0.08	6.98	-1.03	-2.02	-0.60	-0.01	-0.66
19	3.69	35.10	1.43	-1.09	-6.76	-4.83	0.14	-2.09	-2.12	-0.34	-0.91	-0.52	-0.02	1.45
20	-5.65	-27.70	-26.81	-1.12	-3.66	0.78	0.20	-1.55	2.20	-0.07	-0.89	-0.80	-0.01	-4.07
21	3.82	34.28	5.32	1.90	9.80	1.60	-0.67	0.24	-6.47	-1.58	-0.15	2.22	-0.05	-2.04
22	-1.06	-17.15	51.34	6.04	13.13	4.06	-0.71	-1.16	-9.03	3.19	-1.19	1.45	-0.05	3.49
23	0.98	29.58	4.36	-2.79	11.76	8.23	1.28	-0.11	-3.27	-1.80	0.82	0.40	-0.05	2.84
24	-3.33	23.10	-5.27	4.10	1.97	-3.33	0.17	0.38	16.36	0.78	0.86	-0.30	-0.06	3.57
25	3.35	8.98	-9.33	-1.03	2.37	-1.58	-0.58	2.28	3.31	1.55	-1.20	-0.77	-0.04	-2.51
26	1.48	-0.71	-4.79	-4.57	-2.46	-0.97	0.40	-0.02	-2.13	1.38	-0.24	-0.62	0.96	-0.39
27	1.52	-18.46	28.86	-1.11	-1.91	-3.34	0.58	-0.32	-10.76	3.95	0.72	1.00	-0.04	2.24
28	-0.85	8.85	7.14	-1.45	-4.24	2.02	-0.35	-1.01	7.74	0.19	-0.30	-0.16	-0.03	2.93
Mean	**0.00**	**0.07**	**0.05**	**0.00**	**-0.01**	**-0.01**	**0.00**	**0.01**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**-0.01**
SDD	**2.48**	**34.21**	**20.48**	**3.50**	**6.03**	**3.04**	**0.72**	**1.24**	**11.84**	**1.85**	**1.22**	**0.83**	**0.19**	**3.42**

Training and verifying the model using Autoscope data: After training the VCD model developed from FHWA data, the aggregated X1 and X2 values were replaced with actual Autoscope X-values. The purpose of verification was to evaluate the statistical properties of the generated data and to compare those properties with similar properties of the input data. To verify and quantify the accuracy of the VCD model, three datasets were randomly selected for testing purposes, which were excluded from the 28 datasets. The model was first trained with 25 datasets. Table 3-8 shows the compiled 25 sets of both FHWA and Autoscope data. The calculated mean number of cars and the standard deviation for each class (designated by each column) is shown in the last two rows. The eight-step procedure discussed above was repeated and the VCD model generated a new series of 25 datasets.

Table 3-8. Compilation of FHWA data and Autoscope data (25 datasets)

S. No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14	X1	X2
1	7	545	122	16	26	3	3	3	89	1	1	1	0	7	696	193
2	8	680	125	5	28	8	1	1	119	2	3	1	0	19	743	200
3	4	672	120	12	21	6	1	1	128	0	0	0	0	11	700	195
4	6	642	135	5	15	4	1	3	128	0	0	0	0	5	764	182
5	9	694	144	2	21	9	0	1	119	6	1	0	0	7	848	211
6	11	737	148	2	18	5	0	2	99	4	1	1	0	8	891	161
7	9	594	69	5	21	5	0	2	106	0	2	0	0	5	724	161
8	7	676	136	8	26	7	0	2	137	1	0	0	0	15	798	191
9	7	713	128	4	22	5	0	2	146	3	0	0	0	6	811	206
10	7	752	173	3	22	4	1	3	126	3	1	0	0	8	905	244
11	8	785	169	5	15	1	0	3	109	1	3	0	0	7	944	181
12	8	585	129	3	16	5	0	0	107	2	3	1	0	5	816	162
13	11	1299	216	8	33	9	0	2	102	1	5	2	0	16	1454	214
14	15	1471	236	7	37	5	0	6	119	1	3	2	0	14	1638	218
15	10	1583	318	8	33	14	0	2	115	0	0	0	0	13	1824	216
16	16	1550	268	5	23	3	0	0	111	1	1	0	0	15	1721	221
17	7	1388	225	4	23	8	0	0	103	1	1	0	0	8	1634	193
18	12	603	127	8	32	7	0	2	106	1	1	3	0	6	692	174
19	7	664	190	13	38	10	0	1	113	6	0	2	0	13	798	198
20	9	671	137	4	36	14	2	2	117	1	2	1	0	12	757	193
21	4	707	133	12	29	3	1	3	150	4	2	0	0	14	781	220
22	12	666	126	5	25	4	0	4	115	4	0	0	0	6	789	177
23	10	719	140	2	22	5	1	2	116	4	1	0	1	9	847	192
24	11	674	170	4	19	2	1	1	90	6	2	2	0	10	847	158
25	9	673	144	3	15	7	0	0	101	2	1	1	0	10	829	142
Mean	**8.96**	**829.72**	**161.12**	**6.12**	**24.64**	**6.12**	**0.48**	**1.92**	**114.84**	**2.20**	**1.36**	**0.68**	**0.04**	**9.96**	**970.04**	**192.12**
SD	**2.91**	**328.36**	**54.50**	**3.73**	**7.02**	**3.28**	**0.77**	**1.38**	**15.18**	**1.94**	**1.29**	**0.90**	**0.20**	**4.00**	**358.97**	**24.14**

The generated data sets, calculated means, and standard deviations for each class are shown in Table 3-9.

Table 3-9. Output of VCD model (25 datasets)

S.No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14
1	7.522	588.800	124.820	6.786	24.214	5.585	0.791	2.066	120.260	2.748	1.149	0.630	0.050	9.321
2	7.446	636.330	132.460	7.041	25.100	5.768	0.818	2.155	122.430	2.682	1.152	0.552	0.054	9.803
3	7.455	594.220	125.570	6.868	24.504	5.660	0.808	2.100	121.150	2.732	1.155	0.599	0.052	9.461
4	8.286	638.840	131.090	5.986	22.881	5.623	0.592	1.819	114.300	2.497	1.231	0.726	0.049	8.832
5	7.597	738.670	148.760	7.377	26.882	6.173	0.815	2.339	125.550	2.620	1.181	0.463	0.053	10.720
6	9.666	732.690	144.320	4.770	20.570	5.670	0.237	1.340	102.640	2.039	1.414	0.977	0.034	8.044
7	8.847	585.370	121.610	5.105	20.180	5.288	0.419	1.433	105.630	2.341	1.294	0.938	0.044	7.593
8	8.141	677.070	137.990	6.402	24.098	5.766	0.655	1.973	117.640	2.522	1.220	0.643	0.045	9.486
9	7.578	701.540	142.860	7.180	26.134	6.045	0.806	2.259	123.880	2.626	1.198	0.506	0.049	10.381
10	6.735	817.870	163.500	8.889	31.114	6.535	1.112	2.982	138.770	2.835	1.119	0.155	0.061	12.741
11	9.273	797.050	155.170	5.560	23.111	5.934	0.380	1.715	110.560	2.149	1.372	0.776	0.039	9.245
12	9.213	667.360	134.040	4.924	20.461	5.514	0.320	1.394	104.550	2.195	1.342	0.935	0.040	7.838
13	10.691	1275.800	230.830	6.154	28.325	7.244	0.177	2.103	115.350	1.522	1.633	0.568	0.023	12.443
14	11.500	1441.800	256.310	6.017	29.216	7.560	0.026	2.092	113.590	1.195	1.769	0.575	0.013	13.121
15	12.550	1603.400	280.530	5.465	29.336	7.907	-0.197	1.950	108.960	0.862	1.940	0.641	0.006	13.489
16	11.800	1517.800	267.570	5.985	29.817	7.805	-0.040	2.101	113.540	1.076	1.828	0.560	0.012	13.513
17	12.407	1416.600	250.000	4.750	26.111	7.344	-0.234	1.622	102.680	0.963	1.874	0.811	0.011	11.694
18	8.093	568.740	120.050	5.819	21.694	5.396	0.584	1.697	112.430	2.527	1.220	0.779	0.043	8.262
19	7.840	683.510	139.030	6.741	24.950	5.851	0.735	2.129	120.800	2.547	1.221	0.572	0.050	9.849
20	7.841	642.690	133.070	6.648	24.339	5.714	0.730	2.040	119.180	2.612	1.193	0.632	0.054	9.524
21	6.998	687.670	141.890	7.961	27.939	6.098	0.993	2.570	130.510	2.839	1.125	0.386	0.058	11.080
22	8.591	656.670	133.760	5.685	22.291	5.616	0.514	1.710	111.630	2.401	1.291	0.787	0.043	8.656
23	8.329	720.780	144.510	6.361	24.353	5.904	0.623	1.989	116.970	2.431	1.276	0.649	0.047	9.627
24	9.524	690.930	137.310	4.646	19.906	5.475	0.237	1.311	102.380	2.112	1.394	0.964	0.039	7.657
25	10.022	661.510	131.600	3.856	17.895	5.304	0.106	1.007	95.617	1.936	1.467	1.132	0.034	6.837
Mean	**8.958**	**829.748**	**161.146**	**6.119**	**24.617**	**6.111**	**0.480**	**1.916**	**114.840**	**2.200**	**1.362**	**0.678**	**0.040**	**9.969**
SD	**1.690**	**326.354**	**50.476**	**1.135**	**3.464**	**0.803**	**0.367**	**0.428**	**9.775**	**0.607**	**0.250**	**0.212**	**0.016**	**1.941**

The differences between the actual and generated series of datasets are shown in Table 3-10. The values in this table indicate the number of cars in each class that were under-or-over estimated by the VCD model using only Autoscope data, when compared to the actual count obtained by the FHWA axle counters. Although the cumulative relation did not strictly hold true, the model produced 25 values for each class whose average was approximately zero. The last row of Table 3-10 indicates the standard deviation values of the differences (SDD). If the means of the differences (second to last row in Table 3-10) are non-zero whole numbers, then the differences are considered to be significant, indicating either inapplicability of the model, programming errors, or both. This was not the case.

Table 3-10. Summary of differences between FHWA data and Autoscope data (25 datasets)

S.No	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10	Y11	Y12	Y13	Y14
1	-0.522	-43.800	-2.820	9.214	1.786	-2.585	2.209	0.934	-31.260	-1.748	-0.149	0.370	-0.050	-2.321
2	0.554	43.670	-7.460	-2.041	2.900	2.232	0.182	-1.155	-3.430	-0.682	1.848	0.448	-0.054	9.197
3	-3.455	77.780	-5.570	5.132	-3.504	0.340	0.192	-1.100	6.850	-2.732	-1.155	-0.599	-0.052	1.539
4	-2.286	3.160	3.910	-0.986	-7.881	-1.623	0.408	1.181	13.700	-2.497	-1.231	-0.726	-0.049	-3.832
5	1.403	-44.670	-4.760	-5.377	-5.882	2.827	-0.815	-1.339	-6.550	3.380	-0.181	-0.463	-0.053	-3.720
6	1.334	4.310	3.680	-2.770	-2.570	-0.670	-0.237	0.660	-3.640	1.961	-0.414	0.023	-0.034	-0.044
7	0.153	8.630	-52.610	-0.105	0.820	-0.288	-0.419	0.567	0.370	-2.341	0.706	-0.938	-0.044	-2.593
8	-1.141	-1.070	-1.990	1.598	1.902	1.234	-0.655	0.027	19.360	-1.522	-1.220	-0.643	-0.045	5.514
9	-0.578	11.460	-14.860	-3.180	-4.134	-1.045	-0.806	-0.259	22.120	0.374	-1.198	-0.506	-0.049	-4.381
10	0.265	-65.870	9.500	-5.889	-9.114	-2.535	-0.112	0.018	-12.770	0.165	-0.119	-0.155	-0.061	-4.741
11	-1.273	-12.050	13.830	-0.560	-8.111	-4.934	-0.380	1.285	-1.560	-1.149	1.628	-0.776	-0.039	-2.245
12	-1.213	-82.360	-5.040	-1.924	-4.461	-0.514	-0.320	-1.394	2.450	-0.195	1.659	0.065	-0.040	-2.838
13	0.309	23.200	-14.830	1.846	4.675	1.756	-0.177	-0.103	-13.350	-0.522	3.367	1.432	-0.023	3.557
14	3.500	29.200	-20.310	0.983	7.784	-2.560	-0.026	3.908	5.410	-0.195	1.232	1.425	-0.013	0.879
15	-2.550	-20.400	37.470	2.535	3.664	6.093	0.197	0.050	6.040	-0.862	-1.940	-0.641	-0.006	-0.489
16	4.200	32.200	0.430	-0.985	-6.817	-4.805	0.040	-2.101	-2.540	-0.076	-0.828	-0.560	-0.012	1.487
17	-5.407	-28.600	-25.000	-0.750	-3.111	0.656	0.234	-1.622	0.320	0.037	-0.874	-0.811	-0.011	-3.694
18	3.907	34.260	6.950	2.181	10.306	1.605	-0.584	0.303	-6.430	-1.527	-0.220	2.221	-0.043	-2.262
19	-0.840	-19.510	50.970	6.259	13.050	4.149	-0.735	-1.129	-7.800	3.453	-1.221	1.428	-0.050	3.151
20	1.159	28.310	3.930	-2.648	11.661	8.286	1.270	-0.040	-2.180	-1.612	0.807	0.368	-0.054	2.476
21	-2.998	19.330	-8.890	4.040	1.061	-3.098	0.007	0.430	19.490	1.161	0.875	-0.386	-0.058	2.920
22	3.409	9.330	-7.760	-0.685	2.709	-1.616	-0.514	2.290	3.370	1.599	-1.291	-0.787	-0.043	-2.656
23	1.671	-1.780	-4.510	-4.361	-2.353	-0.904	0.377	0.011	-0.970	1.569	-0.276	-0.649	0.953	-0.627
24	1.476	-16.930	32.690	-0.646	-0.906	-3.475	0.763	-0.311	-12.380	3.888	0.606	1.036	-0.039	2.343
25	-1.022	11.490	12.400	-0.856	-2.895	1.696	-0.106	-1.007	5.383	0.064	-0.467	-0.132	-0.034	3.163
Mean	**0.002**	**-0.028**	**-0.026**	**0.001**	**0.023**	**0.009**	**0.000**	**0.004**	**0.000**	**0.000**	**-0.002**	**0.002**	**0.000**	**-0.009**
SDD	**2.380**	**35.516**	**20.566**	**3.562**	**6.141**	**3.184**	**0.676**	**1.311**	**11.632**	**1.840**	**1.269**	**0.877**	**0.199**	**3.505**

Results

To test the VCD model performance, three datasets not included in training the model were run through the VCD model. The first Autoscope dataset generated a set of 14 FHWA values, which were compared with the actual set of 14 FHWA values to determine the accuracy of the generated values. To report the accuracy of the VCD model output, confidence intervals were estimated. For the purpose of research, 95% and 99% confidence intervals were estimated from the following expressions:

95% confidence Interval: mean value from VCD model $\pm$ 1.96 $\times$ (SDD)………………(3.6)

99% confidence Interval: mean value from VCD model $\pm$ 2.575 $\times$ (SDD)……………..(3.7)

SDDs are the conditioned standard deviation values obtained for each class in Table 3-10. This process was employed on all three datasets and a summary of the confidence intervals for these sets is tabulated in Tables 3-11, 3-12, and 3-13. The second and third columns in these tables represent the actual FHWA data and VCD model generated data, respectively. Lower and upper 95% confidence limit values are shown in fourth and fifth columns, followed by 99% confidence limit values in sixth and seventh column. As is expected, the three sets that the 95% confidence interval obtained using the VCD model output included 95% of actual FHWA classes. Outliers are in bold. The confidence interval obtained with 99% confidence contained all the actual FHWA classes.

Table 3-11. Testing dataset 1, 95% and 99% confidence interval for the VCD model output

S.No (1)	Actual FHWA values (2)	VCD model Mean Output (3)	95% Confidence Interval Lower C.L (4)	95% Confidence Interval Upper C.L (5)	99% Confidence Interval Lower C.L (6)	99% Confidence Interval Upper C.L (7)
1	7	8.46	3.79	13.12	2.33	14.59
2	560	541.50	471.89	611.11	450.02	632.98
3	146	115.28	74.97	155.59	62.31	168.25
4	9	5.30	-1.69	12.28	-3.88	14.47
5	27	20.29	8.26	32.33	4.48	36.11
6	4	5.27	-0.97	11.51	-2.93	13.47
7	***2***	***0.50***	***-0.83***	***1.82***	-1.24	2.24
8	2	1.48	-1.09	4.05	-1.90	4.86
9	105	107.70	84.90	130.50	77.74	137.66
10	2	2.49	-1.12	6.09	-2.25	7.23
11	0	1.22	-1.27	3.70	-2.05	4.49
12	1	0.89	-0.83	2.61	-1.37	3.15
13	0	0.04	-0.35	0.43	-0.47	0.56
14	7	7.56	0.69	14.43	-1.47	16.59

Table 3-12. Testing dataset 2, 95% and 99% confidence interval for the VCD model output

S.No (1)	Actual FHWA values (2)	VCD model Mean Output (3)	95% Confidence Interval Lower C.L (4)	95% Confidence Interval Upper C.L (5)	99% Confidence Interval Lower C.L (6)	99% Confidence Interval Upper C.L (7)
1	8	6.72	2.056	11.39	0.59	12.85
2	624	643.44	573.830	713.05	551.96	734.92
3	114	134.87	94.561	175.18	81.90	187.84
4	7	8.04	1.060	15.02	-1.13	17.22
5	21	27.73	15.693	39.77	11.91	43.55
6	8	5.96	-0.281	12.20	-2.24	14.16
7	0	1.03	-0.291	2.36	-0.71	2.78
8	3	2.59	0.017	5.16	-0.79	5.96
9	***156***	***131.45***	***108.652***	***154.25***	101.49	161.41
10	5	2.95	-0.656	6.56	-1.79	7.69
11	1	1.09	-1.398	3.58	-2.18	4.36
12	0	0.36	-1.361	2.08	-1.90	2.62
13	0	0.06	-0.326	0.45	-0.45	0.58
14	6	10.97	4.098	17.84	1.94	20.00

Table 3-13. Testing dataset 3, 95% and 99% confidence interval for the VCD model output

S.No (1)	Actual FHWA values (2)	VCD model Mean Output (3)	95% Confidence Interval Lower C.L (4)	95% Confidence Interval Upper C.L (5)	99% Confidence Interval Lower C.L (6)	99% Confidence Interval Upper C.L (7)
1	***15***	***9.49***	***4.83***	***14.16***	3.36	15.62
2	950	978.49	908.88	1048.10	887.01	1069.97
3	182	184.31	144.00	224.62	131.34	237.28
4	10	6.28	-0.70	13.26	-2.90	15.45
5	28	26.17	14.13	38.20	10.35	41.99
6	6	6.49	0.25	12.73	-1.71	14.69
7	0	0.41	-0.91	1.74	-1.33	2.15
8	2	2.02	-0.55	4.58	-1.36	5.39
9	109	115.45	92.65	138.25	85.49	145.41
10	5	2.01	-1.60	5.62	-2.73	6.75
11	2	1.45	-1.03	3.94	-1.82	4.72
12	0	0.64	-1.08	2.36	-1.62	2.90
13	0	0.04	-0.35	0.43	-0.48	0.55
14	11	10.89	4.02	17.75	1.86	19.91

Conclusions and Recommendations

During the Vehicle Classification Disaggregation (VCD) model development, training, and validation, video and axle data were employed. With a trained VCD model and using only Autoscope data, 10,000 runs were made to produce an output distribution for the 14 FHWA classes. A summary of FHWA axle counter data and Autoscope data is shown in Table 3-5, and the results of the disaggregation model are presented in Table 3-6. A comparison was performed on these two tables and the average deviation of the difference between the FHWA axle count data and the VCD model output is provided in Table 3-7. It can be seen from the tables that for most of the classes, the generated values maintained statistical properties similar to the actual data, and the mean of the differences is close to zero indicating a negligible average difference between the actual and VCD model output data.

The VCD model was verified using three datasets. A comparison was performed between the actual data and the VCD generated classes for the three datasets. Confidence intervals at 95% and 99% were calculated for the generated values, and are presented in Tables 3-11, 3-12, and 3-13.

Based on a review of various methodologies used for vehicle classification, and the findings from the vehicle disaggregation analyses, the following conclusions and recommendations are outlined for using video technology for compositional traffic counts.

- Initial installation costs of employing video for compositional traffic data collection is approximately $11,000.

- Video is inexpensive, portable, and can be installed on a bridge railing or on a side pole in approximately 15 minutes without disrupting traffic. Maintenance costs of video equipment are low.
- Any number of video "virtual" loops can be placed on the target roadway. This translates into less cost when compared to inductive loop detectors.
- Video technology offers simple monitoring of multilane freeways that produces no disruption of traffic, and better safety for data collection staff.
- Autoscope was inefficient in grouping long vehicles. One possible solution would be to mount the camera higher (more than 30 feet above the target roadway).
- The current VCD model produces accurate results at the site where it was trained.
- To further analyze the VCD model, the performance on weekends, peak and off-peak periods, and holidays must be evaluated. This will allow the development of specific models for different time periods.
- Further, to analyze the applicability of VCD model, its performance must be evaluated at different locations.

Section 4
15^{th} Street Corridor Modeling

Introduction

Video technology can be used to obtain information about traffic flow. Parameters such as volume, speed, headway, and queue length can be determined through careful analysis of recorded video. Using video cameras installed and operated by the City of Tuscaloosa and portable University of Alabama video units, video recording was performed on intersections along the 15^{th} Street corridor in Tuscaloosa. Traffic flow parameters were determined from the video recording, and were used to develop a traffic flow model using an industrial engineering simulation software package called ARENA developed by Rockwell Software Inc. (ARENA User Manual, 1999).

Output volume results from the new ARENA model were compared to the actual field data, and ARENA delay values were compared with Institute of Transportation Engineers (ITE) intersection field delay values, Highway Capacity Manual (HCM) 1994, and Highway Capacity Software (HCS) 2000 calculations. Input parameters for the ARENA model and the other methodologies were obtained from video data. Information on traffic flow, signalization, and intersection geometry were provided by the Tuscaloosa Department of Transportation (TDOT).

The objective of this task was to determine if video could be used to collect the required traffic information to calculate volume and delay by different methodologies, one of which, the ARENA model, was developed during this work. Although multiple methods were compared, two methods 1) the new ARENA simulation model based on the arrival distribution, and 2) the ITE intersection formula, were compared in detail.

Background

For this work it was assumed that traffic simulation is analogous to manufacturing. The manufacturing process involves the arrival of raw material at a machine, processing by the machine, and departure as a finished product. A similar methodology was employed to calculate the efficiency of signalized intersections using ARENA. In this process, a vehicle arrives at an intersection, experiences delay due to signal operations, and departs from the intersection as a turn movement or through movement.

Existing intersection traffic models use traffic volumes as input, and do not consider the actual arrival distribution of traffic at an intersection. Two of these models, HCM 1994 and HCS 2000 were investigated. Although these methods consider arrival patterns, the actual arrival distributions are not included as part of the software. This was not as desirable as software that allowed designation of the distributions.

ARENA was selected for simulating signalized intersections based on the following factors:

1) ARENA uses data such as arrival distributions, turn volumes, and signalization phase plan to predict volume and intersection stopped delay associated with a signalized intersection,
2) ARENA provides visualization capabilities, and
3) the output format can be customized to obtain parameters such as volume, queue length, stopped delay, and process delay.

Methodology

Introduction

Video cameras were used to collect field data for this study. A simulation model was developed for one intersection and applied to three additional intersections along the same corridor. The research approach employed in this work is shown in Figure 4-1. Column 1 in Figure 4-1 shows the initial step, video data collection. Input parameters for the ARENA model and ITE method were identified and collected as part of this step. Video technology was used to collect traffic data during morning and evening peak hours.

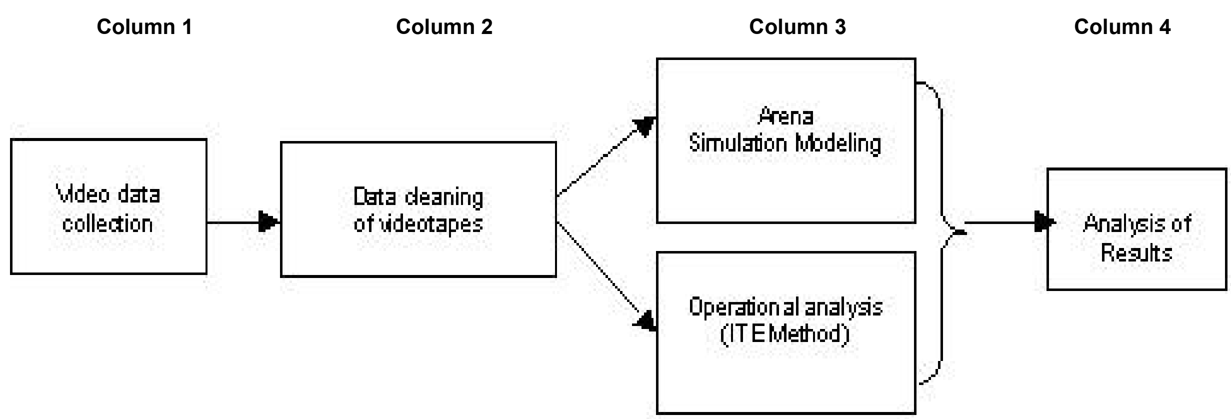

Figure 4-1. Schematic representation of the study approach

As shown in column 2 of Figure 4-1, the recorded videotapes were cleaned and analyzed to determine the input parameters for the methods. Column 3 of Figure 4-1 shows the computation portion of this work, which is divided into two parts: ARENA simulation modeling and operational analysis. Finally, as shown in column 4 of Figure 4-1, ARENA volume and delay results were analyzed and validated; specifically against the field values, ITE method, HCM 1994 and HCS 2000 procedures.

Video Data Collection

The traffic data utilized for this study were obtained at four intersections on 15th Street in Tuscaloosa, Alabama. The 15th street corridor is considered to be one of the busiest corridors in the City, with several intersections experiencing saturation flow during the peak hours of the day, i.e., the morning 7:00 to 9:00 AM period and the evening 4:00 to 6:00 PM period. The following intersections were used for analysis in this research:

1. 15th Street and McFarland Boulevard
2. 15th Street and 6th Avenue East
3. 15th Street and Hackberry Lane
4. 15th Street and 10th Avenue

As shown in Figure 4-2, these intersections are along 15th Street between US 82 and Interstate 359. These intersections were chosen because of the heavy traffic volumes, the associated high delay values, and the location of permanent video cameras owned by TDOT.

A group of six students collected morning peak data from 7:00 to 9:00 and evening peak data from 4:00 to 6:00 during weekdays. The data collection process was spread over a two-month period with the amount of data varying from one day to seven days depending on the approach. Video cameras were used to record traffic movements at these intersections. TDOT provided assistance in the video data collection.

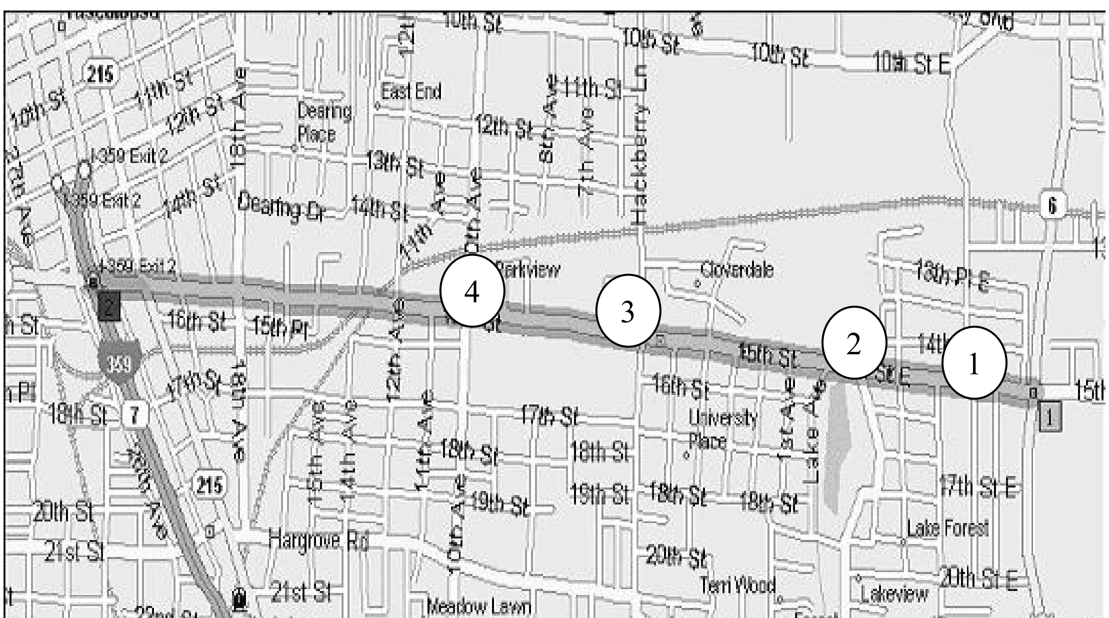

Figure 4-2. Map of the 15th Street corridor

ARENA Input Parameters: Various traffic parameters were measured or calculated based on the input requirements for the simulation model and the operational analysis calculations. The following parameters were identified as input for the ARENA simulation.

1. arrival distributions and time headways (time between two consecutive vehicles in a particular lane),
2. turn volume percentages,
3. signalization data, and
4. number of lanes and signals.

ITE Method Input Parameters: Input data for the ITE method, which involves the calculation of delay based on the number of stopped vehicles and the volume in a given time period, are as follows (Traffic Engineering Handbook, 1994):

1. lane volumes for each approach, calculated from the video data,
2. stopped vehicle-volume data, i.e., the total number of stopped vehicles counted every 15 seconds in a given period of time, and
3. flow rate for each lane/lane group, i.e., the total traffic volume in a lane/lane group in a given time.

A total of 240 hours of videotape were collected during this study. Cleaning of the videotape to collect the required parameters took approximately 360 hours. Although this was a time consuming process, the data produced was very accurate because any tape could be viewed any number of times to verify the data.

ARENA Model Development

ARENA uses modules to define different processes. There are two types of ARENA modules: 1) flowchart modules and 2) data modules. Flowchart modules are connected to form logical relationships dealing with processing a vehicle through an intersection. Data modules, which can be edited by a spreadsheet (ARENA User Manual, 1999), are connected to flowchart modules and control the behavior of those modules, i.e. actual volumes of vehicles arriving or signal timings. ARENA employs a model window that consists of two regions: 1) the model workspace that contains all the model graphics, including the flowchart and animation, and 2) the spreadsheet view that displays the model data.

The development of the ARENA simulation model is based on:

1. arrivals,
2. turn movements, yield on green (YOG) left-turns, and right turns on red (RTORs), and
3. intersection operations.

Actual arrival information was employed to calculate arrival distributions that were used in "Arrive" blocks in the ARENA model. Peak hour field data were collected in eight 15-minute intervals. These eight data sets were used to develop Poisson distributions for arrivals. The method employed in determining Poisson distributions can be found in research done by Pagadala (2001).

Vehicles arriving at an intersection must turn or go through an intersection. An ARENA "Chance" block was utilized to separate YOGs and to delineate RTOR percentages. An ARENA "Inspect" block was used to separate right-turn vehicles from through vehicles in the case of a shared right turn lane.

Finally, each "Arrive" block was assigned a server that processes vehicles. In this model, the server represents the signal for that particular lane. Signal green time and red time are achieved by creating active and inactive phases of the server with the help of logic blocks.

Figure 4-3 illustrates the building units of the ARENA intersection simulation model. Traffic is generated using the ARENA "Arrive" block using Poisson distributions. Each vehicle goes into the server, which is analogous to the traffic signal at the intersection. The vehicle is processed, i.e., the vehicle remains in the queue until the server becomes active (signal turns green) and then it is released to the ARENA "Depart" block that counts the number of departures. The servers follow the actual signal phasing at an intersection. By combining a series of arrive-server-depart building units along with chance and inspection blocks representing turns, an entire intersection can be modeled.

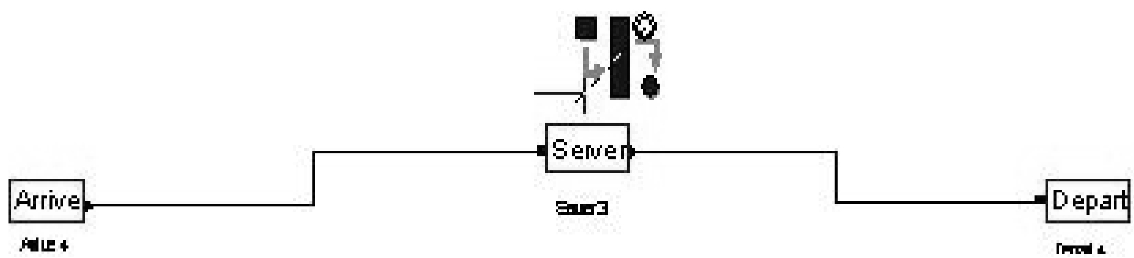

Figure 4-3. Basic intersection process

Figure 4-4 shows a signalized intersection simulation model developed using ARENA. Additional details on ARENA model development for intersection modeling can be found in Pagadala (2001).

Operational Analysis

In addition to developing an ARENA model, an operational analysis was performed based on ITE procedures published in the Traffic Engineering Handbook. This procedure is recommended by the Highway Capacity Manual. Video data was analyzed to evaluate the field stopped delay value.

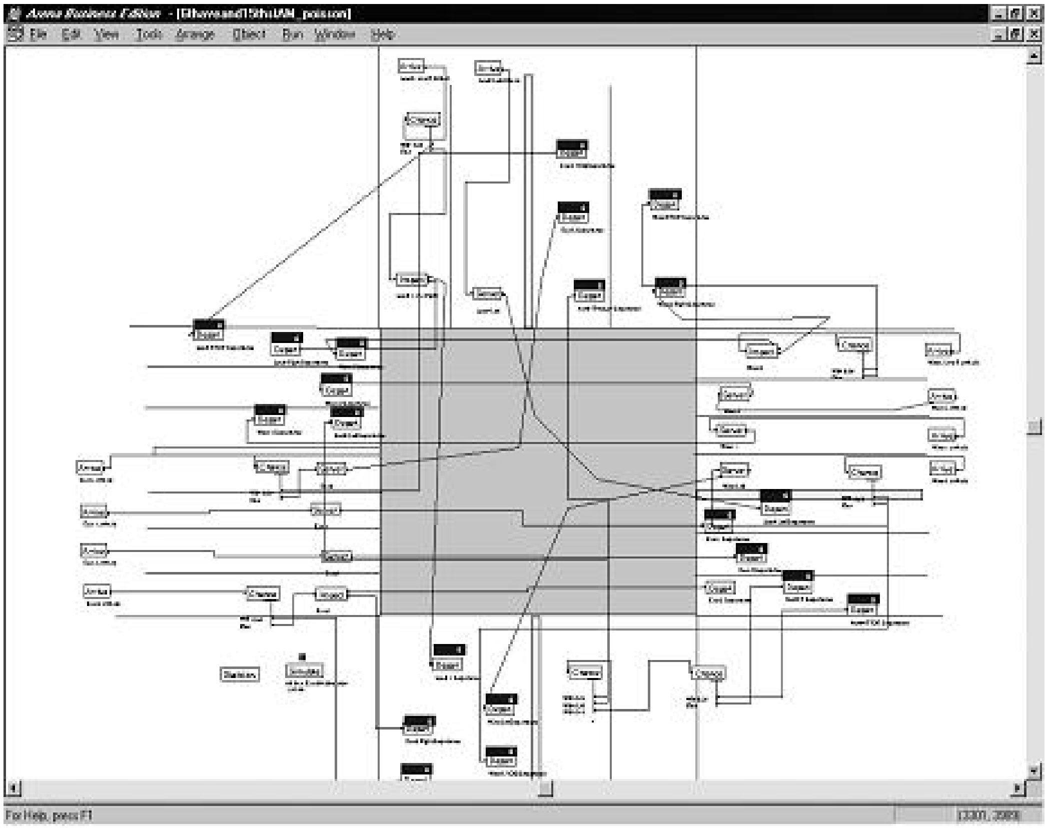

Figure 4-4. ARENA simulation model for a signalized intersection

Equation 4.1 gives the stopped delay value.

$$d = V_s \times t/V \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.1)$$

where d is the stopped delay, t is delay analysis interval, V_s is number of stopped vehicles in the given time, and V is total volume at the approach in the given time. The underlying assumption in this method is that a stopped vehicle during any interval stops for the entire interval length. Hence, the calculation involves t, which is the analysis interval. The methodology is based on stopped vehicle counts at intervals of 10 to 20 seconds. Fifteen seconds is taken as the average count interval (Guidebook for Transportation Corridor Studies). Delay was initially calculated for all lanes and lane groups, and then combined to give the approach delay (equation 4.2). The intersection delay was calculated based on the approach delay (equation 4.3).

$$d_A = \Sigma\,(d_i \times v_i)/\,\Sigma\,(v_i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.2)$$

$$d_I = \Sigma\,(d_A \times v_A)\,/\,\Sigma\,(v_A) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.3)$$

where d_A and d_I are approach delay and intersection delay, d_i is the lane group delay, v_i is the flow rate in the lane group, v_A is approach flow rate.

Results and Discussion

This task employed video data to develop a new traffic simulation model using ARENA, an industrial engineering software package. The model was developed for one intersection, 6th Avenue East and 15th Street in Tuscaloosa, Alabama, and results from the model were compared against field volumes obtained manually and delay values by the ITE method at that intersection and three other intersections: McFarland Boulevard, Hackberry Lane, and 10th Avenue. Apart from comparison of delay results, this task also performed a comparative study of level of service (LOS) results based on the delay values obtained by ITE, HCM 1994, and HCS 2000 methods.

ARENA Simulation Model Results

To begin the evaluation of the ARENA model, it was first necessary to determine the number of replications required to produce consistent results. Because the ARENA model is based on probability distributions, each run produces different results. It was found that twenty replications of two-hour runs were required. The corresponding half width of the ARENA results (average delay value) was found to be within two percent of the mean. Hence, the number of replications was enough for analysis of the model. Volume and delay obtained from the model were compared with field values. In some cases, field data was unavailable for certain approaches because of improper video recording, glare due to excess light, or poor lighting. In those cases the model was compared to those approaches for which there was available field data.

The ARENA volume results for 6th Avenue East and 15th Street, during the AM peak are compared to the field data in Table 4-1. Column one lists ARENA volume, field volume, and the deviation of ARENA from the field data. Four traffic movements are displayed: left-turn lane (left) and the through lanes (East 1, East 2, and East 3). Columns two through nine show volume data and deviation of the two methods for eight 15-minute intervals. These intervals are additive and show how the ARENA model performs for total run times between 15 and 120 minutes.

Table 4-1 shows that the ARENA model yields values within 14 to 20 percent (column nine) of actual field volumes when the total two-hour volumes are considered. Shorter time periods typically produce less accurate results. These discrepancies may be attributed to the fact that the actual vehicle arrivals in the field may not be Poisson distributed, which is an assumption of the model, but rather arrive in platoons or groups because of the signal progression.

The ARENA model was then used to simulate the three remaining signalized intersections with similar conditions for both AM and PM peak hours. Pagadala (2001) provides a detailed comparison of the ARENA model results and field values for the remaining intersections.

Table 4-1. 6th Avenue East and 15th Street AM peak East approach volume data

Volume (1)	15 min. (2)	30 min. (3)	45 min. (4)	60 min. (5)	75 min. (6)	90 min. (7)	105 min. (8)	120 min. (9)
Left ARENA	10	21	32	43	55	66	77	89
Field Volume	-	12	21	35	56	67	81	103
% Deviation	-	75	52	23	2	1	5	**14**
East 1 ARENA	63	138	210	284	360	432	504	580
Field Volume	-	42	113	214	293	349	407	482
% Deviation	-	228	86	33	23	24	24	**20**
East 2 ARENA	63	137	209	281	355	429	505	575
Field Volume	-	49	118	210	283	353	425	498
% Deviation	-	179	77	34	25	21	19	**15**
East 3 ARENA	29	64	97	131	163	197	235	269
Field Volume	-	25	63	119	175	224	271	327
% Deviation	-	156	54	10	7	12	13	**18**

Table 4-2 shows the summary of model and field results for 6th Avenue East and 15th Street for the AM peak. This table illustrates typical intersection results, while the remaining three intersections in this study can be seen in Pagadala (2001).

Table 4-2. 6th Avenue East and 15th Street AM peak volume and delay comparison

Approach Lane/Lane Group (1)	ARENA Volume (2)	Field Volume (3)	Percentage Deviation (4)	ARENA Delay (sec) (5)	Field Delay (sec) (6)	Percentage Deviation (7)
EAST						
Left	89	103	14	55.02	21.55	155
East 1	580	482	20	29.51	23.99	23
East 2	575	498	15	29.53	23.22	27
East 3	269	327	18	29.34	9.39	212
WEST						
Left	114	95	20	53.88	36.97	46
West 1	488	434	12	29.2	19.25	52
West 2	516	456	13	29.46	19.73	49
West 3	251	281	11	29.28	19.06	54
NORTH						
Left Through Right	135	146	8	53.56	32.05	67
SOUTH						
Left	148	136	9	41.88	27.46	53
South 1	176	164	7	41.4	11.55	258

Column one of Table 4-2 shows the approach direction (bold) along with the lane or lane group. Column two provides volume data generated by the ARENA model, and the corresponding field volumes are in Column three. Column four computes the amount of deviation of the ARENA volume from the field volume. Columns five and six give ARENA delay and field delay values respectively. The deviation of ARENA delay results from field delay values are computed in Column seven.

Over the two-hour period, the ARENA model generates traffic volumes with an observed deviation of 7 to 20 percent as seen in Column four of Table 4-2. ARENA was found to greatly over-predict intersection delay by 23 to 258 percent as shown in column seven of Table 4-2. This is shown graphically in Figure 4-5, which is a typical plot produced by plotting the 15-minute interval delay values from ARENA and the field values for the left-turn lane of the eastbound approach. This plot includes the delay values in seconds on the Y-axis and the eight 15-minute intervals in the two-hour peak period on the X-axis. Although the ARENA model generates a delay pattern that is similar to the field values, which is encouraging, the actual value produced by the two methods is quite different, up to 258 percent different. The dissimilarity between the field plots and ARENA plots may be due to the fact that the field values were not following a true Poisson distribution, which was assumed in the ARENA model.

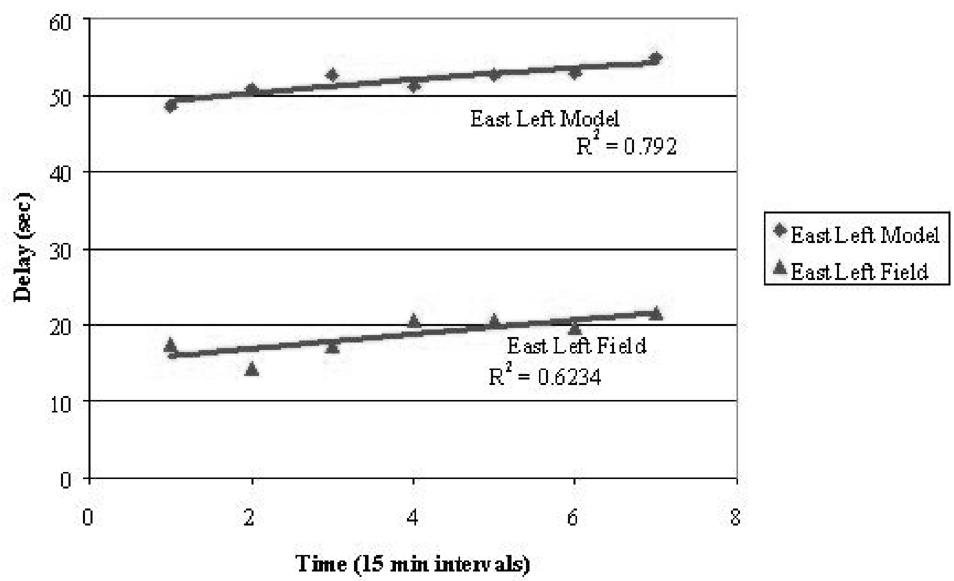

Figure 4-5. 6th Avenue East AM peak model validation: east approach – left lane

In addition, turn lanes or shared through-turn lanes performed worse (53 to 258 percent deviation) when compared to strictly through lanes (23 to 52 percent deviation). This indicates that the ARENA model requires more refinement with respect to turn movements.

Table 4-3 illustrates the LOS of the four intersections in this study in terms of average stopped delay. Column one lists the intersection, while column two indicates the AM and PM peak hours.

Table 4-3. LOS Table: A comparative study

Intersection (1)	Peak Hour (2)	ITE Field (sec) (3)	ITE LOS (4)	HCM 1994 (sec) (5)	LOS (6)	HCS 2000 (sec) (7)	LOS (8)	ARENA (sec) (9)	LOS (10)
15th Street and									
6th Avenue East	AM	19.99	C	28.17	D	41.60	E	33.08	D
	PM	18.72	C	28.18	D	43.20	E	33.00	D
McFarland Blvd.	AM	29.38	D	33.00	D	71.80	F	-	-
	PM	25.14	D	150.63	F	125.30	F	-	-
Hackberry Lane	AM	22.75	C	77.43	F	58.40	E	40.45	E
	PM	19.23	C	124.91	F	61.10	F	38.36	D
10th Avenue	AM	22.27	C	41.50	E	67.30	F	-	-
	PM	21.07	C	30.93	D	55.30	E	45.71	E

Column three provides ITE delay values in seconds, and column four provides the corresponding LOS based on the HCM 1994. Columns five and six show the HCM 1994 results, while columns seven and eight provides HCS 2000 results. Column 9 shows the ARENA model results, while column ten provides the LOS associated with ARENA delay values.

The ITE field delay values at all the four intersections correspond to LOS C and D, where C represents a good intersection performance and D represents a congested condition. It should be noted that ITE field values were obtained from the volume of stopped vehicles in a particular interval of time, while the HCM 1994 and HCS 2000 methods considered delays observed during stopping, starting up, and red time at an intersection. Hence, ITE field values always produce better LOS than these other methods.

The ARENA model produced LOS (column nine) results that were one and two levels lower than the ITE field values, and between the HCM 1994 and HCS 2000 results. This again indicates the need for additional model calibration and refinement. Once the calibration of the model is improved, Table 4-3 can be used to study the change in LOS of a signalized intersection by varying the phase plan. It is a future goal of this work that the LOS estimated by the ARENA model can be studied to evaluate potential improvements to signal timings.

Conclusions

This study used conventional video units and TDOT's traffic surveillance cameras to gather traffic data. The data was used to develop a simulation model for signalized intersections using ARENA software. The ARENA model was developed at one of four intersections and evaluated at all four intersections. An existing intersection performance evaluation method, the ITE field delay estimation method, was used to perform operational analysis on the four intersections. The results of this method were compared to the ARENA results. Although ARENA is an industrial engineering simulation software, it showed encouraging but inaccurate results when used to simulate signalized intersections. Further research is required to improve ARENA's calibration, specifically improving turn lanes and stopped delay calculations.

Conclusions and recommendations about video data collection for model development and analysis are presented here:

- Data collection using video proved to be useful in obtaining information about traffic flow parameters such as volume, turn movements, headway, and delay.
- Unlike manual field data collection, there is always a chance to double-check data that is collected using video technology, which is beneficial for model development.
- Conventional video cameras are efficient for collecting traffic data that are lane-specific, such as left-only turn lanes and through lanes.
- Surveillance cameras can be operated remotely and allow tilting and zooming of the view for traffic recording.
- Video data collection and reduction processes involve a considerable amount of time (the data collection for this study encompassed a two-month period) and resources (several persons were required to handle the video cameras in the field and to collect vehicle arrival time data for estimating arrival distributions).
- Errors can be introduced in video data collection from camera location, camera view, and parallax associated with simultaneous platooning in different lanes. To minimize these problems, cameras should be located at high vantage points that provide a clear view of the intersection.
- Data requirements for a project should be addressed and a comprehensive data collection scheme should be prepared for projects involving video. This enables effective data collection.
- ARENA modeling software has the tools required to model a signalized intersection.
- Although the ARENA model developed in this work was not calibrated to a degree that allowed it to be employed in a real life signal-timing study, the results show potential for future model development.

Section 5
Railroad-Grade Crossing Automated Video Enforcement Analysis

Introduction

There are 252,341 highway-rail grade crossings in America, of which 154,087 are public-at-grade crossings. These crossings can be dangerous when traffic laws are violated. Continual police enforcement at all railroad-grade crossings is infeasible and cost prohibitive. An alternative method of enforcement is automated enforcement. The use of automated enforcement commonly involves video-based technology to photograph the license tag and driver during a violation. Despite the fact that automated enforcement has expanded rapidly worldwide and in the United States, Alabama has yet to implement any such an enforcement program. The state does not have legislation in place that would allow for the operation of an automated enforcement program. However, as automated enforcement continues to grow, pressure will mount on the state government to investigate the implementation of automated enforcement technologies.

The objective of this task was to investigate the use of video-based technology to study traffic behavior and possible violation enforcement at railroad-grade crossing in the State of Alabama. Safety measures at railroad-grade crossings were investigated and recommendations were made for the use of automated enforcement and advance warning of train arrival systems.

Study Approach

The objective of this task was accomplished by:

1. Reviewing literature regarding accident trends and safety measures at railroad-grade crossings;
2. Selecting sites, based on accident history and safety concern, for data collection;
3. Video recording of selected sites; and
4. Analyzing video data to report the type of violations that may lead to an accident.

The scope of this task was to study warning time, frequency, and type of violations at railroad-grade crossings. Further research should be done to study the effect of crossing parameters such as sight distance, speed on approach lane, type of warning device, etc. all of which govern the safety at railroad-grade crossings.

Background

According to 2001 railroad fatality data, the State of Alabama ranks 10th nationally in the number of fatal railroad-grade crossing crashes. Alabama ranked 11th in 2000. Table 5-1 shows fatality rankings by state for years 2000 and 2001. This table lists the total number of fatalities, and is not normalized by population, number of grade crossings, or number of vehicle miles traveled.

Train-vehicle collisions are considered to be more dangerous than vehicle-vehicle collisions. "Compared to a collision between two highway vehicles, a collision with a train is 11 times more likely to result in a fatality, and 5.5 times more likely to result in a disabling injury" (EPA, 2000). Train operations cause delays to motorists at railroad-grade crossings. Collisions at grade crossings are a direct result of misjudgment, or traffic violations by motorists. Research has shown that installing advance train detection systems coupled with visible, high profile variable message signs (VMS), and implementing law enforcement programs are effective in reducing delays, crossing violations, and fatalities at railroad grade crossings.

Table 5-1. Highway-railroad grade crossing fatalities and rankings: 2000-2001

State	Number of fatalities 2000	Rank	State	Number of fatalities 2001	Rank
Texas	52	1	California	53	1
Illinois	31	2	Texas	39	2
Arkansas	27	3	Illinois	31	3
California	27	3	Louisiana	22	4
Indiana	23	4	Mississippi	22	4
Missouri	17	5	Ohio	22	4
Florida	15	6	Georgia	19	5
Mississippi	15	6	Indiana	19	5
Ohio	15	6	Iowa	16	6
Wisconsin	15	6	Florida	14	7
Louisiana	14	7	Michigan	11	8
North Carolina	14	7	Kentucky	10	9
Michigan	13	8	Tennessee	10	9
Oklahoma	12	9	Wisconsin	10	9
Idaho	11	10	**Alabama**	**9**	**10**
Kansas	11	10	Arkansas	9	10
Alabama	**10**	**11**	Minnesota	9	10
Georgia	10	11	Oklahoma	9	10
South Carolina	10	11	-	-	-

Safety at railroad-grade crossings can be improved by carefully monitoring crossings. Video technology can be used to record driver behavior at railroad-grade crossings, and to understand the effect of crossing parameters such as sight distance, speed limit on the approach lane, warning time, and type of warning device. Based on such studies, measures can be implemented to improve the safety at railroad-grade crossings.

Warning time is considered to be one of the most important parameters that govern safety at railroad-grade crossings. According to the Manual on Uniform Traffic Control Devices (MUTCD), there should be a minimum warning time of 20 seconds before a train approaches a crossing (MUTCD, 2001). Sensors, which activate warning devices, are placed on the tracks at a specific distance from the crossing. Therefore, a constant warning time at railroad-grade crossings is difficult because trains move at different speeds. The distance, and therefore the time, is set for the fastest expected train. When a slow moving train approaches warning times increase, which gives motorists a false concept of warning time. As a result motorists try to beat the train and may end up in collisions. Automated enforcement could be implemented to increase the safety by discouraging motorists from trying to beat the train.

Literature Review

The laws that define violations at railroad-grade crossing were examined. A comprehensive review was performed on accident history and safety measures at railroad-grade crossings.

Definition of Railroad-Grade Crossing Violation

"Alabama prohibits motorists from driving through, around, or under any crossing gate or barrier while the gate or barrier is closed or in the process of being opened or closed." (State Laws, 2001)

From the above law a motorist is said to commit a violation if he or she:

1. Drives under the gates as they are descending;
2. Drives through or around the gates when they are in horizontal position; or
3. Drives under the gates as they are ascending.

Any one of the above maneuvers can cause a train-vehicle collision. Driving under the gates when they are descending is dangerous especially with fast moving trains when warning times are reduced. Motorists' misjudgment of train speeds is the most common reason for train-vehicle collisions. This typically occurs when motorists drive through or around the gates before a train approaches. Other train-vehicle collisions occur when motorists cross tracks as the gates are ascending and do not notice a train coming in the opposite direction on a second track.

Railroad-Grade Crossing Accident History and Safety Measures

According to Federal Railroad Administration (FRA) statistics, someone is hit by a train every 115 minutes in America. Also, there are more than nine tractor truck-train collision per week, and there are many more near-hits than collisions. Table 5-2 shows that the total number of collisions and fatalities in the nation were reduced over the past two decades, although the number of fatalities per collision has increased from 0.078 in 1981 to 0.130 in 2001. Based on these statistics, it could be concluded that the accidents that have been reduced are not as severe as the accidents that are still occurring (OLS, 2001). There is no particular trend in the number of injuries per collision.

Table 5-2. National Highway-railroad grade crossing collisions and casualties: 1981-2001

Year	Collisions	Fatalities	Injuries	Number of fatalities per collision	Number of injuries per collision
2001	3,232	419	1,155	0.130	0.357
2000	3,502	425	1,219	0.121	0.348
1999	3,489	402	1,396	0.115	0.400
1998	3,508	431	1,303	0.123	0.371
1997	3,865	461	1,540	0.119	0.398
1996	4,257	488	1,610	0.115	0.378
1995	4,633	579	1,894	0.125	0.409
1994	4,979	615	1,961	0.124	0.394
1993	4,892	626	1,837	0.128	0.376
1992	4,910	579	1,969	0.118	0.401
1991	5,386	608	2,094	0.113	0.389
1990	5,713	698	2,407	0.122	0.421
1989	6,525	801	2,868	0.123	0.440
1988	6,615	689	2,589	0.104	0.391
1987	6,391	624	2,429	0.098	0.380
1986	6,396	616	2,458	0.096	0.384
1985	6,919	582	2,687	0.084	0.388
1984	7,281	649	2,910	0.089	0.400
1983	7,161	575	2,623	0.080	0.366
1982	7,748	607	2,637	0.078	0.340
1981	9,295	728	3,293	0.078	0.354

Table 5-3 illustrates the number of collisions and fatalities at railroad crossings in Alabama for years 1998-2001.

Table 5-3. Alabama highway-railroad grade crossing collisions and fatalities: 1998-2001

Year	Collisions	Fatalities	Number of fatalities per collision
2001	103	9	0.087
2000	95	10	0.105
1999	124	12	0.097
1998	145	11	0.076

As stated earlier, train-vehicle collisions are the direct result of violations of traffic laws by motorists at railroad crossings. Safety measures like highway traffic signals, raised medians, and four-quadrant gates were designed to prevent violations at railroad-grade crossings. Flashing red lights at railroad crossings may be replaced by highway traffic signals based on the assumption that drivers will comply with the traffic signals more often than flashing red lights. While raised medians and four-quadrant gates prevent drive-around violations, they do not prevent violations that occur while the gates are ascending or descending (Fitzpatrick, et al. 1997).

In Alabama, a traffic law violator can be ticketed only by a police officer. There are many safety concerns that limit police enforcement of traffic laws at railroad-grade crossings; sometimes a police officer would have to violate a traffic law (go around the gates) to apprehend a violator. The safety of a police officer is at risk if this is done. Also, police enforcement at 252,341 private and public railroad-grade crossings is not possible. Based on a study in Los Angeles, California it can be said, "the use of photo enforcement cameras for the enforcement of traffic laws at railroad-grade crossings is significantly less costly than the use of police officers." (LACMTA, 1997) Therefore, advanced safety improvement programs like real time surveillance, and automated enforcement could be enhanced by the aid of video technology in enforcing traffic laws to reduce violations and severe collisions at railroad-grade crossings in Alabama.

Video Data Collection

An effort was made in this research project to determine the rate of violations at three railroad-grade crossings in Alabama. The following sections describe the video data collection procedure and data analysis of recorded video. Data were collected at three railroad-grade crossings, two in Tuscaloosa, Alabama and one in Birmingham, Alabama. A team of two graduate students was involved in collecting data over a period of eight months from September 2001 to April 2002. Video technology was used to record traffic movements at railroad-grade crossings for 24 hours a day. TDOT and the Birmingham Traffic Management Center provided assistance in the data collection.

Site Selection and Description

Based on traffic volumes and guidance from TDOT officials, two railroad grade crossings in Tuscaloosa were selected. As shown in Figure 5-1, the Kansas City Southern Railway Company (KCS) and Norfolk Southern Railway Company (NS) line has two tracks, which run in an east-west direction. These tracks run parallel to 15th Street and University Boulevard, between U.S Route 82 and 10th Avenue, before intersecting 15th Street at an angle. 15th Street is considered to be one of the busiest streets in Tuscaloosa, Alabama. The two selected crossings are located at the intersection of the railway tracks with 10th Avenue (Site 1) and Hackberry lane (Site 2). Both sites are equipped with flashing lights and dropping gates. The reason for selecting these crossings is their close proximity to University Boulevard and The University of Alabama Campus, and because they fall within TDOT's traffic surveillance camera locations. Two traffic surveillance cameras (Figure 5-1) located at the target intersections were used to collect video data at these crossings.

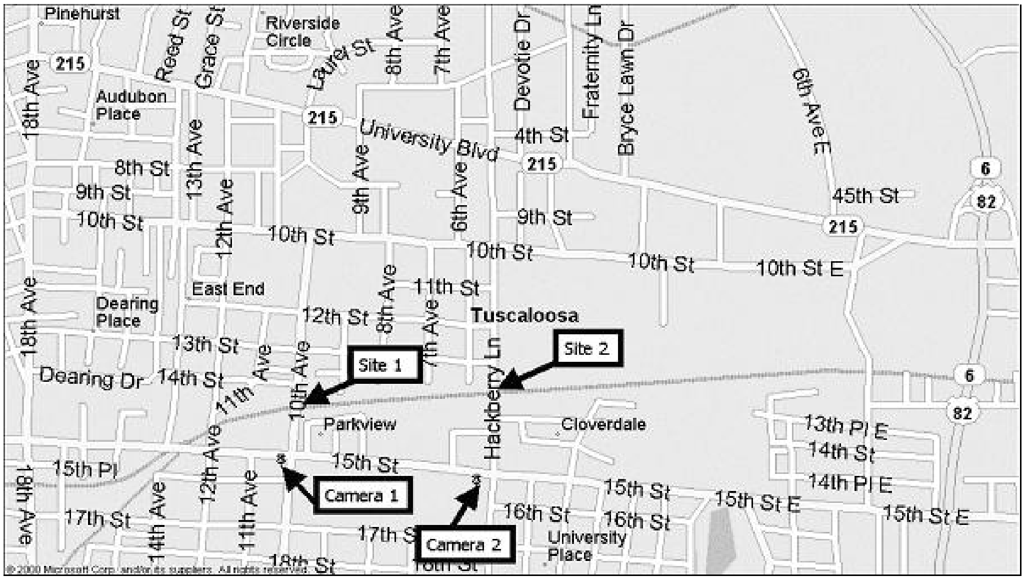

Figure 5-1. Tuscaloosa sites and camera locations

After contacting the Assistant Traffic Engineer for the City of Birmingham, the crossing on 40th Street Southwest (Site 3) was selected based on the high volume of gasoline tanker trucks that use the crossing daily. Figure 5-2 shows the location of Site 3, which is equipped with flashing lights and dropping gates. Two tracks owned by Norfolk Southern Railway Company run in a northeast to southwest direction at this crossing. Officials from the City of Birmingham installed a University of Alabama Autoscope camera (camera 3, Figure 5-2) on a power pole located at the intersection of Gray Avenue and 40th Street Southwest.

Figure 5-2. Birmingham site and camera location

Data Collection

TDOT's traffic monitoring video cameras were used to collect video data at sites 1 and 2. The first camera is located at the intersection of 15th Street and 10th Avenue and recorded traffic movements at Site 1. Traffic movements at Site 2 were recorded with camera two located at the intersection of 15th Street and Hackberry lane. Data were collected for five days in October 2001 and for five days in April 2002. Videotapes were changed every 24 hours by TDOT.

Data were collected for 17 days in March 2002 at Site 3 with the assistance of the City of Birmingham. Officials from the City installed the camera and also a control box on a power pole. The control box stored the Autoscope equipment, computer, and three video cassette recorders (VCR) that were pre-timed to record data for 24 consecutive hours. A team of two graduate students changed the tapes daily.

Analysis and Results

Analysis of video data from the three sites was performed to study the effect of train arrival time on the number of violations. The following section provides a brief discussion on data reduction, processing, and analysis of train arrival timings and violations.

Data Reduction

Data in this study mainly focused on train arrival times, and the types of traffic violations at railroad-grade crossings. An undergraduate student viewed the videocassettes and recorded the following timings manually:

1. Flashing light activation time;
2. Violation time;
3. 3-point and U-turn time (a 3-point turn is a turn made in three stages to travel in the opposite direction from the crossing. A U-turn is similar to a 3-point turn, but is made in one continuous loop);
4. Train arrival time;
5. Train departure time; and
6. Time when the gates were in a vertical position.

Violations were grouped into two categories after the initial data analysis process. The first category, termed "before train" (BT) violations, occurred in the time interval between the activation of flashing signals and the train entering the crossing. The second category, termed "after train" (AT) violations, occurred after the train left the crossing and before the gates were completely raised. A combination of BT and AT violations is referred to as "sneak through" violations. Any 3-point or U-turn is referred to as TPUT.

Although data were collected for 10 days at Site 1, only nine days of data were available for analysis as the TDOT's traffic management center lost signals from the traffic monitoring cameras for a day due to technical problems. Similarly, for Site 2 only eight days of data were available. Seventeen days of complete data were available for Site 3. Thus, 34 days of data (24 hours a day) were available for data analysis.

Violation Data and Observations

Table 5-4 shows a summary of recorded BT violations, AT violations, and TPUTs. A total of 168 sneak through violations and 238 TPUTs were observed in 34 days. The average rate of sneak through violations was 4.94 per day, while the average rate of TPUTs was 7.00 per day. A closer look into the violation rate at each site indicated that the railroad grade crossing at 40th Street Southwest in Birmingham had the highest rate, 7.65 sneak through violations per day. On the other hand, the crossing at 10th Avenue in Tuscaloosa had the highest TPUT rate, 19.44 per day.

Table 5-4. Summary of violations and TPUTs for sites 1-3

Site	BT	AT	Total sneak through violations (BT+AT)	TPUTs	Data collection period (Days)	Number of sneak through violations per day	Number of TPUTs per day
1	23	7	30	175	9	3.33	19.44
2	8	0	8	44	8	1.00	5.50
3	128	2	130	19	17	7.65	1.12
Total	159	9	168	238	34	4.94	7.00

A summary of train arrivals and gate activations for these three sites is illustrated in Table 5-5. A total of 788 trains and 809 gate activations were observed. The difference in the number of trains and gate activations is attributed to the fact that there were 33 gate activations without a train approaching the crossing. Also, there were two instances when a utility truck approached the crossing without the gates being activated.

In addition to the values and information discussed above, there were a few special observations made at these sites:

1. 10th Avenue, Tuscaloosa, Alabama:
    a. Five violations were observed when the gates were activated without a train approaching the crossing;
    b. Six violations were observed when a utility truck took 155 seconds to reach the crossing after the gates had been activated;
    c. One violation was observed when a freight train took 141 seconds to reach the crossing after the gates have been activated;
    d. One train approached the crossing just two seconds after a motorist snuck through the crossing (a near hit); and
    e. Once a train approached the crossing within five seconds after the flashing lights were activated; the gates just started moving down when the train reached the crossing. There was no traffic on the approach lane because it was very early (1:10 AM) in the morning.

2. 40th Street Southwest, Birmingham, Alabama:
    a. Due to technical problems a train stopped on the tracks and blocked the crossing for 21,442 sec (nearly 6 hours). 23 TPUTs were observed during this time, but are not reported in Table 5-5 because the crossing was blocked due to technical problems and not due to train operations.

Table 5-5. Summary of number of trains and gate activations

	Site 1	Site 2	Site 3	Total
Freight Trains	180	130	403	713
Passenger Trains	16	13	28	57
Utility Trucks	9	8	1	18
Total Trains	205	151	432	788
Gate Activations	222	158	429	809
Utility Trucks without Gate Activation	1	1	-	2
Gate Activations without a Train	20	10	3	33
Two Tracks Occupied	2	1	6	9

Violations and TPUTs vs. Train Timings

Figure 5-3 shows a histogram of train approach timings and the number of before-train sneak-through-violations. Approach time is defined as the time taken by a train to reach the crossing after the flashing lights have been activated. The maximum number of violations (69) occurred when the train reached the crossing 41-50 seconds after the flashing lights were activated.

There were not many after-train sneak-through-violations. Figure 5-4 shows a plot of the number of ATs versus train departure times. Departure time is defined as the time required for the gates to return to the vertical position after the train left the crossing. Four violations were observed when the departure time for a utility truck was 91 to 100 sec. Excluding these four violations, only five AT violations were observed in 34 days.

Figure 5-5 illustrates the number of TPUTs for every 30-second time interval when the crossing was blocked. No particular trend was observed for TPUTs. However, the maximum number of TPUTs was observed when the train blocked the crossing for 151-180 seconds.

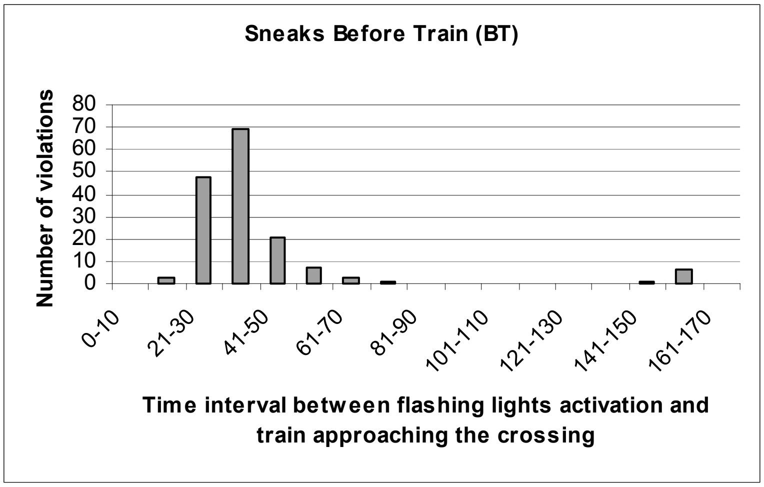

Figure 5-3. Sneak through violations before train

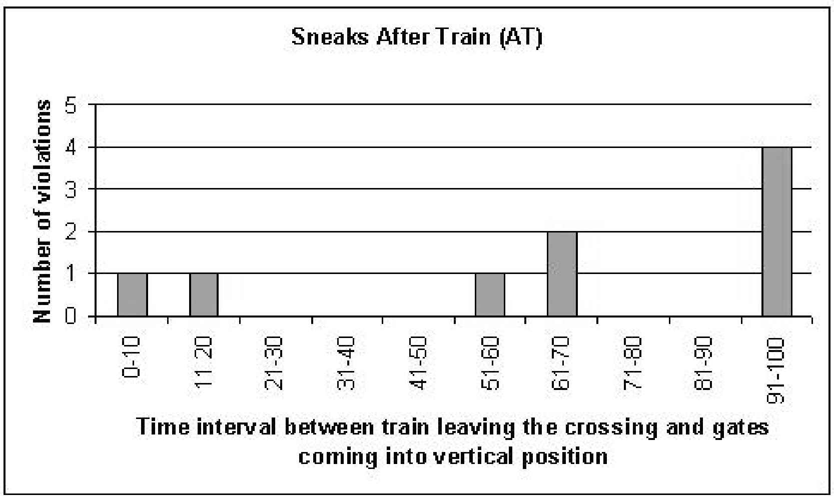

Figure 5-4. Sneak through violations after train

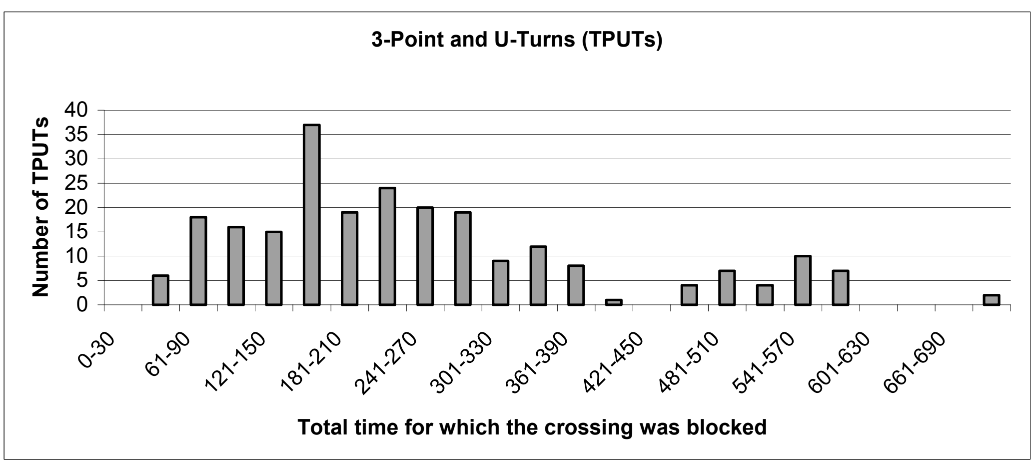

Figure 5-5. 3-point and U-turns

A comparison of day and night violations for sneak through and TPUTs can be seen in Figure 5-6. There were more sneak through violations and TPUTs during the day. This is because there are more traffic movements at railroad-grade crossings during the day.

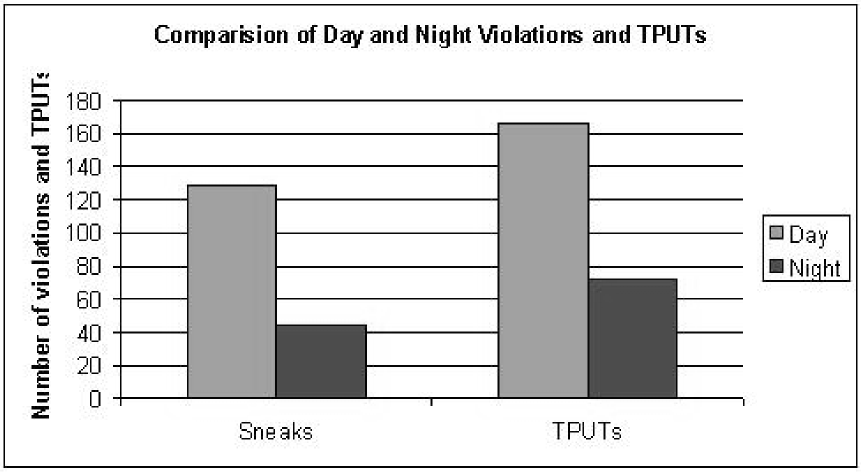

Figure 5-6. Comparison of day and night violations and TPUTs

Discussion

From the above observations it can be seen that there is a need for traffic law enforcement and safety improvement programs at rail-grade crossings in Alabama. Long delays or faulty gate activations without a train approaching the crossing may entice motorists to violate traffic laws, jeopardizing their safety. The scope of this report was limited to studying the effect of train arrival times and total blockage times on the number of violations and TPUTs. Other geometric factors such as sight distance, speed limits on approach lanes, and distance between two tracks that affects the number of traffic violations were not investigated. More research is recommended to study the effects of these factors on motorists, and to address safety improvements at rail-grade crossings.

Conclusions

Video data collection was helpful in obtaining information regarding train arrival times and the number of violations at railroad-grade crossings. The greatest advantage of video data collection is the ability to double check arrival times to eliminate errors in data reduction. However, care should be exercised in installing and operating video equipment; the recorded video was not always clear due to technical problems. The equipment should be checked frequently to eliminate these types of errors because important information might be lost.

A violation rate of 7.65 sneak through violations a day at Site 3 in Birmingham emphasizes the need for automated enforcement of traffic laws in Alabama. A rate of 19.44 TPUTs per day at Site 1 in Tuscaloosa illustrated the need to deploy advance warning of train arrival systems at similar railroad-grade crossings in Alabama.

Recommendations for Future Study

This task was limited to investigate the effect of train arrival times on the number of violations and TPUTs. Other crossing parameters like sight distance, speed limits on approach lanes, number of approach lanes, and type of control device could be studied to predict rate of violations at railroad-grade crossings.

During data collection, care should be exercised in installing the video equipment so that a clear image of the gate activations is visible; video equipment at TDOT had to be adjusted several times to get an optimal view of railroad-grade crossings without compromising the view of the queue length (queue length of vehicles stopped at railroad-grade crossings is helpful in checking TPUTs).

An automated enforcement pilot project should be implemented to gauge the effect of automated enforcement on violators of traffic laws at railroad-grade crossings in Alabama. Similar kind of pilot study at several other critical sites throughout the state is highly recommended to help propose a new legislation on automated enforcement in Alabama.

Section 6
Variable Message Signs for Violation Notification

Introduction

Aggressive driving is one of the most prevalent factors contributing to traffic crashes in the United States. The National Highway Traffic Safety Administration (NHTSA) estimated that about one-third of all crashes and two-thirds of resulting fatalities in the U.S. can be linked to aggressive driving behavior. Speeding and red light running are considered to be the most common characteristics of aggressive driving (NHTSA, 2002). It has been shown that VMS can be employed as a speed deterrent. Mobile VMS, coupled with speed detection devices, can be installed at places where speeding has been a problem. This provides drivers with real-time messages indicating their speeds as well as the posted speed limit. A similar application was examined in this research to improve driver compliance at intersections by providing real-time messages for red-light-runners indicating that they ran a red light.

The objective of this study was to develop a methodology for using traffic-monitoring cameras already installed at highway intersections to detect motorists who had run a red light.

The following tasks were performed in this regard:

1. Twenty seven traffic-monitoring cameras owned by TDOT were checked to determine which had favorable angles and elevations to detect violations;
2. Autoscope software and hardware were combined with conventional traffic surveillance cameras (instead of regular Autoscope cameras) to detect vehicles; and
3. Autoscope hardware was examined to determine if it could trigger a VMS.

Methodology

The Autoscope Solo Wide Area Video Detection System developed by the University of Minnesota and Image Sensing Systems, Inc., uses machine vision technology to collect traffic data. This system can be used to gather vehicle speed, length, traffic volumes, delays, and queue lengths at intersections. Figure 6-1 shows the setup for the Autoscope system. It consists of a machine vision processor (MVP) camera, hub-interface panel, hub, and supervisor computer. MVP is a video processor that accurately detects vehicles by combining a video camera with electronic lens control, a digital image processor, and a communications port. The hub-interface panel serves as a mediator and provides the connection between the MVP and the hub. The hub communicates with the MVP to provide detection information, detection outputs, and video signals which are sent to external devices. The hub is also connected to the supervisor computer.

The Autoscope software on the supervisor computer is used to configure the MVP and the hub, and to set different types of virtual detectors used to monitor traffic (Autoscope User Guide).

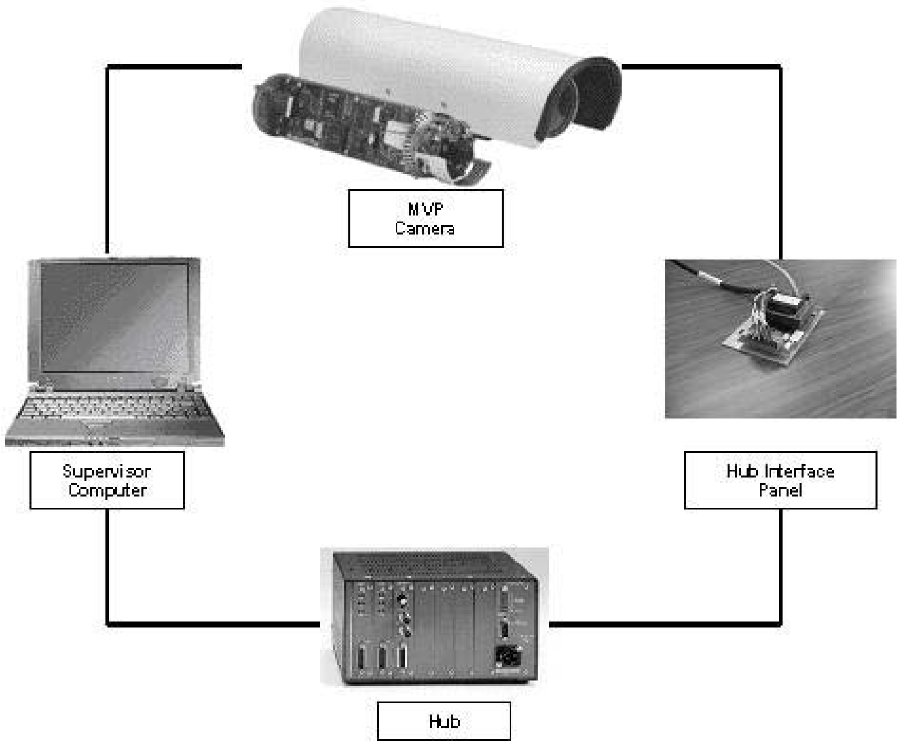

Figure 6-1. Autoscope system setup

The MVP can be installed in the camera or in the Hub. Autoscope systems with the MVP installed in the hub can be connected to common traffic-monitoring cameras to detect vehicles. These cameras are typical video cameras, which are unlike the Autoscope cameras that have the MVP built into the cameras.

TDOT maintains 27 traffic-monitoring cameras for traffic surveillance. They are operated from the traffic management center at TDOT. The TMC has a complete Autoscope system. The MVP and hub-interface panel are at the TMC, thereby allowing any of the 27 traffic-monitoring cameras to act as an Autoscope camera.

After evaluating the field of view provided by all the traffic-monitoring cameras in Tuscaloosa, a camera (camera one) installed at the intersection of Lurleen Wallace North (LWN) and Stillman Boulevard was selected for this study. Figure 6-2 shows the camera location at this intersection. With the help of a technician at TDOT, video output from this camera was fed into the Autoscope hub at the TMC. The image provided by the camera was calibrated using Autoscope software. Figure 6-3 shows the speed detectors and calibration of video image setup for this camera. Speed detectors were placed in each of the three lanes. When the system was run with this setup (Figure 6-4), the software detected vehicle speeds from the video image. Later the setup was checked with a count detector and a presence detector. The software detected vehicles for each of the detector types. It should be restated that this image was produced by a traffic-surveillance camera and not by a relatively expensive Autoscope camera. It can be concluded from this study that typical traffic-monitoring cameras can be used, instead of a regular Autoscope camera, as long as the image is sent to MVP and then run through the Autoscope software.

Figure 6-2. Camera location at Lurleen Wallace North (LWN) and Stillman Blvd

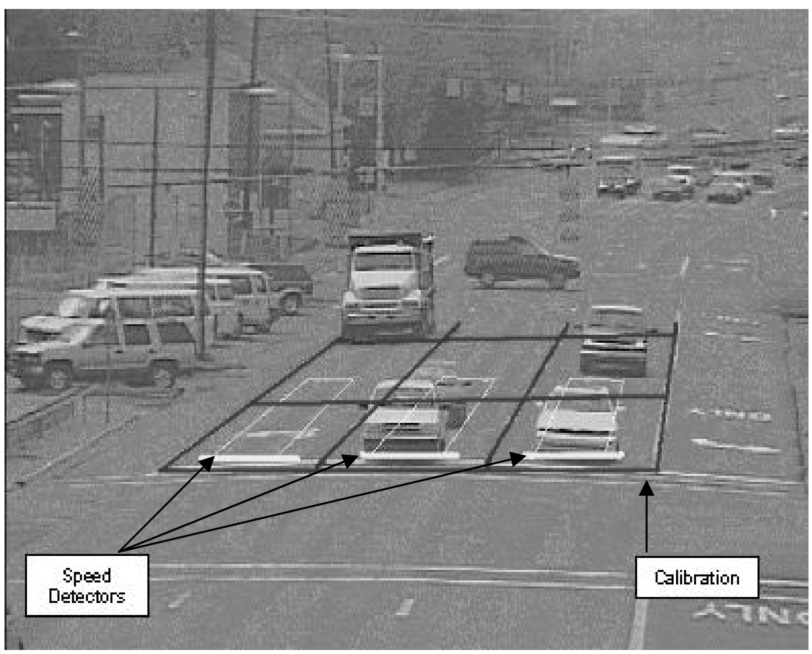

Figure 6-3. Speed detectors and calibration of video image obtained from camera one

This setup can be extended to detect red-light violators, by providing signal phase timings from the signal controller to the Autoscope software. For the purpose of detecting red-light violators, the signal phases (red, green, yellow) were split into two divisions; the red phase (red signal time) and the not-red phase (green + yellow phase time). When these two phases (red and not red) were detected, a signal was sent to the Autoscope software using the input/output port on the hub.

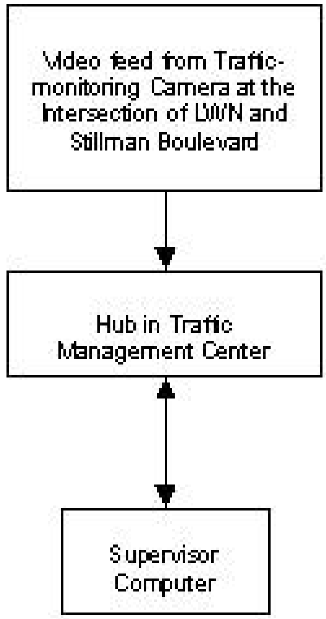

Figure 6-4. Autoscope setup to detect vehicle speeds

Figure 6-5 shows the setup for detecting red light violators. Autoscope only monitors vehicles that pass the detection zone during the red phases. Since the hub at the TMC and the traffic controller at the intersection were far apart, a time lag was observed while detecting red and not red phases. Because of this, the Autoscope red light violation count might not be accurate.

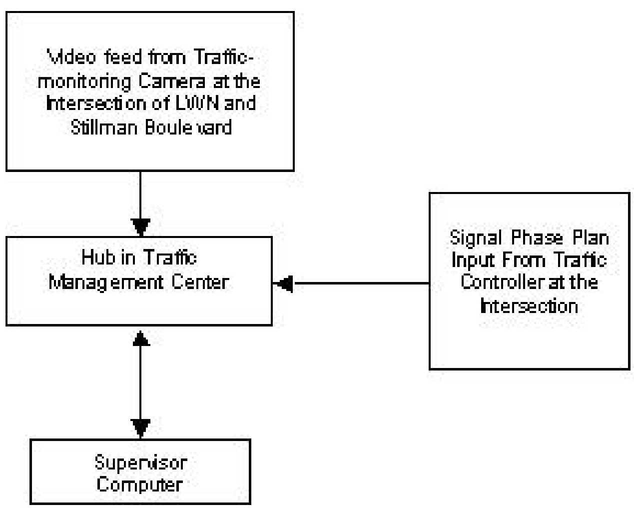

Figure 6-5. Autoscope setup to detect red-light violations at LWN and Stillman Blvd

An alternative method for accurately detecting red light violators at intersections with a pre-timed signal plan is to set up a "dummy traffic controller" at the TMC. The dummy traffic controller has the same signal-timing plan as the traffic controller in the field. Except for the traffic-monitoring camera, the entire Autoscope and controller setup can be installed in the TMC. Figure 6-6 shows the Autoscope setup to detect red light violators at a location with a pre-timed signal plan. The output of this setup will be a count of red light violations at an intersection and a voltage (Figure 6-7) that can trigger a VMS indicating a violation. Video output from traffic-monitoring cameras can be recorded to check the accuracy of the system.

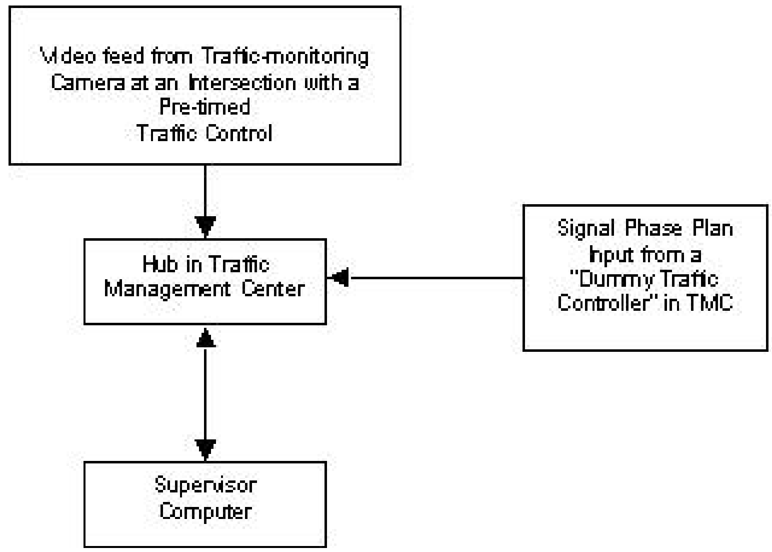

Figure 6-6. Autoscope Setup to detect red light violations with pre-timed traffic control plan

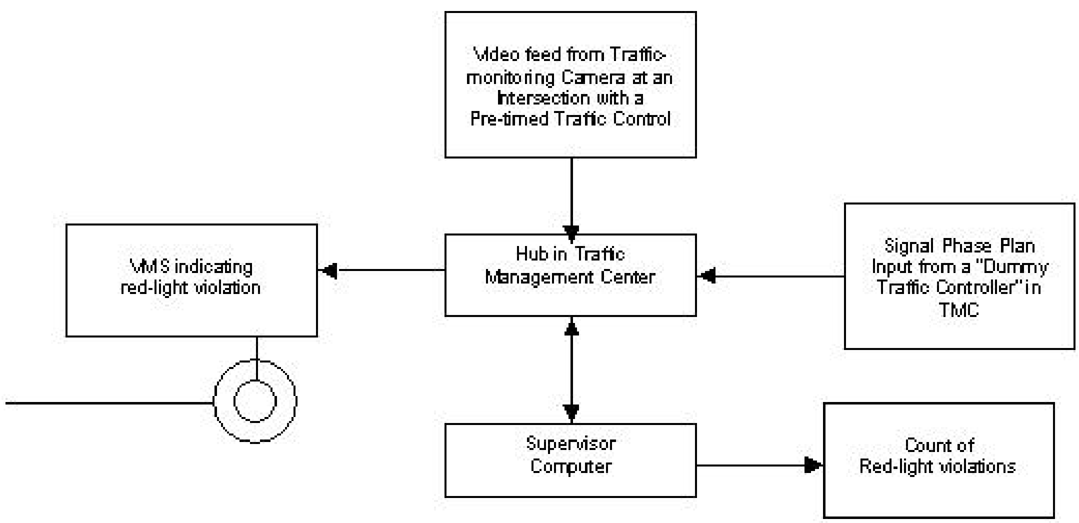

Figure 6-7. Autoscope output used to trigger VMS

Although, the setup was theoretically viable for detection of red light violations, it was not practically tested due to technical issues associated with connections in the TMC besides the time frame and scope of this research project.

Conclusions

A methodology to detect red-light running vehicles with traffic-monitoring cameras was proposed. A quality video image is critical to accurately detect red-light violations. To improve the video image, the camera location should be high (30 feet or more) with a clear view of the intersection. The traffic-monitoring cameras installed by a traffic management center can be used effectively to detect red-light violators, in addition to general surveillance.

The proposed setup to detect red light violators can be tested and verified with video recording of the intersection to determine the accuracy of using traffic-monitoring cameras with Autoscope software, which has the capability of activating a VMS. Triggering a VMS upon detection of a red-light running vehicle appears to be feasible.

Section 7
Mobile Video Units for Intersection Analysis

Introduction

Mobile video units can be used for temporary monitoring of traffic flow for traffic research purposes. Mobile video units can determine traffic flow parameters to suggest specific permanent video applications for traffic management and safety. This section of the report discusses the application and testing of such mobile video units.

The objective of this task was to evaluate mobile video units for temporarily monitoring traffic flow for research purposes. This was accomplished by determining the feasibility of using portable digital video cameras for roadside traffic data collection. Two mobile video units were tested in this regard, a conventional video camera recorder, and a digital video camera recorder.

Background

Video installations can be permanent (pole or building mounted), or mobile (vehicle or tripod-mounted). Each type of installation has its own advantages and disadvantages. The scope of this section of report was limited to only mobile video units that can be used for traffic research purposes. Traffic data collected from these mobile video units can be used to select the best locations to install permanent enforcement cameras. Mobile video units can be used to positively demonstrate the existence of traffic violators at intersections and at rail-grade crossings, proving the need for permanent installation of automated enforcement technologies (McFadden and Graettinger, 2000).

Conventional Video Camera Recorder

Portable conventional video recorders were used to collect traffic data at four intersections on 15th Street in Tuscaloosa, Alabama. A group of six students collected morning peak data from 7:00 to 9:00 AM and evening peak data from 4:00 to 6:00 PM Monday through Friday. The data collection process was spread over a two-month period. Video cameras (Figure 7-1) were set up on a 60-inch tripod by the side of the road to record traffic movements at these intersections. The recorded videotapes were analyzed to obtain volumes, headways, arrival distributions, and queue lengths. For each approach, this data was used to compute the field value of delay at these intersections. Refer to Section 4 of this report for a detailed description of data collection and analysis.

Figure 7-1. Conventional video recording camera

Digital Video Camera Recorder (Camcorder)

Camcorders were used to record traffic movements at three railroad-grade crossings in Tuscaloosa, Alabama. Figure 7-2 shows the setup of a camcorder at a rail-grade crossing. A group of three graduate students collected morning peak data from 7:00 to 9:00 AM, afternoon peak data from 11:00 AM to 1:00 PM, and evening peak data from 4:00 to 6:00 PM, for three consecutive days. Camcorders were set on 60-inch tripods, approximately 10 feet from the edge of the road and 200-300 feet from the crossing, to record traffic movements.

All three railroad-grade crossings were equipped with flashing lights and gates. A total of 18 hours of video data were analyzed to collect violation data with respect to gate, light, and train timings. A student viewed the recorded videocassettes and recorded the following timings manually:

1. flashing lights activation time;
2. violation time;
3. 3-point and U-turn time;
4. train arrival time;
5. train departure time; and
6. time when the gates were in the vertical position.

For each train crossing the videocassettes were viewed several times to record the exact time of violations and train arrivals. Based on this preliminary data, extensive data collection was carried out at two of the three railroad-grade crossings using surveillance cameras installed and operated by the City of Tuscaloosa. Refer to Section 5.0 of this report for a detailed description of data collection and analysis.

Figure 7-2. Digital video camera recorder

Comparison of Conventional and Digital Video Camera Recorders

Both conventional video camera recorders and camcorders were used to collect traffic data for this task. Though camcorders are more expensive than conventional video cameras, they have more capabilities. Unlike conventional video recorders, camcorders are lightweight and smaller, which makes them easy to transport and install. Camcorders record high-resolution digital video, which can be transferred to videotape or a computer. Selected still images and movie files of a violation can be taken from the digital video, which is not possible with the analog recording from a conventional video recorder. Battery life, which is critical for field data collection, is much higher for camcorders compared to conventional video cameras. A camcorder can run for more than 8 hours on a single battery charge. Unlike conventional video recording, video recording from camcorders can be enlarged or zoomed at a later time to get a clear view of the image. For example, this feature is helpful in reading license plates for origin-destination surveys. Camcorders can be assigned an internet protocol address to view real time data from a remote location like the TMC. This feature can be used at locations that have temporary traffic management issues that do not justify permanent camera installations.

I^3 Cam Van

The *I*ntelligent Transportation Systems *I*nformation and *I*nfrastructure Laboratory (I^3 Lab) of the University of Nebraska, Omaha provides real-time traffic data from a fully self-contained mobile machine vision and ITS laboratory, named I^3 Cam Van. As shown in Figure 7-3, I^3 Cam Van consists of two Autoscope Solo Pro cameras mounted 42 feet high on a telescoping mast. The mobile lab is equipped with a computer and a video recording system to store traffic data (I^3 Lab Website). Unlike conventional and digital camera recorders, the I^3 Cam Van is capable of processing a wide range of traffic parameters, and allows multi-tasking on multi-lane roads with ease and safety in various weather conditions.

Figure 7-3. I^3 Cam Van

Conclusions

Mobile video cameras can accurately collect traffic data. However, care should be exercised when collecting data on multi-lane roads. The camera should be located high enough to capture a clear image of vehicles traveling on each lane at all times. Lightning conditions can affect recording quality, and weather conditions should be checked before planning field data collection using video. During data cleaning of recorded video, videocassettes were viewed several times to collect the exact times when events occurred, which obviously cannot be done for manually collected data. Video data collection gives a permanent record of traffic situations, ensuring that accurate and vital information is not lost. For research purposes, a permanent record always provides an opportunity to check videotapes at any time for additional traffic data.

The implementation of mobile video systems and the newly developed cam van technologies depend on factors such as amount of data required, location characteristics, number of intersections or road segments under study, weather conditions, and funds allocated for the task. Mobile video systems can be potentially employed in Alabama for temporary and permanent traffic management and safety purposes.

Section 8
Video for Emergency Response Management

Introduction

Effective detection, response, clearance, and recovery from disabled vehicles or vehicle crashes can save lives, reduce delays, save money, and enhance safety for motorists. Identifying and locating traffic incidents and responding to these emergencies involves many agencies. Coordination between these agencies is very important so that they can verify, locate, and respond appropriately to each emergency. The responsibility of these agencies becomes even more significant during severe transportation conditions like an emergency evacuation when resource allocation is critical. Hence, there is a need for an integrated system that coordinates information about an incident among response teams. Research has demonstrated that incident detection and observation with video technology, coupled with response team communication, offers real-time visual information that enhances response, thereby potentially saving lives and money.

The goal of this task was to cast light on the use of video for emergency response (ER) in Alabama, and to determine if video (surveillance) cameras currently in place and owned by the City of Tuscaloosa could be employed for ER management. This section of the report describes case studies where video applications have been successfully employed for ER.

Background

Disruption of traffic flow can be caused by any number of uncontrollable variables. Congestion, obstructions, power-outages, crashes, etc., are all incidents that have the potential to disrupt traffic. Regardless of the reasons for these incidents, it is the job of emergency response teams to attend to the situation. To successfully respond, interagency coordination is crucial between transportation management and public safety agencies. These agencies use different systems for detecting incidents and collecting information to serve their needs and purposes. An integrated system could improve the response time and resource allocation. The ability of video detection systems to provide accurate, real-time information about an incident will allow transportation officials to almost instantaneously initiate a response plan and make crucial decisions.

Video for Emergency Response Management – National Case Studies

The following sub-sections briefly describe some of the successful national experiences related to the use of video for improving emergency response and incident management.

Multi-Jurisdictional Live-Aerial Video Surveillance System (1991)

The Virginia Department of Transportation (VDOT) used information obtained from live aerial video cameras for incident and congestion management. The live video was provided by a helicopter operated by the Virginia Police Department (VPD) of Fairfax County. A project was conducted to evaluate:

- the use of video imaging for incident and traffic management,
- the capture and transmission of the video images,
- the effectiveness and limitations of traffic surveillance from a helicopter, and
- a video application for multiple agency benefits.

Real-time images from video cameras were provided to VDOT, VPD, emergency services, and a mobile law enforcement van through links to the Fairfax County Public Safety Communication Center (TESCNET, 2001). This concept provided video surveillance over a large geographic area at a low initial cost. The video was used to gather traffic condition information over a planned route, to identify and resolve congestion problems, for traffic studies, and in areas that did not have full time surveillance.

Houston TranStar (1993)

TranStar is a unique multi-agency program developed to provide a coordinated approach toward transportation and emergency operations in the Greater Houston area. Components managed by TranStar include 257 closed circuit television (CCTV) freeway cameras, 100 variable message signs, emergency management operations, and a flood alert system. The video cameras provide continuous images of over 160 miles of freeway, out of a total of 300 miles. This video is sent to all the participating agencies helping them to improve on various transportation practices and emergency management response and recovery functions (TESCNET, 2001). This way of obtaining real-time information created an environment that improved: responsiveness, personnel and equipment resources management, pooling of finances, and eliminated administrative restraints (Houston TranStar, 1999).

NAVIGATOR, Atlanta, Georgia (1993)

One source of data to Georgia's Intelligent Transportation System is NAVIGATOR, which gathers traffic incident information by using a video and traffic detection system. This system provides real-time video images of road conditions that are sent to TMC operators. This video data serves as an incident verification tool, which reduces response time and expedite the removal of incidents thereby minimizes congestion (ITSNEWS, Feb 2001). Interstates 75 and 85 are equipped with over 300 black and white cameras and 67 pan, tilt, and zoom full color cameras, which continuously gather data on incidents, average speed, traffic volume, and vehicle classification. In addition, a camera mounted on a helicopter provides live video within a 50-mile radius of Atlanta.

With the combination of video monitoring, detection, data management, and telecommunications technologies, NAVIGATOR is able to detect, verify, and quickly respond to highway accidents, stalls, or debris (TESCNET, 2001). The agencies that benefit from this system are the Georgia DOT, Highway Emergency Response Operator, fire, police, EMS, and Motor Vehicle Emergency Response.

TransGuide, San Antonio, Texas (1993)

TransGuide is one of the nation's best Intelligent Transportation Systems. It was designed by the Texas Department of Transportation's San Antonio's district. This system was designed to provide real-time information to motorists about traffic condition such as accidents, congestion, and construction. It uses cameras, changeable message signs (CMS), and a fiber optic network to gather traffic information, provide travel times to motorists, and respond rapidly to emergencies on the freeways (TESCNET, 2001). The system has been operational since 1995 and currently utilizes 118 video cameras to monitor 72 of the 289 miles of San Antonio's highways. Maps showing the location of incidents, traffic congestion, and lane closure information are provided on the Internet every five minutes. In addition to location information, the cameras provide live video images to the Internet. The operation cycle of TransGuide is shown in Figure 8-1, wherein an incident occurs on the left side of the figure and within two minutes the TMC detects, verifies, begins response, and posts information for motorists on a VMS.

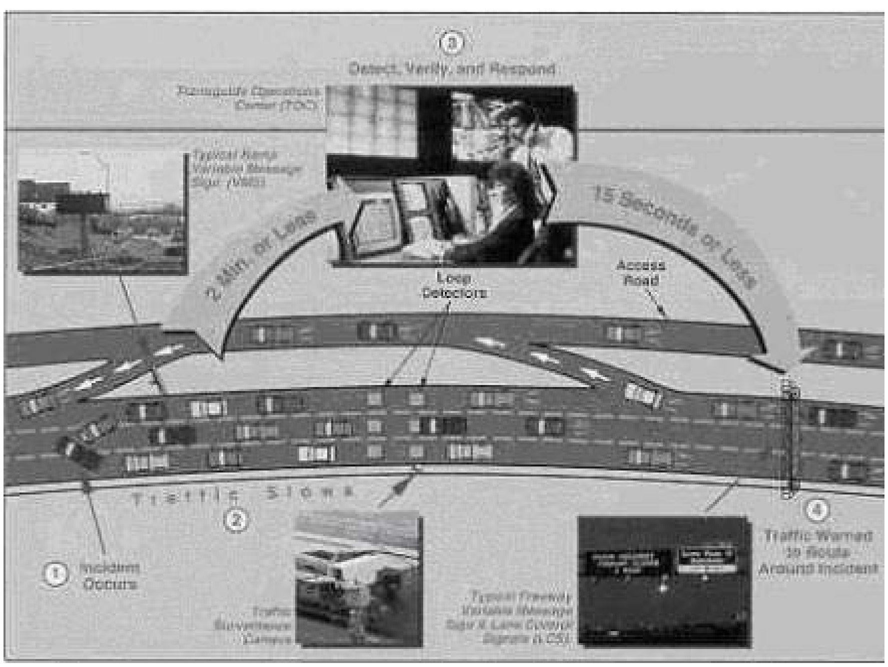

Figure 8-1. Operation cycle of TransGuide

AZTech, Phoenix, Arizona (1996)

The goal of the AZTech project was to develop an integrated ITS for the Phoenix metropolitan area. This system was designed to provide travel information such as real-time traffic conditions, related road closures, and accident information. AZTech incorporated isolated systems of traffic management, incident management, and transit agencies into one integrated system that could provide information to motorists through the use of live traffic cameras and variable message signs. This system is linked through a fiber optic communication system.

AZTech was designed to improve emergency services and incident response by coordinating police and fire departments, the Department of Public Safety, and 911 emergency personnel. The AZTech project included a private company, TRW, which created the integrated system to exchange data and video information between agencies. Information obtained from video is analyzed and information about delay, detour information, etc., are disseminated to motorists through CMSs. The Phoenix Fire Department is able to immediately analyze an incident by monitoring video cameras, which provides an incident management tool (TESCNET, 2001).

Smart Trek, Seattle, Washington (1996)

Smart Trek is an ITS project designed to deliver regional, multimodal traveler information to help motorists and commuters make more intelligent transportation decisions. Communication links were established between the Washington DOT's TMC and local and regional emergency response centers. This transfer of information delivers real-time video traffic data to emergency response personnel, which improves the response times and emergency services. Incident response vehicles are equipped with two-way video communication systems to allow images to be sent to the TMC from the scene of an accident for regional (upstream) traffic management, and to the vehicle for enhanced on-site traffic management. These images are also available through the Internet for use by other emergency responders (TESCNET, 2001).

The City of Bellevue and Washington DOT engineers use the traffic cameras to provide real-time traffic congestion patterns to motorists, to monitor ramps, to evaluate signal performance, and to confirm traffic incidents. Depending upon the traffic flow, appropriate alterations are made to the traffic signal systems. Similarly, Washington DOT's Tacoma Traffic Flow Map uses video detection technology to continuously monitor highway congestion and speeds on the Tacoma Narrows Bridge. The results are shorter traffic delays, faster emergency response, and improved public safety. A screen capture from a Smart Trek traffic television is shown in Figure 8-2.

CommuterLink, Salt Lake City, Utah (2000)

CommuterLink is a computer-controlled system designed to monitor and manage traffic flow on freeways and surface streets through the use of 150 CCTV cameras, 57 variable message signs, 550 traffic signals, ramp meters, traffic speed and volume sensors, pavement sensors, and weather sensors (USDOT News, 1999). Data from these components are gathered and analyzed in the Utah Department of Transportation. The data is then transmitted to the respective Salt

Lake City and Salt Lake County traffic control centers by fiber optic cables. CommuterLink uses over 150 CCTV cameras along surface streets and freeways to monitor traffic and identify the exact location and cause of problems. Appropriate emergency response teams are then dispatched to the accident sites to reduce the delays caused by accidents. For minor accidents or stalled vehicles, operators can notify UDOT's Incident Management Team to provide assistance. For major accidents, the Utah Highway Patrol and other emergency service providers can be alerted (TESCNET, 2001).

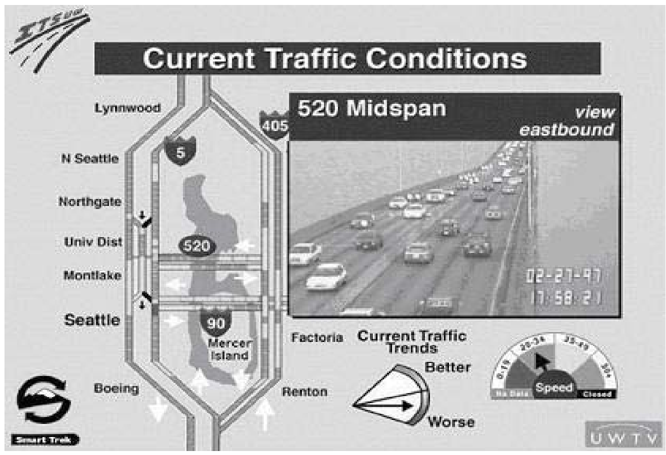

Figure 8-2. SmartTrek-traffic TV

Summary of existing systems

This review of nationwide experiences with video systems highlights the applications of video in the areas of emergency management and public safety. It is a fact that state and local governments suffer from the costs of congestion. Innovative and cost-effective techniques such as video are being implemented around the nation to tackle the challenges of congestion. Real-time video data sharing, either through direct feed or the Internet, has become a common practice between transportation management and public safety agencies. These video technologies allow the state and local agencies to:

- detect congestion caused by accidents and initiate response quicker than before,
- verify accident sites and determine the appropriate emergency response required,
- respond by dispatching appropriate resources,
- provide delay times and detour information to motorists through CMS,
- continuously monitor real-time traffic condition during peak hours, and
- build interagency communications by simultaneously providing the real-time video data to all the participating agencies in emergency management program.

Video for Emergency Response in Tuscaloosa

The primary purpose of this section of the research was to evaluate the use of video camera system currently in place and owned by the City of Tuscaloosa for the purpose of identifying incidents and determining appropriate responses by emergency service vehicles. The analysis focused on ensuring rapid response and efficient use of resources.

The City of Tuscaloosa was chosen because of its developing ITS network, which includes the expansion of the City's traffic control center and installation of CCTV cameras at various locations throughout the city. The City also involves stakeholders such as the Tuscaloosa Police and Fire Departments, and the City of Northport in this program (McFadden and Graettinger, 2000). Tuscaloosa currently has an Advanced Traffic Management System that consists of 27 CCTV cameras on major arterials, and eight video detection systems (Autoscopes) at the TMC. The system will be expanded to include 11 dynamic message signs, a traffic data geographic information system, an integrated emergency management system, and a real-time traffic congestion analyzer.

Autoscope for Emergency Response

Autoscope is a proven video vehicle detection system that combines real-time image processing and computerized pattern recognition within a flexible software platform. This technology offers fully automated remote video detection of incidents and visual verification, thereby permitting early notification of events and improving emergency response times and resource allocation. In addition, the system has the ability to monitor multiple lanes with one camera. The wide range of information gathered provides traffic managers with a means to reduce roadway congestion, improve roadway planning, and provide real-time detection information.

Typically, any incident such as a vehicle pulling over to the side of the road, leads to a slowdown of traffic. As speeds decrease, the slowdown ripples back through the traffic with a certain velocity. An incident detector can process the rate at which a queue builds to determine whether an incident has occurred. Other traffic parameters are monitored that can suggest an incident has occurred, such as an accident or a stalled car that produces a sudden variation in roadway capacity. These monitors actually detect the shock wave (sudden change in traffic flow), which propagates upstream from the site of the incident (Incident Detectors, 2001).

To provide incident detection, the video detection system is interfaced with a machine vision-based Automated/Autoscope Incident Detection Algorithm (AIDA). After these virtual incident detectors are overlaid onto the field of view, the detectors calculate traffic parameters such as speed, volume, occupancy, stopped vehicles, and density. These incident detectors then process information generated by count and speed detector pairs to measure changes in the traffic flow. When the AIDA detects a sudden speed drop, the incident detector generates an audible alarm, a live video is displayed, and the TMC operators take the necessary action to verify a potential emergency. The video obtained from this system can be broadcast to the participating ER teams through television monitors. Although the whole process is not yet operational in the City of Tuscaloosa, efforts are in progress to implement this system (Michalopoulos and Samartin, 1998).

One of the improvements in AIDA is the development of a stopped vehicle detector, which could be used to simply detect stopped vehicles on the shoulder within the camera's field of view. To minimize false alarms due to regular congestion during peak hours, a scheduler can be used to vary parameter thresholds at different times of the day. This helps operators at the TMC and other ER teams identify actual incidents. These systems can use pan and zoom cameras to scan the area to determine the cause or condition of the incident (Samartin, 1997). In addition, videotapes can be recorded when incident alarms are detected, thereby allowing for off-line testing and evaluation of the response efforts. To minimize congestion, a VMS on the upstream side of an incident can be triggered by the Autoscope to display messages indicating the downstream conditions.

Surveillance Cameras for Emergency Response

TDOT currently has 27 CCTV cameras and eight Autoscope cameras placed throughout the city for traffic safety and management purposes. Unlike an Autoscope camera with a built-in machine vision processor, TDOT has a common machine vision processor that allows simultaneous video input from all eight Autoscope cameras, which are controlled remotely from the TMC. An Autoscope camera provides the video feed to a monitor where the image is captured and calibrated. Detection zones are overlaid and the image is sent to the MVP, which analyze the video and process information on speed, volume, occupancy, stopped vehicles, etc.

Any surveillance camera can be used in place of an Autoscope by putting the feed through a bi-link computer that is interfaced with the Autoscope software and the common MVP. The CCTV image shown in Figure 8-3 can be processed by Autoscope and used for traffic detection. This was successfully tested and demonstrated that surveillance cameras can supply video feed in a format that can be processed by MVP. This observation is very significant as the inexpensive CCTV cameras currently in place and owned by the City of Tuscaloosa could be used for incident detection and could improve ER time.

Figure 8-3. Video image monitor

Conclusions

The need for a reliable video system that can improve efficiency by establishing a communication link between various ER teams was investigated. The use of video detection to provide real-time traffic data on incident and emergency management was evaluated from some of the nation’s successful video/emergency experiences. The project also evaluated the current status of Tuscaloosa’s growing ITS network relative to video/emergency detection and response. Using a video camera and the AIDA software, early detection of incidents can be accomplished. It can be concluded that inexpensive CCTV cameras can be deployed in place of Autoscope cameras to provide video input to the MVP interface. Thus video can be effectively used for the purpose of emergency response.

Section 9
Conclusions and Recommendations

The objective of this research was to evaluate various applications of low-cost video technology systems in areas of transportation management and safety in Alabama. Several video systems such as conventional video recorders, digital video cameras, Autoscope cameras, and surveillance cameras were applied and tested at various locations. Listed below are the transportation areas that were investigated in this project, and that showed a potential benefit from video technology:

Conventional video cameras: intersections and mid-blocks,
Digital video cameras: railroad grade crossings,
Autoscope cameras: compositional traffic counts, red-light running, speed violation study, emergency response management, and activating variable message signs, and
Surveillance cameras: red-light running study using Autoscope software, video recording of intersections.

It was shown that video technology could provide an alternative to standard data collection methods like loop detectors, pitot tubes, and manual traffic counters. Video data collection is inexpensive, cost-effective, low-maintenance, provides more data, easy to setup, and requires fewer infield personnel. Video data can be analyzed manually, or automatically using machine vision technology such as Autoscope for vehicle classification of traffic data. In studies related to corridor analysis and railroad grade crossing safety, video allowed examination of recorded data any number of times to report accurate traffic parameters.

In this work, the literature review provided valuable information and identified several areas where video technology can be employed, such as:

- traffic surveillance on freeways,
- incident detection and response,
- electronic enforcement,
- travel time studies, and
- origin-destination survey.

Some problems and issues that were of concern during this research are summarized below:

- safety of the equipment in the field,
- safety of the crew working with the video equipment on high volume roads,
- roadside video setup distracts drivers and gains unwanted public attention,

- video data reduction process involves a considerable amount of time,
- water and dust on the camera lens,
- improper video recording due to technical problems,
- unclear recorded image due to dull lighting conditions,
- blooming of image due to headlights of vehicles at nights,
- occlusion of small vehicles because of tall vehicles moving in an adjacent lane, and
- inaccurate machine counts due to vehicle occlusion.

Some recommendations for successful field video data collection are:

- check weather conditions and perform a preliminary site survey before planning field data collection,
- train the crew in setting up the equipment before conducting the field installation,
- exercise care when installing and operating the video equipment in the field,
- check equipment to eliminate technical problems that might cause loss of vital information,
- provide a housing for the camera to protect the camera and improve the image by reducing distortions caused by wind, snow, rain, frost, and fog, and
- mount video cameras high enough (greater than 30 feet) to obtain a clear view and eliminate obstruction of smaller vehicles by large vehicles.

Based on this research, it can be concluded that agencies in Alabama can employ video technology for traffic data collection and implementation in advanced traffic management systems. This technology can help reduce traffic congestion, improve roadway planning, and provide traffic research opportunities to ensure better traffic management and safety.

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CommuterLink web page, http://www.utahcommuterlink.com
I^3 Lab Website, http://www.i3lab.unomaha.edu
Intelligent Highway System, http://www.sti.nasa.gov/tto/spinoff1996/36.html
Navigator web page, www.georgia-navigator.com
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www.imagesensing.com
www.autoscope.com

Appendix

Program Code	Comments
function UTCA25(Syx,Sxx,Syy,X,AvgY)	Defines function name with input variables
A=Syx × inv(Sxx);	Calculates matrix A by performing matrix operations on Syx and Sxx
BBt=Syy-(Syx × inv(Sxx) × (Syx)');	Calculates matrix BBt by performing matrix operations on Syx, Sxx, and Syy
d=det(BBt);	Computes the determinant of matrix BBt
R=rank(BBt);	Computes the rank of matrix BBt
E=eig(BBt);	Computes eigen values of BBt and reads them into Matrix E to check for positive semi-definiteness of matrix BBt.
[V,D]=eig(BBt);	Generates eigen vector and eigen value matrices of BBt and reads into V and D matrices respectively
B=V × sqrtm(D);	Decomposes matrix BBt into matrix B by performing matrix operations on eigen vectors and eigen values
Z=zeros(14,1);	Generates a zero matrix Z of order 14 × 1
for i=1:10000	Executes loop for 10000 iterations to calculate a set of Y values
W=randn(14,1);	Generates a 14 × 1 matrix of random numbers which follow standard normal distribution (Mean = zero and Standard Deviation = 1)
Y=(A × X') + (B × W);	Calculates one set of Y values for each iteration
G(1:14,i)=Y;	Reads all Y values, generated by each iteration, into matrix G
Z=Z + Y;	Stores the cumulative sum of generated 10000 sets of Y-values into an array “Z” for further statistical analysis
end	Terminates the iteration process
MatY = (Z/i);	Matlab output of a set of Y-values from 10000 iterations
Final=MatY+AvgY';	Stores the sum of corresponding Mean Y values of input data from Excel and Matlab output Y-values into an array “Final”
Final	Displays the array “Final”