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Exploring the Use of Drones for Conducting Traffic Mobility and Safety Studies

Abdallah N. Kinero
University of North Florida, n01483946@unf.edu

EXPLORING THE USE OF DRONES FOR CONDUCTING TRAFFIC MOBILITY AND SAFETY STUDIES

By

Abdallah Kinero

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The thesis titled "Exploring the Use of Drones for Conducting Traffic Mobility and Safety Studies" submitted by Abdallah Kinero in partial fulfillment of the requirements for the degree of Masters of Science in Civil Engineering has been:

Approved by the thesis committee: **Date:**

_________________________________ ___________________

Dr. Thobias Sando,

Thesis Advisor and Committee Chairperson

_________________________________ ___________________

Dr. Ramin Shabanpour,

Committee Member

_________________________________ ___________________

Dr. Eren Ozguven,

Committee Member

DEDICATION

This thesis is dedicated to

My Creator, The Almighty God.

And my lovely Parents.

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I wish to thank all the people whose contribution was a milestone in the success of this thesis. I want to thank my supervisor, Dr. Thobias Sando, for his substantial guidance, support, and encouragement during the whole period of undertaking my Master's Degree at the University of North Florida. His help has been very much significant and needed for the completion of this thesis.

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LIST OF ACRONYMS/ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Official
AVI	Automatic Vehicle Identification
CI	Confidence Interval
DR	Deceleration Rate
DSSM	Deceleration-based Surrogate Safety Measure
EB	East-Bound
ELT	East-Bound Left-Turn
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GIS	Geographical Information System
GPS	Global Positioning System
HCS	Highway Capacity Software
ID	Identification
LAANC	Low Altitude Authorization and Notification Capability
LOS	Level of Service
LT	Left-Turn
NB	North-Bound
OD	Origin-Destination

PET	Post Encroachment Time
PHF	Peak Hour Factor
PKWY	Parkway
RD	Road
RPIC	Remote Pilot in Command
RT	Right-Turn
SB	South-Bound
SLT	South-bound Left-turn
SRT	South-bound Right-turn
SSM	Surrogate Safety Measure
T	Through
TTC	Time to Collision
TUAS	Tethered Unmanned Aerial System
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle
WB	West-Bound

ABSTRACT

Advanced traffic data collection methods, including the application of aerial sensors (drones) as traffic data collectors, can provide real-time traffic information more efficiently, effectively, and safely than traditional methods. Traffic trajectory data like vehicles' coordinates and point timestamps are challenging to obtain at intersections using traditional field survey methods. The coordinates and timestamps crucial in calculating trajectories can be obtained using drones and their particular integrated software. Thus, this study explores the use of unmanned aerial systems (UAS), particularly tethered drones, to obtain traffic parameters for traffic mobility and safety studies at an unsignalized intersection in Tallahassee, Florida. Tethered drones provided more flexibility in heights and angles and collected data over a relatively larger space needed for the proposed approach.

Turning movement counts, gap study, speed study, and Level of Service (LOS) analysis for the stated intersection were the traffic studies conducted in this research. The turning movements were counted through ArcGIS Pro. From the drone footages, the gap study followed by the LOS analysis was carried out. A speed algorithm was developed to calculate speed during a speed study. Based on the results, the intersection operates under capacity with LOS B during the time. Also, the results indicated that the through movement traffic tends to slow down as they approach the intersection while south-bound right and east-bound left-turning traffic increase their speeds as they make a turn. Accuracy assessment was done by comparing the drone footages with the results displayed in ArcGIS software. The drone's data collection was 100% accurate in traffic movement counting and 96% accurate in traffic movement classification. The level of accuracy is sufficient compared to other advanced traffic data collection methods.

In this study, safety was assessed by the surrogate safety measures (SSMs). SSMs can be the viable alternatives for locations with insufficient historical data and indicate potential future conflicts between roadway users. The surrogate measures used in this study include the Time to Collision (TTC), Deceleration-based Surrogate Safety Measure (DSSM), and Post-encroachment Time (PET). TTC and DSSM were used for rear-end conflicts, while PET was used to evaluate cross conflicts and other conflicts such as sideswipes.

The number of potential conflicts obtained in a one-hour study period was around 20 per 1000 vehicles traversing the intersection. The number of potential conflicts in one non-peak hour may indicate a safety problem associated with the intersection. This study's findings can help develop appropriate guidelines and recommendations to transportation agencies in evaluating and justifying the feasibility of using tethered drones as safer and cheaper data collection alternatives while significantly improving intersection safety and operations.

Keywords: Tethered Drones, Traffic Studies, Surrogate Safety Measures, Traffic Safety.

CHAPTER 1 INTRODUCTION

Background

Traffic studies are usually conducted to determine the characteristics of the highway system users and their vehicles, identify problematic and risky areas, monitor system operation, and assist in developing the appropriate countermeasures when required (*FDOT*, n.d.). The principal traffic studies usually conducted are volume studies, speed studies, pedestrian studies, parking studies, travel time, and delay studies. All these studies are geared towards improving traffic safety and operations. Researchers have used various approaches based on traffic studies to assess the safety and mobility of road users on roadway elements, including segments and intersections.

Unsignalized intersections are one of the problematic roadway elements. Annually about 9% (3000) of fatal crashes have been known to occur at these locations in the U.S. (NCHRP, 2006). The extent of the safety issue on unsignalized intersections warrants significant mitigation efforts. Researchers have been using different types of data to assess safety within roadway segments and intersections. Some studies used the actual crash/accident data to measure how safe the road facility is. J. Gu et al. (2021) analyzed the number of crash deaths in a particular population to associate road traffic safety law and traffic crash mortality.

Several studies have used the Surrogate Safety Measures (SSMs) in assessing traffic safety. Some researchers believe the lack of accurate and reliable crash data has impeded its functional analysis (Chaudhari et al., 2021). Some incidents are not well-reported and hence not put in proper records. This challenge related to insufficient and unreliably historical data makes the use of SSMs critical in evaluating roadway safety performance. For this purpose, surrogate measures can provide a reliable risk assessment on road users (Lee & Yeo, 2015; Tak et al., 2020; Yang et al., 2003). Hence, this type of traffic conflicts-based analysis using surrogate measures is advocated to be a viable alternative in safety evaluation studies (Autey et al., 2012; Gallelli et al., 2019; Tarko et al., 2009). Notably, the traffic conflict rate is an appealing safety measure since it provides a standardized measure of the relative safety of roadway entities (X. Gu et al., 2019; Guo et al., 2020; Sayed & Zein, 2007).

Although the traffic conflicts-based analysis using SSMs is suitable for detecting safety hazards and operational problems at suspect locations, it should only be used as a supplement to and not a replacement of accident/crash data (Glauz & Migletz, 1980). Due to that fact, some researchers sought to find a relation between the surrogates and the actual crashes. Anarkooli et al. (2021) established a linear, directly proportional relationship between crashes and surrogate safety measures. One of the essences of the developed conflict-based crash model in their study is to understand the crash frequency in situations where police-reported crash data may be inaccurate and cannot provide essential details to the researcher.

Traffic mobility and safety studies have been usually performed using field surveys where human surveyors in terrain collect and record the traffic data on site. Several more technologically advanced systems can be used for this purpose, such as aerial sensors to obtain real-time traffic data. Field surveys of conflicts are costly to conduct and suffer from inter-and intra-observer variability for the repeatability and consistency of results (Chen et al., 2017). On the other hand, unmanned Aerial Systems (UAS) such as drones, which have been known for easy maneuvering, outstanding flexibility, and low costs, are considered novel aerial sensors (Chen et al., 2017). Compared to point sensors such as loop detectors and pneumatic tubes, drones can be utilized as space (point-to-point) sensors, and microscopic traffic data such as trajectories can be extracted through drone-based data collection (Barmpounakis & Geroliminis, 2020; Khan et al., 2017). However, due to the issue of limited battery, today's UAS have approximately 30 minutes of flying time, which is a significant shortcoming to capture the stochasticity on traffic since the congestion and safety problems on the traffic network generally extend in time and space. To solve this problem, tethered drones (TUAS) with continuous power supply through a cable connection between a ground unit and the aircraft can provide solutions while maintaining unlimited flight time where drones can be used as an eye-in-the-sky.

Study Objectives

The study's main objective is to explore the use of tethered drones to obtain traffic parameters for traffic mobility and safety studies. The two specific objectives are designed in this study to implement the main objective. The first objective is to develop Algorithms for SSMs to assess the safety at unsignalized intersections. The second objective is to illustrate the use of ArcGIS for processing drone-collected trajectories in a traffic study. Thus, this study demonstrates the use of the software to extract, export, and analyze trajectory information.

Potential Study Benefits

The findings could provide one of the most efficient and fast ways of conducting traffic mobility and safety studies. The algorithms could compute different trajectories and SSMs in a click. ArcGIS could display trajectories' attributes aesthetically and makes the turning movement count an effortless job. The final goal of this study is to provide feasibility of using tethered drones to collect traffic data and use the obtained trajectory data to perform different traffic studies and analyze safety. Findings are expected to help integrate these new technologies in day-to-day data collection operations for research, planning, and design purposes.

Thesis Formulation

This thesis consists of six chapters. Chapter one briefly introduces the study by explaining its background and delineating its objectives. Chapter two consists of a synthesis of different literature that focused on the SSMs and the different technologies currently used in traffic mobility and safety studies. Chapter three presents the study location and data collection efforts. Chapter four explains how the research was carried out by explaining the methods used in the study. Chapter five shows the SSMs' algorithms and ArcGIS results and discusses them and the challenges faced during the study. The last chapter, chapter six, discusses conclusions and conclusions and recommendations for future work.

CHAPTER 2 LITERATURE REVIEW

Technologies Used in Similar Studies

The growing pattern of traffic and the emergence of different vehicular technologies have prompted the need to apply more advanced ways for conducting traffic mobility and safety studies (Antoniou et al., 2011). Several existing and emerging technologies with different technical characteristics and operating principles are used for data collection. Modern traffic studies utilize data collected from traffic sensors in simulation models and real-time traffic studies.

Researchers and traffic engineers currently apply different traffic simulation-based models describing all modes of transportation on a bigger scale ranging from individual intersections to extensive regional networks (*Transportation Research Board*, 2015). PTV Vissim, CORSIM, PTV Vistro, Synchro, and PTV Visum Softwares work separately or in conjunction in simulating traffic movements in roadway facilities and networks at large.

Besides collecting data for simulation purposes, traffic sensor technologies obtain real-time traffic data and perform real-time traffic studies (Antoniou et al., 2011). Traffic sensors are categorized into three types: point, point-to-point, and area-wide sensors. The categorization of sensors is based on their functionality and how they can collect traffic data.

Point sensors include loop detectors, radar sensors, video image detection systems, and weigh-in-motion systems. The sensors observe/detect the vehicles passing above or under them. Compared to the point-to-point sensors, the point sensors operate on a small scale. Point-to-point sensors detect vehicles at multiple locations as they traverse the network, which helps provide point-to-point travel times, paths, Origin-Destination (OD) flows, route choices fractions, and paths. The technologies included in this category are Automated Vehicle Identification (AVI) systems and License plate recognition technology.

The third type of sensors is area-wide sensors. Smartphones and Global Positioning System (GPS) are typical examples of area-wide sensors. Area-wide sensors include promising technologies that are currently still under research. Therefore, the type of sensors to be used in a particular study depends on the type, the technical, and the economic feasibility of the study.

Prior Research

Several previous traffic mobility and safety studies used drones (UAV) to collect and process traffic data. For the near-future smart generation cities, drones are essential to embrace airspace to advance the transportation system (Outay et al., 2020). On the safety part, Liu et al. (2017) researched on improving Unmanned Aerial Vehicle (UAV) image processing (Image mosaic technology) for road traffic accident scenes. Raj et al. (2017) developed a prototype system to identify the vehicle involved in an accident along with accident scene creation. Sharma et al. (2017) constructed a multi-UAV coordinated vehicular network to analyze the driving behavior and its effect on road safety.

From the traffic monitoring and management perspective, Cheng et al. (2009), Heintz et al. (2007), and Li (2008) developed algorithms to recognize vehicles and their positions in the imagery. Cheng et al. (2009) developed an algorithm that used background elimination and registration techniques to identify vehicles. The algorithm developed by Li (2008) was a fuzzy segmentation algorithm that combines fuzzy c-partition and genetic algorithm in detecting vehicles. Heintz et al. (2007) created an algorithm based on color and thermal images, which construct and maintain qualitative object structures and recognize the traffic behavior of the tracked vehicles in real-time. Viktor et al. (2012) designed a pilot study that estimates OD matrices at intersections using an airborne video. Ke et al. (2015) did a motion-vector clustering for traffic speed detection from UAV video. From the previous studies reviewed, different ideas that have already been proposed were synthesized and finally helped in modeling the best approach to focus on this study.

Surrogate Safety Measures (SSMs)

Before developing algorithms to calculate SSMs, it is important to understand the different SSMs, their applicability, strengths, and weaknesses. Surrogate safety measures (SSMs) assess safety by observing traffic conflicts that may not lead to crashes but pose a high risk of collision (Gettman & Head, 2003). SSMs are usually applied when particular crashes are less frequent or when the crash record in an area is not sufficient (Peng et al., 2017). Some crashes which might be less frequent are poor visibility kinds of crashes like fog-related crashes, smoke-related crashes, and heavy rain-related crashes. Therefore, in these cases, if safety is assessed based only on the historical number of crashes, which might be few if any, it can sound safe while it is not. The conflicts in fog or heavy rain can be relatively high, which makes the situation unsafe. Also, sometimes poor record-keeping in an area is a factor that may cause inadequate safety assessment.

To observe the effectiveness of the SSMs, Tak et al. (2015), and Tak et al. (2020) used an action point model perspective described in spacing-relative speed plane representing the driving behavior with the psychophysical basis and showing how the driver of the subject vehicle adjusts the differences in locations and speeds between the leader and subject (following) vehicle. In the action point model, a driver's decision is made based on particular perception threshold values. When the preceding vehicle's speed is far greater than the subject vehicle, the state of the subject vehicle exceeds the perception threshold of relative speed. Then, the driver of the subject vehicle most likely will accelerate. On the other hand, when the preceding vehicle's speed is much less than the subject vehicle, the state of the subject vehicle exceeds the perception threshold of relative speed in a negative direction. Then, the subject vehicle's speed will have to be decreased. The spacing adjustment procedure is arranged similarly in the action point model. When the spacing is much greater than the desired spacing, the state of the subject vehicle exceeds the perception threshold of spacing. Then, the subject vehicle will be tempted to increase the speed to reduce the spacing.

In contrast, the state of the subject vehicle exceeds the perception threshold of spacing in a negative direction when the spacing is much less than the desired spacing. Then, the subject vehicle's current speed will have to be reduced. Based on the two kinds of perception thresholds and driving behavior, the driver in the subject vehicle decides whether to accelerate or decelerate. Hence, in the action point car-following process, the spacing and relative speed are essential variables that directly affect the acceleration and deceleration action decision.

There are several SSMs used in previous studies, including but not limited to TTC, PET, DR, DSSM. This study will only focus on TTC, DSSM, and PET because they are the most used and widely accepted SSMs. One of the major SSMs that has been proposed in the literature is the Time to Collision (TTC) (Abdel-Aty et al., 2011; Ali et al., 2013; Gallelli et al., 2019; Hou et al., 2013).

TTC estimates the collision risk between two consecutive vehicles by calculating the remaining time before the following vehicle crashes into a leading vehicle, assuming that the path and speed of two consecutive vehicles are maintained. TTC was first introduced in 1971 and since then has been applied as a safety indicator in most traffic safety analyses. Minderhoud & Bovy (2001) and Svensson & Hydén (2006) concluded that the higher the TTC value, the safer the situation is, and vice versa.

Although TTC has been widely used, it has been observed to have some weaknesses. It only classifies states where the subject (following) vehicle is faster than the preceding (leading) vehicle as dangerous situations. In terms of the action point, car-following perspective, the collision risk could also increase or decrease due to change in acceleration and deceleration of the subject vehicle regardless of which vehicle is moving faster than the other among the two conflicting vehicles.

Deceleration-based Surrogate Safety Measure (DSSM) is another SSM that has also been used to assess traffic safety. DSSM represents the collision risk with a ratio of maximum braking performance of the subject vehicle to a required deceleration rate to avoid an accident when the leading vehicle abruptly reduces its speed with maximum braking performance. Some works of the literature suggest that DSSM is more efficient in determining rear-end conflicts than TTC because DSSM shows more well-matched results to the human driving behavior in terms of the action point car-following process (Tak et al., 2015, 2017, 2020).

Both TTC and DSSM are customarily used to assess the rear-end conflicts. For other types of traffic conflicts like cross conflicts, Post Encroachment Time (PET) is used most of the time (Nasernejad et al., 2021; Paul & Ghosh, 2021). PET is another surrogate safety measure used in particular links or nodes in the traffic network. It represents the time difference between a vehicle leaving the encroachment area and a conflicting vehicle entering the same area (Peesapati et al., 2018).

CHAPTER 3 STUDY SITE AND DATA COLLECTION

Study Site

The study was based on an unsignalized intersection between Apalachee Parkway (US 27) and March Road intersection in Tallahassee, Florida. The site was selected as the study site based on the availability of the drone videos and the primarily extracted trajectories by the vendor when the study was conducted. Another constraint that led to the determination of the study site was the air space classification since a Low Altitude Authorization and Notification Capability (LAANC) certification is required for UAS operations nearby airports. Since obtaining this certification is time-consuming, the research team avoided intersections closer to airports to conduct this exercise and focused on the intersection mentioned above.

Figure 3-1 shows the study site where the major roadway (Apalachee Parkway) lies in the east-west direction with a 55-mph posted speed limit, including two through lanes and a left-turn lane in each direction. The east-bound direction also accommodates a right turn lane for the Tallahassee National Cemetery visitors. The U.S. Veteran Affairs administer this cemetery, and its visitors leave the cemetery using the northbound of the study area where left- and right-turn lanes are present. The minor roadway on the other side, March Road, has a 30 mph posted speed limit, and it carries the commuter traffic of the residents living in the area. There was also a new residential development in the region, which will increase the use of this intersection, and may lead to extra conflicts between vehicles. In addition, occasional long queues have been observed in the northbound, especially after significant funeral events in the cemetery facility.

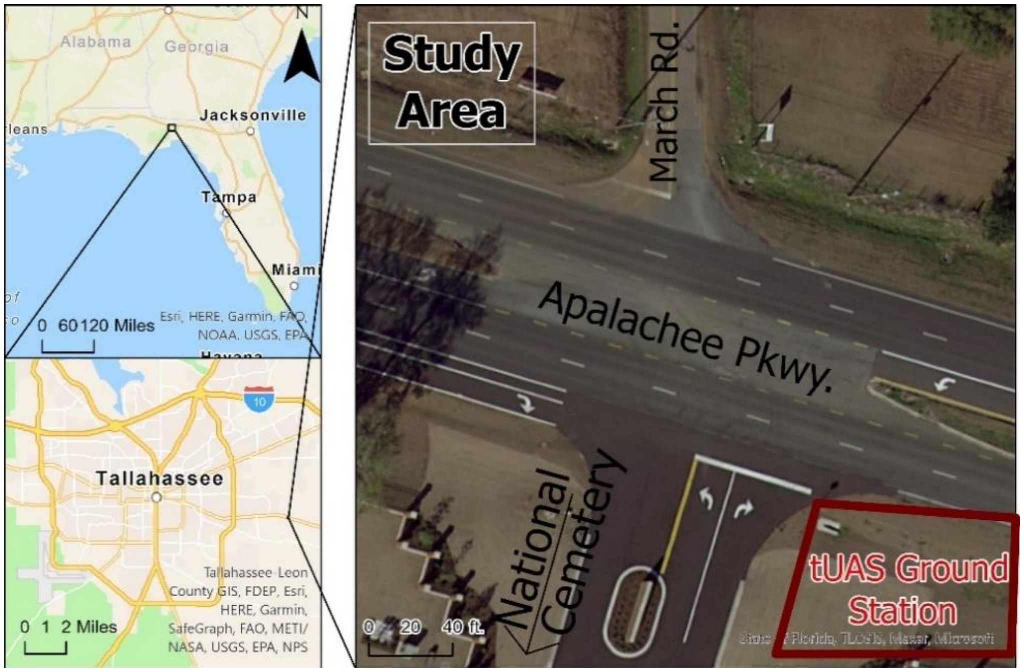

Figure 3-1: Study area and the selected ground station location to operate the tethered drone (TUAS)

Data Collection

The data used in this study is a small sample dataset from a larger experiment where the feasibility of TUAS utilization was evaluated on five different intersections in North Florida for real-time microscopic traffic data collection. Drone-based data collection was performed using a professional UAS service provider, Sinclair Community College National UAS Training and Certification Center from Ohio, identified through a Florida State University procurement process. During this exercise, the vendor complied with all federal and state laws to operate an uncrewed aircraft and provided continuous video of live-stream footage of the intersection and roadway user trajectories to conduct further analyses. Because of the continuous video requirement, a tethered drone was preferred in this experiment, which has a physical cable connection to the aircraft to carry continuous power. The tethered drone could fly for 2 hours and 30 minutes until the batteries from the supply were replaced before it could go up in the air for another 2.5 hours. Each road user's coordinates and timestamps in 33 milliseconds intervals were obtained in CSV and tabular data format.

The contractor also teamed up with Simlat Inc. to conduct the required video image processing tasks. Due to the legal requirements in the State of Florida, the contractor provided four certified drone pilots for a total of 11 workdays between Friday, March 12, 2021, and Tuesday, March 23, 2021. This operation team had two trucks and a trailer, including all the required hardware and software equipment. The equipment list used in this experiment with their brand and model information is presented in Table 3-1. Some items from this list and the drone exercise operation from the current study area are illustrated in Figure 3-2.

Table 3-1: Main equipment used by the contractor and their brands/models

Equipment	Brand / Model
Drone #1	DJI M200
Drone #2	DJI M210/RTK
Camera #1	DJI Zenmuse Z30
Camera #2 (backup)	DJI Zenmuse X4S
Drone Controller Screen	DJI Crystal Sky
Tether	Elistair Light-T
Drone Battery with Tether Connection	Elistair air module for DJI M200/210
Generator for the tether	BS 6500

Due to the tether cable restrictions, the maximum altitude was kept between 100 ft. and 120 ft. for all drone operations. In addition, no operation was conducted when wind speed exceeded 20 Knots (23 mph) due to the 800 W. pull force limitation on the cable. The reason is that high wind swings the cable and creates extra pulling power when it is experienced.

After completing the field experiments and the video/image processing, the vendor provided sample trajectory point data for a 20 minutes (around 09:50 – 10:10 AM) video recorded at the study area on Tuesday, March 16, 2021. This sample dataset included trajectory identification numbers, user types, timestamps, and coordinates for every 33 milliseconds (30 fps) tabular and CSV format. After several days, the vendor provided another sample trajectory point data for two 28 minutes (around 10:10-10:38 AM and 10:38-11:06 AM) videos recorded on the same day. The current study presents a traffic study and safety analysis utilizing the three datasets.

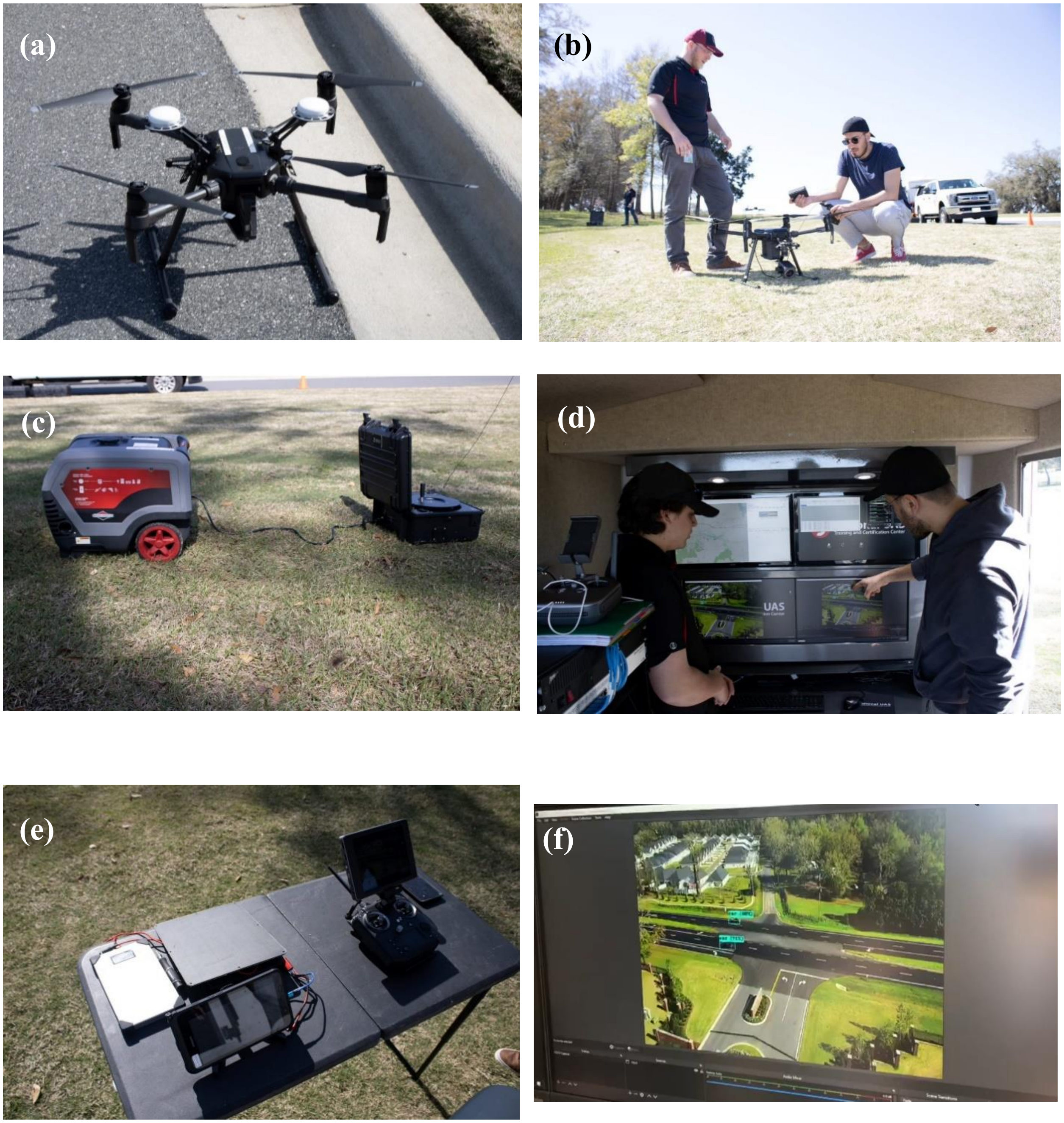

Figure 3-2: Pictures from the data collection exercise a) Drone DJI M210/RTK, b) DJI M200 with Z30 camera attached and batteries, c) Light-T Tether and BS6500 generator, d) Inside the working station, e) Crystal sky screen attached to the master drone controller and tether pulling force observation screen, and f) labeled live feed video

As discussed in chapter 2, different technologies which could have more or less advantages in performing traffic data collection could be used. One of the traffic data collection methods that brings the curiosity of whether it is almost the same as the drone usage is video cameras in traffic data collection. Fixed video cameras could be used for traffic mobility and safety studies. Still, the advantages of using drones outweigh the benefits of using the cameras for the same study. Table 3-2 summarizes the benefits and challenges of using drones in traffic mobility and safety studies over fixed video cameras.

Table 3-2: A summary of pros and cons of using drones compared to fixed video cameras

Advantages	Limitations
Fewer cameras are required. Poles on which cameras are installed are limited in height, and so to cover the same areas as drones that can fly higher, more fixed video cameras are needed.	Availability and affordability problems. Drones are more expensive compared to fixed video cameras.
Infrastructures considerations are eliminated. Most video cameras have to be attached to public infrastructures, such as light poles near the studied road segment.	Some drones have short battery life. Drone batteries generally do not last more than 15 to 20 minutes
Wider coverage due to better video quality and less infrastructure limitations enhance observing queue formation, dissipation, and other traffic metrics that may be observed at a distance from a studied intersection.	Weather dependency. Adverse weather conditions such as strong wind make data collection using drones a challenge.
The eliminated need for nearby poles makes the traffic data collection using drones to cover any road segment or shared space	

CHAPTER 4 METHODOLOGY

Trajectory Clustering

Obtained point datasets of the sample trajectories were preprocessed in ArcGIS Pro v2.8. First, the points were converted into lines through the identification number of each track (vehicle) by the data management tool. Then, these lines were clustered based on their directions to calculate the approach volume.

The stand-alone CSV format table of vehicles' trajectories was input into ArcGIS Pro. The software displayed the X-Y coordinates (longitudes and latitudes/eastings and northings) recorded from the video. Using the imagery-based map, the location points of every vehicle in the vendor's video time inside the intersection were shown. The environment in the software was put in the appropriate coordinate system so that the map's coordinate system would match the points' system well.

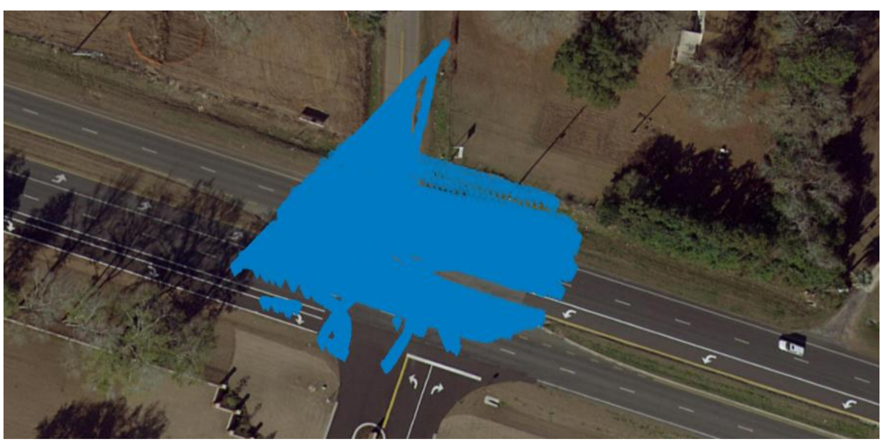

Figure 4-1: X-Y coordinates displayed as points

The points were auto joined to form the trajectory line for each vehicle's path to simplify the movement count and conflict analysis. The lines were clustered according to their approach by selecting them from the trajectory lines shapefile in ArcGIS pro and exporting them.

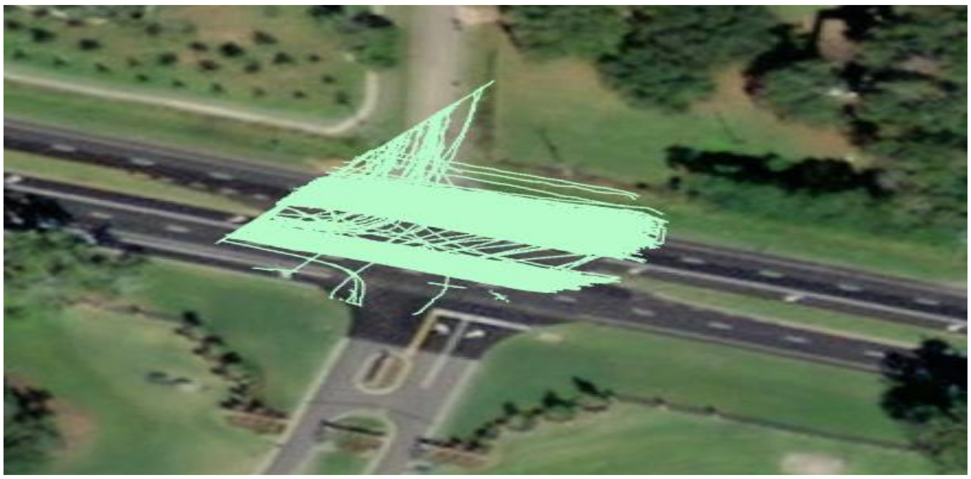

Figure 4-2: Points auto-joined to form trajectory lines

Figure 4-3: Trajectory lines categorized by their turning movements

Gap Study

A gap study was conducted to check on the studied intersection's Level of Service (LOS). From the ArcGIS pro's processed trajectory data points, significant turning movements were identified from their approaches, and the gap study was conducted on those significant movements. In the study period of 1 hour, the significant turning movements were the left-turning movements from the east-bound of the Apalachee Pkwy and the right turners from the south-bound of the March Rd.

From ArcGIS pro, timestamps for the beginning of the required trajectory lines were obtained. Using the timestamps, the time the vehicle represented by the trajectory line appeared in the drone footage was derived. The accepted and rejected gaps by the studied vehicle were observed in the footage.

Critical gap and the follow-up headway were the important two parameters for this part of the study's purpose. The critical gap is the minimum time interval in the major street traffic that allows intersection entry for one minor street vehicle. This study determined the critical gap graphically by Raff's method (Troutbeck, 2016).

The critical gap is when the percentage of traffic accepting the gap equals the percentage of the traffic rejecting the gap. The follow-up headway was determined as the time difference between the two turning vehicles while making a turn at the intersection during an accepted gap. The obtained results were integrated with the count results from clustered trajectories and input in HCS 7 software to calculate the LOS of the intersection.

Speed Study

From the same significant turning movements in the gap study, a speed study was performed to observe the pattern of the turning and through speed while traversing the intersection. The speed algorithm was formulated to track all vehicles' speeds in each second they are within the intersection. The speeds were then classified in colors in ArcGIS pro to present the speed pattern aesthetically.

The initially obtained sample data had only a few helpful pieces of information that enable the calculation of the trajectories like speeds, accelerations, and decelerations which are the most useful in solving the surrogate safety measures of the traffic in the intersection. Speed and acceleration algorithms were developed for speed and safety study purposes. Table 4-1 uses a sample vehicle (vehicle ID 0) to represent the information that was initially obtained from the vendor.

Table 4-1: Originally obtained data set for vehicle ID 0

Track ID.	Timestamp	Class	Longitude	Latitude	Northing	Easting
0	100	car	-84.18856166	30.42752982	158280.0225	629918.6142
0	133.3333333	car	-84.18854885	30.42752722	158279.7377	629919.8454
0	166.6666667	car	-84.18853275	30.42752447	158279.437	629921.3934
0	200	car	-84.18852045	30.42752163	158279.1254	629922.5757
0	233.3333333	car	-84.18851096	30.42751943	158278.8844	629923.4885
0	266.6666667	car	-84.1885081	30.42751743	158278.6633	629923.763
0	300	car	-84.18850055	30.42751563	158278.4661	629924.4895

Speed Calculation

To obtain speed, some algorithms had to be developed first to find the distance and the time difference between any two-vehicle data points. Vehicle Data points were extracted every 1 second.

Algorithm 1

Time difference(t) Calculation(ms)

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$x_1(t)$ and $x_2(t)$= location of V_1 and V_2, respectively at time t

T_1, T_2 = Timestamps recorded for V_1 and V_2, respectively

If $V_1 = V_2$

RETURN

$t = T_2 - T_1$

OTHERWISE

RETURN

"NULL"

Algorithm 2

Distance(d) Calculation(ft)

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$x_1(t)$ and $x_2(t)$= location of V_1 and V_2, respectively at time t

$E_1(t)$ and $E_2(t)$ = Eastings of V_1 and V_2, respectively at time t

$N_1(t)$ and $N_2(t)$ = Northings of V_1 and V_2, respectively at time t

T_1, T_2 = Timestamps recorded for V_1 and V_2, respectively

If $V_1 = V_2$

RETURN

$$d = \sqrt{(E_2 - E_1)^2 + (N_2 - N_1)^2} \qquad \text{(Eq.1)}$$

OTHERWISE

RETURN

"NULL"

Algorithm 3

Speed(v) Calculation(mph)

From the distance and time difference calculations shown in the last two pages, the speed algorithm was developed and summarized in Figure 4-4.

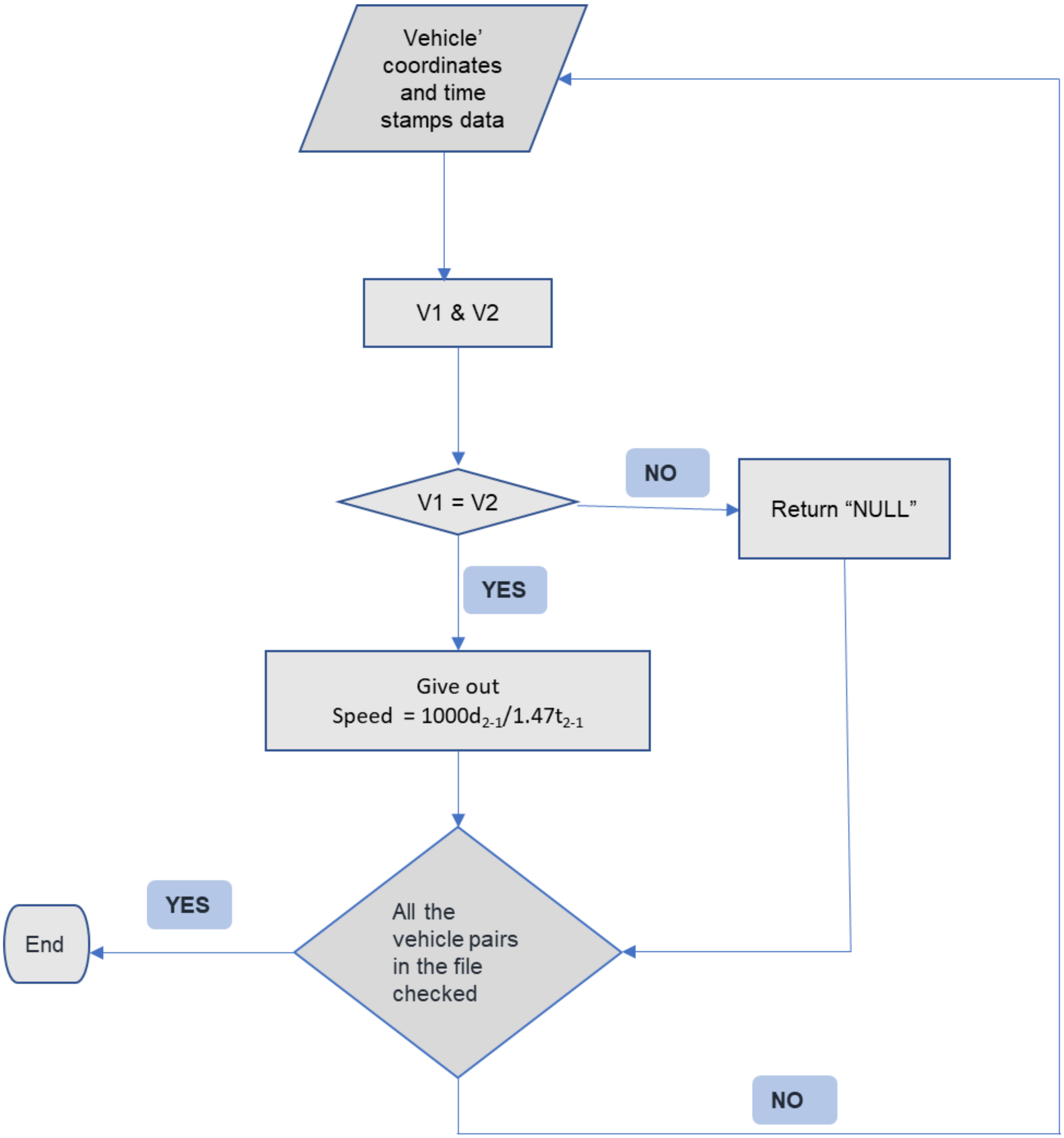

Figure 4-4:Flow chart summarizing speed algorithm

Acceleration Calculation

Acceleration and deceleration are usually crucial in obtaining the deceleration-based Surrogate Safety Measure (DSSM). Drivers usually respond by accelerating or decelerating to the gap and relative speed between them and the leading vehicles in front of them (Tak et al., 2015). The acceleration and deceleration between two conflicting vehicles might increase or decrease their risks of collision.

Algorithm 4

Acceleration(a) Calculation(mph/s)

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$x_1(t)$ and $x_2(t)$= location of V_1 and V_2, respectively at time t

v_1 and v_2 = speed of V_1 and V_2, respectively at time t

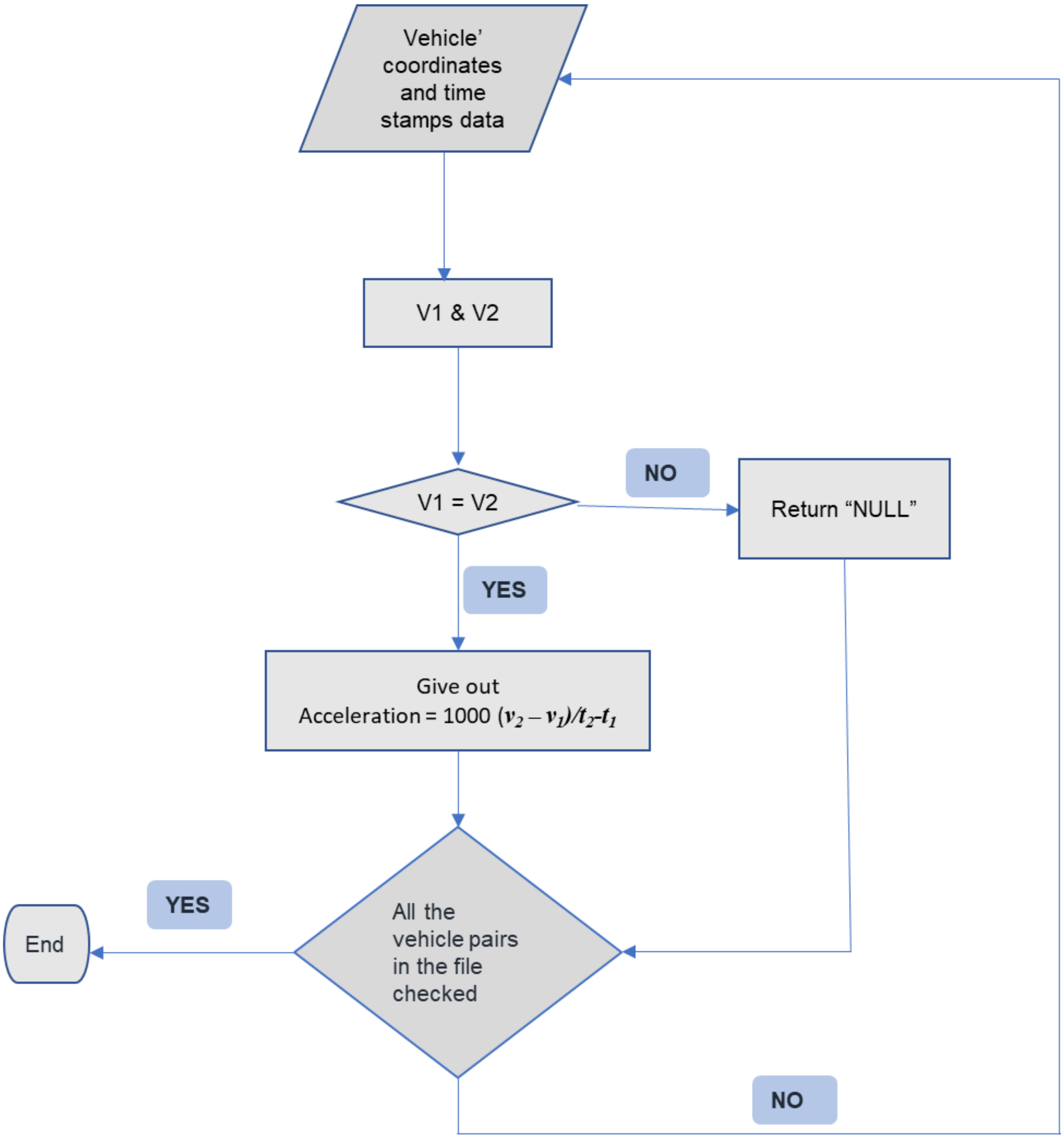

Figure 4-5: Flow chart summarizing the algorithm for acceleration calculation

As seen in the above algorithm sequences, distance and speed needs at least two data points to be calculated while acceleration needs at least three data points to be calculated. Therefore, a moving vehicle's distance and speed can be calculated using the coordinates and timestamps of two points in its path. Acceleration calculation requires coordinates and timestamps of 3 points in the path of the vehicle.

Surrogate Safety Measures

Three surrogate measures were used for the analysis: the Time to Collision (TTC), the Deceleration-based Surrogate Safety Measure (DSSM), and the Post-encroachment Time (PET). The three surrogates were chosen because of their simplicity in analysis and how they simulate the safety issue while providing relevant conflict information similar to and sometimes better than other surrogate safety measures. A level of potential risk, which could be involved between vehicles, was obtained by calculating the TTC, DSSM, and PET parameters using clustered trajectories. The purpose of the three parameters was to obtain a bigger picture of the traffic flow and conflicts at the intersection. TTC and DSSM were used for rear-end conflicts, while PET was used for cross- and side swap-type of conflicts.

Time to Collision (TTC)

As described in Chapter 2, TTC estimates the collision risk between two consecutive vehicles by calculating the remaining time before the following (subject) vehicle crashes into a front (leading) vehicle, assuming that the path and speed of two consecutive vehicles are maintained. Algorithm 1 is developed for this purpose.

Algorithm 5

TTC Calculation

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$x_1(t)$ and $x_2(t)$= location of V_1 and V_2, respectively at time t

$v_1(t)$ and $v_2(t)$= speed of V_1 and V_2, respectively at time t (ft/s)

T_1, T_2 = Timestamps recorded for V_1 and V_2, respectively (ms)

Li = Length of a Vehicle (20 ft. for this study)

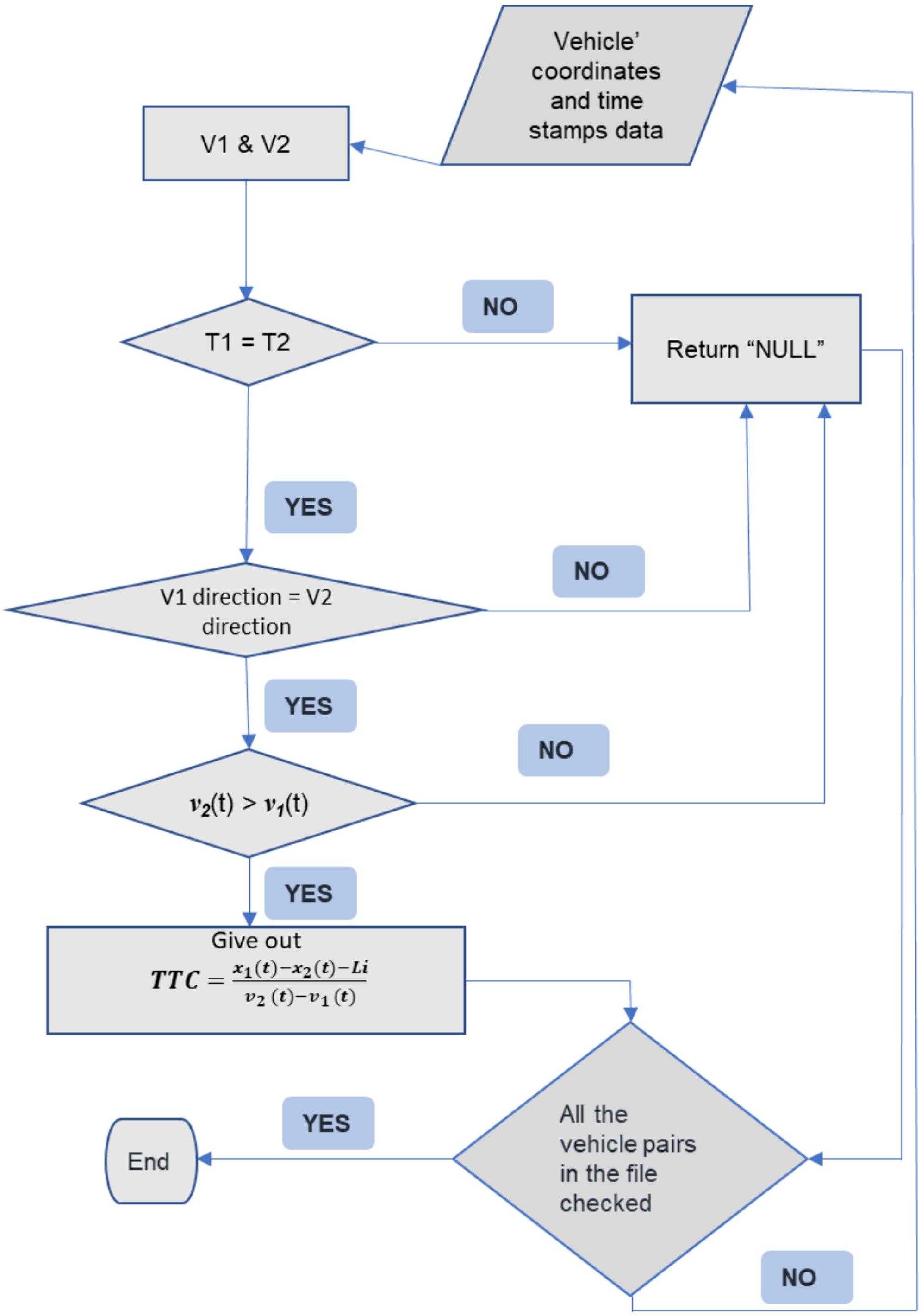

Figure 4-6: Algorithm for TTC calculation

Post-Encroachment Time (PET)

As described in Chapter 2, PET represents the time difference between a vehicle leaving the encroachment area and a conflicting vehicle entering the same area.

Algorithm 6

PET Calculation

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$p_1(t)$ and $p_2(t)$= Coordinates of V_1 and V_2, respectively at time t

$v_1(t)$ and $v_2(t)$= speed of V_1 and V_2, respectively at time t (ft/s)

T_1, T_2 = Timestamps recorded for V_1 and V_2, respectively (ms)

P(c) = Point of conflict

d1 = distance from $p_1(t)$ coordinates to P(c) coordinates (ft)

d2 = distance from $p_2(t)$ coordinates to P(c) coordinates (ft)

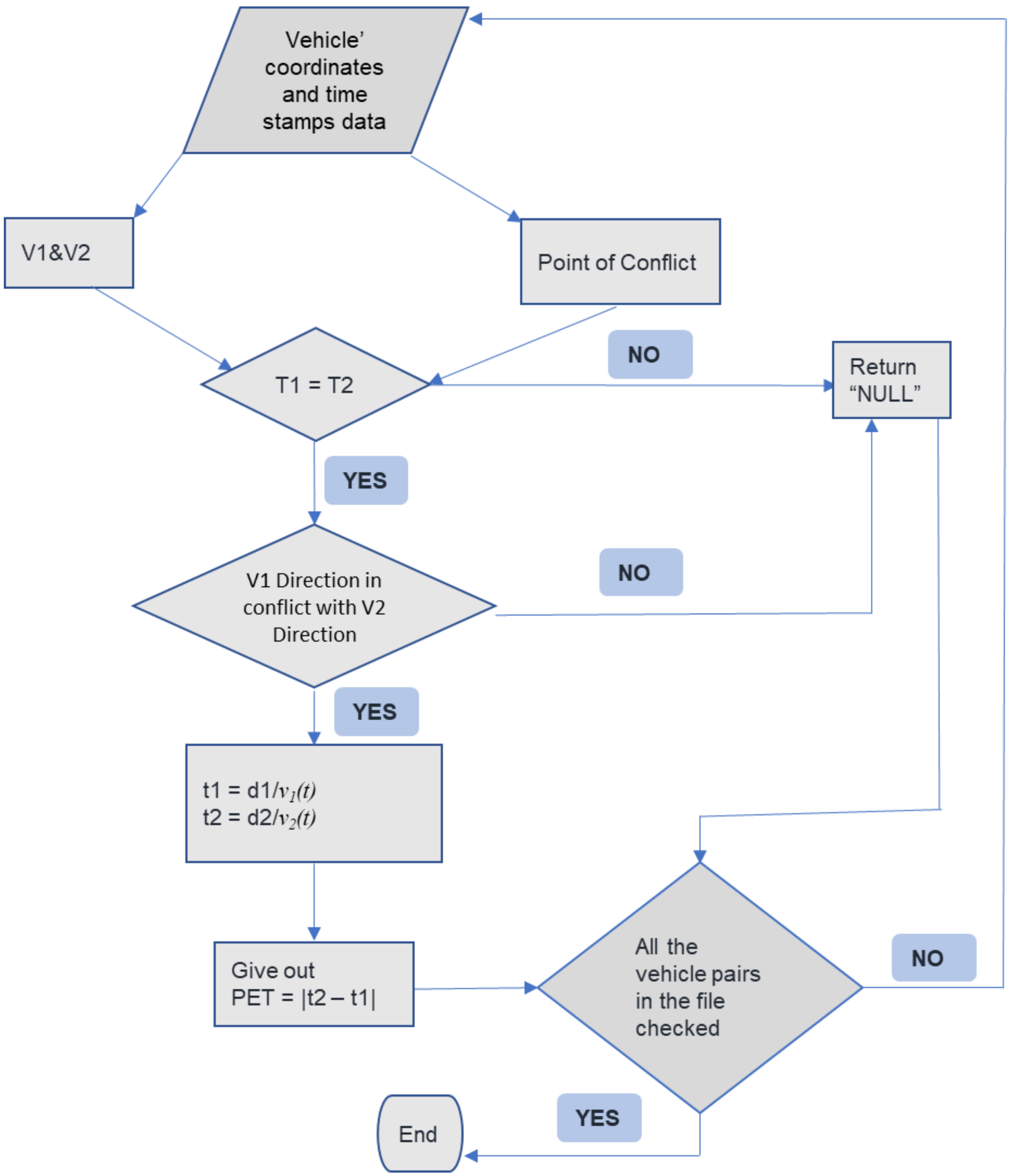

Figure 4-7: Algorithm for PET calculation

Deceleration-Based Surrogate Safety Measure (DSSM)

As described in Chapter 2, The DSSM represents the collision risk with a ratio of maximum braking performance of the subject vehicle to a required deceleration rate to avoid an accident when the leading vehicle abruptly reduces its speed with maximum braking performance.

Algorithm 7

DSSM Calculation

Let V_1 and V_2 be two independent trajectories of the leading and the following vehicles, respectively

$x_1(t)$ and $x_2(t)$= location of V_1 and V_2, respectively at time t

$v_1(t)$ and $v_2(t)$= speed of V_1 and V_2, respectively at time t (ft/s)

T_1, T_2 = Timestamps recorded for V_1 and V_2, respectively (ms)

Prt = Perception-reaction time (2.5s)

Li = Length of a Vehicle (20 ft. for this study)

$a_1(t)$ and $a_2(t)$ = Acceleration V_1 and V_2 , respectively at time t (ft/s^2)

$b_{max}(1)$ and $b_{max}(2)$= Maximum braking rate for V_1 and V_2, respectively (ft/s^2)

l_1 and l_2 = maximum variation of acceleration V_1 and V_2, respectively (ft/s^2)

$b_n(t)$ = needed deceleration rate of the following vehicle to avoid an accident at time t (ft/s^2)

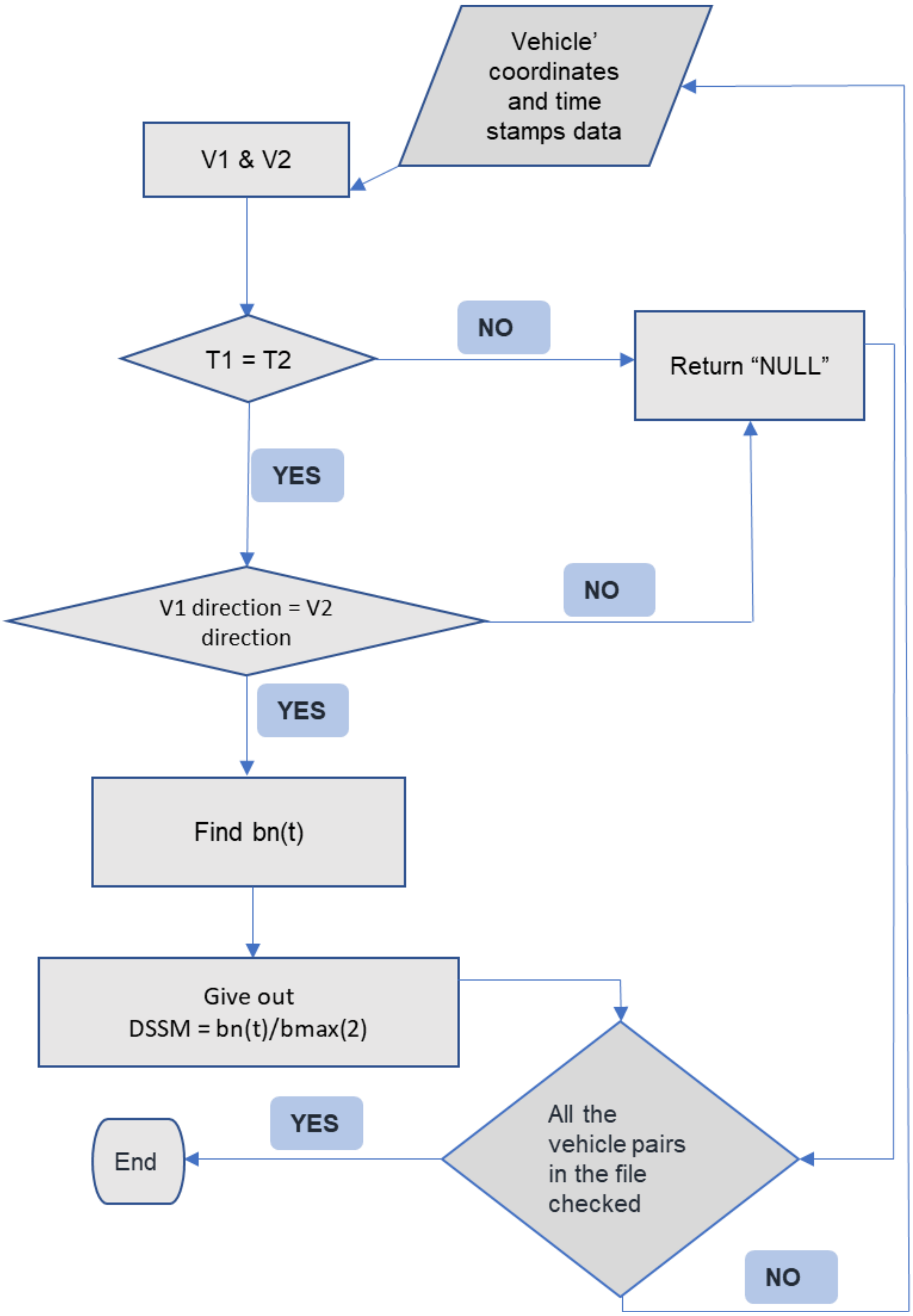

Figure 4-8: Algorithm for DSSM calculation

Formulae

$$b_n(t) = b_{max}(1) * \frac{(V_2(t)+a_2(t)*prt)^2}{2K*b_{max}(1)+V_1(t)^2} \quad \text{(Eq.2)}$$

$$K = (x_1(t) - x_2(t) + Li) + (2v_2(t) + a_2(t) * prt) * \frac{prt}{2} - \left(\frac{v_1(t)}{2} + \frac{a_1(t)+ b_{max}(1)}{4} * \frac{a_1(t)- b_{max}(1)}{l_1}\right) * \frac{a_1(t)- b_{max}(1)}{l_1} + \left(\frac{v_2(t)}{2} + \frac{a_2(t)}{prt} + \frac{a_2(t)+ b_{max}(2)}{4} * \frac{a_2(t)- b_{max}(2)}{l_2}\right) * \frac{a_2(t)- b_{max}(2)}{l_2}$$

(Eq.3)

The same timestamp was used in the algorithms because it had a 100% confidence interval (CI) that both conflicting vehicles were inside the intersection at the time. Suppose a pair of vehicles did not have even a single point with the same timestamp. In that case, this indicates there was no corresponding time during the analysis during which the whole pair was inside the intersection. For the 33 milliseconds interval of timestamps, this hypothesis was credible enough.

Categorization of the Conflicts

Based on an American Association of State Highway and Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA) *(AASHTO, 2010; FHWA, n.d.*) mostly used thresholds, the TTC risk threshold was selected as ≤ 1.5 seconds while the PET risk threshold was used as ≤ 5 seconds. For DSSM (Tak et al., 2015) proposed a risk threshold of ≥ 0.75. However, note that this does not necessarily indicate that any value apart from these thresholds is entirely safe, and more research is needed in this area for different situations. In this study, the thresholds were categorized into levels of risks. Table 4-2 shows the thresholds as the time intervals for the conflicts and associated levels of risks.

Table 4-2: TTC, DSSM, and PET thresholds

Conflict Type	Thresholds	Associated Level of Risk
TTC	(0-0.5]	High Risk
	(0.5-1]	Medium Risk
	(1-1.5]	Low Risk
PET	(0-1]	High Risk
	(1-3]	Medium Risk
	(3-5]	Low Risk
DSSM	(>1.1)	High Risk
	(0.9-1.1]	Medium Risk
	(0.75-0.9]	Low Risk

CHAPTER 5 RESULTS AND DISCUSSION

Trajectory Clustering

In total, 110,418 data points were extracted from the dataset, referring to 1316 trajectories with 30 frames per second (fps) resolution. Figure 5-1(a) displays the trajectory data points for the first 20 minutes of drone footage. This original format with the trajectory points was first preprocessed by converting points to the trajectory lines by point to line data management tool in ArcGIS Pro. With this method, misidentified and discontinuous trajectories were identified and removed. For example, the intersection's southwest corner points were presumably included in the dataset due to misidentification. Since their converted lines do not represent any possible movements in the intersection, they were removed. After the cleanup, a total of 1263 trajectory lines was clustered into each approach of the intersection. Hence, the approach volumes were extracted as seen in Figure 5-1(b) (sample 20 minutes trajectory data points). The results indicate that the major roadway carried approximately 90% of the traffic equally in each direction within the study period. Also, vehicles' positions were obtained every 33 milliseconds.

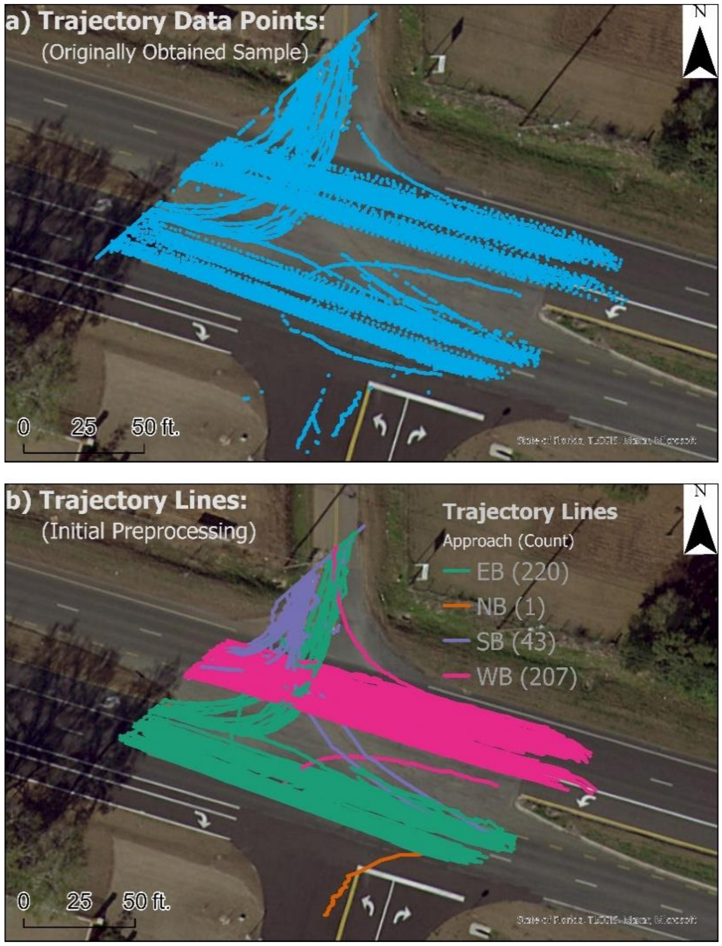

Figure 5-1: Sample trajectory data. a) originally obtained data points. b) preprocessed and clustered trajectory lines for the first 20 minutes

In addition to the approach volume, the number of roadway user classes per approach is illustrated in Figure 5-2. The results indicate a high truck volume on the east-bound at this specific period, indicating that they are leaving the city (i.e., the east-bound direction is towards outside of the city). This pattern can be attributed to the fact that most of the cargo trucks deliver their package to the local career office early in the morning and then return to their central station approximately in the morning time when the data were collected.

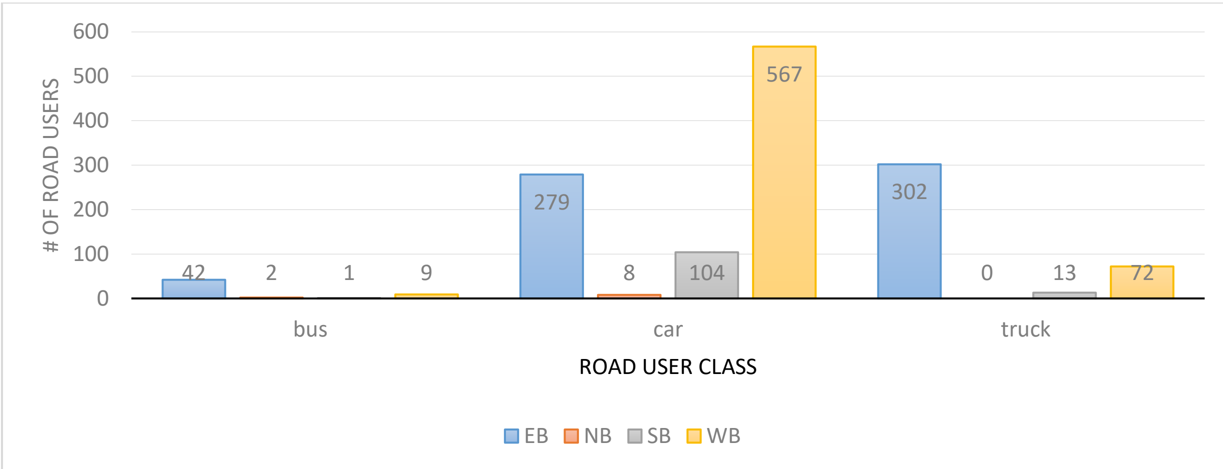

Figure 5-2: Number of classified vehicles per approach in a study period

The 1-hour study period, turning movement count shows that the most significant proportion of the traffic is the through movements in the Apalachee Pkwy followed by the right-turning movements in the south-bound of the March Rd and the left turners in the east-bound of the Apalachee Pkwy.

Table 5-1: Turning movement count for Apalachee Pkwy, March Rd intersection.

Traj.time(mins)	East to North (LT)	East Through (T)	East to South (RT)	West to South (LT)	West Through (T)	West to North (RT)	South to West (RT)	South to East (LT)	North to east (RT)	North to West (LT)
20	19	179	0	1	192	1	41	2	1	0
28	18	245	2	1	278	1	21	2	0	1
12	9	112	3	0	114	0	15	3	2	0
	46	536	5	2	584	2	77	7	3	1

Note: Traj = Trajectory

mins = minutes

Figure 5-3: Vehicle's trajectory lines categorized by their turning movements for the first and second drone footages

Accuracy Assessment

A random sample of 100 trajectory lines was selected, and an accuracy analysis was performed by observing the counting errors and the movement classification errors in the method. The test data was the trajectory lines developed in ArcGIS pro, while the ground truth data to assess the accuracy was the video data.

Statistically the number of sample required to simulate the population while performing the accuracy assessment is expected to be low, due to the level of accuracy drones are expected to give. It is important to find the logical sample to use in assessing accuracy of the method. The following explains how the logical sample size was obtained:

Let p = Proportion of traffic movements correctly classified

q = Proportion of traffic movements wrongly classified

z = Z statistic

α = Significance level

MOE = Margin of error

n = Required sample size

Assuming that the drones used in the study could be at least 95% accurate, let p = 0.95, which makes q = 0.05,

Assuming the MOE of 0.05 to be precise,

$$n = \frac{{z_{\alpha/2}}^2 * p * q}{MOE^2} \qquad \text{(Eq.4)}$$

At a 95% confidence interval, $z_{\alpha/2} = 1.96$, n = 73

Therefore 73 trajectory lines could be used to check the accuracy. But since the accuracy of the drone is not yet known, it is more practicable to use the larger sample size for this study. That is why this study used 100 randomly selected trajectory lines as the study sample.

All 100 trajectory lines represented the drone footages' movements in the sample, making the counting accuracy 100%. In the sample, 96 out of 100 trajectory lines matched the movements' directions observed in the drone videos. The remaining four trajectory lines made no sensible movement. They also did not match with what was happening in the drone footages. The four movements physically happened at the intersection, but the trajectory lines could not define them.

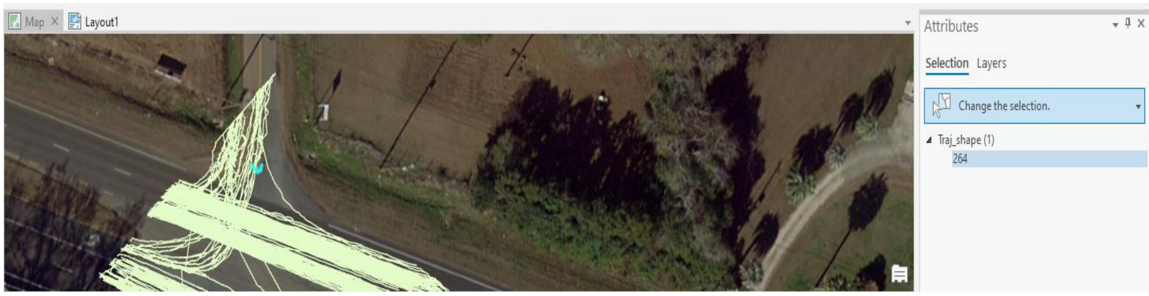

Figure 5-4: Vehicle 264 movement being undefined

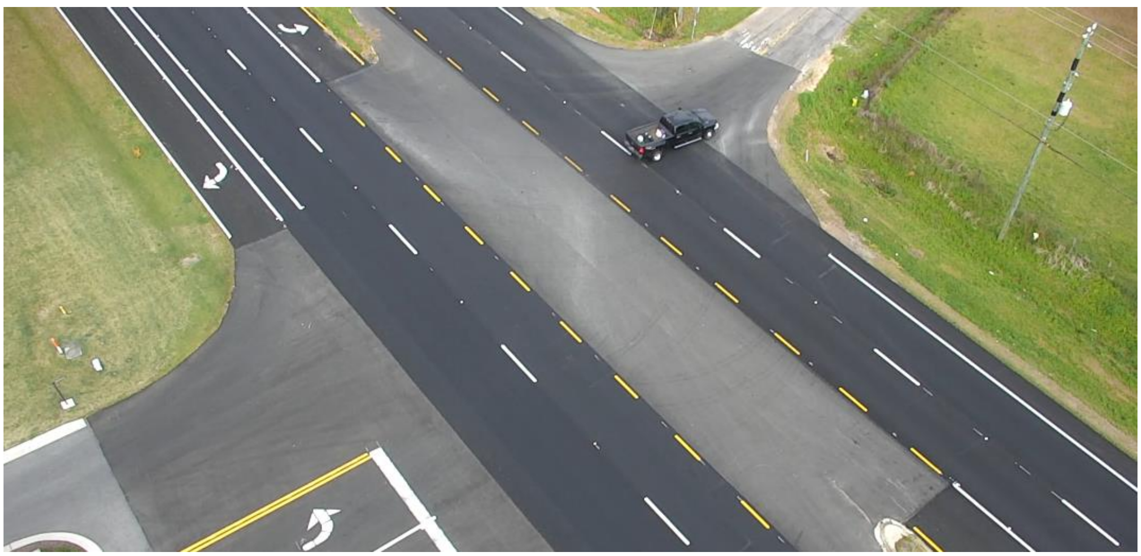

Figure 5-5: Vehicle 264 being LT movement in the drone footage

$$\text{Counting accuracy} = \frac{\text{positively detected movements in the sample}}{\text{total number of sample trajectory lines}} \quad \text{(Eq.4)}$$

Counting accuracy = 100/100 = **100%**

$$\text{Classification accuracy} = \frac{\text{Correctly classified trajectory lines in the sample}}{\text{total number of sample trajectory lines}} \quad \text{(Eq.5)}$$

Movement Classification Accuracy = 96/100 = **96%**

Gap Study and LOS Analysis

From the gap study, the critical gap obtained was 5.6 seconds for south-bound right-turning movements, 5.7 seconds for the east-bound left-turning movements. The seven vehicles in the south-bound left-turning movements indicated a 9 seconds critical gap. The study's level of confidence for south-bound right-turning movements and east-bound left-turning movements is significantly higher than the south-bound left-turning movements simply because of the small sample used (7 vehicles in 1 hour study period). The average follow-up headway in all the left and right-turning movements of 4 seconds was obtained.

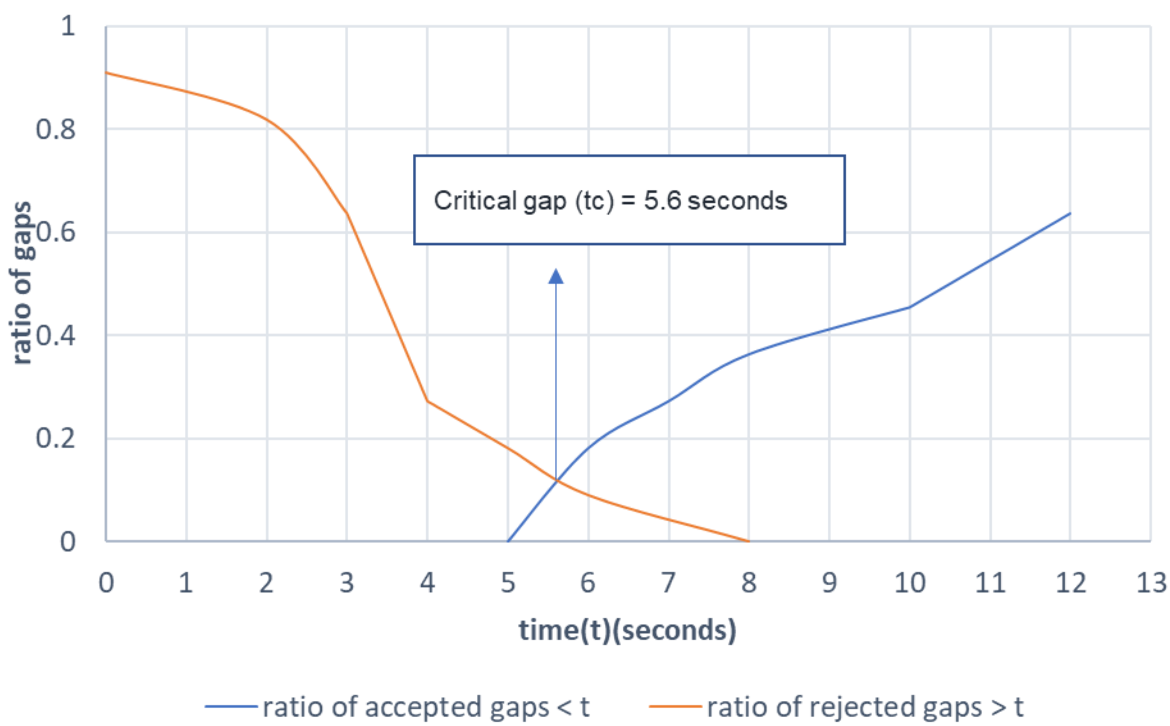

Figure 5-6: Critical gap analysis for the south-bound right-turning movements

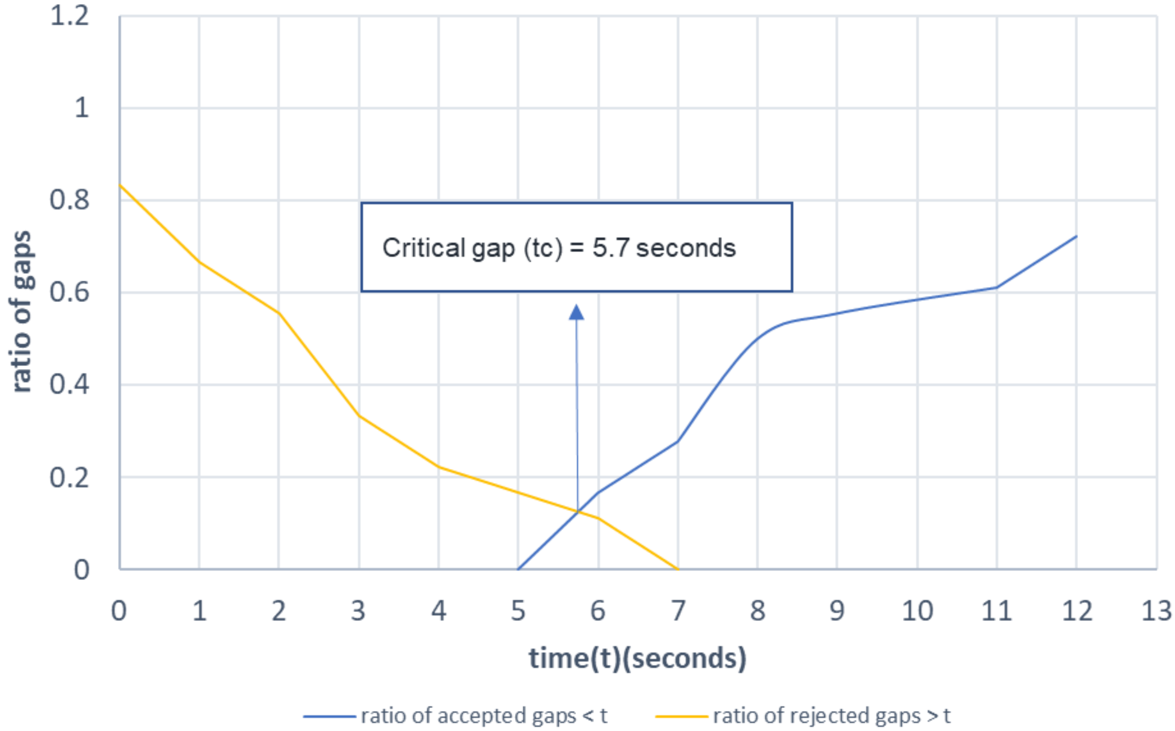

Figure 5-7: Critical gap analysis for the east-bound left-turning movements

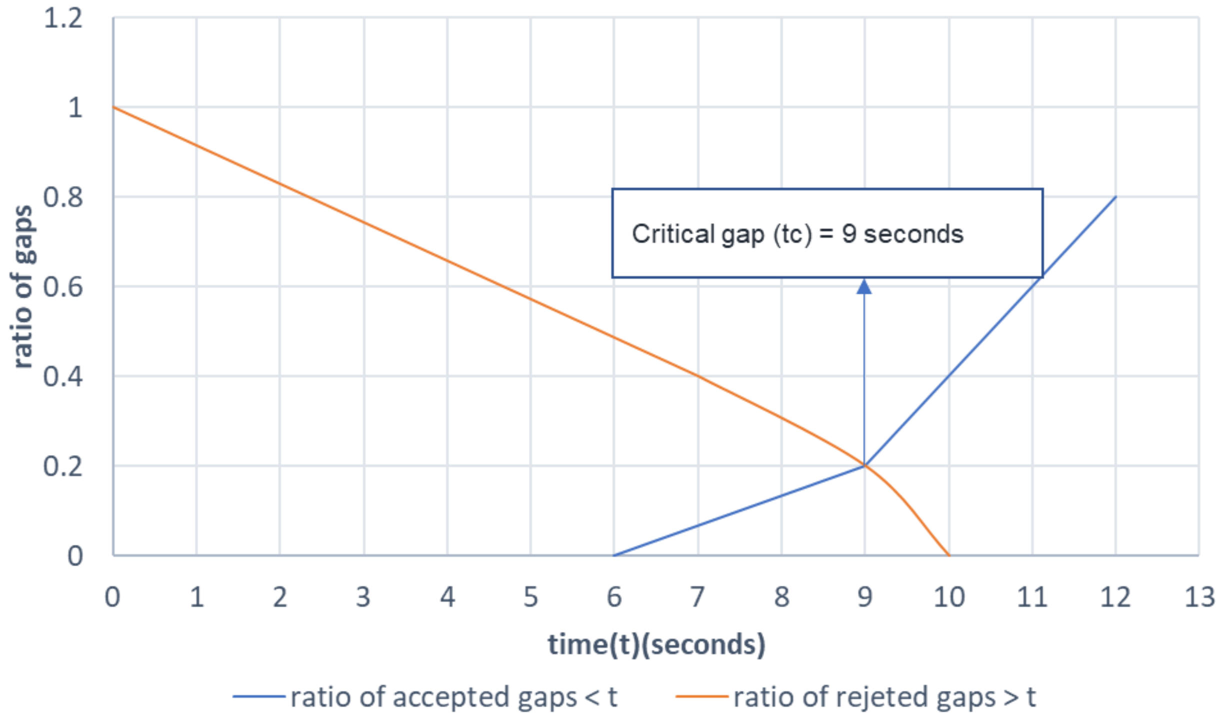

Figure 5-8: Critical gap analysis for the south-bound left-turning movements

To obtain a peak hour factor (PHF), the movement count was done for four 15 minutes data sets.

Table 5-2: Four 15 minutes movement count in the 1 hour study period

Traj. Time (mins)	East to North (LT)	East Through (T)	East to South (RT)	West to South (LT)	West Through (T)	West to North (RT)	South to West (RT)	South to East (LT)	North to East (RT)	North to West (LT)
15	13	137	0	1	133	1	19	2	1	0
15	16	142	1	1	152	0	24	2	0	0
15	8	126	1	0	154	1	16	0	0	1
15	9	131	3	0	145	0	18	3	2	0

PHF = 1-hour traffic Movement count / 4* highest 15 minutes traffic movement count (Eq.6)

$$PHF = \frac{1263}{338*4} = 0.934$$

HCS7 Two-Way Stop-Control Report

General Information		Site Information	
Analyst		Intersection	
Agency/Co.		Jurisdiction	
Date Performed	9/29/2021	East/West Street	
Analysis Year	2021	North/South Street	
Time Analyzed		Peak Hour Factor	0.93
Intersection Orientation	East-West	Analysis Time Period (hrs)	1.00
Project Description			

Lanes

Vehicle Volumes and Adjustments

Approach	Eastbound				Westbound				Northbound				Southbound			
Movement	U	L	T	R	U	L	T	R	U	L	T	R	U	L	T	R
Priority	1U	1	2	3	4U	4	5	6		7	8	9		10	11	12
Number of Lanes	0	1	2	1	0	1	2	0		1	0	1		0	1	0
Configuration		L	T	R		L	T	TR		L		R			LTR	
Volume (veh/h)	0	46	536	5	0	2	584	2		1		3		7	0	77
Percent Heavy Vehicles (%)	3	3			3	3				3		3		3	3	3
Proportion Time Blocked																
Percent Grade (%)									0				0			
Right Turn Channelized	No								No							
Median Type | Storage	Left Only								3							

Critical and Follow-up Headways

	U	L	T	R	U	L	T	R	U	L	T	R	U	L	T	R
Base Critical Headway (sec)		5.7				5.7				7.5		5.6		7.5	6.5	5.6
Critical Headway (sec)		5.70				5.70				9.00		5.66		9.00	6.56	5.66

Base Follow-Up Headway (sec)		4.0				4.0				4.0		4.0		4.0	4.0	4.0
Follow-Up Headway (sec)		4.00				4.00				4.03		4.03		4.00	4.03	4.03
Delay, Queue Length, and Level of Service																
Flow Rate, v (veh/h)		49				2				1		3			90	
Capacity, c (veh/h)		461				486				201		664			567	
v/c Ratio		0.11				0.00				0.01		0.00			0.16	
95% Queue Length, Q_{95} (veh)		0.4				0.0				0.0		0.0			0.6	
Control Delay (s/veh)		13.7				12.4				23.0		10.4			12.5	
Level of Service (LOS)		B				B				C		B			B	
Approach Delay (s/veh)	1.1				0.0				13.6				12.5			
Approach LOS									B				B			

Table 5-3: HCS 7 LOS analysis for the 1 hour study period

The minor approaches operate under LOS B in each direction, meaning the intersection capacity is still sufficient for the incoming traffic at the time. In the table, HCS default values were used in some parameters due to the data limitations encountered in the study. For future studies, a comprehensive data collection will assist in getting all the input parameters for HCS.

Speed Pattern

The speed algorithm showed that the 85^{th} percentile of the through movements moves around 51 miles per hour (mph) for west-bound movements and 53 mph for east-bound. The speed limit in the main approach is 55 mph. The speed reduction is because drivers tend to reduce their speed when approaching an intersection for safety reasons. East-bound traffic reduces traffic speed less than the west-bound traffic because the significant left-turning movement is from east-bound to the March Rd, making the west-bound through traffic more careful while approaching the intersection. There are only a few left-turning movements from the west-bound to the cemetery or the U-turns.

The 85^{th} percentile speed for the east-bound left-turning movements (E-LT) is around 18 mph and 13 mph for the south-bound right turners (S-RT). Vehicles increase their speed as they perform south-bound right-turning and east-bound left-turning turning movements. Speeds were obtained from 7 locations in the intersection to show the turning traffic speed pattern within the intersection. According to (Drivingtips.org, 2010), the ideal speed of performing a right run is 10-15 mph, while for a left turn is usually 15-20 mph. Therefore the turning speeds obtained are within the ideal range.

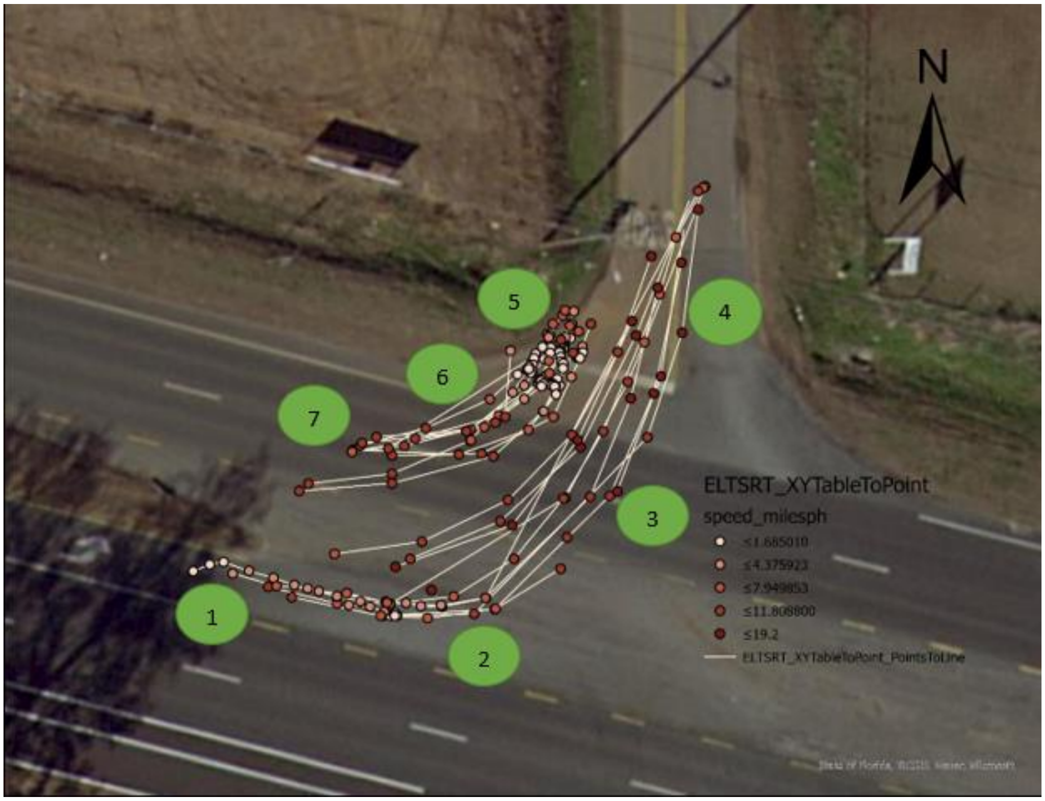

Figure 5-9: Speed data points showing the speed pattern in the intersection for S-RT and E-LT movements

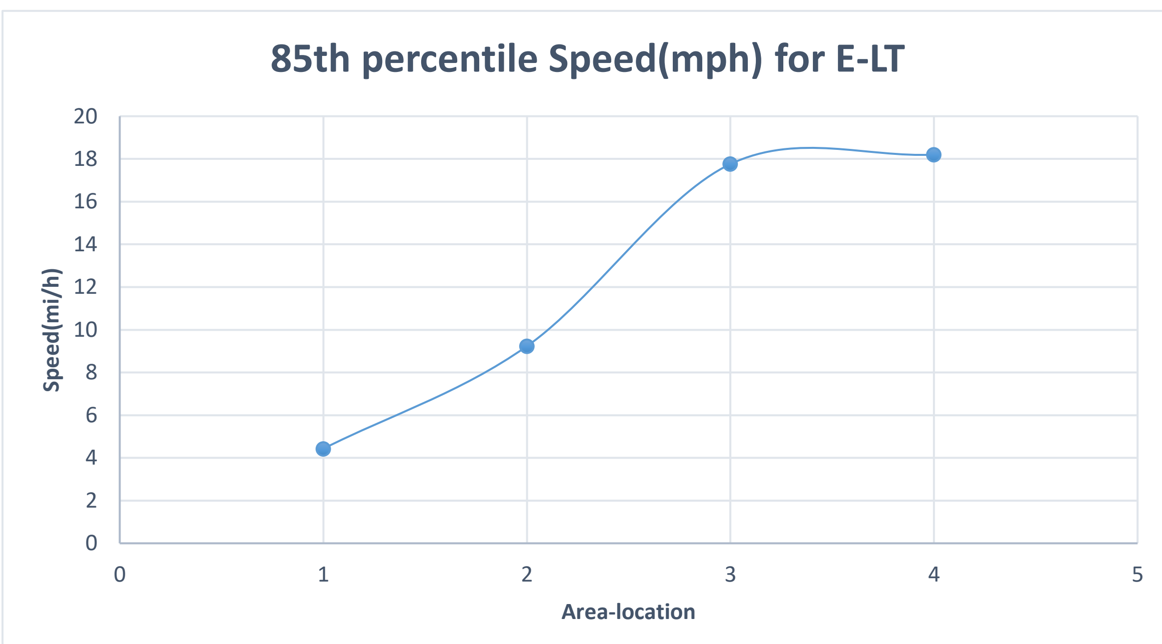

Figure 5-10: 85th percentile speed in location 1-4 during E-LT movements

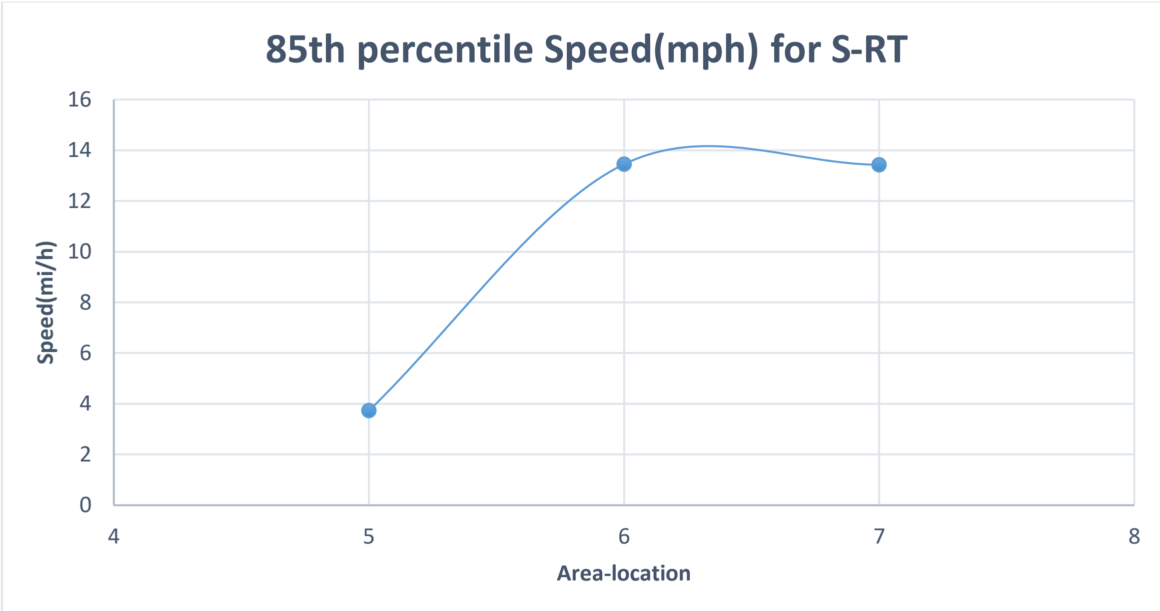

Figure 5-9: 85th percentile speed in location 5-7 during S-RT movements

Surrogate Safety Analysis

With the same number of PET conflicts in the 1 hour study period, the TTC gave a higher total rear-end conflicts than the DSSM as the surrogate safety measure. In the study period, the combination of TTC and PET indicated 25 potential risks per 1000 vehicles, while 19 potential conflicts per 1000 vehicles were identified in the combination of DSSM and PET.

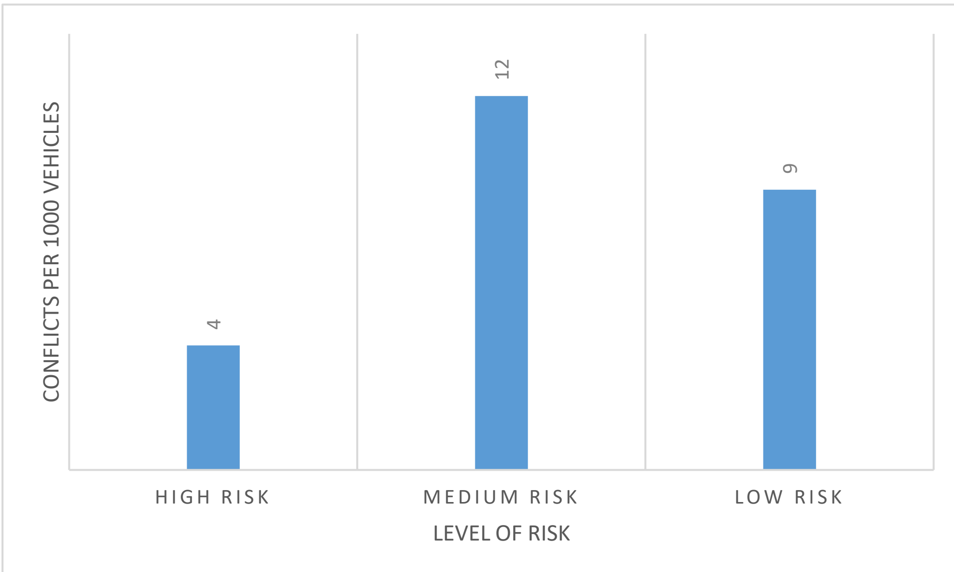

Figure 5-10: TTC & PET risk count during the study period

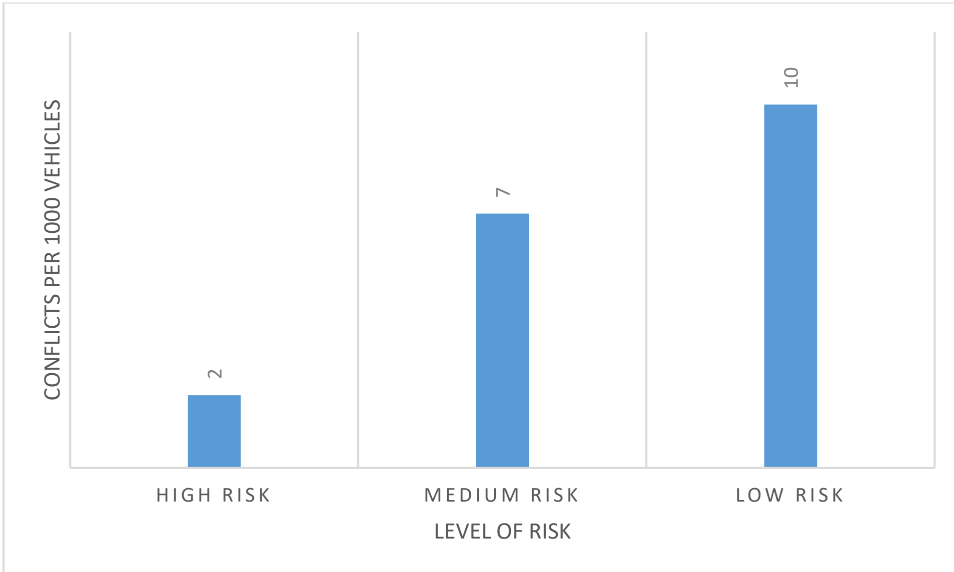

Figure 5-11: DSSM & PET risk count during the study period

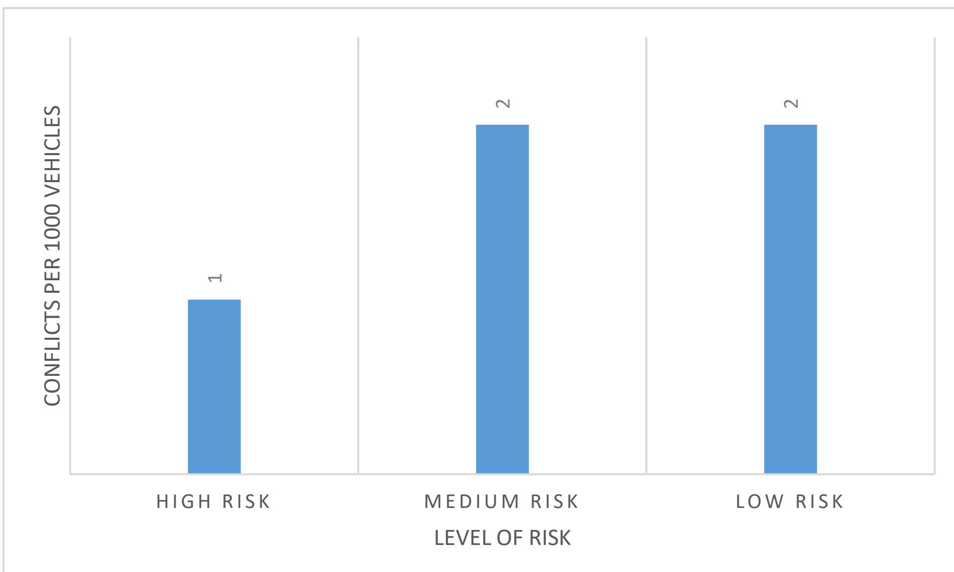

Figure 5-12: PET risk count during the study period

Figures 5-12 and 5-13 show that the Medium risks dominate in the TTC and PET conflicts while Low risks dominate in DSSM&PET conflicts. The difference in number and categories of conflicts between DSSM and TTC is because the DSSM follows the action point model more thoroughly than the TTC. So there are several conflicts identified by TTC which are not seen as potential conflicts or ranked in a lesser or riskier category by DSSM and vice-versa. For example, there are some conflicts in which the following vehicle moves faster than the leading vehicle; however, due to the deceleration action behavior taken by the driver, it is not identified as a risk by DSSM but identified as a risk TTC. Also, sometimes when a leading vehicle moves faster than the following vehicle and the following vehicle takes an acceleration action that can be categorized as a risk by DSSM but will never be seen as a Risk by TTC because the leading vehicle is moving faster.

Figures 5-15, 5-16, 5-17, and 5-18 further illustrate the conflicts, their types, and locations at the intersection. Only 3 types of conflicts were observed during the study hour: merging, cross and rear-end conflicts. The results show that for LT movements, 1 cross conflict is expected per every 15 LT movements conflicting with 195 T movements in one hour. For RT movements, 1 merging conflict is expected per every 38 RT movements merging in a 292 T traffic in one hour. For T movements, there is expected to be 1 rear-end conflict per 42 T traffic in one hour for west-bound and 1 rear-end conflict per 49 T traffic for east-bound (TTC analysis). Using DSSM analysis, 1 rear-end conflict per 53 T traffic is expected for west-bound movements while 1 rear-end conflict is expected per 76 T traffic for east-bound movements.

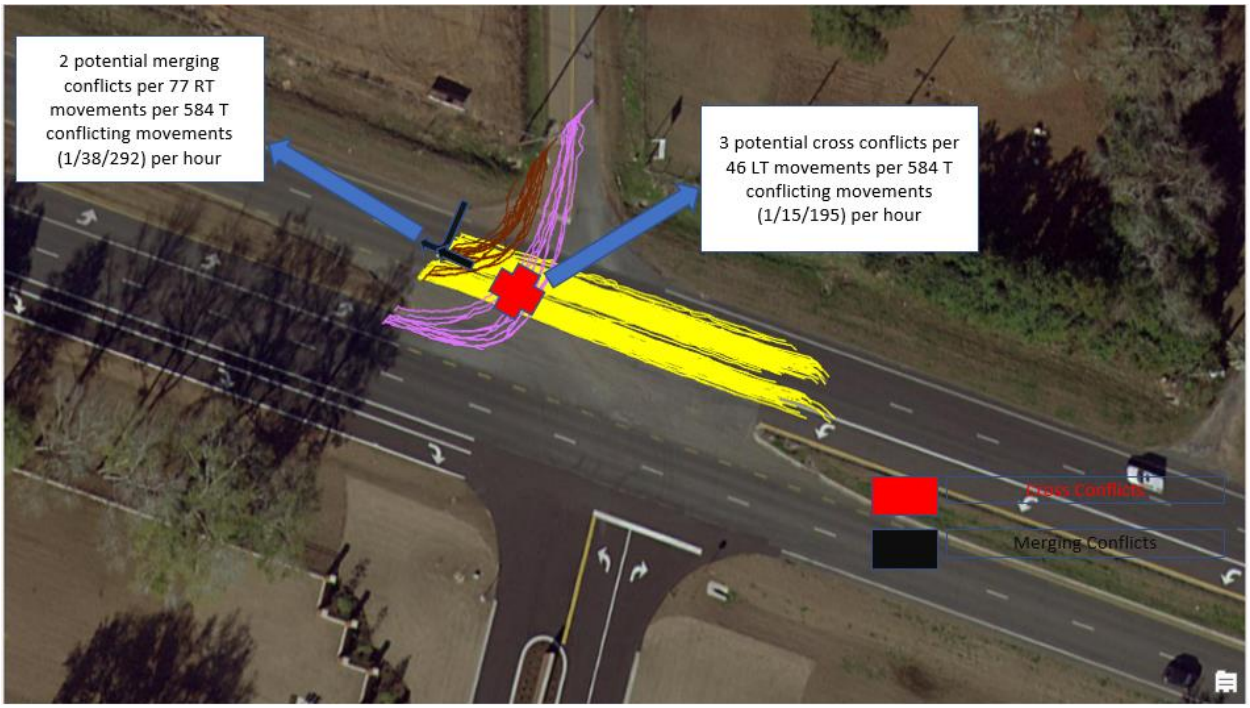

Figure 5-13: Locations and types of conflicts defined by PET

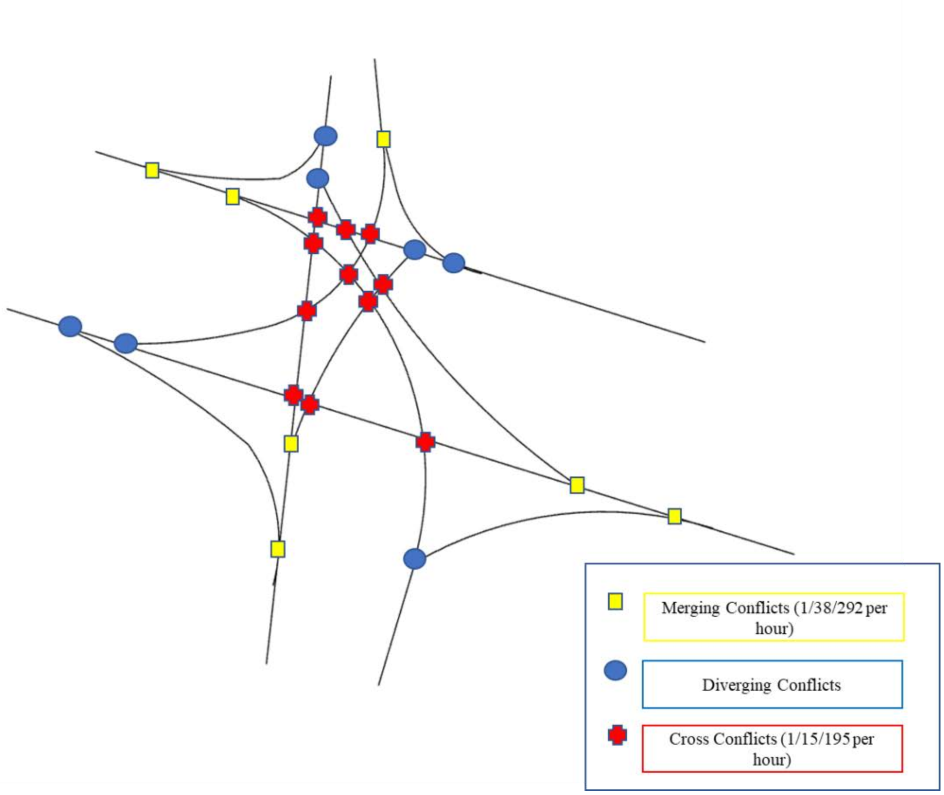

Figure 5-14: A summary representation of conflicts determined by PET

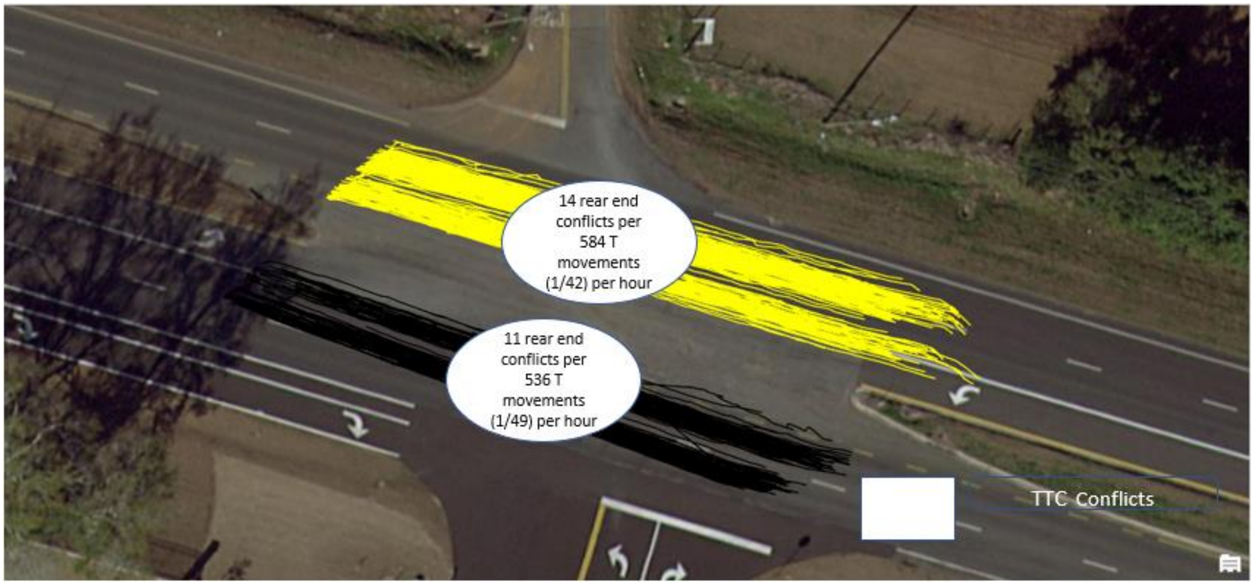

Figure 5-15: Rear end conflicts defined by TTC

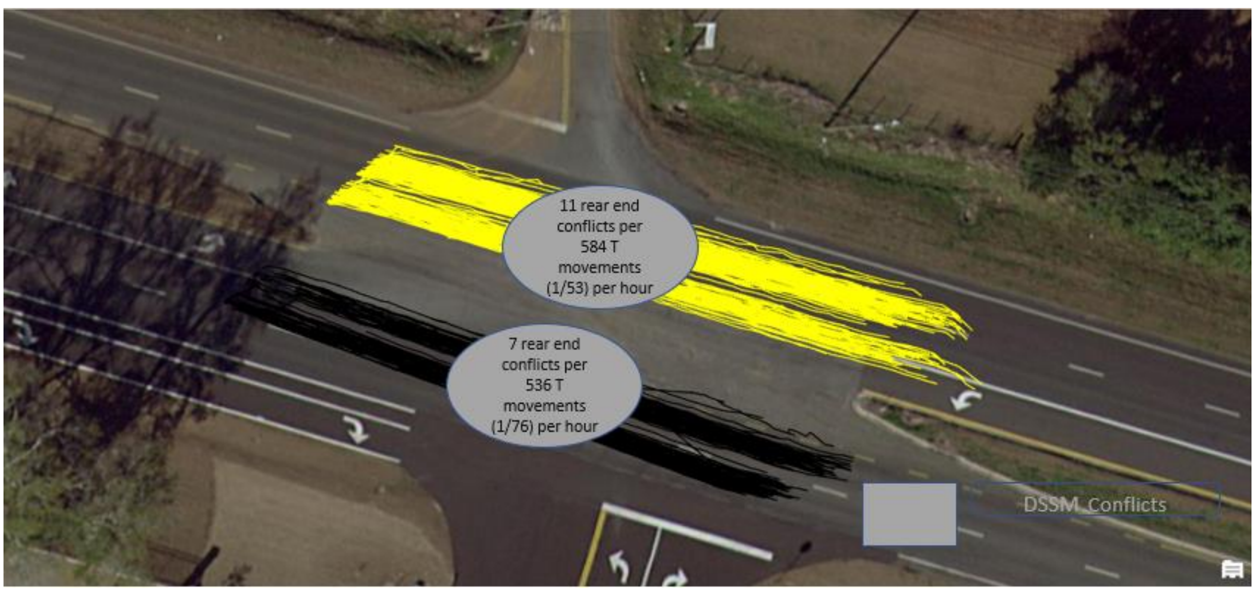

Figure 5-16: Rear end conflicts defined by DSSM

Figure 5-19 also demonstrates an example conflict identified using the drone footage for each risk group. These conflicts were also successfully identified using the proposed methodology, as shown by the associated PET, TTC, and DSSM values shown: high risk (0.9), moderate risk (0.558), and low risk (0.69), respectively.

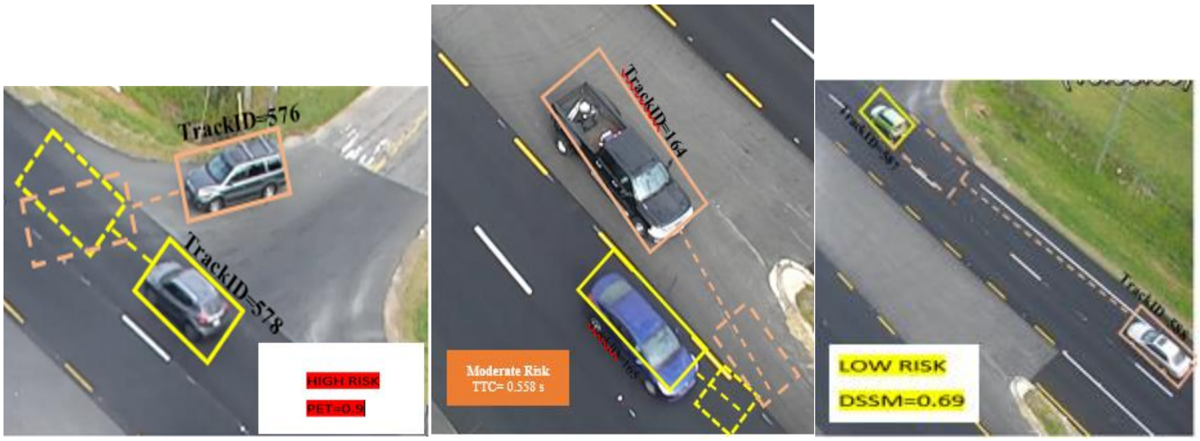

Figure 5-17: Examples of conflicts identified for each category of risk

Since the intersection is prone to around 20 potential conflicts per 1000 vehicles in just a time interval of 1 hour, which is not even in the assumed peak hours, which are usually early in the morning, this may indicate a safety problem associated with the intersection. Most of the conflicts analyzed by the surrogate measures are rear-end conflicts that are not susceptible to correction by signalization. Still, the PET SSM determined 5 cross conflicts per 1000 vehicles, which indicates the likely need for signalization or other mitigation measures such as constructing a roundabout at the intersection. This feasibility analysis shows the need for countermeasures. That is probably why FDOT asked to conduct a signal warrant study based on the safety problems identified at this specific location. Note that signal warrant study is the standard method to conduct an engineering analysis that determines whether a signal control is required on uncontrolled or stop-sign controlled intersections.

This location has been selected for a possible countermeasure to avoid the associated safety problems, and this study proposes a feasibility study in identifying these problems based on a tethered drone-based data collection exercise. The research team will focus on using the proposed methodology for other periods at the same intersection and other intersections in Tallahassee and Jacksonville, which are currently being studied.

Lessons Learned

All in all, the findings demonstrate the capabilities of drone-based microscopic traffic data extraction. There are some challenges present regarding the use of drones, the most significant one being weather dependency. For example, rain can ruin the whole data collection operation. UASs are weather-dependent, and Remote Pilot in Command (RPIC) should continuously check the weather and wind. Beyond general operation challenges, UAS based video-image processing has its problems. In the transportation field, vision-based traffic monitoring dates back to the 1990s. However, the situation gets more challenging for the aerial videos since there are six more degrees of freedom (3 dimensions & 3orientations between the X, Y, and Z axes) related to the camera's movement.

Although mobility is one of the most significant advances for drones, in some cases, stability is more beneficial than mobility to stabilize the background. Some algorithms can align the subsequent frames before detect-and-tract algorithms; however, they increase the computational cost. Another problem is the visibility disruptions due to light. As the performance of UAS-based traffic monitoring relies heavily on clear video footage, the study can be disrupted by occlusion due to clouds or foggy weather. Although drones bring some solutions for this, they are still sensitive to daylight conditions. Another challenge will be locating the tethered drone ground unit since the operation will require a clear distance, and a vertical connection should be kept taut. Locating the unit is also critical since it may require additional permissions from the location owner if it is not part of the right-of-way.

The performance of vision-based detection and tracking algorithms depends on the density of the object to be determined. Therefore, vehicle, bicycle, motorcycle, and pedestrian detection in congested conditions may lack accuracy. Machine learning and deep learning algorithms can overcome this problem as they are trained with positive and negative images of objects. Note that the studied location did not have high pedestrian and non-motorists traffic.

The drone used in this study was not one of the most powerful drones like those that could run for 24 hours straight without the powering batteries needing to be charged (ELISTAIR Inc., n.d.). The batteries for the drone used in this study could operate for the maximum of 2.5 hours before requiring to be charged. This makes the drone applied for the study unlikely to be used in studies that unbiasedly need to be conducted in more than 2.5 hours without a single break.

Although promising, a traffic conflict analysis based on surrogate measures is not enough by itself. Conflicts should also be compared with real-life crash data to identify how successful the conflict analysis simulates the actual crash conflict points. This validation will significantly be impacted by the assumptions and imposed limitations related to the driver compositions, geometric characteristics, and time periods being studied.

Few data in some movements made the analysis less efficient. Turning speed trend and gap study could only be analyzed for south-bound right-turning movements and east-bound left-turning movements since there were a relatively significant number of movements in the one-hour study period than other turning movements.

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS

This study explored the uses of tethered drones in traffic data collection by performing traffic studies and obtaining the surrogate safety measures at an unsignalized intersection in Tallahassee, Florida. The proposed approach provided different vehicle trajectories that manual data collection could not easily capture over a relatively larger space along with the traffic movement counts. Some of those trajectories that could effortlessly be extracted include the vehicle coordinate locations at a specific time, their speeds, and accelerations. These are the crucial parameters in getting the traffic movement pattern and the movement count, which are the essential prerequisites of any traffic and safety study.

The algorithms developed calculated hundreds of thousands of trajectories and SSMs in a click. In less than a minute, a specific trajectory such as speed or one of the SSMs was calculated for around 30,000 data points. The counting accuracy for this approach is 100%. The approach movement classification detection is 96% accurate, with 4% of processed trajectory lines undefined by the drone and its integrated AI (YOLO). This level of accuracy makes the method better than most of the advanced traffic data collection methods

The number of potential conflicts obtained in 1 non-peak-hour may indicate a problem associated with the intersection. The SSMs indicate the likely need for signalization due to the 5 cross conflicts detected by PET in 1 hour duration. Also, due to almost around 20 rear-end conflicts detected by TTC and DSSM in the study hour, some countermeasures could be applied before the intersection. These conflicts could also be minimized by converting the simple cross junction to a roundabout.

In addition, for future work, the resulting conflicts of this analysis could be compared with the crash data for validation purposes after doing the safety studies in other intersections to get more data for statistical purposes. The future work's analysis and the results obtained from it could make the safety guidelines such as warrants to be introduced based on SSMs.

A gap study comparing gaps in different lanes could be done soon to understand the gap acceptance and rejecting behaviors for drivers on different lanes. For multilane highways, drivers are expected to drive at different speeds in different lanes. In the U.S., vehicles in left lanes are supposed to be moving at higher speeds than vehicles in right lanes. Hence understanding the gap acceptance and rejectance for conflicting vehicles in different lanes could be a reasonable study.

A sensitivity analysis focusing on different traffic conflict parameters would be beneficial in identifying the most appropriate parameters for a traffic conflict-based safety analysis at a specific intersection. Modeling factors that could affect the SSMs has the potential for improving the prediction of crashes.

The findings of this study can help develop appropriate guidelines and recommendations to FDOT and other transportation agencies in terms of evaluating and justifying the feasibility of using tethered drones as one of the efficient and effective data collection alternatives while significantly improving intersection safety and operations. The results and recommendations of this research can also be used by the FDOT's and other agencies' consultants who already perform traffic data collection on Florida's roadways. Notably, drone-based traffic data collection requires a full collaboration with traffic engineers, drone operators, and video-image processing professionals because the whole process is fully connected.

REFERENCES

Abdel-Aty, M., Ekram, A. A., Huang, H., & Choi, K. (2011). A study on crashes related to visibility obstruction due to fog and smoke. *Accident Analysis and Prevention*, *43*(5), 1730–1737.

Ali, O. W. Ben, Al-Harthei, H., & Garib, A. (2013). Real-Time Fog Warning System for the Abu Dhabi Emirate (UAE). *Journal of Traffic and Logistics Engineering*, *1*(2), 213–217. https://doi.org/10.12720/JTLE.1.2.213-217

Anarkooli, A. J., Persaud, B., Milligan, C., Penner, J., & Saleem, T. (2021). Incorporating Speed in a Traffic Conflict Severity Index to Estimate Left Turn Opposed Crashes at Signalized Intersections: *Https://Doi.Org/10.1177/0361198120986167*, *2675*(5), 214–225. https://doi.org/10.1177/0361198120986167

Antoniou, C., Balakrishna, R., & Koutsopoulos, H. N. (2011). A Synthesis of emerging data collection technologies and their impact on traffic management applications. *European Transport Research Review 2011 3:3*, *3*(3), 139–148. https://doi.org/10.1007/S12544-011-0058-1

Autey, J., Sayed, T., & Zaki, M. H. (2012). Safety evaluation of right-turn smart channels using automated traffic conflict analysis. *Accident Analysis and Prevention*, *45*, 120–130. https://doi.org/10.1016/J.AAP.2011.11.015

Barmpounakis, E., & Geroliminis, N. (2020). On the new era of urban traffic monitoring with massive drone data: The pNEUMA large-scale field experiment. *Transportation Research Part C: Emerging Technologies*, *111*(October 2019), 50–71. https://doi.org/10.1016/j.trc.2019.11.023

Chapter 3 - Balancing Safety and Capacity in an Adaptive Signal Control System — Phase 1, October 2010 - FHWA-HRT-10-038. (n.d.). Retrieved July 30, 2021, from https://www.fhwa.dot.gov/publications/research/safety/10038/003.cfm

Chaudhari, A., Gore, N., Arkatkar, S., Joshi, G., & Pulugurtha, S. (2021). Exploring pedestrian surrogate safety measures by road geometry at midblock crosswalks: A perspective under mixed traffic conditions. *IATSS Research*, *45*(1), 87–101. https://doi.org/10.1016/J.IATSSR.2020.06.001

Chen, P., Zeng, W., Yu, G., & Wang, Y. (2017). Surrogate Safety Analysis of Pedestrian-Vehicle Conflict at Intersections Using Unmanned Aerial Vehicle Videos. *Journal of Advanced Transportation*, *2017*.

Cheng, P., Zhou, G., & Zheng, Z. (n.d.). *Detecting and Counting Vehicles from Small Low-Cost UAV Images*.

Drivingtips.org. (2010). *Steering A Car*. http://www.drivingtips.org/steering-a-car.html

ELISTAIR Inc., C. (n.d.). *What Are The Benefits Of Tethered Drones?* Retrieved November 2, 2021, from https://elistair.com/tethered-drones-benefits/

FDOT Traffic Studies. (n.d.). Retrieved October 5, 2021, from https://www.fdot.gov/traffic/trafficservices/trafficstudies.shtm

Gallelli, V., Guido, G., Vitale, A., & Vaiana, R. (2019). Effects of calibration process on the simulation of rear-end conflicts at roundabouts. *Journal of Traffic and Transportation Engineering (English Edition)*, *6*(2), 175–184. https://doi.org/10.1016/J.JTTE.2018.03.006

Gettman, D., & Head, L. (2003). Surrogate Safety Measures from Traffic Simulation Models.

Transportation Research Record, *1840*, 104–115. https://doi.org/10.3141/1840-12

Glauz, W. D., & Migletz, D. J. (1980). Application of Traffic Conflict Analysis At Intersections. In *National Cooperative Highway Research Program Report* (Issue 219).

Gu, J., Fei, G., Meng, Y., Sun, Q., Qian, Y., Jiang, X., Wang, X., Stallones, L., Xiang, H., & Zhang, X. (2021). Revised road traffic safety law and years of life lost due to traffic deaths in China, 2002–2019. *Accident Analysis & Prevention*, *161*, 106344. https://doi.org/10.1016/J.AAP.2021.106344

Gu, X., Abdel-Aty, M., Xiang, Q., Cai, Q., & Yuan, J. (2019). Utilizing UAV video data for in-depth analysis of drivers' crash risk at interchange merging areas. *Accident Analysis and Prevention*, *123*(June 2018), 159–169. https://doi.org/10.1016/j.aap.2018.11.010

Guo, Y., Sayed, T., & Essa, M. (2020). Real-time conflict-based Bayesian Tobit models for safety evaluation of signalized intersections. *Accident Analysis and Prevention*, *144*(April), 105660. https://doi.org/10.1016/j.aap.2020.105660

Heintz, F., Rudol, P., & Doherty, P. (2007). From images to traffic behavior - A UAV tracking and monitoring application. *FUSION 2007 - 2007 10th International Conference on Information Fusion*. https://doi.org/10.1109/ICIF.2007.4408103

Hou, T., Mahmassani, H., Alfelor, R., Kim, J., & Saberi, M. (2013). Calibration of traffic flow models under adverse weather and application in mesoscopic network simulation. *Transportation Research Record*, *2391*, 92–104. https://doi.org/10.3141/2391-09

Ke, R., Kim, S., Li, Z., & Wang, Y. (2015). Motion-vector clustering for traffic speed detection from UAV video. *2015 IEEE 1st International Smart Cities Conference, ISC2 2015*. https://doi.org/10.1109/ISC2.2015.7366230

Khan, M. A., Ectors, W., Bellemans, T., Janssens, D., & Wets, G. (2017). Unmanned Aerial Vehicle–Based Traffic Analysis: Methodological Framework for Automated Multivehicle Trajectory Extraction. *Transportation Research Record: Journal of the Transportation Research Board*, *2626*(1), 25–33. https://doi.org/10.3141/2626-04

Lee, D., & Yeo, H. (2015). A study on the rear-end collision warning system by considering different perception-reaction time using multi-layer perceptron neural network. *IEEE Intelligent Vehicles Symposium, Proceedings*, *2015-August*, 24–30. https://doi.org/10.1109/IVS.2015.7225657

Li, Y. (2008). Vehicle Extraction Using Histogram and Genetic Algorithm Based Fuzzy Image Segmentation from High Resolution UAV Aerial Imagery.

Liu, Y., Bai, B., & Zhang, C. (2017). UAV image mosaic for road traffic accident scene. *Proceedings - 2017 32nd Youth Academic Annual Conference of Chinese Association of Automation, YAC 2017*, 1048–1052. https://doi.org/10.1109/YAC.2017.7967565

Minderhoud, M. M., & Bovy, P. H. L. (2001). Extended time-to-collision measures for road traffic safety assessment. *Accident Analysis & Prevention*, *33*(1), 89–97. https://doi.org/10.1016/S0001-4575(00)00019-1

Nasernejad, P., Sayed, T., & Alsaleh, R. (2021). Modeling pedestrian behavior in pedestrian-vehicle near misses: A continuous Gaussian Process Inverse Reinforcement Learning (GP-IRL) approach. *Accident Analysis & Prevention*, *161*, 106355. https://doi.org/10.1016/J.AAP.2021.106355

Outay, F., Mengash, H. A., & Adnan, M. (2020). Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges. *Transportation Research Part A: Policy and Practice*, *141*, 116–129. https://doi.org/10.1016/J.TRA.2020.09.018

Paul, M., & Ghosh, I. (2021). Development of conflict severity index for safety evaluation of severe crash types at unsignalized intersections under mixed traffic. *Safety Science*, *144*, 105432. https://doi.org/10.1016/J.SSCI.2021.105432

Peesapati, L. N., Hunter, M. P., & Rodgers, M. O. (2018). Can post encroachment time substitute intersection characteristics in crash prediction models? *Journal of Safety Research*, *66*, 205–211. https://doi.org/10.1016/J.JSR.2018.05.002

Peng, Y., Abdel-Aty, M., Shi, Q., & Yu, R. (2017). Assessing the impact of reduced visibility on traffic crash risk using microscopic data and surrogate safety measures. *Transportation Research Part C: Emerging Technologies*, *74*, 295–305. https://doi.org/10.1016/J.TRC.2016.11.022

Raj, C. V., Sree, B. N., & Madhavan, R. (2017). Vision based accident vehicle identification and scene investigation. *TENSYMP 2017 - IEEE International Symposium on Technologies for Smart Cities*. https://doi.org/10.1109/TENCONSPRING.2017.8070062

Sayed, T., & Zein, S. (2007). Traffic conflict standards for intersections. *Http://Dx.Doi.Org/10.1080/03081069908717634*, *22*(4), 309–323. https://doi.org/10.1080/03081069908717634

Sharma, V., Chen, H. C., & Kumar, R. (2017). Driver behaviour detection and vehicle rating using multi-UAV coordinated vehicular networks. *Journal of Computer and System Sciences*, *86*, 3–32. https://doi.org/10.1016/J.JCSS.2016.10.003

Svensson, Å., & Hydén, C. (2006). Estimating the severity of safety related behaviour. *Accident*

Analysis & Prevention, *38*(2), 379–385. https://doi.org/10.1016/J.AAP.2005.10.009

Tak, S., Kim, S., Lee, D., & Yeo, H. (2020). A comparison analysis of surrogate safety measures with car-following perspectives for advanced driver assistance system. *Journal of Advanced Transportation*, *2018*. https://doi.org/10.1155/2018/8040815

Tak, S., Kim, S., & Yeo, H. (2015). Development of a Deceleration-Based Surrogate Safety Measure for Rear-End Collision Risk. *IEEE Transactions on Intelligent Transportation Systems*, *16*(5), 2435–2445. https://doi.org/10.1109/TITS.2015.2409374

Tak, S., Lee, D., Choi, S., & Yeo, H. (2017). Collision Avoidance System with Uni-Directional Communication for Mitigating the Adverse Effects on Following Vehicles. https://doi.org/10.2495/UT170361

Tarko, A., Nicolas, S., & Sayed, T. (2009). *(PDF)* Surrogate Measures of Safety. https://www.researchgate.net/publication/245584894_Surrogate_Measures_of_Safety

Traffic and Transportation Simulation Looking Back and Looking Ahead: Celebrating 50 Years of Traffic Flow Theory, A Workshop. (2015). www.TRB.org

Troutbeck, R. J. (2016). Revised Raff's Method for Estimating Critical Gaps: *Https://Doi.Org/10.3141/2553-01*, *2553*, 1–9. https://doi.org/10.3141/2553-01

Unsignalized Intersection Collisions NCHRP Report Description of Problem. (2006).

Viktor, B., Culjak, M., & Segvic, S. (2012). *IEEE Xplore Full-Text PDF:* https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6240785

Yang, L., Yang, J. H., Feron, E., & Kulkarni, V. (2003). Development of a performance-based approach for a rear-end collision warning and avoidance system for automobiles. *IEEE Intelligent Vehicles Symposium, Proceedings*, 316–321. https://doi.org/10.1109/IVS.2003.1212929