Development of Traffic Video Analysis Tool for Highway Safety Performance Evaluation

Final Report

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16. Abstract

Recent advances in computer vision techniques have enabled the use of traffic video data for valuable surrogate safety measures to improve highway safety evaluations. However, few tools specifically target abnormal traffic events like wrong-way driving (WWD) or illegal left turns. This research aims to develop a cost-effective video analytic tool, operational on simpler hardware, focusing on two application domains: (1) detecting WWD incidents at interchange terminals, and (2) identifying traffic conflicts at unsignalized intersections.

This research utilized extensive traffic video data for calibration, validation, and conducting case studies of the tool. The data comprised over 400 hours of footage from portable cameras at 14 partial cloverleaf interchange terminals for WWD incident detection and 72 continuous hours of video from seven unsignalized intersections for illegal left turn analysis. Additional data from fixed detection cameras, including 14 months of WWD incidents and 24 hours of traffic violation monitoring, were also incorporated.

The video analysis tool detection process involves video preprocessing, unsupervised learning to distinguish regular traffic maneuvers, abnormal trajectory detection, and WWD confirmation. The tool proved highly effective, identifying all manually observed WWD incidents, thereby demonstrating its reliability. It recorded an 80% precision rate, highlighting the need for improvements in reducing false positives, particularly for larger vehicles. Nighttime footage processing remains challenging and underscores the importance of interdisciplinary research in transportation and computer science. The continued development of this tool is expected to contribute to enhanced highway safety, especially in detecting and analyzing nighttime incidents and traffic violations.

17. Key Words: Surrogate Safety Measures, Video Data Analytics, Traffic Video Data, Wrong-Way Driving, Computer Vision Techniques

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1 INTRODUCTION

1.1 Background

The highway safety performance assessment mainly relies on the analysis of traffic crash data. Crash data analysis possesses a notable drawback due to its reactive nature. Consequently, safety enhancements are typically implemented in response to past crashes, often resulting in a significant time delay. Collecting, analyzing, and responding to crash data can span years, during which additional crashes may occur. Relying exclusively on crash data may lead to safety measures to prevent the recurrence of specific crash types, but it may overlook emerging or novel safety concerns. This approach fails to proactively identify and address potential hazards before they escalate into crashes. To address this limitation, road safety professionals and transportation agencies increasingly turn to proactive safety system approaches. These methods involve leveraging surrogate safety data and analytics to predict the likelihood of future crashes based on emerging data, traffic patterns, and other relevant factors. Utilizing traffic video data has proven effective in identifying traffic conflicts and undesirable movements like wrong-way driving (WWD), red light running, and other illegal turns.

Every day, transportation agencies amass a large amount of traffic videos from fixed detection cameras, drones, or portable traffic cameras for monitoring traffic conditions, collecting traffic volumes or conflict data, or temporarily investigating traffic incidents. If used properly, these video data can be valuable for highway safety performance evaluation by identifying abnormal traffic movements or recurring traffic conflicts. However, manually sifting through this footage to extract relevant information is daunting.

The research team possesses expertise in manually extracting WWD incident data from over six thousand hours of footage at freeway off-ramp terminals for an Alabama Department of Transportation (ALDOT) research project and an National Cooperative Highway Research Program (NCHRP) project (Zhou, Xue, et al. 2020, Zhou, Chang, et al. 2023). Recently, the team manually captured traffic conflict data from 48-hour videos collected for eight unsignalized intersections on divided highways for another ALDOT project (Zhang and Zhou 2019). Researchers found that it was very time-consuming to manually extract WWD incident and traffic conflict data from traffic videos. Many recently published studies also attest to the labor-intensive nature of manually reviewing vast footage to extract crucial data. The time and effort required for these manual processes highlights the urgent demand for an automated tool that can efficiently detect events like WWD incidents and traffic conflicts from traffic video data.

In recent years, with the rapid development of computer vision techniques and the rising popularity of high-performance computers, video data analytics have become feasible and popular methods for extracting surrogate highway safety measures. While some tools detect general traffic movements, a significant gap remains: few existing tools specialize in extracting abnormal traffic events (such as WWDs or illegal left turns) from traffic videos.

The project aims to bridge this gap by developing an adaptive video analytic method to automatically extract surrogate safety measures from traffic videos recorded by portable traffic cameras with varying mounting heights or angles. This method encompasses vehicle recognition, trajectory generation, and safety performance measurements for different objectives. Specifically, the developed tool can (1) identify abnormal traffic movements (WWD or illegal turns); and (2) identify traffic conflicts or near-crash events. The proposed method can significantly reduce labor costs for reviewing traffic videos to extract the surrogate safety data. Further analysis of the extracted WWD incidents, traffic conflicts, and abnormal traffic movements data can result in more targeted and effective engineering improvements for state and local transportation agencies.

1.2 Research Objectives

1.2.1 Identifying abnormal vehicle movements (wrong-way driving or illegal turns)

Recent ALDOT-funded research unveiled multiple interchange terminals with persistent instances of WWD incidents (Zhou and Atiquzzaman 2019). In the absence of engineering improvements, recurring WWD incidents may lead to crashes on freeways. In rural areas lacking fixed monitoring traffic cameras or detection systems, portable traffic cameras are commonly employed to monitor these terminals and collect data on WWD incidents. Given the rarity of such events, even one incident per weekend is considered a significant safety issue. Manual review of lengthy traffic video footage to identify these rare events is time-consuming. The primary goal of this research is to develop a traffic video analytic tool that extracts WWD incidents and illegal turns from video data collected by portable traffic cameras. The research also aims to develop a machine-learning algorithm that distinguishes normal traffic maneuvers from outliers, revealing abnormal vehicle movements, including WWD, illegal turns, intentional shortcuts, and other undesirable driving behaviors.

1.2.2 Identifying traffic conflicts or near-crash events

Activities such as left turns, right turns, and straight movements occur at the intersection, leading to potential traffic conflicts (Song, et al. 2022). According to the Federal Highway Administration (FHWA), unsignalized intersections are the most common type in the United States, contributing to more than 35,000 traffic fatalities between 2016 and 2020 (NHTSA 2023). Unsignalized intersections on rural divided highways with wide medians carry an increased risk of severe crashes due to numerous conflict points and high speeds. The second objective of this study is to enhance tools for automatically extracting the number of traffic conflicts and near-crash events (safety performance measures) at unsignalized intersections on rural divided highways.

1.3 Summary

Highway safety performance has traditionally been evaluated by examining historical crash data. Utilizing traffic video data can provide supplemental surrogate safety measures such as traffic conflicts and driver behaviors to enhance highway safety performance evaluation methods. To facilitate the traffic video data extraction process, this research seeks to develop a video analytic tool in two different application domains: (1) detecting WWD incidents at interchange terminals and (2) identifying traffic conflicts at unsignalized intersections.

This report summarizes the research activities and results. Chapter 2 presents the literature review results on highway safety performance evaluation methods, existing traffic video analytic tools, and data collection processes, highlighting the shortcomings of current tools for video analysis. Chapter 3 describes the detailed data collected for calibrating the tools and conducting case studies. Chapter 4 delves into the method of developing a traffic video data analytic tool, and Chapter 5 summarizes the software's testing results. Finally, Chapter 6 draws the study to a conclusion.

2 LITERATURE REVIEW

The NCHRP has extensive highway safety research projects spanning several decades. A thorough examination of NCHRP safety projects conducted in the last five years reveals that most relied on historical crash data provided by state Departments of Transportation (DOTs) and other transportation agencies (Srinivasan, Saleem, et al. 2023, Kolody 2020, Srinivasan, Lan, et al. 2021, Gross, et al. 2021, Carter, et al. 2021). This reliance on crash data stems from the fact that understanding the safety effect of any treatment, e.g., the estimation of crash modification factors (CMFs) in the first edition of the Highway Safety Manual (HSM), is predominantly based on crash frequency by various collision types and levels of severity. However, there are multiple challenges associated with only depending upon crash data to quantify safety performance, which may not align with the goal of adopting a safe system approach with proactive road safety strategies. In a recent NCHRP research report, a guide was developed for assessing the effectiveness of safety treatments without crash data (Porter, et al. 2023). This report states that the second edition of HSM is expected to include surrogate measures of safety to evaluate treatments and estimate CMFs to establish more effective road safety management approaches. Examples of surrogate measures include traffic conflicts and other critical safety events such as lane departures and encroachments, traffic control compliance, steering behaviors, stopping behaviors, and so on.

The utilization of crash frequency and crash rate methodologies has been widespread for pinpointing locations of high crash occurrence and allocating safety funding (Lim and Kweon 2013). However, several drawbacks are associated with relying solely on crash data for road safety analysis. Firstly, there are well-acknowledged issues related to the availability and quality of collision data obtained from police crash reports (Sayed and Zein 1999). Secondly, crashes are infrequent and random, necessitating prolonged observation to account for their stochastic nature and potential confounding factors. This makes it challenging to develop CMFs for novel designs and strategies that lack multiple years of crash data. Thirdly, utilizing collision data for safety analysis takes a reactive approach, requiring a substantial number of crashes to occur before any action can be taken (de Leur and Sayed 2003, Imprialou and Quddus 2019). Fourthly, accumulating sufficient historical crash data, especially for rare types of road incidents such as WWD crashes, can be time-consuming (Zhou, Chang, et al. 2023). This also presents challenges in estimating CMFs for dynamic contexts, such as work zones and various operational strategies that fluctuate with traffic and weather conditions. Additionally, any before-and-after study that depends on historical crash records to assess the effectiveness of a road safety countermeasure may be affected by the regression-to-the-mean (RTM) phenomenon (Elvik 2008). Furthermore, significant discrepancies exist in the non-fatal road crash data provided by various data sources (Janstrup, et al. 2016).

As safety analysis continues to evolve, researchers are broadening their range of data sources and incorporating innovative techniques to enhance the comprehension of highway safety. One prominent application in behavioral studies is the proactive assessment of road safety using surrogate safety methods. This approach traces back to the 1960s when efforts were made to predict the number of collisions based on observations of non-collision events rather than relying solely on historical accident records (Perkins and Harris 1968). Numerous surrogate indicators have been proposed for consideration, including traffic operating factors like speed variance, average traffic density, and critical events such as traffic conflict, lane merging, speeding, and violations like running red lights (Kloeden, Ponte and McLean 2001, Sacchi and Sayed 2016). One of the earliest proposed methods was the Traffic Conflict Technique (TCT) (Hydén and Linderholm 1984). TCT involves the observation of qualitatively defined quasi-collision events, such as situations where road users were exposed to probabilities of collision, often referred to as "near-misses." Comprehensive user trajectories offer periodic updates on individual vehicles' position, velocity, and acceleration. The swift progress in naturalistic driving study has also led to a growing abundance of data collected from sensors within vehicles and smartphones that can derive other surrogate safety measures, such as harsh braking/acceleration events (Guido, et al. 2012, Ziakopoulos, et al. 2022). Therefore, surrogate safety measures represent a burgeoning field of study, but additional investigation is required to integrate them into practical procedures for data-driven safety analysis. These data have been gathered through various means to evaluate the safety of specific road entities (Nikolaou, Ziakopoulos and Yannis 2023), including i) field observations, ii) simulation models, iii) video cameras, and iv) open-source crowdsourced data and aggregated datasets. Each of these methods comes with its own set of advantages and drawbacks. For instance, employing field observers for conflict surveys tends to be costly, and it often needs to grapple with inter- and intra-observer variability, posing challenges to repeatability and consistency (Ismail, et al. 2009). On the other hand, incorporating traffic conflict measurements into simulation models can address some of these limitations. However, these models may not accurately capture the diverse and less predictable driver behaviors observed in real road traffic scenarios (El-Basyouny and Sayed 2013).

Various methods for collecting surrogate safety data include field observations, video cameras, traffic detectors, light detection and ranging (Lidar), probe vehicles, and naturalistic driving studies, etc. Among those, video cameras are mostly used to collect surrogate measures by manual or automated processing. Automated video-camera analysis has proven valuable in addressing the significant limitations of collecting safety measures data via field observers and simulation models (Kim, et al. 2005). Vehicle-level surrogate measures can be derived from continuous tracking of vehicles. This approach offers a complementary solution to tackle data collection and reliability issues while providing a more comprehensive analysis. As a result, mobile and fixed video sensors for traffic monitoring and data collection have become increasingly common on highways and urban streets (Kim, et al. 2005, Gordon, et al. 2012). Numerous recent studies have focused on employing computer vision techniques to identify and track vehicles and other road users in video footage, examining conflicts within complex traffic environments (Sacchi and Sayed 2016, El-Basyouny and Sayed 2013, Laureshyn and Ardö 2006). Commercial video analytics software comes with solid capabilities, encompassing tasks such as configuration management, experiment execution, and the handling of data storage and analysis. Regarding traffic data analysis, its primary functions involve considering vehicle and pedestrian counts, evaluating speed and congestion, and overseeing signal timing across different video sources, including temporary, permanent, and drone footage. **Table 1** offers a selection of video analytics software examples along with their respective functions.

Table 1 Commercial video analytic software and functions

Video Analytics Software	Functions
Transoft Solutions	• Utilizes computer vision and artificial intelligence. • Encompasses the counting of vehicles and pedestrians, measuring speeds, and categorizing various types of road users (TRANSOFT SOLUTIONS 2023).
IntuVision	• Provides comprehensive monitoring of both vehicle and pedestrian movements for both short-term traffic surveys and long-term deployments (IntuVision VA Traffic Solutions 2023).
TrafficVision	• Transforms cameras into intelligent sensors to elevate road safety and situational awareness. • Recognizes potential hazards such as WWD, traffic congestion, and debris on the road (TrafficVision-Roadway Monitoring 2023).
BriefCam	• Specializes in enhancing traffic flow efficiency through the utilization of video analytics. • Categorizes and quantifies pedestrians and various types of vehicles, discerns their movement patterns, identifies congested areas, and subsequently optimizes the overall flow of traffic (Traffic Optimization Techniques for Modern Cities. 2023).
CUBIC	• Utilizes GRIDSMART System to provide a solution that combines intersection actuation, traffic data analysis, and enhanced situational awareness by leveraging the video data gathered from multiple cameras (CUBIC Transportation System 2023).
Azena	• Introduces an innovative real-time traffic monitoring solution for smart traffic management and urban planning. • Leverages deep learning and traffic data analytics to transform how vehicle and pedestrian data is extracted and evaluated (Insights on GoodVision 2023).

Most commercial software is capable of extracting data from videos with precision and rapidity. They are versatile enough to interface with various video feeds, including those from temporary or permanent cameras and imagery captured by drones. However, a common issue is that these programs typically demand a significant investment and more advanced hardware. By contrast, the software developed in this project is designed to be cost-effective while running smoothly on less sophisticated hardware. Moreover, the software created for this project excels specifically in efficiently detecting WWD incidents and undesirable traffic movements.

Based on research into the relative contributions of various factors in crashes, it becomes evident that the human factor, either on its own or in conjunction with other factors, plays the most significant role in causing collisions. Accurate statistics regarding the exact number of violations are challenging due to unrecorded violations and the fact that many observable violations go unnoticed by traffic officers. As computing power, data storage, sensor technology ubiquity, and artificial intelligence continue to advance, identifying and analyzing abnormal or unsafe driving behaviors represents a crucial step in mitigating the crashes caused by reckless drivers. This project introduces an innovative video processing tool designed to detect abnormal driving behaviors, such as WWD and illegal turns, from video footage by portable traffic cameras. Such a video analytic tool holds the potential to enhance highway safety evaluation procedures and provide solutions to address risky driving behaviors at specific locations like interchange terminals and unsignalized intersections.

3 DATA COLLECTION

This section describes the video data collected by portable traffic cameras and fixed detection cameras for this project. The collected data was used to validate the developed tool and conduct case studies.

3.1 Video Data by Portable Traffic Cameras

Two types of video data were collected by portable traffic cameras: video data at interchange terminals for detecting WWD incidents and video data at unsignalized intersections for detecting illegal left turns. The typical traffic-counting camera can record videos with a resolution of 480/720P and a frame rate of 10 fps. The video files were often saved at 30-minute intervals for 72 continuous hours based on the battery limit.

Over 400 hours of video data collected at 14 partial cloverleaf interchange terminals were applied to test the software's function of automatically detecting WWD incidents. Portable traffic cameras with a 170° wide viewing angle were stationed at off-ramp terminals, targeting the entire off-ramp view. A general description of these locations and their respective footage durations is listed in **Table 2**.

Table 2 Video footage of 14 partial cloverleaf interchanges terminals

State	Location	Hours Analyzed
AL	I-65 Exit 284 SB	55
AL	I-65 Exit 208 SB	32
GA	I-85 Exit 147 SB	27
GA	I-75 Exit 61 SB	41
AR	I-40 Exit 260 WB	22
AR	I-40 Exit 94 WB	22
AR	I-40 Exit 55 EB	22
TN	I-40 Exit 172 WB	25
TN	I-40 Exit 182 SB	25
NC	I-77 Exit 79 SB	33
NC	I-77 Exit 79 NB	33
NC	Hwy 421 Exit 234C WB	33
SC	I-85 Exit 106 EB	24
VA	I-81 Exit 141 SB	22
Total		**416**

The second type of video data by portable cameras was collected at seven unsignalized intersections for a continuous 72-hour from Monday to Thursday to capture typical weekday traffic patterns. **Table 3** details the types of locations and the number of illegal left-turn movements through manual observation. The data was used to evaluate the effects of no left turn signs, channelizing island, and median treatment on restricting left turns from the minor road.

Table 3 Restricted left turn data across selected seven unsignalized intersections in Auburn, AL

	North College Street/ Publix Entrance	**Shug Jordan Parkway/ Walmart Exit**	**South College Street/ Southparke Dr**	**Glenn Avenue/ Apartment Entrance**	**Donahue Drive/ Baseball Field Exit**	**Magnolia Avenue/ Restaurant Parking Exit**	**Wire Road/ Parking lot Exit**
Roadway Class	Principal Arterial	Principal Arterial	Principal Arterial	Minor Arterial	Minor Arterial	Minor Arterial	Local
Number of Lanes on Main Road	2	4	4	2	2	3	2
Speed Limit (mph)	50	55	45	25	25	25	20
Median Type	Undivided	Undivided	Divided	Undivided	Undivided	TWLTL	Undivided
Type of Intersection	Three-Leg	Three-Leg	Four-Leg	Three-Leg	Three-Leg	Three-Leg	Four-Leg
Type of Traffic Control Devices Present	Channelizing Island, Right Turn Only Sign, Lane Use Arrow	Channelizing Island, Lane Use Arrow	Channelizing Island	Channelizing Island	Channelizing Island	Two Right Turn Only Signs	Channelizing Island, Right Turn Only Sign, Lane Use Arrow
Observation Hours	8	6	8	8	8	2.5	2
Number of Illegal Left Turns	341	20	7	149	30	6	1

Additional traffic video data collected by portable cameras was analyzed to evaluate the performance of a new median treatment (Ceramic Raised Channel Markers in **Figure 1**) on restricting the left turns at the Uncommon Apartment on West Glenn Ave. in Auburn, AL. **Table 4** lists the number of observation hours, traffic conflicts, and illegal left turns manually extracted. This case study focused on the effects of Ceramic Raised Channel Markers on driver behavior at an intersection near downtown Auburn, Alabama. The objective was to reduce illegal left turns from the Uncommon Apartment complex, which had been a persistent issue despite previous interventions like a raised channel island and additional signage. These markers were chosen for their cost-effectiveness and ease of installation. The analysis involved a total of 40 hours of video footage captured before and after the installation of the markers.

Table 4 Detailed illegal left turn and conflict observations at Uncommon Apartment

	Footage Duration (Hours)	Number of Illegal Left Turns	Number of Conflicts
Before Period	20	186	33
After Period	20	26	10
Grand Total	40	212	43

Figure 1 Ceramic raised channel markers at study site

3.2 Video Data by Fixed Detection Cameras

Different from portable traffic cameras, fixed detection cameras can automatically report surrogate safety data such as critical safety events (WWD incidents and illegal turns). This section discusses the data collected by two detection cameras: the Wrong Way Alert System installed at Heisman Dr. of Auburn University campus and GRIDSMART detection cameras at Glenn Ave. and Gay St. by the City of Auburn.

3.2.1 Video data on wrong-way driving

The "Wrong Way Alert System" is an advanced Intelligent Transportation System (ITS) using thermal cameras to detect vehicles traveling in the wrong direction (illustrated in **Figure 2**). Upon detecting an object moving in the wrong direction within the specified detection zone, the system activates confirmation cameras to record a 2-minute video clip on the wrong-way movements. Every recorded incident is then uploaded to the BlinkLink cloud database, which archives reports on various entities such as vehicles, pedestrians, bicycles, scooters, skateboards, and emergency response vehicles. All reports are meticulously timestamped and dated for accuracy.

Figure 2 Wrong-way alert system configuration

The Wrong Way Alert System collected WWD video data from May 1, 2022, to June 18, 2023. Each incident captured by the system was subject to manual review to confirm. For every detected incident, the system automatically generated 15 consecutive images along with a 2-minute video clip for further analysis. To facilitate analysis, all incidents were manually classified into four distinct categories: Continued wrong-way (WW), Self-Corrected WW, Authorized Motor Vehicles which includes Emergency Response and Maintenance, and Non-Motor Vehicles (pedestrians and bicycles). **Table 5** provides an overview of the total incident data in these four categories for 14 months.

Table 5 Overall distribution of wrong-way driving incident types

Resolutions	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Sun**	**Total**
Continued WW	15	18	22	15	30	237	37	374
Self-Corrected WW	11	11	7	3	5	16	12	65
Authorized Vehicles	106	98	85	105	138	347	59	938
Non-Motor Vehicles	155	143	182	150	172	597	165	1,564
Total	**287**	**270**	**296**	**273**	**345**	**1,197**	**273**	**2,941**

3.2.2 Video data on red-light running and illegal turns

The City of Auburn employed the GRIDSMART system at some intersections for traffic detection. The GRIDSMART detection camera system can track vehicles into and out of the intersection while providing surrogate safety measures such as illegal turns and red-light running movement counts. **Figure 3** illustrates the GRIDSMART detection camera at the Glenn Ave/Gay St. intersection in Auburn, AL.

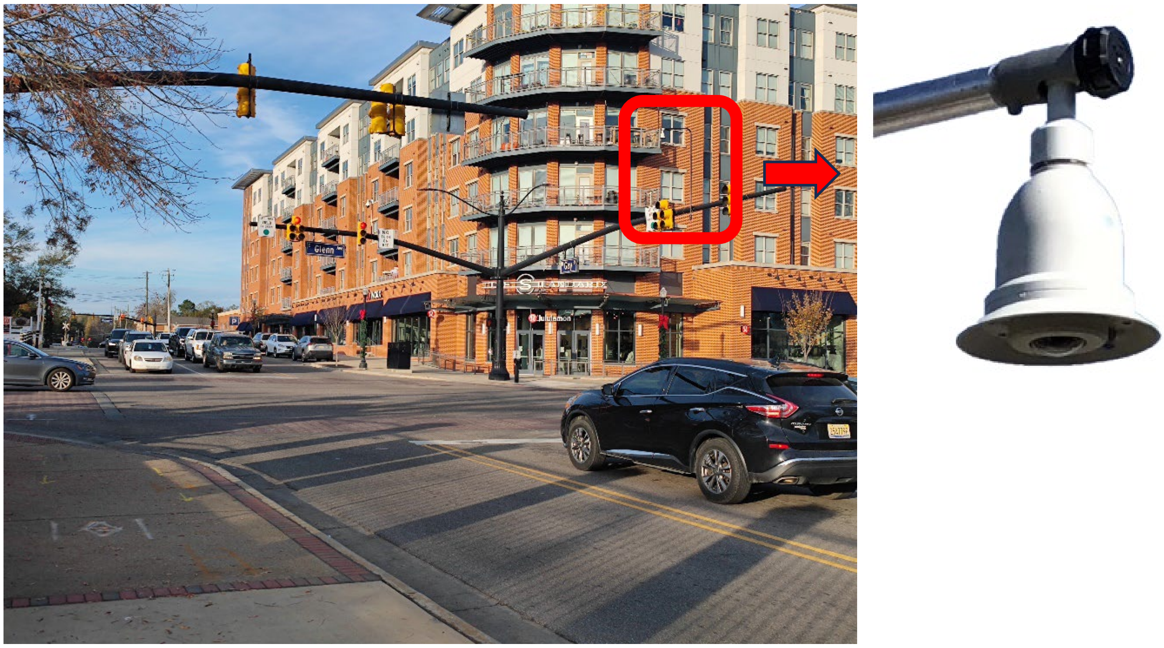


Figure 3 GRIDSMART bell camera

A case study compared incident data that was automatically collected by the camera system with manual observations from recorded video footage. It is essential to highlight that the system's detection zones require manual calibration. This calibration process involves delineating the frame and specifying the operational area for the algorithm. Such calibration provides the necessary granularity, designating details like the boundaries of the through lanes, left-turn lane, right-turn lane, and the location of stop bars.

The analysis of exits-on-red incidents, as shown in **Table 6**, reveals a notable discrepancy between the reports generated by the GRIDSMART system and manual observations. Notably, the system consistently records a higher number of incidents throughout various periods. It is important to note that right turns on red were included as exits-on-red in the system's reporting and were correspondingly counted in manual observations. The difference in reported incidents is measured by the percentage of errors, calculated by subtracting the system-reported incidents from manual observations and then dividing by the manual observations. A negative percentage indicates that the system-reported incidents exceed manual observations. The higher error rate is primarily attributed to the increased traffic volume during these peak times. More importantly, manual observations by researchers suggested this consistent overreporting was linked to drivers not fully stopping at the stop bar and engaging in "false starts." A false start occurs when a driver incorrectly assumes it's their turn to move, such as misreading traffic signals or misjudging right-of-way rules, leading to an initial forward movement followed by a quick stop upon realizing the mistake. An interesting finding is that the westbound lane shows the lowest error rate in the data. The field observation found that GRIDSMART fisheye camera was mounted directly above the westbound lane. Further investigation is recommended to check if the placement of the camera has a direct impact on the errors.

Table 6 Comparison of manually reviewed and system report results of exits-on-red incidents

	Northbound			**Eastbound**			**Southbound**			**Westbound**			**Total**			
Time	Manual		System	Manual		System	Manual		System	Manual		System	Manual		System	% of Errors
	True exit-on-red	Right turn on red		True exit-on-red	Right turn on red		True exit-on-red	Right turn on red		True exit-on-red	Right turn on red		True exit-on-red	Right turn on red		
00:00	0	0	3	1	2	3	0	3	3	0	0	0	1	5	9	-50%
01:00	0	0	0	0	0	0	0	1	0	0	1	3	0	2	3	-50%
02:00	0	0	1	0	0	2	0	3	3	0	1	1	0	4	7	-75%
03:00	0	0	1	0	0	0	0	0	1	0	0	0	0	0	2	NA
04:00	0	1	2	0	1	5	0	0	1	0	2	2	0	4	10	-150%
05:00	0	1	6	0	2	6	0	3	3	0	1	2	0	7	17	-143%
06:00	0	1	6	1	3	10	1	6	7	0	6	6	2	16	29	-61%
07:00	0	2	4	2	9	18	1	2	5	1	4	7	4	17	34	-62%
08:00	0	2	9	0	5	13	0	6	6	0	8	7	0	21	35	-67%
09:00	0	5	12	2	10	16	0	5	6	0	4	4	2	24	38	-46%
10:00	0	9	27	0	6	16	1	4	8	2	4	8	3	23	59	-127%
11:00	0	14	38	3	12	26	0	2	6	0	6	4	3	34	74	-100%
12:00	0	13	37	2	5	15	2	3	6	0	11	8	4	32	66	-83%
13:00	0	7	17	4	6	16	0	7	10	0	4	2	4	24	45	-61%
14:00	0	13	32	2	8	11	0	5	7	1	2	4	3	28	54	-74%
15:00	0	11	31	0	9	14	1	3	5	1	9	12	2	32	62	-82%
16:00	0	13	33	2	12	15	0	6	9	3	6	12	5	37	69	-64%
17:00	1	9	42	2	9	26	0	4	3	1	9	12	4	31	83	-137%
18:00	1	10	34	0	7	11	0	6	12	1	4	7	2	27	64	-121%
19:00	0	11	37	0	6	16	0	10	10	0	9	7	0	36	70	-94%
20:00	0	8	31	2	10	15	1	5	6	0	7	5	3	30	57	-73%
21:00	1	10	35	0	5	13	0	4	6	1	6	9	2	25	63	-133%
22:00	1	7	23	0	3	9	0	7	7	0	11	7	1	28	46	-59%
23:00	0	2	11	1	1	3	0	7	13	1	1	1	2	11	28	-115%
Total	4	149	472	24	131	279	7	102	143	12	116	130	47	498	1,024	-88%
% of Errors	**-208%**			**-80%**			**-31%**			**-2%**			**-88%**			

Similar to the analysis of the exits-on-red incidents, a comparison was made regarding illegal turn incidents, defined here as lane changes made near an intersection. Unlike the consistent overreporting observed in exits-on-red incidents, the illegal turn incidents revealed varying discrepancies across different times and directions, lacking a clear pattern. Notably, the system erroneously reported illegal U-turns, which were not observed during manual checks. This randomness in reporting discrepancies highlights the critical importance of system calibration, particularly in accurately defining traffic lane frames to detect illegal turns. Additionally, the system's reporting format, which aggregates incidents into 30-minute intervals, limits the ability to ascertain the causes of these discrepancies precisely. This lack of detailed incident timing hinders a thorough understanding and analysis of the specific reasons behind the reported variances.

Both Wrong Way Alert System and GRIDSMART software can detect the surrogate safety measures without manually reviewing extensive raw videos. The surrogate safety data collected from these kinds of systems can be used to evaluate the intersection safety performance. However, they tend to be more expensive to install and often unavailable at every intersection. The subsequent section will delve into the details of the methodology for developing a traffic video analysis tool for detecting abnormal movements and conflicts from videos recorded by portable traffic cameras.

Table 7 Comparison of manually reviewed and system report results of illegal turn incidents

	Northbound		Eastbound		Southbound		Westbound		Total		% of Difference
Time	**Manual**	**System**	**Manual**	**System**	**Manual**	**System**	**Manual**	**System**	**Manual**	**System**	
00:00	0	0	3	1	0	0	1	0	4	1	75%
01:00	0	0	2	0	1	0	0	0	3	0	100%
02:00	1	0	3	0	0	0	0	0	4	0	100%
03:00	0	0	2	1	0	0	0	0	2	1	50%
04:00	1	0	3	2	0	0	0	0	4	2	50%
05:00	0	1	2	0	0	0	0	3	2	4	100%
06:00	1	0	3	0	0	2	2	2	6	4	33%
07:00	2	8	7	6	1	2	2	3	12	19	58%
08:00	2	3	4	0	0	0	0	0	6	3	50%
09:00	1	1	1	3	0	1	1	0	3	5	67%
10:00	4	0	0	0	1	3	1	1	6	4	33%
11:00	4	3	3	9	0	0	1	1	8	13	-63%
12:00	1	1	5	7	0	2	2	2	8	12	-50%
13:00	2	5	2	10	1	6	5	1	10	22	-120%
14:00	5	8	2	3	0	4	2	0	9	15	-67%
15:00	3	1	4	0	1	4	2	1	10	6	40%
16:00	1	2	6	1	0	4	0	0	7	7	0%
17:00	3	10	9	2	1	2	1	4	14	18	-29%
18:00	3	11	0	0	1	6	2	0	6	17	-183%
19:00	1	5	5	4	2	1	5	0	13	10	23%
20:00	0	6	2	2	1	1	0	2	3	11	-267%
21:00	3	3	3	0	4	2	0	2	10	7	30%
22:00	2	2	4	3	0	0	2	3	8	8	0%
23:00	0	7	3	2	3	0	1	1	7	10	-43%
Total	40	77	78	56	17	40	30	26	165	199	-21%
% of Difference	**-93%**		**28%**		**-135%**		**13%**		**-21%**		

4 METHODOLOGY

The proposed method for detecting WWD via videos at interchange terminals comprises four sequential steps: video preprocessing, unsupervised learning, abnormal trajectory detection, and WWD confirmation, as illustrated in **Figure 4**. The video input consists of recorded footage by portable cameras. During video preprocessing, vehicle trajectories are extracted and converted into text files. In the subsequent unsupervised learning step, routine traffic maneuvers are identified based on these trajectories, and abnormal vehicle trajectories are filtered out in the third step. Finally, WWD trajectories undergo further confirmation. Using these trajectories enables the development of accurate traffic volume measurement techniques and effective detection of potential conflicts. This trajectory-based approach ensures a more data-driven technique, potentially yielding more reliable and insightful results. The detailed operation of these steps is elaborated in the following sections.

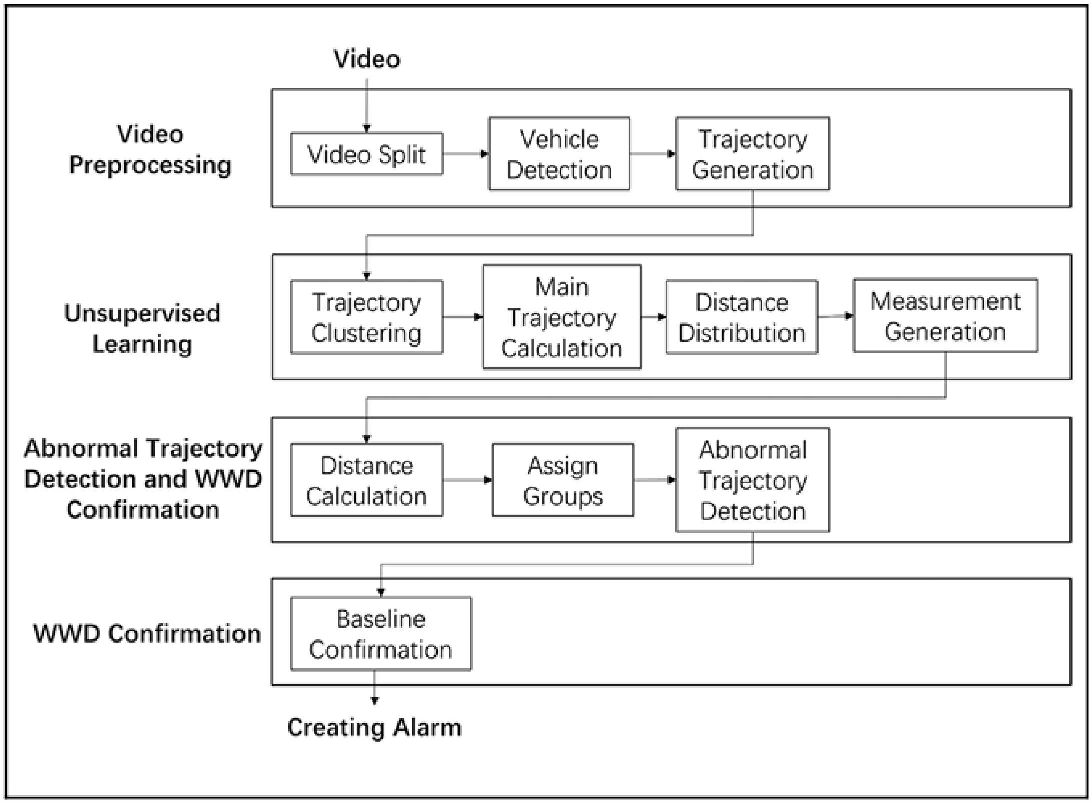


Figure 4 Architecture of the wrong-way driving detection method

4.1 Video Preprocessing

The video preprocessing stage was to extract vehicle trajectory details from the video and transform them into text-based files for subsequent analysis. In object detection algorithm's initial phase, videos must be divided into individual frames. The Opensource Computer Vision Library was used to break down continuous frames into images, which were then stored locally for object detection (Lee, Han and Whang 2007).

Numerous well-trained algorithms can be utilized to perform object detection tasks, and these algorithms often make a tradeoff between speed and precision. A notable example is Fast R-CNN, a classical object detection algorithm that prioritizes detection precision at the expense of speed (Girshick 2015). In this research, YOLOv3, a versatile algorithm configured for either speed or precision based on specific research requirements (Redmon, Divvala, et al. 2016), was selected. Notably, YOLOv3 represents the third generation of the YOLO algorithm, showcasing significant improvements in both speed and precision compared to its predecessor. YOLOv3, capable of identifying 80 object categories from the Common Objects in the Context training dataset, was tailored for this study to focus exclusively on vehicle detection. The original YOLOv3 code was modified to recognize only the following categories: car, bus, and truck. The images generated in the preceding step were input into the YOLOv3 algorithm, which identified and outlined vehicles in each image using rectangles, as shown in **Figure 5 (a)**. Subsequently, the coordinates of the all the vertices defining each rectangle were recorded into a text file, representing the vehicles' positions in each image.

Utilizing the vehicle position information in each frame, the SORT algorithm produced vehicle trajectories across multiple continuous frames (Redmon and Farhadi 2018). Introduced in 2016, SORT stands out as a multiple-object tracking algorithm with state-of-the-art performance. It takes a sequence of coordinates generated by YOLOv3 as input and employs the intersection over union (IOU) distance to correlate each rectangle between frames. IOU distance signifies the overlapping ratio between two rectangles, with a higher IOU value indicating a greater likelihood that two rectangles from different frames pertain to the exact vehicle. Leveraging the coordinates of the rectangles, SORT matches them in the current frame with those from the previous frame, enabling the generation of trajectories for each rectangle (representing a vehicle). These trajectories are then recorded as a text file, as depicted in **Figure 5 (b)**. At this process stage, the vehicle trajectories have been extracted from the videos and presented in a text format.

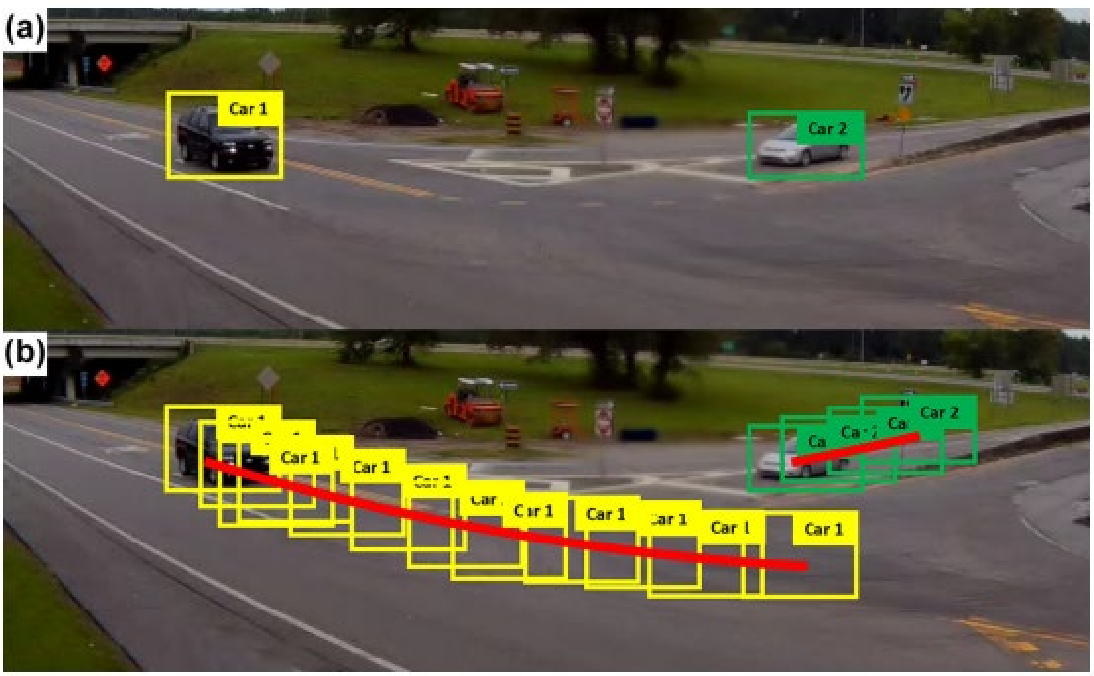


Figure 5 Vehicle detection and tracking: (a) object detection and (b) object tracking

4.2 Unsupervised Learning

The initial phase in performing WWD detection involves recognizing routine traffic maneuvers by analyzing diverse vehicle trajectories—a stage characterized as self-learning. Abnormal vehicle trajectories are notably infrequent compared to the common patterns exhibited by routine vehicle trajectories. Researchers manually scrutinized several hundred hours of traffic videos and observed that most vehicle trajectories adhered to the correct traffic maneuvers at each testing location. Therefore, the self-learning stage effectively generated routine vehicle trajectories by clustering similar trajectories, contingent upon the input of a substantial volume of data.

Several trajectory clustering algorithms are capable of grouping similar trajectories into a single cluster and generate a representative trajectory for that cluster. This representative trajectory can then be utilized to identify routine traffic maneuvers (Bewley, et al. 2016, Yuan, et al. 2017, Won, et al. 2009). However, a crucial consideration precedes the selection of a trajectory clustering algorithm: some vehicle trajectories derived from the preceding stage may not always be continuous. Instead, a complete trajectory may consist of multiple sub-trajectories. This issue may arise from either failure in object detection in specific frames or interruptions in tracking due to overlapping vehicles. In such cases, it is vital to consider the sub-trajectories since they constitute essential components of the complete trajectories. To address this concern, a trajectory clustering algorithm based on a partition-and-group framework was employed (Won, et al. 2009).

The partition-and-group framework offered the advantage of identifying common sub-trajectories by dividing a trajectory into a set of line segments based on the minimum description length, as shown in **Figure 6 (a)**. Following this partitioning, all trajectories were transformed into line segments, and a density-based clustering algorithm was applied to create clusters of similar trajectories using these line segments (Lee, Han and Whang 2007) (**Figure 6 (b)**). Subsequently, the representative trajectory that characterizes the overall movement of each cluster was computed (**Figure 6 (c)**). Given the abundance of detailed information on the partition-and-group framework, this report provides only the foundational aspects of the theory. Interested readers can refer to the work of Won et al. for further insights (Won, et al. 2009). At the end of this process, the algorithm had acquired the ability to discern routine traffic maneuvers, contingent upon the availability of sufficient training data.

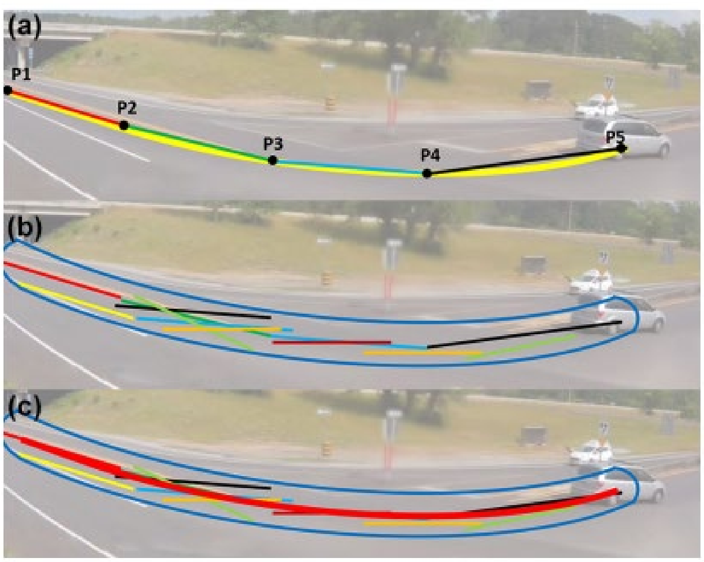


Figure 6 Partition-and-group based trajectory clustering: (a) raw trajectory partition, (b) density-based clustering, and (c) representative trajectory.

4.3 Abnormal Trajectory Detection

During the unsupervised learning step, representative trajectories were identified for each cluster to portray normal traffic maneuvers. Establishing an acceptable range becomes crucial when determining whether a new trajectory aligns with normal traffic maneuvers, as new trajectories seldom overlap entirely with the representative trajectories. To accomplish this, a set of distances was computed for each cluster, encompassing the distances between each trajectory and its representative trajectory. This distance set enables the estimation of the overall dispersion for each cluster, and an acceptable range can be established using the mean and standard deviation of the distance set. **Figure 7**, coupled with **Equations (1)** to **(5)**, visually demonstrates the distance calculation between trajectories. Notably, this distance calculation is rooted in part of the trajectory clustering algorithm devised by Lee et al. (Lee, Han and Whang 2007).

The calculation procedure involves partitioning two trajectories, T_1 and T_2, into line segments represented by s_i and e_j, as illustrated in **Figure 7 (a)**. To compute the distance from T_1 and T_2, the distance of each line segment from T_1 and T_2 needs to be considered. As per **Equation (1)**, the distance between T_1 and T_2 is calculated by averaging the distances between s_i and T_2. The distance between each line segment s_i and T_2 is determined by finding the minimum distance from s_i to any e_j generated by T_2, as shown in **Equation (2)**.

$$dist(T_1, T_2) = AVG\{dist(s_i, T_2), s_i \in T_1\} \tag{1}$$

$$dist(s_i, T_2) = min\{dist(s_i, e_j), s_i \in T_1, e_j \in T_2\} \tag{2}$$

$$dist(s_i, e_j) = a_1 \cdot d_\perp + a_2 \cdot d_\theta \tag{3}$$

$$d_\perp = \frac{L_{\perp 1}^2 + L_{\perp 2}^2}{L_{\perp 1} + L_{\perp 2}} \tag{4}$$

$$d_\theta = \begin{cases} ||e_j|| \cdot sin\theta, if\ 0° \leq \theta \leq 90° \\ ||e_j||, if\ 90° \leq \theta \leq 180° \end{cases} \tag{5}$$

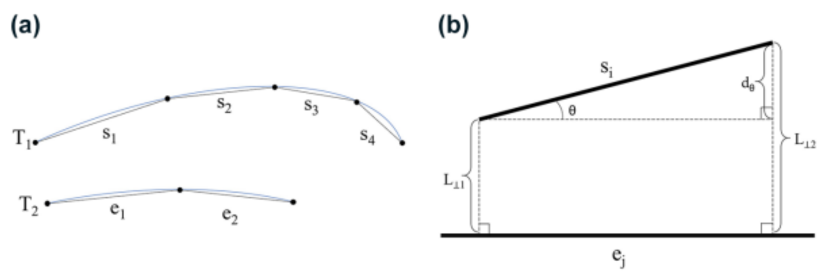


Figure 7 Distance calculation between two trajectories: (a) distance between trajectories and (b) distance between line segments

For computing the distance between line segments, as depicted in **Figure 7 (b)**, a longer line segment was designated as e_j, and a shorter line segment was denoted as s_i. The distance between s_i and e_j (dist (s_i, e_j)) was composed of two components: the perpendicular distance ($d_\perp$) and the angular distance (d_θ), as expressed in **Equation (3)**. The parameters a_1 and a_2 represent the weights assigned to these two distances, allowing for adjustment based on specific research requirements. For instance, if the study aims to discern differences in directions between line segments, the parameter a_2 could be heightened to increase the sensitivity of d_θ. **Equations (4)** and **(5)** were employed to calculate $d_\perp$ and d_θ, where $L_{\perp 1}$ and $L_{\perp 2}$ denote the Euclidean distances from the two endpoints of s_i to the projection point on e_j; k e_j k represents the length of e_j; and u signifies the angle between s_i and e_j.

After generating the distance set between each trajectory and the main trajectory for each cluster, the mean and standard deviation of this distance set were computed. Following the empirical rule, which states that 99.7% of data following a normal distribution fall within the mean ± 3*standard deviation, this statistical information was utilized. Given that the majority of trajectories represent the normal operation of a vehicle, a factor of mean ± 3*standard deviation was applied to create a buffer around the main trajectory in each cluster, thereby establishing an acceptable range. When a new trajectory was introduced, it was assigned to the nearest cluster based on its distance to each representative trajectory. The determination of whether the trajectory fell within the category of abnormal trajectories depended on whether it fell within the acceptable range. It is important to note that an abnormal trajectory might also occur in the training set; in such cases, it would be promptly identified, and the confirmation of WWD would be conducted in the subsequent stage.

As shown in **Figure 8**, the black curve represents the representative trajectory characterizing the paths taken by left-turn vehicles from the crossroad toward the entrance ramp. The green band is generated by buffering the representative trajectory using the mean and standard deviation of the distance set, allowing for adjustment in various scenarios. Notably, the distance between the blue and representative trajectories falls within the green acceptable range. Consequently, the blue trajectory is categorized as a routine trajectory. In contrast, the red trajectory is identified as abnormal due to its substantial deviation from the representative trajectory. At this point, the red trajectory is flagged as a potential WWD incident that necessitates confirmation.

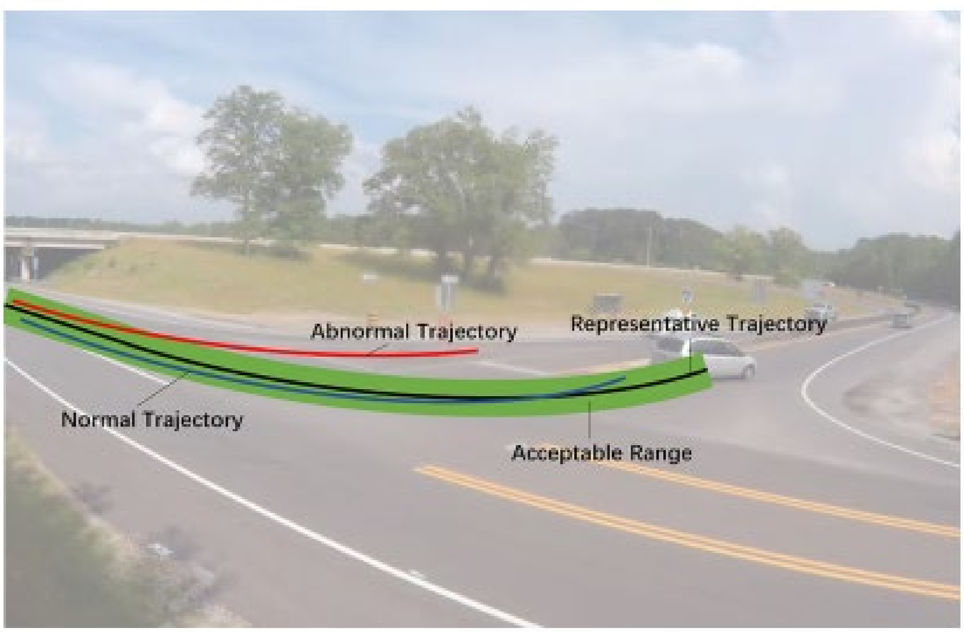


Figure 8 Abnormal trajectory detection

4.4 Wrong-Way Driving Confirmation

After completing the preceding steps, trajectory clustering can extract abnormal trajectories from videos. However, since this project aims to identify WWD incidents, further screening of abnormal trajectories is necessary. In this stage, a baseline for the potential WWD route is selected, and WWD candidates are identified based on whether the abnormal trajectories intersect with this baseline. It is important to note that the line segments generated by the trajectory are still utilized for this calculation. Before delving into the details of how this calculation is carried out, some notations need to be defined: the coordinates of the two ends of the line segment from a trajectory are represented as $V_1(x_1, y_1)$ and $V_2(x_2, y_2)$, while the coordinates of the two ends of the baseline are represented as $B_1(w_1, z_1)$ and $B_2(w_2, z_2)$. To ascertain whether these two segments intersect, the cross product can be employed, as illustrated in **Equations (6)** and **(7).**

$$\begin{cases} d_1 = (V_2 - V_1) * (B_1 - V_1) \\ d_2 = (V_2 - V_1) * (B_2 - V_1) \\ d_3 = (B_2 - B_1) * (V_2 - B_1) \\ d_4 = (B_2 - B_1) * (V_1 - B_1) \end{cases} \quad (6)$$

$$\begin{cases} Yes \quad When\ d_1 * d_2 < 0\ and\ d_3 * d_4 < 0 \\ Yes \quad When\ d_1 * d_2 = 0\ or\ d_3 * d_4 = 0 \\ No\ Otherwise \end{cases} \quad (7)$$

Table 8 Operation and performance of detection function

Module name	**Input data**	**Output data**	**Time spent by computer (second)**	**Time spent by humans (second)**
Video split	Five 30-min videos	5 × 18,000 frames	229	0
Object detection	5 × 18,000 frames	Vehicle coordinates in 5 × 18,000 frames	2,700	0
Object tracking	Vehicle coordinates in 5 × 18,000 frames	Vehicle trajectories in 5 videos	61	0
Trajectory clustering	Vehicle trajectories from 1 video (training set)	5 clusters with the representative trajectory	74	0
Abnormal trajectory detection	(1) 5 clusters with representative trajectory and the correspondence trajectories	(1) Acceptable range	9	0
WWD confirmation	(2) Vehicle trajectories from the other 4 videos (testing set) Abnormal trajectories	(2) Abnormal trajectories	<1	9,000

In the calculation, each line segment produced by the abnormal trajectories needs to be considered, as only one segment will intersect with the baseline if the trajectory indicates a WWD incident. Ultimately, the abnormal trajectories intersecting with the baseline are identified and reported as WWD candidates. Additionally, the timestamps corresponding to these trajectories are reported for further verification. **Table 8** summarizes the operational performance of the software detection functions, including the input data and output data for each step of the automatic detection tool. It also contains the estimated time for analyzing five thirty-minutes videos by both the software and human observer.

4.5 Trajectory-based Off-line Conflict Detection

The system dissects each trajectory into segments and discerns conflicts by examining the intersections of these segments within specific time intervals. This approach enables the precise detection of potential traffic conflicts based on movement patterns and timing. Calculating the intersection between two directly continuous trajectories poses challenges. To overcome this issue, several segments are utilized to approximate the trajectories, as depicted in **Figure 9**. Through this segmented approach, one can systematically pair segments from two trajectories and assess for intersections. Identifying any intersecting segment pairs indicates a potential conflict or crossing of paths between the original trajectories. This method facilitates a more computationally efficient and accurate analysis.

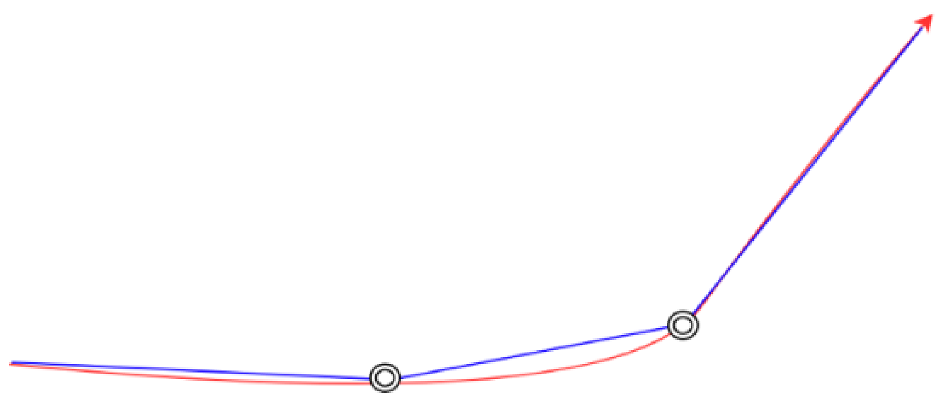


Figure 9 Trajectory segmentation

For each trajectory, the system follows the process illustrated in **Figure 10**. In this depiction, the red line signifies the target trajectory. At the same time, the black bars represent trajectories with timesteps falling within the Potential Conflict Evaluation Time range, commencing from the initial timestep of the target trajectory. Initially, the trajectories were simplified into several segments for enhanced computational efficiency. Following this, the intersection points between the target trajectory and those delineated by the blue lines were identified. With all intersection points identified, verifying whether they lie within the conflict area becomes straightforward.

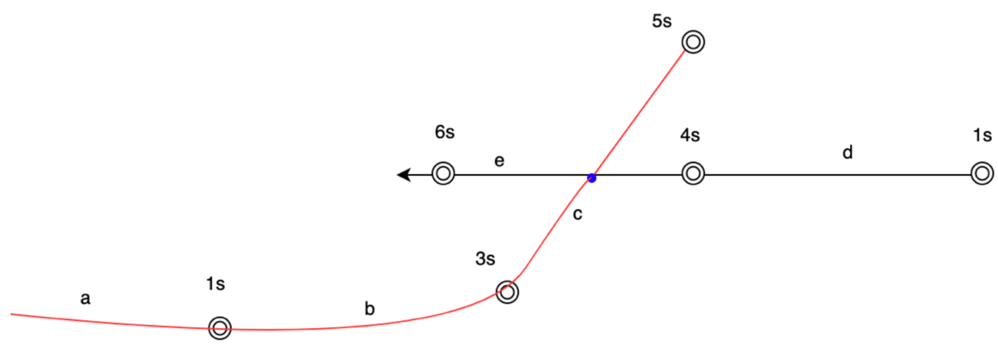


Figure 10 Conflict detection

4.6 Program Graphical User Interface

A user interface was developed to facilitate the process. The user can click the "START" button to start this application. Then, the user can select a video file for analysis. A detailed description of the user interface is contained in Appendix A.

5 ANALYSIS RESULTS

This section presents the results of comparing WWD incident data extracted by the tool and manual method. The results of case studies of the effects of channelized islands and no-turn signs on illegal left turns are contained in Appendix B. A case study of the effectiveness evaluation of Ceramic Raised Channel Markers in restricting illegal left turns is contained in Appendix C. The detailed evaluation results of the Wrong-way Alert System are contained in Appendix D.

In this study, the developed video analytics software was tested by a comprehensive dataset encompassing 416 hours of video footage. This footage was sourced from 14 partial cloverleaf interchange terminals, as outlined in Chapter 3. The algorithm's performance was evaluated by examining two crucial metrics: completeness and precision, serving as indicators of the algorithm's detection reliability and accuracy. **Table 9** illustrates the counts of manually observed actual WWD incidents in comparison to those detected by the software at each location. To evaluate the effectiveness of the detection algorithm, several key terms were defined as follows:

- “WWD incidents” are considered to be a negative class.
- “True Positive” (TP) refers to instances where the algorithm correctly identified a WWD incident.
- “False Positive” (FP) refers to instances where the algorithm mistakenly flagged a normal driving maneuver as a WWD.
- “False Negative” (FN) refers to instances where the algorithm failed to recognize a WWD incident, incorrectly marking it as a normal driving maneuver.

As normal driving actions were too widespread to quantify in the video data manually, the statistics for "True Negative" (TN) are not provided. In evaluating the algorithm, two metrics were employed:

- Precision – indicates the proportion of actual WWD incidents detected by the algorithm.
- Completeness – indicates the proportion of all actual WWD incidents that the algorithm successfully detected.

Table 9 Detection results for different locations

State	Location	No. of WWD (manual)	No. of WWD (detected)	TP	FP	FN	Completeness (%)	Precision
AL	I-65 Exit 284 SB	11	15	11	4	0	100	81
AL	I-65 Exit 208 SB	3	6	3	3	0	100	50
GA	I-85 Exit 147 SB	12	15	12	3	0	100	80
GA	I-75 Exit 61 SB	8	11	8	3	0	100	73
AR	I-40 Exit 260 WB	3	5	3	2	0	100	60
AR	I-40 Exit 94 WB	1	2	1	1	0	100	50
AR	I-40 Exit 55 EB	7	7	7	0	0	100	100
TN	I-40 Exit 172 WB	2	2	2	0	0	100	100
TN	I-40 Exit 182 SB	1	1	1	0	0	100	100
NC	I-77 Exit 79 SB	20	24	20	4	0	100	83
NC	I-77 Exit 79 NB	1	1	1	0	0	100	100
NC	Hwy421 Exit 234C WB	8	10	8	2	0	100	80
SC	I-85 Exit 106 EB	3	3	3	0	0	100	100
VA	I-81 Exit 141 SB	3	4	3	1	0	100	75
Total		**83**	**102**	**83**	**23**	**0**	**100**	**80**

Note: TP = True Positive, FP = False Positive, FN = False Negative

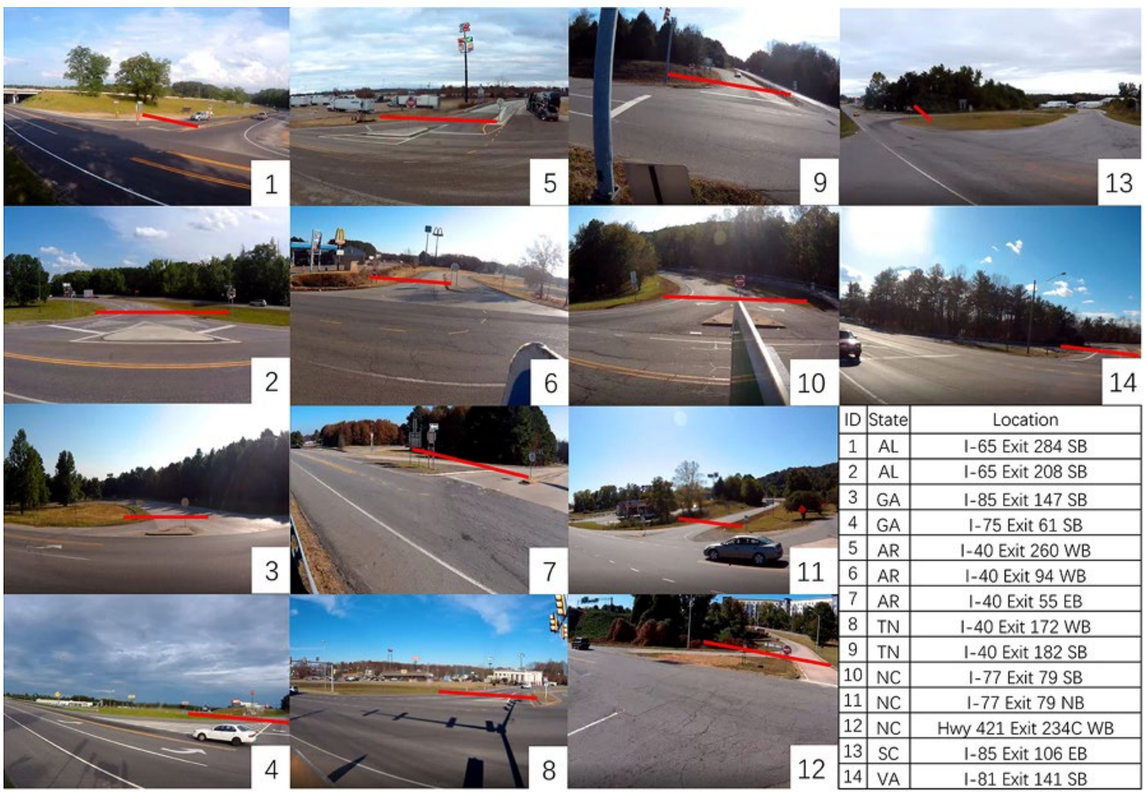
These metrics are mathematically defined in **Equations (8) and (9)**, respectively.

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Completeness = \frac{TP}{\#WWD(Manually\ Observed)} \tag{9}$$

Referring to **Table 9**, the total completeness of 100% signifies that the algorithm successfully detected all manually observed WWD incidents. However, the presence of false alerts (FPs) resulted in an average precision of 80% for the algorithm. As explained in the Methodology section of Chapter 4, the detection results underwent filtering through the final WWD confirmation process, emphasizing the significant impact of the baseline setting on the ultimate output. **Figure 11** visually depicts the design features for each location, including the actual baseline set by the researchers. However, despite adjustments to the baseline settings, certain FPs persisted. A thorough examination of the source videos revealed that these FPs were frequently associated with trucks. Two primary issues related to trucks contributed to these inaccuracies. Firstly, due to their larger size than regular passenger vehicles, trucks generate oversized detection rectangle markers, particularly those with single or multi-trailers. If the training data lacks sufficient truck examples, the SORT algorithm might produce a trajectory significantly deviating from the representative trajectory, as depicted in **Figure 12a**. Consequently, these trajectories are erroneously classified as abnormal. Secondly, trucks transporting cars on their flatbeds pose another challenge. The detection system may mistakenly identify the carried vehicles as operational individual vehicles on the road, leading to additional abnormal trajectory data intersecting with the baseline, as illustrated in **Figure 12b**.

Overall, the analysis of the video analytics software's performance in detecting WWD incidents reveals significant achievements and areas for improvement. The algorithm achieved a 100% completeness rate, successfully detecting all manually observed WWD incidents and demonstrating its reliability in identifying true incidents. However, the precision rate stood at 80%, primarily due to false positives associated with larger vehicles, particularly trucks. Challenges included oversized detection rectangles for trucks and the misidentification of vehicles on flatbeds as operational vehicles, indicating a need for more diverse training data and refined detection algorithms. The impact of baseline settings on the algorithm's output was also evident, suggesting that fine-tuning these parameters could enhance precision. These insights highlight the algorithm's potential in traffic monitoring while underscoring the necessity for further development to improve accuracy, especially in complex vehicle detection scenarios.



ID	State	Location
1	AL	I-65 Exit 284 SB
2	AL	I-65 Exit 208 SB
3	GA	I-85 Exit 147 SB
4	GA	I-75 Exit 61 SB
5	AR	I-40 Exit 260 WB
6	AR	I-40 Exit 94 WB
7	AR	I-40 Exit 55 EB
8	TN	I-40 Exit 172 WB
9	TN	I-40 Exit 182 SB
10	NC	I-77 Exit 79 SB
11	NC	I-77 Exit 79 NB
12	NC	Hwy 421 Exit 234C WB
13	SC	I-85 Exit 106 EB
14	VA	I-81 Exit 141 SB

Figure 11 Design features and baseline setting for each location

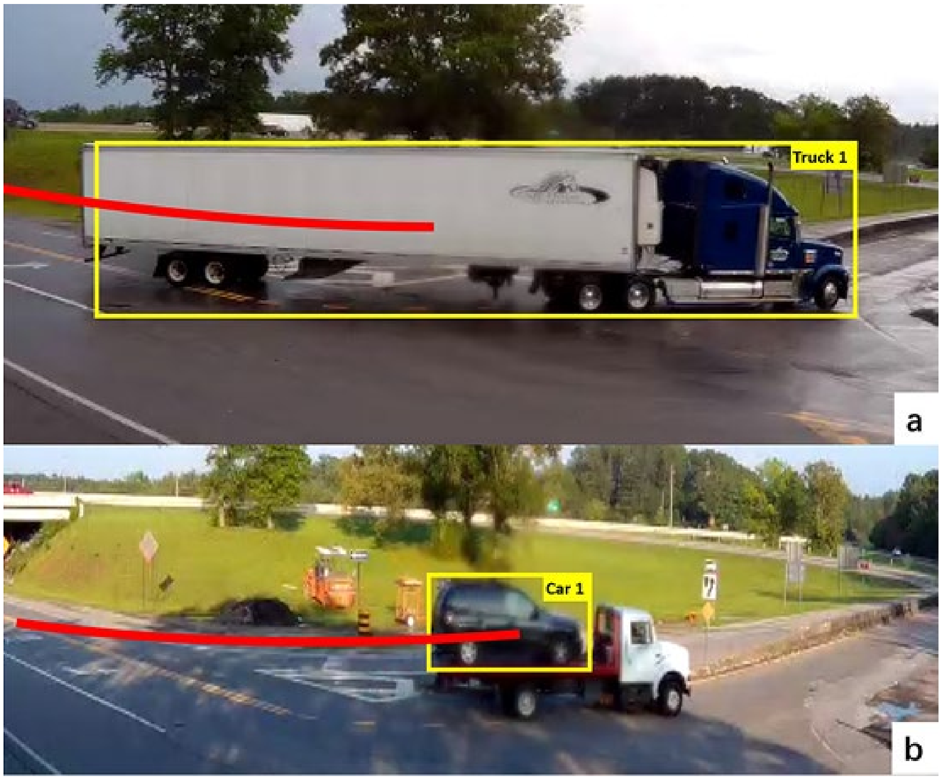


Figure 12 Two types of false alert: (a) oversized vehicle and (b) passenger vehicle carried by truck

6 CONCLUSIONS

This study represents a significant advancement in the proactive assessment of highway safety performance, particularly in WWD incidents and illegal left turns using traffic video data. The development and implementation of the video analytics software, tested across a comprehensive dataset of 416 hours of footage by portable traffic cameras from various interchange terminals, have yielded crucial insights into the potential and challenges of employing technology in detecting WWD incident. The software demonstrated exceptional performance in terms of completeness, successfully identifying 100% of manually observed WWD incidents. This achievement underscores the software's capability to reliably detect actual traffic safety incidents. However, the precision rate of 80%, affected primarily by false positives related to larger vehicles like trucks, indicates areas for improvement. Issues such as oversized detection rectangles and misidentification of vehicles on flatbeds highlight the need for a more diverse training dataset and refined algorithmic approaches to enhance the accuracy of abnormal traffic movement detection.

The persistence of false positives despite adjustments in baseline settings further suggests that while the software is a significant step forward, there is a need for continuous development and refinement. Addressing these challenges will improve the tool's precision and contribute to the broader goal of enhancing road safety through technology-driven solutions. Additionally, a significant limitation of the tool is its inability to process footage captured at night effectively. This shortcoming is particularly concerning given the known correlation between WWD incidents and impaired driving, often related to alcohol consumption, which tends to be more prevalent during nighttime hours. Factors like insufficient lighting and challenges in retroreflectivity further exacerbate the risk of WWD movements under low visibility conditions. Recent interdisciplinary studies and projects, which combine expertise from transportation and computer science with a focus on machine learning, are increasingly addressing the challenge of vehicle identification in nighttime conditions. Incorporating advancements from these fields into the development of the tool could significantly enhance its effectiveness, particularly in detecting and analyzing nighttime traffic incidents, thereby bolstering its overall contribution to highway safety.

This study also demonstrates the feasibility and effectiveness of video analytics in traffic safety evaluation projects through three case studies in Appendices B-D. It emphasizes the importance of adopting proactive strategies in highway safety performance evaluation, moving beyond traditional methods to embrace technological innovations. The insights and findings from this research provide a solid foundation for more sophisticated and accurate tools for traffic safety analysis and intervention.

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APPENDIX A: User Interface Instructions

Figure A-1 shows the user can click the "START" button to start this application. Then, the user can select a folder or single video for analysis. If a user selects a single video file, the canvas will display the uploaded video's first frame. If the user selects a folder with multiple files for analysis, the canvas will list all file names in the same folder.

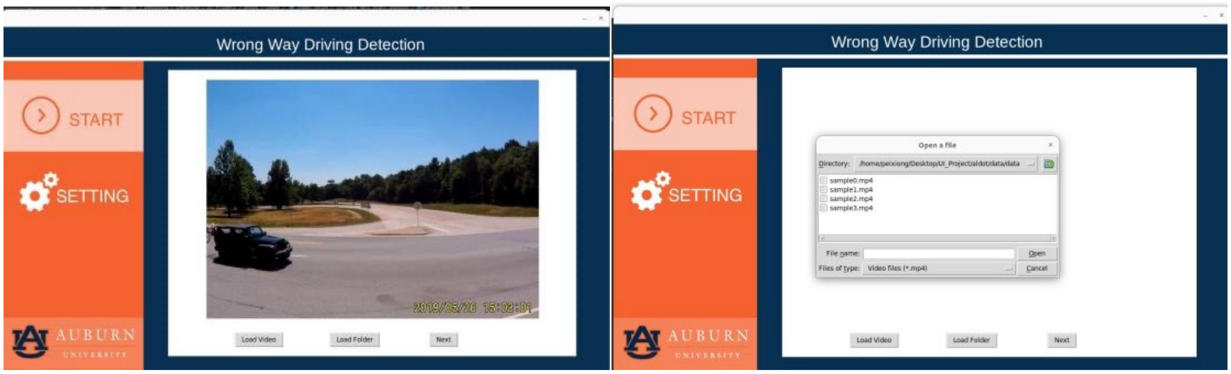

Figure A-1 Application instruction at the starting stage

Second, the user clicks the "Next" button to jump to the interface of the progress bar, then click on the button "Run Detection," the progress bar starts working to show the user the loading status of a file or folder.

Then, the user clicks “setting” to enter a page of setting parameters and then clicks “load” to select the video to be analyzed (**Figure A-2**). After the video is selected, the interface will display the first frame of the current video (**Figure A-3**).

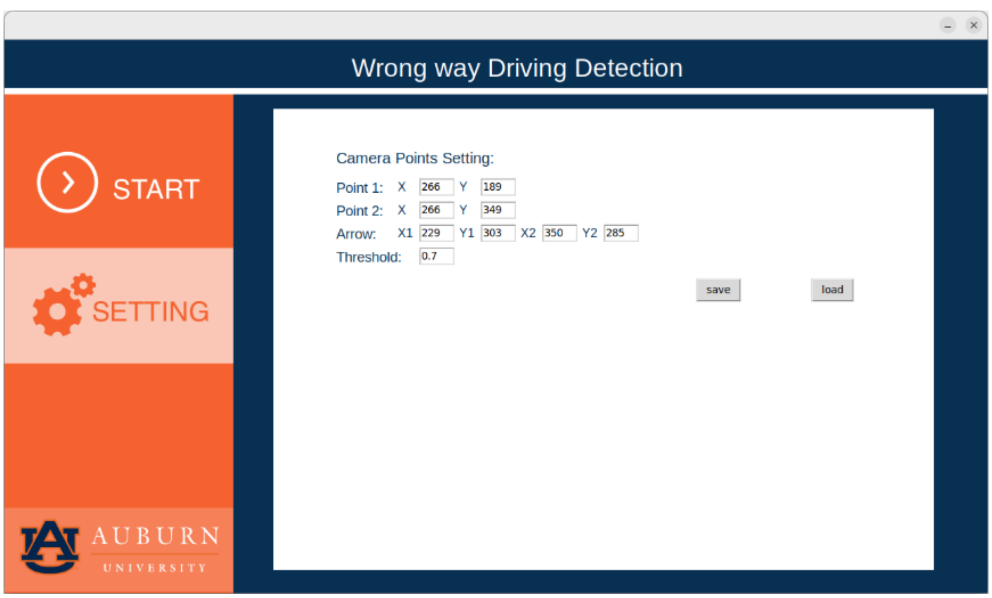

Figure A-2 User interface of setting

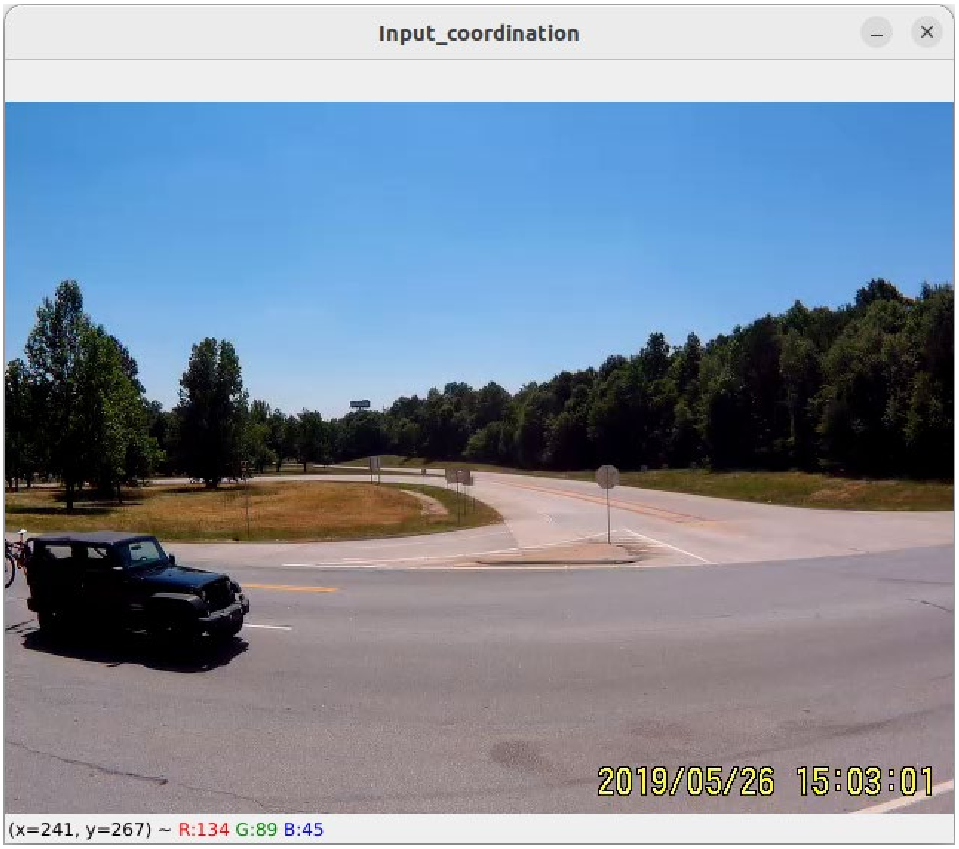

Figure A-3 The first frame of the selected video footage

Then, the user defines the wrong way on the current picture. First, the user marks the road section that needs to be tested in the image, as shown in **Figure A-4**. The user clicks the left mouse button on the location that needs to be marked in the picture, and the coordinates of the current point will be displayed. Then, the user will continue to click the left mouse button on other locations needing marking.

After defining the wrong way in the picture, if the user wants to re-mark it, press “C” (c means clean) on the keyboard, and if the mark is confirmed, press “Q” (q means quit) on the keyboard. Then, these parameters will be saved and applied automatically in the user interface of the setting, which means the wrong way movement has been defined.

Then, the user can click the "START" button and upload the video for analysis by clicking “upload.” If a user selects a video, the canvas will display the uploaded video's first frame immediately (**Figure A-5**).

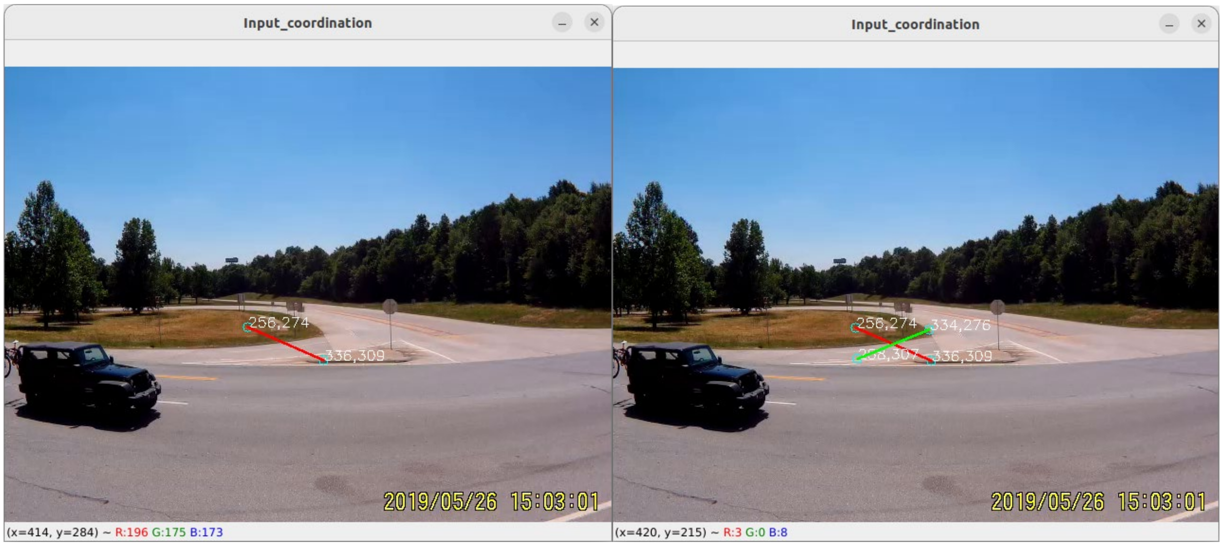

Figure A-4 Configuration of coordinates for identifying WWD incident

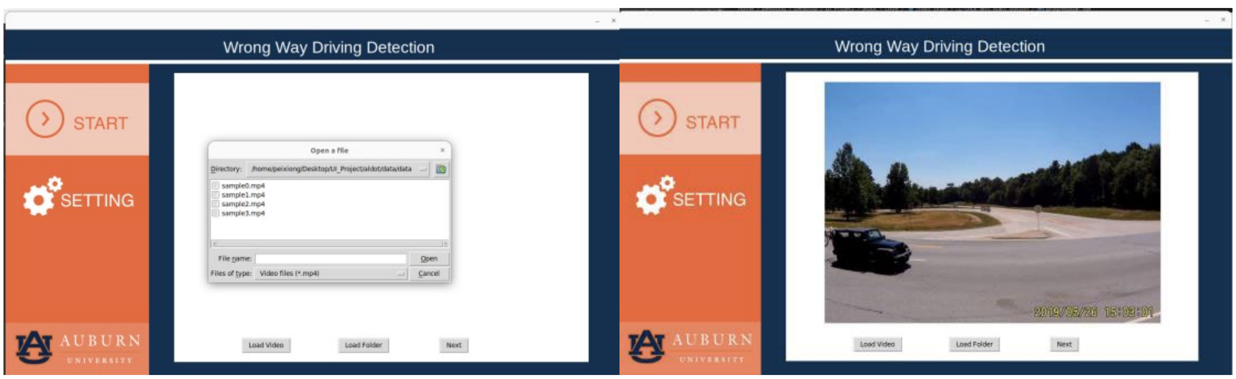

Figure A-5 User interface of the application at the start of analysis

After that, the user clicks the "Next" button to jump to the interface of the progress bar, then clicks the "Run Detection." The progress bar shows the user the loading status of a file and displays a piece of information to tell the user how many frames of the wrong-way movement were tested. Please see **Figure A-6**.

The user clicks "Details," It will jump to the following interface and show the corresponding picture (frame) of the detected wrong-way movement (**Figure A-7**).

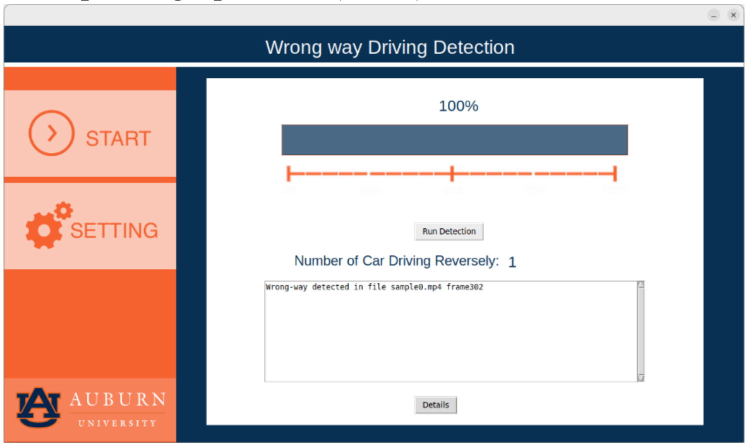

Figure A-6 User interface of file loading

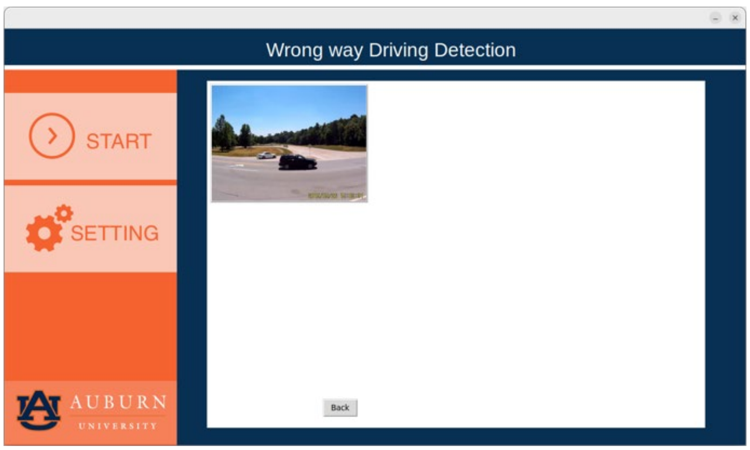

Figure A-7 User interface of detected incident screenshot

Finally, click the picture, and the user will see the short video clip of the WWD incidents (**Figure A-8**).

Figure A-8 Detected WWD incident video clip

APPENDIX B: A Study of Driver Behavior at Access Points with Restricted Left Turn Movements: Case Studies in Alabama

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ABSTRACT

The objective of this study is to study driver behaviors, such as undesirable movements and traffic conflicts, at access points with restricted left turn design. Three unsignalized intersections with restricted left-turn designs in Auburn, AL, were selected for this study. 72-hour traffic video data were collected at each location. The undesirable movements and traffic conflicts were recorded for analysis of driver behavior. In addition, eye-tracking devices were used to see what traffic control devices drivers use at the study sites. The data analysis showed the impact of pavement conditions, traffic signage, and median types on driver behavior. The results recommended that channelized islands alone at driveways cannot restrict left-turn movements. It should work together with a raised median, enhanced signage, and pavement marking to restrict left turns and make right-turn only intersections safer.

Keywords: driver behaviors, undesirable movements, restricted left-turn design, channelized island

INTRODUCTION

Restricted left turn design has been widely implemented by transportation agencies to reduce left-turn related conflicts and crashes at unsignalized intersections. There have been numerous studies (*1-6*) in the past to study the safety and operational effects of using a right turn followed by U-turns to replace direct left-turn movements. Most of these studies (*2*) analyzed the historical crash or traffic conflict data before and after the improvements. Few studies investigated driver behavior at restricted left-turn access points. Some of these behaviors reflect public perception or acceptance of this type of design. Engineers have developed detailed design guidelines on how to apply different geometric design elements and traffic control devices to restrict left-turn movements and provide an alternative for them. For example, a raised channelized island is often installed on minor roads to direct traffic into turning right. A "Right Turn Only" sign is required to convey to motorists the need to turn right instead of left when coming out of an access point. The lane-use arrows are recommended for providing additional guidance to the driver (*7*). Sometimes, a "Do Not Enter" (DNE) sign is used to keep traffic from driving on the wrong side of the channelized island.

The objective of this study is to explore driving behavior at restricted left-turn access points through case studies in Alabama. Three locations were selected to represent three different general types of intersections in Alabama. A 72-hour traffic video was collected at each location. Driver behavior data (illegal left-turns), wrong-way movements, and traffic conflict data were recorded by manually watching these videos. They will then be analyzed to evaluate how the access control strategies affect driver behavior at this type of intersection.

LITERATURE REVIEW

Field review results indicated that there are many restricted left-turn access designs using the raised channelized island on minor roads in Alabama. Some of them are on undivided highways and applied in urban areas. Besides the restricted raised median that prevents traffic flow across the major road, channelized island, and traffic control devices (signs and pavement markings) are used to restrict the left-turns from the minor roads. Currently, there are no specific design guidelines in the ALDOT Access Management Manual (*8*) on where and how restricted left-turns should be installed. Some other states' access management manuals (*1, 2, 9-18*) provided more guidelines on how to use the raised median for a restricted left-turn design. For example, the FDOT Median Design Handbook states that "restrictive medians and well-designed median openings are also a key component of access management. Raised or restrictive medians are paved or landscaped areas that separate vehicular traffic. The documented benefits of raised medians are so significant that FDOT requires a raised or restrictive median on divided roadways with a design speed of 45 mph or greater, per FDM 210 – Arterials and Collectors. Medians should be installed whenever possible on multi-lane arterial roadways". It also included that "directional median openings are designed to restrict certain traffic movements. The main characteristic of a directional median opening is that vehicular traffic from the cross streets cannot conduct left turns or cross the arterial. The only movements allowed are right turns onto the arterials" (*1*).

The Manual on Uniform Traffic Control Devices (MUTCD) (*7*) provided guidance on using traffic signs and pavement markings to restrict left turns, including a Right-Turn Only sign, lane use arrows, etc. Geometric design guidelines for access points (*6*) provide information on how to use channelized islands to restrict the left-turns. However, a few past studies (*4, 5*) investigated how these signs, pavement markings, and channelized islands affect driver behavior.

METHODOLOGY

Study Locations

Restricted left-turns were studied during April, May, and June of 2021 at various locations in Auburn, Alabama. Three locations were selected to conduct the study including the Publix entrance on North College Street, the Walmart gas station on the Shug Jordan Parkway, and the Burger King entrance/exit on South College Street. **Table B-1** describes the roadways involved in the study.

Table B-1 Roadways studied in Auburn, Alabama

	North College Street	**Shug Jordan Parkway**	**South College Street**
Roadway Classification (*19*)	Principal Arterial	Principal Arterial	Principal Arterial
Number of Lanes	2	4	4
Speed Limit	50 MPH	55 MPH	45 MPH
Median Type	Undivided	Undivided	Divided

Location 1 – Publix Entrance on North College Street

North College Street is a two-lane principal arterial with a speed limit of 50 miles per hour at the Publix entrance. The Publix entrance has one lane coming out of Publix. This lane is designed for right-out only traffic. Traffic coming into the Publix is allowed to turn in from both the north and southbound directions. Channelized island, right-turn only sign, and lane use arrows are installed on the minor road to restrict left-turns from driveways. **Figure B-1** and **Figure B-2** show this location from an aerial and ground view, respectively.

Figure B-1 Aerial view of North College Street at the Publix entrance (*21*)

Figure B-2 Ground view of North College Street at the Publix entrance (*21*)

Location 2 – Walmart Gas Station on Shug Jordan Parkway

Shug Jordan Parkway is a four-lane undivided principal arterial, with a speed limit of 55 miles per hour. There is only one lane for traffic exiting the gas station. There is a channelized island encouraging people to turn right out of the gas station. There is a DNE sign and a lane-use arrow on the pavement to deter people from driving on the wrong side of the channelized island. **Figure B-3** and **Figure B-4** show this location from an aerial and ground view, respectively.

Figure B-3 Aerial view of Shug Jordan Parkway at the Walmart Gas Station entrance (*21*)

Figure B-4 Ground view of Shug Jordan Parkway at the Walmart Gas Station entrance (*21*)

Location 3 – Burger King entrance on South College Street
South College Street is a four-lane undivided principal arterial, with a speed limit of 45 miles per hour. The entrance at Burger King is a right-in-right-out only access design. There is a raised concrete median separating the two directions of traffic flow on South College Street. **Figure B-5** and **Figure B-6** show this location from an aerial and ground view, respectively.

Figure B-5 Aerial view of South College Street at the Burger King entrance (*21*)

Figure B-6 Ground View of South College Street at the Burger King entrance (*21*)

Data Collection
The research team installed portable traffic cameras mounted near the respective locations. The videos were recorded for 72 hours during the three weekdays (Monday to Thursday). The videos were analyzed by observing the driver's behavior and actions when approaching the restricted left turn. The total number of vehicles that approached the restricted left turn was counted, as well as the number of vehicles that made an illegal left turn. This would give a percentage of the drivers that would make an illegal left turn. Other abnormalities, such as driving on the wrong side of the channelized island, were noted.

In addition, Tobii pro eye tracking glasses (*20*) were used by two participants at the Publix location and the Walmart gas station location to determine which traffic control devices drivers looked at when approaching the intersection. The eye tracking software was used to analyze the data collected to determine the time and location where drivers glanced. This technology was used during the day and night to study the driver's focus while making the left turn.

Data Analysis
Driver behavior in this study was defined by the vehicles' actions that were taken at the restricted left turn. While making an illegal left turn, the driver's behavior showed vehicles yielding at the channelized island and making a large J turn to go around the channelized island and turn left. In addition, when there were no pavement markings and few signs to direct drivers, there were behaviors of driving on the wrong side of the channelized island. The behaviors were analyzed by reviewing the videos recorded by portable traffic cameras and eye-tracking videos.

RESULTS
From the Publix entrance location on North College St, it was found that roughly 1 in every 3 vehicles made an illegal left turn. **Table B-2** represents a sample of vehicles that approached the restricted left turn in 30-minute periods. In addition, it was also determined that 1 in 20 vehicles that made an illegal left turn made the left turn from the wrong side of the channelized island. Also, there was a close conflict in approximately 1 out of every 33 vehicles turning out of Publix access. A close conflict was defined when vehicles made an illegal left turn and would interfere with cars on the major road. As shown in **Figure B-7**, an illegal left turn can be found at this location. In addition, in **Figure B-8**, an example can be seen of a vehicle driving on the wrong side of the channelized island.

Table B-2 Count of illegal left turns at Publix entrance on North College Street

Video (30 min. Period)	Total Vehicles Approached Turn Lane	Total Vehicles that Made Wrong Movement
05/2/21 @ 07:54:36	27	9
05/2/21 @ 10:24:36	78	26
05/2/21 @ 20:00:49	55	19
05/2/21 @ 20:58:14	31	9
Total	**191**	**63**

Figure B-7 Illegal left turn onto North College Street at Publix entrance location

Figure B-8 Vehicle on the wrong side of the channelized island at Publix entrance location

At the Walmart gas station location on Shug Jordan Parkway, it was found that approximately 1 in 15 vehicles were making an illegal left turn. **Table B-3** represents the number of cars that approached the restricted left turn in the 30-minute time intervals. There were some cases at this location where drivers drove over the channelized island or waited in the striped median to merge into oncoming traffic. At this location, there were no cases of driving on the wrong side of the channelized island. This is because this location has a “DNE” sign and pavement markings in the entrance lane. An example of an illegal turn at this location can be seen in **Figure B-9** below.

Figure B-9 Illegal left turn onto Shug Jordan Parkway at the Walmart Gas Station location

Table B-3 Count of illegal left turns at the Walmart Gas Station on Shug Jordan Pkwy

Video (30 min. Period)	Total Vehicles Approached Turn Lane	Total Vehicles that Made Wrong Movement
05/11/21 @ 15:32:47	44	0
05/12/21 @ 08:32:17	31	4
05/12/21 @ 12:32:10	20	1
05/12/21 @ 13:02:09	25	1
05/12/21 @ 13:32:08	30	2
05/12/21 @ 14:02:07	29	1
05/12/21 @ 14:32:06	19	2
05/13/21 @ 09:01:30	13	2
05/13/21 @ 09:31:29	15	1
05/13/21 @ 10:01:28	27	3
05/13/21 @ 10:31:27	20	2
05/13/21 @ 11:01:26	20	1
Total	**293**	**20**

At the Burger King location on South College Street, 1 in every 60 vehicles made an illegal movement. Most illegal movements were made were illegal left turns, but there were a couple of cases where drivers illegally drove straight through the intersection. **Table B-4** represents a sample of vehicles that approached the restricted left turn in 30-minute periods. It was observed at this location that drivers would wait in the left turn lane on South College Street to merge into oncoming traffic. It was also observed that the small concrete median installed at the major road was effective in preventing illegal left turns, but there are still points of improvement. **Figure B-**

10 shows an example of a vehicle making an illegal left turn and waiting in the left turn lane to yield onto South College Street.

Table B-4 Count of illegal movements at the Burger King on South College Street

Video (30 min. Period)	Total Vehicles Approached Turn Lane	Total Vehicles that Made Wrong Movement
06/14/21 @ 08:14:32	19	0
06/14/21 @ 08:44:35	27	0
06/14/21 @ 09:14:35	20	0
06/14/21 @ 09:44:35	13	0
06/14/21 @ 10:14:33	11	1
06/14/21 @ 10:44:32	26	0
06/14/21 @ 11:14:31	38	1
06/14/21 @ 11:44:30	45	1
06/14/21 @ 12:14:29	35	1
06/14/21 @ 12:44:28	30	0
06/14/21 @ 13:14:27	31	1
Total	**295**	**5**

Figure B-10 Illegal left turn onto South College Street at Burger King location

Data was also obtained from the eye-tracking software used in the research. Based on this data, it was shown that drivers look for traffic control signs and pavement markings during the daytime and nighttime. The experiment was done using two participants to see the differences when driving at the locations that were being studied. The driver's eye glance data revealed that drivers noticed each sign and pavement markings for approximately 0.5 seconds. This time was measured by analyzing the heat maps on the eye tracking software that showed these locations were frequent places that drivers viewed. The data from the experiment is shown in **Table B-5** and **Table B-6**, below.

Table B-5 Daytime eye tracking study

Movement	Location	Right Turn Pavement Marking		DNE Sign		Right Turn Only Sign	
		User 1	User 2	User 1	User 2	User 1	User 2
Right Turn	Publix Entrance	Yes	Yes			Yes	Yes
Illegal Left Turn	Publix Entrance	Yes	Yes			Yes	Yes
Right Turn	Walmart Gas Station	Yes	Yes	Yes	Yes		
Illegal Left Turn	Walmart Gas Station	Yes	Yes	Yes	Yes		

Table B-6 Nighttime eye tracking study

Movement	Location	Right Turn Pavement Marking		DNE Sign		Right Turn Only Sign	
		User 1	User 2	User 1	User 2	User 1	User 2
Right Turn	Publix Entrance	No	No			Yes	No
Illegal Left Turn	Publix Entrance	No	No			Yes	No
Right Turn	Walmart Gas Station	Yes	Yes	Yes	Yes		
Illegal Left Turn	Walmart Gas Station	Yes	Yes	Yes	Yes		

CONCLUSIONS AND RECOMMENDATIONS

This research examined the effects of driver behavior at access points with restricted left-turn movements at three locations in Auburn, Alabama, United States. According to the data that was collected from all three locations, it was concluded that the following improvements are recommended at these locations to aid driver behavior and create a safer intersection when approaching a restricted left turn:

1. Qwick curb (**Figure B-11a**) be built as a median along North College Street at the Publix access. An opening is recommended to allow for southbound traffic along South College to turn into Publix. The justification for this is that approximately 1 illegal left turn is made every minute during the peak hours during a typical weekday at the location.
2. A channelized island is to be built at the Publix location where the striping separates the northbound traffic, turning into Publix, from the southbound traffic, turning into Publix with a "Do Not Enter" sign on top of the island. This prevents motorists from driving on the wrong side of the existing channelized island when leaving Publix. In addition, a "Right Turn Only" sign should be mounted on the existing channelized island. Roughly 1 in 20

illegal left turns were made from the wrong side of the channelized island. These changes are therefore warranted. It is strongly recommended that directional arrows be added to the pavement for traffic entering Publix.

3. Qwick curb be built as a median along Shug Jordan Parkway at the Walmart gas station access. An opening is recommended to allow for southbound traffic along Shug Jordan to turn into the gas station. The justification for this is that approximately 7 illegal left turns are made every hour during a typical weekday at the location. In addition, a “Right Turn Only” sign (**Figure B-11b**) to be mounted on the existing channelized island where no signs exist.

At the Burger King access on South College Street, no improvements are needed as very few illegal left turns were made.

Figure B-11 (a) Qwick curb and (b) RIGHT TURN ONLY sign

The study recommended that changes need to be made to the ALDOT access management manual regarding access points with restricted left turn movements. For example, when a restricted left turn is made, a U-turn needs to be provided for drivers to allow them to safely go in the needed direction. Another example would be to require a raised median when building a restricted left turn to prohibit illegal left turns. These alternatives would depend on the type of roadway, number of lanes, AADT, and speed limit of the road.

FUTURE RESEARCH
More research could be done at locations throughout Alabama like those in this report. There are some limitations to this paper including the limited data and participants that were used to compile this report. The restricted left turn design is not rare in Alabama, and more locations can be identified throughout the state.

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AUTHOR CONTRIBUTIONS
The authors confirm contribution to the paper as follows: study conception and design: Huaguo Zhou; data collection: Anthony Aspito, Caleb Rogers, and Qing Chang; analysis and interpretation: Anthony Aspito, Caleb Rogers, and Huaguo Zhou; draft manuscript preparation: Anthony Aspito, Caleb Rogers, Huaguo Zhou and Qing Chang. All authors reviewed the results and approved the final version of the manuscript.

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APPENDIX C: Effects of Raised Ceramic Channel Marker on Prohibiting Left Turns from Driveway: A Before and After Study

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ABSTRACT

The purpose of the study is to analyze driver behavior at an unsignalized intersection with raised channel markers to prevent left turns from the driveway. The study intersection is located near downtown Auburn, AL. Traffic volume increased significantly after a new high-rise apartment (Uncommon) was built. To improve safety at this intersection, the city traffic engineer installed a new traffic control device (Ceramic Raised Channel Marker**)** to prohibit direct left turn movement at one of two exits for the building. Traffic video was recorded at the study location before and after the channel markers were installed. Data collected for a 15-minute interval includes traffic conflicts, traffic volumes, and trajectories by direct left turns. The Wilcoxon signed-rank test and Fisher's exact test were conducted to examine if there was a statistically significant difference in traffic volumes and traffic conflicts by the left turns. The analysis results indicated that the channel markers, although not harmful to the structure of a vehicle, disincentivized drivers from making illegal left turns and incentivized them to make right turns followed by left turn movements to reroute. Overall, instances of traffic conflicts caused by left turns decreased significantly after installing the markers. Additionally, total traffic volumes from the driveway decreased because some drivers used another exit. The study results can help local transportation agencies better understand the effectiveness of raised channel markers as a traffic device prohibiting left turns in small urban areas.

Keywords: Raised Channel Marker, Access Management, Before and After Study, Prohibition of Left-Turn

INTRODUCTION

A novel and low-cost traffic control device, the Ceramic Raised Channel Marker, has been introduced at the median of an urban location near downtown Auburn, AL, to enforce a restriction on direct left turns from one of two exits of a newly constructed apartment complex, the Uncommon Apartment. The yellow ceramic raised channel marker was chosen following a thorough evaluation involving longitudinal channelizers and raised medians. The selection was motivated by factors such as limited median space, land use considerations, and the inherent attributes of the devices—such as cost-effectiveness, straightforward installation, and ease of maintenance. Refer to **Figure C-1** for a depiction of a ceramic raised channel marker and an instance of its installation within the median of the study area. Primarily designed for access management within urban roadways and streets equipped with street lighting, ceramic-raised channel markers serve a vital role. By utilizing rumble effects, these markers discourage drivers from crossing them and offer a sensory and audible alert to those venturing into restricted medians or deviating from designated travel lanes.


Figure C-1 Ceramic Raised Channel Marker at Study Site

This study aims to assess the impact of raised channel markers on driver behavior at a specific intersection. The investigation takes place at a three-way unsignalized intersection between a three-lane major road and a driveway leading to a student apartment building in Auburn, Alabama (refer to **Figure C-2a**). The emergence of the new apartment complex has contributed to an upsurge in traffic volume, particularly towards downtown Auburn. As a countermeasure to enhance safety, the city of Auburn introduced ceramic raised channel markers to restrict left turns at this intersection. Notably, the residential apartment complex features two exits—one that prohibits left turns and another that permits them. **Figure C-2b** presents an alternate exit that facilitates left turns.

Figure C-2 (a) Restrict Left Turn Exit and (b) Alternative Exit at Study Site

An overarching objective of implementing ceramic markers is to divert a portion of traffic toward the alternative exit. Before adopting raised channel markers, the city's efforts included the installation of a raised channelized island and a right-turn-only sign at the driveway (refer to **Figure C-3**), both aimed at prohibiting left turns. Regrettably, the study discerned the ineffectiveness of measures in deterring left turns by drivers. This issue has amplified the occurrence of unauthorized left turns, becoming a principal factor for vehicle conflicts and collisions. The central purpose of introducing ceramic markers is to curtail these conflicts and crashes arising from illegal left turns made while exiting the driveway.

Figure C-3 Treatments of Channelized Island

The study examined 40 hours of video footage captured at the targeted intersection. Specifically, 20 hours of footage were captured before the deployment of the raised markers, and an equal duration of 20 hours was documented after their installation. Over this span, the data revealed 587 instances of right turns, 212 direct left turns, and a further 148 instances where right turns were followed by subsequent left turns.

To delve deeper into the data, the research team conducted a rigorous examination to ascertain any discernable shifts in driver behavior following the installation of the raised markers. The study utilized a before-and-after approach to evaluate the effectiveness and overall impact of the newly implemented ceramic raised channel markers over these two time periods at the study intersection.

LITERATURE REVIEW

Raised Pavement Markers

The Manual for Uniform Traffic Control Devices (MUTCD) defines a raised pavement marker (RPM) as an apparatus that stands at a minimum of 10 mm (0.4 in) tall, affixed either on or within the road's surface. These markers are designed to guide vehicular positioning, either to supplement or replace existing pavement markings (*1*). In accordance with the guidelines established by the MUTCD, raise channel markers must adhere to specific color criteria under both daylight and nighttime conditions. This entails ensuring that the color of the raised markers corresponds to the color of the marking they are meant to guide, supplement, or substitute.

RPMs exhibit a range of shapes, colors, and sizes tailored to specific road conditions. Diverse types of RPMs serve distinct purposes, leading to their classification based on key features:

1. **Various Designed RPMs:**
   1.1. Retroreflective RPMs (RRPMs):
   - **Purpose:** Complements other pavement markings.
   - **Benefits**: Particularly effective in discouraging wrong-way driving and enhancing highway delineation.
   - **Research:** Numerous studies (*2-6*) have emphasized their crucial role in preventing head-on collisions during nighttime and adverse weather conditions.

   1.2. Snowplowable RPMs:
   - **Purpose:** Designed to provide enhanced visibility during wet and nighttime conditions.
   - **Benefits:** Especially beneficial in regions with heavy snowfall, minimizing RPM damage and enhancing highway safety (*7, 8*).
   - **Special Feature:** Rumble insert markers, part of these RPMs embedded in rumble strips, have proven to mitigate damage while improving nighttime centerline delineation (*9*).

   1.3. Post-Mounted Delineators:
   - **Research:** Investigations by the Kansas Department of Transportation (*10*) have highlighted the safety effectiveness of these delineators.

- **Benefits:** They significantly reduce lane departure crashes and fatal/injury incidents on curved rural two-lane roads.

2. **Physical Attributes: Shape, Size, and Materials:**
   - **Common Types:** Standard 4 x 4-in. amber 2-sided markers.
   - **Material Variants:** Include plastic, ceramic, thermoplastic paint, glass, and occasionally metal. RPMs resist submersion, with non-retroreflective ceramic buttons serving as supplementary markers (*11*).
   - **Special Type:** Surface-Mounted Traffic Spikes, a metallic RPM variant, deter wrong-way driving.
   - **Material Benefits:** All these materials enhance retroreflective capability (*12, 13*), but they differ in durability, cost, and retroreflective intensity.
3. **Color Coding:**
   - **Guidelines:** White and yellow markers generally indicate the middle and sides of roads, corresponding to road stripe colors.
   - **Driver Comprehension:** RPMs aid in comprehending directional messages in the pavement system (*14, 15*).
   - **Specific Markers:** Red or yellow markers are placed at locations where wrong-way drivers would encounter them. Two-way red markers indicate no-entry zones, green markers show permissible routes and blue markers represent fire hydrant locations, a standardized practice.

This study focused on an 8x8 in. ceramic yellow marker functioning as a raised channel marker. The marker was dual sided, emitting amber light, and was situated at the center of the roadway. Material acquisition and installation costs per location amounted to approximately $5000. These markers have been set up in two distinct locations within Auburn City. Notably, of the two sites, only one has video documentation before the marker's installation. Therefore, the focus of this paper will be limited to that specific site. While previous research (*16-18*) has extensively examined the safety aspects of diverse RPM variants, a notable scarcity exists in studies evaluating RPM efficacy in mitigating driveway left turns within small urban locales.

METHODS

A comparative analysis of driver behavior was conducted to determine the effectiveness of ceramic raised channel markers in deterring illegal left turns. Observations were made on a typical weekday in September 2021, before marker installation, and again in February 2022, after installation. These markers were set up towards the close of 2021. It's notable that most residents at the Uncommon Apartment are students, with leases typically expiring in late July. This suggests a consistent driver population across the study periods, ensuring drivers had at least two months to familiarize themselves with the new traffic feature. **Figure C-4** offers a view of these markers from a driver's vantage point, taken at the exit of Uncommon Apartments on West Glenn Avenue, Auburn, AL. This exit operates on a right-in, right-out system, complemented by a raised channelized island at the driveway. To determine any statistically significant shifts in driver behavior, a Signed Rank Wilcoxon Test was utilized. The study primarily delved into discerning discrepancies in traffic volumes, conflict rates, and trajectories of left-turning vehicles between the two observation periods.

Figure C-4 Driver's View of Stop Sign and Raised Markers

Wilcoxon Signed-Rank Test

To assess the significance of changes between the 'before' and 'after' periods in this study, the Wilcoxon Signed-Rank Test was employed. This non-parametric statistical test compares two related or matched samples to determine if there are differences in their population mean ranks. It was chosen due to the non-normal distribution of the data and the presence of paired samples — measurements taken before and after an intervention within a consistent driver population.

The study's data included paired observations across several categories: the number of vehicles exiting the driveway, illegal left turns, right turns to the left-turn lane, and standard right turns made by vehicles, along with the number of traffic conflicts resulting from illegal left turns. To control potential bias associated with varying traffic volumes, the total number of vehicles exiting the driveway was first quantified. Subsequently, all drivers' exit choices, including illegal left turns, right turns, and right turns into the left-turn lane, were meticulously recorded.

Given that the study site features two exits, the analysis was designed to determine whether there is a statistically significant reduction in illegal left turns and a corresponding increase in right turns following the implementation of raised ceramic channel markers. Such findings indicate that the intervention effectively deters illegal left turns from the exit driveway. Additionally, the number of traffic conflicts arising from illegal left turns was included as a metric to evaluate the traffic safety impact of the new treatment. It is important to note that the measurement of traffic conflicts relied on a subjective assessment without the aid of advanced technological tools. Conflicts were identified by observing vehicles' temporal and spatial proximity, using parameters like postencroachment time (PET) and headway, following the methodologies outlined by previous studies. Evasive actions such as braking and swerving were also considered.

Fisher's Exact Test (for distribution of vehicle types)

To evaluate the differences in the distribution of vehicle types between the before and after periods, Fisher's Exact Test was utilized. This test is particularly adept at examining the association between two categories of categorical data represented in a contingency table and is especially beneficial when dealing with small sample sizes. Fisher's Exact Test was chosen due to the notably reduced sample sizes in some vehicle categories in the after-period. This necessitated a more accurate assessment method than the Chi-square test for these conditions.

The dataset comprised counts of different vehicle types (PC, SUV, Pickup-Truck) observed during both the before and after periods. The primary hypothesis tested was whether there was a significant shift in the proportions of these vehicle types from the before period to the after period. This analysis aimed to determine if implementing specific measures or changes in the environment had a quantifiable impact on the distribution of vehicle types at the study site.

DATA COLLECTION

The research team installed a traffic camera at a designated study site over three consecutive weekdays, from Monday to Wednesday. This installation was for periods before and after raising channel markers were placed. Data collection covered the pre-installation period (September 13-15, 2021) and the post-installation period (February 7-9, 2022). To ensure consistent data, 20-hour video recordings, including peak traffic hours, were used for both periods. The study involved manually observing and recording the exiting behaviors of vehicles from a driveway.

Drivers' decisions were categorized into right turns, right turns into the left lane, and left turns. Data was methodically recorded in 15-minute intervals (*19, 20*), providing 79 valid data points for each period. This interval length aligns with recommendations from previous traffic studies.

The study also focused on vehicles making illegal left turns, categorized by vehicle type: passenger cars, SUVs, and pick-up trucks. Instances of conflict due to these illegal turns were recorded every 15 minutes. Detailed summaries of total and average data for both periods are shown in **Tables C-1** and **C-2**.

Table C-1 Driver Behaviors of Recorded Data for Before and After Periods

	Right Turns	Right Turns to Left Lane	Illegal Left Turns
Before Period Total	313	44	186
After Period Total	274	104	26
Before Period Average per 15 Minutes	4.0	0.6	2.4
After Period Average per 15 Minutes	3.5	1.3	0.3

Table C-2 Vehicle Types of Recorded Data for Before and After Periods

	Illegal Left Turn Vehicle Types		
	Passenger Car	**SUV**	**Pickup Truck**
Before Period	41	131	14
After Period	8	15	3

Three distinct illegal left turn trajectories were identified, illustrated in **Figure C-5**:

- Type 1 Left Turn: Drivers merged two lanes (through and left turn only lanes) and crossed the raised channel markers.
- Type 2 Left Turn: Drivers turned into the opposite left turn only lane, and went beyond pavement markers, and merged into the desired lane.
- Type 3 Left Turn: Drivers make an illegal turn, leading to an incorrect exit from the island.
- These classifications provide a detailed understanding of driver behaviors and methods of executing illegal left turns.

Figure C-5 Three Types of Illegal Left Turn Trajectories

Additionally, two primary conflict scenarios were identified from these illegal turns:

Conflict Scenario 1: Illustrated in **Figure C-6**, these occur when a vehicle exiting the driveway makes an illegal left turn, forcing oncoming vehicles in the through or left turn lane to brake or stop, risking head-on or T-angle crashes.

Conflict Scenario 2: This involves vehicles making illegal left turns, causing opposite lane vehicles to brake or stop, increasing the risk of sideswipes or rear-end crashes.

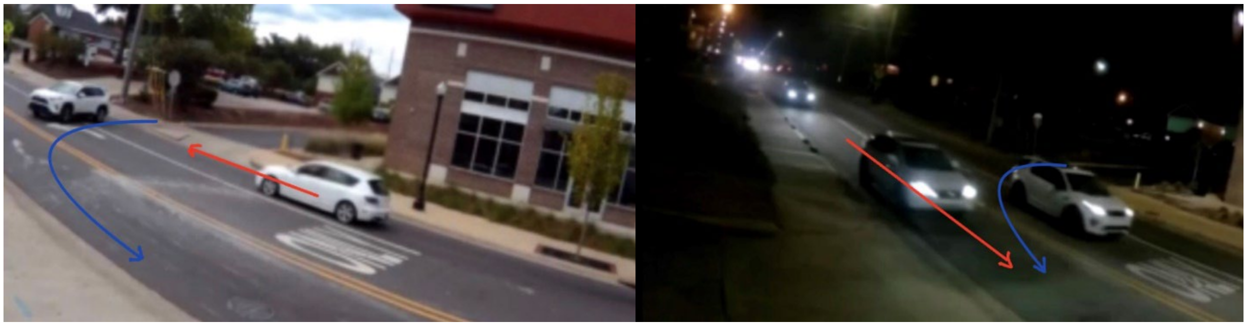

Figure C-6 Two Scenarios of Conflict

DATA ANALYSIS & RESULTS

Statistical Tests

Wilcoxon Signed-Rank tests were performed to assess the impact of ceramic raised channel markers on deterring illegal left-turn movements. Traffic volumes for total, right turn, right turn to left-turn lane, and illegal left turn were compared pre- and post-installation. The significance level was set at $\alpha=0.05$. Data were derived from 79 paired 15-minute segments of 20-hour video footage, as described in the methodology. The outcomes are summarized in **Table C-3**:

Table C-3 Hypotheses and Test Results

Outcome Measure	Sample Size (N)	Shapiro-Wilk Test P-value	Test Statistic (W)	Wilcoxon Test P-value	95% CI for Median Difference
Total Traffic	79	0.002	1385	2.63e-04	(0, 3)
Illegal Left Turn	79	1.35e-06	1401.5	5.32e-10	(1, 3)
Right Turn	79	0.007	931	0.176	(-1, 1)
Right Turn to Left-turn Lane	79	2.04e-07	87.5	5.29e-06	(-1, 0)

All Shapiro-Wilk test p-values were below 0.05, indicating non-normal distribution and justifying the use of the Wilcoxon test. The Wilcoxon test revealed a statistically significant decrease in total and illegal left turn traffic volumes post-treatment, as evidenced by their p-values and positive median difference intervals. Specifically, the confidence interval for illegal left turns (1 to 3) strongly suggests reducing these movements. In contrast, right turn volumes showed no significant change (p-value = 0.176; CI = -1 to 1). However, right turn to left-turn lane movements significantly increased post-treatment (p-value = 5.29e-06; CI = -1 to 0).

These results indicate that installing raised channel markers successfully reduced illegal left turns, with a notable shift in driver behavior towards right turn to left-turn lane movements. This outcome demonstrates the effectiveness of the implemented traffic control measure.

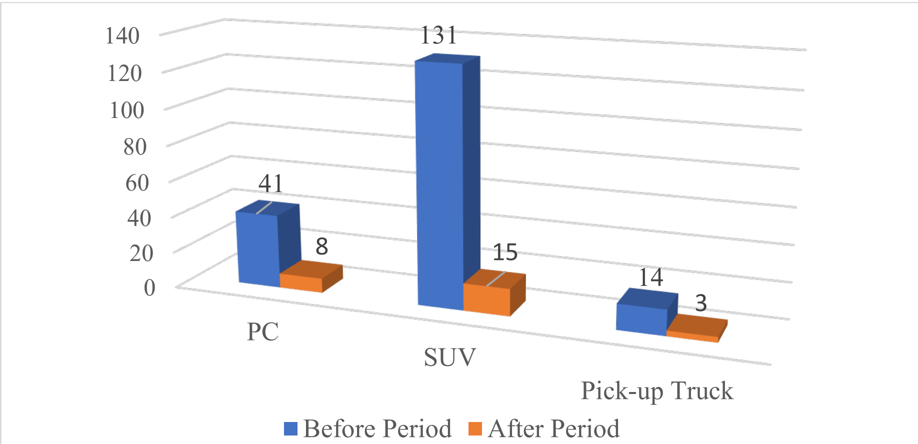

Figure C-7 Distribution of Types of Vehicles Making Illegal Left Turns

Figure C-7 presents the distribution of vehicle types executing left turns before and after installing raised channel markers. Using Fisher's Exact test, the analysis yielded a p-value of 0.418. This suggests no significant change in the proportions of different vehicle types making illegal left turns after the installation compared to before. This outcome was somewhat unexpected, considering the raised channel markers' design, which was anticipated to particularly deter drivers of standard passenger cars, such as sedans, coupes, and hatchbacks, due to their height.

However, this result could be attributed to certain drivers maneuvering around the raised markers before merging into the desired lane. Additionally, the limited duration of data collection, encompassing only 20 hours before and after the installation, might have affected the robustness of these findings. A more extended observation period might clarify the markers' impact on different vehicle types.

Descriptive Statistics

Descriptive statistics were employed to evaluate changes in the distribution of left turn trajectories and conflict types associated with left turns before and after the installation of raised channel markers. The goal was to discern any shifts in the frequency and nature of these maneuvers and conflicts.

From **Table C-4**, there was a notable shift in the distribution of illegal left turn trajectories following the installation of the raised channel markers. Specifically, the Type 1 trajectory, which was overwhelmingly predominant before the intervention, decreased significantly afterward. In contrast, Type 2 trajectory, which was initially rare, became the most common type of illegal left turn post-intervention. This shift suggests that drivers frequently making illegal left turns now opt for riskier maneuvers, such as a brief stint of WWD, rather than crossing over the raised channel markers and experiencing a bump.

Regarding conflict scenarios, while Scenario 1 decreased, it remained the more common in both periods. Scenario 2, though initially less frequent, saw a relative increase in the after period. This change could be attributed to the raised channel markers adding complexity to the decision-making process for drivers attempting illegal left turns. Specifically, as more drivers shifted to the Type 2 trajectory, they needed to pay increased attention to oncoming traffic on their left, potentially leading to a higher likelihood of conflicts with vehicles on their right. By complicating the maneuver, the raised channel markers appear to have inadvertently increased the risk of certain types of conflicts.

Table C-4 Comparison of Illegal Left Turn Trajectories and Conflict Types in Before/After

	Before Period		After Period	
Illegal Left Turn Trajectory				
Type 1	181	97%	7	27%
Type 2	4	2%	18	69%
Type 3	1	1%	1	4%
Conflict Scenario				
Scenario 1	30	91%	6	60%
Scenario 2	3	9%	4	40%

CONCLUSIONS AND RECOMMENDATIONS

This research analyzed the effects of a ceramic raised channel marker on driving behavior at an unsignalized intersection with a restricted left turn design in Auburn, Alabama. According to the data collected and the statistical tests, the following can be concluded:

1. **Effectiveness of Ceramic Raised Channel Markers:** The deployment of raised channel markers successfully decreased the total traffic volume and, more notably, the number of illegal left turns and increased right turn to left turn lane maneuvers.
2. **Vehicle Type Distribution:** Contrary to expectations, there’s no significant change in the distribution of vehicle types making illegal left turns post-installation. This finding was unexpected, particularly as the markers were assumed to deter standard passenger vehicles more effectively. However, this could be due to drivers adapting their maneuvers to avoid markers or limitations in the duration of data collection.
3. **The Shift in Driver Behavior:** Post-installation, there was a noticeable change in driver behavior, especially in the type of left turn trajectories. The predominant pre-treatment Type 1 trajectory saw a substantial decrease, while Type 2 trajectory, previously rare, became the most common post-treatment. This shift suggests drivers’ preference for riskier maneuvers, such as brief WWD, to avoid the discomfort or challenge posed by the raised markers.
4. **Impact on Conflict Scenarios:** While Scenario 1 conflicts diminished, they remained the most common type in both periods. Scenario 2 conflicts, on the other hand, increased

relatively in the post-treatment period. This indicates that while the markers dissuaded straightforward illegal left turns, they introduced complexities in decision-making for drivers, leading to an increased likelihood of certain conflict types.

In conclusion, this study emphasizes the importance of ceramic raised channel markers treatment in deterring illegal left turns from a driveway on one specific urban street. These findings underscore the importance of considering unintended behavioral adaptations when implementing traffic control measures. For a more comprehensive understanding, further extended observation and analysis would be beneficial, particularly to assess the long-term impact on different vehicle types and to solidify these initial observations.

LIMITATIONS AND FUTURE STUDIES

Limitations of this study include the lack of multiple sites collected before and after installation. Future research could be done at multiple locations, specifically ones with a more random location, to prevent repeat drivers at the intersection. In addition, different traffic control devices prohibiting left turns could be studied to compare the effectiveness to cost for each.

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AUTHORS CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: Huaguo Zhou; literature review: Zijie Zhao; data collection: Alison Yan, Andrew Yang, Zijie Zhao; data analysis and interpretation of results: Alison Yan, Andrew Yang, and Huaguo Zhou; draft manuscript preparation: Alison Yan, Andrew Yang, and Huaguo Zhou. All authors reviewed the results and approved the final version of the manuscript.

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APPENDIX D: Effectiveness of LED Enhanced Blinker WRONG-WAY Signs on Deterring Wrong-Way Driving: A Before and After Study

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ABSTRACT
Wrong-way driving (WWD) crashes pose a significant threat to road safety, often resulting in severe injuries and fatalities. Traditional WRONG WAY and DO NOT ENTER signs have limitations in attracting and forewarning WWD drivers, especially under the influence or on wide one-way roads. This study evaluates the effectiveness of light-emitting diodes (LEDs) that enhance Blinker Wrong Way signs in deterring WWD incidents. These signs, featuring flashing LEDs as auxiliary devices, were installed on a one-way street on the Auburn University campus. Data was collected over 162 days before and 122 days after removing the flashing LEDs on Wrong Way signs. Statistical analyses reveal a significant improvement in WWD behavior, with turnaround rates increasing by 15 % when the flashing LEDs were activated. Implementing LED-enhanced Blinker Wrong-Way signs could offer a valuable approach to mitigating WWD incidents and enhancing road safety.

Keywords: Flashing LEDs, Wrong-Way Signs, Before and After Study, One-Way Street, Effectiveness

INTRODUCTION

Wrong-way driving (WWD) is defined as the act of driving a motor vehicle against the direction of traffic, typically occurring on one-way streets or divided highways. While WWD crashes occur less frequently than other types of crashes, they tend to be more severe, resulting in a higher likelihood of injuries and fatalities (*1*). To address this problem, policymakers and agencies require access to comprehensive resources that offer detailed information about WWD countermeasures, including their effectiveness and costs, to make informed decisions on suitable systems for their specific locations (*2*). Over the past few decades, various states and local agencies have proposed, implemented, and tested different engineering countermeasures to mitigate WWD incidents.

Recently, Departments of Transportation (DOTs) have increasingly implemented WRONG WAY signs with flashing LEDs around the border. For instance, in 2012, the Illinois Center for Transportation analyzed wrong-way crashes on freeways in Illinois over a six-year period and recommended installing the enhanced WRONG WAY signs at high-frequency crash locations (*3*). The WisDOT used solar-powered WRONG WAY signs with flashing LEDs around the border during the twilight hours at two ramps at the end of 2012 (*4*). In 2011, the Harris County Toll Road Authority (HCTRA) spent approximately $38,788 per mile on the wrong-way driver detection system, and flashing LED signs became one of the important features (*5*). In 2011, TxDOT implemented two signs on each exit ramp for the 15-mile selected US 281 corridor from I-35 to just north of Loop 1604 (the far north central side of San Antonio) (*6*).

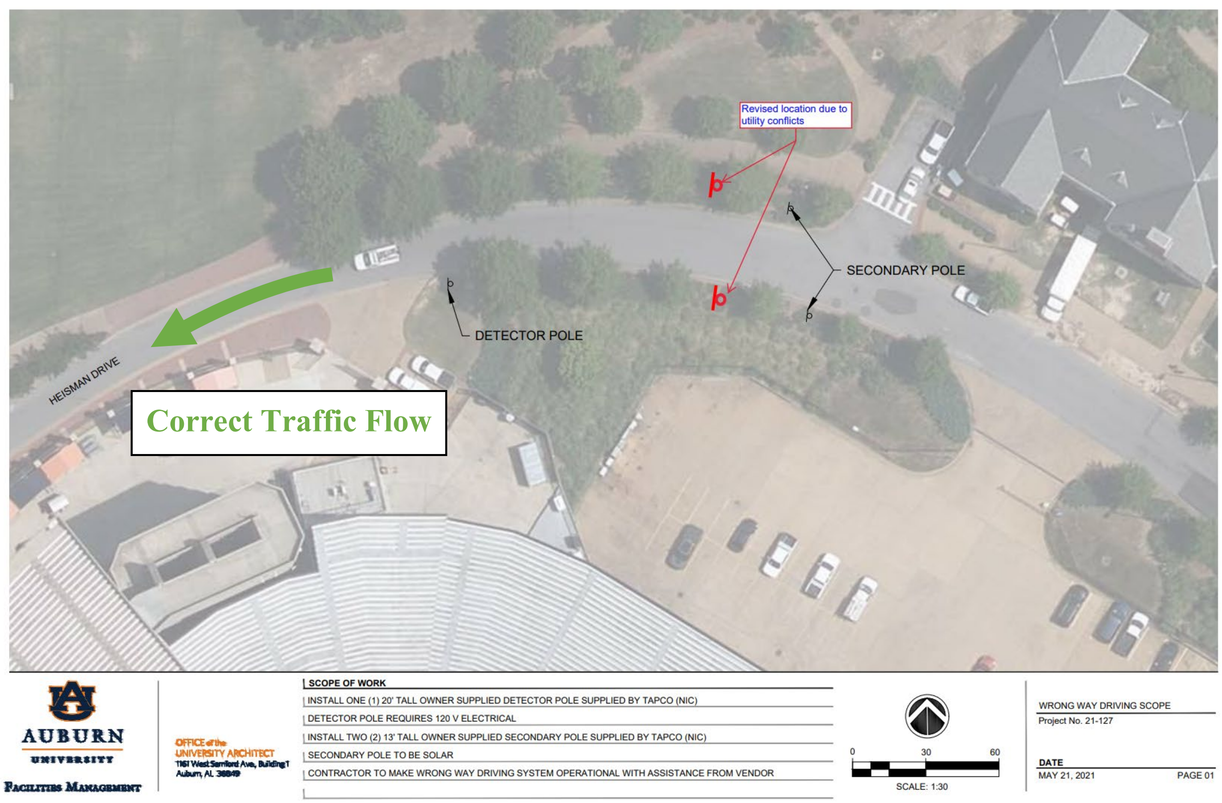


Figure D-1 Wrong-Way Alert System layout plan

Typically, these flashing LEDs are activated by advanced Intelligent Transportation Systems (ITS) detection technologies, such as radar, LiDAR, or cameras (*2,3*). The flashing LED on the WRONG WAY sign in this study is activated by a radar detector (at the detector pole), as shown in **Figure D-1**. Once it detects a WWD movement, the flashing LEDs around the three WRONG WAY signs (first one at the detector pole, second pair at the red points) border begin to blink. A notification alert will immediately be sent to a linked website, and two monitors will start to record 2-minute short videos from the front and back of wrong-way vehicles and 15 continuous images for officials to check.

The objective of this study is to quantify the effectiveness of the flashing LEDs around the WRONG WAY signs border on mitigating WWD incidents on a one-way road (Heisman Dr.) around the Auburn University football stadium. Chi-squared and Welch's t-test were conducted to determine how the results differed after the LED flashing was manually turned off. The collected data, from 2021 to 2023, were captured by the Wrong-Way Alert System and first recorded as images and 2-minute short video files through a BlinkLink® Remote System Management, then manually labeled into various categories. The results of this research provide insights into the effects of flashing LEDs on correcting WWD incidents on one-way roads. By virtue of the fact that many state DOTs are currently putting ITS into practice, the outcome of this research effort may contribute as a significant resource for the economic appraisal before installation.

LITERATURE REVIEW

Traditional WRONG-WAY, DO-NOT-ENTER, ONE-WAY signs are widely deployed in different facilities and roads. Although transportation agencies keep enhancing these traditional signs by changing the signs mounting height, adjusting the signs' size, improving the retro-reflectiveness of the sign, etc. (*7,8*), they may still not be as effective in alerting impaired drivers, especially during nighttime hours. As most WWD incidents occur during nighttime and are often caused by drivers under the influence of alcohol (*9-12*), more attractive countermeasures for those DUI drivers have been pointed out in recent decades.

In 2015, Pour-Rouholamin (*13*) in his study found that using border-illuminated signs could improve 15.4% the visibility of wrong-way signs; Adding a strip of retroreflective material to the sign support could increase 61.5%; Adding a red or yellow flashing beacon could increase 7.7%.

In 2022, Yukun Song (*14*) conducted a driving simulator study by analyzing drivers' behavioral data collected from the driving simulator and eye-tracking device. The result found that when highly intoxicated drivers faced a single traffic control device, flashing LED WW signs deterred more WWD events than regular WRONG WAY signs. Similarly, in 2018, Melisa Finley (*15*) conducted a simulator study and concluded that normal-size WRONG WAY signs equipped with flashing red LEDs around the border were less difficult for drunk drivers to locate the signs. In 2018, Imrul Kayes (*16*) found a significant reduction in WWD events in South Florida due to the implementation of LED signs. For instance, a 49% reduction in WWD 911 calls and a 38% reduction in combined WWD 911 calls. A similar study had been done by the Texas Transportation Institute for LED signs installed in Texas, which found a 38% reduction in WWD 911 calls (*17*).

Traditional countermeasures have seen improvements over time, but their effectiveness in alerting impaired drivers, especially during nighttime, remains limited. In contrast, Intelligent Transportation Systems (ITS) offer a more innovative approach to address this challenge. Examples of ITS WWD countermeasures include "Wrong Way" signs equipped with either LEDs or Rectangular Flashing Beacons (RFBs), detection devices, cameras, and communication capabilities with Traffic Management Centers. When a wrong-way vehicle is detected, the LEDs or RFBs flash to alert the wrong-way driver, and images of the wrong-way vehicle are taken and sent to the TMC (*18*). The Washington State DOT implemented a system to warn and monitor wrong-way drivers using LEDs, flashers, and video cameras (*19*). The Arizona DOT installed thermal wrong-way vehicle detection and warning systems at exit ramps on 15 miles of I-17 between I-10 and State Road (SR) 101 (*20*). The Rhode Island Department of Transportation (RIDOT) installed advanced wrong-way detection systems at 24 locations across the state. These systems alert the wrong-way driver, police, and other nearby motorists in the area of a potential wrong-way driver (*21*). Taken as a whole, these results confirm that ITS is an effective strategy for addressing WWD at a system level.

Previous research shows that WWD crashes were severe and hard to eliminate with traditional signs. LED signs and advanced WWD ITS technologies were recently implemented to help deter WWD incidents and the results were remarkable. However, a comparison experiment, especially the before and after cases study has not been conducted due to the difficulties in collecting before-period data. This paper will evaluate the performance of the flashing LEDs around the WRONG WAY signs' border on deterring WWD. Approximately 200 WWD incident data were collected and analyzed from before and after periods, respectively to evaluate the effectiveness of flashing LEDs using various methods.

METHODOLOGY AND DATA COLLECTION

Before and After Cases Definition

The study aims to evaluate the effectiveness of LED-enhanced blinker WRONG-WAY signs in deterring WWD incidents. The study was conducted in two periods. The before period of the study lasted for 162 days, from May 1st, 2022, to February 9th, 2023, when the LED-enhanced blinkers were fully operational. The ITS detection system automatically collected data on WWD incidents in this period, and researchers then manually reviewed and categorized the data for further analysis.

The after-period began on February 10th, 2023, and lasted for 122 days until June 18th. This period was initiated once enough data from the before period had been collected, reviewed, and deemed sufficient for conducting a robust before-and-after comparison experiment. In the after-period, the LEDs on the WRONG-WAY signs were manually turned off by the researchers to test the effects of the absence of LED-enhanced blinkers on WWD incidents (as shown in **Figure D-2**). This change was the primary difference between the two periods, while all other ITS system functions remained operational. The categorization and analysis of the after-period data were conducted in the same way as the before-period data.

Data Categorization Process

In this study, the BlinkLink remote system management was used to identify and categorize various incidents detected by the Wrong Way Alert System. When the radar detector senses a WWD movement, the detection and confirmation cameras are triggered, recording a 2-minute short video, respectively. **Figure D-3** shows the WWD ITS configuration, which includes a radar sensor, detection and confirmation cameras on the top, LED enhanced Wrong Way sign, an illuminator, and a system control cabinet.

The database encompasses incident reports for a range of entities, including vehicles, pedestrians, bikes, scooters, skateboards, and emergency response vehicles. Each report includes accurate timestamps and date information. All incidents were classified into four distinct categories: Continued Wrong-Way, Self-Corrected Wrong-Way, Authorized Motor Vehicles (which includes Emergency Response and Maintenance vehicles), and Non-Motor Vehicles (including pedestrians and bicycles). Analysts followed specific criteria to ensure accurate classification, which will be detailed in the following paragraph.

(a) (b)

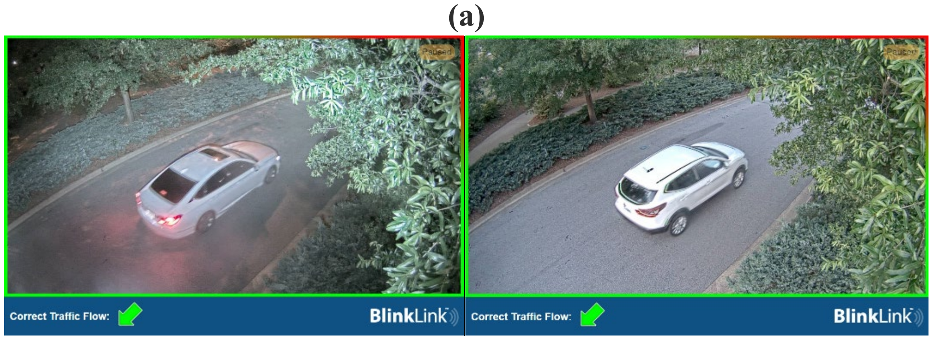
Figure D-2 (a) WRONG WAY sign with flashing LEDs around the border, and (b) Flashing LEDs were turned off

Figure D-3 Configuration of the Wrong-Way Alert System

Pedestrians and bicycles were easily distinguishable, and the presence of the Auburn University Logo identified maintenance vehicles. Emergency response vehicles, such as police cars, fire trucks, and ambulances, were also recognizable. The system monitored two fundamental movements: "Continued Wrong-Way" and "Self-Corrected Wrong-Way." For wrong-way maneuvers, Continued Wrong-Way is defined as the vehicle that has continued through with no evidence of self-correction, and Self-Corrected Wrong-Way is the vehicle that has been visually confirmed as self-correcting (as shown in **Figure D-4a**).

It's important to note that this research focuses on WWD incidents and the behavior of WWD drivers. Manual notes are essential for recording crucial details, such as whether the vehicle is braking (as illustrated in **Figure D-4b**) and the duration of their self-correction (turnaround time).

(a)



(b)

Figure D-4 (a) Self-Corrected Wrong-Way vehicles turnaround movements, and (b) Braking and not braking vehicles in Continued Wrong-Way vehicles

Verification of Radar Detection Results

To ensure the radar system's reliability in detecting all WWD incidents, the research team implemented a manual verification process. On a specific high-traffic day (GameDay), when a football game was held at Auburn Stadium on September 3rd, 2022, a portable traffic camera was employed to record 72 hours of footage at the study location. GameDays are characterized by a substantial increase in both traffic and visitor volume, often resulting in a higher number of WWD incidents. Testing the system's accuracy and reliability under these peak conditions provides a robust evaluation of its performance.

Researchers meticulously reviewed the 72 hours of recorded footage, searching for any potential WWD incidents that might have been missed by the radar system. This manual review was an exhaustive process, ensuring the absence of any unidentified events during the recording period. The review results indicated that the system effectively captured all relevant incidents, demonstrating the radar system's reliability in identifying WWD incidents.

Statistical Hypothesis Test

To determine if it is statistically significant based upon a pre-defined threshold probability (α), Chi-Squared tests and Welch's t-test examine the difference between daytime and nighttime WWD incidents frequency and before-after cases WWD self-correction rates. The fundamental equations for the test are shown in **Equation D-1**, using Welch's formula to calculate the degrees of freedom for the t-distribution.

$$df = \frac{\left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)^2}{\frac{\left(\frac{\sigma_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{\sigma_2^2}{n_2}\right)^2}{n_2 - 1}} \tag{1}$$

where:

σ_i^2 is the population variance.

R and R Studio software was applied to compute the p-value automatically. The confidence level in this study was set as default 95 percent (i.e., p-value equals 0.05) for the two-tailed t-test.

Welch's t-test is designed for unequal population variance, but the assumption of normality is maintained. A paired t-test not only requires normality but also needs the dependent variable to be continuous, and the observations are independent of one another. Shapiro-Wilk test was applied to ensure the normality for this study. Wilcoxon test was also applied to this study due to the unpaired sample size and non-normal distribution.

Daytime and Nighttime Definition

It needs to be noted that different studies have used varying definitions of daytime and nighttime intervals. For example, Zhang et al. (*22*) defined daytime as the period from 6 a.m. to 5:59 p.m., while Liu et al. (*23*) focused on North Carolina's crashes and defined daytime as 6 a.m. to 5 p.m. To ensure consistency in comparing results across studies, researchers have opted to use the definition of daytime as 6 a.m. to 5:59 p.m. for conducting paired t-tests. However, it's important to be aware of these differences in definitions when interpreting study findings.

RESULTS AND DISCUSSION

Descriptive Statistics for Incident Analysis

Descriptive statistics were employed to analyze the dataset after the data-cleaning process. This process involved removing unresolved data, such as those incidents that had not been manually checked or those not continuously collected due to power shutdowns during campus summer and winter vacations. GameDay incidents were also removed from this set, given that these occasions experience a significant surge in traffic volume compared to regular weekends. These GameDay incidents were segregated and analyzed separately to better understand their distinct characteristics and impacts.

Table D-1 provides an overview of the overall data, classified into five categories captured on weekdays and weekends. The detection accuracy, calculated by dividing the sum of all detected vehicles by the total incidents, was 50%. It's crucial to note that this figure represents the percentage of incidents correctly identified and classified by the system. **Figure D-5** displays all the incidents represented in a bar chart format.

Table D-1 Overall incidents distribution

Resolutions	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total
Continued Wrong-Way	12	14	17	14	26	66	32	181
Self-Corrected Wrong-Way	8	10	6	3	4	11	9	51
Total Wrong-Way Incidents	20	24	23	17	30	77	41	232
Authorized Motor Vehicles	86	88	71	88	125	136	44	638
Non-Motor Vehicles	108	102	140	115	137	143	125	870
Total	**214**	**214**	**234**	**220**	**292**	**356**	**210**	**1,740**

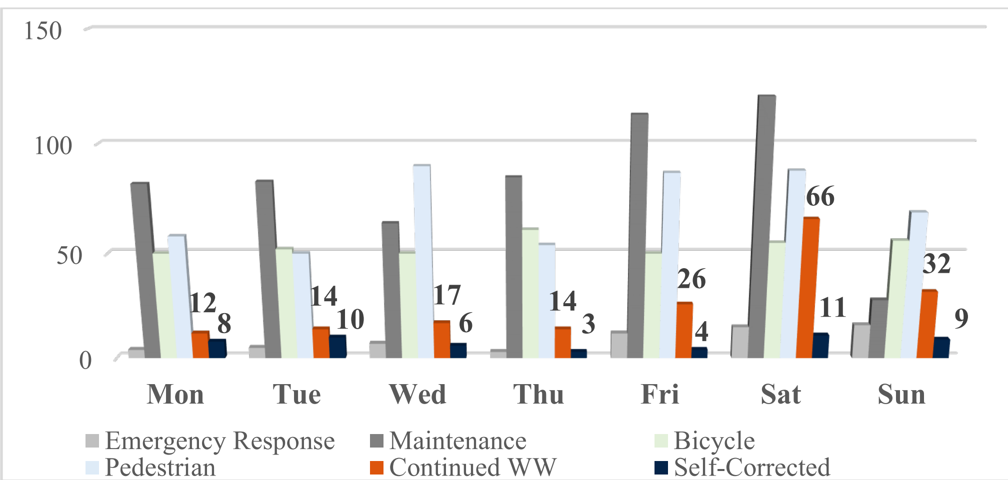


Figure D-5 Overall incidents distribution

Based on the classification of incidents and manual observation of vehicle brake lights during the before and after periods, researchers conducted a brief comparison of the turnaround rate and braking rate. Turnaround rate refers to the percentage of wrong-way drivers who corrected their course, while braking rate represents the proportion of wrong-way drivers who visibly slowed or stopped their vehicles.

Table D-2 presents the results, which indicate a decrease in the turnaround rate from 28% in the before period to 13% in the after period. This suggests that the LED-enhanced signs may have encouraged more drivers to correct their direction. However, due to a significant difference in the number of incidents between the two periods, a statistical test is required to confirm the significance of this turnaround rate difference.

Similarly, the difference in the braking rate between the two periods was not immediately apparent through simple descriptive statistics. This implies that further statistical analysis is necessary to understand whether the LED-enhanced signs influenced braking behavior.

It is worth noting that the average turnaround time of 55 seconds only represents the average of 25 self-corrected incidents. Some WWD drivers promptly returned to the correct direction as soon as they noticed the flashing LED alert, resulting in a negligible shorter average turnaround time.

Table D-2 Before and after turnaround rate comparison

	Before Period	**After Period**
Continued Wrong-Way	98	83
Self-Corrected Wrong-Way	38	13
Total Nuber of Wrong-Way Incidents	136	96
Turnaround Rate	28%	13%
Change in Turnaround Rate	15%	
Braking Rate	89%	90%
Avg Turnaround Time	55 seconds	

WWD Incident Frequency During Before and After Periods

As mentioned in the previous section, the descriptive statistics found that there could be differences in before and after periods of turn-a-round rate and braking rate. The Chi-Squared Test was conducted to statistically calculate whether significant differences existed before and after the flashing LEDs were turned off. The test results are presented in four hypotheses, which the following are discussed in more detail:

To conduct the Wilcoxon test, a null hypothesis (i.e., the number of true WWD frequencies is not statistically different between before and after periods) was considered. Considering a significance level of 95 percent, the null hypothesis is rejected in favor of an alternative. Due to the rare and random occurring characteristics of WW incidents, the sample size for the before period lasted 162 days, and the after period lasted 122 days. The WWD frequency means the number of the sum of continued WWD and self-corrected WWD incidents per day. According to the obtained results (**Table D-3**), a p-value larger than 0.05 indicates no significant difference in WWD frequency between the before and after periods. That means although the before and after periods were not the same date of different years, the probability of true WWD incidents occurring per day is the same, which minimizes the bias for using different dates.

Table D-3 Hypothesis and test results of WWD incidents frequency of before and after periods

	Before Period	**After Period**
Continued Wrong-Way	0.84	0.79
Self-Corrected Wrong-Way	162	122
w	5913.5	
p-value	0.545	

Turnaround Rate for the Before and After Periods

As shown in **Table D-4**, a before and after period matrix was formed. As was mentioned earlier, the turn-around rate in the before period is 14% higher than the after period. The obtained p-value (0.0144) is less than the commonly used significance level of 0.05. This indicates that there is a statistically significant difference in the turnaround rate before the flashing LEDs turn off compared to the signs without the assistance of flashing LEDs. In other words, the presence of flashing LEDs appears to have a considerable impact on the turnaround rate, leading to higher rates compared to situations where such LEDs are not used.

Table D-4 Hypothesis and test results about number of Self-Corrected WWD incidents for the before and after periods

	Before Period	**After Period**
Continued Wrong-Way	98	83
Self-Corrected Wrong-Way	38	13
p-value	0.014	

Braking Rate for the Before and After Periods

As for the braking rate, according to the obtained results (**Table D-5**), the p-value is higher than 0.05 which indicates that there's no significant difference in braking rate between before and after periods.

Table D-5 Hypothesis and test results of braking rate for the before and after periods

	Before Period	**After Period**
Continued Wrong-Way	49	75
Self-Corrected Wrong-Way	6	8
Braking Rate	11%	10%
p-value	1	

Turnaround Rate for Daytime and Nighttime

Table D-6 presents the results of the hypothesis test, which assesses the impact of flashing LEDs on the turnaround rates of WWD incidents based on daily time periods. The analysis reveals a notable 19% difference between the before and after daytime periods when comparing the presence of flashing LEDs on signs. The obtained p-value (0.0130) is less than the significance level of 0.05, indicating that the turnaround rate during the daytime is significantly higher when the signs are equipped with flashing LEDs compared to signs without flashing LEDs. During the nighttime, there is a 7% improvement in the turnaround rates with the presence of flashing LEDs. However, the p-value (0.6228) is higher than the significance level, suggesting that there is no significant difference in the turnaround rates between the presence and absence of flashing LEDs during nighttime. These findings emphasize the effectiveness of flashing LEDs on signs in improving the turnaround rates of WWD incidents during both daytime and nighttime hours, with a more pronounced impact during the daytime.

Table D-6 Hypothesis and test results of Self-Correction rate for daytime and nighttime

	Before Period Daytime	After Period Daytime
Continued Wrong-Way	60	54
Self-Corrected Wrong-Way	26	7
Turnaround Rate	30%	11%
Change in Turnaround Rate	19%	
p-value	0.013	
	Before Period Nighttime	**After Period Nighttime**
Continued Wrong-Way	38	29
Self-Corrected Wrong-Way	12	6
Turnaround Rate	24%	17%
Change in Turnaround Rate	7%	
p-value	0.623	

Figure D-6 provides a comprehensive comparison of WWD incidents between GameDay weekends and regular weekends. Out of 4 GameDay weekends (8 days total), there were 128 continued WWD incidents, significantly higher than the 47 incidents observed during 25 normal weekends (50 days). Conversely, self-corrected WWD incidents showed an opposite trend, with only three instances recorded during GameDay weekends compared to 11 during normal weekends. This indicates a significantly lower turnaround rate of 2.3% during GameDay events, compared to 25.5% on normal weekends.

Although the likelihood of encountering an intoxicated driver was higher on GameDay weekends, a closer examination of **Table D-7** reveals a remarkable difference in the turnaround rates based on the time of day. During the nighttime, the turnaround rate was substantially higher at 8%, compared to the daytime result of 1%. However, even during the GameDay weekends, the braking rates remained consistently high at around 94% during the daytime and 100% during the nighttime. This implies that flashing LEDs effectively captured the attention of wrong-way drivers, prompting them to brake and slow down.

In summary, the data highlights the significance of GameDay weekends as a unique scenario with a higher incidence of continued WWD incidents but a lower turnaround rate. The implementation of flashing LEDs demonstrated its effectiveness in improving driver response, leading to higher braking rates, and thereby contributing to enhanced road safety during both normal and GameDay weekends.

Table D-7 GameDay and normal weekends daytime/nighttime comparison

	Game Day Weekends		Normal Weekends	
	Daytime	**Nighttime**	**Daytime**	**Nighttime**
Continued Wrong-Way	101	24	27	8
Self-Corrected Wrong-Way	1	2	10	2
Turnaround Rate	1%	8%	27%	20%
Did brake	95	24		
Did not brake	6	0		
Braking Rate	94%	100%		

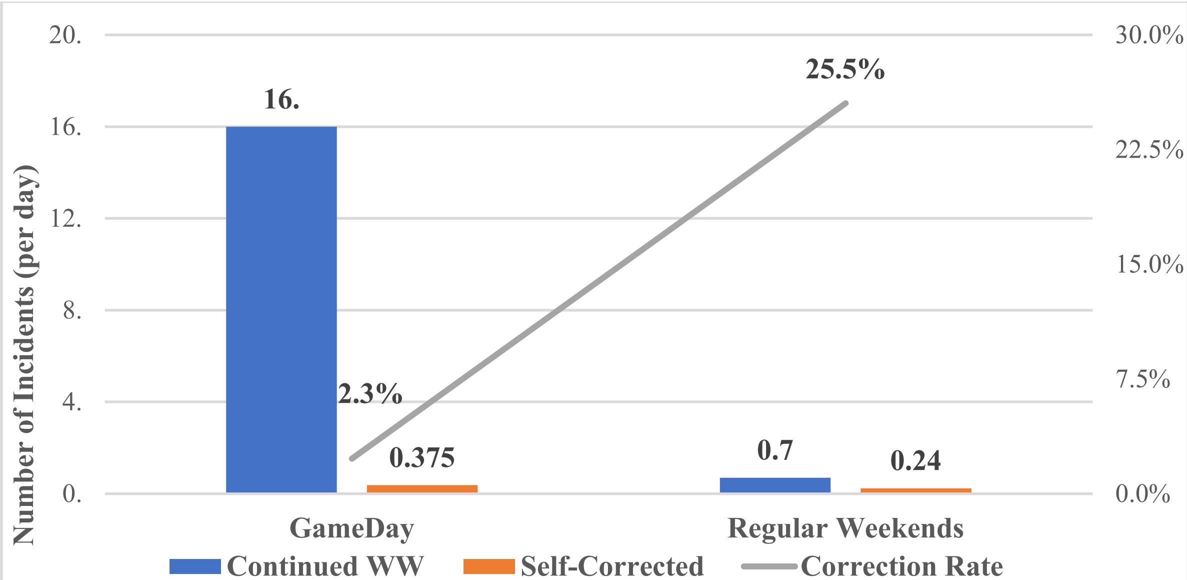


Figure D-6 GameDay and normal weekends comparison

CONCLUSIONS

This research strived to analyze the effects of the flashing perimeter LEDs on WWD movements with the assistance of advanced WWD ITS detection technologies at a one-way road in Auburn, Alabama. According to the data collected and the statistical tests, some of the key findings are listed as follows:

- The implementation of flashing LEDs has led to a noticeable decrease in continued WW movements, demonstrating a 15% increase in the turnaround rate when functional flashing LEDs are present around the border of the WRONG WAY signs.
- Compared to the traditional WRONG WAY signs without flashing LEDs, a significant reduction (19%) in turnaround rate in the daytime was found due to the implementation of flashing LEDs. However, contrary to expectations, the nighttime comparison did not yield a statistically significant difference, despite the anticipation of a significant impact since flashing LEDs command more attraction to impaired drivers.
- There was no observed statistically significant difference in the braking rate between flashing LEDs being turned on or off, indicating that the duration of the experiment did not have a notable impact on the braking behavior.
- The overall accuracy of the WWD radar detection stands at 50%, indicating that half of the detected objects were motor vehicles, while the remaining half consist of pedestrians, bicycles, scooters, and other non-motor vehicles. The system's lower accuracy can be attributed to the limitation of the radar sensor, which struggles to accurately identify objects. However, recent advancements have introduced thermal and thermal-radar sensors as potential solutions to address this issue.
- Compared to regular weekends, GameDay weekends exhibited a significant increase in WWD movements, whereas self-corrected incidents were significantly lower than regular weekends. The flashing LEDs demonstrated their potential effectiveness in deterring intoxicated drivers' WWD movements.

The system operates continuously, relying on a consistent supply of AC power and the internet, enabling continuous data collection. This presents the opportunity for ongoing updates and refinements in future research based on the study's findings. Additionally, by the end of this year, the system will gather data for the same period of six months, both before and after the case. This aspect is particularly significant as it allows for a reduction in testing bias by comparing data collected during the same month in both 2022 and 2023.

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AUTHOR CONTRIBUTIONS
The authors confirm their contribution to the paper as follows: study conception and design: Huaguo Zhou, Zijie Zhao; data collection: Zijie Zhao, Tonghui Li; analysis and interpretation of results: Zijie Zhao, Tonghui Li, Fangjian Yang; draft manuscripts preparation: Zijie Zhao, Huaguo Zhou. All authors reviewed the results and approved the final version of the manuscript.

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