Comparison of Connected Automated Vehicle to Pedestrian Interaction Systems to Reduce Vehicle Waiting Times

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Abstract—As autonomous vehicle technology starts to become more common in daily life, a degree of uncertainty arises with respect to pedestrian safety. As the technology gets more and more advanced, there becomes greater possibility for lapses in connectivity and miscommunications between pedestrians and vehicles. Hence, it is important that society finds the best way for pedestrians to interact with all types of vehicles in order to keep them safe, in the midst of a continuous increase in pedestrian incidents. Thusly, the focus of this investigation is to determine the feasibility of crossing intersections reliant on pedestrian to vehicle connectivity. As vehicles increase in complexity with respect to their interaction with other vehicles, pedestrians, and the environment, intersections may not require physical infrastructure - autonomous vehicles may be built to recognize pedestrians and to stop accordingly, and signal timing may be periodically uploaded in the form of continuously changing datasets. Such intersections have ambiguous effects on pedestrian and vehicle interactions, partially due to the uncertainty of afore mentioned connectivity dynamics. Connected and Autonomous Vehicles (CAVs) rely primarily on obstacle detection systems, a main connectivity dynamic between pedestrians and vehicles, to tell them to stop for pedestrians. These systems, many still deep in the development phase, may be flawed. This paper describes an experiment developed with the intention of comparing a traditional obstacle detection approach to pedestrian crossing with one in which vehicles stop based on pedestrians notifying them of their presence. More specifically, in order to cross, pedestrians must “signal” to vehicles that they are in the crossing area (in the real world, this could be done on a mobile phone) so that the vehicles will stop for them. The model, developed using Simio, outputs queue timing and density values for the vehicles and pedestrians. Data was gathered related to average wait times and flow of pedestrians and vehicles over a simulated time frame of a 4 week period. The results indicate that utilizing a pedestrian to vehicle communication framework, either in place of or in addition to traditional obstacle detection and avoidance systems, would prove beneficial in developing more efficient intersections.

Index Terms—CAV, queue, waiting, model, obstacle detection, autonomous, mobile phone

I. Introduction

As connected and autonomous vehicle (CAV) technology continues to develop, it will not be long before roadways worldwide will be dominated by vehicles which navigate by themselves. In addition to the benefits of this technology, including increased efficiency and potentially fewer vehicle incidents, the developments come with tremendous uncertainty. Are current obstacle detection technologies, developed to prevent CAVs from impeding the surrounding environment, sufficient to deal with complex situations such as pedestrian buildup? An investigation was conducted to attempt to determine how important vehicle connectivity can be in relation to preventing delays that are caused by object detection technology by creating a computer model representing a pedestrian/vehicle crossing. The model compares a more mainstream obstacle detection system with an “A-B” threshold crossing system, in which pedestrians themselves communicated with oncoming vehicles. The model was simulated to produce vehicle queue waiting times, which were used to make conclusions about the benefits of the two connected vehicle systems. With the future impacts of CAVs and the technology surrounding them being so uncertain, this study into the effectiveness of both detection systems could lead to a variety of positive pedestrian safety and traffic efficiency impacts.

II. Background

There is an ongoing societal responsibility to address pedestrian safety issues by considering alternative infrastructure changes, societal attitudes, and technological tools to keep vehicles and pedestrians from unwantedly crossing paths. The number of pedestrian injuries and fatalities continues to increase according to the Governor's Highway Association; the numbers from 2019 are higher than they have been in the last 30 years.[1] The addition of CAVs to current transportation systems adds a layer of complexity to this ongoing problem. Although CAVs present the opportunity to reduce vehicle crashes, some pedestrians are concerned about how CAVs might make the issue even worse. One case that often gets brought up by concerned individuals comes from Waymo, an AV technology group. Waymo reported that 18 of its robo-taxi service vehicles were involved in an accident with pedestrians. [2] Waymo is just one of the companies that has reported issues in its AV testing. It is reports like these that have led to the many uncertainties with CAV technology, such as the obstacle detection system. CAVs will have a multitude of impacts on society but even before their mass implementation, there are discussions and concerns about their true level of safety. It was determined thusly to investigate potential short comings of CAV obstacle detection systems. Xiaoyan Yu and Marin Marinov examined the obstacle detection technology and its current status in 2020. Yu and Marinov state that "a sophisticated obstacle detection system will detect any static, moving object and alarm for any potential risk of accidents." But in their research, the duo found that the detection system was not successful during night, smoke or poor weather. [3] In addition to the environmental concerns of obstacle detection systems, many studies have shown that different obstacle sensing technologies need to be fused together in order to get a completely effective detection system. These complications with the detection system are being worked on every day. Something that is not often researched or talked about is the possible impact of CAVs on vehicular traffic. After researching a variety of papers on the dynamic between pedestrians and CAVs, attention was turned to the impact of the object and A-B detection systems on traffic flow.

III. Methodology

A. Generalized Model and Methodology

One of the most important factors in the implementation and working of an autonomous car is its ability to detect obstacles. Cars should "be able to detect the obstacles...to avoid accident and collision" [4]. Generalized systems known as Advanced Driver Assistance Systems (ADAS) have been developed which integrate a computing unit into vehicles to accurately model the driving environment, as well as features such as adaptive cruise control and lane keeping assistance.

ADAS will make fully autonomous driving possible, primarily through obstacle detection technologies [3]. Obstacle detection systems may be flawed due to their potential for false detection: sensors have been known to mistake "a person standing idle on the sidewalk for one preparing to leap into the road." [3] At a busy intersection, in which all vehicles approaching are autonomous, the potential for a false detection, causing unnecessary vehicle stoppage, may lead to significant traffic buildup. To remedy this issue, a system known as an "Integrated Smart Spatial Exploration System" (INSPEX) can be created in which a mobile device communicates with the infrastructure (or vehicle) to "let it know" that they are in the area. Hence, the goal of the experiment was to determine partial benefits of an INSPEX connected vehicle crossing system, where autonomous vehicles would cross the intersection after pedestrians had crossed both an "A" threshold and "B" threshold, versus a more mainstream "obstacle detection" crossing system where vehicles would stop if a pedestrian was detected in a certain area. Utilizing an INSPEX (which can be called an "A-B" system), where the pedestrian would communicate their intention to cross the intersection, rather than an "obstacle detection" system where the vehicle is unsure whether or not the pedestrian intends to cross, may present significant benefits with respect to vehicle waiting times at a busy intersection.

B. Technical Model and Data Collection

A main point of comparison between the two systems relates to the time vehicles waited for pedestrians to cross through the intersection, so our team believed it to be pertinent to focus primarily on vehicle waiting times. The data collected for our investigation was taken from a team generated model of a pedestrian-vehicle interaction at an intersection using the modeling software Simio. A simple system was developed consisting of a pedestrian inception source, vehicle inception source, a server (acting as the "intersection"), and a separate endpoint for the vehicles and pedestrians after processing through the server. There were two processing states for the

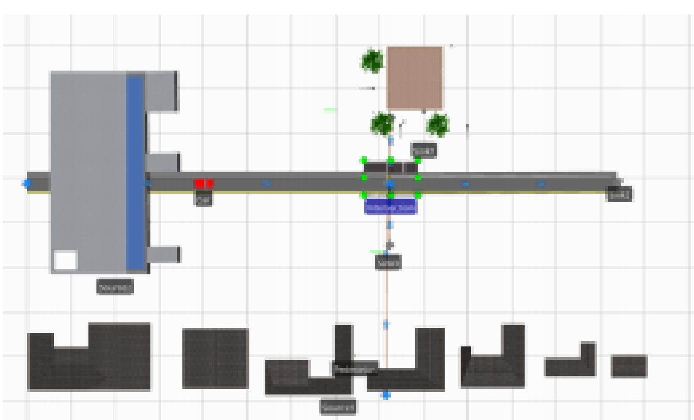


Figure 1. Overhead view of the Simio Model

system: one representing the "A-B" model (treatment), and

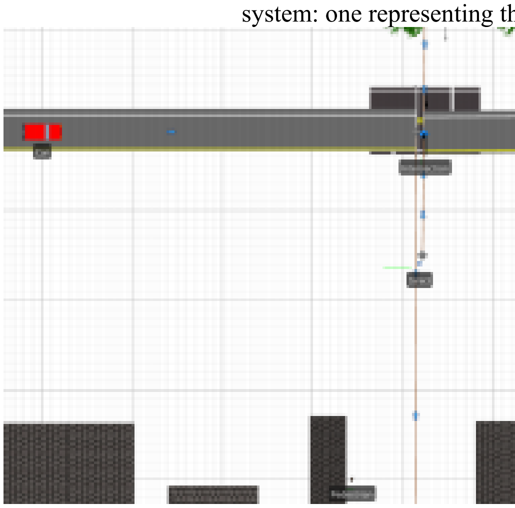


Figure 2. Closeup overhead view of intersection and model entities.

one representing an "obstacle detection" model (control). The treatment model was set up so that pedestrians were prioritized over cars in processing; if a pedestrian was processing through the model at the same time as multiple vehicles, the pedestrian would be processed before the vehicles as if the vehicles were aware of the pedestrian and stopped accordingly. The control model was set up similarly, however there was more variation in pedestrian behavior including balking and waiting which forced vehicles to continue to wait even if the pedestrians had not yet crossed. This would create a situation where a pedestrian may have been "standing" at the crosswalk with no intention to cross, which tricked the vehicles into stopping continuously to wait - as in an "obstacle detection" design. Pedestrian and vehicle processing times - namely, the times for pedestrians and vehicles to cross the intersection once allowed - were generated using exponential distributions with theorized values of 19.173s and 6.71s, respectively. These values were generated assuming the "intersection" was roughly 30m in width and length, and that vehicles traveled at an average speed of 10mph through the intersection and pedestrians walked at an average speed of 3.5mph. Vehicle arrival times were generated through a model created by Austin Angulo, a graduate student at the University of Virginia who developed the times through his own research, and pedestrian arrival distributions were generated using an assumed average arrival rate of 150 pedestrians per hour [3]. Using the arrival and processing times, and model set up, the Simio model gave output continuously of vehicle queue waiting times over the simulation period. Such waiting times were the primary source of data for analysis.

C. Analysis Method

In an effort to compare the "A-B" model to the "Obstacle detection" model vehicle queue waiting times were prioritized as a primary metric. The simulation was replicated for a 4 week period 25 times, generating a robust data source. Given this, vehicle queue waiting times from each of the two models

Type	Process Time
1	Random.Exponential(19.173)
2	Random.Exponential(15)
3	Random.Exponential(6.71)

Figure 3. Simio implementation of statistical distributions of processing times

were analyzed through a comparative t-test of sample means. For two samples of unpaired data, it is understood that

$$H_0 : X_1 = X_2 \quad (1)$$

$$H_1 : X_1 != X_2 \quad (2)$$

$$T = (\bar{X}_1 - \bar{X}_2)/\sqrt{(s^2_1/N_1) + (s^2_2/N_2)} \quad (3)$$

where

H_0

represents the null hypothesis that both sample means are equal,

H_1

represents the alternate hypothesis that the means are unequal, N_1

the sample size of the treatment,

$$N_2$$

the sample size of the control, and the s values the sample standard deviations of the treatment and control. T represents the test statistic.

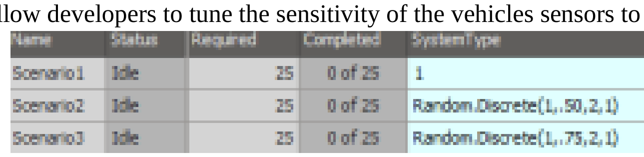
IV. Results

Multiple scenarios were developed, each modeled to reflect a system where the AV is able to identify a percentage of pedestrians either walking along the street(pedestrian type 2) or those seeking to cross using the app (pedestrian type 1). Each scenario was replicated 25 times using a discrete distribution function in simio with the following percentages:

Table 1. Pedestrian type distributions

Pedestrian Type 1 (x100%)	Pedestrian Type 2 (x100%)
1	0
0.75	0.25
0.5	0.5

The mixed percentage scenarios represented a hybrid system where the vehicle would focus more or less of its computing power trying to identify and simulate the actions of each pedestrian while also relying on the app to communicate with pedestrians. This would allow developers to tune the sensitivity of the vehicles sensors to reduce confusion when trying to



Name	Status	Required	Completed	SystemType
Scenario1	Idle	25	0 of 25	1
Scenario2	Idle	25	0 of 25	Random.Discrete(1,.50,2,1)
Scenario3	Idle	25	0 of 25	Random.Discrete(1,.75,2,1)

Figure 4. Simio implementation of percentages and functions.

object detect. These specific percentages were chosen due to limitations with the simio modeling process, specifically there was no reliable way to develop a sliding scale of percentages that could be used to optimize computing power. As expected, it was found that in the system where 100% of pedestrians used the app when intending to cross, the average number of time spent per vehicle over the 4 week period was the lowest at 2.09 minutes. Within the hybrid systems, it was found that a 50-50 split would result in an average in system time of 4.73 minutes while the 75-25 system had an average 6.05 minutes. The hybrid system can be envisaged to be the best in a real world scenario as it encapsulates object recognition. The data is displayed in the following table:

Table 2. Final Results

Scenario	Mean (minutes)	Std. Deviation (minutes)	Number of Observations
All App	2.094	0.006	80678
75% App and 25% Detection	6.052	0.103	80688
50% App and 50%	4.734	0.056	80658

Detection			

In comparing the two systems, a two tailed t-test of sample means at a 0.05 confidence level was utilized to determine if there were any statistically significant differences in average travel times. Comparing the "All App" scenario with the "75% App 25% detection", it was determined that the means are statistically significantly different with a p value less than 0.0001 at a 0.05 confidence level. Comparing the "All App" to the "50% App, 50% Detection", it again can be found that the means are statistically different with a p value less than 0.0001 at the 0.05 confidence level. Comparing the two hybrid systems again yielded statistically significant differences with a p-value less than 0.0001.

V. CONCLUSION

With this data, it can be theorized that by using the app, the travel times for AV's can be improved. The hypothesis was that the difference between each mean would not be equal to 0 i.e. each of these hybrid scenarios would have a higher average time in system than the system where all pedestrians use the app. Using Welch's t-test, the team determined that each of the average times spent in the system were indeed statistically significantly different from the null mean given by the system with all pedestrians using the app. By having pedestrians interact with these vehicles in a safe and reliable manner, not only can pedestrian accidents be reduced, travel time for passengers can be improved.

VI. LIMITATIONS

A large portion of the data used to model vehicle and pedestrian speeds were collected from research from the internet that has the potential to be incorrect, outdated, or designed for very specific use cases (such as the pedestrian arrival volumes, taken from a generic planning standard which was reported in 1965). Additionally, the system models a closed system where no other extraneous variables/objects are in play. This limits how accurate the time in the system could be because it does not account for scenarios where objects such as bicycles are involved. The system also does not account for jaywalkers or anyone who may stray into the street while trying to avoid an object which would cause any vehicle, whether autonomous or not, to slow down or even stop. It cannot definitively be concluded that the app and the surrounding communication system does work as intended in all cases, but it does make a strong case for having infrastructure that can communicate that to vehicles.

VII. FUTURE WORK

Ideally, the work will drive others to further examine and investigate current and future technologies which are being integrated into autonomous vehicles. Considering the scale of autonomous vehicle integration – potentially, CAVs will completely dominate roadways – every aspect of autonomous vehicle technology should be investigated to ensure there are no deep shortcomings or dangers of this advanced technology. Rather than focusing on the explicit functionality of CAVs at an individual level, simulation studies of full roadway systems may be suggested, with investigations targeted at specific technologies used in CAV development. For example, a study could be conducted that examines the effectiveness of LiDAR sensors versus traditional camera sensors with respect to traffic pattern efficiency with a road system populated solely with autonomous vehicles. Furthermore, studies could be conducted examining the effect of harmful outside actors on an autonomous system. Perhaps a cyberattack threatens autonomous vehicles and their internal technologies. How may this affect the vehicles, those around them, or the entire surrounding traffic area? Investigations could also be done to confirm the robustness of obstacle detection technology in the presence of large crowds, after a special event such as a concert in which large swaths of pedestrians will continuously both be crossing and in the side of the road. Will the obstacle detection system be overloaded, overwhelmed, or work properly? Investigations such as these help to ensure that CAV technology is being developed properly for its integration into society.

VIII. ACKNOWLEDGMENT

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