# ASSESSMENT OF SAFETY BENEFITS OF TECHNOLOGIES TO REDUCE PEDESTRIAN CROSSING FATALITIES AT MIDBLOCK LOCATIONS

**Final Report**

by


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**May 2020**


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# ACKNOWLEDGMENT

*The authors would like to thank the South Carolina Department of Transportation, in particular, Jennifer Rhoades and Andrew Stokes, for providing redacted crash reports and data for this project. We could not have done this project without your assistance.*

**Technical Report Documentation Page**

| **1. Report No.** | **2. Government Accession No.** | **3. Recipient's Catalog No.** |
|---|---|---|
| | | |

| **4. Title and Subtitle**<br>Assessment of Safety Benefits of Technologies to Reduce Pedestrian Crossing Fatalities at Midblock Locations | **5. Report Date**<br>May 2020<br>**6. Performing Organization Code** |
|---|---|
| **7. Author(s)**<br>Jennifer H. Ogle, Ph.D., ORCID: 0000-0003-0521-3104;<br>Sababa Islam, M.Sc., ORCID: 0000-0003-075202832;<br>Kweku T. Brown, Ph.D., ORCID: 0000-0001-6497-8479;<br>Judith Mwakalonge, Ph.D., ORCID: 0000-0002-7497-6829;<br>Dimitra Michalaka, Ph.D., ORCID: 0000-0001-7001-0579;<br>Mashrur "Ronnie" Chowdhury, Ph.D., ORCID: 0000-0002-3275-6983 | **8. Performing Organization Report No.** |
| **9. Performing Organization Name and Address**<br>Clemson University<br>212 Lowry Hall<br>Clemson, SC 29634-0911 | **10. Work Unit No.**<br>**11. Contract or Grant No.**<br>69A3551747117 |
| **12. Sponsoring Agency Name and Address**<br>Center for Connected Multimodal Mobility ($C^2M^2$)<br>Clemson University<br>200 Lowry Hall, Clemson<br>Clemson, SC 29634 | **13. Type of Report and Period Covered**<br>Final Report (Mar 2018 – Mar 2020)<br>**14. Sponsoring Agency Code** |

**15. Supplementary Notes**

**16. Abstract**

In 2015, South Carolina ranked third in the nation in pedestrian fatalities per 100,000 population. Out of 979 total motor vehicle fatalities, 123 involved pedestrians, accounting for over 12% of all road user fatalities in South Carolina. While some individuals make conscious choices to walk and dwell in transit-oriented or mixed-use walkable communities, for others, vehicle availability or physical disability may dictate the pedestrian mode. Thus, pedestrian crashes and resulting deaths and injuries can disproportionately affect these segments of the population. Often, these crashes occur due to driver detection errors, such as: 1) inability to identify specific types of road users or looking at the direction that is appropriate due to the gap of cognitive expectation; and 2) failure in understanding stimuli when adequate lighting is not available or when a vehicle approaches in the periphery of the visual field for the road user. Historically, pedestrian detection has been the responsibility of the driver and is prone to errors related to expectation, visual acuity, visual contrast, etc. With the growing market of vehicle sensing, smartphones, and smart infrastructure, there exists a plethora of opportunities to aid the driver and pedestrian with enhanced sensing capability and visibility. This research lays the foundation of knowledge for pedestrian midblock crashes at nighttime, their exposure characteristics, and the potential effectiveness of existing sensing technologies. Through data analytics, this research advances knowledge for technology adoption to foster safer and more effective mobility for our society.

| **17. Keywords** | **18. Distribution Statement** |
|---|---|
| Pedestrian, crash detection, autonomous vehicles, midblock, nighttime | No restrictions. |

| **19. Security Classif. (of this report)** | **20. Security Classif. (of this page)** | **21. No. of Pages** | **22. Price** |
|---|---|---|---|
| Unclassified | Unclassified | **96** | NA |

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# EXECUTIVE SUMMARY

In 2015, South Carolina ranked third in the nation (behind Delaware and Florida) in pedestrian fatalities per 100,000 population (NHTSA, 2017)[1]. Out of 979 total motor vehicle fatalities, 123 involved pedestrians, which accounts for over 12% of all road user fatalities in South Carolina. While some individuals make conscious choices to walk and dwell in transit-oriented or mixed-use walkable communities, for others, vehicle availability or physical disability may dictate the pedestrian mode. Thus, pedestrian crashes and resulting deaths and injuries can disproportionately affect these segments of the population. Often, these crashes occur due to driver detection errors, such as: 1) unable to identify specific types of road users or looking at the direction that is appropriate due to the gap of cognitive expectation; and 2) failure in understanding stimuli when adequate lighting is not available or when a vehicle approaches in the periphery of the visual field for the road user.

Historically, pedestrian detection has been the responsibility of the driver and is prone to errors related to expectation, visual acuity, visual contrast, etc. With the growing market of vehicle sensing, smartphones, and smart infrastructure, there exists a plethora of opportunities to aid the driver and pedestrian with enhanced sensing capability and visibility. This research lays the foundation of knowledge for pedestrian midblock crashes at nighttime, their exposure characteristics, and the potential effectiveness of existing sensing technologies. Through data analytics, this research advances knowledge for autonomous vehicle technology adoption to foster safer and more effective mobility for our society. Future research will assess short-term deployable technologies for these crashes - such as pedestrian to vehicle notification systems and infrastructure warning systems based on pedestrian to infrastructure communication.

This research began with a characterization of pedestrian nighttime crashes to gain a complete understanding of qualitative and quantitative aspects of these crashes. Factors of interest included: patterns of pedestrian walking maneuver type, time of day, day of week, geographic distribution, infrastructure classification, design characteristics of high crash locations, characteristics of impacting drivers, behavioral factors associated with decisions to cross, and socioeconomic factors of pedestrians involved in fatal and severe injury crashes. The outcomes of this analysis will help to identify areas of high pedestrian crash potential around the state, what roadway design features are most common at crash sites, and which population demographics are most at risk. The crash data analysis was followed by a literature review and brief assessment of the potential of autonomous vehicles to bring a paradigm shift in pedestrian and vehicle interactions. The literature review was intended to gauge the efficacy of the sensor technologies for different types of crashes. Finally, some short-term implementation solutions were recommended based on the patterns identified in the crash data analysis.

In this project the researchers conducted a detailed analysis on the pedestrian crash types presented in chapter 4. The key findings from the analysis are:

- On average 80 percent of fatal crashes happened at night for the year from 2007-2016.
- About 86 percent of the night-time fatal pedestrian crashes occurred at the midblock locations
- Analysis conducted on the night-time fatal mid-block crashes shows that pedestrian who are walking along the road and in the opposite direction of the vehicles are the most vulnerable to be hit by vehicles. The second most vulnerable maneuver is when pedestrians cross the road approaching from the left of the driver.

[1] NHSTA, Traffic Safety Facts. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812493

- While investigating the crashes where the pedestrians were fatally injured walking-along road (same or opposite direction), it was found that these crashes often happened on undivided two-lane two-way roads with no sidewalks.
- For crossing crashes, where the pedestrians are crossing the road approaching the driver's side from the left (most common) or right, it was found that these types of crashes happened on multi-lane facilities which lacked refuge spaces for pedestrians to wait for oncoming cars to pass.
- Another key factor for night-time fatal midblock crashes is the lack of illumination at the crash locations.

An analysis of pedestrian crash social media was completed to determine the role of the media in portraying pedestrian crashes. This analysis was used to ascertain if educational information was being provided on the known dangers and precautionary measures. Before creating the word clouds, the news articles and tweets were thoroughly read, and researchers concluded that the messaging focused on reckless driving as the main culprit for the pedestrian deaths in South Carolina State over the last 5 years. The social media was largely devoid of dangers and risks assumed by pedestrians involved in these crashes.

The research team also analyzed the sociodemographic characteristics of the home locations of fatal and injured pedestrians by matching their 9-digit zip code with Census block groups information. Census information used in the analysis included: population, gender, race/ethnicity, age, median household (HH) income, educational attainment, poverty level, vehicles available, and vehicle age. Average values were computed for the state as well as the sample of fatally injured pedestrian crashes containing 9-digit zip codes. The differences were significant in many cases. The population density at the home location of the fatally injured pedestrians was much higher with 201 pedestrians per square mile versus 150 for the state average. This indicates that there is an urban trend – higher density development in pedestrian crashes. The median household income is also significantly lower, and there is a propensity for toward lower education levels (higher involvement of only a high school education). Overall, there was some variation in age and race/ethnicity, but chi square tests of the resulting distributions were not independent.

All pedestrians should be able to use roadway facilities safely and without having to go significant distances out of their way. Therefore, it is the responsibility for the roadway planners, designers and engineers to consider pedestrians as a critical system user and plan, design, and install safe crossing/walking facilities or by providing engineering modifications to the built environment. In general, there are three types of engineering modifications for the built environment to increase pedestrian's safety, including: pedestrian separation from vehicles by space and time, vehicle speed reduction, and increasing pedestrian's conspicuity and visibility (Retting et al., 2003).

One clear finding from the research is that pedestrian infrastructure, especially sidewalks, is lacking and recommendations would suggest investment in pedestrian sidewalks or paths where there are known exposures or where historical crash data exists. Proper street lighting is also recommended where practical and efficient lighting methods may be deployed. To improve conditions related to crossing crashes at night, the availability of street lighting is crucial along with pedestrian refuge islands on wide multi-lane facilities. Training and public service announcements relaying lack of pedestrian visibility and contextual clues of higher risk sites may also play an important role for both pedestrians and drivers alike.

# CHAPTER 1

## Introduction

In 2015, South Carolina ranked third in the nation (behind Delaware and Florida) in pedestrian fatalities per 100,000 population (NHTSA, 2017). Out of 979 total motor vehicle fatalities, 123 involved pedestrians, which accounts for over 12% of all road user fatalities in South Carolina (SCDOT Crash Data, 2015). While some individuals make conscious choices to walk and dwell in transit-oriented or mixed-use walkable communities, for others, vehicle availability or physical disability may dictate the pedestrian mode. Thus, pedestrian crashes and resulting deaths and injuries can disproportionately affect these segments of the population. Often, these crashes occur due to driver detection errors, such as: 1) unable to identify specific types of road users or looking at the direction that is appropriate due to the gap of cognitive expectation; and 2) failure in understanding stimuli when adequate lighting is not available or when vehicle approaches in the periphery of the visual field for the road user (Rumar 1990).

Historically, pedestrian detection has been the responsibility of the driver and is prone to errors related to expectation, visual acuity, visual contrast, etc. With the growing market of vehicle sensing, smartphones, and smart infrastructure, there exists a plethora of opportunities to aid the driver and pedestrian with enhanced sensing capability and visibility. This research lays the foundation of knowledge for pedestrian midblock crashes at nighttime, their exposure characteristics, and the potential effectiveness of existing sensing technologies. Through data analytics, this research advances knowledge for autonomous vehicle technology adoption to foster safer and more effective mobility for our society. Future research will assess short-term deployable technologies for these crashes - such as pedestrian to vehicle notification systems and infrastructure warning systems based on pedestrian to infrastructure communication.

This research began with a characterization of pedestrian nighttime crashes to gain a complete understanding of qualitative and quantitative aspects of these crashes. Factors of interest included: patterns of pedestrian walking maneuver type, time of day, day of week, geographic distribution, infrastructure classification, design characteristics of high crash locations, characteristics of impacting drivers, behavioral factors associated with decisions to cross, and socioeconomic factors of pedestrians involved in fatal and severe injury crashes. The outcomes of this analysis will help to identify areas of high pedestrian crash potential around the state, what roadway design features are most common at crash sites, and which population demographics are most at risk.

The crash data analysis was followed by a literature review and brief assessment of the potential of autonomous vehicles to bring a paradigm shift in pedestrian and vehicle interactions. The literature review was intended to gauge the efficacy of the sensor technologies for different types of crashes. The final step in the first phase of this research was to pilot test video collection of pedestrian exposure data in a controlled low/no light nighttime environment. In future phase, actual exposure data will be needed at areas of high pedestrian crash potential to determine the extent of pedestrian crossing maneuvers at these locations. Finally, some short-term implementation solutions were recommended based on the patterns identified in the crash data analysis. Recommendations for the second phase of research include parameters required to conduct a follow-on simulation study.

After a thorough analysis of contextual parameters surrounding pedestrian crashes, the research team chose to focus on the study of midblock fatal crashes at nighttime. A 2-year limited-scope detailed qualitative analysis was followed by an expansive 10-year quantitative analysis. In this research it was found that most of the pedestrian crashes are injury-related (80%), some are fatal crashes (14%) and few involve property damage only (6%). Approximately 80% of the pedestrian crashes occur at night although pedestrians are exposed to more vehicles during the daylight hours and the pedestrian volume during the day is also higher compared to the night. This finding reveals the vulnerability of pedestrians at nighttime.

The location of nighttime fatal pedestrian crashes was also studied and on an average 86% of the crashes occurred at midblock locations where walking along the road or crossing are unprotected movements. In most of the crashes, pedestrian infrastructure, such as sidewalks and marked or otherwise controlled crosswalks, does not exist. Moreover, there is a lack of driver expectation of pedestrians at midblock locations.

The researchers drilled down in the midblock fatal pedestrian crashes at night and categorized them based on the maneuver of the pedestrians with respect to the vehicles involved in the crash. Pedestrian crashes are categorized into the following types: walking along the roadway with respect to direction of oncoming traffic (Ped-Along/Same, Ped-Along/Opposite), midblock crossing with respect to which side of the drivers vehicle the pedestrian was approach from (Ped-Right and Ped-Left), crashes where pedestrians are involved in activities other that walking or crossing (Ped-Standing/Working/other), and some were categorized as unknown because there was not enough information available to categorize them. Researchers found that maneuver categories of Ped-Along/Same and Ped-Left crash types outnumbered the rest.

After identifying the predominant maneuvers, infrastructure characteristics were studied to determine whether patterns may exist for each type of maneuver. Predominant patterns emerged with midblock crashes where pedestrians were walking along the road occurred more frequently at locations where sidewalks are not available and lighting is inadequate. These crashes were also occurring on lower classification facility types (secondary routes), most with two-lanes two-way operations and no medians. In contrast, pedestrian crossing crashes tend to occur on urban multilane roadways with higher route types (US or SC routes), many with bituminous medians (indicative of two-way left-turn lanes).

An analysis of pedestrian crash social media was completed to determine the role of the media in portraying pedestrian crashes. This analysis was used to ascertain if educational information was being provided on the known dangers and precautionary measures. Before creating the word clouds, the news articles and tweets were thoroughly read, and researchers concluded that the messaging focused on reckless driving as the main culprit for the pedestrian deaths in South Carolina State over the last 5 years. The social media was largely devoid of dangers and risks assumed by pedestrians involved in these crashes.

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In the next to final step, the research team developed a test method to gauge the efficacy of camera technologies for detecting pedestrians at night. The goal for this task was to develop an effective method for capturing pedestrian exposure data from sites of interest. The study results indicated that for the dark not lit condition infrared camera outperformed the night vision PTZ camera. There wasn't a single tested scenario where the infrared camera did not produce a discernable human figure. However, the performance of the Night-vision PTZ camera was not satisfactory. The only clothing that could produce a visible image was the bio-motion suit. For the dark, but lit with vehicle headlight condition, both infrared and night vision PTZ performed well. The performance of the night vision camera deteriorated with the increasing distance of camera from the crossing location. This also magnified the disparities in the headlight patterns with respect to pedestrian illumination in various positions in front of the vehicle. Pedestrians to the right of the driver are illuminated for a much greater distance and further to the side of the center and side of the road, but illumination area to the left was close to the center line boundary and closer to the front of the vehicle. Pedestrians to the left at greater distances were often not visible.

Finally, the research team conducted a technology gap analysis to determine the limitations of the detection technologies that are currently being used on autonomous vehicles for detecting pedestrians. A literature review highlighted the pros and cons of these technologies. The review included numerous technologies such as: the visual light cameras, LiDAR, RADAR and thermal cameras. Each technology has its own limitations. However, the studies conducted on these technologies have recommended how the performance of these technologies can be augmented by combining them with machine leaning techniques. The contextual information provided in this paper provide much needed guidance for clues to provide in that learning process.

# CHAPTER 2

## Literature Review

The literature review was conducted on two distinct areas related to pedestrian crashes:

1. Pedestrian crash analysis and historical trends, and
2. Socioeconomic concerns related to pedestrian crashes.

## 2.1 Pedestrian Crash Analysis and Historical Trends

Comparing the nationwide mileage death rates, South Carolina is one of the highest for many years which also exceeds the national fatality rate. On average in South Carolina in 2016, one person was killed every 8.6 hours in a crash, and approximately every four hours a crash is being reported. More specifically, one pedestrian was killed in South Carolina every 3 days (South Carolina Traffic Collision Fact Book 2016). The trend of pedestrian fatalities in South Carolina has been on the rise over the last decade, increasing from 10% of total fatalities in 2007 to 15% in 2016 in the last 10 years (Figure 2.1) (South Carolina Traffic Collision Fact Book 2016, 2011).

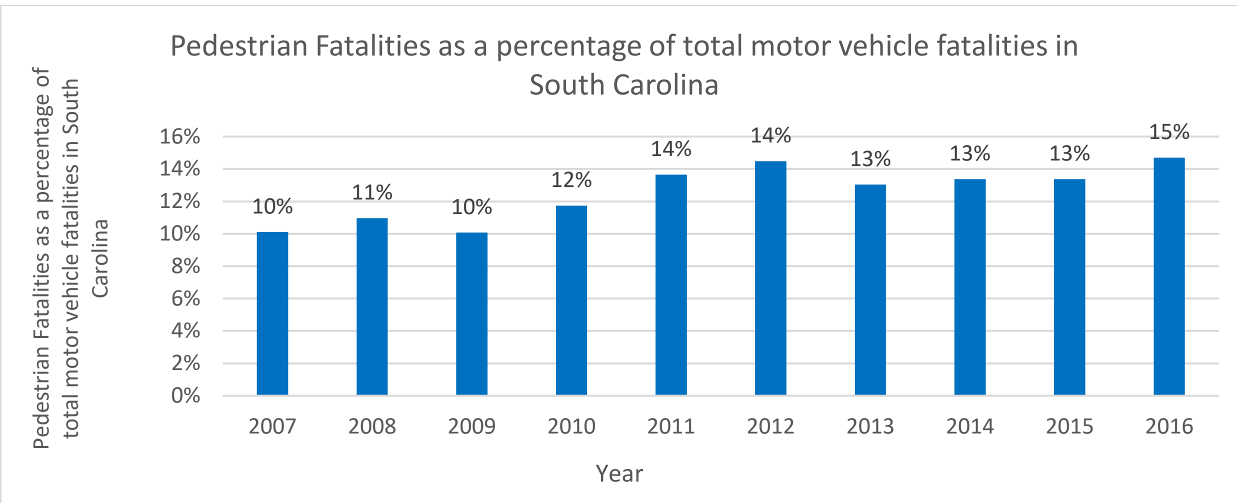



**Figure 2.1 Pedestrian Fatalities as a percentage of total motor vehicle fatalities in South Carolina (Source: South Carolina Traffic Collision Fact Book 2016, 2011)**

For the year 2016, the highest numbers of pedestrian fatalities and injuries occur in April and November. Across the year, there is approximately 100 pedestrian injury and fatality crashes each month. Figure 2.2 shows a slight decrease in pedestrian crashes over the winter months starting in December, however, given the temperate climate of South Carolina, no distinct pattern exists. After analyzing the pedestrian fatalities by light condition and weather, pedestrian injury and fatality crashes are most prevalent in dark/clear conditions. In general, approximately 60% of pedestrian fatal and injury crashes occurred after dark (see Figure 2.3). Figure 2.4 reinforces the fact that pedestrian fatalities/injuries are prevalent at night, with the highest number occurring between 6 PM and 9 PM at night. Crash location is one of the key factors in pedestrian crashes. Figure 2.5 shows that highest number of pedestrian fatalities occur on US primary roadways and highest pedestrian injuries occur on secondary roadways. While these statistics give a general idea about the pedestrian crashes in South Carolina based on the data from SCDOT traffic collision fact books, a detailed crash pattern analysis will be presented in latter sections.

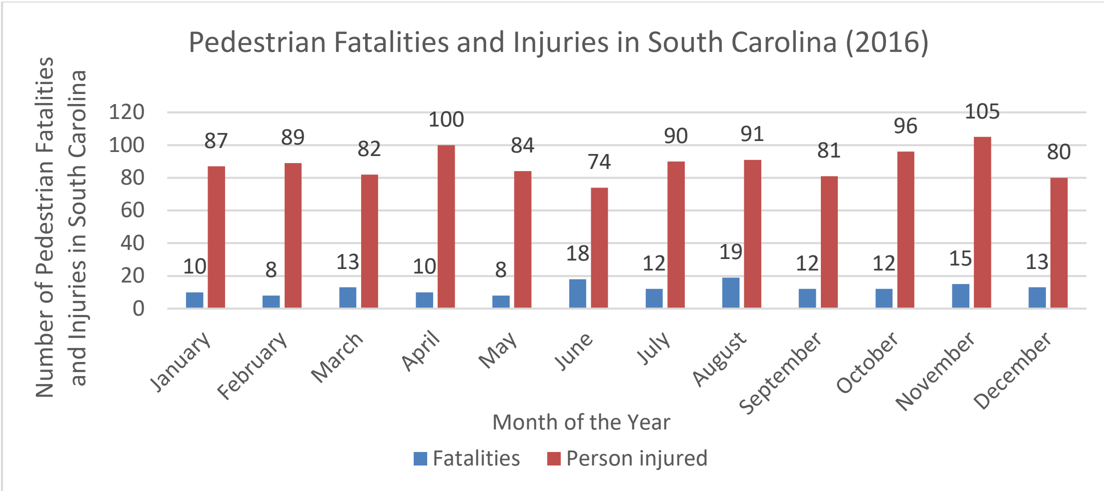



**Figure 2.2 Pedestrian Fatalities and Injuries in South Carolina (2016) (Source: South Carolina Traffic Collision Fact Book 2016)**

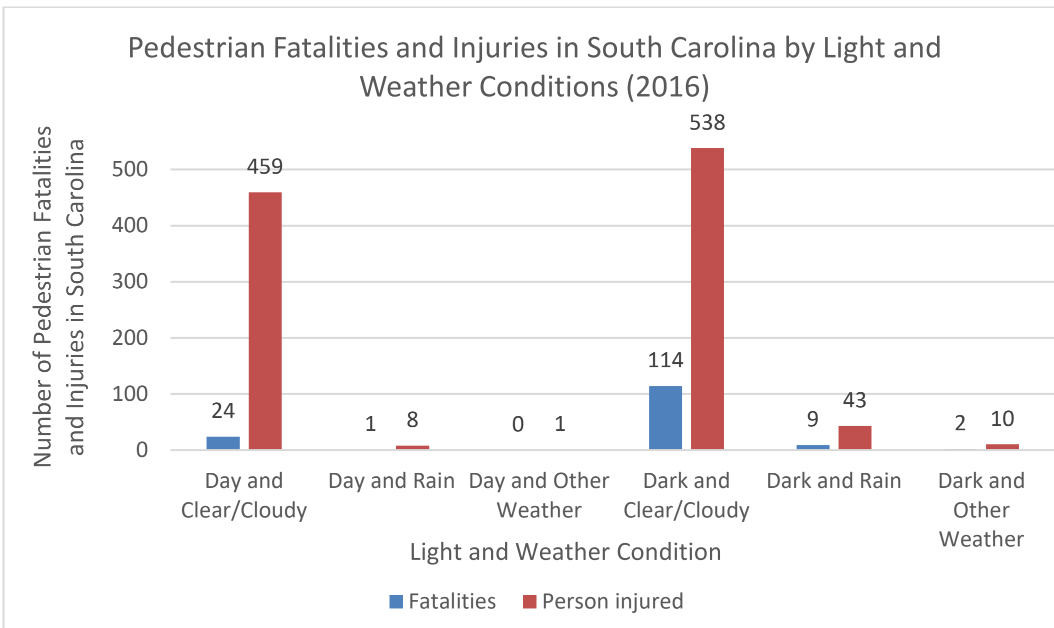



**Figure 2.3 Pedestrian Fatalities and Injuries in South Carolina by Light and Weather Conditions (2016) (South Carolina Traffic Collision Fact Book 2016)**

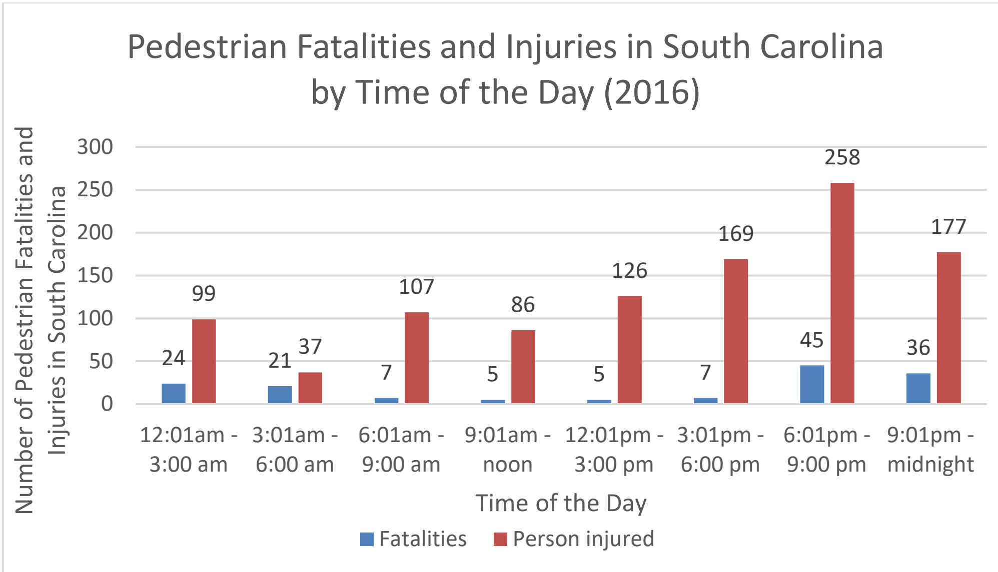



**Figure 2.4 Pedestrian Fatalities and Injuries in South Carolina by Time of the Day (2016) ) (South Carolina Traffic Collision Fact Book 2016)**

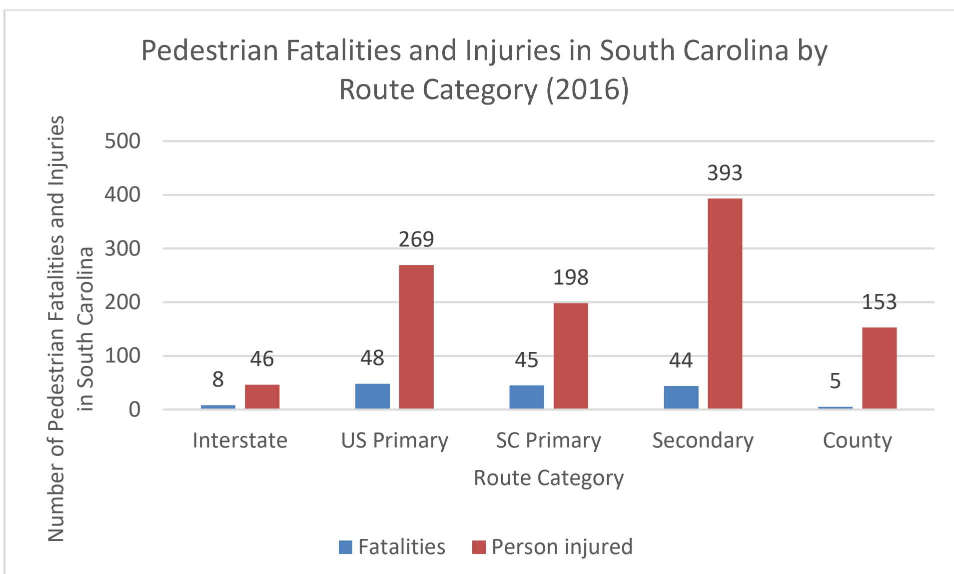



**Figure 2.5 Pedestrian Fatalities and Injuries in South Carolina by Route Category (2016) ) (South Carolina Traffic Collision Fact Book 2016)**

Previous research reveals the prevalence of pedestrian crashes in urban areas than the rural areas, and a significant portion of urban pedestrian crashes are located at midblock locations rather than at intersections (GHSA, 2015). In large urban areas, many roads are designed for motor vehicle mobility with numerous lanes and high speeds. Often, intersections are spaced far apart to control access and aid in progression. However, this type of design is not amenable to pedestrian crossing movements, and pedestrians tend to choose the more direct and often illegal midblock crossings rather than traversing out of their way to have protected crossings at signalized locations.

According to a report by NHTSA, the percentage of pedestrian fatalities out of total fatalities increased from 11% in 2004 to 16% in 2016 (NHTSA, 2016). With increasing pedestrian fatalities on roadways in the US, research has been conducted for modeling crash consequences to determine the severity of motor vehicle crashes. Eluru et al. (2008) conducted a literature review on previous research and classified the factors associated with pedestrian crashes into six classes, they are: (1) pedestrian characteristics (e.g. age, gender, state of soberness), (2) motorized vehicle driver characteristics (e.g. state of soberness, age), (3) motorized vehicle characteristics (e.g. vehicle type, speed), (4) roadway characteristics (e.g. speed limit, road system) (5) environmental factors (e.g. time, weather conditions, light condition), and (6) crash characteristics (e.g. vehicle motion prior to crash). Among these different characteristics, light condition was critical. Analysis of fatal crashes in USA revealed that 72% of the pedestrian fatalities occurred in dark conditions.

Several studies support the fact that pedestrian crashes are more sensitive to lighting conditions (Owens & Sivak, 1996; Sullivan & Flannagan, 2002 and Siddiqui et al. 2006). This is because typically clothed pedestrians are difficult for the drivers to detect and identify during twilight or dark conditions (Hazlet, 1968). This situation becomes even more challenging when a poorly visible pedestrian overestimates his/her visibility and makes a crossing maneuver on a section of unlit road (Allen et al., 1970). Rumar (1990) describes two important driver detection errors for this scenario: 1) unable to identify specific types of road users or looking at the direction that is appropriate due to the gap of cognitive expectation; and 2) failure in understanding stimuli when adequate lighting is not available or when a vehicle approaches in the periphery of the visual field for the road user.

The detection range of a driver at nighttime varies based on the location of the pedestrian, whether the roadway is illuminated or not, the color of the pedestrian clothing, and the presence of opposite direction vehicles (Ising, 2008). Olson and Sivak (1996) conducted a test to find the visibility of pedestrians wearing dark and light clothing at night. In the test, pedestrians wore black and white clothing and stood on a dark unlit rural road. The subjects of this test were the passengers and drivers in a car, which was traveling at a speed of 40 mph. Both the drivers and the passengers were given a control box with buttons signifying the type and location of different targets. Based on that data recorded in the control box, the response distance of different subjects from the pedestrians was measured. The subjects in the vehicle were divided into two age groups: subjects with 18-30 years old (young) and subjects with 65 years or more (older). The key factors affecting the study results are: the that the pedestrians were waiting with respect to the vehicle, the color of the clothing that the pedestrians were wearing and age of the subjects.  The study results showed that younger drivers predicted the presence of pedestrians faster than the older drivers did, which is quite predictable. The study by Olson and Sivak, revealed that the pedestrians on the right side of vehicles were identified sooner (at a larger distance away) than the pedestrian on the left side. This is because the low beam is designed in a way to illuminate the roadway in front of the vehicle at the same time not affecting the opposite direction vehicle. For this reason, the lighting beam is skewed toward the right making it easier for the driver to identify obstacles in the right. Wood et al. (2005) conducted a study to measure the ability of the drivers to recognize pedestrians at night. A closed-circuit road was used as the test site. The participant drivers were divided into young and older age groups. Four different types of pedestrian clothing and two beam types were used in the study. Age of the driver, types of clothing, glare and beam of the headlamp were found to be significantly affecting pedestrian detection at night.

The detection ranges of pedestrians also varied based on drivers' expectations. A study was conducted by Roper and Howard (1938) for two different scenarios of pedestrian detection, in one scenario the drivers are aware that pedestrians may cross their path and in the second scenario, the drivers were not made aware of a potential pedestrian presence. The study results revealed that the drivers detected the dummy pedestrians twice as far away when they were expecting the pedestrians.

## 2.2 Socioeconomic characteristics of the pedestrians involved in crash

Among different road user groups, pedestrians are most vulnerable from a transportation safety standpoint. This is especially the case in South Carolina where 15% of total fatalities in 2016 were pedestrians (SC Traffic Collision Fact Book, 2016). South Carolina also and had the second highest pedestrian fatality rate of 2.9 pedestrian fatalities per 100,000 population in 2016 in the U.S. (NHTSA, 2016). There has been extensive research done on the socio-demographic characteristics of pedestrians involved in crashes over the past few decades. The two major characteristics investigated over the years have been age of pedestrians and the household income (relative to poverty or socio-economic status) of pedestrians or neighborhood with disproportionately high pedestrian crash frequency and severity.

In 2016, 20% of pedestrian fatalities fell within the 50 to 59-year range (NHTSA 2016). This was the highest 10-year range. Also, the average age of pedestrians killed from 2007 to 2016 was 47 years (NHTSA 2016). The results from the previous research conclude that the elderly (65 year and older) are prone to more severe pedestrian crashes compared to younger pedestrians (Xin et al. 2017, Pour-Rouholamin & Zhou 2016 and Hanson et al, 2013) and that higher crash severity is seen in older populations due to them being less mobile and more fragile with regard to recovery from a crash (Prato et al. 2018). However, middle-aged and younger pedestrians are associated with a higher risk of involvement in pedestrian crashes overall due to higher levels of exposure (Moreno et al. 2016). Simply put, younger people walk and run more, hence, there is an elevated risk considering only exposure. This reasoning is supported by research results from Florida DOT, which suggests that pedestrian crashes occur more frequently in the areas with less number of older adults (Lin et al. 2017). Although the elderly do not constitute the highest proportion of overall pedestrian crashes, their crash severity levels within that group are disproportionately high compared to other age groups.

Household income directly imputes the socio-economic status of an individual or area which also correlates with many characteristics of concern in traffic safety such as vehicle ownership, travel patterns, the built environment and the lifestyle of pedestrians as a whole. A study in Canada by Morency et al. (2012) concluded that areas with lower income in Canada reported a higher rate of pedestrian injury which was almost 7 times higher than areas classified as having a high income. To add to this, pedestrian crashes have been found to be more prevalent and of more concern in low income areas (Cottrill & Thakuriah 2010, Shah et at. 2017 and Moreno 2016). The ownership of vehicles has a direct correlation to socio-economic status in most areas in the nation. In areas where households own one or fewer vehicles on average, the pedestrian crash rate is higher than in areas with higher auto ownership levels (Lin et al. 2017). Households with 1 vehicle or less often have no choice but to use public transportation, bike, or walk, hence increasing their exposure to vehicle traffic (Chimba et al. 2018 and Shah et al. 2017). Unfortunately, low income neighborhoods also tend to lack pedestrian safety infrastructure - especially for children (Hwang et al. 2017).

Other significant factors related to pedestrian crash experience include minority population density, lifestyle, land use and the built environment. Minority populations, mainly Hispanics and African Americans are represented disproportionately in pedestrian fatality statistics and crash frequency (Cottrill & Thakuriah 2010 and, Lin et al. 2017). Research conducted by the Florida DOT reports that pedestrian crashes occur more frequently in areas with high proportions of minority populations (Lin et al. 2017). In 2018, Chimba et al. studied socio-demographic characteristics of pedestrian crashes in Tennessee. They concluded that a pedestrian risk analysis could not be performed without involving factors related to socio-demographics and the built environment. Minority groups differ through low vehicle ownership, taking residence in areas with lower income and high density of traffic volume - they and also walk more than the high-income population. (Chimba et al. 2018).

To some extent, the land use and built environment also dictate travel patterns and lifestyles of residents in an area. The infrastructure and land use in bigger cities (e.g., commercial districts and dense residential areas), tend to require more public transportation, walking and other active transportation modes (Burbidge 2018). Research shows that individuals from the millennial generation are driving less in urban areas due to availability and ease of alternate transportation options such as buses, trains, Uber, and Lyft (Burbidge 2018) – hence, increasing pedestrian activity. One of the reasons for the high pedestrian crash rate in urban areas is high pedestrian exposure (Cottrill & Thakuriah 2010 and Shah et al. 2017). In 2016, 76% of pedestrian fatalities in 2016 were in urban areas (NHTSA 2016). However, the severity of the injury for pedestrians is less in urban areas (Pour-Rouholamin & Zhou 2016) primarily due to reduced vehicle speeds in urban areas.

## 2.3 Literature Review Summary

This section summarizes the key points from the literature review

### 2.3.1 Pedestrian crash analysis and historical

- According to a study by Hazlet (1968), typically clothed pedestrians are difficult for the drivers to detect and identify during twilight or dark conditions.
- One of the findings from the study by Allen et al. (1970) is that pedestrian overestimates his/her visibility.
- Two important driver detection error for the scenario when the roadway section is unlit are: 1) unable to identify specific types of road users or looking at the direction that is appropriate due to the gap of cognitive expectation; and 2) failure in understanding stimuli when adequate lighting is not available or when a vehicle approaches in the periphery of the visual field for the road user (Rumar 1990).
- Younger drivers predicted the presence of pedestrians faster than the older drivers and pedestrians on the right side of vehicles were identified sooner (at a larger distance away) than the pedestrian on the left side (Olson and Sivak 1996).
- The lighting beam of a vehicle is skewed toward the right making it easier for the driver to identify obstacles on the right side of the road.
- The drivers detected the dummy pedestrians twice as far away when they were expecting the pedestrians than the scenario when they were not expecting them (Roper and Howard 1938).

### 2.3.2 Socio economic characteristics of the pedestrians involved in crash

- The elderly (65 years and older) are prone to more severe pedestrian crashes compared to younger pedestrians (Xin et al. 2017, Pour-Rouholamin & Zhou 2016 and Hanson et al, 2013.
- Middle-aged and younger pedestrians are associated with higher risk of involvement in pedestrian crashes overall due to higher levels of exposure (Moreno et al. 2016).
- Areas with lower income in Canada reported a higher rate of pedestrian injury which was almost 7 times higher than areas classified as having high income Morency et al. (2012)
- Areas with households with an average vehicle ownership of 1 vehicle or less experience a higher incidence of pedestrian crashes (Lin et al. 2017).
- Low income neighborhoods also tend to lack pedestrian safety infrastructure - especially for children (Hwang et al. 2017).
- Minority populations, mainly Hispanics and African Americans are represented disproportionately in pedestrian fatality statistics and crash frequency (Cottrill & Thakuriah 2010 and, Lin et al. 2017).
- One reason for high pedestrian crash rate in urban areas is high pedestrian exposure (Cottrill & Thakuriah 2010 and Shah et al. 2017).

# CHAPTER 3

# Methods

In preparation for a simulation study of autonomous vehicle pedestrian detection, several key pieces of information are needed, including typical and atypical pedestrian crash scenarios, socio-demographic factors, exposure metrics, and relative detection rates for autonomous vehicle pedestrian detection. This research defined patterns associated with pedestrian crossing fatalities at midblock locations where they are most vulnerable to injury and death from motor vehicle crashes. Both social media listening, and sociodemographic factors were analyzed to support the crash analysis. A pilot test of camera technologies to support data collection for pedestrian exposure metrics was conducted in a controlled environment. Further, a review of literature on autonomous vehicle sensing technologies showcased potential safety benefits and shortcomings to reduce pedestrian crashes in the future, and cost-effective infrastructure treatments and technologies were also identified for adoption in the short-term for some sample locations identified in this research. The methods used to successfully complete each of these tasks are detailed in the sections to follow.

## 3.1 Method for Pedestrian Crash Analysis

Prior to initiating this research, years of experience with crash analysis led researchers to notice what appeared to be an overabundance of pedestrian crashes involving midblock road crossings and pedestrians approaching the striking vehicle from the left. The researchers approached this research with the following hypothesis:

Pedestrians crossing at midblock locations and approaching vehicles from left are less visible for three factors:

- Headlight pattern is skewed to the right side of the road,
- Drivers visual search pattern is concentrated in the central cone, and
- Drivers do not expect pedestrians to cross the road in the middle of a roadway segment with no crosswalk, rather they expect pedestrians on the right side of a roadway in a sidewalk facility

Therefore, the researchers expected that crashes at intersections at night would be lower, especially with light and pedestrians crossing at midblock at night approaching from left to be higher. With these assumptions, the researchers coded crashes for location (mid-block or intersection), pedestrian direction (crossing/direction or walking along road/direction), light condition, presence of sidewalk, presence of light pole, route type, route division type, roadway functional class, number of lanes, median type and land use.

This section of the paper details the method followed to investigate factors of roadway design, pedestrian and vehicle direction of travel, visibility and weather during pedestrian crashes in dark (night) lighting conditions. The pedestrian crash analysis follows two separate but related approaches, the first is qualitative in nature and the second is quantitative. During the first qualitative assessment which was a thorough assessment of the TR 310 crash report forms, the researchers manually reviewed the textual and graphic data directly from police crash reports for fatal pedestrian crashes to define coding schemes for pedestrian maneuvers. This subset of crash sites was investigated using Google Earth to determine commonalities among roadway design features, lighting conditions, for various pedestrian crash types. The quantitative analysis deals with a much larger volume of crashes but is limited to elements contained in the crash database and excludes the graphical representation of the crash and the police officers' statement. The manual analysis of crash reports informed the development of sophisticated queries of the crash database entries to mimic the review of drawings and written descriptions. The crash database was used in conjunction with the RIMS database to provide the complete picture of the nighttime pedestrian crashes and related factors. This section will review the data sources and compilation efforts, as well as the detailed steps in both the qualitative and quantitative approaches.

### 3.1.1 Data Sources and Compilation

Several data sources were required to complete the analysis of pedestrian crashes in dark. These included: SCDOT Crash Database, TR 310 Crash Report Forms, Roadway Inventory Management Systems (RIMS) Database, Additional Roadway and Traffic Control Data Obtained from Google Earth. Each of these data sources and the processes required to compile them for use are described below.

#### 3.1.1.1 SCDPS/SCDOT Crash Database

SCDOT maintains a database of all crashes by county, severity, route category, date of crash, light and weather condition, traffic control type, information about the units in the crash, direction of travel of vehicle and pedestrians (if any) etc. The SCDOT crash database contains the crash information from the year 2001-2016. The crash date base was used as a source of data for both the qualitative analysis and quantitative analysis. To acquire the data for the quantitative analysis the crash database was queried for all crashes involving pedestrian at night for all severity levels for the year 2007-2016. The three severity levels of the crashes accounted for the crash-data analysis were a) fatal b) injury and c) property damage only (PDO) crashes. For example, for the year 2015, there were 130,426 crashes, and out of these, 902 crashes were pedestrian crashes. One of the most important tasks was to identify the night-time crashes, and the crashes were identified based on the light condition. The crashes were not selected based on the time of the day due to the variation throughout the year (i.e. the summer days are very long compared to the winter days). After running the query, it was found that 524 crashes occurred during dark lighting conditions for all severity levels. Of the 524 crashes, 102 crashes were fatal for the year 2015.

#### 3.1.1.2 TR 310 Crash Report Forms

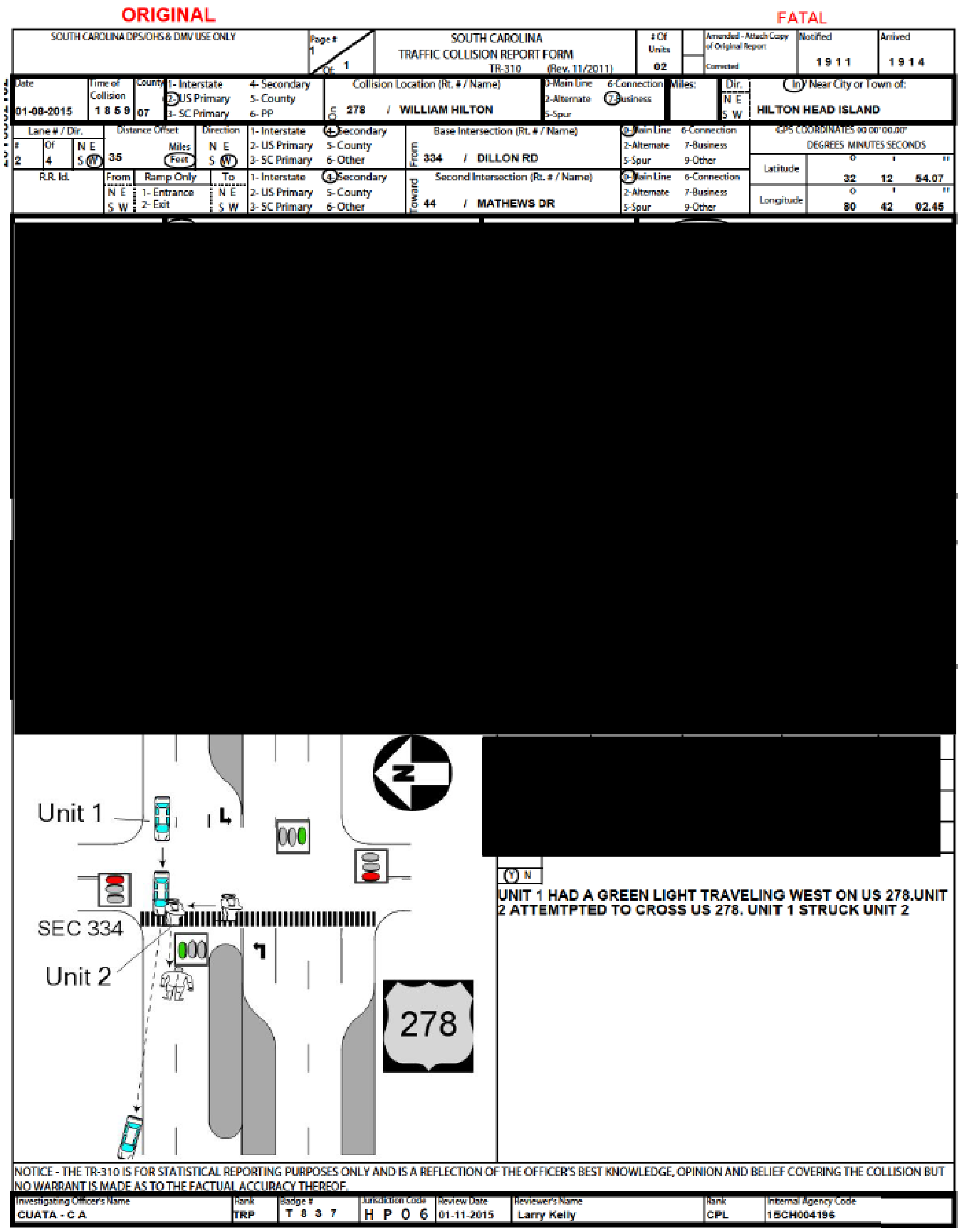
The crash database is the compilation of all the data from the crash reports. However, it is not possible to conduct a detailed manual analysis on the entire crash database; thus, only a subset of data from the crash-database was used for a detailed qualitative analysis. The 102-nighttime fatal pedestrian crash reports were requested from South Carolina Department of Transportation (SCDOT) for the year 2015. SCDOT provided the section of the reports that contains the police officers sketch and written statement after redacting all the personal information from the report. Additionally, all 98-nighttime fatal pedestrian crash reports were also collected from SCDOT for the year 2014 under a separate request. The analysis of the crash reports helped to discern the crash patterns using direction of travel of the vehicles and the pedestrians from the graphical representation and narration. Figure 3.1 contains a sample TR 310 Crash Report Form used in this study. The two large boxes at the bottom of the figure showing the locations of units (vehicles and pedestrians) and their respective positions before and after the crash, and the narrative description are not found in the crash database. However, these two pieces of information are invaluable for understanding the scenario in which the crash occurred.

#### 3.1.1.3 Roadway Inventory Management System (RIMS) Database

RIMS is a geospatial data system which contains all the aspects of SCDOT's roadway inventory. For instance, RIMS contains data for route type, number of lanes, AADT, functional class, street networks, etc. While the data is maintained using a linear referencing system, crash locations can be overlaid on the RIMS linear network, and attributes from the underlying RIMS can be selected and joined with the crash data. For all geolocated crashes, RIMS was queried for attributes including route type, route division, median type, total number of lanes, functional class and land use type. This provided information about the physical characteristics of the roads on which the pedestrian crashes occurred.

#### 3.1.1.4 Google Earth

Google Earth was used only in conjunction with the TR 310 crash reports to obtain a detailed understanding of the site characteristics where the crash occurred. Based on the literature review conducted during the initial phase of the research, it was found that lighting, presence of sidewalk, presence and types of medians are all critical for pedestrian crash analysis. All these roadway design elements were collected for each fatal crash pedestrian site using Google Earth. In addition, the presence of sidewalks was also collected. While these are all key characteristics needed for pedestrian crash analysis, some are not included in the SCDOT roadway inventory database (i.e., sidewalks, crosswalks, lighting, full description of median type). Unfortunately, these elements are missing in the larger quantitative data analysis. However, through the fatal crash analysis, a significant number of pedestrian crash patterns were identified. This research highlights the need for more comprehensive site characteristics to be maintained in the roadway characteristics database particularly for pedestrian crash types where the information about the presence of sidewalk, location and presence of lighting are very important to the outcomes. For getting lighting and sidewalk information researchers pulled individual sites from Google Earth for qualitative analysis for all nighttime fatal pedestrian crashes for the year 2014 and 2015. Table 1 contains a summary of all the crash queries that were conducted and the elements that were collected from different sources for the qualitative and quantitative analysis.



ORIGINAL

FATAL

SOUTH CAROLINA DPS/OHS & DMV USE ONLY

Page # 1 Of 1

SOUTH CAROLINA
TRAFFIC COLLISION REPORT FORM
TR-310 (Rev. 11/2011)

# Of Units 02

Amended - Attach Copy of Original Report
Corrected

Notified 1911

Arrived 1914

Date 01-08-2015 | Time of Collision 1859 | County 07 | 1- Interstate 2- US Primary 3- SC Primary 4- Secondary 5- County 6- PP | Collision Location (Rt. # / Name) On 278 / WILLIAM HILTON | 0-Main Line 2-Alternate 5-Spur 6-Connection 7-Business | Miles: | Dir. N E S W | In/ Near City or Town of: HILTON HEAD ISLAND

Lane # / Dir. # 2 Of 4 N E S W | Distance Offset 35 Miles Feet | Direction N E S W | 1- Interstate 2- US Primary 3- SC Primary 4- Secondary 5- County 6- Other | Base Intersection (Rt. # / Name) From 334 / DILLON RD | 0-Main Line 2-Alternate 5-Spur 6-Connection 7-Business 9-Other | GPS COORDINATES 00 00' 00.00" DEGREES MINUTES SECONDS Latitude 32 12 54.07

R.R. Id. | From N E S W | Ramp Only 1- Entrance 2- Exit | To N E S W | 1- Interstate 2- US Primary 3- SC Primary 4- Secondary 5- County 6- Other | Second Intersection (Rt. # / Name) Toward 44 / MATHEWS DR | 0-Main Line 2-Alternate 5-Spur 6-Connection 7-Business 9-Other | Longitude 80 42 02.45

[redacted]



[redacted]

Y N

UNIT 1 HAD A GREEN LIGHT TRAVELING WEST ON US 278.UNIT 2 ATTEMTPTED TO CROSS US 278. UNIT 1 STRUCK UNIT 2

NOTICE - THE TR-310 IS FOR STATISTICAL REPORTING PURPOSES ONLY AND IS A REFLECTION OF THE OFFICER'S BEST KNOWLEDGE, OPINION AND BELIEF COVERING THE COLLISION BUT NO WARRANT IS MADE AS TO THE FACTUAL ACCURACY THEREOF.

| Investigating Officer's Name | Rank | Badge # | Jurisdiction Code | Review Date | Reviewer's Name | Rank | Internal Agency Code |
|---|---|---|---|---|---|---|---|
| CUATA - C A | TRP | T 8 3 7 | H P O 6 | 01-11-2015 | Larry Kelly | CPL | 15CH004196 |

**Figure 3.1 Sample TR 310 Crash Report Form**

**Table 3.1 Data Sources and Variables Used in this Research**

| Type of analysis | Year of data used for analysis | Crash Database Query | Additional Data Sources |
|---|---|---|---|
| Qualitative analysis | 2014-2015 | Unit type:<br>• Pedestrian | TR 310 Crash reports:<br>• Pedestrian and vehicle movements and direction of travel |
| | | Light condition:<br>• Dark (Lighting unspecified)<br>• Dark (Street lamp lit)<br>• Dark (Street lamp not lit)<br>• Dark (No lights) | Google Earth:<br>• Presence of light pole<br>• Presence of sidewalk<br>• Crash location:<br>➢ Intersection<br>➢ Midblock<br>• Number of lanes<br>➢ One lane in each direction<br>➢ Multi-lane |
| | | Severity level:<br>• Fatal only | |
| Qualitative analysis | 2007-2015 | Unit type:<br>• Pedestrian | Crash Database:<br>• Pedestrian and vehicle direction of travel<br>• Lighting<br>• Weather condition |
| | | Light condition:<br>• Dark (Lighting unspecified)<br>• Dark (Street lamp lit)<br>• Dark (Street lamp not lit)<br>• Dark (No lights) | RIMS Database:<br>• Route type<br>➢ Interstate<br>➢ US route<br>➢ SC route<br>➢ Secondary route<br>• Route division<br>➢ Not-divided<br>➢ Divided<br>• Functional class of the road<br>➢ Rural - Principal Arterial - Interstate<br>➢ Rural - Principal Arterial - Other<br>➢ Rural - Minor Arterial<br>➢ Rural - Major Collector<br>➢ Rural - Minor Collector<br>➢ Rural - Local |
| | | Severity level:<br>• Fatal crash<br>• Injurious crash | |

| Type of analysis | Year of data used for analysis | Crash Database Query | Additional Data Sources |
|---|---|---|---|
| | | | ➢ Urban - Principal Arterial - Interstate<br>➢ Urban - Principal Arterial - Other Freeways<br>➢ Urban - Principal Arterial - Other<br>➢ Urban - Minor Arterial<br>➢ Urban - Collector<br>➢ Urban - Local<br>• Median type*<br>➢ Non-divided<br>➢ Divided - Earth median<br>➢ Divided - Concrete median<br>➢ Multi-lane - bituminous Median<br>➢ Divided - Raised Concrete & Surfaced Median<br>➢ Divided - Physical Barrier<br>➢ Divided - Cable Stay Guardrail<br>➢ One-way street<br>• Land use<br>➢ Urban<br>➢ Rural<br>• Total number of lanes |

*In addition to median type, median width is also recommended for future studies to ensure that pedestrian refuge can be accommodated.

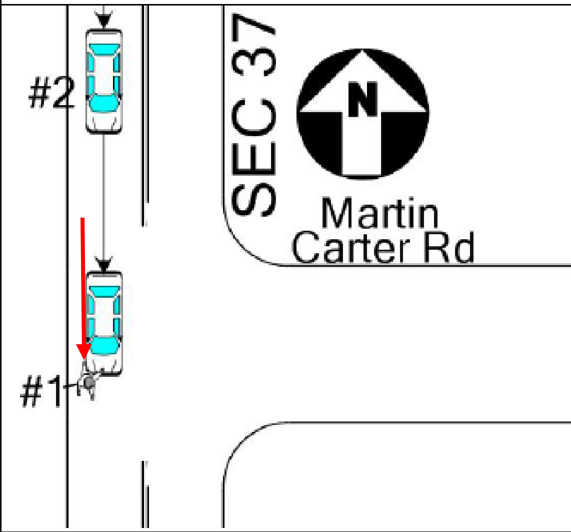
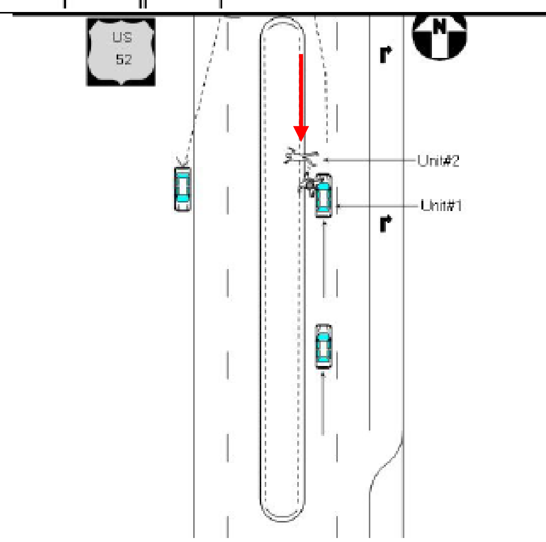
### 3.1.2 Qualitative analysis of TR 310 Crash Reports and Google Earth

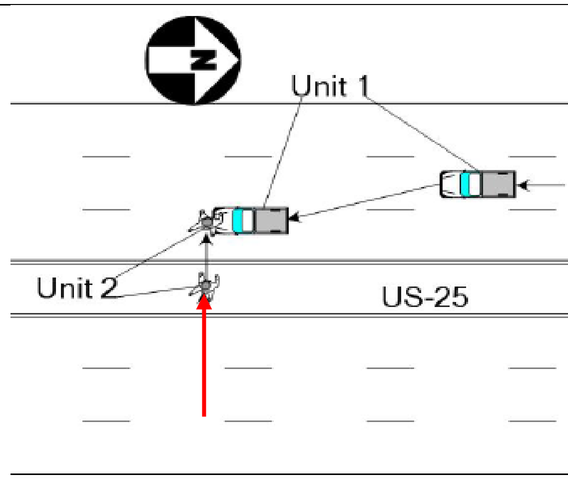
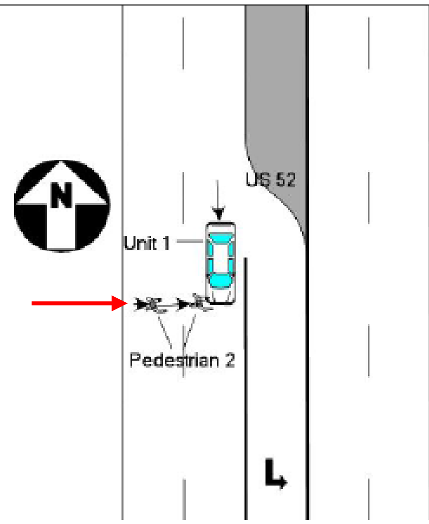
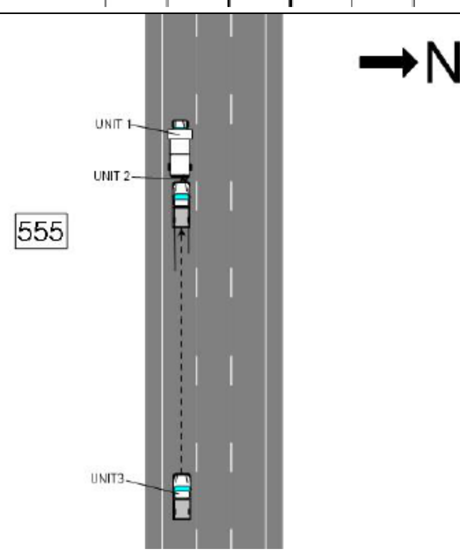
The first step of the qualitative analysis was to code the TR 310 Crash Report Forms. The main goal of this step was to discern the direction of travel of the vehicles and the pedestrians from the narration and graphical representation provided on the TR 310 report by the police officer. A knowledge of crash reconstruction helped to determine the pre-crash conditions and assisted in determining the underlying scenario during the crash. Two individuals with expertise in crash analysis independently conducted manual reviews of the crash reports, and later came together to compare findings for the year 2014. This step was done to discern the quantity and reason for any discrepancies in the coding. When discrepancies were noted, the two individuals discussed and scrutinized the information provided in the description of the crash report until they reached consensus. The process was repeated for a second year of data (2015), and the match rate for this year was 100 percent.

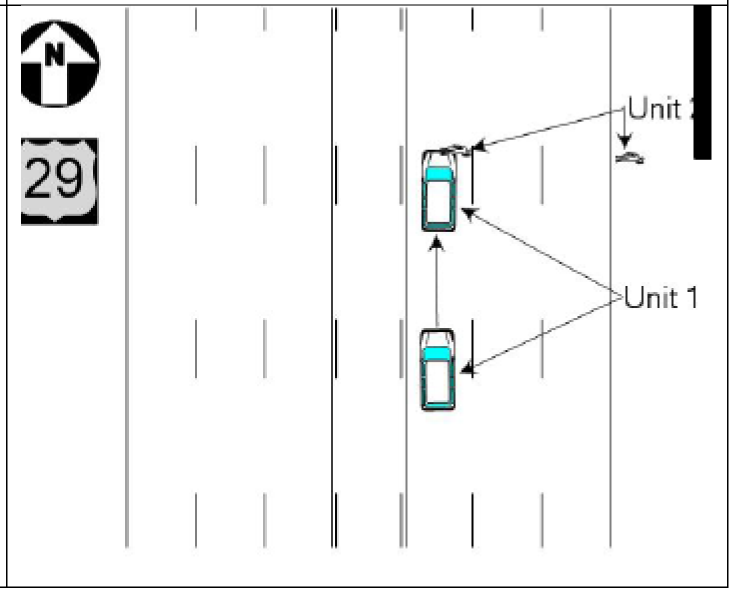
While coding, the direction of pedestrian travel was divided into several categories. A study by Schneider and Stefanich (2016) introduced the location-movement classification method (LMCM) for classifying pedestrian and bicycle maneuvers, which was partially applied in this study. The researchers reviewed the paper and studied their coding structure for different types of crashes. However, some of their coding structures were aggregated because the researchers were not interested in some of the level of details. The study by Schneider and Stefanich has 20 variations in their coding schemes for pedestrian maneuvers. The current study aggregated only a portion of the 20 variations into 6 according to the need for the analysis. Before aggregating the coding scheme, crash reports were reviewed case by case and it was found that an aggregated scheme is more appropriate for this analysis than the detailed coding scheme used in the paper by Schneider and Stefanich (2016). The most common coding schemes used in this study are: pedestrian walking along the road in the same direction of the traffic, pedestrian walking along the road in the opposite direction of the traffic, pedestrian crossing the road approaching from left of the driver and crossing the road approaching from the right of the driver etc. Additionally, crashes where the pedestrian was either standing or working in the road, lying on the road or doing something else other than walking or crossing that crashes were treated as "other". There were some crashes that were not described in enough detail to discern the correct scenario - these were identified as "unknown" category. Table 3.2 summarizes these most typical pedestrian travel maneuvers (pedestrian direction of travel) that were considered in the analysis with an example of a schematic diagram found in the crash reports. While the last scenario in Table 3.2 appears to be a crossing crash, this was not indicated in the police narrative, nor in the drawing as there is no direction of travel provided by the graphic. To avoid combining these incorrectly, they were listed as unknown and essentially removed from the pattern analysis.

One of the objectives of the qualitative research was to identify the pedestrian crash patterns that are most prevalent. This pattern analysis went beyond the crash characteristics to also include roadway characteristics (midblock/intersection crash, presence of median and median type, presence of streetlight, presence of sidewalk, and number of lanes and traffic operation (two-lanes two-way or multilane). Information for the roadway characteristics came from Google Earth (see Table 3.1).

## Table 3.2 TR 310 Crash Report Coding Schemes

| Direction of Travel of Pedestrian | Figure |
|---|---|
| Ped-Along/Same- Pedestrian walking along the road in the same direction of traffic |   |
| Ped-Along/Opposite - Pedestrian walking along the road in the different direction of traffic |   |

| Direction of Travel of Pedestrian | Figure |
|---|---|
| Ped-Left/Mid-block- Pedestrian crossing the road approaching from left of the vehicle (Mid-block scenario) |   |
| Ped-Right/Mid-block- Pedestrian crossing the road approaching from right of the vehicle (Mid-block scenario) |   |
| Other (Crashes associated with roadwork, pedestrian standing/lying on the road or doing something else other than walking/crossing) |   |

| Direction of Travel of Pedestrian | Figure |
|---|---|
| Unknown (Sufficient information is not provided in the figure and description by the police officer) |   |

### 3.1.3 Quantitative Analysis and Data Validation

In the qualitative analysis, the crash reports were analyzed for only two years (2014-2015) of fatal pedestrian crash data, but the researchers wanted to replicate the manual work into an automated system to conduct a quantitative analysis using several years of data. In the process of automation, a combination of the maneuver of the vehicle and pedestrian was used to predict the direction of travel of the pedestrian with reference to the vehicles, like the maneuvers presented in Table 3.2. In the qualitative analysis, these directions were identified by hand but for the quantitative analysis, a code was developed to discern the directions using the ArcGIS API for python. At the beginning of the quantitative analysis, the pedestrian crashes were separated from total crashes followed by identifying the fatal pedestrian crashes from the location files (our primary concern in this paper was to look at the fatal pedestrian crashes at night at midblock locations), once this is done, a new field was added to the pedestrian crash location files called "PedApp" signifying the directional approach of the pedestrian with respect to the direction of the vehicle. The unit file of a crash database contains directional information of the units (vehicle and pedestrians in this case) for a particular year. Using this directional information, combinations of pedestrian and vehicle directions were coded with respect to one another. For example, if prior to the crash, the vehicle was traveling north and the pedestrian was traveling north, the "PedApp" field would be coded as Ped-Along/Same indicating the pedestrian is walking along the road (not crossing) and in the same direction as the vehicle. As mentioned earlier, the coding was automated using the ArcGIS API for python. Table 3.3 shows the "PedApp" coding output for variations of pedestrian and vehicle movements of interest.

## Table 3.3 PedApp Field Coding Guide

| Direction of the Vehicle | Direction of the Pedestrian | Direction of travel for pedestrian with respect to the vehicle |
|---|---|---|
| North | North | Ped-Along/Same |
| South | South | Ped-Along/Same |
| East | East | Ped-Along/Same |
| West | West | Ped-Along/Same |
| North | South | Ped-Along/Opposite |
| South | North | Ped-Along/Opposite |
| East | West | Ped-Along/Opposite |
| West | East | Ped-Along/Opposite |
| North | West | Ped-Right |
| South | East | Ped-Right |
| West | South | Ped-Right |
| East | North | Ped-Right |
| North | East | Ped-Left |
| South | West | Ped-Left |
| West | North | Ped-Left |
| East | South | Ped-Left |

After the “PedApp” field population was completed, a multi-tiered query was developed. Figure 3.2 illustrates the step by step process for the quantitative analysis. Starting at the top, from all crashes in the database, pedestrian crashes that involve fatalities are selected, then further filtered to only include night-time crashes. The next step was to separate the fatal pedestrian night-time crashes at night into intersection and midblock crashes, and discard intersections. Buffers were created for all the intersections and a spatial join was completed with the fatal pedestrian nighttime crashes. The crashes falling within the intersection buffer were removed leaving only midblock crashes. Once the midblock crashes were selected, then the pedestrian walking, crossing, other and unknown crashes were separated. Figure 3.2 illustrates the step by step process for the quantitative analysis.

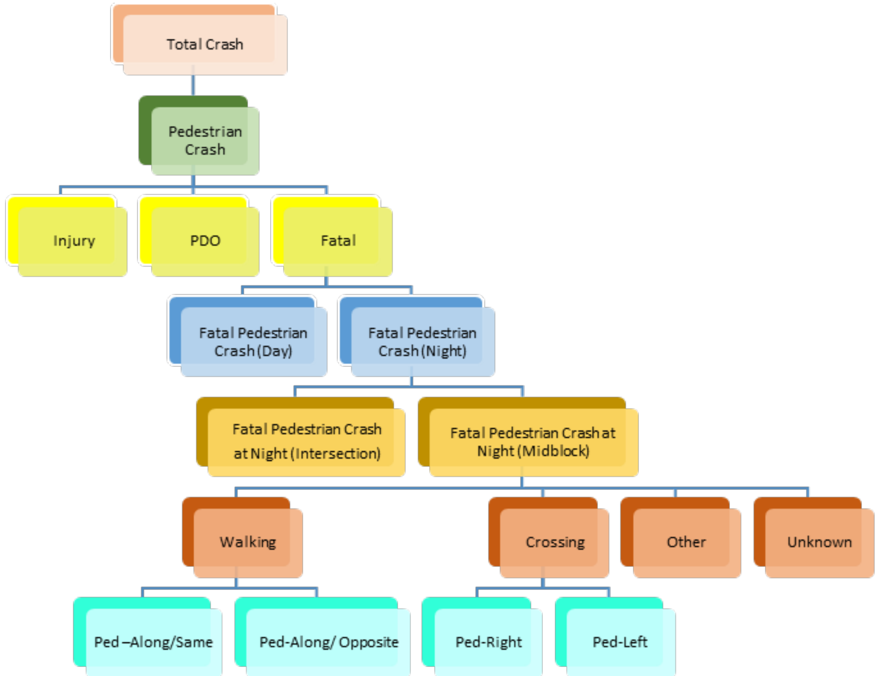



**Figure 3.2 Step by step process for crash data analysis**

To check the accuracy of the automated system with manual coding and analysis, the output of the two was compared for the years 2014-2015. Upon conducting the validation process, it was found that the manual qualitative analysis and the automated quantitative analysis matched 97% for Ped- left, 85% for Ped-right and 100% for both Ped-Along/Same and Ped-Along/Opposite. The high percentage of matching indicates that the accuracy of the coding was satisfactory to conduct a quantitative analysis for the expanded period of 2007-2016. During the 2015 qualitative analysis, 22% of fatal pedestrian crashes were identified as unknown due to the ambiguity of textual and graphic information about the pedestrian and vehicles' maneuvers in the crash reports. However, the automation of the "PedApp" coding field allowed directional information on units from the crash database to be used in lieu of graphical and narrative information, thus making the analysis more complete. In the 10-year quantitative analysis, only 2% crashes were identified as null (unknown) due to the absence of directional information of the vehicle and pedestrians.

The next step of the quantitative analysis was to summarize all the crashes for the years 2007-2016. Once the summarization was completed, the researchers conducted some statistical testing to assess trends across time and determine if the differences were significant or not.

## 3.2 Method for Analyzing Pedestrian Crash Social Media

This section will provide methods used to analyze media messaging from several news sources in the state, as well as a separate but related analysis of the sociodemographic characteristics for pedestrians involved in nighttime fatal midblock crashes.

The methods used to determine the role of the media in portraying pedestrian crashes are discussed. Media can be a powerful outlet for providing information on current events (i.e., portraying pedestrian crashes) as well as a means of educating the masses on dangers faced by pedestrians. To determine the role of local media in pedestrian crash information distribution, the research team collected multiple forms of news from various outlets. The study utilized four media portals namely, Twitter and two online newspapers (The Greenville Online and The State), and an online newsfeed from WYFF News Channel 4. The study focusses on pedestrian accidents that happen in South Carolina between 2014 and 2018. The number of articles or tweets within the time period is shown in Table 3.4. A total of 285 news stories/feeds/tweets related to pedestrian crashes were reported by the four media sources in South Carolina for the period of 2014-2018.

**Table 3.4 News source, time period, and the amount of data collected**

| SL. No. | Source | Articles/Tweets | Time Period |
|---|---|---|---|
| 1 | Greenville Online | 56 | July 11, 2014, to April 13, 2018 |
| 2 | The State | 50 | April 8, 2016, to September 5, 2018 |
| 3 | WYFF News 4 | 52 | June 10, 2017, to September 30, 2018 |
| 4 | Twitter | 127 | January 1, 2015, to November 2, 2018 |

The articles and the tweets were imported from the sources into Microsoft Excel-VBA manually and the latter is used to re-arrange the data. The application, WordArt.com, was utilized to create the word clouds. First, four word-clouds (one for each news outlet) were prepared and then a combined word cloud was generated using all 285 news/tweets. The results were assessed for content and messaging themes.

## 3.3 Method for Analyzing the Sociodemographics of Fatally Injured Pedestrians

The research team also analyzed sociodemographic information for pedestrians who had been involved in crashes. This analysis requires information on the pedestrians' 9-digit zip code - unfortunately, this was not available for all pedestrians. Of 1946 number of pedestrian nighttime fatal and injury crashes for the year 2014-2016, 9-digit zip codes were available for 273 (7.12%). For these pedestrians, their 9-digit zip codes were geocoded to enable them to be joined with the socio-demographic information from the 2010 census. The spatial join function in the ArcGIS spatial analysis platform was used to impute sociodemographic characteristics of the block groups to the approximate home locations geocoded within a specific block group. The socio-demographic data obtained from the U.S. Census Bureau included the following categories: Population, Gender, Race/Ethnicity, Age, Median Household (HH) Income, Educational Attainment, Poverty Level, Vehicles Available, and Vehicle Age. Average values were computed for the state as well as the sample of fatally injured pedestrian crashes containing 9-digit zip codes.

Proximity analysis was done to determine any significant trends between pedestrian crash locations their distance to the residences of the pedestrians involved in crashes. The crash location was geocoded using the coordinates; latitude and longitude recorded in the crash database files. As alluded earlier, the pedestrian residential locations were obtained by geocoding 9-digit zip code locations of pedestrians involved in crashes. The two location coordinates were linked together using a geo-relational join where both sets of data had a common accident number. Coordinates were paired if the crash accident number matched the pedestrian accident number.

The two sets of paired coordinates (approximate home location and crash location) served as vertices (nodes) of lines created in ArcGIS. These lines represented the Euclidean distance (straight line distance) between the two points and hence the approximate distance between the crash location and the pedestrian residence. Using the proximity categories chosen, further investigation into the socio-demographic characteristics of pedestrians involved in crashes was done.

## 3.4 Method for Conducting Pilot Test on Pedestrian Detection Technologies

In this task, the researchers conducted a pilot test to gauge the efficacies of two types of camera technologies for detecting pedestrians at night. The goal for this task was to develop an effective method for capturing exposure data form sites of interest. To do this, the research team prepared a controlled field test for two conditions: dark not lit and dark lit with standard headlamps (no alternate lighting sources were available beyond a quarter moon. The tested conditions included four scenarios as follows:

- Dark not lit
  - Pedestrian detection with night vision camera in a dark not lit section
  - Pedestrian detection with infrared camera in a dark not lit section

- Dark Lit
  - Pedestrian detection with night vision camera in a dark section lit with vehicle light
  - Pedestrian detection with infrared camera in a dark section lit with vehicle light

The researchers conducted the tests in a dead-end section of roadway in the absence of street lighting. Figure 3.3 shows the test site location near Clemson University in Oconee County. The following sections contain additional details about the field test.

For this test, the researchers chose a roadway section where there are no streetlights. The test location was a dead-end cul-de-sac, and no developments with ambient lighting were nearby. The only source of lighting was provided with the presence of vehicle lights when the lit condition was tested. The researchers also took account of the moon please for choosing the date of the data collection. On the night of the data collection, the moon was about to reach its first quarter, so little moonlight was available. Researchers had to use flashlights when the vehicle lights were off to move about safety. The selected roadway was an undivided two-lane two-way roadway, with traffic control to prevent other vehicles from entering. The date was collected on March 12, 2019, between 8:15 PM and 10 PM.

In this field test, two types of cameras were used. One is a PTZ IP camera with night vision capabilities and the other is a fixed focus thermal IP camera. Table 3.5 contains the details of the two cameras. Both cameras were installed on a permanently mounted hydraulic mast in the research van. The height of the cameras was 15 feet as determined based on the height of the van plus the height of the mast as extended.

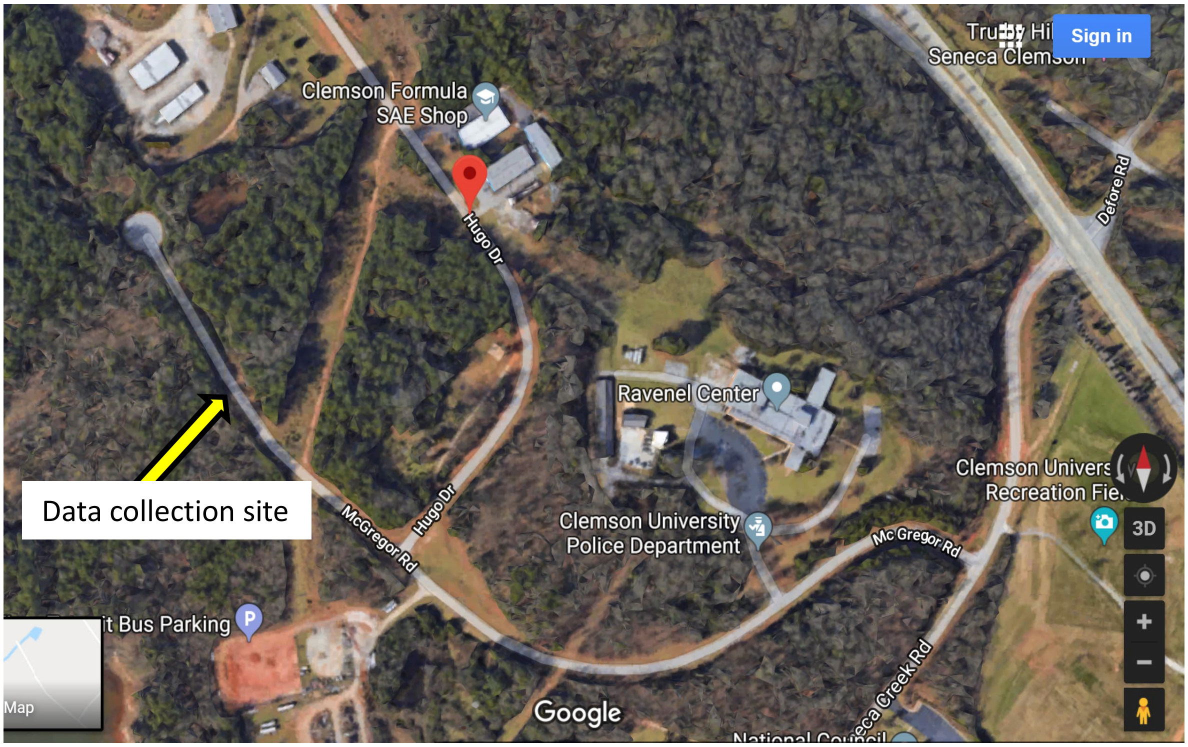



**Figure 3.3 Data collection site**

**Table 3.5 Details on pedestrian detection technologies**

| Vendors for the sensors | Technology | Power | Mounting Height (Ft) |
|---|---|---|---|
| Jide Tech PTZ IP Camera POE | Night Vision Video | DC 12V/2A | 15’ |
| DRS Watch Master IP Elite Camera | Fixed Focus Thermal Video | 12-24 V DC or 24 V AC | 15’ |

There were a total of 8 crossing locations for the pedestrians. The crossing locations were marked throughout the 300’ stretch of the McGregor road starting at 0+00, 0+25, 0+50, 1+00, 1+50, 2+00, 2+50, 3+00. Figure 3.4 provides a diagram of the field measurements, and Figure 3.5 has cones marking the crossing locations. The first location where the pedestrians started crossing is at a station 0+00 and was the station closest to the research van containing the two cameras. A serpentine pattern was used to minimize unnecessary backtracking across the roadway. The crossing pattern can be seen in Figure 3.4, with the first crossing shown in blue at station 0+00. After crossing number 8, the pedestrian subjects followed the black arrows on their return crossing at each location in the opposite direction. Only one pedestrian crossed the roadway at a time and in a specific order by expected visibility level.

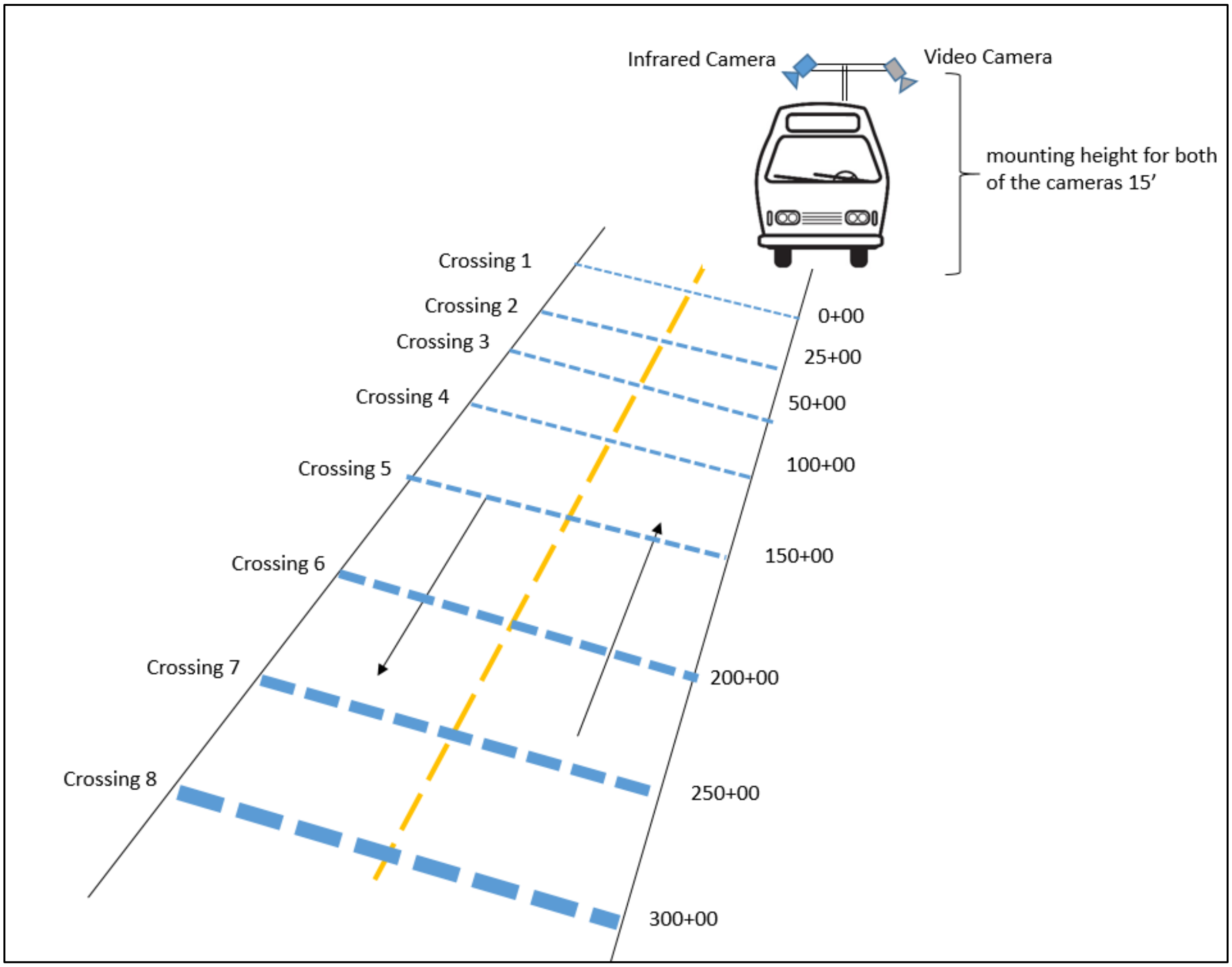



**Figure 3.4 Schematic diagram of the field implementation for dark not lit condition**

For the second scenario, everything remained the same except a light source was provided by the headlamps of a Dodge Dakota truck parked in the right lane just in front of the research van. Headlights were placed on low beam setting. This scenario mimicked a typical scenario where the headlights are the only source of lighting along a road section. In both scenarios, the two camera feeds were collected over ethernet connections to two laptops each running the data capture software for their respective cameras. The frame rate was set to 15 and 10 frames per second for the DRS Watch Master IP Elite Camera and Jide Tech PTZ IP Camera POE respectively, and the camera angles were placed as close as possible to one another.

In this test there were 5 pedestrians wearing 5 different types of clothing as shown in Figure 3.6

- Retroreflective vest: Orange vest with retroreflective panels
- Retroreflective vest: Yellow vest with retroreflective panels
- White clothing: White sweatshirt and dark pants
- Black clothing: Black sweatshirt and black pants
- Improvised bio-motion clothing: This is the clothing from the Black condition with the addition of retroreflective straps around the wrists, elbows, shoulders, knees and ankles.

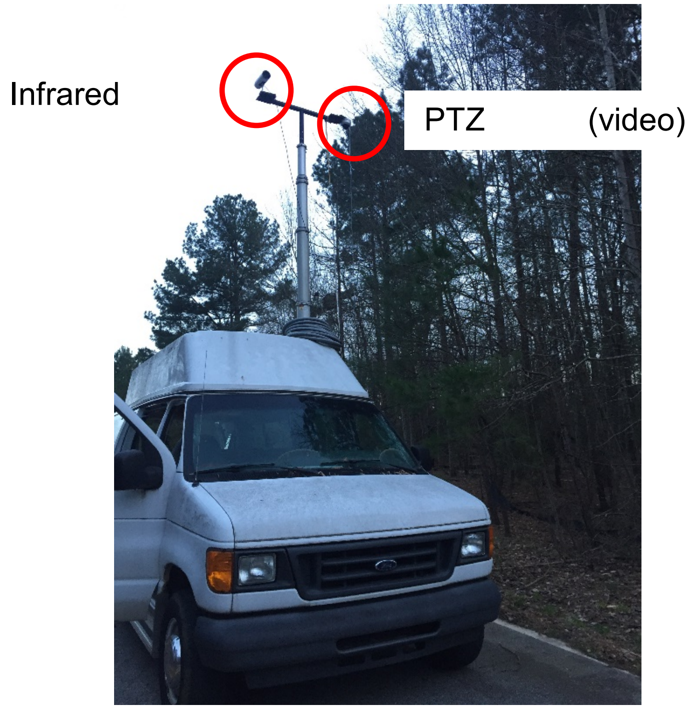



**Figure 3.5 A: Cameras Mounted with the Transportation Van**

**Figure 3.5 B: Crossing Locations Identified with Traffic Cones**

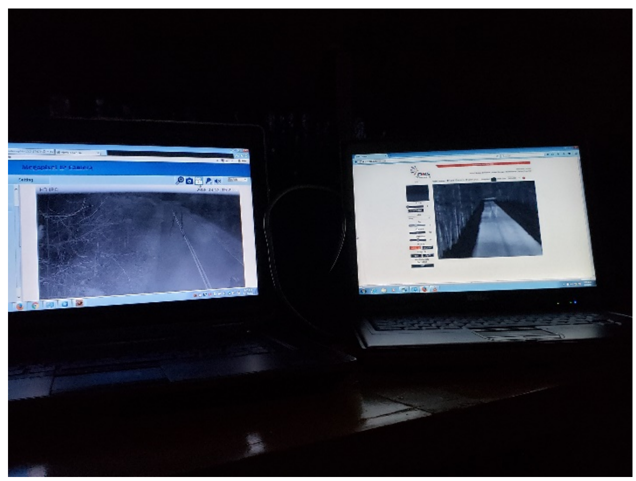


**Figure 3.5 C: Computer Set up at the Field**

**Figure 3.5 Field set up**

**Figure 3.6: Clothing worn during the field test by pedestrian subjects**

## 3.4 Method for Assessing Potential Gaps in AV Technologies to Detect Pedestrian in Nighttime Scenarios

This research identified potential gaps in current vehicle sensing technologies for various pedestrian crash factors. A thorough literature review was conducted to determine the pros and cons of different detection technologies utilized by autonomous vehicles and how well these technologies may perform in the critical crash scenarios identified in the previous stage of this project.

# CHAPTER 4

# Results

## 4.1 Results from Pedestrian Crash Analysis

This section summarizes the results from the crash analysis in two major sections 1) Qualitative analysis from the TR310 pedestrian fatal crash reports, and 2) Quantitative analysis for the crash database. Each of these two sections also summarizes the results based on different pedestrian maneuvers with respect to the vehicles.

### 4.1.1 Qualitative analysis

#### 4.1.1.1 Distribution for Direction of Travel for Pedestrians with Respect to Vehicles

This section contains a summary of the analysis of the TR 310 crash reports for the year 2014 and 2015. A total of 200 fatal night-time pedestrian crash reports were analyzed. The crash reports included both crashes occurring at midblock and intersection locations. However, this research is predominantly focused on crashes occurring at midblock locations, so the crashes were separated based on the graphics and narrative contained in the crash reports. After the analysis 78 and 73 fatal pedestrian crashes at night were found to occur at midblock for the years 2014 and 2015 respectively. After the midblock crashes had been separated the rest of the pedestrian crashes were divided into 6 categories as mentioned in the methods section (i.e. Ped-Along/Same, Ped-Along/Opposite, Ped-Right, Ped-Left, Ped-Standing/Working/Other and Unknown). The distribution of the crashes is presented in Figure 4.1

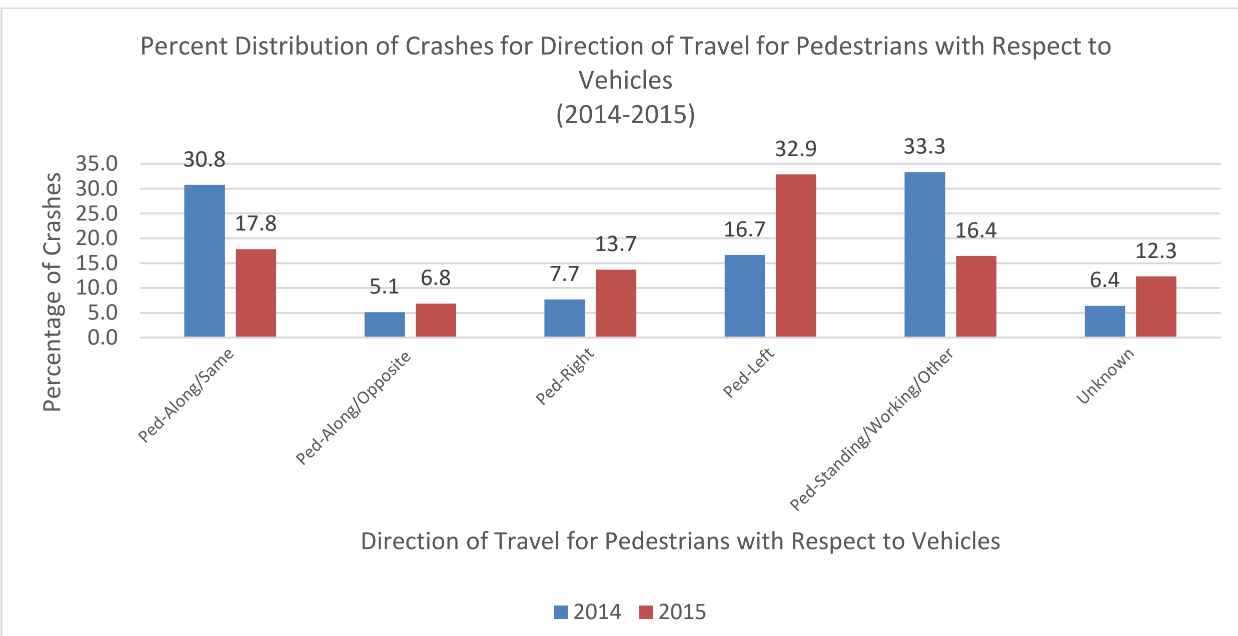



**Figure 4.1 Percent Distribution for Direction of Travel for Pedestrians with Respect to Vehicles**

For the year 2014, ped-Standing/Working/Other had the highest percentage (33.3%) but for the year 2015 ped-left crashes had the highest percentage (32.9%). Given the random nature of crashes, it is difficult to discern if there is a pattern using only a two-year period and 151 crashes. However, the following quantitative analysis presents data from 10 years of crash databases.

In addition to studying the distribution of different pedestrian maneuvers, roadways infrastructure information at the crash location was also investigated using Google Earth. The roadway infrastructure data that were collected during the qualitative analysis are presence of light-pole, presence of sidewalk, and number of lanes.

#### 4.1.1.2 Presence of Light-poles at the Crash Locations

Figure 4.2 presents information on the presence of light-poles at the crash locations. Google Earth imagery is collected during the daytime, so researchers were not able to determine if the lights are operational – especially at the time of the crash. However, the presence of the light-pole does indicate the probability of lighting at the site. There is a strong correlation between night-time fatal pedestrian crashes at mid-block with light pole not present. For all the four types of pedestrian crash maneuvers, the majority condition is light pole not present. For some of the crashes, the presence of the light-pole information is unknown because those crashes were not properly geolocated.

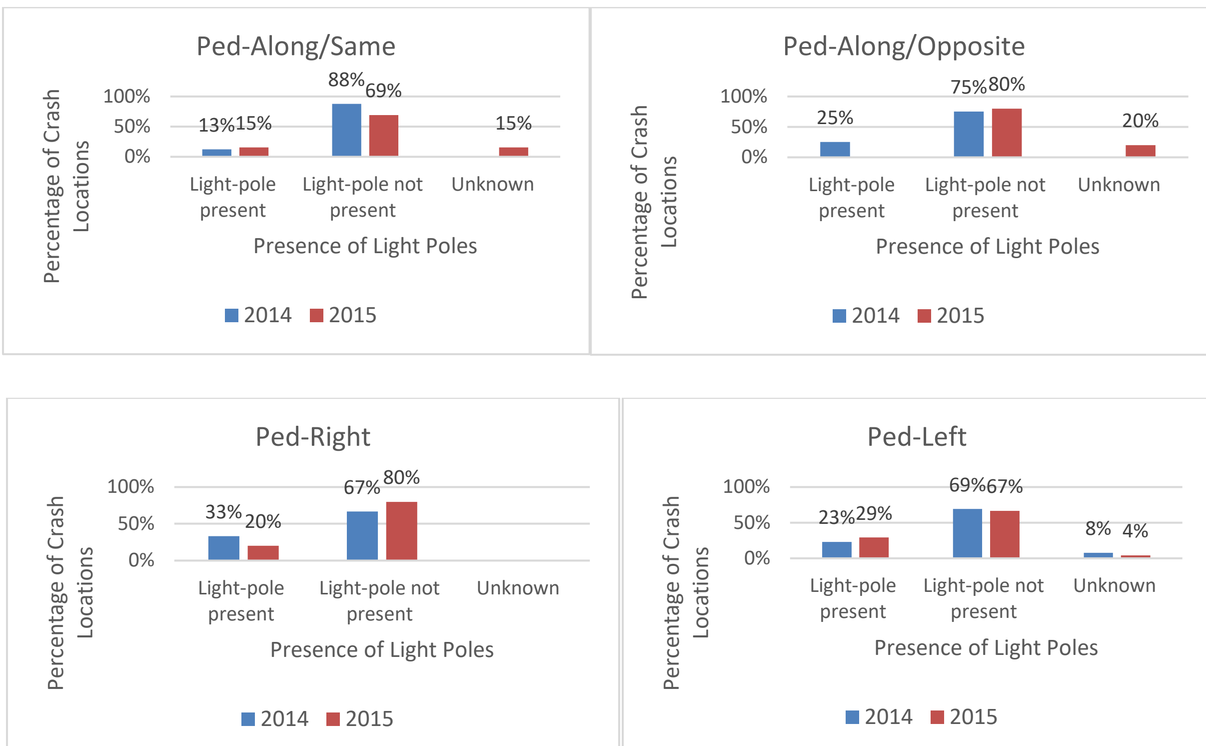



**Figure 4.2 Presence of Light-pole by Pedestrian Crash Maneuver**

#### 4.1.1.3 Presence of Sidewalk at Crash Locations

Figure 4.3 shows the percentage of fatal night-time pedestrian crashes at midblock based on the sidewalk presence for different types of pedestrian maneuvers. The most prominent pattern involves crashes where the pedestrians are walking along the road at night either in the same or opposite direction of the traffic. With the lack of an appropriate sidewalk facility, pedestrians will often use the road. No crashes involving walking along the road occurred when there was a sidewalk present at the crash location. On the contrary, there is not really a trend visible on crossing crashes (Ped-Right/Ped-Left) with the presence of sidewalks. For some of the crashes, the presence of the sidewalk information is unknown because those crashes were not geo-located properly.

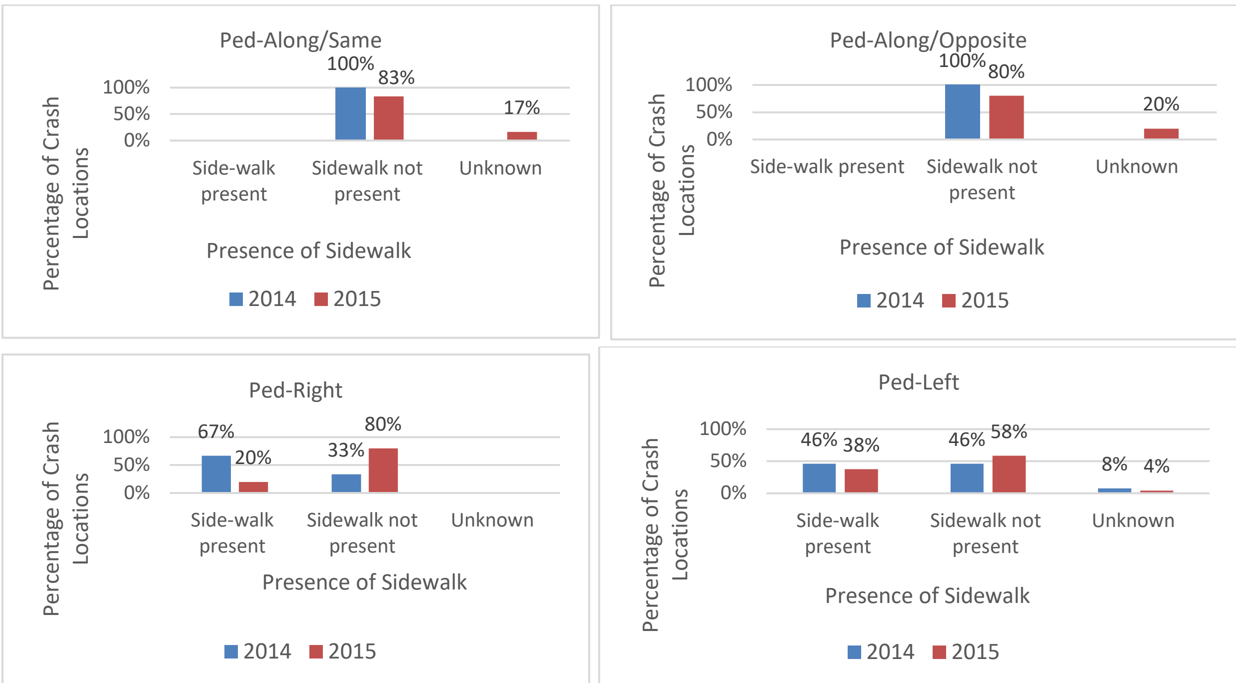



**Figure 4.3 Presence of Sidewalk by Pedestrian Crash Maneuver**

#### 4.1.1.4 Number of Lanes at Crash Locations

Figure 4.4 shows the number of lanes at the crash locations for the different types of pedestrian crashes. The charts reveal that for both types of walking along the road crashes (Ped-Along/Same and Ped-Along/Opposite) two-lane two-way roads are more probable crash locations. This is because most of these two-lane two-way roads are local roads that may not have sidewalk facilities. A different scenario is noted for the crossing crashes and indicates that multilane facilities are more probable locations for pedestrian crossing crashes. When pedestrian cross the road at midblock at night, drivers do not have any expectation that they will be there, and the multilane scenario may also cause pedestrians occluded by vehicles in adjacent lanes.

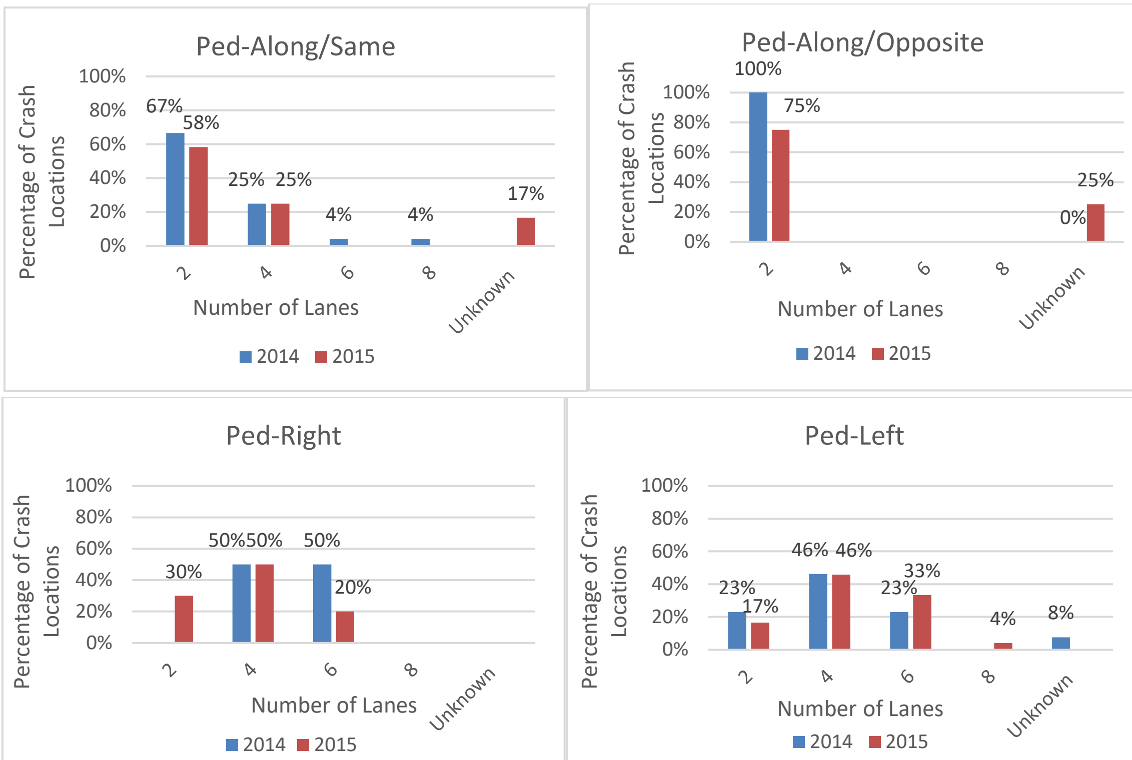
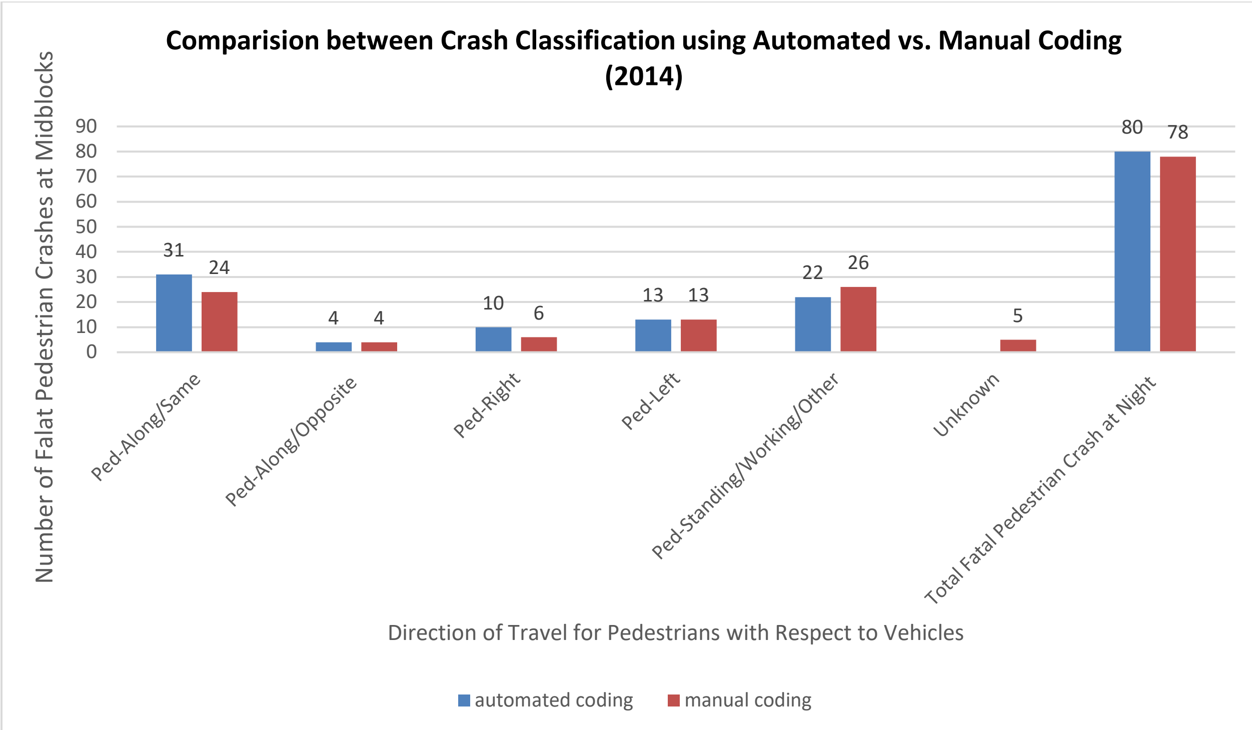



**Figure 4.4 Number of Lanes by Pedestrian Crash Maneuver**

### 4.1.2 Quantitative analysis

This section summarizes the results from the crash analysis using 10 years of crash data from 2007-2016. As previously mentioned, once the qualitative analysis was complete, the researchers wanted to automate the process for analyzing multiple years of data to find the trends in different types of pedestrian crashes. Upon developing a code in ArcGIS using the python script, the researchers compared the results from manual and automated analysis for the years 2014 and 2015 (shown in Figure 4.5). The comparison was done to determine how well the results matched for pedestrian night-time fatal crashes at midblock locations for different types pedestrian direction of travel with respect to vehicles.



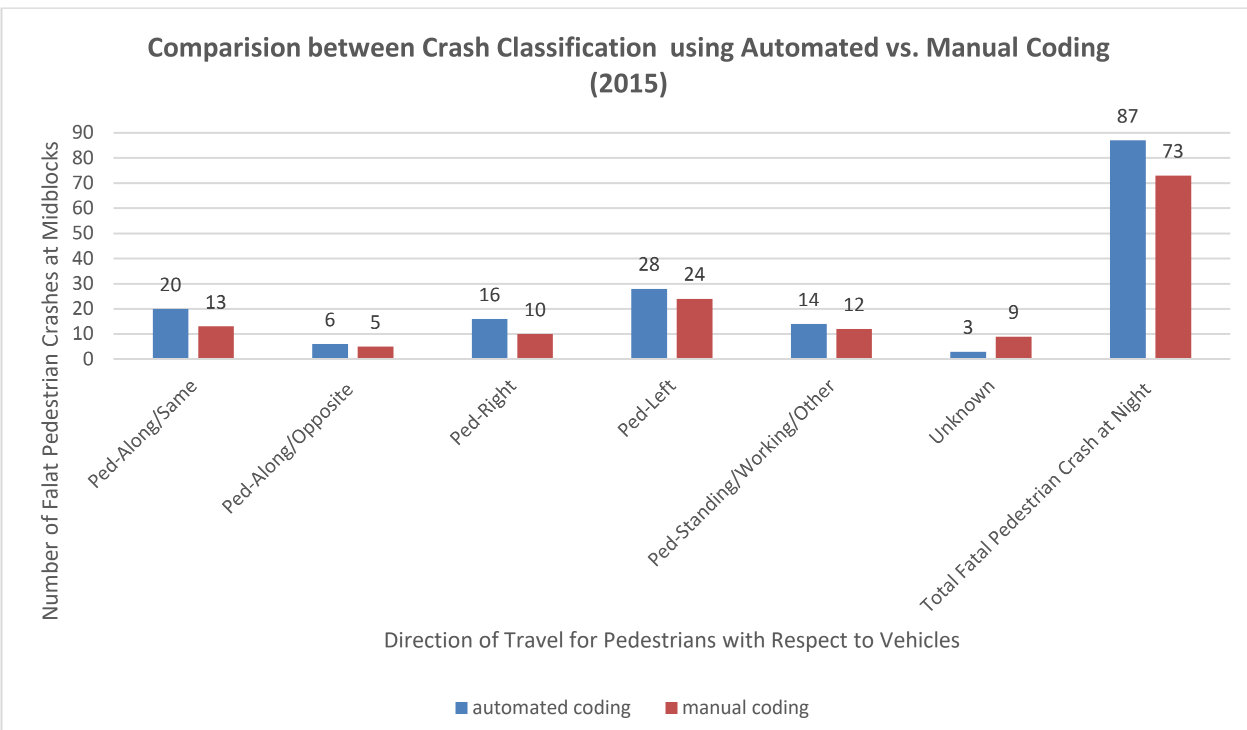




**Figure 4.5 Comparison of manual and automated coding of pedestrian fatal crashes at midblock by maneuver**

The number of crashes for both years for both automated and manual coding show a similar pattern. After matching individual crashes, on average an 84% match was found. Also, it was found that there were fewer unknown crashes for automated coding which is a positive outcome from the automated analysis. The police officers must provide a graphic as well as directional coding. In some cases, the information is duplicated in both areas. In others the directional information is provided in the directional coding, but not on the graphical representation. So, when coding solely from the graphical representation, determining the pedestrian maneuver with respect to the vehicle was not possible using graphics alone. Finding 84% match to be satisfactory, given the slight difference and improvement in unknown, the research team was confident about the reliability of the results from quantitative analysis. In the following sections, the results from the quantitative analysis are presented.

#### 4.1.2.1 Pedestrian Crashes vs Total Crashes

The trend for total crashes and all pedestrian crashes in South Carolina for the years from 2007-2016 is shown in Figure 4.6. The number of crashes from 2007 to 2010 show a decreasing trend, and an increasing trend is visible from the year 2011 to 2016. A similar trend is noted in the national crash statistics with a drop in vehicle miles traveled and therefore a similar drop in crashes after the economic recession hit the US at the end of 2007. However, as the economy started improving from 2011 the crash trend began to increase again, but at a much greater rate. A similar trend is also visible for the number of pedestrian crashes in South Carolina. One of the concerning facts is that there has been a 37% increase in the total number of pedestrian crashes from the years 2011 to 2016. The percentage of pedestrian crashes with respect to total crash is on an average about 0.75 percent for the last 10 years.

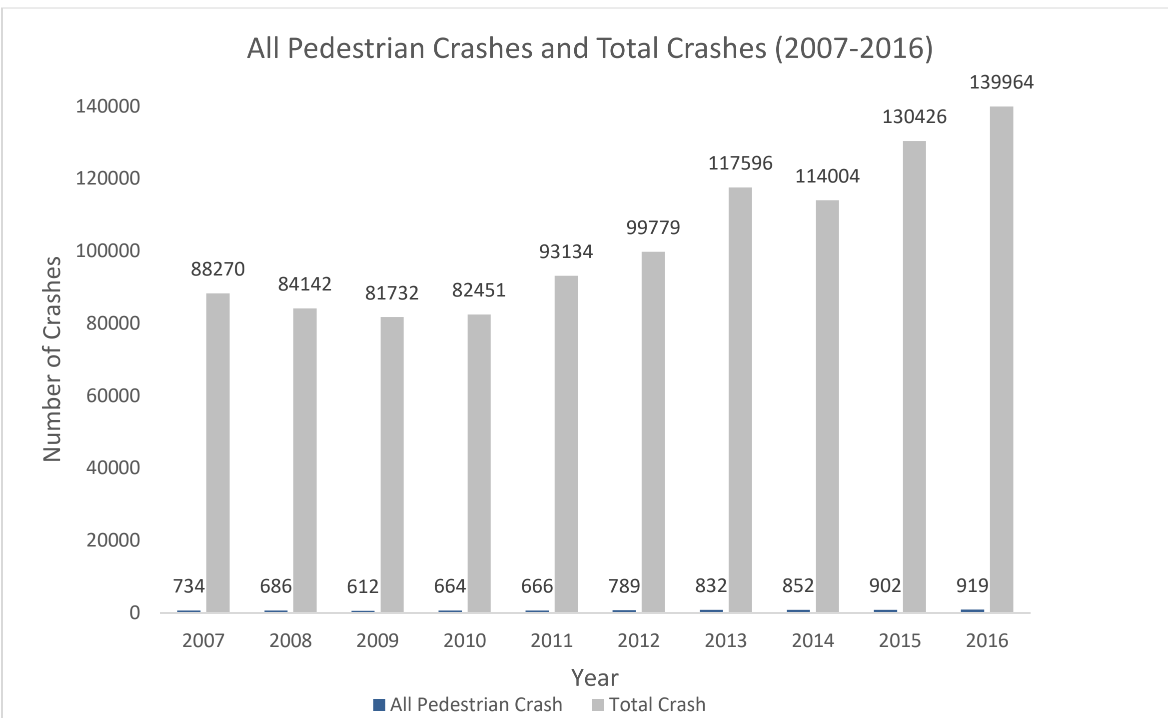



**Figure 4.6 All Pedestrian Crashes and Total Crashes (2007-2016)**

#### 4.1.2.2 Distribution of Pedestrian Fatality Types (2007-2016)

Figure 4.7 presents the distribution of pedestrian crash severity in South Carolina for the years from 2007-2016. On an average more than 80% of pedestrian crashes are injury types of crash, about 14% of crashes are fatal and 6% are property damage only types of crashes. Another disturbing trend is the increase in the percent of fatal pedestrian crashes from 12% in 2014 to 16% in 2016 – a 4% increase over 2 years.

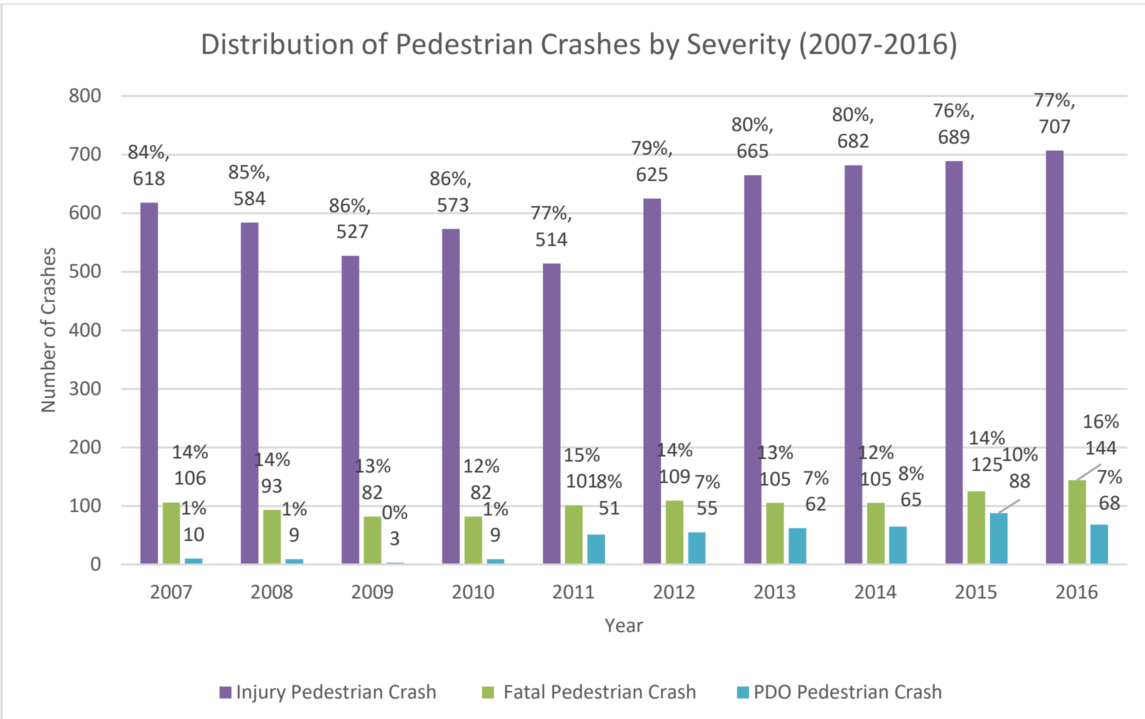



**Figure 4.7 Distribution of Pedestrian Crashes by Severity (2007-2016)**

#### 4.1.2.3 Fatal Pedestrian Crash Types: Day Vs Night (2007-2016)

This section presents the percentage of fatal pedestrian crashes for different times of the day in South Carolina. Data shown in Figure 4.8 reveals that pedestrians are more susceptible to fatal crashes at nighttime than during the day. On an average about 80% of the crashes occurred at night. Due to the high percentage of the fatal pedestrian crashes at night the authors were interested to investigate the reasons behind these crashes.

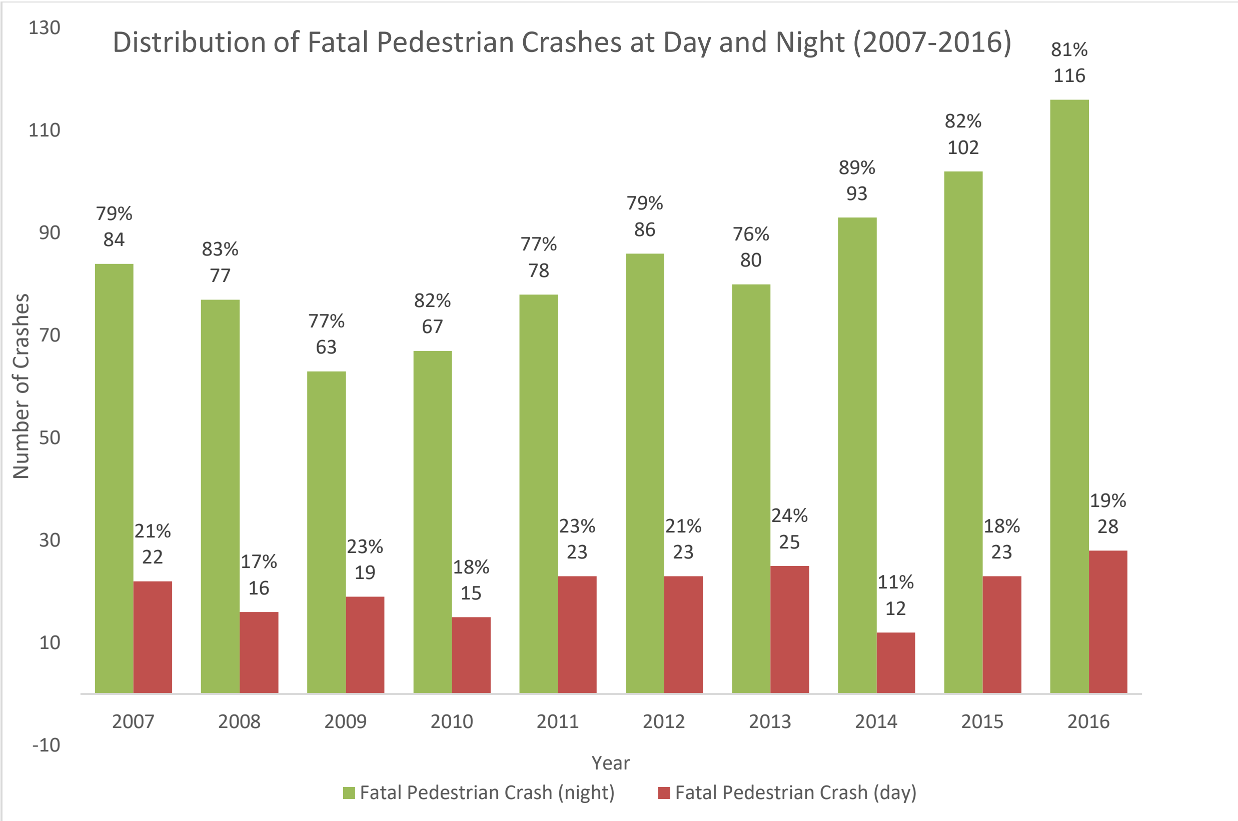



**Figure 4.8 Distribution of Fatal Pedestrian Crashes at Day and Night (2007-2016)**

#### 4.1.2.4 Distribution of Fatal Pedestrian Crashes at Night: Midblock Vs Intersection (2007-2016)

Once the research team found the overabundance of fatal pedestrian crashes at night, they proceeded to investigate the location of these crashes. After analyzing the nighttime fatal crashes, it was found that most of these crashes were occurring at midblock locations. On average, 86% of the pedestrian fatal night-time crashes occurred at midblock locations (see Figure 4.9).

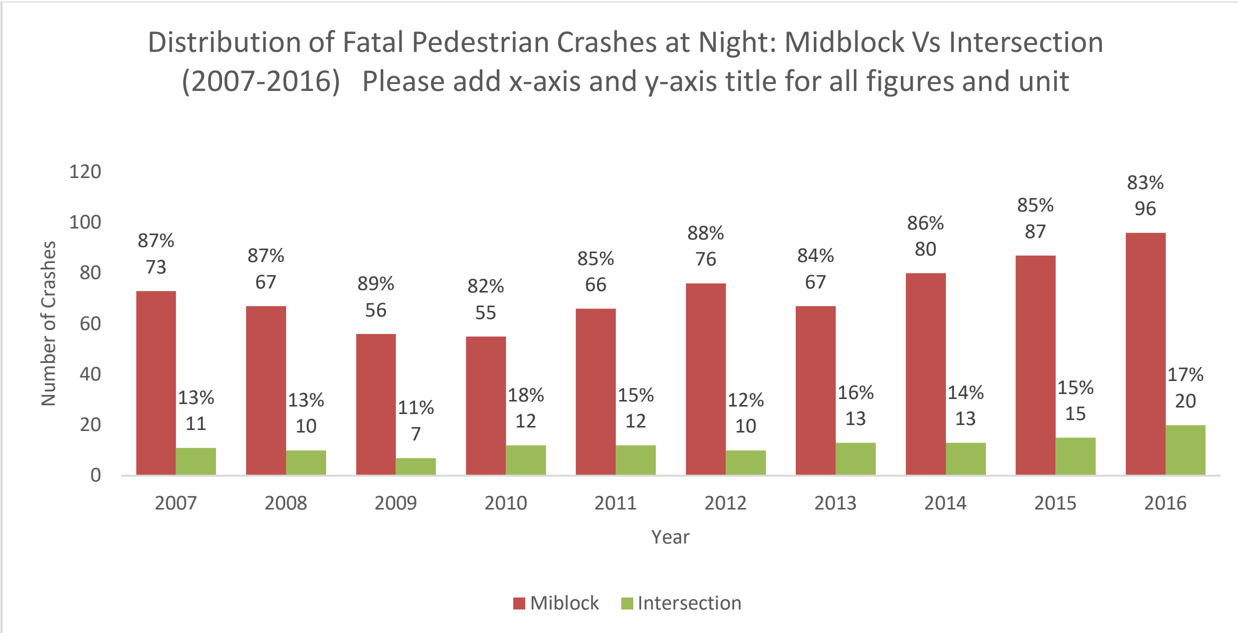



**Figure 4.9 Distribution of Fatal Pedestrian Crashes at Night: Midblock Vs Intersection (2007-2016)**

#### 4.1.2.5 Distribution of Pedestrian Maneuvers for Fatal Pedestrian Crashes at Night at Midblock (2007-2016)

A critical task in this research was to categorize the fatal pedestrian crashes during night-time at midblock locations based on the direction of travel of pedestrians with respect to the vehicles. These pedestrian maneuvers are listed in Table 3.2 with graphical representations. Figure 4.10 shows the percentage distribution of all fatal pedestrian crashes at night that occurred at the midblock locations. From the figure, Ped-Along/Same maneuvers have the highest percentage of crashes for most of the years (26.1% on average). In second place is Ped-Left (20.2% on average) which is a crossing type of crash and in third is Ped-Standing/Working/Other (19% on average). One of the hypotheses the authors had at the beginning of the paper is the expectation about an overabundance of the pedestrian crashes at night where a pedestrian is crossing road approaching from left of the oncoming vehicle at midblock locations. This is, indeed, a problem identified in this analysis.

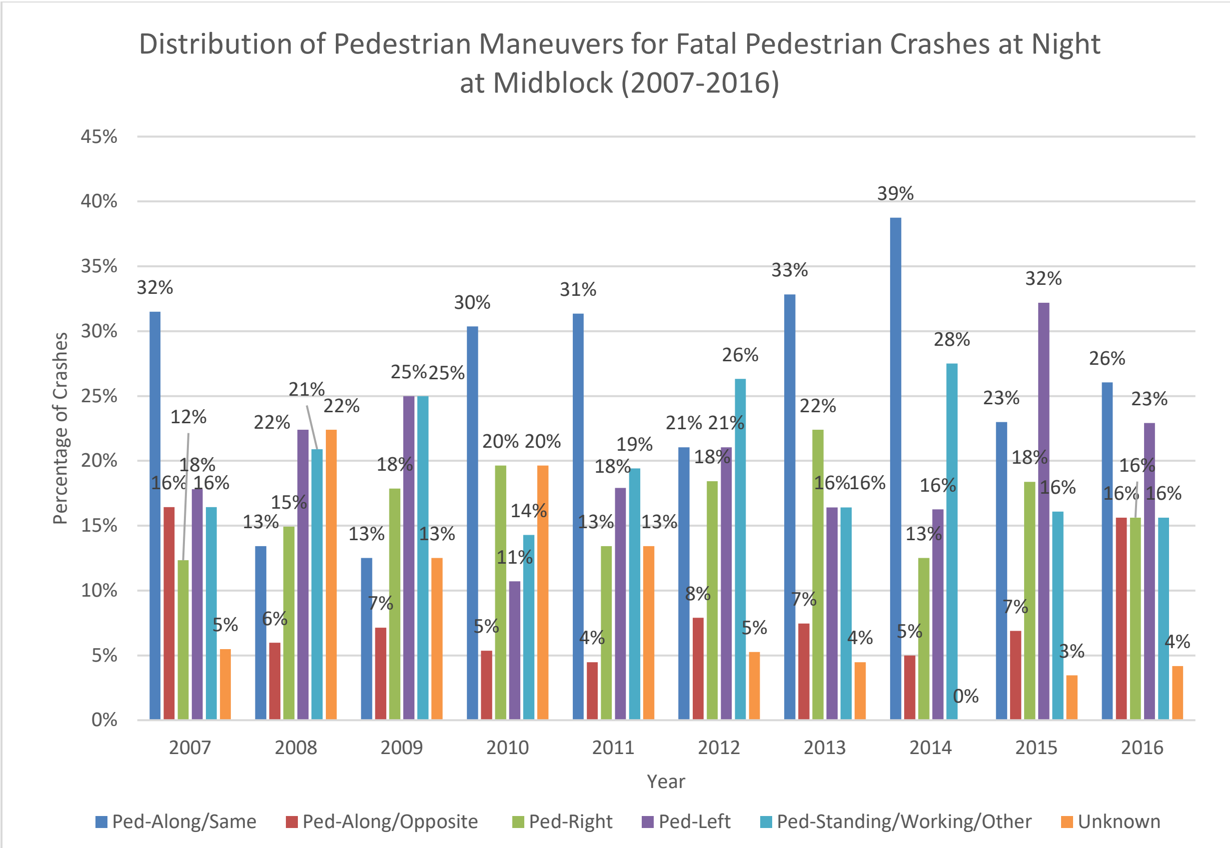



**Figure 4.10 Distribution of Pedestrian Maneuvers for Fatal Pedestrian Crashes at Night at Midblock (2007-2016)**

The next few analyses will present the different roadway features associated with walking and crossing night-time fatal pedestrian crash at midblock locations. These roadway features for different types of pedestrian crash were obtained by joining the crash data base with the RIMS database, which has been described in greater detail in the method section. The roadway features of the crash locations that will be presented in the following sections include route type, route division, median types, total number of lanes, functional class and land use.

### 4.1.2.6 Route Type

Figure 4.11 show the route types at the crash locations for the different types of pedestrian maneuvers. Results from the crash data reveal that for both types of walking crashes (Ped-Along/Same and Ped-Along/Opposite) secondary types of routes are more susceptible to these crashes. For the Ped-Right type of crashes, SC routes are more predominant, and for Ped-Left types of crossing crashes, US routes are the locations with a higher percentage of crashes.

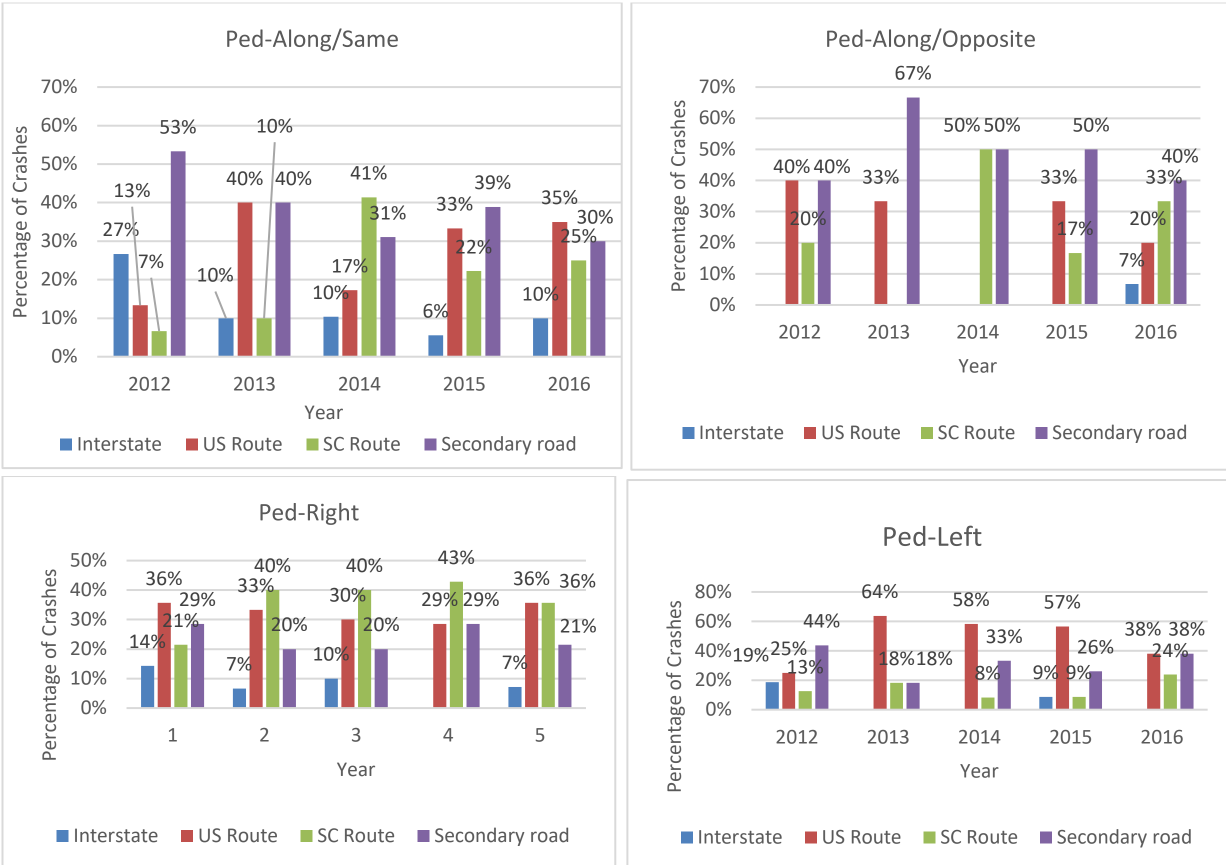



**Figure 4.11 Pedestrian Maneuvers for Fatal Pedestrian Midblock Crashes at Night by Route Type (2007-2016)**

### 4.1.2.7 Route Type

Pedestrian maneuvers for fatal pedestrian midblock crashes at night were also categorized by whether the route was divided or undivided. Figure 4.12 shows a similar pattern for all four types of crashes – with the predominant type being undivided facilities. On average, less than a quarter of the subject crashes are on divided roadways.

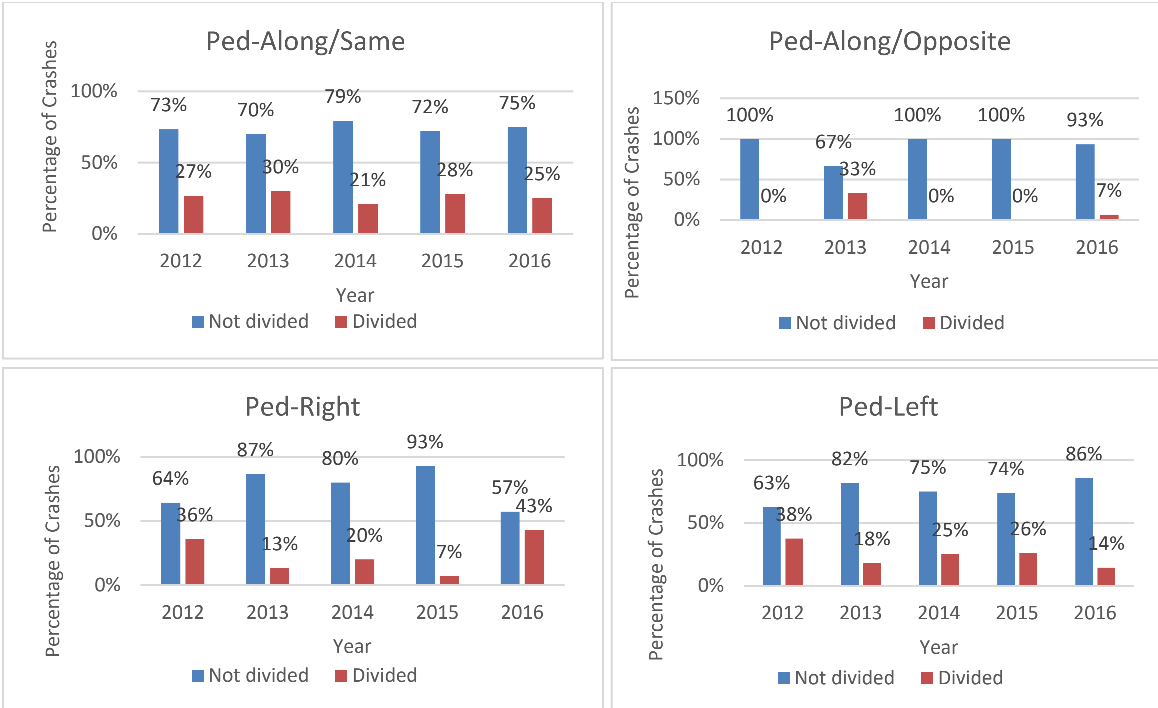



**Figure 4.12 Pedestrian Maneuvers for Fatal Pedestrian Midblock Crashes at Night by Route Division (2007-2016)**

#### 4.1.2.8 Route Type

The distribution of fatal nighttime pedestrian crashes happening at midblock locations were divided by maneuver type and median type as shown in Figure 4.13. With the knowledge that most of the walking along the road type crashes are on two-lane secondary type roads, it is not surprising to see most median types as non-divided. Whereas, for both crossing crash types, multi-lane bituminous medians are prominent. These are typically representative of dedicated median turn-lanes or two-way left-turn lanes. Bituminous medians can also be flush medians painted two double yellow lines or filled with diagonal lines, but this is less common. Note that turn-lanes do not provide a pedestrian refuge.


**Figure 4.13 Pedestrian Maneuvers for Fatal Pedestrian Midblock Crashes at Night by Median Type (2007-2016)**

#### 4.1.2.9 Total Number of Lanes

Figure 4.14 shows the number of lanes at the fatal night-time pedestrian midblock crash locations for the different types of pedestrian maneuvers. The charts reveal that for both types of walking along the road crashes (Ped-Along/Same and Ped-Along/Opposite) two-lane two-way roads are the most probable crash locations, although some do occur on four-lane and six-lane roads. This is because most of these two-lane two-way roads are secondary roads that may not have sidewalk facilities. A different scenario is visible for the crossing crashes and indicates that multilane facilities are more probable locations for crossing crashes. When pedestrians cross the road at midblock at night, drivers do not have any expectation that they will be there, and the multilane scenario may also cause pedestrians to be blocked from view by vehicles in adjacent lanes.


**Figure 4.14 Pedestrian Maneuvers for Fatal Pedestrian Midblock Crashes at Night by Number of Lanes (2007-2016)**

### 4.1.2.10 Roadway Area Type

In South Carolina, there are numerous roadway functional classes. So, instead of presenting the different types of pedestrian crashes for all the roadway functional classes, the authors aggregated the functional classes based on their area type. Area type describes whether the road section is in an urban area or a rural area. Figure 4.15 shows that for both types of walking along the road crashes, the area type is relatively evenly split among rural and urban. However, most of the crossing types of crashes occurred in urban areas, with only a little over a quarter occurring in rural areas on average.

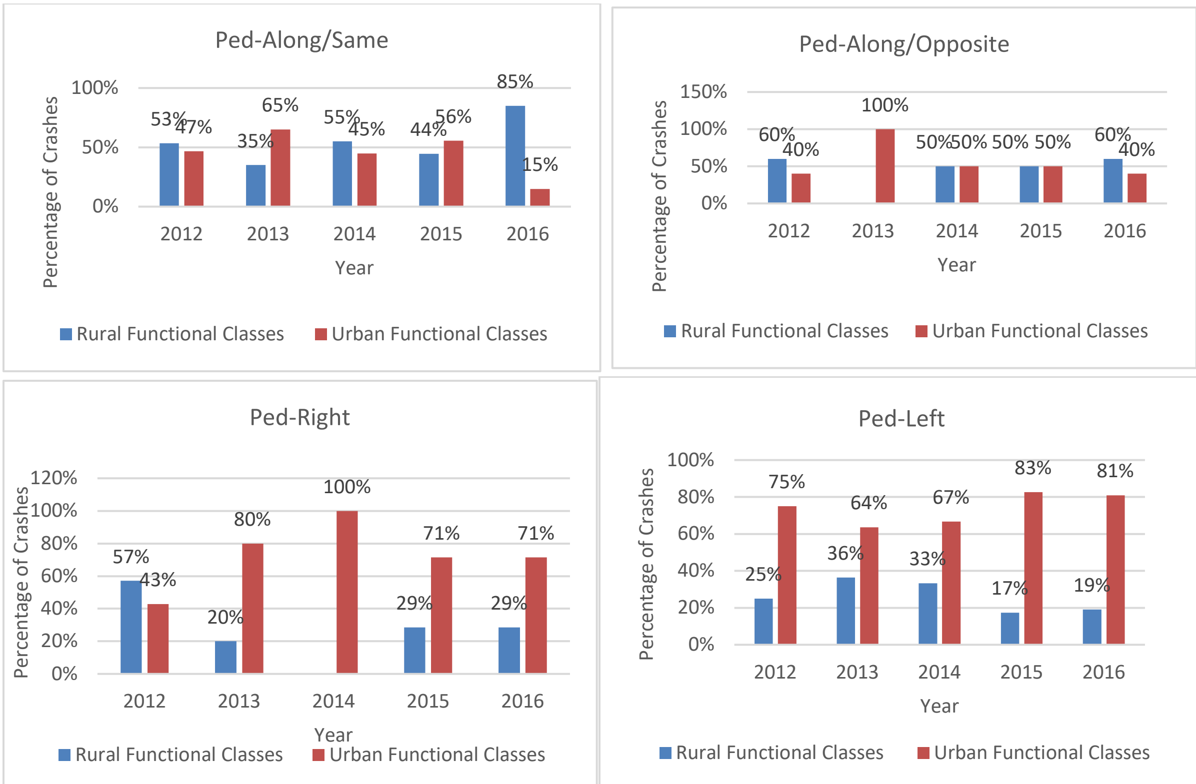



**Figure 4.15 Pedestrian Maneuvers for Fatal Pedestrian Midblock Crashes at Night by Roadway Area Type (2007-2016)**

Figures 4.16 and 4.17 provide the geospatial mapping of crossing crashes and walking along crashes respectively. Note that Figure 4.16 shows crashes predominantly clustered around major urban areas of the state, whereas Figure 4.17 shows crashes more dispersed outside the urban core areas.

In summary, the crash analysis provided much insight into the predominant types of pedestrian crashes occurring in South Carolina. Night-time midblock crashes are the most predominant type of fatal pedestrian crash. The most common pedestrian maneuver prior to the crash is either crossing from left or right, and then followed by walking along the road in the same direction as the vehicle. Crossing crashes are more prominent on multilane urban facilities where consistent lighting across a four or six lane section may be impractical. Walking along the road crashes are more predominant in rural areas on secondary roads where sidewalk facilities are often lacking.

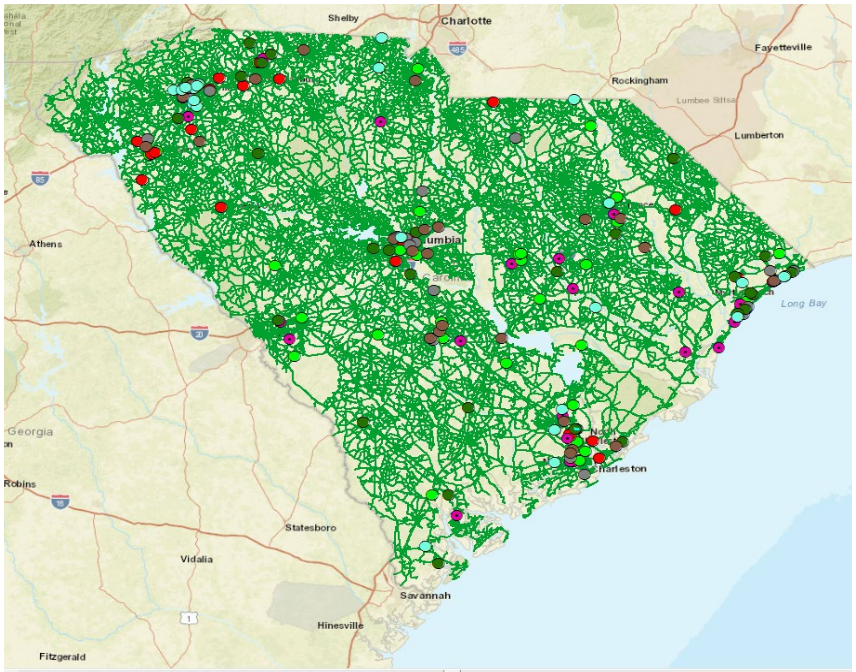



**Figure 4.16 Distribution of night time pedestrian fatal crossing crashes at midblock locations**

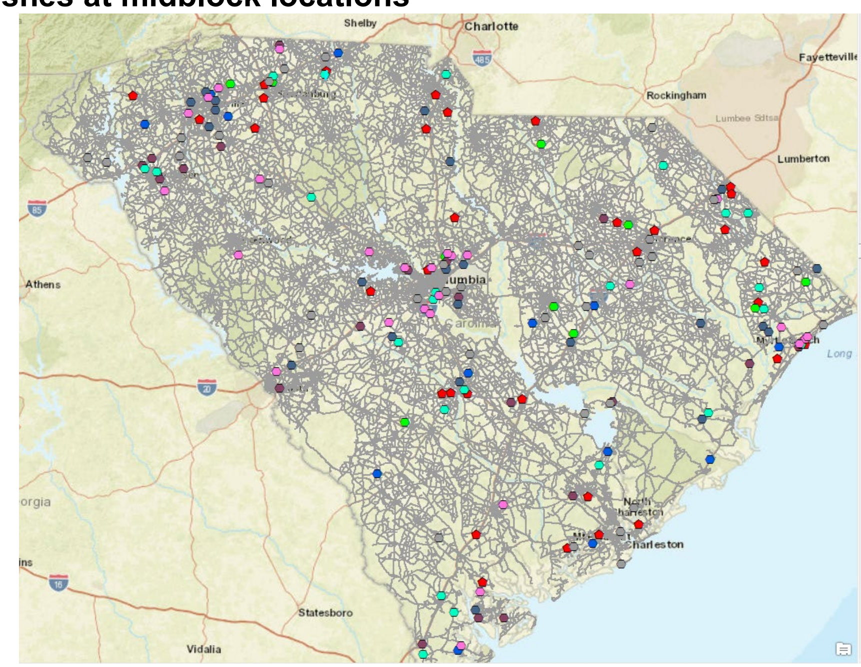



**Figure 4.17 Distribution of nighttime pedestrian fatal walking-along crashes at midblock locations**

## 4.2 Results from Analysis of Pedestrian Crash Social Media

This analysis was completed to determine the role of the media in portraying pedestrian crashes and to ascertain if any potential educational information was being provided on the known dangers and precautionary measures. Before creating the following word clouds, the news articles and tweets were thoroughly read, and researchers concluded that the messaging focused on reckless driving as the main culprit for the pedestrian deaths in South Carolina State over the last 5 years. The word clouds from different sources and a combined word cloud are provided below.

### 4.2.1 Word Cloud for the Greenville Online

Between July 11, 2014, and April 13, 2018, Greenville Online had 56 articles related to pedestrian crashes. According to the Greenville Online, the major causes of the pedestrian fatalities on SC roadways are being hit or being struck by a vehicle with the pedestrian being killed. These stories had an accusatory tone with the presumption that the driver is at fault. These articles also highlighted the reports by patrol officers and coroners regarding blunt force trauma sustained by pedestrians at the scene. The word cloud can be seen in Figure 4.18.

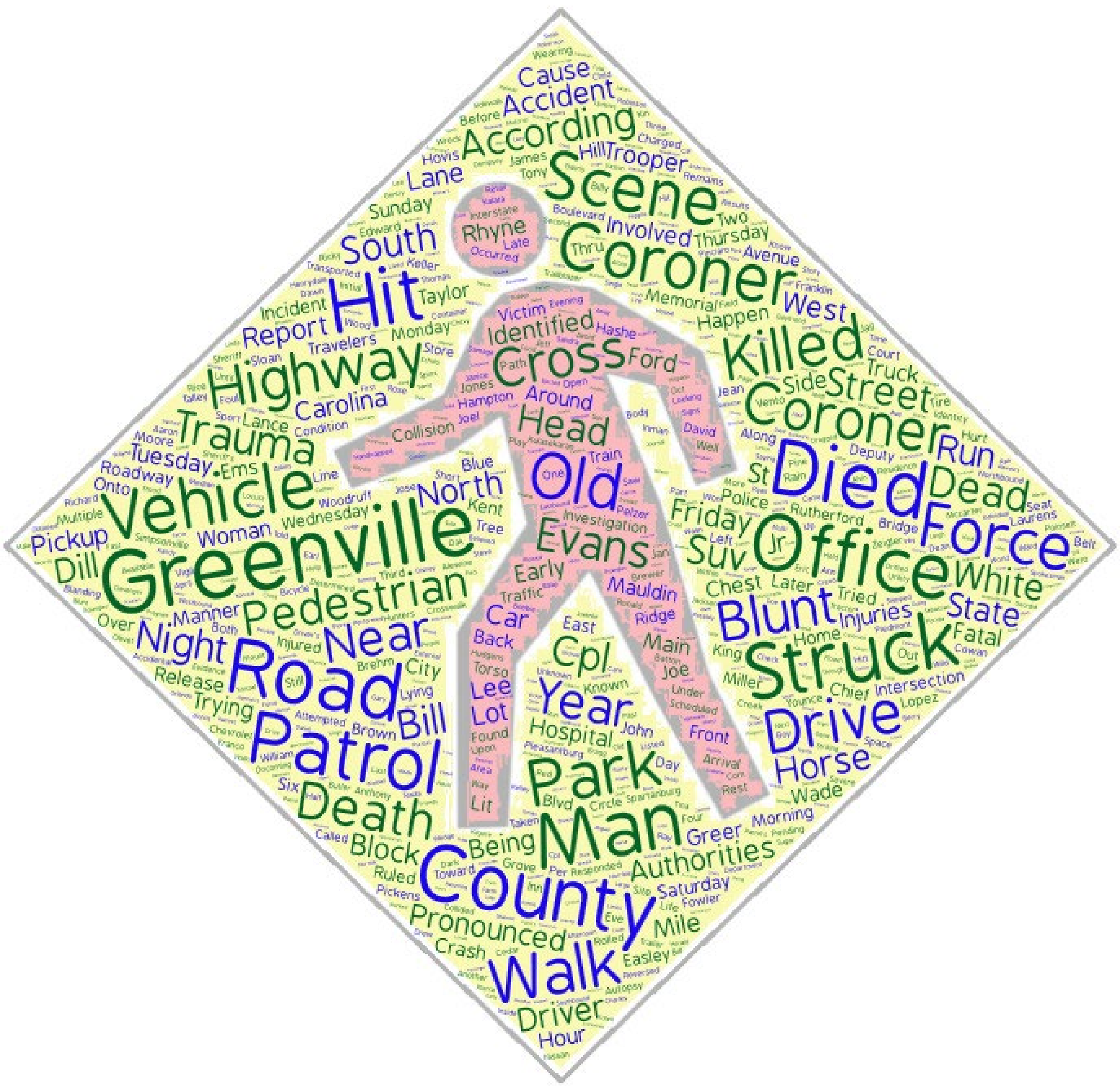



**Figure 4.18 Word Cloud of Pedestrian Crashes as reported by the “Greenville Online”**

### 4.2.2 Word Cloud for The State

Between April 8, 2016, and September 5, 2018, the State had 50 articles related to pedestrian accidents. As per the news of The State, the driver of a vehicle plays a vital role in hitting or collision with the pedestrian during crossing the road. The State provides details of the location with indications of being near or around a lane or street. The pedestrians are reported to have died slightly more than being killed. The accidents are occurring more at night than in the morning. The findings from this newspaper are depicted in Figure 4.19.

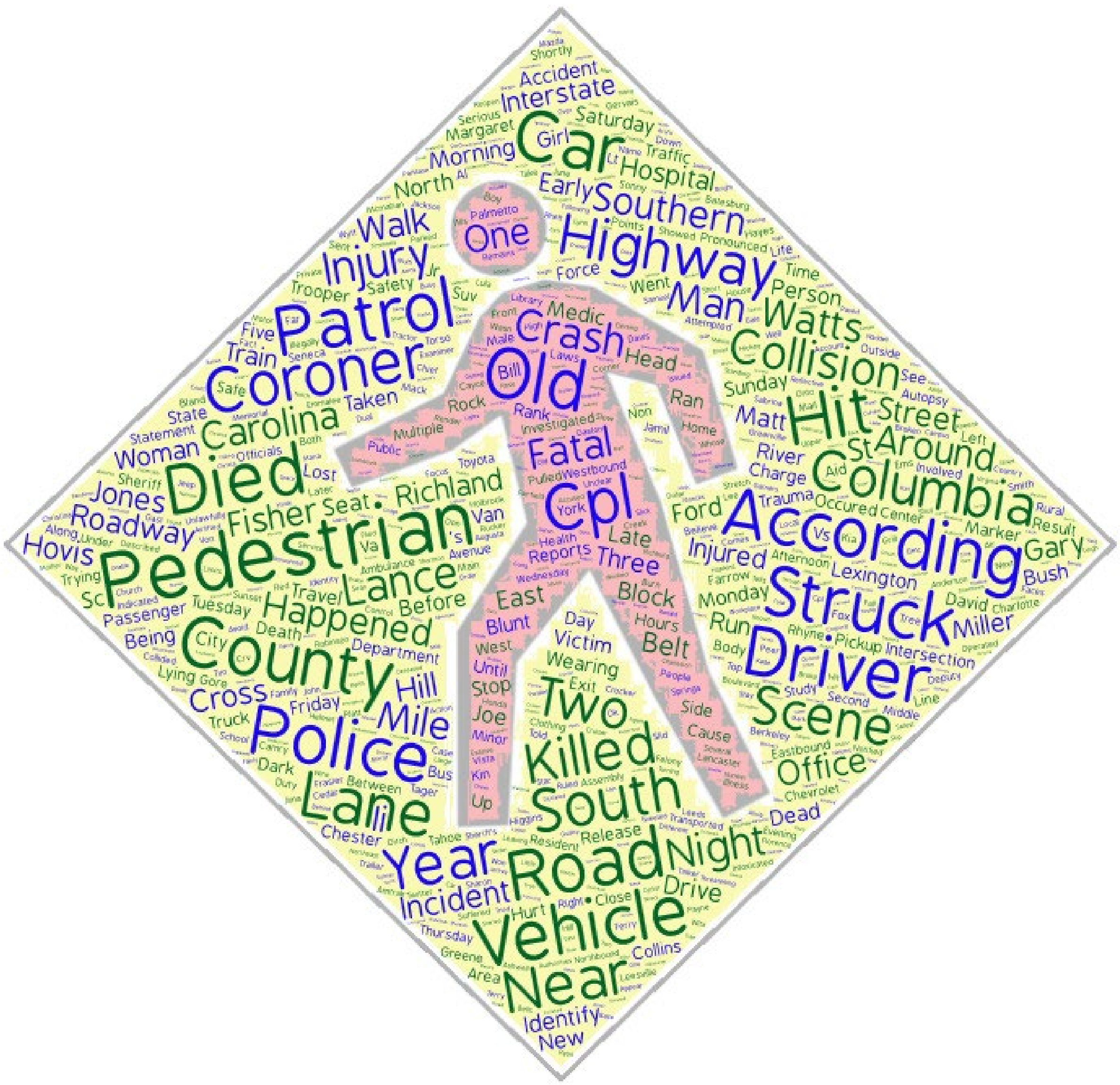



**Figure 4.19 Word Cloud of Pedestrian Crash as reported by "The State"**

### 4.2.3 Word Cloud for WYFF News 4

Between June 10, 2017, and September 30, 2018, the WYFF News 4 had 52 articles related to pedestrian accidents. The WYFF News 4 reports contained a common story of a vehicle hitting pedestrian, and the pedestrian died at the scene. Other common elements are coroner pronouncing death and investigation by highway patrol. Most of the accidents were in Greenville County, but this is expected given the source location. The findings from this news source are depicted in Figure 4.20.

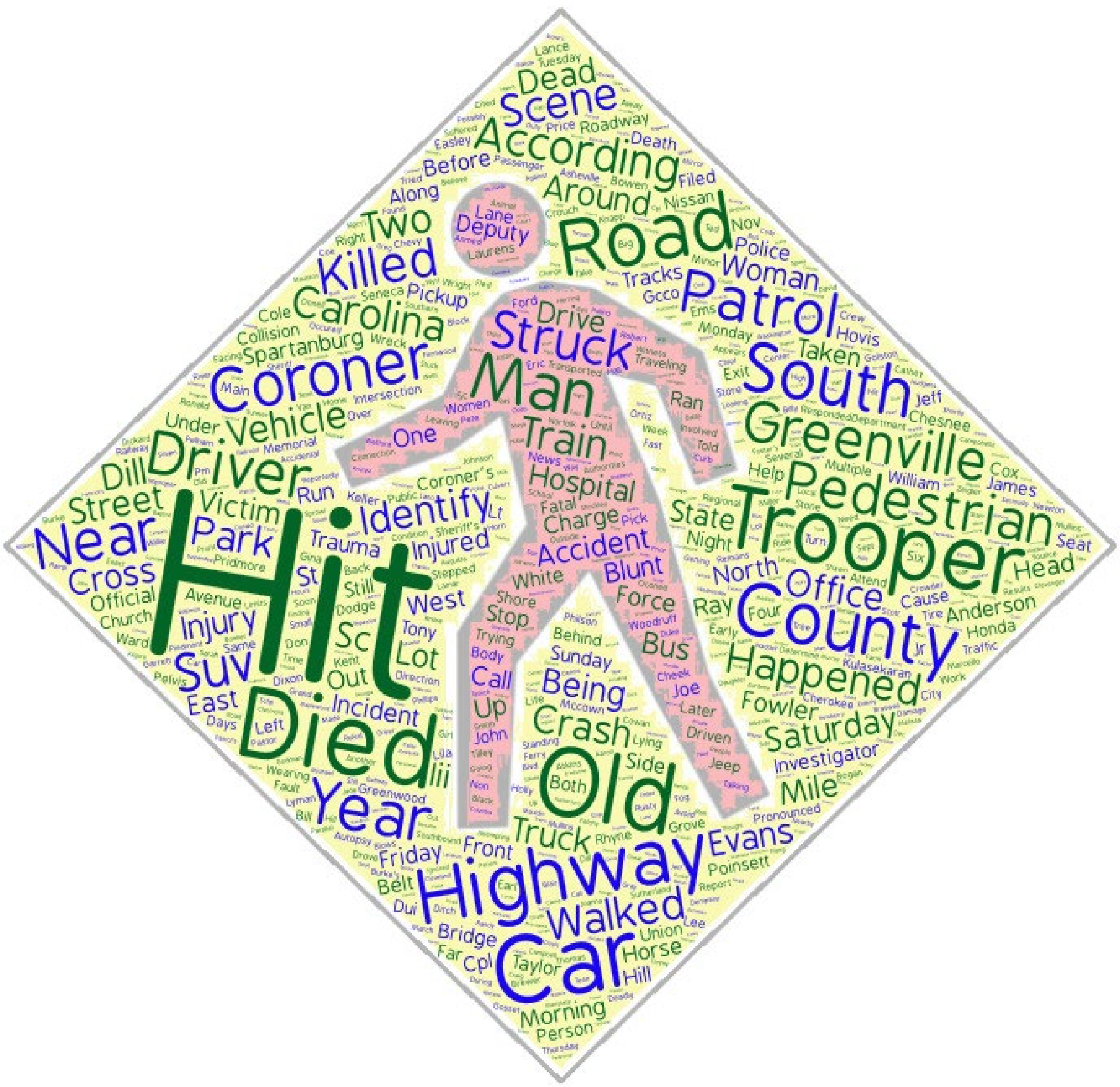



**Figure 4.20 Word Cloud of Pedestrian Crash in "WYFF News 4" newspaper**

### 4.2.4 Word Cloud for Twitter

Between January 1, 2015, and November 2, 2018, the Greenville Online had 127 tweets related to pedestrian accidents. After analyzing 127 tweets, it was determined that they were very litigious in nature. Numerous **law firm**s were mentioned, as well as legal aspects of pedestrians in **crosswalk** having right of way, and drivers fleeing the scene after **hit and run**. Figure 4.21 shows the word cloud of pedestrian crashes based on the tweets.


**Figure 4.21 Word Cloud of Pedestrian Crash as reported in "Twitter"**

### 4.2.5 Word Cloud for the Combined News/Tweets Data

Every year roughly 100 people die in pedestrian crashes in South Carolina. The preceding news sources provided various details regarding pedestrian crashes, some with a different slant than others, but none included information on preventative measures, visibility of clothing choice, lack of visibility in low light conditions, driver detection errors, or errors in discerning crossing time or speed of oncoming cars. Each of these unfortunate events provides an opportunity to inform the public about the potential dangers of pedestrian activity – especially in night-time conditions. Figure-5 represents a combined word cloud for the total of 285 news stories.

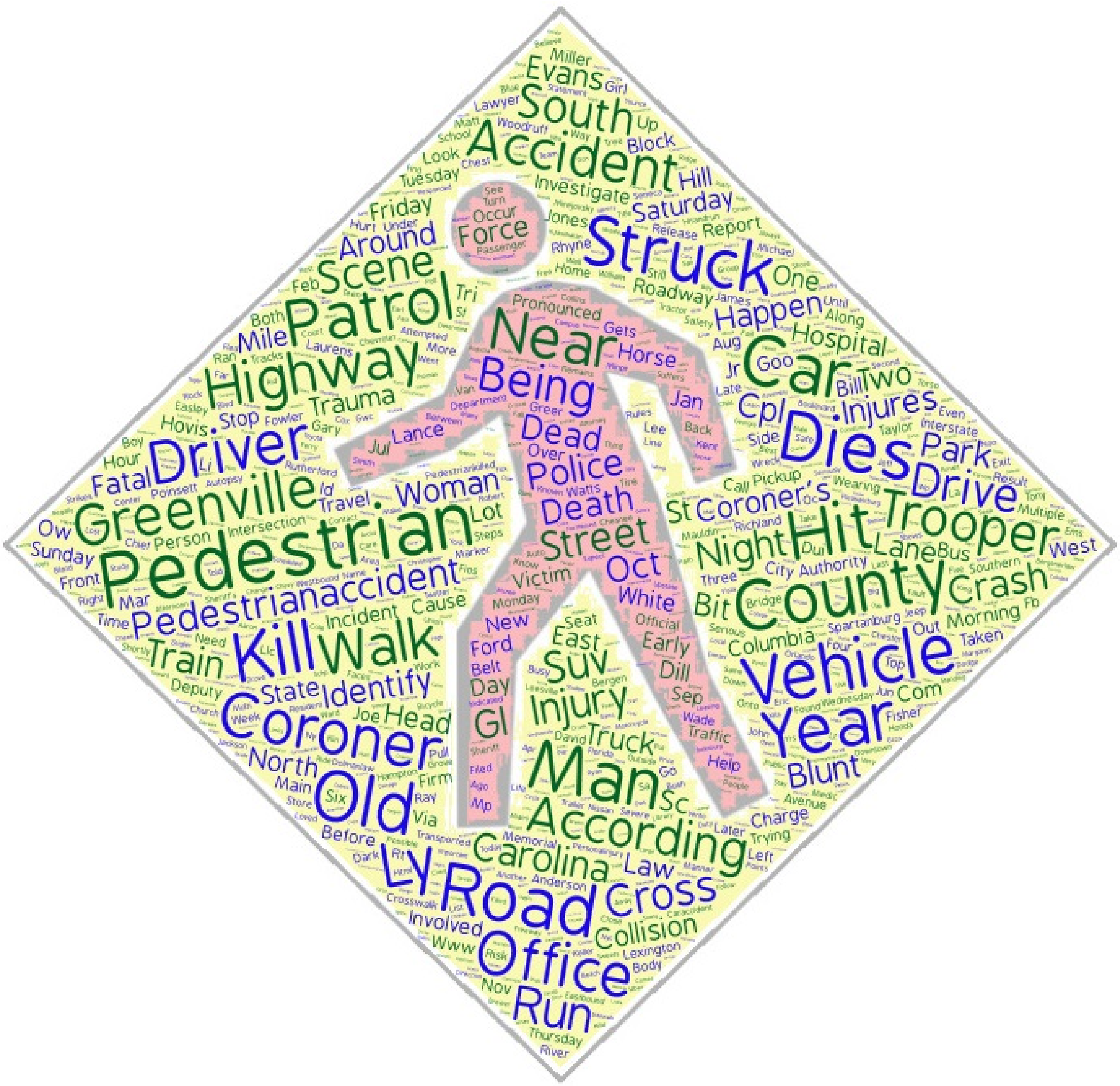



**Figure 4.22 Combined Word Cloud of Pedestrian Crash in South Carolina for last 5 years**

## 4.3 Results for Analysis of Socio-demographics of Fatally Injured Pedestrians

The research team analyzed the sociodemographic information for fatal and injured pedestrians who had been involved in crashes by matching their 9-digit zip code with Census block groups. Information obtained included: Population, Gender, Race/Ethnicity, Age, Median Household (HH) Income, Educational Attainment, Poverty Level, Vehicles Available, and Vehicle Age. Average values were computed for the state as well as the sample of fatally injured pedestrian crashes containing 9-digit zip codes. The differences were significant in many cases. The population density at the home location of the fatally injured pedestrians was much higher with 201 pedestrians per square mile versus 150 for the state average. This indicates that there is an urban trend – higher density development. The median household income is also significantly lower, and individuals with only a high school education is slightly higher. Overall, there was some variation in age and race/ethnicity, but chi-square tests of the resulting distributions were not independent.

**Table 4.1 Summary form the Socio-Demographic Analysis**

| Category | Pedestrians (All) | State Average |
|---|---|---|
| Population Density | 201.0 | 150.0 |
| Average Median HH Income | 40609.8 | 44337.4 |
| % Individual In Poverty | 17.9 | 17.8 |
| % Edu Attainment - At Least Col Diploma | 30.3 | 32.3 |
| % Edu Attainment - High School(HS) Only | 32.9 | 31.2 |
| % Edu Attainment - No HS Diploma | 15.6 | 16.0 |
| Age < 35 (%) | 47.9 | 46.5 |
| Age 35 - 65 (%) | 39.4 | 39.9 |
| Age > 65 (%) | 12.7 | 13.7 |
| Caucasian % | 63.2 | 66.2 |
| African American % | 30.4 | 27.9 |
| Hispanic % | 5.5 | 5.1 |
| Asian % | 1.3 | 1.3 |
| Average Vehicle Age (Years) | 9.4 | 9.0 |
| Vehicles Available Per Household | 1.8 | 1.8 |

A similar analysis was completed, but this time the fatally involved pedestrians were split into groups based on the Euclidean distance between the approximate household location based on the 9-digit zip code and the crash location. Groups included <0.1 mile, 0.1-0.5 miles, 0.5-5.0 miles, 5.0-10.0 miles, and > 10 miles. Figure 4.23 gives an example of this analysis. The selected block group on the right contains the household location. Census data from all households in the block group are used to impute the socio-demographics of the fatally involved pedestrian. The crash location is shown in red to the left. The straight-line distance between these two was measured for each pedestrian household and crash pair. The number of pedestrians falling into each of distance ranges is shown in Table 4.2.

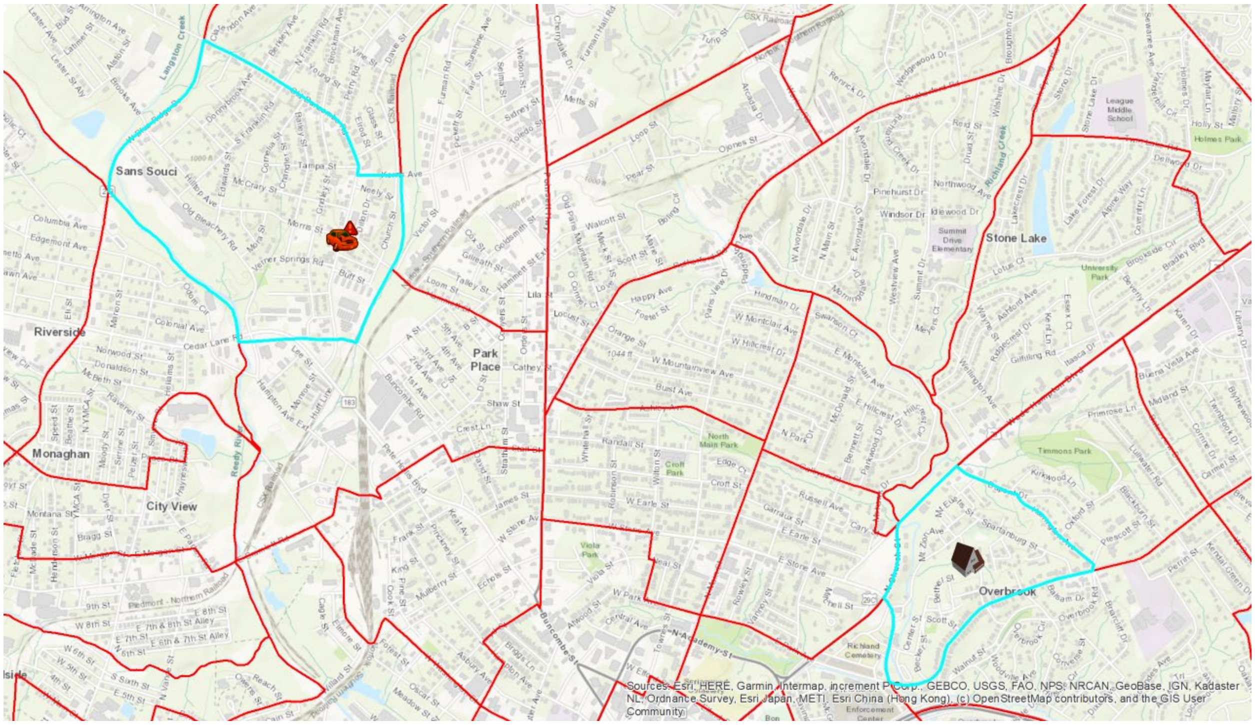



**Figure 4.23 Example of Euclidean Distance between House Block Group and Crash Site**

**Table 4.2 Summary of Home to Crash Distance by Range**

| Miles From Crash | Number of Peds | Percentage of Total |
|---|---|---|
| Less Than 0.1 | 90 | 35.2 |
| 0.5 | 50 | 19.5 |
| 5 | 33 | 12.9 |
| 10 | 34 | 13.3 |
| Above 10 | 49 | 19.1 |
| **Total** | **253** | **100** |

The proximity results showed that the average distance from home at which a pedestrian was involved in a crash was 6.5 miles. A detailed summary from the proximity analysis is available in Table 4.3. These results provide an important picture of fatal crashes. Those crashes occurring within a very short distance (< 0.10 miles) of one's home show tendencies to be a lower income levels, have the highest percentage of population in poverty, and have the highest percentage with NO high school diploma. These pedestrians are also more likely to be Caucasian or Hispanic. Pedestrians involved in fatal crashes at distances between 0.5 and 5.0 miles from their home have the highest income level and the smallest percentage of population in poverty. At the opposite end of the distribution, the lower income trend re-emerges.

**Table 4.3 Fatally Involved Pedestrian Socio-demographic Data by Home to Crash Distance**

| Category | Grouping - Miles from Crash | | | | |
|---|---|---|---|---|---|
| | **0.1 Miles** | **0.5 Miles** | **5 Miles** | **10 Miles** | **> 10 Miles** |
| Average Median HH Income | 37690.8 | 41173.1 | 48779.2 | 40267.8 | 39952.9 |
| % Individual In Poverty | 21.7 | 20.4 | 16.7 | 17.9 | 19.1 |
| % Edu Attainment - At Least Col Diploma | 29.3 | 31.4 | 34.5 | 24.8 | 32.5 |
| % Edu Attainment - High School (HS) Only | 32.8 | 33.9 | 29.2 | 36.0 | 32.5 |
| % Edu Attainment - No HS Diploma | 16.8 | 14.5 | 13.6 | 15.6 | 14.2 |
| Age < 35 (%) | 47.7 | 45.5 | 48.0 | 51.6 | 45.9 |
| Age 35 - 65 (%) | 39.4 | 40.5 | 39.0 | 37.9 | 41.0 |
| Age > 65 (%) | 12.8 | 14.0 | 13.1 | 10.5 | 13.2 |
| Caucasian % | 65.4 | 64.4 | 60.5 | 61.5 | 66.4 |
| African American % | 27.8 | 29.8 | 33.7 | 32.0 | 28.1 |
| Hispanic % | 6.0 | 4.7 | 4.9 | 5.1 | 4.5 |
| Asian % | 1.4 | 1.4 | 1.4 | 1.4 | 1.2 |
| Average Vehicle Age (Years) | 9.4 | 9.4 | 8.8 | 9.1 | 9.3 |
| Vehicles Available Per Household | 1.6 | 1.6 | 1.7 | 1.7 | 1.6 |

## 4.4 Results from Pilot Test on Pedestrian Detection Technologies

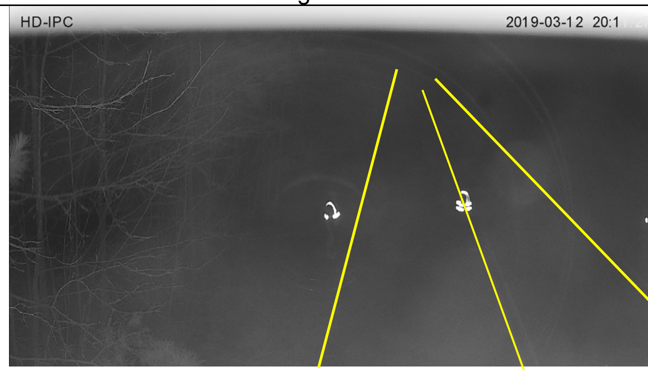
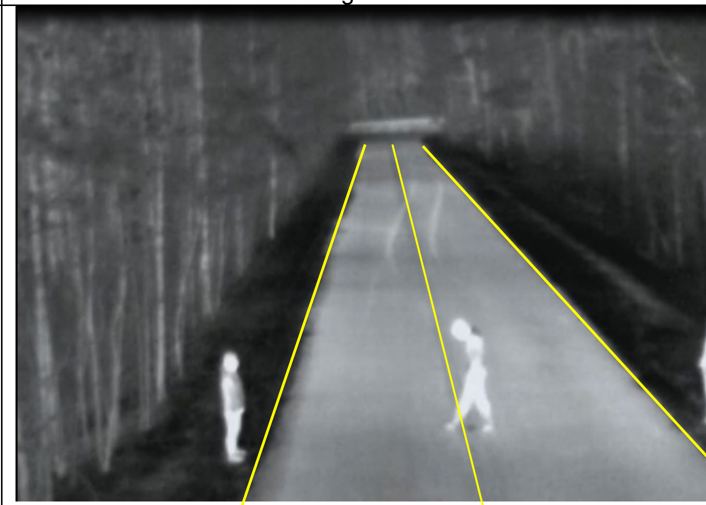
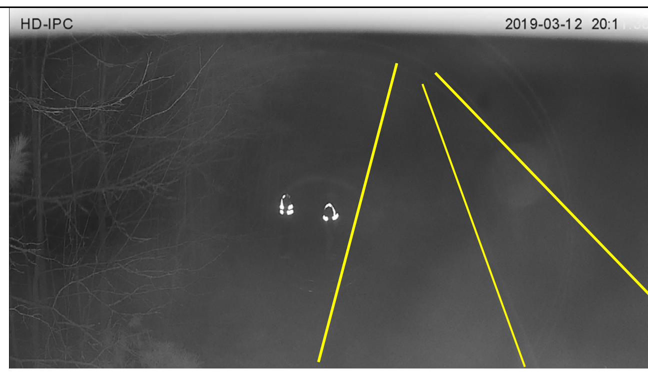
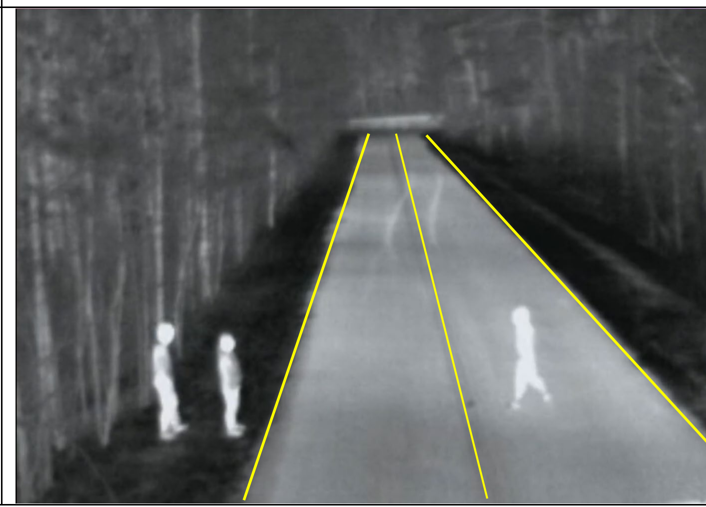
The researchers conducted a pilot test to gauge the efficacies of two types of camera technologies for detecting pedestrians at night. The goal for this task was to develop an effective method for capturing exposure data from sites of interest. To do this, the research team prepared a controlled field test for two conditions: dark not lit and dark lit with standard headlamps (no alternate lighting sources were available beyond a quarter moon. The tested conditions included four scenarios as follows:

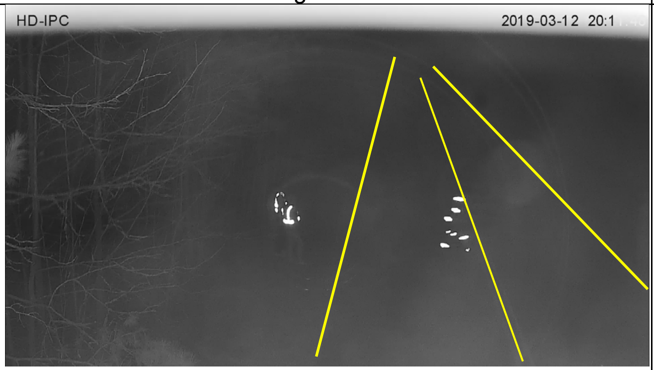
- Dark not lit
    - Pedestrian detection with night vision camera in a dark not lit section
    - Pedestrian detection with infrared camera in a dark not lit section

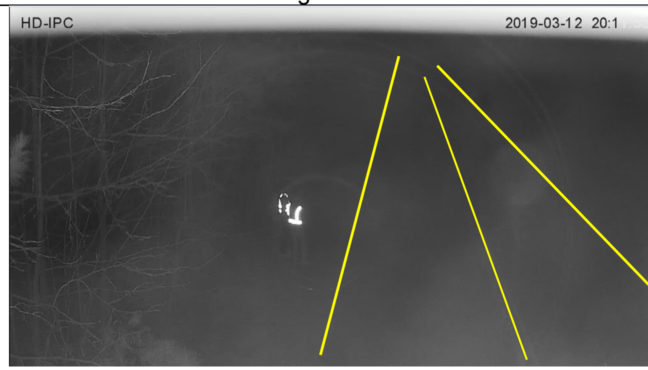
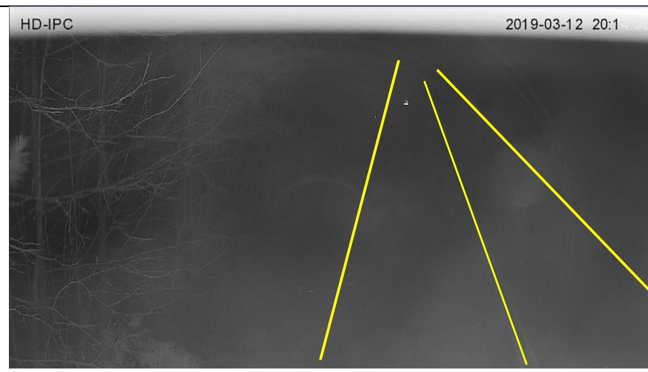
- Dark Lit
    - Pedestrian detection with night vision camera in a dark section lit with vehicle light
    - Pedestrian detection with infrared camera in a dark section lit with vehicle light

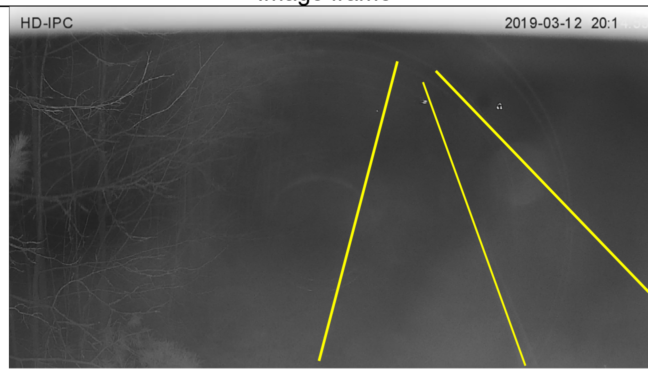
For all the four scenarios, five test pedestrians were assigned to cross the road wearing an orange retroreflective vest, a yellow retroreflective vest, a white shirt, an improvised bio-motion clothing and full black clothing respectively. The pedestrian started crossing the road from the right side of the transportation van that was used to mount the cameras. Table 4.4 shows the comparison for dark not lit conditions, and Table 4.5 shows the comparison for dark but lit with vehicle headlamps only. Table 4.6 provides a summary of the graphic depictions. In all cases, the infrared provides detectable pedestrian imagery within the range of 0-300 feet. In dark conditions, the night vision camera only picked up discernable imagery for bio-motion up to 100 feet and not for any other clothing options. In dark conditions lit with headlamp lighting, the night vision camera picked up all clothing until 200 feet. No discernable images were picked up beyond 200 feet with vehicle headlamps. Note that this study did not include vehicle traffic which could block the visibility of the pedestrian from view, typically referred to as occlusion. In addition, the weather was clear, and the moonlight was minimal. As weather changes or moonlight increases, additional visibility may occur.

## Table 4.4 Dark not lit section with no lighting

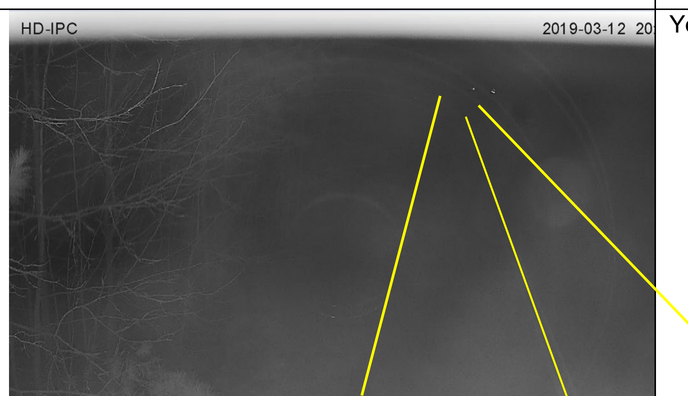
| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 Yellow vest | Yes, but not discernable pedestrian shape |  | Yes |  |
| 0+00 White cloth | No |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 Bio-motion | Yes |  | Yes |  |

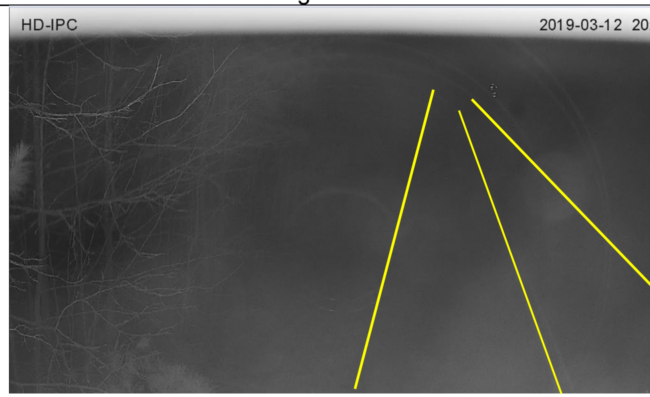
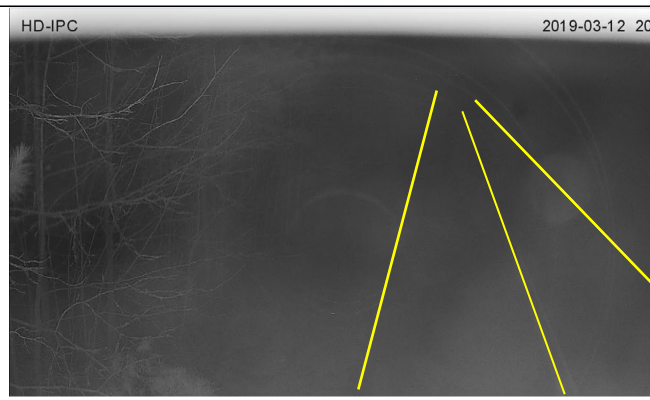
| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 Black clothes | No |   | Yes |  |
| 100+00 Orange vest | Yes, but not discernable pedestrian shape |   | Yes |  |

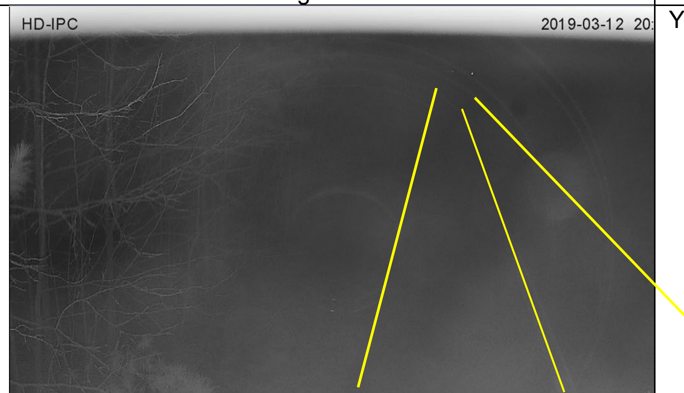
| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 100+00 Yellow vest | Yes, but not discernable pedestrian shape |   | Yes |  |
| 100+00 White shirt | No |   | Yes |  |

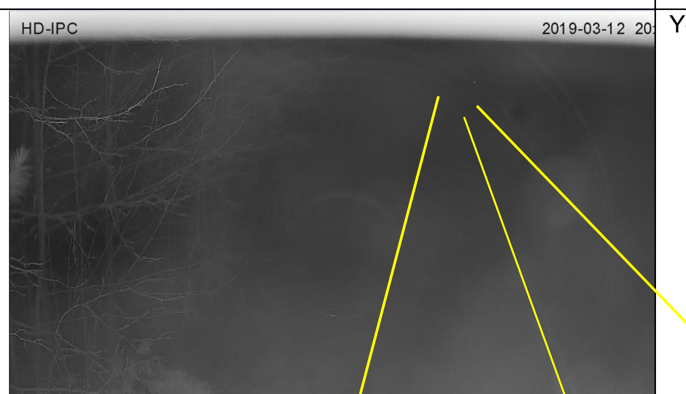
| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 100+00 Bio motion | Yes |  | Yes |  |
| 100+00 Black clothes | No |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 200+00 Orange vest | Yes, but not discernable pedestrian shape |   | Yes |  |
| 200+00 Yellow vest | Yes, but not discernable pedestrian shape |   | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 200+00 White shirt | No |  | Yes |  |
| 200+00 Bio-motion | Yes, but not discernable pedestrian shape |  | Yes |  |

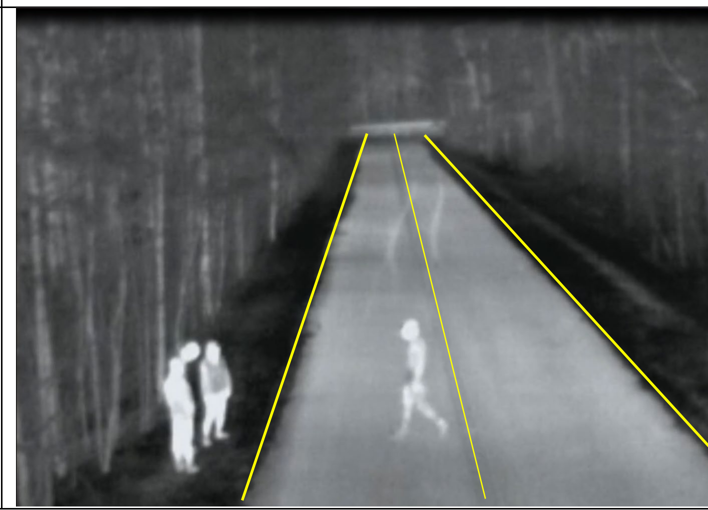
| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 200+00 Black Clothes | No |  | Yes |  |
| 300+00 Orange vest | No |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 300+00 Yellow vest | No |  | Yes |  |
| 300+00 White shirt | No |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 300+00 Bio-motion | No |  | Yes |  |
| 300+00 Black clothes | No |  | Yes |  |

## Table 4.5 Dark lit with presence of vehicle light

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 (vehicle light) Orange vest | Yes |  | Yes |  |
| 0+00 (vehicle light) Yellow vest | Yes |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 (vehicle light) White shirt | Yes |   | Yes |  |
| 0+00 (vehicle light) Bio-motion clothing | Yes |   | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 0+00 (vehicle light) Black clothing | Yes |  | Yes |  |
| 1+00 (vehicle light) Orange vest | Yes |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 1+00 (vehicle light) Yellow vest | Yes |  | Yes |  |
| 1+00 (vehicle light) White shirt | Yes |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 1+00 (vehicle light) Bio-motion clothing | Yes |   | Yes |  |
| 1+00 (vehicle light) Black clothing | Yes |   | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 2+00 (vehicle light) Orange vest | Yes |  | Yes |  |
| 2+00 (vehicle light) Yellow vest | Yes |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 2+00 (vehicle light) White shirt | Yes |  | Yes |  |
| 2+00 (vehicle light) Bio-motion clothing | Yes |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 2+00 (vehicle light) Black clothing | Yes |  | Yes |  |
| 3+00 (vehicle light) Orange vest | Yes, but not discernable |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 3+00 (vehicle light) Yellow vest | Yes, but not discernable |  | Yes |  |
| 3+00 (vehicle light) White shirt | No |  | Yes |  |

| Stations | Night Vision PTZ | | Infrared | |
|---|---|---|---|---|
| | Visible? | Image frame | Visible? | Image frame |
| 3+00 (vehicle light) Bio-motion clothing | Yes, but not discernable |  | Yes |  |
| 300+00 (vehicle light) Black clothing | No |  | Yes |  |

**Table 4.6 Summary of Camera Field Test**

| Scenario | Camera | Station | Orange Vest | Yellow Vest | White Shirt | Bio Motion | Black Clothes |
|---|---|---|---|---|---|---|---|
| **Dark Not Lit** | **Night Vision PTZ** | 0+00 | Y/N | Y/N | N | Y | N |
| | | 1+00 | Y/N | Y/N | N | Y | N |
| | | 2+00 | Y/N | Y/N | N | Y/N | N |
| | | 3+00 | N | N | N | N | N |
| | **Infrared** | 0+00 | Y | Y | Y | Y | Y |
| | | 1+00 | Y | Y | Y | Y | Y |
| | | 2+00 | Y | Y | Y | Y | Y |
| | | 3+00 | Y | Y | Y | Y | Y |
| **Dark, but Lit with Vehicle Headlight** | **Night Vision PTZ** | 0+00 | Y | Y | Y | Y | Y |
| | | 1+00 | Y | Y | Y | Y | Y |
| | | 2+00 | Y | Y | Y | Y | Y |
| | | 3+00 | Y/N | Y/N | N | Y/N | N |
| | **Infrared** | 0+00 | Y | Y | Y | Y | Y |
| | | 1+00 | Y | Y | Y | Y | Y |
| | | 2+00 | Y | Y | Y | Y | Y |
| | | 3+00 | Y | Y | Y | Y | Y |

One final note for the field study is to recognize the standard illumination pattern found on most automobiles. The pattern, as shown in Figure 4.24 is shorter on the left and more focused toward the ground; whereas on the right, the beam is much longer and spreads to the right side of the road for a much greater distance. This pattern is intentional to reduce glare for oncoming vehicles. However, a pedestrian approaching from the left near the white “x” is far less likely to be illuminated. Thus, not only are pedestrians approaching from the left less likely to be expected, they are less likely to be illuminated at an appropriate distance to be able to react in a timely manner.

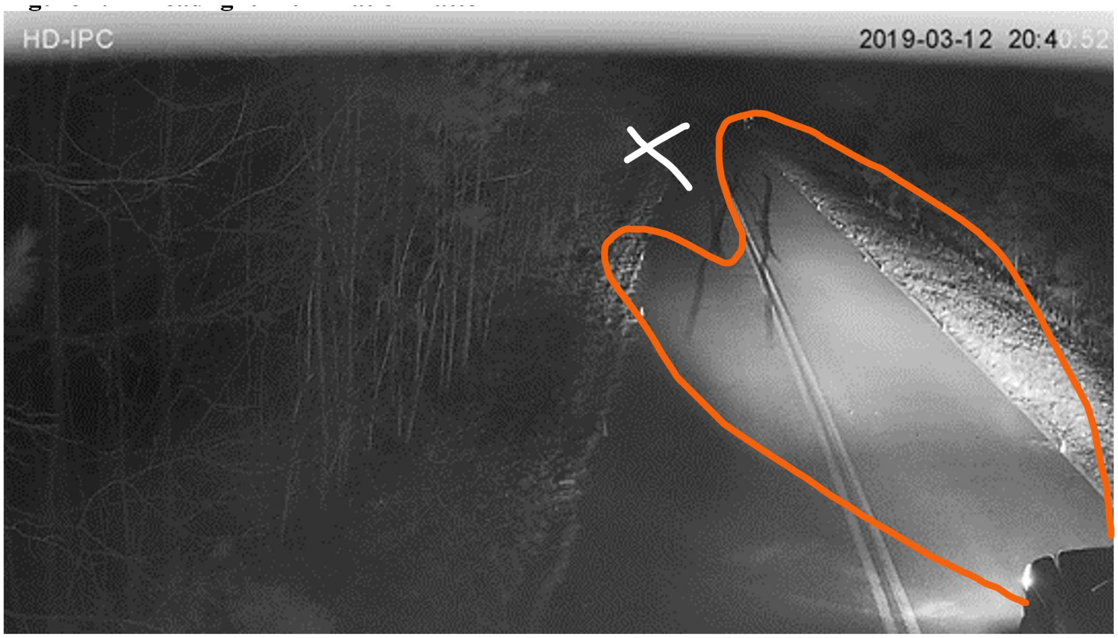



**Figure 4.24 Headlight Illumination Pattern**

## 4.5 Results of Literature Review on AV Technologies to Detect Pedestrian in Nighttime Scenarios

Even in a fully autonomous transportation system, pedestrian movement will continue to be one of the most unpredictable elements of the system. Hence, pedestrian detection, tracking and movement prediction (Navarro et al., 2016) is a critical component of autonomous vehicle functionality and will be key to the success of the system.

Pedestrian detection has been a topic of keen interest in the computer vision field, particularly over the past decade. In 2014, an extensive synthesis on the performance of over 40 detectors on the Caltech-USA dataset (a challenging training dataset) by Benenson et al (Benenson, 2014) concludes that the detection prowess of most detectors is commensurate, although different learning techniques are employed. The synthesis also concluded that progress made in pedestrian detection over that past decade was mainly due to improved detection features (Benenson 2014).

Visible-light cameras (VLC), light detection and ranging (LiDAR), and radar are the most common types of sensors that are used in automated driving applications (Combs 2019 and Baldwin 2018). Thermal cameras are also in use nowadays. Each of these technologies has its own pros and cons and the following section summarizes them.

LiDAR stands for Light Imaging, Detection and Ranging. LiDAR emits laser at a very high rate, which is usually millions of pulses at each second. Once the laser hits a surface it bounces off and measures the time the laser takes to reflect. It then generates a three-dimensional image of the object (Eric Brandt, 2017). LiDAR has the capability of detecting the direction where the pedestrian is facing making it easy for an autonomous vehicle to take decision about the movement for pedestrians (Eric, 2017). LiDAR has the capability to work in all light conditions but it's performance gets worse in adverse weather conditions such as rain, fog, snow, and the presence of dust particles in the sir because it uses the light spectrum wavelengths (Barnard, 2016; and Turnbull, 2017). LiDAR that are used for autonomous vehicles are typically mounted on top of the vehicle for clear line of sight and due to this reason, the visibility of the surrounding is obstructed by the vehicle making detection at close range harder (Combs 2019 and Barnard 2016). One of the major drawbacks for LiDAR is its high implementation cost (Turnbull 2017).

Visual Light Cameras (VLC) are widely used in autonomous vehicle systems. Usually, an array of VLCs is applied which work as human eyes to see the environment around the vehicles. The array of images created by this camera assembly are transferred to the vehicles on board unit at real time to analyze the situation around the car. These are usually good for detection roadside signs, speed limits and detecting pedestrians at the side of the road (Charlton, 2018). However, the system does have some limitations: The system works best when the light condition is good. The performance for these cameras tends to deteriorate with the lack of light and glare also with the presence of very bright light in the background object detection gets harder (Barnard, 2016; and Simonite, 2017).

RADAR is one of the most commonly used technologies in the autonomous vehicle technology. This technology uses radio waves for detecting objects and can be used for determining the distance of objects and their speed (Charlton, 2018; and Combs, 2019). The performance of RADAR is not affected by the amount of light however, adverse weather conditions diorites the quality of the image (Charlton, 2018; and Turnbull, 2017). In addition to this RADAR sensors can't provide very detail image such as LiDAR (Simonite, 2017)

Many of the limitations of the sensors who are affected by the weather condition and light can be ignored with the use of thermal cameras. Thermal cameras can create a sharp image of the animals or human beings than the regular cameras because of the contrast of the temperature of the object compared to the surrounding environment (Thermal, 2017). The thermal sensors can easily classify different objects such as car, animals, human beings or roadways based on their thermal signature, which may not be as accurately classified by other sensors (Baldwid, 2018)

Although there has been significant progress in pedestrian detection in monocular images with improved detection technology, algorithms and approaches in recent years, detection in low lighting conditions (Qi et al., 2016) and in low resolution images (Dollar, 2012) is still a problem. Occlusion was observed to be another issue plaguing detection systems. Whereas the heads of pedestrians are rarely occluded the lower extremities of the pedestrian is typically are where occlusion is detected (Dollar, 2012). Research by Dollar et al show a 70 percent detection success rate for bigger pedestrians (80 pixels tall) and an even lower detection rate for smaller pedestrians (Dollar, 2012).

Qi et all (Qi et al., 2016) proposed a new detection approach using thermal imagery rather than images from the visible spectrum due to the challenges faced by computer vision technology in detecting pedestrians because of factors such as occlusion and complex backgrounds. The proposed methods were concluded to be superior approaches to earlier methods especially for pedestrian detection in darker lighting conditions. Also, Navarro et al investigate by LiDAR for pedestrian detection and suggest that LiDAR could potentially be an alternative or could supplement existing pedestrian detection systems (Navarro et al., 2016). More recent breakthroughs in pedestrian detection explore the deep learning approach of Convolutional Neural Network (CNN). Although the CNN approach has shown significant gains in detection accuracy (Shi et al. 2017 and Tome et al. 2016), the computational cost seems to be the primary drawback. This has led to further research on ways to reduce the cost of running complex algorithms without compromising accuracy (Shi et al., 2017).

# CHAPTER 5

# Conclusions and Future Directions

## 5.1 Conclusions

After a thorough analysis of contextual parameters surrounding pedestrian crashes, the research team chose to focus on the study of midblock fatal crashes at nighttime. A 2-year limited-scope detailed qualitative analysis was followed by an expansive 10-year quantitative analysis. In this research it was found that most of the pedestrian crashes are injury-related (80%), some are fatal crashes (14%) and few involve property damage only (6%). Approximately 80% of the pedestrian crashes occur at night although pedestrians are exposed to more vehicles during the daylight hours and the pedestrian volume during the day is also higher compared to the night. This finding reveals the vulnerability of pedestrians at nighttime.

The location of nighttime fatal pedestrian crashes was also studied and on an average 86% of the crashes occurred at midblock locations where walking along the road or crossing are unprotected movements. In most of the crashes, pedestrian infrastructure, such as sidewalks and marked or otherwise controlled crosswalks, does not exist. Moreover, there is a lack of driver expectation of pedestrians at midblock locations.

The researchers drilled down in the midblock fatal pedestrian crashes at night, and categorized them based on the maneuver of the pedestrians with respect to the vehicles involved in the crash. Pedestrian crashes are categorized into the following types: walking along the roadway with respect to the direction of oncoming traffic (Ped-Along/Same, Ped-Along/Opposite), midblock crossing with respect to which side of the drivers' vehicle the pedestrian was approaching from (Ped-Right and Ped-Left), crashes where pedestrians are involved in activities other than walking or crossing (Ped-Standing/Working/other), and some were categorized as unknown because there was not enough information available to categorize them. Researchers found that maneuver categories of Ped-Along/Same and Ped-Left crash types outnumbered the rest.

After identifying the predominant maneuvers, infrastructure characteristics were studied to determine whether patterns may exist for each type of maneuver. Predominant patterns emerged with midblock crashes where pedestrians were walking along the road occurred more frequently at locations where sidewalks are not available and lighting is inadequate. These crashes were also occurring on lower classification facility types (secondary routes), most with two-lanes two-way operations and no medians. In contrast, pedestrian crossing crashes tend to occur on urban multilane roadways with higher route types (US or SC routes), many with bituminous medians (indicative of two-way left-turn lanes).

An analysis of pedestrian crash social media was completed to determine the role of the media in portraying pedestrian crashes. This analysis was used to ascertain if educational information was being provided on the known dangers and precautionary measures. Before creating the word clouds, the news articles and tweets were thoroughly read, and researchers concluded that the messaging focused on reckless driving as the main culprit for the pedestrian deaths in South Carolina State over the last 5 years. The social media was largely devoid of dangers and risks assumed by pedestrians involved in these crashes.

The research team also analyzed the sociodemographic characteristics of the home locations of fatal and injured pedestrians by matching their 9-digit zip code with Census block group information. Census information used in the analysis included: population, gender, race/ethnicity, age, median household (HH) income, educational attainment, poverty level, vehicles available, and vehicle age. Average values were computed for the state as well as the sample of fatally injured pedestrian crashes containing 9-digit zip codes. The differences were significant in many cases. The population density at the home location of the fatally injured pedestrians was much higher with 201 pedestrians per square mile versus 150 for the state average. This indicates that there is an urban trend – higher density development in pedestrian crashes. The median household income is also significantly lower, and there is a propensity toward lower education levels (higher involvement of only a high school education). Overall, there was some variation in age and race/ethnicity, but chi-square tests of the resulting distributions were not independent.

In the next to the final step, the research team developed a test method to gauge the efficacy of camera technologies for detecting pedestrians at night. The goal for this task was to develop an effective method for capturing pedestrian exposure data from sites of interest. The study results indicated that for the dark not lit condition infrared camera outperformed the night vision PTZ camera. There wasn't a single tested scenario where the infrared camera did not produce a discernable human figure. However, the performance of the Night-vision PTZ camera was not satisfactory. The only clothing that could produce a visible image was the bio-motion suit. For the dark, but lit with vehicle headlight condition, both infrared and night vision PTZ performed well. The performance of the night vision camera deteriorated with the increasing distance of the camera from the crossing location. This also magnified the disparities in the headlight patterns with respect to pedestrian illumination in various positions in front of the vehicle. Pedestrians to the right of the driver are illuminated for a much greater distance and further to the side of the center and side of the road, but the illumination area to the left was close to the centerline boundary and closer to the front of the vehicle. Pedestrians to the left at greater distances were often not visible.

Finally, the research team conducted a technology gap analysis to determine the limitations of the detection technologies that are currently being used on autonomous vehicles for detecting pedestrians. A literature review highlighted the pros and cons of these technologies. The review included numerous technologies such as: the visual light cameras, LiDAR, RADAR and thermal cameras. Each technology has its own limitations. However, the studies conducted on these technologies have recommended how the performance of these technologies can be augmented by combining them with machine learning techniques. The contextual information provided in this paper provides much needed guidance for clues to provide in that learning process.

## 5.2 Recommendations for Short-term Infrastructure Changes

One clear finding from the research is that pedestrian infrastructure, especially sidewalks, is lacking and recommendations would suggest investment in pedestrian sidewalks or paths where there are known exposures or where historical crash data exists. Proper street lighting is also recommended where practical and efficient lighting methods may be deployed. To improve conditions related to crossing crashes at night, the availability of street lighting is crucial along with pedestrian refuge islands on wide multi-lane facilities. Training and public service announcements relaying a lack of pedestrian visibility and contextual clues of higher risk sites may also play an important role for both pedestrians and drivers alike.

In this project, the researchers conducted a detailed analysis of the pedestrian crash types presented in chapter 4. The key findings from the analysis are:

- On average 80 percent of fatal crashes happened at night for the year from 2007-2016.
- About 86 percent of the night-time fatal pedestrian crashes occurred at the midblock locations
- Analysis conducted on the night-time fatal mid-block crashes shows that pedestrian who are walking along the road and in the opposite direction of the vehicles are the most vulnerable to be hit by vehicles. The second most vulnerable maneuver is when pedestrians cross the road approaching from the left of the driver.
- While investigating the crashes where the pedestrians were fatally injured walking along road (same or opposite direction), it was found that these crashes often happened on undivided two-lane two-way roads with no sidewalks.
- For crossing crashes, where the pedestrians are crossing the road approaching the driver's side from the left (most common) or right, it was found that these types of crashes happened on multi-lane facilities that lacked refuge spaces for pedestrians to wait for oncoming cars to pass.
- Another key factor for night-time fatal midblock crashes is the lack of illumination at the crash locations.

All pedestrians should be able to use roadway facilities safely and without having to go significant distances out of their way. Therefore, it is the responsibility for the roadway planners, designers and engineers to consider pedestrians as a critical system user and plan, design, and install safe crossing/walking facilities or by providing engineering modifications to the built environment. In general, there are three types of engineering modifications for the built environment to increase pedestrian safety, including: pedestrian separation from vehicles by space and time, vehicle speed reduction, and increasing pedestrian's conspicuity and visibility (Retting et al., 2003).

Traditionally, crosswalks have been used to make crossing areas safer for pedestrians. They are usually used at signalized intersections, but they are sometimes used at uncontrolled mid-block locations. A study by the FHWA's Pedestrian and Bicycle Safety Research Program recommended that pedestrian crossing facilities need to be reinforced with traffic calming treatments, traffic signals and pedestrian signals for high speed multilane roads (Zegeer et al., 2002). The same study suggested that when the AADT is high, raised medians with pedestrian refuge areas should be provided. The study suggested some key features to help pedestrians cross streets safety. They are listed below:

- Education and enforcement programs, as well as new legislation, should be provided in place with engineering treatments for safe pedestrian crossing
- Raised medians (at least 4' wide) can significantly reduce pedestrian crashes at multilane roads - a crash modification factor for installing raised medians at unmarked uncontrolled crosswalk is 0.61 (CMF clearinghouse)
- Bulb-outs should be provided for effectively reducing the crossing widths
- Installation of traffic calming measures can reduce vehicles speeds (Ewing 1999)
- Providing streetlights at the crossing locations provides better illumination and visibility of pedestrians
- Follow MUTCD guidelines when installing traffic signals at the locations where a warrant is made.

Zhang et al. (2017) conducted a study where they identified illegal mid-block crossing locations and installed various median treatments. After analyzing the effectiveness of those countermeasures, the research team found that the median treatments helped to significantly reduce the total number of crashes and fatalities. The study results indicated a CMF of 0.14 for fatal vehicles/bicycle and vehicle/pedestrian types of crashes in urban areas – a 14% reduction in total crashes.

To make the roadways safe for pedestrian walking along the road, sidewalks are predominant engineering measure. According to a study by Knoblauch (1988) pedestrian crashes are as much as twice as likely to happen in residential and mixed-residential areas where there are no sidewalks. The study results revealed that although the residential areas had only 3% pedestrian exposure with no sidewalks; commercial areas that had no sidewalks were found to be slightly more hazardous than commercial areas that had no sidewalks.

While sidewalks provide separation of pedestrians from the vehicles, it is also essential to increase the conspicuity of pedestrians on or near the road during night-time. Polus and Katz (1978) conducted a before and after study on the effectiveness of installing lights at ninety-nine crosswalks and found a significant change in pedestrian crashes at night compared to the daytime crashes. Pegrum (1972) designed a study to find the effectiveness of increasing the intensity of night-time lighting at 57 urban crosswalks. Study results revealed that there was a 59% decrease in night-time pedestrian crashes after installing lights where the daytime crashes remained unchanged.

In conclusion, the most promising countermeasures for reducing pedestrian-vehicle crashes are: providing sidewalks and exclusive signal phasing for pedestrians, increasing the lighting intensity of sidewalks/roadway and installing refuge islands for pedestrians. Other countermeasures include: pavement flashing lights, advance stoplights, raised crosswalks, and automatic pedestrian detection at signals.

## 5.3 Recommendations for Future Research

This research was the predecessor to a follow-on simulator study to address the simulated effectiveness of AV pedestrian detection technologies based on active field of view and pedestrian exposure and behavior. The two most common cases for night-time pedestrian fatalities (walking along the road in same or opposite direction on two-lane roads and crossing the road at midblock on multilane facilities) will be tested. While thermal camera technology has been shown to be effective for pedestrian detection in low to no light, and will be used in lieu of other sources, researchers have recently been made aware of a source of high-level pedestrian cell phone detection for pedestrian flow detection. The research team has identified roadway traffic level, design features, and crossing locations that are prone to crashes. With a thorough understanding of light patterns, vision capabilities of different technologies, and fleet characteristics and operations, the team is set to move forward with the simulation.

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