INVESTIGATION OF PEDESTRIAN-CYCLIST INTERACTIONS THROUGH MACHINE VISION

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Investigation of Pedestrian-Cyclist Interactions through Machine Vision

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For pedestrian-cyclist facilities where collisions and resulting injuries may not be fully covered in police reports, there is a need for improved safety indicators. After fifteen hours of video observation at Pickard Passageway, College Station, there appears to be four broad types of pedestrian-cyclist interactions: passing, weaving, turning, and avoiding. Within each of these behavior categories, there are both safe and unsafe maneuvers. In order to determine whether an event should qualify as a safety-critical event or near-miss, multiple factors should be taken into account, including relative distance, sudden change in velocity, and sudden change in path. While an improved understanding of the general interactions between pedestrian and cyclists in these underpass facilities can lead to an improvement of the safety research field, analyzing each path manually would take a prohibitively excessive time. This paper suggests ways in which machine learning can implement the behavior categorization of pedestrian-cyclist interactions for safety evaluation at pedestrian-cyclist facilities throughout the identification, classification, and safety evaluation phases.

ACKNOWLEDGEMENTS

I would like to thank my faculty advisors, Dr. Dominique Lord and Dr. Kay Fitzpatrick, for their valuable input and constant guidance throughout the research process. I would like to also thank the various people I have worked with at Texas A&M Transportation Institute for nurturing my passion for research and guiding me along my current path.

I would like to also thank Tyler Buffington, a fellow student at Texas A&M and a co-founder of the student organization Engineers Serving the Community, for inspiring me to pursue this project. A team in our organization originally developed a rudimentary mirror solution to mitigate conflict at the passageway, and I could not be more proud of how far this project has come.

TERMINOLOGY

The following terminology is employed throughout the thesis. It will be explained in context, and this section functions as an easy reference to the general definition of each of these terms.

Pedestrian-Cyclist Interactions	Any near-misses, conflicts, or collisions between a cyclist and a pedestrian.
Pedestrian-Cyclist Under/Overpass	Pedestrian-cyclist facilities that go above or below roadway grade to separate pedestrians and cyclists from motorized vehicles and provide improved safety conditions.
AdaBoost	Boosting algorithm designed to create a strong classifier from a set of weak classifiers (~50%).
Background Subtraction	Image processing method to remove pixels associated with the background by assuming the background is composed of the pixels that did not move between frames.
Kalman Filter	Algorithm that inputs speed, direction, and position over time to generate an optimized future prediction.
OpenCV	A library of programming functions aimed at real-time computer vision. These are written in C++. Bindings and wrappers exist in Python, Java, Matlab, Octave, C#, Perl, Ch, Haskell, and Ruby.
Hard-Negative Training	Process in machine learning where the inputs are explicit false positives and the output is correct false classification.

CHAPTER I

INTRODUCTION

In recent years, there has been an increased effort to improve vehicle-pedestrian and vehicle-cyclist interactions through the form of safety initiatives, integrated road networks, and awareness campaigns. These steps reflect a generally positive progression towards a safer infrastructure for pedestrians and cyclists; however, they tend to not address the interactions between pedestrians and cyclists. Pedestrian-cyclist interactions are when a pedestrian is in conflict with a cyclist, instead of with a motor vehicle. While the majority of these conflicts will occur on sidewalks or in neighborhoods, one particular area wherein pedestrian-cyclist interactions are prevalent are pedestrian-cyclist underpasses and overpasses. These bridges can either go over the pre-existent structures (overpass) or underneath them (underpass). Their primary benefit is to create an alternative pathway for pedestrians and cyclists separate from motor vehicle traffic.

Designed to improve safety of travel for pedestrians and cyclists, these passageways may still present a risk of collision for pedestrians compared to at-grade (e.g. sidewalks) alternatives. Even though motor vehicles have been removed from the equation, higher-speed vehicles – cyclists – are present. While underpasses/overpasses have a mix of traffic, they do not have the same level of traffic control and coordination. Accordingly, a risk of collision between pedestrians and cyclists may exist without preventative measures. Although they typically result in less severe injuries, Chong et al. indicate that pedestrian-cyclist collisions still can result in injury and do send people to the hospital (*1*).

One of the issues in evaluating pedestrian-cyclist facilities is the lack of a fundamental measure that quantifies their safety. The primary method to measure the safety of pedestrians and cyclists is to evaluate the crash data. Unfortunately, the data available is quite limited; especially for underpasses and overpasses. Efforts have been made to improve evaluations of crashes for pedestrians and cyclists, such as encouraging agencies to use the Pedestrian Bicycle Categorization (PBCAT) tool from the Pedestrian Cyclist Information website, but these crash evaluation methods are concerned with vehicle-pedestrian and vehicle-cyclist interactions (*2*). Other methods of evaluation for pedestrians and cyclists include Bicycle and Pedestrian Level of Service Ratings and Walking Security Index (*3*,*4*). However, both of these metrics are relative and indirect measures of safety based upon the site characteristics.

In order to gain an understanding of the safety conditions in a pedestrian-cyclist environment, the current body of research requires a significant time investment wherein the team gathers a significant amount of video data, collects surveys, and performs other traditional safety evaluations. Once the data is collected, student workers typically have to work for several months to complete the data reduction. While efficient on the cost-scale, these tasks cannot be objectively quantified or compared between student workers. Accordingly, without a consistent machine vision approach to analyze safety critical components of the interactions, a holistic measure that adequately represents the safety of a pedestrian-cyclist facility cannot be developed.

This paper suggests the development of an objective measure to quantify the number of near-misses of cyclist-cyclist and pedestrian-cyclist interactions and ways in which machine learning can be applied in future studies to estimate this measure. Through these near-misses from video footage, an objective measure of safety for these passageways can be applied and unsafe locations can be properly identified for remedial engineering.

CHAPTER II

METHODOLOGY

This chapter documents the methodology for how the data was gathered and subsequently discusses potential analysis paradigms in machine learning to evaluate the data. The first section describes the location and process for the data collection. The second section introduces potential machine learning solutions. The third section discusses the ways in which safety critical events can be evaluated.

Video Collection

In order to conduct this research, the first step was to choose a pedestrian-cyclist facility that would provide enough representative data to collect pedestrian cyclist interactions and merge them into similar categories. For this reason, the research team decided to focus on facilities with potential conflicts to ensure an adequate interaction sample size. After investigating these sites, Pickard Passageway was chosen. An aerial view of the facility from Google Earth (left) is provided alongside a wide-view picture on top of West Campus Garage (right) for perspective in Figure 1.

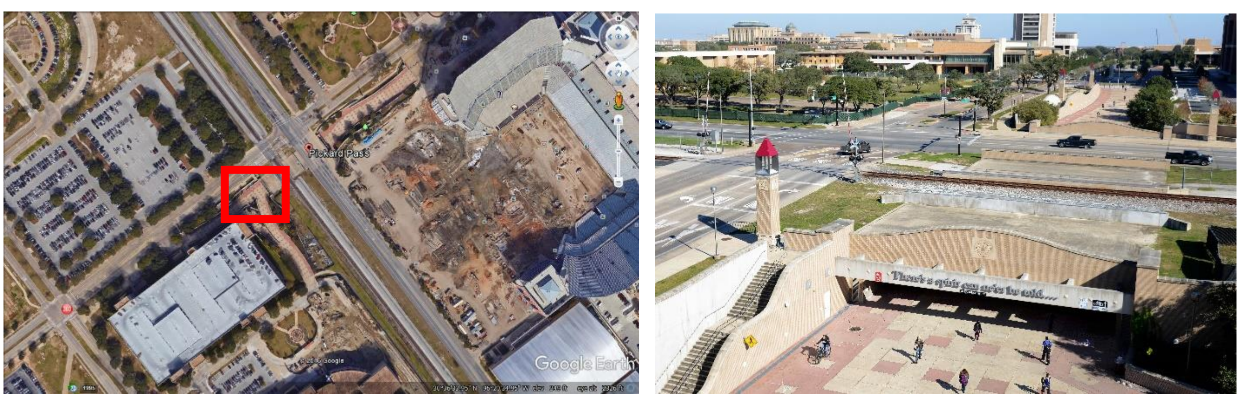


FIGURE 1 – Aerial and Side View of Pickard Passageway

Pickard Passageway is an example of a pedestrian-cyclist facility in College Station, Texas. It was chosen for its unique blind corner at the T-intersection, which may allow for more pedestrian-cyclist interactions to be observed. The video data was gathered from a camera placed in the window of West Campus Garage pointed with an aerial view of Pickard Passageway. The red box on Figure 1 illustrates the study space on the Google Earth image.

This data collection process spanned over the course of one month, and collected approximately 15 hours of video footage. Four camera configurations were used to offer differing perspective angles and heights of observation. In further detail, there were two configurations per floor, with two floors (4th and 5th) chosen. These two floors were chosen in order to minimize privately identifying information while ensuring enough detail for image processing evaluations. The two configurations were the sites on the staircases closer to the West Campus Garage and the Recreational Center approaches respectively. Additionally, each of the four locations acquired the same number of hours. Approximately three hours of daytime data were collected at each site, and about forty minutes of nighttime data. Although the pedestrian-cyclist facility had sufficient lighting infrastructure, the nighttime data was recorded in small amounts in order to observe any potential difficulties of the process. After reducing the video data, some of the viewpoints allow for improved viewpoints of segments of the passageway, while obstructing others. For example, the lower angled configuration may have a small portion of the center of the passageway obstructed from view due to a tree in the line of sight. However, the higher angled configuration might result in losing details from farther along the passageway. Accordingly, one must plan ahead in terms of the interested line of sight and overall study area before planning camera configurations at the study site. From a rudimentary post-reduction sensitivity analysis, future practitioners will have a better understanding of appropriate use cases for the analysis.

Behavior Grouping

In order to understand the natural behaviors and interactions of the pedestrians and cyclists of the underpass, the manual footage was reduced to instances of pedestrian-cyclist interactions. Pedestrian-cyclist interactions were defined as any time in which a pedestrian or cyclist's path influenced the path of another pedestrian or cyclist. While this definition remains relatively broad, it allows for a simple approach to analyzing all types of pedestrian-cyclist interactions and their relative safety when compared to one another. For example, a pedestrian walking on one side of the passageway and a cyclist speeding down on the opposing side would not be determined as an interaction, as neither's behavior influenced the path of the other. However, if in a hypothetical scenario wherein a cyclist abruptly turns in front of the pedestrian's apparent path, then this would be determined as an interaction.

At the beginning of the video reduction period, there were no pre-defined categories for which pedestrian-cyclist interactions would be observed. By maintaining our broad definition for a pedestrian-cyclist interaction, all of the possible types of interactions can be gathered. Once each pedestrian interaction was recorded, the portions of the video around the pedestrian-cyclist interaction were revisited to attempt to group similar interactions. For example, if a cyclist swerved to avoid an incoming cyclist, the seconds preceding the interaction as well as the seconds after the interaction would be observed for any distinguishable features. The interactions recorded in an Excel sheet each had a line of information, documenting the time in the video when the pedestrian-cyclist interaction took place, the preceding events and actions of the two actors, and the possible categorization of the event in terms of the type of behavior observed. In review of each of these pedestrian-cyclist interactions, the overarching goal was to identify similar events to better understand pedestrian-cyclist interactions and categorize which sets of behaviors may translate to unsafe situations.

While many of these interactions may be subjectively evaluated differently by human observers, they may exhibit similar visual traits that cue certain people to the safety critical nature of the event. For example, many might believe that the closeness between the entities would determine its safety, whereas others may cite the importance of their velocity. For this reason, a systematic approach to the evaluation of a pedestrian-cyclist interaction should be developed through established image processing and machine learning techniques.

Machine Learning

As a broad field, machine learning falls under artificial intelligence as a method to develop programs that adapt or change when exposed to new data. While the growing popularity and usage of these techniques can be traced to the advent of higher power computing, machine learning is a well-researched field dating back to the 1950s. In order to properly classify pedestrians and cyclists, there are a wide variety of approaches taken by the image processing community. These include, but are not limited to, neural networks, Haar features cascade training through the Viola-Jones framework (*5*), and Histogram of Oriented Gradients (HOG) training (*6*). However, in the realm of image processing and pedestrian-cyclist classification, the accuracy of these efforts can sometimes be jeopardized by the unique and difficult conditions per the viewing environment. To demonstrate this concept with a controlled dataset, the OpenCV library Linear Support Vector Machine (SVM) trained with HOG for pedestrian classification was run on the INRIA dataset (*7*).

The complete training and testing datasets for this project comes from the Daimler cyclist (*8*) and INRIA pedestrian (*6*) benchmarks. For the sake of clarity, the original INRIA pedestrian dataset was developed to test the HOG method for pedestrian-cyclist detection. These datasets are collected natural footage of pedestrians and cyclists in a number of different environments. However, this dataset was first generated with multiple objects of interest per image with many irrelevant detractors in the image. In order to ensure an adequate training process, a script was developed to input the text annotation files describing the number and location of persons in the image, perform rudimentary analysis to determine the positions of the persons within each image, and output a complete image training dataset with each image pertaining to only one person. In this situation, there are few errors and a relatively successful classification effort. This test represents an optimum case for identifying pedestrians, and does not perform as well under varying light and distance conditions.

For situations with weak classifiers (~50% accuracy), boosting algorithms can be applied to improve results; one such example would be AdaBoost. AdaBoost is one specific example of a boosting algorithm by which weak classifiers can be combined to form strong classifiers. A candidate set of weak classifiers was developed from a literature review of other AdaBoost implementations in pedestrian detection, particularly from work done by Wang et al. (*9*). One of the prerequisite statements of the AdaBoost assumption is that the weak classifiers are at least greater than 50% accurate. In order to ensure this assumption is not violated in this application, each of the candidate measures should be tested and validated prior to application. The unique benefit of applying a wide range of measures is that AdaBoost determines the appropriate weighting and success cases for each of the individual classifiers. These measures are:

- Intensity Histogram
- Linear Binary Pattern
- Histogram Oriented Gradients
- Haar Features
- First Order Statistics (Mean, Standard Deviation, Skewness, Kurtosis)
- Second Order Statistics (Correlation, Energy, Homogeneity)
- Hu's Invariant Matrix

Within the classification process, there are two juxtaposing and competing problems; locating a region of interest and identifying the classified object within that region. Since the video recording will be intended to capture a wide area of pedestrian-cyclist interactions, determining the relevant region of interest presents its own challenges. To overcome this challenge of identifying the relevant region, background subtraction will be applied to the 15 hours of pedestrian-cyclist footage. Although there are a host of widely available models for the task, the specific implementation and successful performance depends heavily upon the tuning parameters. Despite these adjusted values, certain shakiness in the video was captured by the background subtraction. Whenever the leaves moved on the tree or the light changed on the overhanging concrete from the overpass, the object may be considered no longer part of the background. A simple contour edge detection developed by OpenCV, the Douglas-Peucker algorithm, was applied to the background-subtracted photo, and these results are shown in Figure 2 (*10*). Although the algorithm successfully identifies four of the moving entities in this image, a false positive does occur. The slight motion of the tree along with its significant contour area cause the algorithm to falsely identify it as a moving entity. This is shown by the red circle in Figure 2.

FIGURE 2 – Sample Background Subtraction

The black segments of the image represent the background, as it is the part of the image with minimal motion. In order to adequately estimate whether a near-miss event occurred or whether it was a typical pedestrian-cyclist interaction, precise information regarding the updating position of the pedestrian and cyclist must be obtained. For a given lighting situation, the shadow extracted version of the background subtraction algorithm applied above can give a strong indication as to the ground for the pedestrian or cyclist. Since the passageway has a unique curvature (downhill from all paths towards the center), utilizing the lowest point where the pedestrian or cyclist is touching the ground provides a common comparison point for conflict analysis. Additionally, to sift between false positives and minimize any missed pedestrians or cyclists, a few simple rules have been added to the algorithm to remove contours with limited area and boxes that do not represent a general pedestrian or cyclist shape (i.e. large proportion rectangles, 20:1 ratio). However, despite these efforts to remove false positives, the tree was unable to be removed. In future efforts, an iterative user process to harness the power of hard negative training could be applied. The following paragraphs discuss a potential option for future development through guided machine learning in pedestrian-cyclist classification and near-miss analysis.

The user would then be presented a randomly generated set of images from the video collection, and request the user's feedback as to whether the bounding box contains a pedestrian, cyclist, or neither. After the first training phase, the coefficient for the AdaBoost algorithm is adjusted, and a new set of images are presented. The new set is generated for hard-negative training, a process by which the previous false positives are correctly identified. A performance measure and confidence in current classifier is given to the user and the user can decide what the appropriate confidence is for their application. This application for specific safety-related analysis would require a high level of confidence and would therefore encourage further iterations towards higher confidence levels. However, if the algorithm is trained with an excess portion of the dataset, the model may be over-trained and perform poorly on dissimilar datasets. Accordingly, a reasonable balance must be struck between providing enough training data to acquire an appropriate confidence level while preventing the model from becoming overfit.

Quantifying Safety Critical Events

At the fundamental level for near-miss analysis, the goal is to observe patterns of behavior that relate to or cause unsafe conditions and events. However, since pedestrian-cyclist interactions are heavily situation dependent, near-misses can appear vastly different from instance to instance. When the event happens in close focus of the camera, the relative distance between the two entities in terms of pixels may appear quite far apart. While watching the event though, it becomes apparent that the pedestrian or cyclist had to take significant action. Accordingly, multiple indicators should be taken into consideration when deciding whether an event is safe or unsafe, or whether it should be classified as a near-miss or as an intentional detour to avoid conflict. Derived from both independent and interrelated properties of near-miss events and pedestrian-cyclist interactions, the three primary characteristics are sudden changes in velocity, proximity of distance to another entity, and sudden changes in path. Whereas the first two characteristics can be directly measured from the contours in the previous steps, the evaluation of “sudden changes in path” seems quite subjective: at what point should the event be determined to have a sudden change in path? To develop the methodology surrounding the sudden change of path algorithm, the first step was to evaluate known extrapolation methods and see how future path can be predicted. Once a future path can be predicted, the sudden change in the current path could be better predicted.

As one example, the Kalman filter is an iterative process of predicting and updating a projected state that can account for noisy data (*11*). Once each of these moving entities are appropriately classified as pedestrians and cyclists through the application of the AdaBoost-trained algorithm within the frame of the video, then a Kalman filter is applied to determine its future position and speed. The process for applying this is shown in Figure 3.

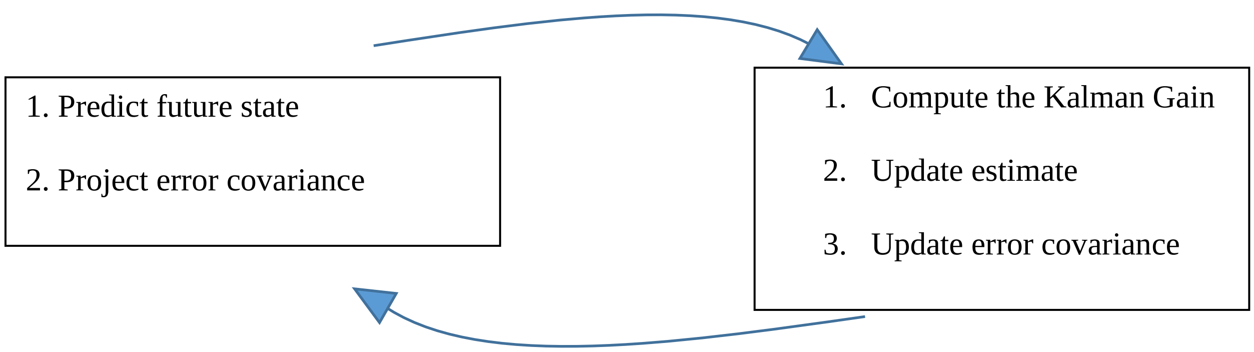


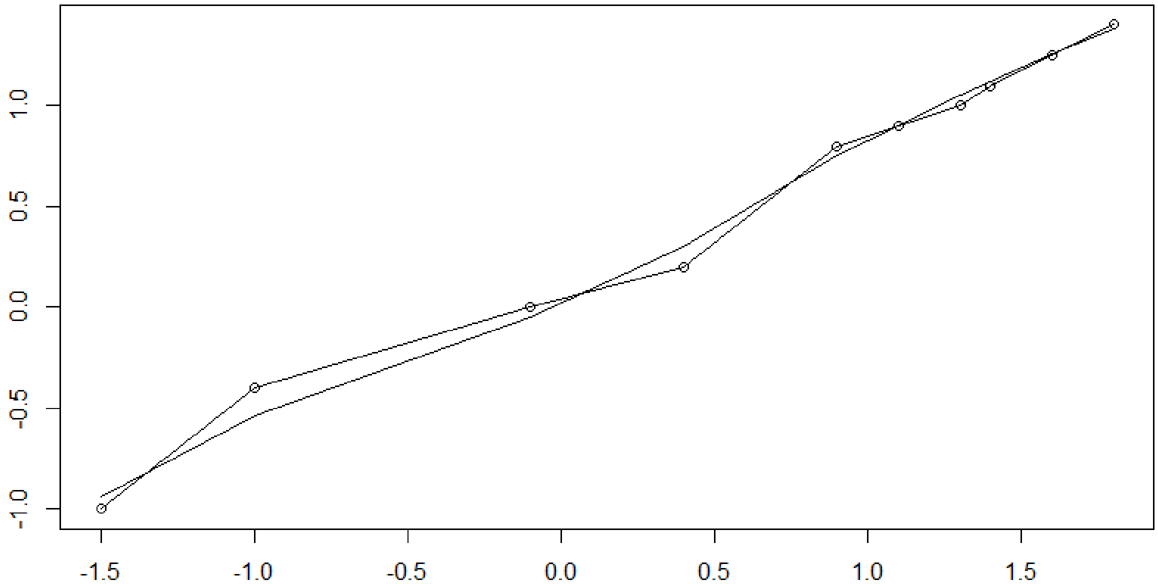
FIGURE 3 – Iterative Kalman Filter Process

Specific to this analysis, the fundamentally most important part of the Kalman Filter is the Kalman Gain. The Kalman Gain provides an estimate of how much to adjust the estimation by given the true measurement. Since the analysis is undertaken posteriori, the true future position and speed of any given pedestrian or cyclist is already reduced and analyzed. Accordingly, the deviations between the predicted future position provided by the Kalman Filter and the true future position will determine when and where the pedestrian or cyclist drastically changed paths. The Kalman Gain is calculated as shown below, where K_k stands for the Kalman Gain, P_k^- represents the a priori estimate error covariance, R_k represents the measurement error covariance matrix, and H_k and H_k^T stands for the observation and transposed observation matrix respectively.

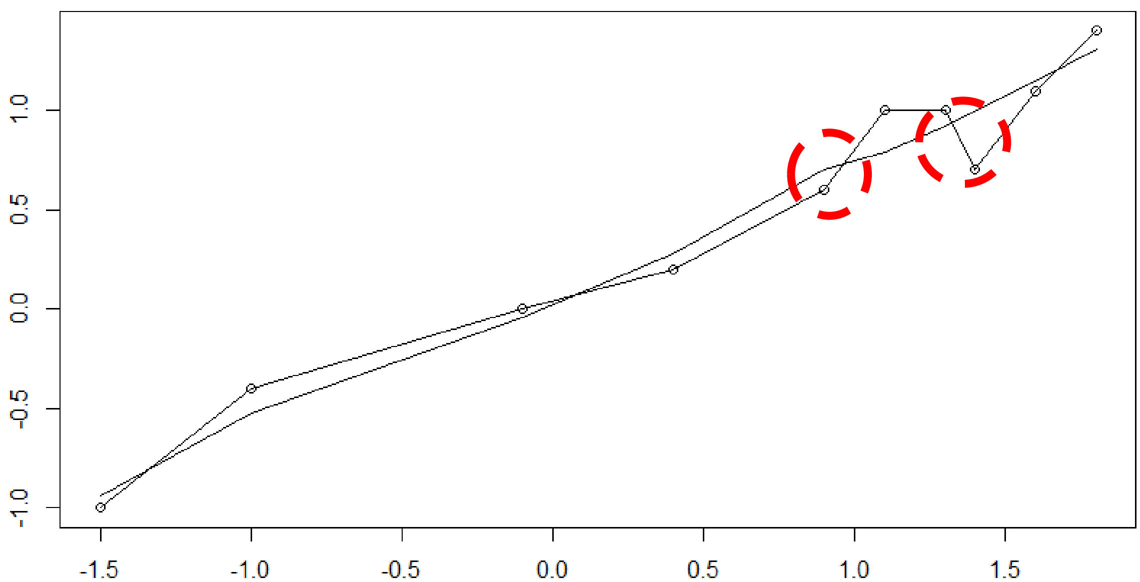
$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{Eq. 1}$$

Accordingly, a lower Kalman Gain would indicate that the prediction a priori has a closer match to the truth a posteriori and vice versa. A suddenly large Kalman Gain would show that a sudden change of direction took place. However, the suddenness and degree of change for Kalman Gain depends on several initial parameters. For example, if the framerate is excessively quick, then the Kalman Gain will routinely be smaller. The reason for this is that the time difference between state estimations will be smaller and the distance between each subsequent estimation step will be similarly reduced. Additionally, the location under analysis may also impact the way Kalman Gain should be interpreted. For example, if the path in the video frame features a long straight segment followed by a sharp curve, then the Kalman Gain would indicate a large shift at the point of the curve. This point would not be a near-miss; rather, the shift in the value for Kalman Gain would predominately be caused by the geometry of the road. Ideally, additional preliminary variables can be included in the Kalman Filter estimation in order to predefine the facility geometry and give an underlying shape to the early predictions. Finally, if the pedestrian or cyclist decides to completely change paths in the opposing direction, the Kalman Filter will indicate a significant shift in gain, despite no conflict with opposing actors.

While the Kalman Filter provides a reasonable estimation of future data points, there are a number of alternative forecasting methods that could be employed, such as weighted-smoothing, time series decomposition, or autoregressive integrated moving average (ARIMA) model (*12*). The fundamental necessity for the Kalman Filter algorithm is a prediction of future position, and any number of these alternative methods could function in this role. The near-miss event will be largely determined by the deviation between predicted and true paths within proximity to another actor (pedestrian or cyclist). However, computing the full predicted path at each time step seems computationally steep. A simple local regression model can be fit to provide an approximation of the path direction. Then, the areas of large difference between the predicted curve and the true curve will indicate where there were significant changes of direction. This concept is illustrated in the two graphs from Figure 4. These two graphs represent the simulated trajectory of a cyclist going along the passageway, with the first graph showing no disruption and the second graph showing a pedestrian-cyclist interaction. By monitoring the absolute value of the difference between these two paths, the location and time of the event can be narrowed down. The red circles on Figure 4b demonstrate where the algorithm detects significant or sudden path changes.



(a) Sample Trajectory of Smooth Path



(b) Sample Trajectory of Pedestrian-Cyclist Interaction

FIGURE 4 – Path Differences for Near-Miss Identification

Before applying these ideas to evaluate the relative safety of a pedestrian-cyclist facility, further research must be conducted regarding the path prediction and near-miss determination methodology. For example, if the true paths of pedestrians and cyclists were analyzed and applied as ground truth models for the general shape of the trajectories, the models could be more adequately tuned to individual pedestrian and cyclist choices on that path. Another way to improve prediction would be to further break down the ground truth path choices by actual pedestrians and cyclists into types of pedestrian-cyclist interactions. In order to robustly handle a variety of geometric facilities, the model should be able to predict in a multi-dimensional space.

Chapter Summary

This chapter has described the nature of the data analyzed and discussed the multiple avenues for future progress in machine learning and pedestrian-cyclist interactions. Specifically, this chapter reviewed the state of the industry, evaluated current pedestrian classification through OpenCV, and explored ways in which safety critical events may be identified. The next chapter describes the video observation results and how they relate to future machine vision applications.

CHAPTER III

RESULTS

This chapter reviews the data from the video observation period. The first section details the four primary pedestrian-cyclist interaction behaviors observed. The second section discusses how the process can be generalized and how any pedestrian-cyclist facility can be evaluated.

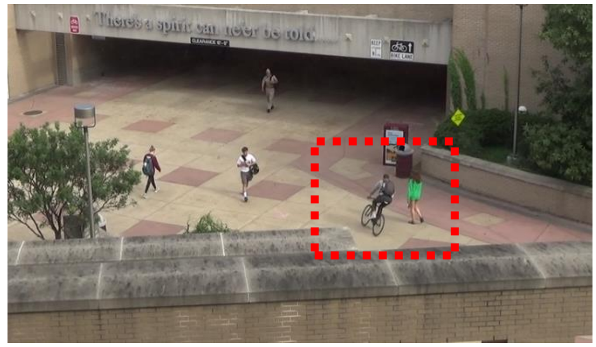
Video Observations

During the manual reduction of the video data, some interesting qualities of near-miss interactions between pedestrians and cyclists were observed. Firstly, there can be different visual cues depending upon the type of near-miss. One might assume a threshold for a constant number of pixels to function as a near-miss classifier. However, this assumption may fail in over and under-classification. For example, if the cyclist and pedestrian are both in the same line of sight to the camera, then their interaction may appear to be a near-miss, despite being several feet apart. In terms of under-classification, near-miss interactions between cyclists travelling in opposing directions may have several pixels of separation. Despite this separation, this event is still a near-miss; if evasive action was not taken, their paths were likely to collide. Due to their increased speeds, cyclists must take evasive maneuver a significant distance in advance; accordingly, the pixel threshold that may be assumed as a near-miss between pedestrians and cyclists would not apply for cyclist-cyclist interactions.

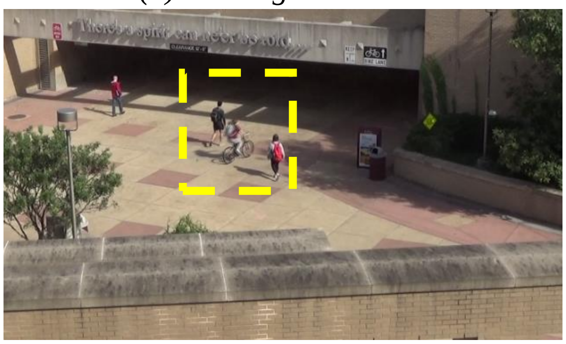
Secondly, the near-miss behaviors of cyclists with pedestrians and other cyclists can be summarized under four general categories: passing, weaving, avoiding, and turning. Similarly to the PBCAT classification of conflicting events between pedestrians-vehicles and cyclists-vehicles, the manual reduction of the video generated general categories of near-miss events that summarize the ways in which cyclists and pedestrians could interact. However, these categories were those observed from the manual reduction of the video; within other geometric configurations or situations, it could be easily conceivable that alternative conflicts could arise. While this list provides a groundwork for understanding the conflicts between pedestrians and cyclists, further analysis should be undertaken to ensure all potential events are considered.

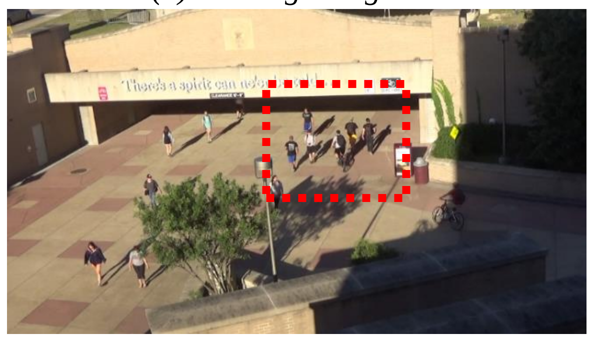
There were a total of 31 pedestrian-cyclist interactions. While this number seems disproportionately low relative to the total hours observed, the criteria for an interaction is relatively strict – the path of one entity must influence the other, whether it occurs in a safety-critical event or not. On a large facility such as Pickard Passageway, much of the traffic occurs such that two entities are travelling independently. Accordingly, after collecting the footage from these 31 instances, it was found that each of these behaviors did not carry an inherent risk to them – passing, weaving, turning, and avoiding each could be a safe or unsafe maneuver. Within these four groups; however, there were examples of how a maneuver could be performed with a higher or lower degree of risk. In the passing condition, the primary factor in increased risk associated with the maneuver was the degree of the turn the cyclist took. Passing typically occurs between a cyclist and a pedestrian, though it may also apply to the dynamic of a faster pedestrian and another pedestrian. In the yellow box (a), note how the cyclist angle with the ground is relatively upright; in contrast in the red box (b), note how the cyclist is at a much closer angle to the ground and with fewer pixels separating them. These sorts of interactions are very common on shared-use passageways, such as Pickard Passageway. Weaving can be seen as an ideologically similar behavior to passing, but occurs under different circumstances. While observing the footage, the behavior during weaving segments with higher density was distinctly different and deserved its own category. Note in the yellow box (c) that the cyclist takes a minimal deviance, straight path through two groups of pedestrians, whereas in the red box (d) the cyclist forces their way through a group of three pedestrians.

The third and fourth category of pedestrian-cyclist interactions are turning and avoidance respectively. Both of these behaviors share similar goals, with a pedestrian or cyclist making their way from point A to B with a small deviation (a turn or avoidance) along the way. Turns are unique in that the angle of the cyclist in taking the turn, the amount of space given to the pedestrian, and the amount of time the pedestrian was forced to wait can impact the overall safety and quality of the intersection. While turning may appear similar to passing, passing is in the same direction of travel of the other pedestrian or cyclist and turning is generally perpendicular to the other pedestrian or cyclist. In general, turning points are critical in pedestrian-cyclist design as these segments highlight the issues of a large speed differential with minimal (if any) traffic guidance in most pedestrian-cyclist facilities. Safe and unsafe versions of these behaviors can be seen in e and f for turning, and g and h for avoidance. Images are shown in Figure 4 for reference.

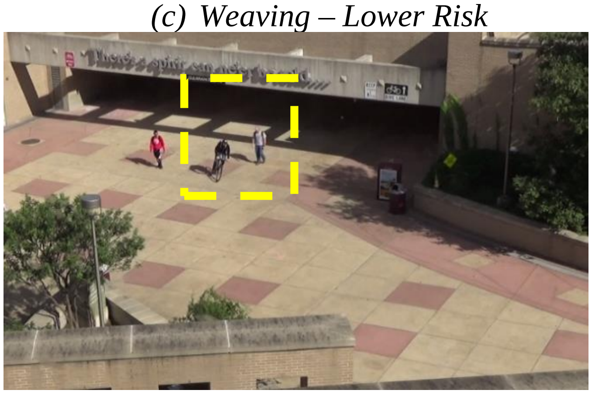


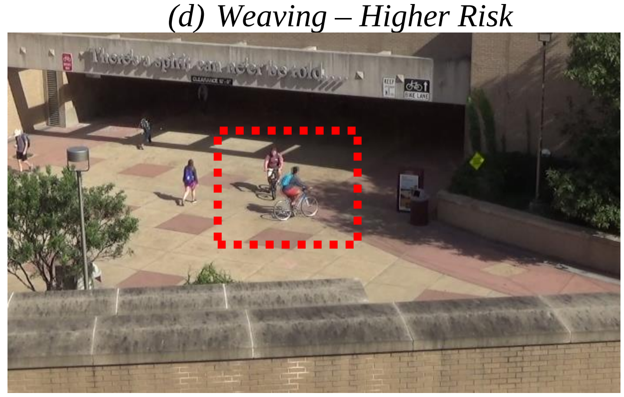
(a) Passing – Lower Risk *(b) Passing – Higher Risk*



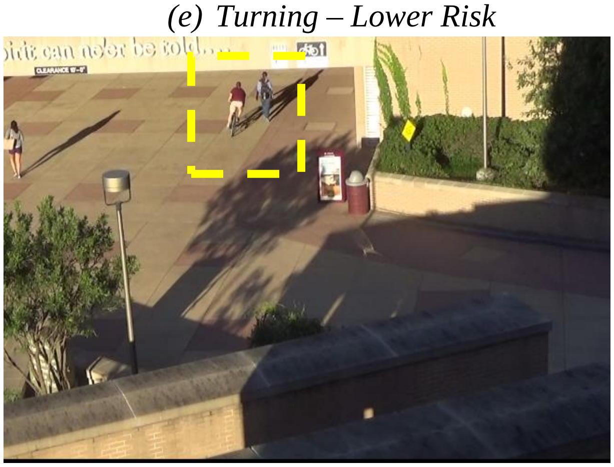


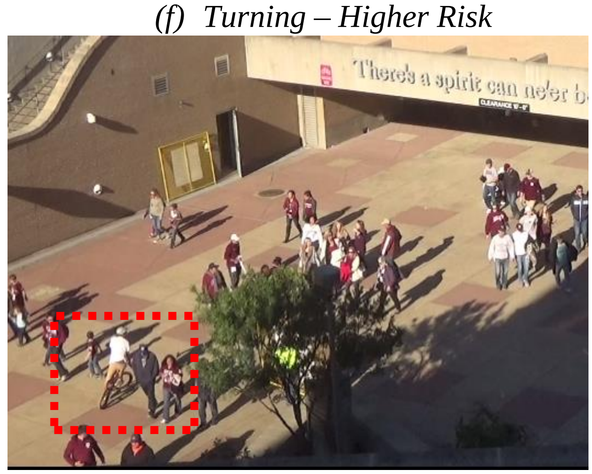
(c) Weaving – Lower Risk *(d) Weaving – Higher Risk*





(e) Turning – Lower Risk *(f) Turning – Higher Risk*





(g) Avoiding – Lower Risk *(h) Avoiding – Higher Risk*

FIGURE 5 – Types of Pedestrian-Cyclist Conflicts

Generalized Process

Although it would be ideal if these four categories represented all types of behaviors and interactions between pedestrians and cyclists, it is highly unlikely. The primary reason for this are the geometric considerations. Since the footage for this project was taken from Pickard Passageway at its T-intersection, the majority of the movements were influenced by the geometry. For example, avoidance maneuvers had to be taken if a pedestrian was inside of the cyclist lane and the cyclist just finished performing their turn. Additionally, Pickard Passageway maintains a relatively steep downward slope from each of the three legs towards the center. Accordingly, while the results cannot be immediately applied to all pedestrian-cyclist facilities, the process can be adapted for an improved perspective on the pedestrian and cyclist safety at a given facility.

The process can be generalized into three steps: video observation, analysis of safety critical events, and safety evaluation. The video observation phase provides two key pieces of information. Firstly, it provides a ground truth dataset. While there are flaws associated with manual data reduction, such as limitations of reproducibility and human error, manual data reduction remains the industry standard for these forms of safety evaluations and allows for sufficient testing. Additionally, the video observation phase highlights any and all pedestrian-cyclist interactions for further viewing. The second step in the process is to analyze these safety critical events, both manually and algorithmically. Since the interactions may be unique by site, the number of and types of interaction categories may vary. Manual analysis allows for researcher intuition, and the categories can be better refined to the exact geometry. The algorithmic analysis can provide further information about the types of features in each of these behaviors. For instance, the videoclips with the interactions can be analyzed for the severity of path or velocity change, the density surrounding the event, or the proportion of cyclists and pedestrians. If desired, these metrics could be clustered into similar groups and the behavior groupings determined from these clusters. Finally, the safety of these behaviors must be determined. While this is more subjective, the video observation and safety critical metrics provide the information required. The relative safety can be determined from the video, and the difference between the safe and unsafe interactions should be marked with significant differences in the safety critical metrics.

Chapter Summary

This chapter has evaluated the video observation results and discussed the value of the results in the broader industry. Specifically, this chapter introduces four pedestrian-cyclist interaction behaviors and provides a generalized process to extend the results of this project to other pedestrian-cyclist facilities. The next chapter concludes the report and summarizes previous chapters, along with suggestions regarding future research.

CHAPTER IV

SUMMARY AND CONCLUSIONS

Chapter 1 underscores the issue of pedestrian-cyclist facilities and the need for improved safety metrics. Chapter 2 explains how the data was collected and explores the potential interactions and uses of powerful machine vision algorithms to analyzing pedestrian-cyclist interactions. Chapter 3 discusses the findings of the video observation data and frames it within the context of potential future development. This chapter will summarize the critical features of the report in the first section, and suggest future avenues for development in the second section.

Primary Takeaways

Pedestrian-cyclist facilities provide convenient access points that are intended to improve safety conditions and improve the travel time and experience for pedestrians and cyclists in the area. However, without metrics to evaluate the safety and near-misses through an efficient or objective means, it is difficult to determine the optimum design criteria for these facilities. Accordingly, this project aimed to fill this research gap and define the general modes of pedestrian-cyclist interactions, evaluate the possibility of using machine learning applications that can automate the analysis process and minimize costs to interested state agencies, and discuss the future research potential of the project to perfect the near-miss method. A few critical points from this project are shown below:

- Over the course of 15 hours, pedestrian-cyclist video data was sampled across multiple lighting, volume, and time of day conditions. Through manual observation, a total of 31 pedestrian-cyclist interactions were cataloged. After reviewing the segmented portions of the video data with manually recorded pedestrian-cyclist interactions, the behaviors were reduced to four general categories of behaviors: passing, turning, avoidance, and weaving.

- While many of these behaviors share common features of path change, proximity to other entities, and velocity change, there are distinct differences within each. The primary differences are in the intent of the action, gleaned by careful video observation, and the situation in which it occurs. For each of these types of behaviors, there are safe and unsafe versions of the behavior. For example, if a cyclist attempts to weave through a mixed crowd including cyclists, the risk is much higher since the collective speed is higher and there are more entities to consider.
- Machine learning provides a wide array of potential solutions for the analysis of pedestrian-cyclist interactions, ranging from AdaBoost to ARIMA models. Due to the innate difficulty of classifying pedestrians and cyclists in unique environments or the challenge of predicting future paths, there will be small proportions of false positives and negatives. Through future development, these issues can be resolved and these algorithms can save significant amounts of time for researchers and improve safety for pedestrians and cyclists.

Future Research

There are two general paths for future development of this project: algorithmic improvement and applicability. Within the algorithm, the classification and path prediction are the areas with the greatest potential improvement. Pedestrian and cyclist classification remains a daunting task in unique environments, and further efforts should be made to improve the methodology. HOG-trained models have shown success in pedestrian identification in the past, but adaptive algorithms should be considered in order to handle the unpredictable and difficult nature of the pedestrian-cyclist environment. One such example would be a minimal-feedback AdaBoost system. This system would use the background-subtracted contours from a test environment as the training dataset. Then, the researcher would be questioned as to the classification of the box – pedestrian, cyclist, neither. By using the context of moving cyclists and pedestrians within a pedestrian-cyclist facility, the task of generating a training dataset is not insurmountable. Another way in which the algorithm could improve is in its path prediction. While local regression appears to adequately represent sudden changes of path choice, another way in which the typical paths could be determined would be through another learning application. Using the trajectories of the known entities after classification, a map of the typical pedestrian or typical cyclist paths can be determined. Then, when a pedestrian or cyclist begins along a certain path, a general structure is applied to their time series and the local regression model will be more representative of the pedestrian or cyclist path choice.

Another area of future development would be applicability. This paper explores a variety of potential metrics that could be applied to estimate the safety of an interaction. Accordingly, future research efforts should narrow down the most critical metrics and their thresholds (path, velocity, density, etc.) across a wide variety of volume conditions and geometries. From this information, these proxy safety metrics can be compared across multiple situations to determine an ideal threshold for pedestrian-cyclist safety given the conditions and peak hours. Similarly to how crash modification factors allowed road designers to get a better understanding of how various roadway design features influenced crash safety, an improved pedestrian-cyclist safety metric could lend itself to more uniform and improved pedestrian-cyclist facility designs in the future.

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