A Cloud-Based Emergency Route Collision Avoidance System for IoT-Enabled Vehicles

A Thesis

presented to

School of Applied Computing, Faculty of Applied Science and Technology

of

Sheridan College, Institute of Technology and Advanced Learning

by

Devon A. Fazekas

in partial fulfilment of the requirements

for the degree of

Honours Bachelor of Computer Science (Mobile Computing)

April 2021

A Cloud-Based Emergency Route Collision Avoidance System for IoT-Enabled Vehicles

by

Devon A. Fazekas

Submitted to the School of Applied Computing, Faculty of Applied Science and Technology
on April 20, 2021, in partial fulfillment of the
requirements for the degree of
Honours Bachelor of Computer Science (Mobile Computing)

Abstract

For emergency responders, every delay in reaching their destination could be the difference between life and death for those involved in accidents, which is why they must reduce their arrival time as much as possible. ERs are legally permitted to exceed speed limitations, run red lights, and ignore stop signs, all of which put them and nearby civilian drivers at risk of accidents. The traditional methods of using emergency lights and sirens are ineffective at providing civilian drivers with enough warning and context to negotiate traffic in urban areas, resulting in congestion and delays. This thesis describes an innovative cloud-based route collision avoidance system and reports on real test case scenarios. The system, built upon IoT-enabled vehicles and cloud computing, aims to minimize the risk of emergency vehicle-involved accidents by providing civilian drivers with early warnings and detours around possible route collision areas along their commute, reducing localized traffic volume around the emergency vehicles.

Keywords: IoT, emergency responders, traffic routing, reducing arrival time, reducing traffic volume, improving road safety, cloud computing.

Thesis Supervisor: Dr. Richard Pyne
Title: Professor, School of Applied Computing

Acknowledgments

I want to thank Professor Richard Pyne for his endless patience and guidance and for my beloved friends and family for all their support throughout the making of this thesis.

Contents

List of Figures

Glossary

A* algorithm A best-first, graph search algorithm that can find the shortest path from an origin to the destination.. 28

Active EV An Emergency Vehicle with its lights and/or siren activated. 18–21

Code Three Running A mode of response for an emergency vehicle responding to a call, permitting the use of warning lights, sirens, exceeding speed limits and crossing against stop signs and red lights to minimize travel time. 17

LIDAR A detection system which works on the principle of rader, but uses light from a laser.. 25

localized traffic volume A measure of the number of vehicles within a given area around an observing vehicle. 18–20

RADAR A detection system which works with radio waves to determine the range, angle, or velocity of objects.. 25

route collision The event of a CV getting closer than the safety threshold to an active EV.. 19, 21, 35

Route Guidance The computation of an optimal route (by some criteria) between an origin and a destination.. 27

Acronyms

DSRC Dedicated Short-Range Communication. 24, 26, 28

EMS Emergency Medical Service. 17, 18

ER Emergency Responder. 9, 17–21, 23, 25–29, 31–33, 35–41

EV Emergency Vehicle. 13, 17–20

GUI Graphical User Interface. 26

IoT Internet of Things. 19, 20

ITS Intelligent Transport System. 24, 26, 29

LEO Law Enforcement Officer. 17, 18

LoS Line-of-Sight. 24–26

MOT Ministry of Transportation. 18, 19

NLoS Non-Line-of-Sight. 25

RSU Road-Side Unit. 19, 26, 27

V2I Vehicle-to-Infrastructure. 26

VANET Vehicular Ad-Hoc Network. 27

Chapter 1

Introduction

Emergency Responders (ERs) are persons with specialized training who arrive first at scenes of emergency and typically include Law Enforcement Officers (LEO), firefighters, and Emergency Medical Service (EMS) technicians [1]. Given the time-sensitive nature of emergencies, ERs need to quickly and safely reach their destinations [2]. They thus are authorized to operate Emergency Vehicles (EVs) with the *Code Three Running* option permitting use of warning lights, sirens, exceeding speed limits and crossing against stop signs and red lights to minimize arrival times [1, 2, 3].

As the number of registered vehicles continues to grow each year, the increase in urban traffic volume leads to congestion and delays, resulting in increased emergency arrival times and the risk that ERs face when responding to calls [4]. For ERs, crash-related fatalities are up to 4.8 times more likely than any other driving-related occupation in the United States, given that they operate under stressful driving conditions, time pressure, and multitasking activities [1]. The relevant causative factors attributing to these crashes include:

- Complicated urban intersections [1, 5];
- High traffic volumes [1, 4];
- Lack of recognition by other drivers [1, 4, 6]; and
- Human error [3, 6].

In the United States, EV-involved crashes account for thousands of injuries and hundreds of fatalities each year. Between 2004 and 2006, 37,600 LEO were reported injured [1], 17,000 firefighters in 2015 [1], and 1,500 EMS technicians in 2009 [1]. The average annual fatality count for ERs as a result of these accidents is approximately 100 for LEOs [1, 7, 8], 45 for EMS technicians [1, 7], and 15 for firefighters [1, 7]. Furthermore, reports from [1] show an average of 60 civilian fatalities each year due to these accidents, which also incur many lawsuits costing the cities millions of dollars due to these injuries, property damage, and life loss [1].

1.1 Statement of the Problem

The Ministry of Transportation (MOT) in Canada is dedicated to moving people safely, efficiently, and sustainably through promoting innovative technology and infrastructure. When it comes to emergency calls, EVs are equipped with sirens and lights, and there are laws in place that dictate how civilian drivers should respond to nearby Active EVs. For instance, failure to slow down and make room when approaching an Active EV or failure to maintain at least 150-meters from a travelling ER will result in fines between $400 to $2,000 and three demerit points in Ontario based on Section 159(2) and (3) of the Highway Traffic Act [9, 10].

Unfortunately, the traditional methods used by EVs (i.e., lights and sirens) have been proven ineffective at attaining attention of civilian drivers (civilian drivers) and negotiating traffic in urban areas. By the time civilian drivers recognize the signals, they have difficulty identifying the EV's direction and distance, thereby not having enough time or context to react effectively [11].

Continuing with the reliance on human perception-based warning signals results in additional traffic chaos and accidents [11]. Developing a more sophisticated and assistive system for ERs and civilian drivers could help the Ministry of Transportation reduce occupational risk for ERs by reducing localized traffic volume around and ahead of their vehicles (e.g., helping civilian drivers maintain a minimum distance from an EV) when responding to emergency calls.

1.2 Purpose of the Study

The study will be limited to IoT-enabled vehicles (hereafter referred to as *connected vehicles*), equipped with an interface for our mobile application, operated by ERs and civilian drivers. The mobile application will use cellular data to connect with our cloud server for our system to consume traffic data and communicate with the *connected vehicles* and drivers. We define a *route collision* as the event of a civilian vehicle getting closer than the safety threshold, enforced by the Ministry of Transportation [9, 10], to an Active EV. For the system to avoid route collisions, drivers of both types of vehicles (i.e., an ER's vehicle and civilian vehicle) need to enter their destinations before driving and follow the routes provided by our mobile application. This study explores the relationship of the localized traffic volume from an EVs' perspective to reduce occupational risks for ERs responding to calls within urban areas such as Toronto, Ontario.

1.3 Outcomes & Contributions

The study by [12] uses a centralized traffic control server to improve road safety and reduce arrival times for Active EVs. The server notifies civilian drivers with a message to pull over and halt until the approaching ERs pass. The server also generates the EV's optimal routes using real-time traffic information collected from Road-Side Units (RSUs) installed at every intersection. This approach relies too heavily on high penetration rates of RSUs in urban areas' infrastructure, posing scalability, security, and adoption challenges. Additionally, research shows that warning drivers of approaching Active EVs without providing suggestions results in panicking the driver as they're left to evaluate the situation themselves, increasing the risk of further accidents with the ER or neighbouring civilian drivers [3, 6].

In this research, we will focus on preemptively assisting civilian drivers in avoiding route collisions. Our *Route Collision Avoidance System* will guide civilian drivers to maintain the safety threshold of 150-meters [9, 10] from all Active EVs during their commute. Our system warns the drivers of connected vehicles minutes before decisions need to be made and reduces their cognitive workload by offloading the maneuvering decisions in potentially complicated and stressful environments to our server, reducing human error. All of this, combined with minimizing localized traffic volume for EVs, reduces the risk of EV-involved accidents during emergency calls.

This research aims to provide vehicle manufacturers with our cloud-based *Emergency Route Collision Avoidance System* to embed as standard within their IoT-enabled motor vehicles, helping drivers make better decisions that result in safer and smoother commutes when near the path of Active EVs.

1.4 Research Question

The topic of this study explores the use of real-time route guidance for connected vehicles during emergencies. This study's factors include the distance between the civilian vehicle and Active EVs, as well as the time it takes for a civilian driver to acknowledge a nearby Active EV. The populations that this study will explore are civilian drivers and ERs in urban areas, such as the city of Toronto. This study aims to answer the research question: Does preemptively warning and guiding civilian drivers out of the path of Active EVs reduce human error and help maintain a distance between them greater than the safety threshold?

1.5 Significance of the Study

By leveraging cloud computing and IoT technologies, civilian drivers will overcome human perception limitations at identifying Active EVs, more effectively avoid Active EVs, and ERs will have fewer vehicles in their path to maneuver around when responding to emergency calls. All of this contributes to minimizing the risk of EV-involved accidents, reducing arrival times, and creating safer and smoother commutes for road users.

1.6 Overview of Methodology

Our experiment will be performed with human participants after developing a cloud-hosted server and complementary navigation mobile application on Android. The experiment involves a minimum of two participants divided into two types; one as acting civilian driver and the other as acting ER. Each driver type has a dedicated version of the application that generates a route between an origin and destination location. When the server generates the civilian drivers' route, it searches for any possible route collisions with Active EVs within the city. It uses the respective vehicle's current location and speed to estimate whether the vehicles could collide (i.e., appear within the 150-meters [9, 10] threshold of each other). The application periodically updates the server with the vehicle's speed, location, and heading data, enabling the server to update its predictions. If a route collision is likely, we provide the civilian driver with an alternative route detouring them around the area of their predicted route collision.

1.7 Organization of the Thesis

This chapter introduced our topic and the problem we will be studying. We looked at why we need to study this and how we will benefit from it. In chapter 2, we explore the review of related literature. Chapter 3 incorporates the methodology that we are going to use to conduct our experiments. Chapter 4 reports on our findings. Chapter 5 provides our conclusions and recommendations.

Chapter 2

Literature Review

2.1 Introduction

In 2019, the U.S. Department of Transportation reported more than 36,000 fatalities and 4.4 million critically injured individuals due to accidents involving vehicles [13], making motor accidents the third leading cause of death in the United States [14]. Among these reports, 90% result from human error (i.e., the improper reaction to impending danger) [15]. As urbanization continues to grow, so does the expected number of drivers on the road, ultimately increasing traffic congestion, reducing the space between vehicles, shortening the window of time drivers have to assess a situation, evaluating their options, and reacting safely. These factors increase delays and the risk of ER-involved accidents during an emergence call [16]. Additionally, traffic congestion due to inefficient avoidance of ERs and emergency sites drastically damages our environment from the emissions of each car [17, 18]. Some of the main factors contributing to ER-involved accidents relating to human error include biological limitations, such as perception, communication and processing, as outlined below:

- Perception is the ability to sense and identify emergencies. While humans rely on various biological senses to navigate the world, only a select few provide relevant data while operating a vehicle, such as sound and sight [6]. Drivers generally only use sound to identify honking and sirens; they filter out most other noises. Sight is the most used sense by drivers, but every vehicle has an array of blind spots, and many threats live outside their Line-of-Sight (LoS), usually obstructed by other vehicles, buildings, trees, and poor weather conditions [6];

- Communication is the ability to perceive neighbouring drivers' intentions unambiguously and clearly express your intentions. Standard vehicles are equipped with few external indicators, including a monotone horn, signal lights, and brake lights. But the use of these indicators varies between cultures;

- Processing is the ability to plan strategies for avoiding or preventing dangerous situations by collecting environmental data and assessing the surroundings. Drivers already have potentially high cognitive workloads given many factors such as unfamiliar roads, poor weather conditions, and multitasking, to name a few. Even in optimal conditions, drivers often only have a few seconds to react given the high speeds they travel at, and the decisions they make tend to be ill-informed guesses that often lead to accidents [3].

2.2 Intelligent Transport Systems

Intelligent Transport Systems (ITS) are advanced systems improving efficiency and safety of various transport-related situations, enabling drivers to make better informed, safer, and more coordinated decisions [12, 19, 20, 18]. Vehicles using ITS applications are hereafter referred to as *connected vehicles*.

One medium for *connected vehicles* to communicate is through the Dedicated Short-Range Communication (DSRC) protocol, also known as IEEE 802.11p. DSRC periodically broadcasts messages every 300 milliseconds, where each message contains the vehicle's speed, acceleration, location, and heading [21, 19].

Throughout the last decade, many countries have been investing in standardizing traffic management communication infrastructure, hoping to increase the demand for *connected vehicles* [12]. Nevertheless, despite the promising results in the literature, *connected vehicles* are not yet highly available on the market, and their safety and assistive features are yet to be fully realized [22, 23]. However, with the recent growth of popularity surrounding autonomous vehicles over the last decade, the growing demand for vehicular safety features and stringent government rules for improved traffic management, more comprehensive implementation of *connected vehicles* is inevitable [6, 24, 25].

2.3 ITS in Accident Prevention

Civilian drivers rely too heavily on LoS to perceive their surroundings, often having difficulty seeing or sensing obstacles obstructed by other vehicles, buildings, trees, or weather conditions [6]. Even with the technological advances offered by modern cars such as LIDAR, RADAR, and cameras, these sensors fundamentally rely on LoS, thus performing poorly in terrible weather conditions [6]. This review highlights two problem areas including Non-Line-of-Sight (NLoS) vehicle sensing and guided driving.

2.3.1 NLoS Vehicle Sensing

In 2018, there were more than 12 million reported car-related accidents in the United States [26], with more than 36,000 involving fatalities [26]. The root of many of these accidents stems from the obstructed vision of drivers, either due to blind spots, poor weather conditions, or any number of other causes. NLoS vehicle sensing enables *connected vehicles* to sense each other despite obstacles that would otherwise hide their presence [27].

One study by [3] focused on ER's safety. Many ERs reported driving more than 5 million miles a year and often operated under heavy visual, mental, and cognitive workloads, potentially driving at high speeds through difficult traffic and weather conditions [3]. ERs traditionally rely on sirens and lights to gain nearby civilian drivers' attention but have been proven inefficient at negotiating congested urban traffic. The warning is often recognized too late and conveys only the general location of an ER when outside the LoS of the civilian driver [3]. Without communicating intent and context, civilian drivers will continue making poorly-informed decisions that could lead to further accidents. Multiple studies leveraged V2I communication by installing RSUs near major intersections and using a centralized server to manage traffic data and disseminate information via DSRC [3, 12]. Major drawbacks to this approach are its dependency on the high number of RSUs needed throughout a city to ensure high coverage and the short-range of DSRC which means *connected vehicles* are not communicating in real-time. The results from these studies support that communicating vehicular information to *connected vehicles* will provide civilian drivers with enough context to make safer and better-informed decisions.

2.3.2 Guided Driving

Lane changes are among the most fundamental processes for drivers. However, they account for about 5% of traffic accidents [28] and 10% of traffic congestion [28]. Among these reported accidents, 75% of them were caused by human error [28]. With the advances in *connected vehicles*, more optimized lane changing planning and speed control strategies can be suggested to the driver.

There are many studies on cooperative lane changing algorithms. One study proposes a multi-vehicle cooperative lane change strategy in which the decision-making control is decentralized [28]. This approach creates a more comfortable experience for the involved drivers than unaided lane changes while simultaneously increasing traffic flow and road safety due to offloading the calculation of optimal decisions to an ITS. Unfortunately, the research failed to consider the perceived errors, delays in communication, and systems response times. Additionally, this approach requires a high penetration rate of *connected vehicles*, which is yet to be seen globally.

A DSRC-based freeway merging assistant system was developed [23]. Various lane merging scenarios were tested using a smartphone as a GUI for displaying advisory messages and three *connected vehicles*. Although the tested scenarios were basic, involving only single-hop broadcasting, they were performed in an uncontrollable environment, demonstrating that real-world route guidance systems are feasible and effective even in complex environments.

In the third study, authors [22] focused on improving and maintaining traffic flow during emergency evacuations. The experimenters varied the penetration rate of *connected vehicles* from zero-percent (i.e., base scenario) to 30-percent (i.e., the predicted rate by 2018). The algorithm suggested which lane and speed to maintain based on neighbouring *connected vehicles'* traffic flow data. The study results demonstrated that increasing the percent of *connected vehicles* present in an emergency evacuation led to significant traffic delays early into the situation and that the delay benefits would become positive only after approximately 1/3 of the overall time. It also demonstrated that the amount increased is proportional to the penetration rate of *connected vehicles.* The study's limitations were in the assumptions that drivers of *connected vehicles* would obey every suggestion given by the system.

2.4 ITS in Road Optimization

2.4.1 Route Guidance

We define Route Guidance as the problem of computing an optimal route (by some criteria such as distance or time) between an origin and a destination and adapting to real-time traffic updates guiding the driver on how best to avoid congested traffic. Given the time-sensitive nature of emergencies, ERs need to minimize arrival times by maintaining high speeds and avoiding unnecessary delays. In addition to the high accident risk, civilian drivers' ill-informed decisions also delay ERs. For example, in traffic jams, confused drivers often do not know how and where to form a suitable corridor to let the emergency vehicle through [3].

The study by [29] uses real-time traffic information to avoid congested road sections. The proposed model takes the approach to minimize prerequisite infrastructure by using *connect vehicles* within a VANET as information servers instead of relying on RSUs.

In the second study by [12], the use of a centralized server controls all traffic lights and traffic information. It is also responsible for computing the shortest-time plan and alternative routes, calculated with the *A* algorithm* based on distance and average expected speeds, for ERs. The *A* algorithm* is a best-first graph search algorithm that can find the shortest path. The authors used the relationship between the distance from a given location along the vehicle's route and the its average velocity as the heuristic function used within this algorithm. The first issue addressed is computing the fastest route from the source to the event (destination) for the ERs and adjusting this route based on real-time traffic. The second challenge is to disseminate the warning messages to nearby *connected vehicles* along the ER's route, advising them to move or stay put to avoid route collisions.

2.4.2 Traffic Light Preemption

Many factors contribute to the increasing traffic congestion in urban areas, but intersection traffic lights play a significant role in regulating traffic flow. Traditional approaches use inefficient timer-based decision logic, merely toggling the right-of-way (i.e., green light) signal between the competing directions at a fixed interval. Unfortunately, traffic flow for most of the time is not symmetric, resulting in unnecessary traffic congestion. One study implemented DSRC-actuated traffic lights using off-the-shelf hardware and software to reduce traffic congestion by prioritizing *connected vehicles* [30]. The significant reduction in traffic congestion despite a low *connected vehicle* penetration rate, combined with a cost-effective implementation, makes this approach easily deployable. Another approach makes use of a centralized server to preempt all traffic lights (i.e., displaying a red light to all directions) when an ER is approaching [4]. The intent is to stop all traffic such that no driver will collide with the ER.

Consequently, they cannot control traffic flow without traffic lights and may cause more chaos in nearby roadways. Similarly, another approach entails giving the direction of an approaching ER the right-of-way (i.e., displaying a green light) such that vehicles can move and clear a path [3]. This approach does not warn civilian drivers of the approaching ER, and it also relies heavily on the presence of modified traffic lights to control traffic flow.

2.5 Conclusion

This chapter highlighted the importance of *connected vehicles* and the multitude of advantages they offer over regular vehicle's daily use and emergencies, as well as their respective limitations. We explored existing literature that leverages ITS applications and *connected vehicles* to combat the perception, communication and processing issues civilian drivers face in emergencies.

Chapter 3

Methodology

3.1 Introduction

Given the average driver's biological senses, they only have a few moments to react upon acknowledging the warning signals from ERs. Within these moments, the drivers must identify the ER's location and heading, understand their maneuver options, and safely execute their plan. Unfortunately, ERs are often upon the drivers (i.e., within 150-meters of them) before they can clear a path, causing chaos and congestion. These increases in traffic volumes around and ahead of ERs constitute a significant cause for delays when responding to emergencies and increase the risk of other accidents [1, 3, 4, 6]. By creating an emergency route avoidance system, we aim to proactively guide civilian drivers away from ERs such that they maintain a distance greater than 150-meters at all times. This chapter will outline how the data is collected, how we designed the software, and how the experiments will be performed.

3.2 Research Design

Before the emergency guidance experiment in this thesis can begin, a mobile application and centralized server are needed. The server will facilitate route generation for civilian vehicles and ER vehicles communicated to the driver through the application.

Figure 3-1: An example of overlapping routes for ERs and civilian vehicles.

We chose the origins and destinations to mimic a fire-related emergency and a student commuting to school. The ER representing a firetruck originates near a fire station (2028 Madden Blvd, Oakville, ON L6H 3L6) and travels to two possible locations based on the scenario. In one instance, the destination is a plaza (1130 Eighth Line, Oakville, ON L6H 2R4), and in the other instance, it is along the side of the road somewhere along the route of the civilian vehicle. Simultaneously, the civilian driver, a student, starts from a representation of home (2163 Sixth Line, Oakville, ON L6H 3N7) and commutes across town to school (1430 Trafalgar Rd, Oakville, ON L6H 2L1). We chose these locations to ensure Google Maps would return the same overlapping routes, as shown in Figure 3-1.

The application will only be developed for the Android platform to keep development times short and minimize costs. To avoid possible compatibility issues and to reduce setup times when configuring the participants' phones, we will instead provide them with a phone preconfigured for our experiments.

3.3 Data Collection Methods

3.3.1 Participants

Volunteers will be involved in this experiment. All participants must have a valid driver's license and an insured vehicle. The participants must also be willing to commute to Oakville, Ontario, Canada. We planned to have the participants sampled from Sheridan College's population in Oakville. Unfortunately, with the introduction of remote learning due to COVID-19, we opted for convenience sampling. Each participant will be told that the experiment would involve using vehicular GPS tracking and evaluates how they react with a vehicle in the presence of an *active ER*. We also inform them that they only need to complete an even number of the six total variations, and we will compensate them for their time and gas.

3.3.2 Mobile Application

We provide the participants with a mobile phone equipped with our application and the required features such as GPS and cellular data to communicate with our server. The phone is to be mounted on their vehicle's dashboard, enabling them to read the display while driving safely.

The application tracks the vehicle's position in real-time using the GPS module built into the mobile phone, providing longitude and latitude values. We deduce the vehicle's speed and heading by calculating the differential between their current location and the previous location.

The server provides the client (ER or civilian driver) with their route based on their origin and destination coordinates. The server also tracks and uses the client's current location, speed, and heading to predict when and where a civilian vehicle and ER are likely to collide (Figure 3-2). If a collision is predicted, the routes for any involved civilian vehicle will be updated, guiding them away from the collision site.

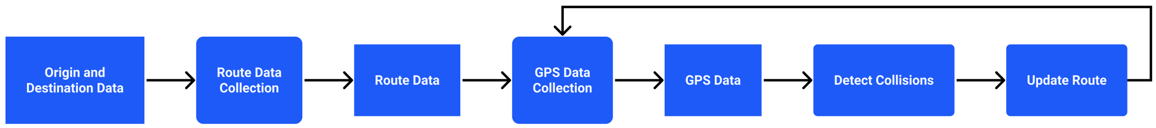

Figure 3-2: Main pipeline used to build Route Avoidance System using GPS.

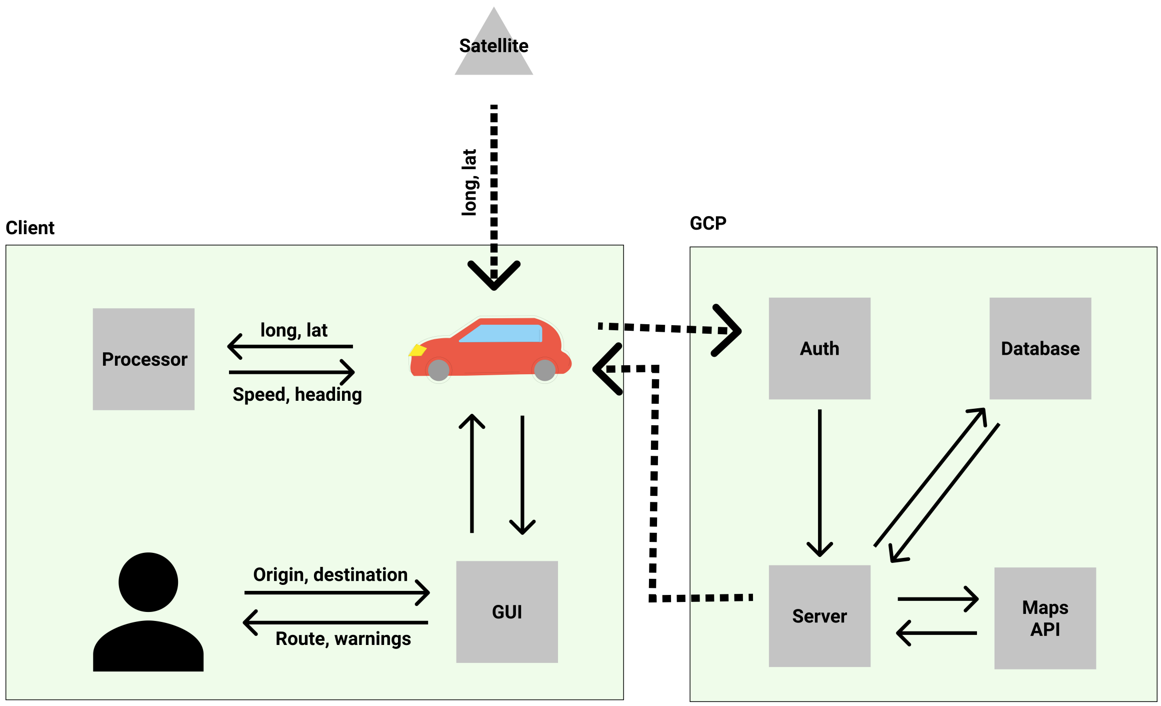

Figure 3-3: Software System Design Diagram.

3.4 Software & Technology Related Design

3.4.1 System Architecture Design

As shown in Figure 3-3, our *Route Collision Avoidance System* comprises of three major entities:

1. Client component;
2. Cloud component; and
3. GPS satellites.

The participants interface with our system in the client component through our app's GUI, either a mounted smartphone or an embedded screen in the vehicle's dashboard. The interface is primarily a map view, showing the user's route, directions, and warning signals. Initially, we planned to allow the user to enter their origin and destination locations, but we opted to hardcode the locations for our experiment's purposes and to ensure consistent scenarios between each experiment and participant. The application requires a GPS module to estimate the vehicle's current location up to 20 meters [31] by communicating with GPS satellites. The application then locally calculates the vehicle's average speed and heading by a comparative analysis between consecutive GPS readings [32, 33]. Every sixty-seconds, the application saves a snapshot of the vehicle's current speed, heading, and location, storing it in local memory. The client application is also responsible for updating the cloud-based system with the new batch of snapshots every five-seconds.

The authentication node is an essential middleware between the client and our server components, distinguishing each client's identity, including civilian drivers or ERs. The server node within the cloud component is responsible for consuming traffic data from the client component, processing and comparing the data to predict route collision, generating collision avoidance routes, and updating the affected clients. When a client initiates communication with the server, the client provides its origin and destination locations, and the server responds with the optimal route provided by the Google Maps API and modified by our *path collision avoidance algorithm*. As the client begins and continues its commute along the provided route, the server node uses the collected snapshots to monitor the distances between civilian drivers and *active ERs*, storing the results in a cloud database for later analysis.

3.4.2 Route Collision Detection Algorithm Design

The server is responsible for predicting when and where civilian vehicles might collide with *active ER*s and decides how best to avoid the collision. The pseudocode in Figure 3-4 elaborates on the process of detecting all possible collision points, and Figure 3-5 visualizes the process. The Directions API by Google Maps provides an array of intermediate steps between an origin and destination and a polyline that connects them. From the PolyUtil library, the 'locationIndexOnEdgeOrPath' function takes a

```
function FindCollisionPath(er_polyline, cv_polyline, er_steps, cv_steps)
    overlaps = []
    overlaps.append(findPathOverlaps(er_polyline, cv_steps))
    overlaps.append(findPathOverlaps(cv_polyline, er_steps))
    overlapPolyline = generatePolyline(overlaps)
    return {overlapPolyline, overlaps}
end function

function FindPathOverlaps(polyline, steps)
    result = []
    for step in steps do
        overlapPosition = locationIndexOnEdgeOrPath(step, polyline)
        if overlapPosition > -1 then
            result.append({step, overlapPosition})
        end if
    end for
    return result
end function
```

Figure 3-4: Pseudocode for path collision detection between the routes of an ER and civilian vehicle.

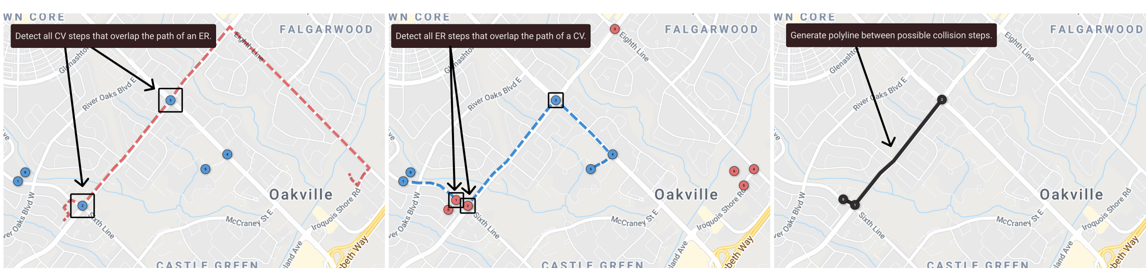

Figure 3-5: Illustration of the path collision detection algorithm between the routes of an ER and civilian vehicle.

```
function ComputeDetour(collisionPath, cv, er)
    stepsToAvoid = []
    waypoints = GenerateWaypoints(collisionPath.polyline)
    for step in waypoints do
        cv_arrivalInMinutes = CalculateArrivalTime(step, vc.currentSpeed, vc.currentLocation, "minutes")
        er_arrivalInMinutes = CalculateArrivalTime(step, er.currentSpeed, er.currentLocation, "minutes", SAFETY_THRESHOLD)
        absArrivalDifferenceInMinutes = |ar_arrival - cv_arrival|
        if absArrivalDifferenceInMinutes <= 2.0 then
            stepsToAvoid.append({step, absArrivalDifferenceInMinutes})
        end if
    end for
    cv.route = Detour(cv.route, stepsToAvoid)
    return cv
end function
```

Figure 3-6: Pseudocode for collision avoidance algorithm.

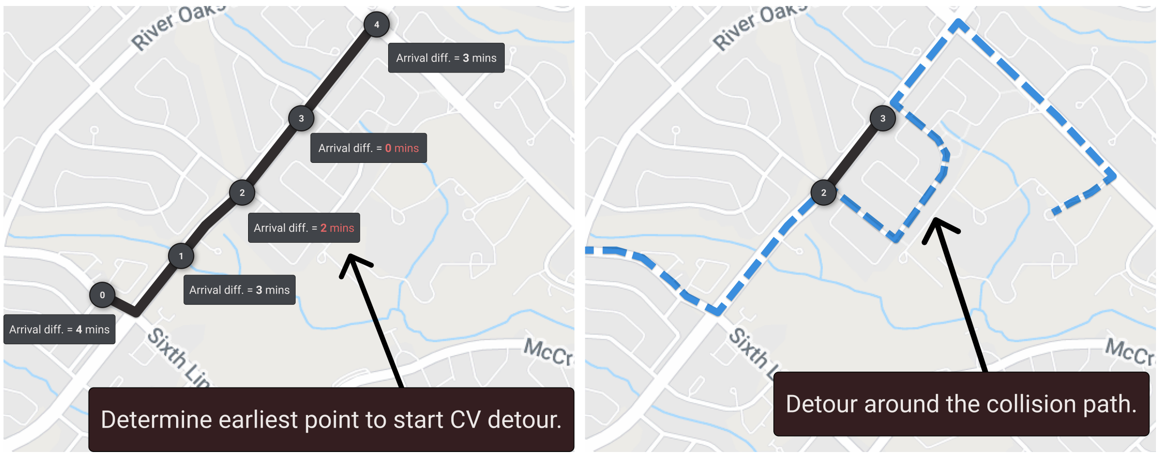

Figure 3-7: Illustration of the collision avoidance algorithm.

polyline and a single location and checks if the point lies on the line. We leverage this function to identify if and where the routes overlap for ERs and civilian vehicles and generate a polyline between all collision steps.

3.4.3 Collision Avoidance Algorithm Design

Knowing the overlapping regions between the two routes is not enough to determine whether a collision would happen. The pseudocode in Figure 3-6 elaborates on the process of predicting the exact locations and times that collisions could happen based on the average speed and current locations of both vehicles. As shown in Figure 3-7, the algorithm compares the arrival times for both vehicles within the array of possible collision locations provided by the *path collision detection algorithm*. To account for any estimation errors from the average speeds and GPS accuracy, we arbitrarily chose a period of two-minutes to be a responsible minimum window that allows these two vehicles to approach the same location without *route collisions*. The algorithm then decides that a detour is necessary if the absolute difference between their times is less our time threshold of 2-minutes.

3.5 Comprehensive Experiment Framework

Before each experiment, we allow the participants to get familiar with following navigational instructions from a mounted smartphone while driving by guiding them to their respective starting locations and sampling the various warning signals between each of the six scenarios. When both the participants (civilian vehicle and ER) have arrived at their starting places for a particular scenario and confirmed that they are ready to begin the experiment, the application will initiate a countdown timer. When the timer ends, the application displays their new destination and the route they must follow.

The civilian driver must follow proper protocol when being approached by an *active ER*, such as slowing down, moving over, and halting until the ER is 150 meters away [9, 10]. The application helps the driver identify our acting ER by quietly emitting a siren-like noise whose volume increases proportionally to the two vehicles' decreasing distance.

There are three scenarios with unique origin and destination locations and starting delays. There are two copies of each of these three scenarios, one with and without the *Route Collision Avoidance algorithm*. As the participants drive towards their destination along the route provided, our system will track and record their progress and save it in our cloud database for later analysis.

In scenario one, shown in Figure 3-8, we aim to create a situation where the civilian driver is approached from behind by an *active ER* exceeding speed limits. We observe how fast and efficiently the civilian driver yields or evades the ER. To achieve this, the civilian driver a start delay of zero seconds (i.e., no delay) while the ER driver has a start delay of two minutes. The difference in delay allows the civilian driver to drive without any *active ER* for a short period. After this period, the vehicles' distance

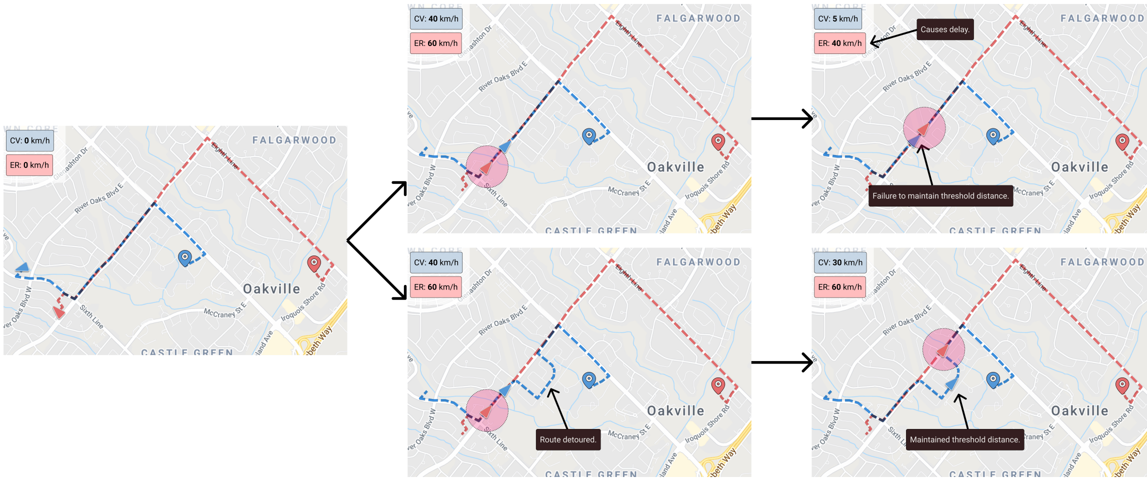

Figure 3-8: How the civilian driver reacts to an approaching ER when their distance falls below the safety threshold.

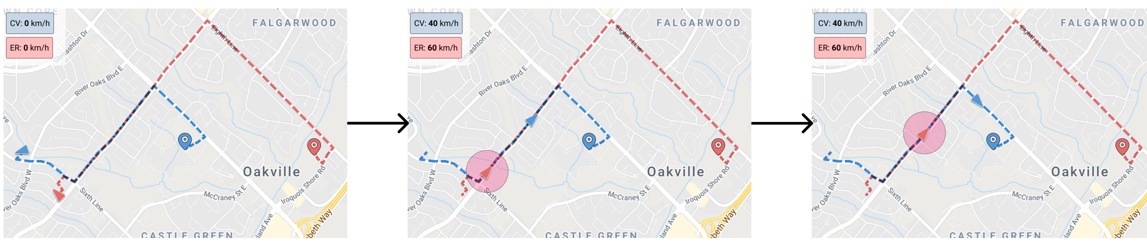

Figure 3-9: How the civilian driver reacts to an approaching ER when their distance never falls below the safety threshold.

should be small enough that the ER can catch up and overtake the civilian vehicle before their routes diverge. In the version without the *Route Collision Avoidance algorithm*, the civilian driver relies only on a siren-like warning emitted from the application as the ER inevitably approaches and overtakes the civilian vehicle. In the version with the algorithm, the system will periodically change the civilian vehicle's route to avoid having the two vehicles break the safety threshold.

In scenario two, as shown in Figure 3-9, we aim to create a situation where an *active ER* approaches the civilian driver but whose distance can not be reduced before their respective routes diverge. With that, the civilian driver has a zero-minute start delay and the ER driver a five-minute start delay. This delay difference distances the two vehicles such that they will never overlap during their commute. We do not expect any difference between the versions with or without the algorithm as no detour

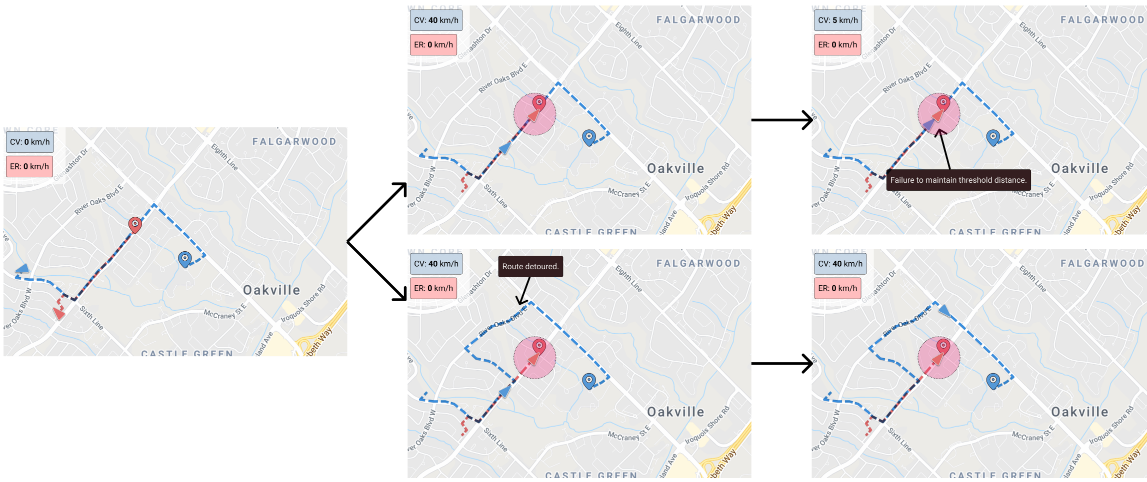

Figure 3-10: How the civilian driver reacts to an upcoming ER when their distance falls below the safety threshold.

would occur, but the civilian driver may acknowledge the ER via the siren signal and change their driving behaviour.

For scenario three, the aim is to create a situation where a civilian driver approaches a parked *active ER*, as depicted in Figure 3-10. We give the civilian driver a five-minute start delay and the ER a zero-minute start delay. Additionally, the ER's destination now resides on the default route for the civilian vehicle, representing the event that a civilian vehicle approaches an accident site. The civilian driver has to slow down in the version without the algorithm as it passes the parked ER. In the second version, the civilian driver is detoured around the road using our system, ensuring the safety threshold is maintained.

3.6 Data Analysis Methods

Throughout each experiment, we record snapshots containing data of both vehicles. By performing comparative analysis between both vehicle's locations at identical timestamps, we can measure the trend of their distance with and without the support for our *route collision avoidance algorithm*. We will also compare the estimated arrival times to the collision sites to the actual arrival times to test our predictions' accuracy.

3.7 Research Validation

The Ministry of Transportation of Canada made it law to keep at least 150-meters (aka. legal threshold) from any *active ER* [9, 10]. One of the leading factors contributing to ER crashes is the failure to maintain this distance. Although ERs use warning signals to gain civilian driver's attention, they are proven inadequate as providing enough context, confusing drivers and leaving them to decide for themselves how best to react [11]. The data analysis phase results include the absolute distance trends between the vehicles with and without the *Route Collision Avoidance algorithm* in various situations. By comparing which versions resulted in greater absolute distances and quicker response times, we can determine whether our system offers advantages over the status quo (i.e., driving without guidance) in any or all situations in this report.

3.8 Assumptions & Limitations of the Study

In the real world, ERs use the *code three running* option when responding to calls [1, 2], enabling them to exceed speed limits and use warning signals like a siren. The ability to exceed speed limits means they can overtake any law-abiding driver on the road. To mimic their range of speed within our experiments without breaking the law, we chose to constrain our participants' maximum speeds to 70% of the speed limit of any given road. We reserve the remaining 30% for our ER drivers. As for mimicking the sirens used by actual ERs, based on Section 75(6), it is illegal in Ontario to mount any horn that may be mistaken for an emergency siren under the Highway Traffic Act [9, 10]. Alternatively, we chose to have the application emit an initially quiet sound whose volume increases proportionally to the vehicles' decreasing distance. This noise will inform the civilian driver of a nearby *active ER* without providing context to its exact current location and heading.

3.9 Summary

In this chapter, we described the design and rationale of the experiments' setup, defined the system architecture design and data collection processes, explained the various experiment scenarios, explaining how the results will be used to validate our research, and highlighted any assumptions and limitations.

Bibliography

[1] Hongwei Hsiao, Joonho Chang, and Peter Simeonov. Preventing emergency vehicle crashes: Status and challenges of human factors issues. *Human factors*, 60(7):1048–1072, 2018.

[2] Ali S. Al-Ghamdi. Emergency medical service rescue times in riyadh. *Accident analysis and prevention*, 34(4):499–505, 2002.

[3] A. Buchenscheit, F. Schaub, F. Kargl, and M. Weber. A vanet-based emergency vehicle warning system. In *2009 IEEE Vehicular Networking Conference (VNC)*, pages 1–8, 2009.

[4] R. C. Vlad, C. Morel, J. Y. Morel, and S. Vlad. A learning real-time routing system for emergency vehicles. In *A Learning Real-Time Routing System for Emergency Vehicles*, volume 3, pages 390–395. IEEE, 2008.

[5] R. A. Retting, A. F. Williams, D. F. Preusser, and H. B. Weinstein. Classifying urban crashes for countermeasure development. *Accident analysis and prevention*, 27(3):283–294, 1995.

[6] Sukru Y. Gelbal, Bilin Aksun-Guvenc, and Levent Guvenc. Collision avoidance of low speed autonomous shuttles with pedestrians. *International journal of automotive technology*, 21(4):903–917, 2020.

[7] Emergency vehicles, 2020.

[8] Law enforcement officer motor vehicle safety in 2020, 2020.

[9] Move over for emergency vehicles - it's the law!, 2021.

[10] Dealing with particular situations, 2020.

[11] Sr McDonald, William G. PhD thesis.

[12] C. Huang, C. Yang, C. Tseng, and C. Chou. A centralized traffic control mechanism for evacuation of emergency vehicles using the dsrc protocol. In *2009 4th International Symposium on Wireless Pervasive Computing*, pages 1–5, 2009.

[13] Preview of motor vehicle traffic fatalities in 2019-2020, 2020.

[14] Leading causes of death in 2021, 2021.

[15] 2021 driving statistics: The ultimate list of canadian driving, 2021.

[16] More vehicles on the road in 2019, 2020.

[17] Emission impacts resulting from vehicle idling in 2016, 2016.

[18] Natalia Drop and Daria Garlinska. Evaluation of intelligent transport systems used in urban agglomerations and intercity roads by professional truck drivers. *Sustainability*, 13(5):2935, 2021.

[19] Smith K. Khare. Fast-track message authentication protocol for dsrc using hmac and group keys. *Applied Acoustics*, 165:107331, 2020.

[20] PhD. Benekos, Ioannis, PhD. Mavromatis, Stergios, Alexandra Laiou, and George Yannis. The use of intelligent transportation systems in risk and emergency management for road transport planning and operation. *Institute of Transportation Engineers.ITE Journal*, 89(1):44–49, 01 2019.

[21] K. A. Hafeez, L. Zhao, B. Ma, and J. W. Mark. Performance analysis and enhancement of the dsrc for vanet's safety applications. *IEEE Transactions on Vehicular Technology*, 62(7):3069–3083, 2013.

[22] Karzan Bahaaldin, Ryan Fries, Parth Bhavsar, and Plaban Das. A case study on the impacts of connected vehicle technology on no-notice evacuation clearance time. *Journal of advanced transportation*, 2017:1–9, 2017.

[23] Md Salman Ahmed, Mohammad A. Hoque, Jackeline Rios-Torres, and Asad Khattak. Demo: Freeway merge assistance system using dsrc. In *Proceedings of the 2nd ACM International Workshop on Smart, Autonomous, and Connected Vehicular Systems and Services*, CarSys '17, page 83–84, New York, NY, USA, 2017. Association for Computing Machinery.

[24] Global v2x market for automotive market by communication type, by connectivity type, by offering type, by technology type, by propulsion type, by company and by geography, forecast & opportunities, 2025: Global v2x market for automotive market by communication type (v2c, v2g, v2p, v2i, v2v, v2d), by connectivity type (dsrc connectivity and cellular connectivity), by offering type (hardware and software), by technology type (emergency vehicle notification, automated driver assistance, passenger information system, line of sight and others), by propulsion type (ice vehicles and electric vehicles), by company and by geography, forecast & opportunities, 2025, Jun 26 2020.

[25] F. Lyu, H. Zhu, N. Cheng, H. Zhou, W. Xu, M. Li, and X. Shen. Characterizing urban vehicle-to-vehicle communications for reliable safety applications. *IEEE Transactions on Intelligent Transportation Systems*, 21(6):2586–2602, 2020.

[26] I Wagner. Road accidents in the united states, 2020.

[27] Biraj Subedi, Sherif M. Gaweesh, Guangchuan Yang, and Mohamed M. Ahmed. Connected vehicle training framework and lessons learned to improve safety of highway patrol troopers. *Transportation research record*, 2674(12):447–463, 2020.

[28] Jie Ni, Jingwen Han, and Fei Dong. Multivehicle cooperative lane change control strategy for intelligent connected vehicle. *Journal of advanced transportation*, 2020:1–10, 2020.

[29] S. R. Rizvi, S. Olariu, M. C. Weigle, and M. E. Rizvi. A novel approach to reduce traffic chaos in emergency and evacuation scenarios. In *2007 IEEE 66th Vehicular Technology Conference*, pages 1937–1941, 2007.

[30] Ozan K. Tonguz and Rusheng Zhang. Harnessing vehicular broadcast communications: Dsrc-actuated traffic control. *IEEE transactions on intelligent transportation systems*, 21(2):509–520, 2020.

[31] Find and improve your location's accuracy, 2021.

[32] Kevin Godden. Algorithm to calculate speed from two gps latitude and longitude points and time difference, 2013.

[33] Kiel von Lindenberg. Comparative analysis of gps data. *Undergraduate Journal of Mathematical Modeling: One + Two*, 5(2), 2013.

Appendix A

Tables