Impact of Geometric, Traffic, and Environmental Conditions on Video Detection Performance: A Case Study in Baton Rouge Metropolitan Area

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Abstract—**This study investigates the impact of different site-related factors such as traffic conditions, lighting conditions, turning movements, and geometric characteristics of intersections on the accuracy of video detection. A sample of intersections was selected from the Baton Rouge Metropolitan (BR-MPO) Area. For each intersection, traffic counts were collected with video detection technology and manually to represent ground truth data. Comparative statistical analysis results indicated that only lane configuration, time of day, and traffic conditions were statistically affecting video detection accuracy. The impact of these factors was further analyzed using t-test. The results indicated that the peak hours and night periods contained the least accurate counts. The analysis results indicated that detection accuracy was negatively affected by heavy traffic conditions. For the lane configuration, there were statistical differences for the through lanes, right lanes, and shared right/through lanes. As 60% of the sampled intersections provided reliable performance, the research team attributed the poor performance of the detection system at some intersections to lack of calibration and maintenance. It was concluded that recalibrating the detection systems, improving lighting conditions, and realigning the cameras can significantly improve the performance of the detection system and improve the reliability of traffic counts.**

Index Terms—**video detection, lighting conditions, traffic conditions, lane configuration, Baton Rouge Metropolitan (BR-MPO) Area**

I. Introduction

Traffic data collection at intersections is a very demanding task due to the number of different movements that could be occurring simultaneously. Currently, inductive loops are commonly used for data collection. When properly installed, they provide accurate data. However, inductive loops are of intrusive nature that involve lane closure while installation. Surveillance cameras, on the other hand, do not involve such intrusive nature. They are not only used as a means of security but also for video detection purposes to capture traffic flow parameters such as speed and flow. Video detection combines real-time image processing and computerized pattern recognition in a flexible platform. In video detection systems, the camera, which is the image sensor, captures and transmits videos to vision microprocessor that is either located in the camera or as an attached module to the controller cabinet. The transmitted video signal is then analyzed and the analysis results are recorded. The detection process in the camera is performed using two main categories of algorithms: trip line and video tracking. For trip line techniques, studied in [1]-[5], video images of a target area on pavement are analyzed. A vehicle passing across the target area is identified as a change in the target area through sequential photos. On the other hand, video tracking techniques, studied in [6], [7], employs algorithms to identify and track vehicles as they pass through the camera's field of view.

Video detection systems have many benefits and can be used for evaluation of transportation networks. For instance, some detection systems can provide traffic performance measure such as Level of Service (LOS), space mean speed, acceleration, and density. Another benefit of video detection is its adaptability for changing conditions at intersections (e.g., lane reassignment and temporary lane closure for work zone activities). Additionally, it can be used to automatically detect incidents in tunnels and on freeways, which improves emergency response times by local authorities. Finally, it can provide documented videos for any incident occurring in their field of view which can be used to determine driver's liability whenever required. Despite of all the advantages and benefits video detection systems offer, several reports [8]-[10] have documented missed and false calls during night at low light intensity and when shades exist. Severe weather conditions such as rain, snow and wind also compromise the performance of

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these systems. Other factors that can also negatively impact the performance of video system include occlusion, camera motion, seasonal changes in sun's position, glare and spray from vehicles, and particularly salt, which can accumulate on the camera's lens.

In view of the above discussion, the main objective of this study is to evaluate video-detection systems accuracy under different site conditions (e.g. Lighting conditions, weather…etc.). More specifically, this papers documents the findings of an evaluation study performed to assess the accuracy of video detection systems implemented for intersections in Baton Rouge Metropolitan Area (BR-MPO).

II. Background

Over the past few years there has been significant research effort to evaluate video detection systems and study the impact of site conditions on its accuracy. For instance, MacCarley [8] conducted an evaluation study on eight different video detection systems under same traffic, lighting and weather conditions considering two different detection algorithms. The authors identified 28 different parameters for their study including camera angle, camera mounting position, departing or arriving traffic, lighting, weather, vibration, and electromagnetic noise. The results showed that all detection algorithms were affected by the tested parameters. The accuracy of video image processing systems was evaluated in cooperation between Virginia Department of Transportation (VDOT) and the Maryland State Highway Administration (MSHA) [9]. The study showed that the accuracy of video detection was not consistent. The study also showed that for the cameras to provide acceptable accuracy, they need to be mounted above the traffic lanes of interest. Another joint effort was conducted in 1998 between the Minnesota Department of Transportation (MnDOT) and SRF Consulting Group, Inc. [10]. This study investigated four image sensors under different environmental and traffic conditions at intersections and freeways. The study results showed that video detection accuracy was negatively affected when traffic becomes congested. In addition, lighting conditions, wind, and snow were found to have the strongest impact on the performance of all detection systems. Martin [11] conducted an evaluation study for the Utah Department of Transportation (UDOT) on different video detection systems. The study showed that despite some detection systems are superior to the others, all systems' performance was significantly affected by site conditions.

The previous discussion showed that video detection accuracy is significantly affected by several factors. As such, there has been a significant effort to come up with detection algorithms that can reduce the effect of those factors. For instance, Chao *et al*. [12] developed an algorithm to distinguish vehicles from shadows. When tested, the algorithm showed reduction in false–alarm rate caused by the existence of vehicle shadows. Similarly, Huang [13] tried to overcome the problem of shadow existence using a real-time multi-vehicle detection and tracking system. His approach proved to be of better performance and accuracy. Kamijo *et al*. [14] developed a tracking algorithm to overcome the effect of conflicting movements in the video images. The performance of their algorithm was tested and showed promising results to reduce the confusion caused by conflicting movements. In a more generalized study, Mo and Zhang [15] tried to improve video detection accuracy through adoption of multiple video object segmentation algorithm which gave more reliable results. Similarly, Bramhe and Kulkarni [16] presented a moving object detection algorithm to improve video detection accuracy. Their algorithm helped to give more accurate traffic counts that can be used for traffic control purposes. Finally, Shuguang *et al*. [17] developed a new technique for video-based traffic data collection that allows detecting and classifying vehicles under mixed traffic conditions. This technique is a color image processing-based system that can detect vehicles' speeds and types. The developed technique gives comprehensive traffic data for different vehicle types with high accuracy.

The evaluation of commercial video detection indicates that they have problems with several factors such as congestion, occlusion, camera vibration due to wind, lighting transitions between night and day, and long shadows linking vehicles together [11]. Commercial companies have been continually improving the ability of their video detection systems to account for these factors. However, the fact that these systems detect vehicles from videos using artificial algorithms dominates, the absences of human intelligence persists, and the different factors still impact video detection accuracy. Yet, video detection is a promising technology that is still have space for improvement. As such, this study investigates the impact of the different site conditions on the accuracy of the implemented video detection technology in Baton Rouge Metropolitan (BR-MPO) Area. The rest of the paper is organized as follows. Section III discussed the study methodology. Section IV presents a discussion for the study results. Finally, in Section 5 the study effort is summarized and conclusions are made.

III. Methodology

The main objective of the paper is to study the impact of site conditions on video detection accuracy in Baton Rouge Metropolitan Area (BR-MPO). An inventory of all intersections with video detection systems in BR-MPO was first developed. The inventory included a total of 235 intersections with information on the technology used, mounting type, geometric characteristics of the intersection, lighting condition, and turning movements/lanes. In the developed inventory, the intersections were categorized according to several factors such as lighting conditions, traffic volume conditions, lane configuration, and mounting conditions among others.

Based on the developed inventory, a sample of intersections was selected for the study. The sample size was determined assuming a 90% level of confidence as follows:

a) Assuming Confidence level (P) = 90%

b) Z value for 90% confidence level = 1.645
c) Assumed margin of error (D) = 10%
d) Finite Population of Size (N) = 235
e) Sample Size for infinite population (n_0) =

$$Z^2\left[\frac{P(1-P)}{D^2}\right] = (1.645^2)\left[\frac{.90(1-.90)}{.10^2}\right] = 24.35 \quad (1)$$

f) Sample size for finite Population of Size 235:

$$\frac{n_0}{1+\frac{n_0}{N}} = \frac{24.35}{1+\frac{24.35}{235}} = 22 \quad (2)$$

The sample intersections were selected so that all site conditions are covered including day/night and weather and also to allow for geographical diversity.

A. *Data Collection*

The collected data for this study were of two categories: video-detection based traffic counts and manual traffic counts. For the video-detection based data, traffic counts reports were obtained from the city of Baton Rouge. Each report included traffic counts for each lane, turning movement, direction, and signal phase broken down for each 15-min. A sample of these reports is shown in Fig. 1.

Total Volume Report

Group/Device: Florida Blvd @ Central Thrwy/O'Neal
Resolution: 15 Minutes
Run Date: 4/4/2014 5:19:04 PM
Date Range: 4/3/2014-4/3/2014

Time	Florida Blvd @ Central Thrwy/O'Neal - EB Phases 2 & 5 det 150 (EB Phase 2 Right Turn Lane)	Florida Blvd @ Central Thrwy/O'Neal - EB Phases 2 & 5 det 151 (EB Phase 2 Thru Lane 2)	Florida Blvd @ Central Thrwy/O'Neal - EB Phases 2 & 5 det 153 (EB Phase 2 Thru Lane 1)	Florida Blvd @ Central Thrwy/O'Neal - EB Phases 2 & 5 det 154 (EB Phase 5 Left Turn Lane 2)	Florida Blvd @ Central Thrwy/O'Neal - EB Phases 2 & 5 det 156 (EB Left Turn Lane 1)	Florida Blvd @ Central Thrwy/O'Neal - NB Phases 3 & 8 det 150 (NB Phase 8 Right Turn Lane)
00:00 - 00:15	4	3	8	1	0	1
00:15 - 00:30	4	9	7	1	2	1
00:30 - 00:45	4	3	1	0	0	3
00:45 - 01:00	4	4	4	1	1	1
01:00 - 01:15	3	5	4	1	0	0
01:15 - 01:30	3	8	1	0	0	0
01:30 - 01:45	2	4	0	1	0	1

Figure 1. Total volume report.

In order to assess the accuracy of traffic counts collected from the video detection system, manual traffic counts were also obtained from each intersection to represent the ground truth data. For the manual counts, the recorded videos using the installed video cameras were used. Manual counting was performed on each recorded video. The counts were collected so as to have the exact break down as in the video-detection based counts. This break down was easy to obtain given the video detection system capabilities to show signal phases and timing; see Fig. 2.

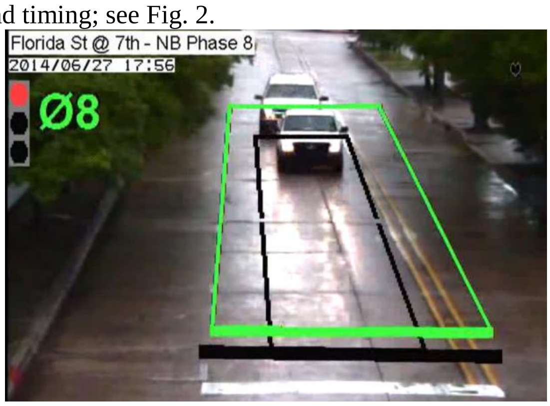

Figure 2. A Scene from the Recorded Videos.

B. *Statistical Analysis*

Video detection accuracy was evaluated using statistical analysis. The percent error was used as the primary performance measure for video-detection accuracy as in equation (3). It was assumed that 5% error in video detection accuracy was acceptable in practice, therefore up to 5% error was categorized in the same group as when no error was detected.

$$\%\,Error = \frac{Camera\ Count - Manual\ Count}{Manual\ Count} * 100 \quad (3)$$

Basic summary statistics were obtained in order to assess the overall distribution of the video detection system accuracy. Then, Multiple Logistic Regression (MLR) analysis was performed to statistically assess the significance of the different factors in determining video detection accuracy. The studied factors included lighting condition, time of day, weather condition, lane configuration, and traffic conditions. Further statistical analysis using t-test was then performed by accounting for only the factors that were found to be significant in determining video detection accuracy. The latter analysis was conducted to investigate the statistical significance of traffic counts' errors and evaluate video detection accuracy. Paired t-test was used to compare the video-detection based traffic counts to the manual counts. The null hypothesis for each t-test assumed the means of the manual count and camera based counts were equal at 0.05 level of significance. This test aimed at finding out the values for each factor where the error values were significant.

IV. Discussion of Results

The evaluation period for each of the sampled intersections was broken down into 15-min. intervals which resulted in a total on 3084 15-min intervals. For each interval, traffic counts were produced by the video detection system and the pertinent ground truth data from manual counts were also obtained. The error in traffic counts was then calculated. The results showed that out of the 3,084 records, 526 (17%) had no detection errors (there was 0% difference between the ground truth counts and the camera based counts). For the records where the error had a value, 43% were because of false calls and 40% were because of missed calls. Detailed information about the distribution of errors is in Fig. 3. The figure shows that around 24% of the records had an error value in the range of 0-5%, while 67% had an error value higher than 10%.

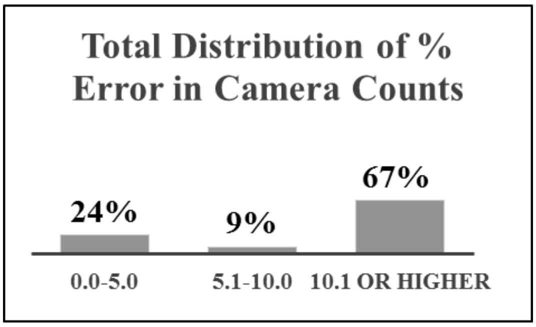

Figure 3. Total Distribution of Percent Error in Camera based Counts

The error distribution in Fig. 3 shows that the video detection errors are considerable high for most of the intersections. In order to measure the statistical significance of the obtained error values, t-test analysis was conducted for each intersection in the sample. The results showed that 40% of the intersections had statistically significant errors. The significant error values were attributed to the poor calibration and absence of regular maintenance for the detection systems at these sites. More specifically, absence of calibration of system to overcome adverse effects of site conditions significantly impacted their performance and accuracy, which is not the case for the remaining 60% of intersections that did not show significant errors. Calibration of detection systems should account for different site conditions such as weather conditions, lane configurations, lighting conditions, time of the day and traffic conditions. In order to investigate the conditions that contributed the most to the obtained errors in the 40% of the sampled intersections, Multinomial Logistic Regression (MLR) analysis was performed. In the following the results of this test are discussed.

TABLE I. SUMMARY OF MLR RESULTS

Dependent Variables	Effect Type in Model	Time of Removal from Model	p-value at Removal Point
Traffic volume*Lane configuration	Interaction	Removed 1st	0.2463
Lighting (shade or no shade at intersection)	Main	Removed 2nd	0.1530
Traffic Volume*Weather	Interaction	Removed 3rd	0.1419
Weather	Main	Removed 4th	0.0748
Time of Day (hour)	Main	-	< 0.05
Lane configuration	Main	-	< 0.05
Traffic volume	Main	-	< 0.05

A. MLR Results

The Backward Elimination technique was used to run the MLR analysis. This method began with all the five variables determining the site conditions, namely weather conditions, lane configurations, lighting conditions, time of the day and traffic conditions represented by traffic volumes. The process of elimination was then performed by removing the each of the five variables (one at a time) until only the variables that contributed the most to the error values are kept in the model. This is determined in the test by a significant p-value at 0.05 significance level. Table I summarizes the results of the MLR analysis. The effect types in the table is to identify how each variable was represented in the model: main effects mean that each variable was analyzed independently and interaction effects means that the cross relationship between each two variables is analyzed. The results, as shown in the table, indicate that only three variables contributed to the error values: time of day, lane configuration, and traffic volume. Therefore, the rest of the analysis was conducted by only accounting for these three variables. Paired t-test was conducted on the error values to investigate what values of each variable contributed the most to the error values. The analysis was conducted considering each of the three significant variables obtained from the MLR independently.

B. T-test Results-Time of Day

The results considering the time of day are shown in Fig. 4. The figure shows that there was a statistical difference in the accuracy of the counts during six one-hour timeslots throughout the day: 6:00-7:00AM, 3:00-4:00PM, 4:00-5:00PM, 8:00-9:00PM, 9:00-10:00PM and 11:00PM-12:00AM. When investigating the type of errors took place in each hour, two hours (6:00-7:00AM and 3:00-5:00PM) included missed calls as the main reason source of error. This could be due to high traffic volumes during morning and afternoon peak periods. According to the percent error distribution during these two hours, the video detection system underestimated the video-based traffic counts, meaning that there were some uncounted vehicles. This could be resulting from small time gaps between two or more consecutive vehicles so that they are counted as one in the video. For the evening periods, 8:00-10:00 PM and 11:00-12:00AM, the significant errors can be attributed to the low light intensity. These errors included both missed and false calls. Darkness and poor lighting conditions can increase probability of missed calls for vehicles without their headlights on. Also reflection of headlights on pavement can increase false calls under poor lighting (low intensity) conditions.

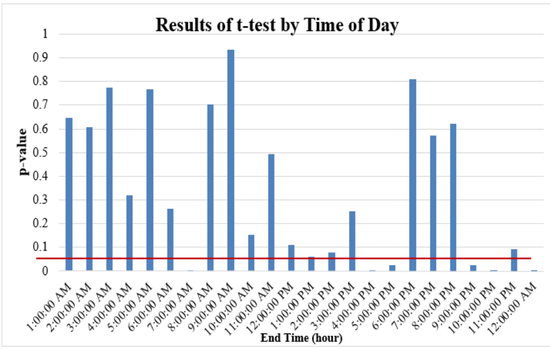

Figure 4. Total distribution of percent error in camera counts

C. T-test Results-Lane Configuration

The t-test results analyzing lane configuration, depicted in Table II, showed that there were statistical differences in the counts for the through lanes, right lanes, and shared right/through lanes. This finding was expected due to the cameras physical location, as they were positioned on traffic-signals' posts closer to left-lanes' centerlines (Far left position). This positioning caused occlusion while counting other movements. The farther away lanes are from left lanes, the more occlusion and counting errors are encountered. This is clear in the resulting p-values in Table III. Lower p-values were observed for right and through lanes compared to left and shared left movements.

TABLE II. SUMMARY OF T-TEST CONFIGURATION RESULTS

Lane Type	t-value	P-value	Conclusion
Through	2.95	0.0032	Different
Left	-0.34	0.7338	No Difference
Right	4.2	<0.0001	Different
Left/Through	-1.12	0.265	No Difference
Right/Through	4.72	<0.0001	Different
Left/Through/Right	-0.83	0.4092	No Difference

D. *T-test Results-Volume*

The manually counted data was used represent in-situ traffic conditions for the analysis. The manually counted traffic volumes was grouped into five categories: 0-50, 51-100, 101-150, 151-200 and 201-300 vehicles per 15 minutes. Based on this categorization, paired t-test was conducted. The results, in Table II, show that higher traffic volumes lead to significant errors in video detection. As traffic volumes go beyond 100 vehicles per 15 minutes, traffic counting error becomes significant, except for traffic volumes higher than 200 vehicles per 15 minutes whereat counting errors are not as significant. This can be explained by the reduced spacing headways between vehicles for higher traffic volumes which might lead to missed counts (two vehicles counted as one vehicle by the video detection system). When traffic volumes go beyond a specific value (may be roadway capacity), vehicles speeds decrease significantly which could give the video detection systems a better chance to count vehicles correctly even with reduced spacing headways.

TABLE III. SUMMARY OF T-TEST LANE CONFIGURATION RESULTS

Volume (15 min.)	t-value	P-value	Conclusion
0-50	0.61	0.5414	No Difference
51-100	-1.7	0.091	No Difference
101-150	-3.85	0.0002	Different
151-200	-3.7	0.0005	Different
201-300	-2.11	0.0564	No Difference

V. CONCLUSIONS

This paper examined the Impact of site conditions on the accuracy of video-detection systems at intersections within the Baton Rouge Metropolitan Area (BR-MPO). Site conditions can compromise detection accuracy by the triggered missed and false vehicle counts. Missed counts refer to the instance when two or more vehicles are counted as one, while false counts refer to instances when nonexistent vehicles are counted (shadow of a vehicle). In order to study the causes of the different error types in BR-MPO, an inventory of all of the intersections equipped with video detection systems was compiled and a random sample was selected from this inventory to be tested. For each of the sampled intersections, manual traffic counts and video counts were collected under different conditions including lighting, time of day, condition, lane configuration, and traffic conditions.

Statistical analysis was performed in three steps to investigate the significance of errors in video-based traffic counts. First, a separate t-test analysis was conducted for each intersection in the sample, in order to measure the statistical significance of the obtained error values. Second, the t- test was followed by MLR to detect the factors that contributed the most to the obtained errors. These factors include weather conditions, lane configurations, lighting conditions, time of the day and traffic volumes. Finally, separate paired t- tests were performed considering only the significant factors determined by the MLR test. This test was intended to determine the values of each factor where the error values were significant.

In order to measure the statistical significance of the obtained error values, t-test analysis was conducted for each intersection in the sample. The results showed that 40% of the intersections had statistically significant errors. The significant error values were attributed to the poor calibration and absence of regular maintenance for the detection systems at these sites. More specifically, absence of calibration of the system to overcome adverse effects of site conditions significantly impacted their performance and accuracy, which is not the case for the remaining 60% of systems that did not show significant errors. This was supported by the MLR test results which indicated that among the five factors tested the time of day, lane configuration, and traffic volumes had the most significant impact on the error values in traffic counts. This was investigated further using paired t test analyses, which indicated the specific values for each of the three factors having the most significant impact on video detection accuracy.

For the time of day, the least accurate counts were recorded during the morning, afternoon, and night periods. While missed counts were the only contributor to errors in the morning and afternoon periods, counting errors at night resulted from both missed and false counts. Missed calls occurring during the morning and afternoon peak periods were ascribed to the high traffic volumes during these periods. In such an environment, spacing headways between vehicles are minimal which lead to a high probability of counting two or more vehicles as one. For the night time period, darkness and poor lighting conditions increased the probability of missed calls, especially for vehicles with turned off headlights. More so, turned on headlights reflections on pavement triggered false calls. For traffic conditions, higher traffic volumes lead to a significant drop in video detection accuracy. As traffic volumes increase, interaction between vehicles increase and the headway between consecutive vehicles decrease significantly. This leads to a higher probability for the detection systems to count more than one vehicle as one. As traffic volumes go beyond a specific threshold (could be roadway capacity) and congestion spreads on larger areas of the detection zones, the reduced travel speed provides higher detection time for the camera. This reduces the probability of missed calls which results in a relatively better detection accuracy. Finally, for the lane configuration there were significant differences for the through lanes, right lanes, and shared right/through lanes. The left and shared left movements provided the highest detection accuracy. This was caused by the cameras' physical location relative to each lane. The way cameras are installed at intersections provided an optimum angle of view for left lanes compared to through and right lanes. Thus, an increased occlusion was associated with the detection zones of through and right lanes which significantly affected video detection accuracy.

Overall, site conditions could significantly compromise detection accuracy of video detection systems. They might trigger missed and false calls reported which could lead to significant errors in video-based traffic counts. Calibration and continuous maintenance for video detection systems can significantly reduce such errors by accounting for the different site conditions in the context of weather, lane configurations, lighting, time of day and traffic conditions. These conditions are specific to each intersection and need to be investigated carefully while calibrating each installed video detection system. This does not necessarily mean that video-based counts will be error free. It means that the errors will be minimal which could change with time as the camera set up changes due to wind or similar factors. Therefore, the associated error values with each collected video-based counts need to be investigated all the time. This is to assess the accuracy of the collected data and determine whether further calibration and maintenance are required. Thus, a mathematical model that gives video detection accuracy as an output in terms of the associated site conditions and camera set up parameters is required. This is to be investigated by the research team in a future research

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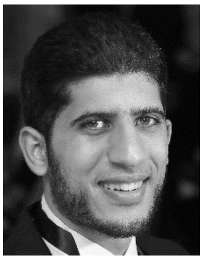

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While pursuing her graduate studies, she was awarded three fellowship awards: The Federal Highway Administration's Dwight D. Eisenhower Transportation Graduate (GRAD) Fellowship, the National GEM Consortium's GEM Fellowship, and the American Association of University Women's Selected Professions Fellowship. She was awarded first place for her research presentation at the GEM Fellowship's National Conference in San Diego, CA in 2014.
She presented her graduate thesis results in January 2016 at the 95th Transportation Research Board Annual Meeting in Washington, DC. During this conference, she was recognized as the National Center for Intermodal Transportation for Economic Competitiveness Outstanding Student of the Year. Her thesis work has also been accepted for presentation at the 7th International Conference on Applied Human Factors and Ergonomics (AHFE) 2016 in Orlando, FL. Syndney currently works as at transportation engineering consultant for Kimley-Horn & Associates, Inc. in Atlanta, GA.

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Bakhit is a recipient of Enrichment Award scholarship at Louisiana State University. He participated in Cooperative Mobility project held in Redondela, Spain in 2013 representing Egypt. Bakhit is also a member of ASCE and ITE organizations in addition of being one of the team members representing LSU who won the Deep South Institute of Transportation Competition in 2016 (DSITE, Mississippi, 16').

Sherif Ishak, Ph.D., PE was born in Egypt in 1964. He received his B.S. degree in civil engineering in 1987 from Cairo University, Egypt, and both M.S. and Ph.D. degrees in civil engineering from the University of Central Florida in 1994 and 1998, respectively. From 1998 to 2001 and prior to joining the civil engineering department at LSU he served as a visiting Assistant Engineer and Manager of the Intelligent Transportation Systems Lab for the Transportation Systems Institute at the University of Central Florida. He is currently employed as Lloyd J. Guillory Professor of Civil Engineering at LSU. He also acts as the Interim Associate Dean for Academic Affairs at LSU. His areas of research interest include applications of intelligent transportation systems, traffic operations and control, microscopic/mesoscopic traffic network modeling and simulation, human factors and traffic safety, artificial intelligence applications, and others.