Title

Generative Pedestrian Behavior Modeling for Autonomous Vehicle Testing in Urban Roads.

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Publication Date

2024

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
SANTA CRUZ

GENERATIVE PEDESTRIAN BEHAVIOR MODELING FOR AUTONOMOUS VEHICLE TESTING IN URBAN ROADS.

A dissertation submitted in partial satisfaction of the
requirements for the degree of

DOCTOR OF PHILOSOPHY

in

COMPUTER SCIENCE

by

Golam Md Muktadir

September 2024

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Abstract

Generative Pedestrian Behavior Modeling for Autonomous Vehicle Testing in Urban Roads.

by

Golam Md Muktadir

The adoption of autonomous vehicles in urban areas necessitates thorough safety validation and assurance, particularly in response to the complex behaviors of pedestrians. Current testing methods involve simulations that create challenging and risky scenarios for autonomous driving systems. However, these simulations are overly simplistic and do not reflect the diverse and complex nature of real-world pedestrian behaviors and situations. This inadequacy hinders effective safety validation and reporting.

To address this gap, this work aims to systematically define pedestrian behaviors on the road, highlighting the need for more realistic simulation models. It identifies key pedestrian types and proposes a pedestrian behavior ontology to improve simulation efficacy and facilitate better communication among stakeholders in the autonomous vehicle industry.

Modeling rich and diverse pedestrian behaviors and scenarios is challenging and requires integrating various methods. This work introduces a multi-state pedestrian model, where each state captures specific behaviors, including essential micro-behaviors like stopping in the middle of the road. Scenario-based testing often fails to produce

long-tail (rare) pedestrian and traffic scenarios. To address this, the work proposes RePed, a novel method to reproduce and adapt long-tail scenarios in simulations. Additionally, it introduces HyGenPed, a system to procedurally generate diverse pedestrian routes in polymorphic crosswalk areas, enhancing real-world diversity in simulations.

In summary, the work outlines a clear approach for defining and modeling real-world pedestrian behaviors and scenarios for simulation-based testing of autonomous vehicles, aiming to make test results more interpretable, reliable, and communicable. It presents innovative methods to achieve these goals.

To my father who guided me to understand the social impact of the

work,

and my family, friends, and mentors I found along the way.

Acknowledgments

I would like to thank the following people, who guided me through this research and without whom I would not be able to undertake the adventure of developing the research line and complete my Ph.D:

My supervisor Professor Jim Whitehead, for his enthusiasm for the project, his support, encouragement, and patience. There were times when I was lost, and he always got me out of a rut.

Professor Mahmuda Naznin, the one person who encouraged me to pursue a Ph.D. career, for her support and encouragement, for her involvement in research collaboration with Bangladesh University of Engineering and Technology.

Professor Renran Tian, for his support in my dissertation and *2nd Workshop On The Prediction Of Pedestrian Behaviors For Automated Driving* at IEEE Intelligent Vehicle Symposium, Aachen, Germany, 2022. I presented my first work in this workshop and met researchers who shaped my research plan and questions. His Pedestrian Situated Intent 2.0 dataset was instrumental in my most promising research contribution.

Dr. Amir Rasouli, who discussed cross-cutting issues with pedestrian behavior modeling and research gaps with me at at IEEE Intelligent Vehicle Symposium, Aachen, Germany, 2022. He also directed me to the appropriate venues to publish my works.

Dr. A. B. M. Alim Al Islam, for his leadership in research collaboration with Bangladesh University of Engineering and Technology and continuous support in Pedestrian Behavior Research projects.

Dr. Alessio Gambi, for his support in my dissertation and being an organizer of *SceGen: Workshop on Scenario Generation for Testing Autonomous Vehicles*, Anchorage, Alaska, USA, 2023. He played a crucial role in gathering scholars in simulation-based testing of autonomous vehicles which supported my discussions on challenges in the domain.

Mr. Abdul Jawad, for regular discussions on ideas and problems in the research lab and in the woods which helped me to clear my mind and see the problems from different perspectives.

Mr. Taorui Huang, for co-leading the *Pedestrian Behavior Ontology* research.

My wife, Shahanaj, who took complete responsibility at home to allow me to put more time into the research in my final year.

My father, a scholar and leader, for his mental and financial support, for his guidance in discovering the social impact of my research and encouragement to work on broader problems in the domain.

My mother, who would be the happiest person on my graduation, for always keeping me in her prayers and preserving all my belongings in Bangladesh with utmost sincerity and care.

All the contributors to my research projects including but not limited to Xuyuan Cai, Abdul Jawad, Zarif Ikram, Ryan Suematsu, and Taorui Huang.

The text of this dissertation includes reprints or reproductions of the following previously published material:

1. Golam Md Muktadir and Jim Whitehead. *Adaptive Pedestrian Agent Modeling for Scenario-based Testing of Autonomous Vehicles through Behavior Retargeting.*, 2024 IEEE International Conference on Robotics and Automation (ICRA), May 13-17, 2024, Yokohama, Japan.

2. Golam Md Muktadir, Xuyuan Cai and Jim Whitehead. *HyGenPed: A Hybrid Procedural Generation Approach in Pedestrian Trajectory Modeling in Arbitrary Crosswalk Area*, 2024 IEEE Intelligent Vehicle Symposium (IV), Jeju Island, Korea.

3. Golam Md Muktadir and Jim Whitehead. *Adversarial Jaywalker modeling for simulation-based testing of Autonomous Vehicle Systems*. 2022 IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany.

4. Taorui Huang*, Golam Md Muktadir*, Srishti Sripada, Rishi Saravanan, Amelia Yuan and Jim Whitehead. PedAnalyze-Pedestrian Behavior Annotator and Ontology, 2024 IEEE Intelligent Vehicle Symposium, Jeju Island, Korea

Mr. Xuyuan Cai implemented a major part of the Path Planning method in *HyGenPed: A Hybrid Procedural Generation Approach in Pedestrian Trajectory Modeling in Arbitrary Crosswalk Area*. Taorui Huang, Srishti Sripada, Rishi Saravanan, and Amelia Yuan contributed to developing the Ped Analyze, an annotation tool, which is instrumental in the development of Pedestrian Behavior Ontology. Professor Jim Whitehead directed and supervised the research works which formed the basis for the dissertation.

Part I

Why Pedestrian Behavior Modeling

Chapter 1

Introduction

Courageous or cautious pedestrians are dangerous

Pedestrian safety is a major concern in urban planning, [7, 94, 177]. The pedestrian safety research in urban planning identifies how pedestrians use the road space and interact with other traffic participants and objects—the pedestrian behavior models. Based on the behavior models, the research aims to reduce pedestrian-vehicle interactions, conflicts, and accidents. This reduction is often achieved by regulating vehicle traffic, designing corridors and sidewalks, and traffic calming measures such as speed humps and signals. However, even with the advancement of research and development of pedestrian safety measures, the number of pedestrian accidents and fatalities has been consistently increasing every year, both in developed and under-developed countries. According to the Traffic Safety Facts published by the National Highway Traffic Safety Association (**NHTSA**) for years 2020 and 2021, pedestrian fatalities increased from 6,565 to 7,388, a 12.5 percent increase, and pedestrian injuries rose from 54,771 to 60,577, an 11 percent increase, [167, 172]. Often, safer design choices reduce the severity of accidents in exchange for an increased number of accidents. For example, in [95], researchers found that urban arterial roads, designed to reduce city street traffic, contributed to a 15 percent increase in total crashes. Accidents spiked because the streets are designed to be wide and straight to increase *sight distance*. The assumption is that sight distance will give human drivers more opportunities to perceive dangerous situations early and safely avoid them. However, because of the wide and straight roads, drivers can drive at much higher speed which offsets the benefit of higher sight distance and leads to more accidents.

It is challenging to reduce pedestrian accidents because the road scene has two human participants: the human driver and the human pedestrian. Accidents happen due to mistakes made by either party. Human drivers often get angry and drive aggressively which is a leading cause of fatal accidents. *Section [1.1]* elaborates on human driving behavior responsible for pedestrian accidents. Pedestrians also contribute significantly to the accidents. About 31 percent of the pedestrians in fatal accidents were intoxicated with BACs of 0.08 g/dL or higher according to the 2021 NHTSA traffic safety report, [166]. *Section [1.2]* sheds light on the diversity of pedestrians involved in accidents.

This work is based on the assumption that artificial intelligence can become a better driver on city streets, as many accidents happen due to human drivers' negligence, perception, or incompetence. Autonomous vehicles do not drink, sleep, play with phones, or grow angry and impatient. They have eyes on their back and remember to check the side mirrors. Moreover, they are not opportunists who speed on empty streets at night. *Section [1.3]* explains how autonomous driving can ameliorate pedestrian safety.

While autonomous vehicles have a great potential to reduce accidents on the road and save human lives, there are several challenges in their adoption and safety validation. Safety standards are in a nascent stage and public sentiment is against driverless cars. *Section [1.4]* contains a synopsis of the challenges. This dissertation aims to provide clear directions to identify and tackle the challenges and introduces several novel methods to deal with some of the challenges. *Section [1.5]* describe the research questions and work summary.

1.1 Limitations of the Human Driving

To understand how autonomous driving can bring value to city dwellers, one needs to understand the limitations of human drivers that driverless vehicles can remove. Limitations of the human driver belongs to two categories: (a) emotional limitations and (b) perception limitations. *Emotional limitations* stem from emotional states such as anger, distraction, and aggression. An expert driver can make mistakes based on their emotional state. Perception limitations originate from physical and cognitive capabilities and the external world. Human drivers may have nyctalopia (night blindness), disability, or weather can be adverse, leading to poor perception of the surroundings and inevitable accidents. With both limitations at work, it is often difficult for human drivers to deal with risky situations.

1.1.1 How pedestrian accidents happen due to human driver emotions

The AAA Foundation for Traffic Safety developed the Traffic Safety Culture Index [1] based on a survey of drivers' emotional states (e.g., distracted, aggressive, and safe). According to the 2022 index [1], only 41% are Safe Drivers. Only distracted are 15%, only aggressive are 22.7%, and both distracted and aggressive are alarmingly 17%. Pedestrians cross the roads daily where 59% of drivers are dangerous.

The National Highway Traffic Safety Administration (NHTSA) publishes reports on accident data. According to the NHTSA, aggressive driving causes 66% of traffic fatalities. Table 1.1 summarizes the emotional states of human drivers from the literature and statistical reports. As physically impaired drivers comprise only 1.3% of the total, human drivers' emotional state and perception capacity are the main determinant of how dangerous they are on the road.

1.1.2 How pedestrian accidents happen due to human driver perception

Time of the day, weather conditions, and road structure all impact human perception of their surroundings. In 2021, more than 80% of all US pedestrian fatalities on these roads happened in dark lighting conditions, a figure that has been consistently increas-

Human Driver Behavior	**Statistics**
Distracted Driving	
Writing a text/email message on a cell phone	27%, [1]
Holding and talking on a phone	38%, [1]
Reading a text/email on a cell phone	37%, [1]
Using a hands-free technology to talk/text/email	59%, [1]
Aggressive Driving	
Driving more than 10 mph over the speed limit on residential street	35%, [1]
Running red lights	25%, [1]
Risky lange change	22%, [1]
Traffic fatalities are caused by aggressive driving	66%, NHTSA
Drowsy and Impaired Driving	
Exhausted and extremely drowsy	18%, [1]
Driving drunk	7%, [1]
Driving under impairing drugs	3%, [1]
Risky lange change	22%, [1]
Top Frustrations Triggered by Others' Driving Behavior	
Distracted Driving	63%, [231]
Getting cur off	49%, [231]
Tailgating	49%, [231]
Not using turn signals	51%, [231]
Traffic jams	46%, [231]
Speeding	34%, [231]

Table 1.1: Frequent Human Behavior while Driving

ing over the last ten years (*see figure 1.1*). In addition, about 79 percent of accidents happen due to poor light conditions (*see figure 1.1*), and 71 percent of accidents occur between 6 p.m. and 9 p.m., ((see figure 1.3).

Though intersections are complicated to understand, *most pedestrian accidents do not take place at intersections at all*. A staggering 77 percent of accidents happened at midblocks of roads in 2021, (*see figure 1.2*).

Based on this data, one can argue that *being unable to see or anticipate pedestrians on the road is a significant limitation of human drivers in different conditions*.

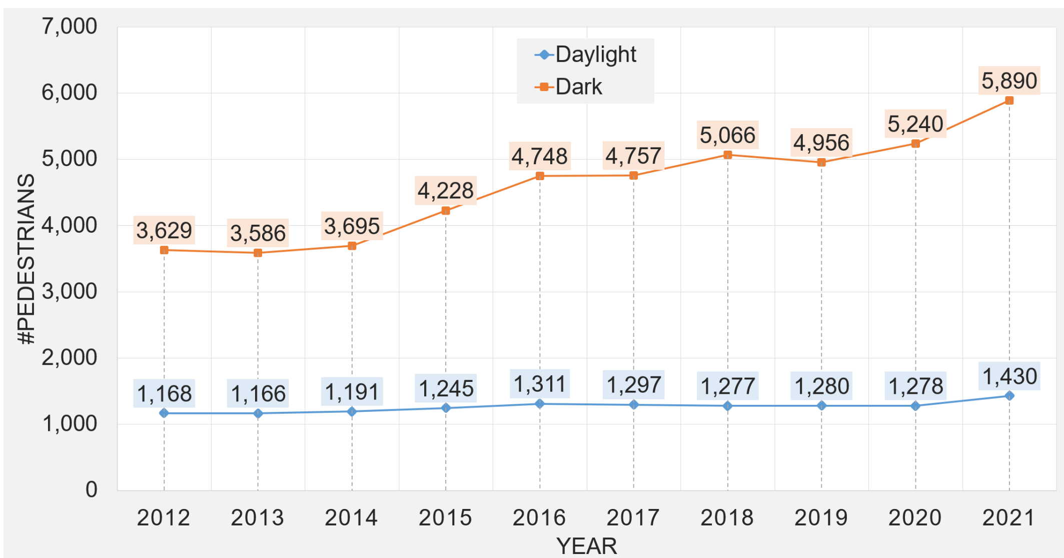


Figure 1.1: Pedestrian Fatalities in USA, 2012-2021, Dark vs Daylight. *Data Source: Fatality Analysis Reporting System (FARS).*

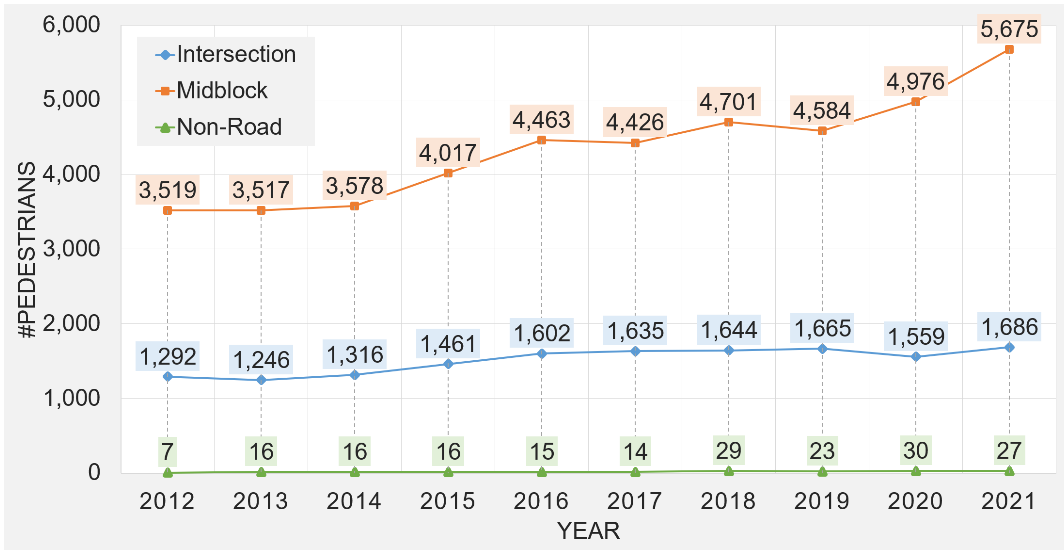


Figure 1.2: Pedestrian Fatalities in USA, 2012-2021, Intersection vs Midblock vs Non-Road. *Data Source: Fatality Analysis Reporting System (FARS).*

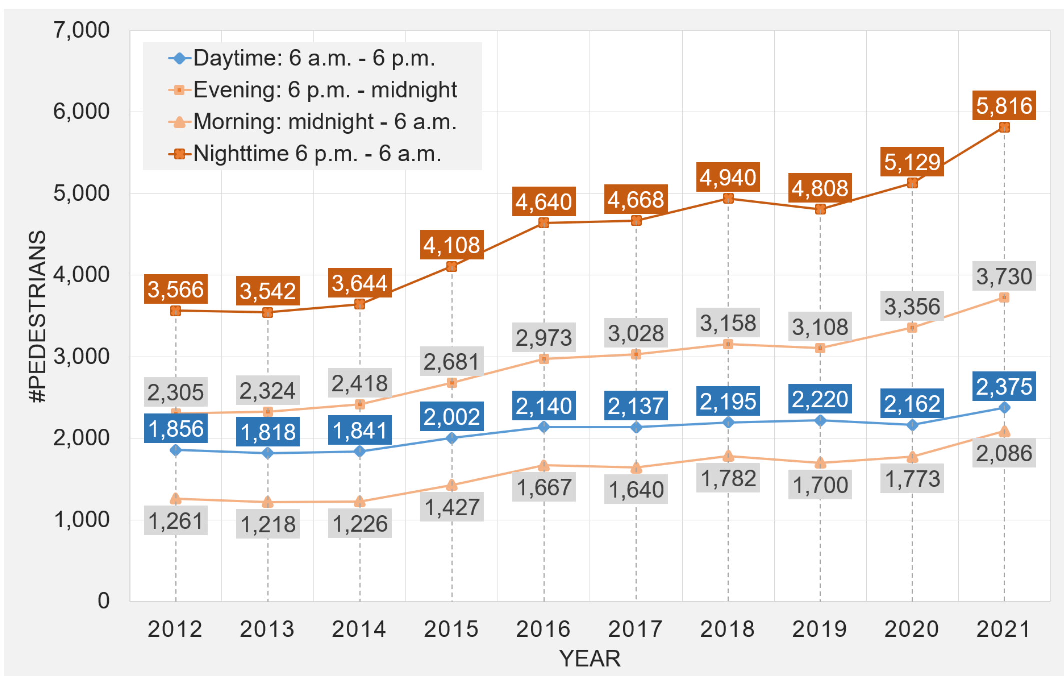


Figure 1.3: Pedestrian Fatalities in USA, 2012-2021, Nighttime vs Daytime. *Data Source: Fatality Analysis Reporting System (FARS).*

1.2 How Pedestrians contribute to Accidents

Pedestrians show extreme diversity in behavior, and many have physical and mental impairments. Pedestrians can cross the road while talking on the phone, being intoxicated or impaired.

Figure 1.4 shows that running across the roads is one of the major causes of fatal accidents. Similarly, they can dart out from occlusions, which is equally dangerous. While jaywalking and not yielding the right-of-way are the most common behaviors in fatal accidents, an astonishing 13 percent of fatal accidents involve pedestrians engaged in activities other than crossing. *They can work, play, stand, or lie down on the road*, which contributed to over eight thousand pedestrian accidents.

They can work, play, stand, or lie down on the road.

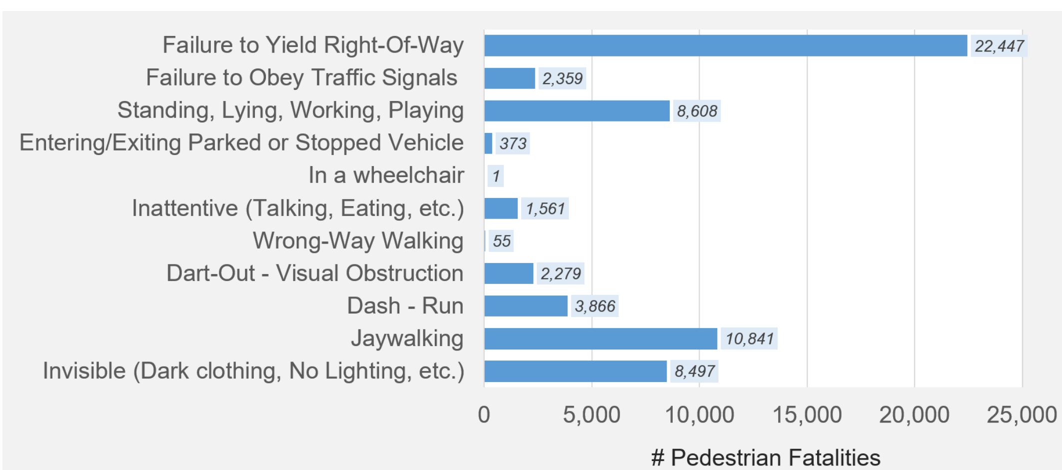


Figure 1.4: Pedestrian Fatalities in USA, 2012-2021, behavior on road. *Data Source: Fatality Analysis Reporting System (FARS).*

Figure 1.5 shows that over 57 percent of pedestrian deaths involved some form of impairment between 2012 and 2021 in the USA. Many pedestrians cross under the influence of alcohol, drugs, or medication. Many deaths involve angry or depressed pedestrians. Surprisingly, there were 169 accidents where the pedestrian passed out in the middle of the road. Some pedestrians are deaf or blind, so they cannot perceive the world using all the senses. Pedestrian movement capabilities and perception are often significantly limited by these impairments, leading to behavior that is very different from the average pedestrian.

Pedestrians can pass out while crossing.

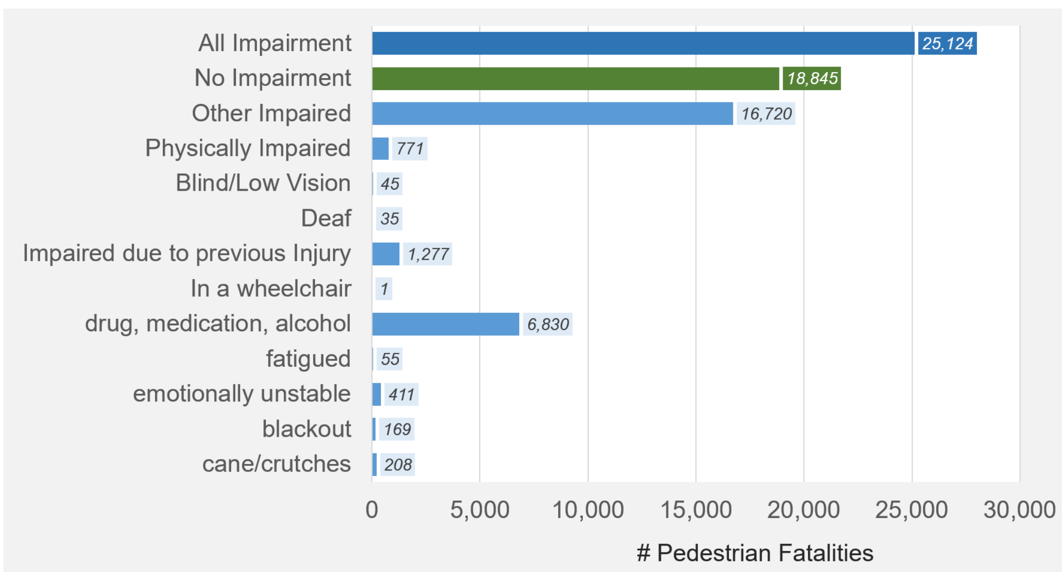


Figure 1.5: Pedestrian Fatalities in USA, 2012-2021, distribution of physical and mental impairments. *Data Source: Fatality Analysis Reporting System (FARS).*

1.3 AV's potential in increasing Pedestrian Safety

To understand how Autonomous Driving has high potential to improve pedestrian safety, one needs to know how autonomous vehicles perceive road scenarios and drive through traffic and how they are different from human drivers. The substantial benefits come from the fact that autonomous vehicles (a) can theoretically better perceive the world due to different kinds of sensors that can be tested and replaced, and (b) do not exhibit emotional instability.

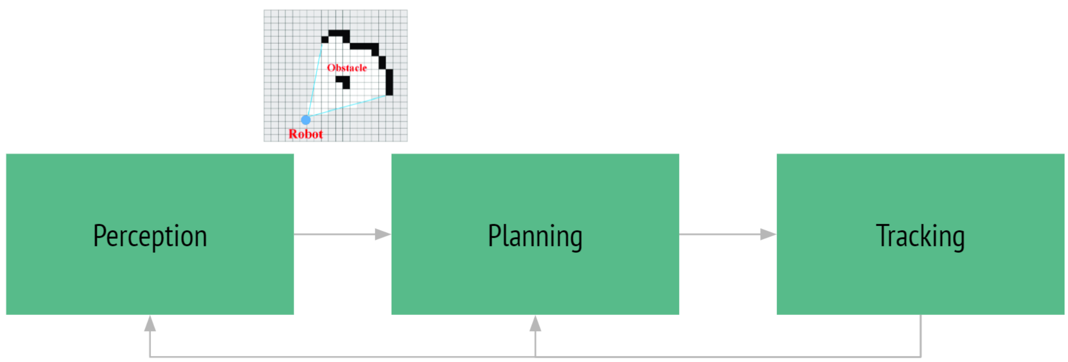


Figure 1.6: Three components of Autonomous Driving Systems. The perception component senses the surroundings, detects objects and traffic participants, and creates a detailed local map. It uses several types of sensors such as camera, LiDAR, and radar. The planning components process the maps over a short period, predict how the scenario may evolve, and what the autonomous vehicle should do next. The tracking component tries to execute the plan and reports the realization of the plan.

Autonomous driving systems have three logical components: Perception, Planning, and Tracking, (*see figure 1.6*). The Perception component is responsible for object detection and identification such as identifying the lanes on the road. It tries to estimate the local 3-D map of the surroundings. The Planning component takes a sequence of historical data from the Perception component to understand the dynamics of the world and plan the AV's behavior and trajectory. The Tracking component executes the trajectory plan for the autonomous vehicle and reports any differences between the planned and realized trajectories.

The perception component is equipped with sensors that can see the surroundings better than humans in different weather and traffic conditions. Typically, an autonomous vehicle has an *array of cameras* to capture a 360° view by combining multiple images, permitting the AV to look at everything around it. It does not need to change its direction of gaze to collect information from different directions. Therefore the AV has access to information faster. In [143], researchers showed that the state-of-the-art AI model can anticipate crashes earlier than humans because humans change their gaze to collect information sequentially. Thus, having an array of cameras ensures faster access to information around a vehicle. One can argue that assisting human drivers with a 360° view will enable them to perform as well as the AI. However, humans must still change their gaze to see different images sequentially and process all the information. There is a limitation on how much cognitive load human brains can take, [127]. Autonomous vehicles can simultaneously process multiple streams of images by extending their computing power to handle more cognitive load. Access to and capability of processing image streams simultaneously makes AV perception systems superior to humans. Other sensors such as LiDAR and radar can detect and localize objects and pedestrians in adverse weather conditions such as low lighting, snow, and rain.

All these different types of sensors work together to understand the surroundings. With a better understanding, the planning can produce a safer vehicle driving plan. After the object and road detection, the AV predicts the future trajectories of moving objects and traffic participants and plans its trajectory. Assuming the AV can perfectly plan a safe trajectory and avoid accidents, the execution is not impacted by exhaustion, distraction, aggression, or anger. Because it has no other purpose in life, it always does what it is supposed to do. As most fatal pedestrian accidents happen at night, autonomous vehicles are well-suited to replace human drivers at night, making roads safer.

1.4 Self-driving vs Pedestrians

There are several challenges to advancing the adoption of self-driving vehicles in urban streets. The overshadowing challenge is the rippling effect of accidents caused by any specific make and model on the entire autonomous vehicle industry. Mistakes made by one self-driving company lead to public reactions and negative sentiment about driverless vehicles. People get scared easily when a driver is missing. Accidents and errors involving pedestrians have a severe impact on the adoption of AV technology. The Safe Street Rebel Group in San Francisco, California, started ConeSF: *A Campaign to Rein In Robotaxis* in which they place traffic cones for the purpose of stalling autonomous vehicles, [228, 175]. Their main concern is pedestrian safety. The Cruise driverless car ban, [226], and recall were caused by a grisly pedestrian accident in 2023, [170]. Similarly Waymo expansion halted, [230], due to a collision with cyclist that resulted in non-life-threatening injuries, [216]. Recently, a crowd vandalized, broke, and set a Waymo driverless car on fire in Chinatown, San Francisco, [164], which can be correlated with recent Cruise accidents. Even Tesla, without recent accidents with pedestrians or cyclists, experienced arson of two of their autonomous vehicles in San Francisco on February 26, 2024, [217].

People get scared easily when a driver is missing.

In the Cruise accident on October 2, 2023 [170], a human driver collided with a pedestrian and threw the pedestrian into the Cruise AV's path. The Cruise AV initially stopped, but soon, it started to pull over dragging the pedestrian 20 feet before making a full stop. When an accident is inevitable, the aim is to reduce the impact of the accident (*post-collision response*). In this scenario, the generic pull-over maneuver is not the desired post-collision response, [170] according to the NHTSA investigation. In another accident, a Tesla AV killed a 52-year-old man who was fixing a flat tire on the left shoulder of an expressway [146]. Both scenarios are so rare that most human drivers never face them. The adverse public reaction to the Cruise accident included the following:

- "Scary thing to think about is, what if Cruise couldn't find an adequate pull over spot within 20 feet? The nightmare of being dragged by this oblivious robot while it stupidly looks for an open curb."

- "...should be criminally charged for fraud..."
- "No human would have done that, especially after they collided with a human."
- "This cruise car crap treat there [sic] employees like crap..."

The commentators assumed a human driver is perfect. They invented and shared reasons why the Cruise AV dragged the pedestrian. However, there are many incidents where human drivers made the same mistakes [136], and no one shared their concerns about human driving. The conclusion is that AVs need to be a much better drivers than humans to be acceptable.

Pedestrians challenge the planning and maneuvering algorithms of AVs in many different ways. As AV companies share the repercussions of failures, they must also share the testing knowledge and methodologies against pedestrians. The concern is that such scenarios are the rarest and, therefore, cannot be automatically learned using real-world data, which is the everyday recipe for autonomous driving. However, the AV can learn how to deal with such situations if one can create such incidents in a simulation. This work aims to encourage and unravel the essential methodologies and pedestrian behaviors with transparency and collaboration.

1.5 Summary

The driving force behind this work is the fact that over 77 percent of pedestrian fatal accidents happen during jaywalking in the midblock of roads. Additionally, over 79 percent of deaths happen in dark lighting conditions. 31 percent of dead pedestrians are intoxicated. So, pedestrian accidents happen due to pedestrian behaviors, impairments, and dangerous scenarios during crossing. Unfortunately, existing literature on pedestrian crossing behavior is minimal. Most work addresses crossings at intersections and pedestrian crossing decisions, or generalized pedestrian trajectories that do not capture irrational and accidental behavior. Therefore, this work sets out to model rational and irrational pedestrian behavior under different traffic conditions.

The dissertation addresses three broad research questions (RQs):

- **RQ #1: How do pedestrians behave while crossing the road?** The answer is crucial to finding research gaps in pedestrian behavior modeling and developing safe driverless vehicles.

- **RQ #2: How to model the diverse and rich pedestrian behaviors and scenarios for simulation-based testing of autonomous vehicles?** The answer is crucial to assess the effectiveness of different methods of modeling pedestrian behaviors and identifying the research gaps. To answer the question effectively, we address the following questions:

  - *RQ #2.1: How would simulation-based testing methods use the simulation* *models to serve the test goals?*

- *RQ #2.2: Can one method capture all the behaviors and facilitate the requirements of a simulation model given the current data sources?*
- *RQ #2.3: How to produce realistic long-tail scenarios that have an extremely low probability of emergence through scenario search-based algorithms?*

- **RQ #3: How to interpret pedestrian behavior in the generated scenarios?** The answer is crucial to understand what kind of pedestrian behavior and scenarios the AV can deal with.

Chapter [3] illustrates the ontology that describes how pedestrians in different physical and mental states and different situations behave while crossing the road. The ontology is the culmination of all the research work presented in this dissertation. **Chapter [4]** illustrates key personality types of pedestrians gleaned from pedestrian crossing videos from different sources. It aims to enlighten the reader about the diversity in pedestrian behavior and the scope of research on simulation models for pedestrians. The findings in this study led to the rest of the work presented in the dissertation. **Chapter [5]** discusses the properties and challenges of the ideal model required for simulation-based testing of autonomous driving against pedestrians. It gives a high-level overview of gaps in the existing literature and a clear path to developing rich pedestrian behaviors on the road.

Chapter [6] is the first contribution that established the ground for this research work. This work proposes an adversarial jaywalker with different states while crossing. In each state, it can show unpredictable and adversarial behaviors to confuse the vehicle drivers. It identifies the critical issues with existing methodologies and hints at the possible solutions. **Chapter [7]** addresses the gap in simulation models to produce rare pedestrian scenarios. It proposes a hybrid method of pedestrian behavior modeling that connects various existing methods to formulate a rich generative model and uses real-world rare scenarios to produce a variety of new scenarios through a novel behavior augmentation method. **Chapter [8]** proposes a novel generative method in route planning for pedestrian crossings to cover the shared space on the road that pedestrians can use while crossing. The technique allows pedestrians to adapt to the dynamic nature of available space for crossing in any traffic situation.

Part II

Research Contributions

Chapter 2

Research Gaps and Goals

2.1 Four Serious Gaps

This work identifies and builds upon four serious gaps in pedestrian behavior modeling for simulation-based testing of autonomous driving:

- **Gap #1**: Evidence of pedestrian behaviors is spread over different sources and there is no curated information. The lack of curated information makes it hard to find research gaps and opportunities. Existing literature revolves around the same set of behaviors without addressing a broad range of behaviors essential for testing. For example, there is a score of research in gap-acceptance to explain when a pedestrian decides to cross the road from a sidewalk. However, there are few research that model when a pedestrian makes a stop in the middle of the road.
- **Gap #2**: The requirements of a pedestrian simulation model are not defined.

Because of this gap, existing literature does not focus on generating rare and dangerous pedestrian behavior. In addition, literature needs to address jaywalking behavior and its diversity while crossing. The simulation models need to show both rational and irrational behaviors and allow control over how the models act to produce specific kinds of behaviors based on the test goals.

- **Gap #3**: Interpretable modeling is necessary for different stakeholders. One can produce numerous critical scenarios in simulation. However, without interpretability, it cannot be guaranteed whether the test methods cover the diversity of pedestrian behaviors. For example, if the simulation model cannot retreat in the middle of the road, millions of generated scenarios will not have a single scenario where the pedestrian retreats. Without interpretability, one cannot categorize the emerging scenarios into behaviors to make sure the test results align with stakeholder concerns. Interpretability is needed for vehicle companies, regulatory bodies, and the general public.

- **Gap #4**: There is no method for rare mid-block crossing. The crossing models either focus on crosswalks or very rational and collision avoidance behaviors in the mid-block. For example, the rolling-gap models make a safe decision when the pedestrian needs to cross multiple lanes of traffic. No model captures the behavior where the pedestrian overlooks the traffic in further lanes and takes a huge risk in crossing. Research in long-tail pedestrian scenarios is hindered by this gap.

2.2 Goals for the Gaps

Based on the gaps, this research pursues two goals:

- **Understanding the Pedestrian**: This goal addresses **Gap #1, #2**. The objective is to identify unique pedestrian types, behaviors, and dangerous situations on the road which supports formulating a rich behavior set for simulation models. This work proposes:
  - **Pedestrian Behavior Ontology:** The behavior ontology aims to develop a representative set of behaviors and maneuvers that pedestrians exhibit on the road using all sorts of data sources such as autonomous vehicle datasets (e.g., InD [14], PSI 2.0 [186]), car dashcam compilations, traffic images, and accident reports. The ontology defines what to model and test against. It identifies unique microscopic behaviors and how their interplay describes different types of pedestrians.
  - **The Dangerous Pedestrian Archetypes:** Each pedestrian archetype is a unique combination of behaviors and physical and mental attributes. Archetypes directly address public concerns and are communicable. Often long-tail dangerous situations emerge due to archetype characteristics. Archetypes greatly help in testing against long-tail scenarios and making scenarios interpretable.
  - **Expressive Generative Behavior Modeling:** The purpose of this work is

to define how to develop pedestrian models for simulation-based testing. It specifically targets coverage-based testing methods that require testing against various scenarios and unpredictability with a fine-grained control on how the simulation models can act in simulation.

- **Hybrid Modeling for Simulation-based Testing:** To address **Gap #3, #4**, this work focuses on hybrid modeling for pedestrian behaviors and scenarios. A hybrid modeling approach that can incorporate existing modeling methods and tap all sorts of data sources. Using the same method to model all sorts of pedestrian behaviors and produce important and rare scenarios is not easy. This research aims to develop novel methods to create rich and interpretable pedestrian models. The proposed methods are:
  - **Adversarial Jaywalker Model:** This work proposes a novel multi-state pedestrian model that captures different sets of behaviors in different states. It makes the state behaviors configurable giving the testing methods fine-grained control on which behaviors can act during the simulation. It allows the integration of different methods for different behaviors making the resulting model highly expressive and extendable.
  - **RePed:** RePed can capture long-tail pedestrian scenarios and reproduce them in simulation in such a way that the vehicle under test cannot escape the desired events. It adapts the pedestrian in the scenario to the changing behavior of the ego vehicle and road structures. In addition, it can augment

the scenarios by changing pedestrian behaviors. The generated scenarios are interpretable as RePed identifies and encodes the behavior patterns in its scenario representation.

– **HyGenPed:** HyGenPed addresses pedestrian route diversity and offers a generative method that can cover polymorphic and dynamic crossing areas on the road in a very efficient manner. It can quickly generate a set of routes that reflects real-world route patterns and cover the shared road space available to pedestrians. It is also integrated with the multi-state jaywalker model which generates diverse trajectories by adding behaviors.

Chapter 3

Pedestrian Behavior Ontology

Different pedestrians show different kinds of behavior while crossing the road. In addition, the behavior of the same pedestrian may change due to external influences such as the weather or the presence of other traffic participants, or internal influences such as intoxication and age. Pedestrian behavior can be broken down into microscopic behaviors such as running and impulsive stopping, and physical constraints such as acceleration and speed. These micro-behaviors and physical constraints are interrelated. Their plausible compositions create the diversity of pedestrian behavior on the road. The archetypes in **Chapter [4]** hint at such compositions. The goal of the ontology is to identify such micro-behaviors and physical constraints and plausible compositions to represent real-world pedestrians.

3.1 Purpose of The Ontology

A robust pedestrian behavior ontology serves several key purposes in the autonomous driving research and industry:

First, the ontology gives clarity on what behaviors need to be modeled in order to craft real-world pedestrians in simulation. The existing methods on pedestrian agent modeling has so far been limited due to the lack of such an ontology. For example, no method modeled how a kid can take a round-trip in the middle of a four-way intersection seen in *Section [4.10]* as this is an extremely rare scenario which has not been documented in pedestrian behavior literature before.

Second, the ontology facilitates coverage-based testing and reporting. Behavior-coverage-based testing is important to ensure that a autonomous driving system is well-equipped to handle all possible dangerous situations on the road. Modern self-driving systems are often neural-network-based, which cannot be proven to work in all possible situations. Thus, exhaustive testing is required to ensure the safety of their behavior space. In addition to testing, interpretable reporting is also necessary for the public and the regulators. Autonomous vehicle companies publish safety testing reports [243, 244, 72]. However, these reports summarize test reports and do not shed light on what kind of pedestrians their autonomous driving systems are tested against. With such an ontology, autonomous driving companies can conduct tests that cover the ontology and publish detailed results.

Third, the ontology also creates a vocabulary of terms describing types of pedestrian behaviors which creates a language of communications among the public, regulators, and businesses. Currently, the public is concerned about pedestrian safety and recently demonstrated aggressive behavior against driverless cars [226, 230, 228, 175, 217, 164]. People want to know whether autonomous vehicles can safety interact with different types of pedestrians, especially children. However, they also need the ontology to clearly understand pedestrian behavior to set realistic expectation of autonomous driving. Regulators can use the ontology to assess risks of AVs interacting with different types of pedestrian behaiors and develop safety requirements. Autonomous vehicle companies can share how their driving agents perform against specific behaviors described in the ontology without revealing their technology secrets. In addition, different stakeholders can collectively develop testing scenarios based on the ontology which can amount to a standard suite of tests. This can facilitate safety comparisons of different self-driving vehicles.

Finally, the ontology also provides a terminology that reduces ambiguity in describing traffic scenarios. Pedestrian datasets are annotated by human annotators. However, human annotators are free to use different words to describe the same event. For example, instead of stating, "A pedestrian has stopped in the middle of the road," another annotator may describe the same behavior as "a pedestrian frozen in the center of the lane". With such differences in the scenario description language, it becomes difficult to search for specific scenarios by specific terms which makes it harder for further research. With an ontology, annotators can use the same terminology to describe scenarios, achieving consistency in wordings in datasets [213].

3.2 Literature Review

While there is no comprehensive existing ontology on pedestrian behaviors, research in pedestrian behavior modeling has defined several high-level categories, intentions, and demographic tags for categorizing pedestrians. In [10, 9], pedestrian behavior is categorized according to activity choice, mode choice, route choice, destination choice, walking behavior, and interactions. They discuss different pedestrian interactions (e.g., group behavior), however, such interactions are not extensively explored and enumerated, especially in the context of road crossing. Moreover, their walking behavior and route choice models do not cover erratic movement on the road depicted in *Figure [4.12]*. In [121, 176], a limited ontology is developed which does not include rare pedestrian behaviors. None of the existing ontology works focus on the diversity of crossing behaviors, especially the dangerous behaviors.

The PIE Dataset [189] offers text labels for pedestrian actions (*“walking”, “standing”, “looking”, “not looking”, “crossing”, “not crossing”*)’ as well as a 5-interval scale for annotations involving whether the pedestrian wants to cross the street. The JAAD Dataset [190] utilizes video attributes (*"time of day", "weather", "location"*), pedestrians with behavior annotations, traffic information (e.g., signs, traffic light), and vehicle actions, but these behavior tags are fairly limited and provided only within single frames. The PSI 2.0 Dataset [186] concerns "*the dynamic intent changes for* *the pedestrians to cross in front of the ego-vehicle*." However, the dataset utilizes *text-based explanations* of the driver reasoning process when estimating pedestrian intents and predicting their behaviors during the interaction period. PSI 2.0 offers only three behavior tags: (a) not cross, (b) not sure, and (c) cross. Even though their corresponding text-based explanations reveal certain pedestrian behaviors, vehicle behaviors, and environmental conditions, the comments are not structured, and using them for further research is inconvenient.

Several articles focus on behavior modeling based on demographics such as gender [257], culture [116], and age [139, 257]. In [257], walking and running speed statistics are given for males and females across different age groups. In addition, the manner of movement is also categorized into one of "Slow", "Ordinary", "Fast", "Running", and "Sprinting". These movements belong to essential microscopic behaviors that describe how pedestrians walk on the road.

3.3 Methodology

The ontology defines behaviors from the perspective of the ego vehicle and its lane. It tries to represent how a driver, while driving, sees the pedestrian. For example, the "Flinch-out" behavior denotes that the pedestrian flinches out of the lane that the ego vehicle is taking, and the "Flinch-in" behavior describes a situation where the pedestrian flinches out of another lane and enters the ego vehicle's lane suddenly. The initial ontology has been developed by analyzing pedestrian videos, datasets, and existing literature and focuses on the decisions that pedestrian makes while crossing [213]. It is being revised and expanded. The updated ontology can be found at https://pedanalyze.readthedocs.io

3.3.1 Data Sources

- Public dashcam compilations: Many dashcam companies publish compilations of pedestrian behavior on road [36, 37, 38, 122, 60]. The compilations are curated from videos collected from dashcam users across the world. There are several advantages to using such videos over the ones recorded for research and development of autonomous driving. First, video datasets such as Waymo Open Dataset [225] are collected in selected cities in the world and along very specific map areas. So, such datasets do not represent pedestrian behavior in general. Second, datasets collected for autonomous driving do not have many rare scenarios (e.g., accidents, near-miss, risky behaviors). However, the dashcam compilation videos are rich in rare scenarios.

- Literature on pedestrian behavior: research works focused on pedestrian behaviors such as [9, 257] reveal essential behavior patterns. Though these works are often focused on traffic flow analysis and capacity planning, they identify key microscopic behaviors applicable to road crossings.

- Autonomous driving datasets: Annotated datasets such as [186] have not defined a rich set of behaviors for pedestrians. However, their videos contain interesting pedestrian behavior (*see Section [4.1] for an example*). Analysis and re-annotation of their videos revealed some key pedestrian maneuvers and decisions while crossing the road.

3.3.2 Annotation Tool

A specialized open-source tool, PedAnalyze, was created to develop the ontology along with annotated datasets using car dashcam videos found on public platforms such as YouTube. There are several key features that distinguish the tool from existing ones:

- PedAnalyze allows for annotation of behaviors over a sequence of frames and allows multiple annotations per pedestrian over the same sequence. This helps to create rich annotations without repetitions. In existing tools, annotations are made per frame, making the annotation job repetitive and harder and producing redundant information.

- PedAnalyze encourages the usage of existing behavior tags to ensure consistency in wordings of the behaviors. In addition, extending the set of predefined tags is easy through configurations.

The tool can be found at https://pedanalyze.readthedocs.io

3.3.3 Pedestrian Behavior Tags

Every distinguishable decision and maneuver is given a tag. Currently, the tags are organized into several categories as follows:

3.3.3.1 Manner of Walking

Manners are determined by pedestrian gait properties, such as walking speed, acceleration, and direction changes. In addition to common manners such as running, this work identifies some rare manners seen on road such as "Crawling" where pedestrians cross the road by crawling.

3.3.3.2 Navigation

Navigation categorizes behaviors that determines various routes pedestrian can take and voluntary violation of rules and norms. For example, "Along-lane" behavior describes a pedestrian who walks along a driving lane without showing the intent to cross the road.

3.3.3.3 Instant Reaction

These are instantaneous maneuvers (e.g., flinch, sudden stops) that are impulsive and happen quickly (often in a second). Often these maneuvers are to avoid collisions. However, as the pedestrians do not have enough time to check the surroundings, the instant reaction decisions can lead to risky situations.

3.3.3.4 Collision

These behaviors result in collisions or near-miss scenarios between the pedestrian and the ego vehicle or other traffic participants

3.3.3.5 Interaction

Interactions cover verbal or non-verbal communication among traffic participants where one or more pedestrians are involved. The interactions are further divided into sub-groups to delineate different kinds of interactions such as group interactions and vehicle pedestrian interactions (**VPI**):

- **Interaction: Group:** Group interactions involve multiple pedestrians. These interactions revolves around group dynamics, activities and communication with group members and other traffic participants. For example, in the "Street-fight", two or more pedestrians fight on the roads having traffic.

- **Interaction: VPI:** VPI interactions capture how pedestrians communicate with the ego vehicle and interact with any vehicles on the road. For example, a pedestrian can board a halted or slow vehicle on the road denoted by "Getting-in" behavior.

- **Interaction: Object:** Object interactions include any interactions with objects beyond other traffic participants. For example, the "Change-tire" behavior captures the situation where a pedestrian is fixing a vehicle tire and dangerously close to or on a driving lane.

3.3.3.6 Intention

Intentions cover predictable crossing decisions taken by a pedestrian (e.g., "cross", "not cross"). These are different from instant reactions as instant ones are unpredictable and sudden. Intention behaviors kept separated from "Mental State", 3.3.3.7, behaviors because existing literature established this category.

3.3.3.7 Mental State

This category encapsulates all the behaviors concerning the pedestrian's mood, awareness, and responsiveness of the surrounding environment, which can be perceived by other traffic participants. While the actual mental state may be unknown or ambiguous, the ontology suggests identifying behaviors from the driver's or ego vehicle's perspective.

3.3.3.8 Physical State

Physical state contains physical attributes, impairments, or augmentation that changes the walking behavior. For example, the "Bicycle" state denotes that the pedestrian may walk along with a bicycle while crossing the road.

Manner of Walking	gait properties such as walking speed, acceleration, and direction change
Brisk-walk	Walk fast

Run	Running while crossing
Retreat	Walk backward or return to the origin
Speed-up	Sudden change from slow to fast
Slow-down	Sudden change from fast to slow
Pause-start	Stop momentarily, and proceed afterward, [21, 101]
Drunken-walk	Unsteady walking patterns where the pedestrian finds it hard to keep balance and often fails to walk towards a single destination, [76, 87, 77, 88]
Crawling	Crawling on the road, [89, 90]
Wavering-direction	Fluctuate in directions of travel, [87]
Navigation	violating rules and norms of crossing the road
Along-lane	Walking along a driving lane instead without showing the intent to cross the road for a while (more than 3 seconds), [78, 79, 23, 24]
Jaywalking	Not crossing at marked crosswalk, [39, 235, 75, 40, 123, 122, 234]
Cross-on-red	Crossing on red light for pedestrians
Walking-around-vehicle	Walking around a halted or slow vehicle on a driving lane
Instant Reaction	impulsive and instantaneous actions
Trip	Pedestrian falling or collapsing on the road
Swerve	Abrupt change in direction
Break	Abrupt stop at the lane boundary and yield
Flinch-out	Jump out of ego's lane, [36, 41, 196, 42, 37]
Flinch-in	Jump into the ego's lane, [36, 41, 196, 42, 37]
Frozen	Stop in the middle of a lane

Collision	collision with a vehicle
Collision	Colliding with a vehicle leading to injury
Near-miss	Nearly missing a collision with a vehicle, [43, 20]
Run-into-traffic	Creating near-miss/collision with vehicles, [33]
Thrown-back	Thrown backward by vehicle collision, [170]
Interaction: Group	Group behavior and formation
Group-walk	Walk in a group, [44, 192, 69]
Group-disperse	A group dispersing in the middle of the road, [35, 173, 154, 256, 71]
Re-group	Reformation of a dispersed group in the middle of the road, [197, 34, 173, 154, 256, 71]
Pet-walk	Crossing the road with a pet such as a dog, [4]
Street-fight	Fighting on the road, [61, 62, 60]
Interaction: VPI	Vehicle-Iedestrian-Interactions. Voluntary interactions with a vehicle on the road
Make-stop	Gesturing to vehicle to stop
Make-go	Gesturing to vehicle to go
Aggression	Aggressive gestures to vehicle, [183]
Assault	Assault the vehicle, [45]
Observing	Standing still and observing vehicle's behavior
Getting-off	Getting off a vehicle on a driving lane, [25]
Getting-out	Getting out of a vehicle on a driving lane, [25]
Getting-in	Getting in a vehicle on a driving lane, [25]
Load-unload	Loading or unloading goods from a vehicle on a driving lane, [198]
Interact-non-ego-participant	Interacting with other traffic participants, [195]

Interaction: Object	Voluntary interactions with an object while crossing the road
Phone	Texting or talking over phone, [199, 124]
Porter	Pedestrians carrying large objects
Hauler	Hauling objects such as bicycle and sleds [35]
Photography	Taking photos while crossing the road
Drop-object	Drop an object in the middle of a lane, [46, 209, 200]
Pickup-object	Pick up an object in the middle of a lane, [46, 209, 200]
Change-tire	Changing tires on the road, [146]
Intention	
Cross	Clearly shows the intent to cross, [186]
Not-cross	Clearly shows no intent to cross, [186]
Not-sure-cross	Does not clearly show the intent to cross, [186]
Mental State	Mood, awareness, and responsiveness to the surroundings
Looking	Looking at the oncoming traffic (>1s), [192]
Glancing	Glancing at the oncoming traffic (<1s)), [192]
Never-looking	Never looking at the oncoming traffic, [192]
Distracted	Distracted and not responding to the surroundings, etc., [208]
Fixated	Fixated on a direction different from the direction of an approaching vehicle, or another object, [47, 195]
Music	Listening to music using headsets or earphones, [208]

Agitated	Showing agitation in general and does not need involvement with the vehicle, [45, 48, 49]
Cautious	Showing careful deliberation
Indecisive	Faltering in decision to proceed, [50, 201, 34]
Late-response	Taking actions too late, leading to dangerous situations, [21]
Ignorant	Not knowing the rules and social norms of the road, [22]
Physical State	Physical attributes, impairments, or augmentation changes their walking behavior
Under-teen	Aged below 13, [26, 27, 28]
Walking-stick	Using a stick to walk, [171]
Walking-crutch	Using a crutch to walk, [171]
Wheel-chair	Crossing on a wheel-chair, [202, 171]
Scooter	Crossing on a scooter, [212]
Unicycle	Crossing on a unicycle, [16]
Bicycle	Crossing with a bicycle (may or may not ride it), [203]

Table 3.1: Pedestrian Behavior Tags: behaviors from the perspective of the ego vehicle and its lane.

3.4 Conclusion

The pedestrian ontology opens up new research directions on how and what to study about pedestrian behavior on the road. It also serves the behavior-coverage-based testing standards for autonomous vehicles for pedestrian safety. With explicit behavior-based testing, autonomous driving agents can achieve better interpretability of their actions.

The hybrid approaches for generative pedestrian behavior modeling such as [157, 158, 128, 103] depends on micro-behavior models. Such an ontology can greatly improve the expressiveness of hybrid approaches in simulation-models.

It is important to note that development of a comprehensive ontology is a challenging task, requires collaboration, and consensus. This work only includes behavior with evidences curated, defined, and annotated by a group of nine collaborators including the authors of PedAnalyze, [213]. PedAnalyze and Youtube dashcam videos was extensively used by the collaborators to develop this ontology to extract behaviors. Behavior naming and categorization ambiguities were resolved through discussions and voting. It is challenging to measure the completeness of the ontology. We used over fifty Youtube dashcam videos and PSI 2.0 datasets for evaluation and the current ontology covers all the behaviors seen in the videos.

Chapter 4

The Dangerous Pedestrian Archetypes

A safe pedestrian is a predictable and law-abiding citizen. In the presence of traffic, a safe pedestrian:

- Does not violate road signals.
- Crosses the road using crosswalks.
- Is always attentive to the road situation.
- Communicates with other traffic participants effectively and makes their intentions clear to others.
- Does not quickly change their behavior.
- Avoids risky decisions.

A dangerous pedestrian violates one or more of the characteristics of a safe pedestrian. Often, unsafe behaviors seem benign as accidents are rare. However, pedestrians can avoid accidents if they always make safe decisions while on the road. But, being always safe is strenuous. As to err is human, to be a pedestrian is often to be dangerous. Dangerous pedestrians pose a risk to themselves or others. This work proposes pedestrian archetypes to identify, communicate, and address public concerns about dangerous pedestrians.

A pedestrian archetype is *a composition of behaviors that uniquely identifies a specific personality of pedestrians*, e.g., drunk pedestrians, and addresses public concerns. This chapter identifies several unpredictable and irrational pedestrian archetypes that lead to dangerous situations and accidents on roads. These archetypes pose several challenges in pedestrian behavior modeling. The major challenge is that many of these archetypes lack adequate data for rigorous analysis and modeling for simulation. These archetypes delineated research gaps and fueled this research endeavor through the unexplored territory of pedestrian behavior research in general.

The archetypes have been identified after analyzing datasets from the following diverse sources:

- NHTSA Traffic Safety Facts reports: The National Highway Traffic Safety Administration (NHTSA) publishes traffic safety facts every year based on accident analysis, [166, 167, 172]. In their reports, they mainly categorize pedestrians by age, gender, distractions, and alcohol level.
- FARS Data: NHTSA uses a Fatality Analysis Reporting System (FARS) to serve both data visualizations [169] and queries [171]. This work extensively uses the

FARS Query tools to extract pedestrian behavior (see *Figure [4.1]*).

- PSI 2.0 dataset: [186] contains videos with pedestrian behavior annotations. This dataset contributes to several archetypes.
- Pedestrian Video Compilations: While NHTSA data contain major characteristics of pedestrians involved in accidents, the data is essentially text. So, it is difficult to understand the scenarios of the accidents. To understand the scenarios, this work utilized pedestrian video compilations from car dash-cams. The compilations can be found on YouTube [36, 236, 237, 46, 37, 51, 122, 29, 20, 45, 77, 21].

The archetypes are not categories of behaviors where behaviors denote specific maneuvers such as stopping and running, or decision choices such as direction change and intent to cross. Often different archetypes have *overlaps* in behaviors. For example, "The Blind" overlaps with "The Distracted". However, it is important to make this distinction as it can be important to someone concerned about blind pedestrians on the road. There is a huge number of pedestrian personality types. For example, an adult can show behaviors similar to "The Kid". However, archetypes only include "The Kid" as it is a major concern. The purpose of the archetype is to identify a unique combination of behaviors so that:

- The combination of behaviors is realistic.
- The correlation of behaviors can be measured.

- How the archetype modifies the behavior can be modeled conditionally. For example, how a pedestrian makes a stop in the middle of the road greatly depends on whether they are intoxicated or indecisive. The intoxicated person often shows an unsteady stop.

- Various stakeholders can discuss safety testing based on the archetypes.

The archetypes emerge from the pedestrian's internal factors and how they tend to react to the surroundings. Such factors have been studied in [148, 178, 192]. However, research into the resulting observable pedestrian models is limited and mostly non-existent. This research focuses on identifying the emergent pedestrian types that facilitate further modeling research.

4.1 The Wanderer

The wanderer type loves to wander along the driving lanes and often ignores the traffic. It is challenging for the driver to understand their intentions. PSI 2.0 [1], Video_0019 portrays a wanderer, figure 4.2. Illustration 4.3 shows key points in time in the pedestrian's trajectory where they exhibit changes in behavior. There is a one-way road with 4 driving lanes. A vehicle is cruising at 22 mph along the second lane. So is the pedestrian along the lane immediately to its right. At time step 1, the pedestrian walks towards the vehicle lane. 50 percent of the annotators estimated a "crossing",

[1] PSI 2.0 is a pedestrian crossing dataset with three crossing intent annotations on video frames: cross, not cross, not sure, [186].

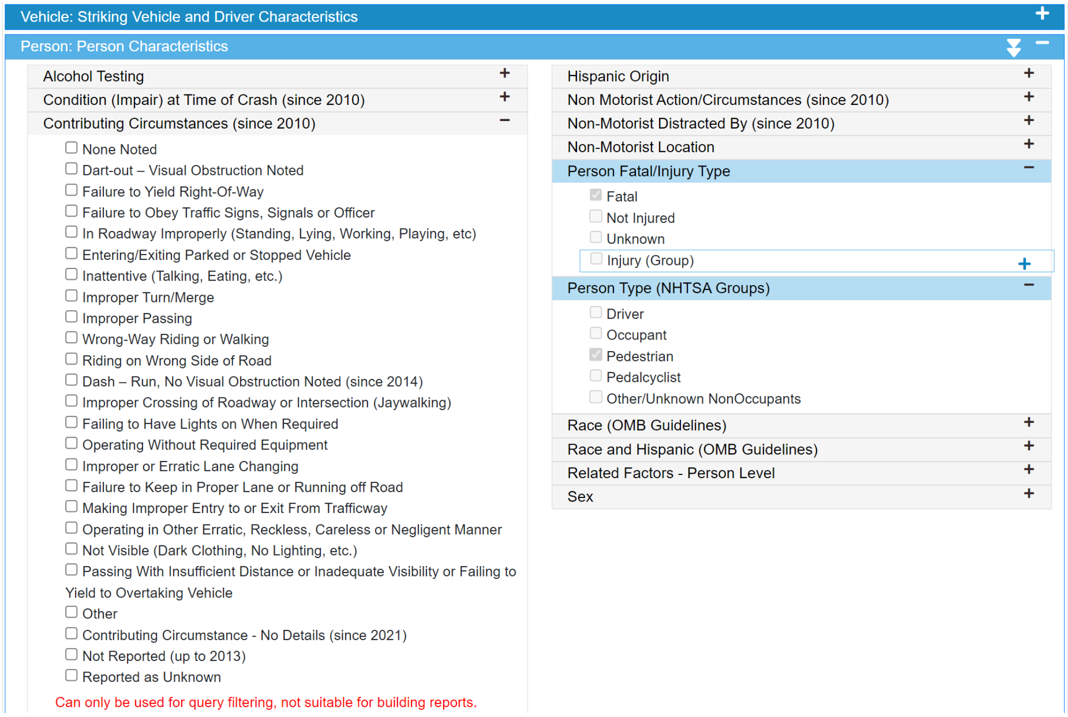


Figure 4.1: Fatality Analysis Reporting System (FARS) Query Interface.

10 percent "not cross" and 40 percent "not sure". This clearly shows how difficult it is to understand a wanderer's mind. The driver slows down a little bit, anticipating a distracted person.

To the driver's surprise, at time step 2, they start moving away. All the annotators agree that the pedestrian will not cross. To everyone's surprise, at time 3, the pedestrian again starts getting closer to the vehicle lane, and at step 4, they suddenly make a sharp direction change and cross the road.

Wanderers show diverse behaviors. In [78], the pedestrian runs towards the approaching vehicle from the opposite of the driving direction, makes the car stop, and climbs the hood. In [79], they dance on the highway and stop the traffic. The wanderer becomes much more dangerous while they are drunk [87] as they can quickly change directions and accelerate or stop.

(a) (b) (c) (d)

Figure 4.2: The wanderer from PSI 2.0, Video_0019, who loves to walk along the road and keeps changing the intention to cross the road.

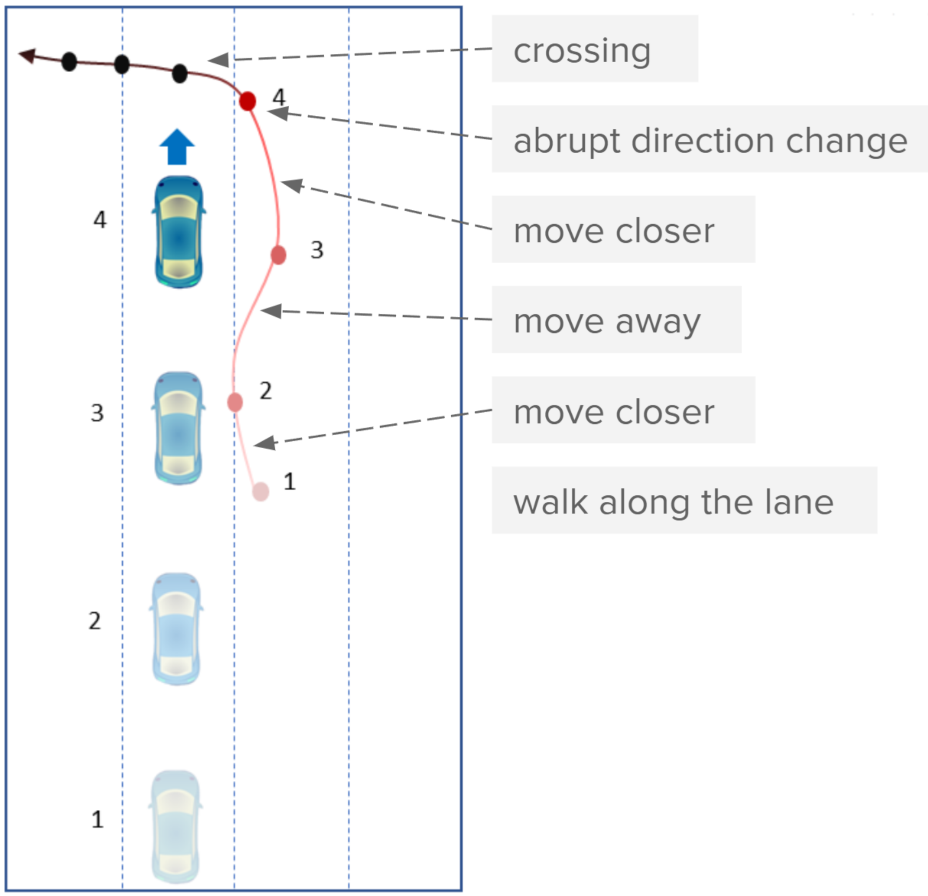


Figure 4.3: The trajectory of the wanderer from PSI 2.0, Video_0019. Here the number represents interesting points in time, the circles denote the pedestrian.

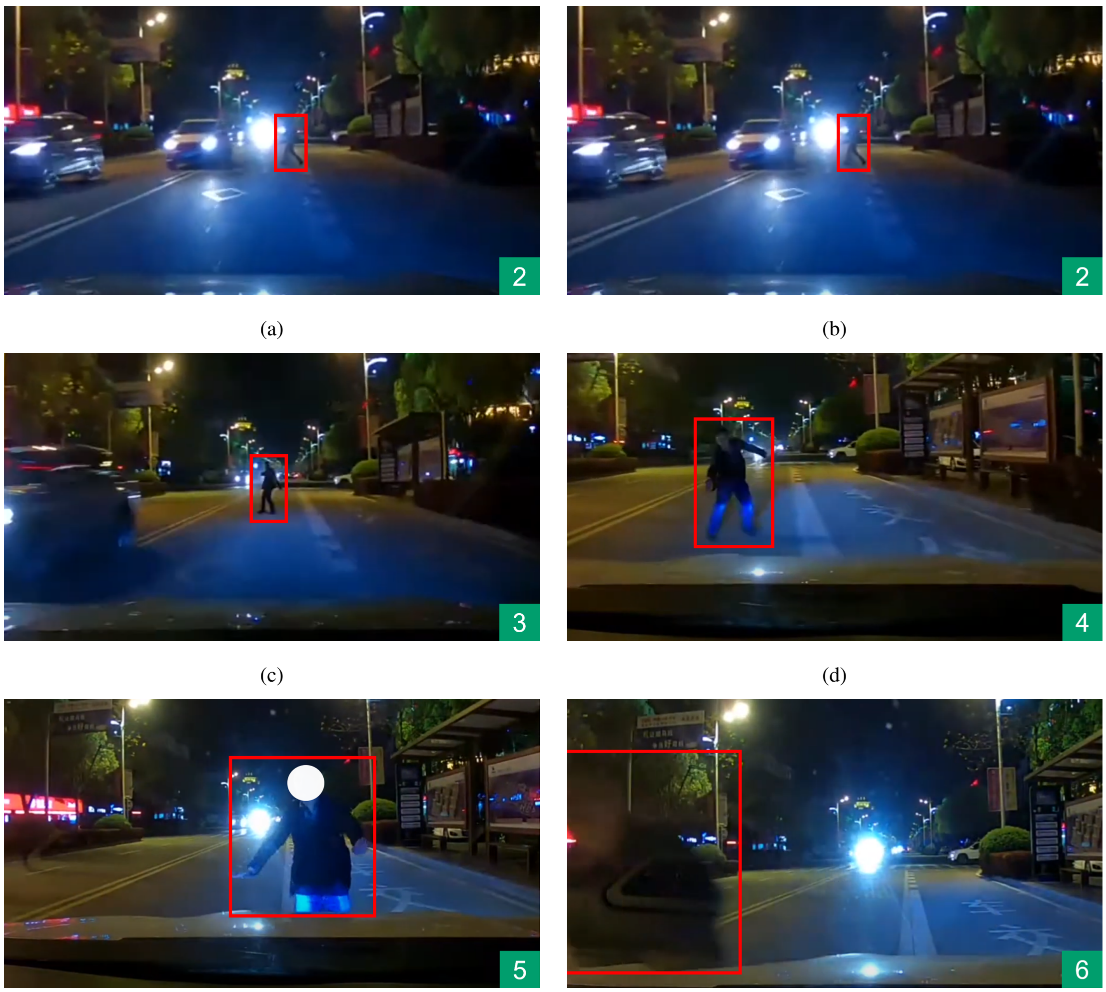
4.2 The Drunk

About 31 percent of pedestrian fatalities were intoxicated with BACs of 0.08 g/dL or higher in the USA in 2021 based on NHTSA's traffic report, [166]. This fact calls for attention and results in the drunk archetype. The illustrated dashcam video in *Figure [4.4]* shows a drunk pedestrian that stupefies even the veteran drivers.

In this video, the pedestrian finds it very hard to understand where they are on the two-way four-lane road. First, they completely cross two lanes and retreat though they could have crossed the full road. The traffic in the remaining lanes is stopped due to a red signal. Second, While retreating they dance toward the approaching vehicle, requesting it to stop. When the vehicle stops they slide along the front of the vehicle to cross the lane again.

In video [88], the drunk pedestrian is standing outside the highway lanes, and suddenly starts falling on their back. They recover themselves but also enter the driving lane in the process. With no intention or action to cross, the drunk still manages to put themselves at risk of colliding with high-speed vehicles on the road.

Like the Wanderer, the Drunk comes in many forms. In video [89, 90], the drunk crosses by crawling (using legs and hands). In video [91], the drunk walks blindly and crushes into the midsection of a moving bus. In [87], they wander along the driving lane. The drunk type modifies all the other archetypes making their behavior more erratic and showing additional maneuvers.



(a) (b) (c) (d) (e) (f)

Figure 4.4: The drunk on the road from [76]. It is hard to predict whether they are done with crossing or not.

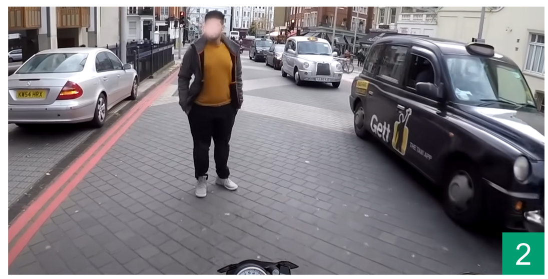
4.3 The Distracted

The distracted are often fixated on something other than the approaching vehicles [47, 195]. They are able to come back to their senses. The distracted is different from the drunk, as they can act rationally if other actors in the situation communicate with them. There are several patterns in distracted pedestrians:

- Looking at the phone screen [199, 208].
- Talking to the phone [124].
- Listening to music [208].
- Interacting with another traffic participant [195].
- Fixated on a direction different from the direction to approaching vehicle [47]

Figure [4.5] shows a rare event where the pedestrian talks to a taxi driver while walking against a driving lane. Suddenly, they discover themselves to be very near to the approaching vehicle and jump out of the lane.

(a) Talking to a driver ignoring the approaching vehicle.



(b) Eventually looks at the approaching vehicle.

(c) Startled!

(d) Moves out quickly.

Figure 4.5: The distracted from [195] keeps talking to a taxi driver for a while without noticing the approaching vehicle. When the vehicle is very near, they get startled and jump out of the way.

4.4 The Flash

The flash dashes into traffic and sprints through traffic, often making things happen. In the case of the flash, something else is more important than safety. Though being sober and grownups, the flash does not stop at anything. *Figure [4.6]* shows two such pedestrians beaming through the traffic.

The main characteristic of the flash is they sprint. There is a sense of urgency in their behavior. They do not necessarily travel along the shortest path. In [32], they appear running from behind a parked vehicle and cross the street straight. However, in [33], they follow a curved path to reach their destination.

Kids often run on the streets. But their behavior is different. The kid is defined in section 4.10.

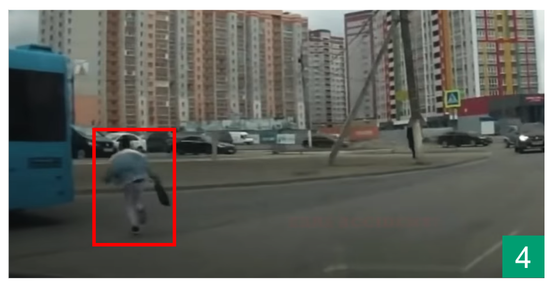
(a)

(b)

(c)

(d)

(e)



(f)

Figure 4.6: The flash in (a) and (b) dashes into the traffic and almost gets hit by the approaching vehicle, from [32]. The second flash (c)-(d) sprints through traffic to catch the bus, from [33].

4.5 The Indecisive

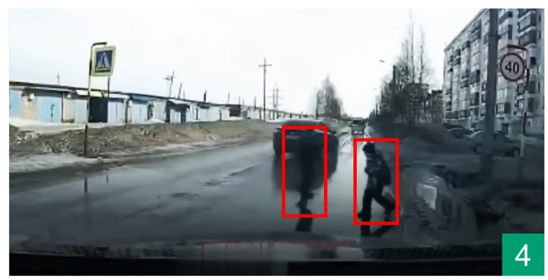
The indecisive falters in their decisions which results in dangerous and involuntary maneuvers such as flinching back to another driving lane. A quick decision without proper judgment forces one to change the decision frequently. Such indecisiveness [50, 34, 201] creates confusion for everyone and can influence the other traffic participants to falter in their decisions.

Figure [4.7] shows a pair of pedestrians who change their decisions several times while crossing the road. Their decision to cross the road is too early to be safe. Without observing the traffic well one of them paces up and nearly misses another vehicle in the next lane. Shocked, they retreat and go back to where they came from. Readers are strongly suggested to watch the scenario at [34] for a better understanding of the events.

(a) Jogs into the driving lane.

(b) Makes a momentary stop.

(c) One starts crossing by running without looking at the traffic on the next lane.



(d) Meet each other again.

(e) Decide not to cross at all.

(f) Go back to where they came from.

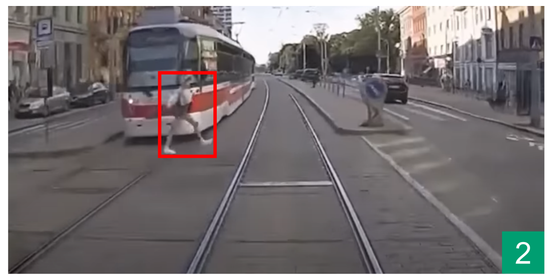
Figure 4.7: The indecisive on the road from [34]. Watching the video is strongly recommended to get the full experience of the events.

4.6 The Blind

The blind comes in two flavors: (a) intentionally ignoring and (b) failing to notice. They can turn a blind eye to traffic and signals. *Figure [4.8]* illustrates the pedestrian who intentionally ignored an approaching tram and crossed the road. The tram barely avoided an accident by making a stop. Similar intentionally blind pedestrians can also be found in [52].

In [43], while crossing, the pedestrian not only listens to music but also plays with their phones. The approaching vehicle honks at them, but they do not even budge from their path. Without noticing the surroundings, they cross a four-lane road on a green signal. Such behavior is often common in rare scenarios [53, 54].

(a) The car on the left stopped to let the tram pass.



(b) The pedestrian keeps crossing.

(c) The completely ignores the approaching tram.

(d) The tram makes a stop to avoid an accident.

Figure 4.8: The blind from [20]. In this example, the pedestrian intentionally avoids the approaching tram and crosses the road. This leads the tram to make a hard stop and nearly hit the pedestrian.

4.7 The Flock

The flocks (a group of pedestrians) are dangerous when they do not precisely fly together. *Figure [4.9]* depicts a woman hauling a sled with two kids. They decide to cross the road. However, they do not notice the kids falling off the sled while crossing. Even the animal flock crosses the road better [44]. In [210], one flock member leaves others behind, scared by the approaching vehicle. One wants to continue crossing in [211], but the other drags them and retreats off the road. In [204], one of the two pedestrians crosses the road and the other retreats to the previous lane. Things get more complicated when they are on scooters and violate the signal on high-speed roads [123].

Where pedestrian flocks usually move as a body, in rare scenarios, the group can have multiple choices for the next action. Then, the flock may disperse (often involuntarily) or negotiate on the next action, creating confusion on the road. The main characteristics of the dangerous flock are:

- They can disperse while crossing the road.
- They can re-group while on the road.
- They can cross or retreat after dispersing or re-grouping.

(a) Hauling two kids.

(b) Crossing the road without looking back.

(c) Kids falling off the sled.

(d) The guardian finishes crossing the road while the kids are on a driving lane.

(e) One kid gets up and runs to the guardian. The other is still on the ground.

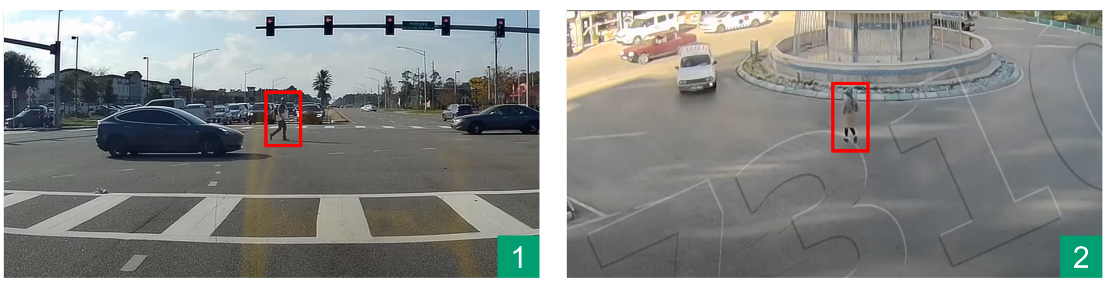
(f) The guardian comes back to carry the kid and cross the road.

Figure 4.9: The flock from [35]. In this scenario, the guardian is sledding the kids across a two-lane road. While crossing, they fail to notice that the kids fall off the sled in the middle of the first lane. After completely crossing the road, they notice that the kids are on the road. One of the kids runs to the guardian, but the other fails to get up. So, the guardian comes back to carry the other kid on the other end of the road.

4.8 The Jaywalker

The jaywalker will cross at any point, over anything. They may cross at the right time, with the right people, but not at the right place. About 73 percent of accidents happen due to mid-block jaywalking, [168].

However, it is not only the mid-block where the jaywalking happens. Video [122] shows a very large intersection with six lanes on one axis and four lanes on the other. The jaywalker crosses the road along the longer axis. However, they walk along the center line between the four lanes. Video [234] (***viewer discretion is advised as this leads to an accident***) shows a large roundabout. The pedestrian decided to cross the road by taking the shortest path over the middle island. The exceptional crossing locations of the jaywalkers are shown in *Figure [4.10]*



(a) Crossing inside a large intersection.

(b) Crossing in the middle of a roundabout.

Figure 4.10: The jaywalker can cross the road anywhere. (a) taken from [122], (b) taken from [234]

4.9 The Elderly

Based on the literature, age is correlated with response time. When one has a high response time, they appear to take action too late. In this work, the Elderly is defined as a person who takes an action when they already lost the opportunity to take the action safely. One might assume that the pedestrian in [55] took a risk to cross the road by accelerating. However, these events often happen because it is already too late by the time they start to cross. They tend to follow the habits from a younger age. However, the declining sensory and motor functions lower their crossing efficiency and, thus, elevate the risk. The video is a counter-example of gap acceptance models that assume older people reject shorter gaps. The gaps might be longer in their mind, but they emerge as shorter in reality.

Figure [4.11] visualizes an example where an elderly pedestrian makes decisions too late endangering the pedestrian on the other side of the road and derailing the approaching truck.

In addition to accepting higher risk while crossing, older people have a higher chance of death from injuries though they walk less [168].

(a) The elderly on the left cruising into the road slowly.

(b) They suddenly start jogging. The pedestrian on the other side of the road makes a full stop.

(c) The truck swerves off its lane to avoid the elderly pedestrian. The pedestrian on the right retreats to save themselves. The elderly pedestrian makes a full stop in the middle of the lane.

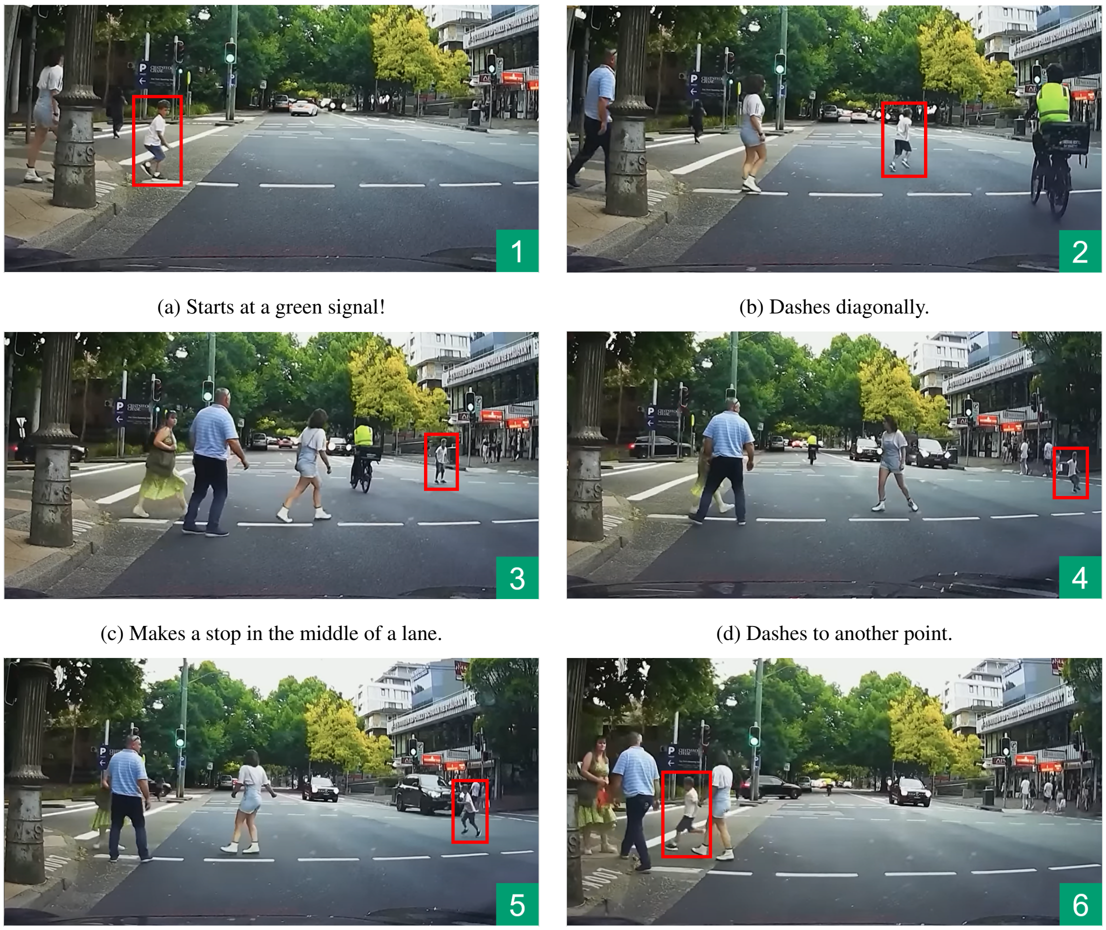
(d) The elderly pedestrian crosses the road after the truck passes.

Figure 4.11: The elderly from [21]. In this example, the elderly pedestrian seems to make decisions too late which causes a near accident situation for the approaching truck and the pedestrian on the other side of the road.

4.10 The Kid

Though the number of accidents involving under-teens is relatively lower than in other age groups when kids cross the road, they may show extremely dangerous behavior due to a lack of inexperience and understanding of the rules of the roads. On top of that, it is also important to define this archetype as autonomous driving systems may have problems recognizing children [227].

Figure 4.12 shows the round-trip taken by a kid in a four-way intersection. Their destination changed twice before they came back to the source location. They ran during the trip. In [205], a two-year-old crosses the road ahead of their parents.



(a) Starts at a green signal!

(b) Dashes diagonally.

(c) Makes a stop in the middle of a lane.

(d) Dashes to another point.

(e) Guardians retreat.

(f) Dashes to the guardians.

Figure 4.12: The kid from [22] took a round trip inside a four-way intersection on the green light. They have no understanding of the rules of the road, keep dashing to destinations, and misinterpret guardians' intentions.

4.11 The Eventful

The eventful pedestrian is a victim of a situation over which they have no control. Such incidents include pedestrians tripping over, popping out of occlusions, and dropping items on the road.

Pedestrians can fall on the road in many different ways. In [56], slips on an icy road while crossing. In [57], they trip over from the middle island as the island was at a level higher than the road surface, and the pedestrian failed to consider that. NTHSA reports fatal accidents involving pedestrians collapsing on the road while crossing, *Figure [1.5]*.

Another example is a pedestrian dropping items on the road [46, 200]. In [200], a kid crossing with a group drops one of their sandals on the road and falls behind the group.

Occluded pedestrians pop out of thin air [38, 125]. Occluded pedestrians can appear anywhere on the road. While in the more common scenarios, occluded pedestrians appear from around a stopped vehicle, in [125], we see an event when the occluded pedestrian appears from the front of a high-speed vehicle moving at over 40 mph!

4.12 The Parked Pedestrian

This archetype defines the pedestrian interacting with a parked vehicle. The behaviors these pedestrians show are inherently different from those crossing the road. They purposefully move on the road while interacting with the parked vehicle. They can load/unload a vehicle, get in or get off on the driving lane, or walk along the parked vehicle. They are also often less distinguishable when near the vehicle. In [198], the pedestrian loading the vehicle is barely visible to the human eye. Also, at the same time, two more pedestrians are interacting with the vehicle.

Each archetype exhibits a unique set of behavioral patterns, entangling the pedestrian behavior modeling researchers' work. Formulating these behaviors is painstakingly difficult. The impact is so severe that researchers, even acknowledging these patterns, avoid addressing them in their work. However, research on archetypes can greatly contribute to the safety testing of autonomous vehicles and wider adoption. They provide a platform to discuss pedestrian safety, quantitatively evaluate, and develop consensus for acceptable performance of autonomous driving systems.

4.13 Archetype Patterns

Each archetype consists of some essential and some occasional behavior patterns. The behavior patterns come from the pedestrian behavior ontology (**Chapter [3]**). The essential patterns define the archetype. For example, *"The Wanderer"* must have the *"Along-lane"* behavior, e.g., they must walk along a driving lane for a while without showing the intention to cross the road. The occasional behaviors are commonly seen with the essential behaviors adding variations to the essential behaviors or creating more dangerous events. For example, *"The Wanderer"* can also be *"Distracted"*, failing to notice traffic around them, which can lead to more dangerous situations. Table 4.1 catalogues the pedestrians and their behaviors. The occasional behaviors are not exhaustive, e.g., *"The Wanderer"* can also have the "Porter" behavior, carrying large objects.

Archetype	**Essential Behaviors**	**Occasional Behaviors**
The Wanderer	Along-lane	• Wavering-direction, • Distracted • Never-looking
The Drunk	Drunken-walk	• Make-stop • Near-miss • Collision

The Distracted	Distracted, Never-looking	• Phone • Music • Interact-other-participant • Fixated
The Flash	Run-into-traffic	• Brisk-walk • Never-looking

The Indecisive	• Retreat, or • Flinch-in, or • Flinch-out, or • Frozen, or • Swerve	Near-miss
The Blind	Not-looking	Distracted
The Flock	Group-walk	• Group-walk • Group-disperse • Re-group • Pet-walk • Street-fight

The Jaywalker	Jaywalking (any place except crosswalks)	• Make-stop • Near-miss • Collision
The Elderly	Late-response	• Make-stop • Near-miss • Collision
The Kid	Under-teen and Ignorant	• Make-stop • Near-miss • Collision

The Eventful	• Drop-object, or • Pickup-object, or • Trip, or • Pop-out of occlusion	• Make-stop • Near-miss • Collision
The Parked Pedestrian	• Getting-off, or • Getting-in, or • Change-tire, or • Load-unload	-

Table 4.1: Pedestrian Behavior Tags: behaviors from the perspective of the ego vehicle and its lane.

Chapter 5

Toward Expressive Generative Pedestrian Modeling

*Safe and Dangerous pedestrians are **equally** wanted.*

This work guides how to develop rich simulation models for pedestrians. In simulation, autonomous driving agents are often tested against critical scenarios [126, 11, 100, 112, 113, 153, 220, 85, 12, 150, 194, 265]. Some methods search for emergent critical scenarios based on the interplay of traffic agents such as vehicles and pedestrians or road structures [98, 141, 142, 8, 165, 84, 223, 261, 97, 110, 105]. In such a search-based setting, to reliably validate driving agents against pedestrians, a generative pedestrian model needs to support some essential characteristics such as adaptability, controllability, and variations. Adaptability ensures that the pedestrian adapts to the evolving scenario during the search. Controllability exposes parameters the search method can use as the behavior search space. Variations capture the randomness in behavior given the same situation.

In addition to the key characteristics, the generative simulation model must create safe and dangerous pedestrians to cover a wide range of scenarios, including rare cases, for testing purposes. However, generative modeling of rare behavior is a complex problem.

Furthermore, different components in the autonomous driving stack require various input modalities. Perception systems often take visual inputs or 3D point clouds, which contain human locomotion. Locomotion is essential to understanding human body language and can reveal what a pedestrian is going to do next. For example, the future trajectories can be more accurately predicted if the perception systems can understand whether a pedestrian is falling on the road by analyzing the locomotion. Planning systems mainly deal with trajectories. However, it can be further improved if the planning system knows more about the human states. For example, at the trajectory level, a pedestrian can be static. However, the pedestrian can be standing or lying on the road, which may require the AV to follow different plans. This work assumes that various modalities are available in the simulation models. MotionGPT, [131] demonstrate how behavior, trajectory, and locomotion can be generated simultaneously for humans.

Last but not least, the approach to a simulation model with diverse pedestrian behaviors with requirements for test facilities can be complex, which is addressed at the end of this chapter.

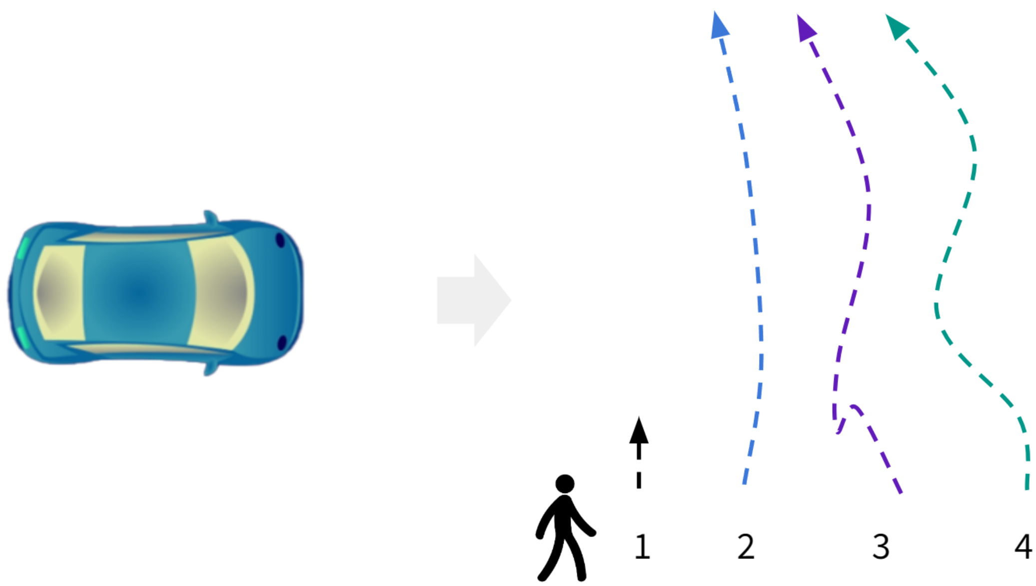


Figure 5.1: In this traffic context, a vehicle is approaching the crossing pedestrian. Pedestrians can show different types of behavior. (1) They may make a stop and let the vehicle pass, (2) They can ignore the vehicle and cross the road, (3) They can momentarily flinch back and cross if the vehicle yields, or (4) they can take an unexpected route and cross the road. Given the same situation, pedestrians may have different adaptation strategies or can completely ignore the approaching vehicle. So, both adaptability and variability are important aspects of a robust pedestrian model. Controllability is required so that during the test, one can deterministically produce all of the four scenarios.

5.1 The Ideal Pedestrian Model

The ideal pedestrian model tests autonomous driving in both safe and unsafe scenarios and shows different crossing strategies while a scenario evolves during simulation (see *Figure [5.1]*). The following components are derived from the archetypes (**Chapter [4]**), ontology (**Chapter [3]**), and pedestrian choice model [9]:

- **Appearance**: Pedestrians come in different shapes, wear clothes with an infinite variety, and may carry objects such as a storage box. Appearance is important when the autonomous perception methods are dependent on the 3D shape of the pedestrians and visual colors.

- **Locomotion**: Locomotion is how the animal moves their body parts to specific tasks related to movement maneuvers such as walking, jumping, falling, and stopping. Each maneuver has a unique locomotion. Locomotion tells what the pedestrian is doing and often hints at what they can or cannot do next.

- **Activity Choice:** The pedestrian decides what to do next voluntarily or involuntarily [9]. For example, the pedestrian may impulsively stop in the middle of the road or start running suddenly. External control is needed for specific test goals as there can be a score of options for the next activities. The ontology, **Chapter [3]**, presents the essential set of activities.

- **Maneuvers**: maneuvers capture the diversity in temporary motion to support a pedestrian's activity, e.g., where to stop to let an oncoming vehicle pass. They also capture the maneuvers' timing constraints, such as how long it takes to complete a maneuver. The stopping behavior from [206, 207] is very different from [21] (*see Figure [4.11]*).

- **Destination Choice**: The destination is related to the activity the pedestrian has chosen. It can be on other sidewalks, or their current location, or at any other location on the road. *Section [4.10]* shows a child changing their destinations three times in the middle of a four-way intersection.

- **Mode Choice**: While crossing, pedestrians can walk on foot, or use a wheelchair, or ride a scooter or skateboard. They can use devices such as a walking stick to help them cross or haul a sled (see *Section [4.7]*). The mode introduces constraints on movements or increases some movement capacity, such as speeding due to scooters.

- **Route Choice**: Pedestrians take diverse routes while crossing a road. They do not necessarily confine themselves to staying on a crosswalk. Often, they cross on the midblock of the streets or in the middle of an intersection, a move which is unexpected by an AV (see *Section [4.8]*). Also, pedestrians do not necessarily always want to cross. *Section [4.1]* shows examples where pedestrians choose to wander on the roads without crossing. *Section [4.10]* shows how kids and 4.5 show how indecisive pedestrians can quickly change their trajectories while crossing. They can even take a U-turn and return to the sources after crossing a lane. The route diversity drastically changes the situation and can invalidate the ego vehicle's prediction of a pedestrian's next action. The route choices can be sparse and difficult to control [157, 158].

- **Gait Properties**: gait relates to pedestrian speed, acceleration/deceleration, and rotation capacities. The controllability of these properties allows one to generate different types of pedestrians with different physical constraints. For example, to test self-driving against running pedestrians, one needs to control the speed of the pedestrians in a higher range than the usual walking range.

- **Interactions**: Pedestrians can show gestures or interact with other pedestrians, traffic participants, and objects on the road in many different ways, e.g., a dog companion can change how a pedestrian moves while crossing. *Section [4.7]* illustrates how group behavior emerges due to interactions among a group of pedestrians crossing together.

- **Interactions**: Control of interactions is also desired since it leads to considerable scenario diversity. For example, a pedestrian may or may not follow the leader in a group, [58, 210, 211, 204, 35, 197, 123], or a pedestrian may drop an object while crossing and impulsively stop to pick it up [46, 209].

Each component of a robust generative pedestrian model may require support for adaptability, variability, and controllability for test goals and methods.

5.2 Modeling Adaptability

The adaptability property ensures that pedestrians adapt to the diverging scenarios in the simulation, producing the expected behavior set by the test plans. Humans adapt fast. A pedestrian can effortlessly jump over a pothole, cross streets with different shapes, navigate through complex and ever-changing traffic, and read the minds of others. Humans also adapt to any given context. For example, assume a scenario where the purpose of the test is to ensure the ego vehicle avoids an accident when the pedestrian already started crossing the road. The ego vehicle can speed up to escape the pedestrian or slow down to let them pass. However, if the pedestrian does not adapt to the changing speed of the ego vehicle, it cannot challenge the ego vehicle well. So, the ego vehicle may actually fail if the pedestrian also speeds up.

5.2.1 Adaptability Challenges

There are two major challenges in modeling adaptability: (a) identifying which behaviors can be adaptive and (b) how to make a behavior adaptive.

- Identifying adaptive maneuvers is challenging as it requires analysis of all sorts of data available on pedestrian crossings. Humans show a wide range of maneuvers and richness in adaptation. However, to model adaptability, one needs data on all the behaviors, including rare ones, [160]. A promising approach to identifying all possible human behaviors can be found at [213].

- Once the adaptability behavior is discovered, the challenge of choosing the right modeling method comes. The methods that can learn different types of maneuvers are often data-driven systems requiring a representative data set. Using some rule-based systems faces the challenge of analyzing and hand-crafting hundreds of rules. In addition, rule-based systems often require calibration of some data. However, in many rare cases, extracting necessary information from the data sources is impossible. For example, a picture showing a pedestrian jumping on the road does not tell how high they can jump or whether they were also moving on the horizontal axis. For such a situation, one often needs to hand-craft the model using many different sources.

5.2.2 Adaptability Literature

In rule-based systems, a pedestrian follows a set of discrete choice models and a set of physics models to interact with the surroundings and move toward their destinations. There is a score of physical social-force-based models [145, 249, 248, 114, 258, 65, 174]. Social forces are any human-created ways of doing things that influence, pressure, or force people to behave, interact with others, and think in specified ways. An approaching vehicle can push a pedestrian away, but the destination always draws the pedestrian to it. The resultant force of all the influential factors determines the direction and speed of the pedestrian. However, these are only physical models and do not model many behaviors, such as jumping over a pothole or making a hard stop to avoid collisions. Discrete choice models [10] and cellular automata-based approaches can capture such behavior [17, 138, 13, 263]. However, though these methods are powerful, they can grow very complex [10].

In a data-driven system (specially neural networks) ([224, 140, 83, 120, 2, 246, 259, 144, 80, 68, 184]), the model automatically learns from data. While this approach can theoretically learn to adapt to any situation, it also requires all the data about pedestrians, and the data have to be high quality and is still infeasible. In addition, such a model is often hard to control as the testing may require many control parameters (*more at Section [5.4]*). In addition, these methods have difficulties adapting to unseen situations or scene contexts.

5.3 Modeling Variability

The variability property ensures that, given the same context, the pedestrian can exhibit all possible variety in their acts. The unpredictability of pedestrian behavior on the road originates from psychological and physical diversity and a plethora of choices. Variability in behavior can be modeled as emergent behaviors due to the personalized properties of a pedestrian, such as age, gender, height, impairment, etc. However, hundreds of such properties exist, [191]. An opposite way is to model based on the observed behavior. Instead of diving into the minds of the modeled pedestrians, it is possible to record and categorize their observable actions under variability. The urge is to recognize the effect even when the cause is concealed. Variability differs from adaptability as pedestrians often do not adapt to a situation at all, forcing others to adapt to them.

The pedestrian model requires diversity in each component defined in *Section [5.1]*. Each component relates to a broad domain of research. This work discusses and summarizes the variability of the main components that challenge autonomous vehicle planning algorithms only. Components related to visual perception, such as "Appearance" and "Locomotion", has a long line of research which are applicable but not exclusive to pedestrians.

5.3.1 Decision Variability

Pedestrians make discrete decisions on the road, including choosing their next activity and destination. The decisions can be voluntary or involuntary. Decision variability refers to the possible discrete decisions a pedestrian can make in a situation. For example, different persons accept different amounts of gap with approaching vehicles when they make a decision to cross the road from a sidewalk [15, 264, 67, 134, 137, 232].

5.3.1.1 Challenges and Research Gaps

There are several challenges in capturing the decision variability:

- *Exhaustive studies do not exist on decision variability in every situation.* For example, there exists no method that models pedestrians falling on the road while crossing [56, 57] or crawling on the road [89, 90].

- *Existing studies on specific situations may not cover all the possible decisions*. For example, the Rolling Gap models capture the gap accepted by pedestrians in multi-lane traffic scenarios [132, 133, 255, 161]. However, none of the models capture the counter-examples where the pedestrian completely ignores the vehicle on far lanes as seen in [30, 237, 238]. These studies often confine themselves to datasets covering a particular season and specific geographical locations.

- *Decisions are correlated with many factors, and some are confounding factors*. Sometimes, it is evident when the pedestrian shows a particular behavior. But sometimes, it is challenging to associate decisions with specific situations. For example, when a pedestrian starts crossing by running, it is highly likely that they will continue to run while crossing [32, 59, 33]. However, one starting slow can suddenly begin to run without any observable reason, [21]. Thus, it is challenging to map a specific situation to possible pedestrian decisions.

5.3.2 Maneuver Variability

The maneuver refers to how a pedestrian executes a behavior over time. For example, when a pedestrian retreats to a safer location, they can turn and walk or run back. It is also possible that they retreat without turning back. In addition, the time it takes to turn back depends on the pedestrian's physical and mental capacity and state.

5.3.2.1 Challenges & Research Gaps

Maneuver variability challenges differ from decision variability as the action is already identified. However, they have a different set of challenges:

- *Many maneuver trajectories need to be learned from high-quality data.* The velocity profile modeled by rule-based methods such as Helbing's Social-Force-based model [115] is too simple to capture real-world situations. One can model the retreat maneuver with social forces. However, the social force model cannot capture behaviors such as impulsive turning back and fast acceleration and deceleration.

- *Many maneuver trajectories cannot be learned from data due to the lack of high-quality data.* Thus, one needs to create a highly sophisticated rule-based model. However, existing literature using rule-based systems only captures simpler versions of the maneuvers. For example, the crowd simulation models [74, 93, 179, 252, 69, 135] miss the opportunity to model the dangerous flock depicted in *Section [4.7]*. The existing simulation models do not capture group dynamics found in [71, 154, 173, 256]. According to the literature, there is a diversity in group shapes, and groups can dynamically break off or merge.

- *Multiple maneuvers in a single crossing trajectory share common properties.* *Figure [4.7]* shows two pedestrians. The maneuvers shown by the indecisive leader are much quicker than those of the follower. So, maneuvers need to consider archetype properties. Conditional maneuver dynamics make it even harder due to the increasing complexity and the rarity of data.

5.3.3 Route Variability

Route diversity comes from different paths pedestrians take in the shared space on the road. The different paths can emerge due to the traffic participants and obstacles. However, diversity can also emerge in the absence of any factors at all.

5.3.3.1 Challenges & Research Gaps

- *Rare routes are infrequent, and no knowledge base covers rare routes.* While almost all the routes taken in a given traffic context are predictable and very similar to each other, some routes taken by pedestrians are unimaginable and inexplicable (see *Figure [4.2]* and *Section [4.2]* for such examples). Existing literature on pedestrian route choice and planning produces optimal routes only based on some goal or utility function [3, 6, 119, 215, 233]. However, testing requires unsafe and irrational routes. **Chapter [7]** proposes a novel method for capturing rare routes from real-world scenarios and using them in simulation.

- *Data-driven methods may not produce rare routes.* Several data-driven works produce route plans based on existing traffic participants and obstacles in the shared space [247, 266]. However, these methods only produce paths similar to those seen in the data given the scene context.

- *Given a shared space on the road, the possible number of routes can be prohibitively large to test against [119].* So, the random generation of routes makes the testing plan lengthy and extremely costly. **Chapter [8]** proposes a novel method to reduce the search space of extraordinary routes while covering the shared space well.

5.3.4 Interaction Variability

Pedestrians interact with other traffic participants and objects while crossing the road. Sometimes, they cross together in a group or play with their mobile phones while crossing. In [9], four categories of interactions have been identified: (a) group, (b) leader-follower, (c) collision avoidance, and (d) other scene objects. Group behaviors refer to socially connected people who tend to be close to each other spatially while crossing. Leader-follower behaviors refer to the tendency of pedestrians to follow a leading pedestrian. Collision avoidance refers to the behaviors where a pedestrian tries to avoid collisions with other pedestrians or traffic participants. Scene object interactions refer to interacting with other objects in the world, such as boarding on a parked vehicle.

5.3.4.1 Challenges & Research Gaps

- *Group shapes and dynamics are complex [69, 135].* A group can break off and regroup in the span of a crossing [173, 154, 256, 71]. *Section [4.7]* shows rare group interactions that are very different from each other. So, such interaction modeling requires exhaustively enumerating group interactions and modeling them using rule-based systems because of the scarcity of data.

- *In case of crossing, the leader-follower interactions show different structures*, such as followers failing to keep up with the leader or followers out-walking the leader. At some point, the follower may stop following the leader completely [34]. Diversity and elasticity in the leader-follower interactions make it harder to model.

- *Collision avoidance interactions depend on pedestrian perceptions*. Existing literature assumes that pedestrians always apply a collision avoidance mechanism. However, in the real world, pedestrians often fail to avoid collisions with other pedestrians, vehicles, or objects. Video [147] shows some pedestrians bumping into objects or other pedestrians. Also, in a given situation, there can be several evasive strategies for collision avoidance [156].

- *Pedestrians can interact with different scene objects differently*. How they interact with a handheld device is very different from how they interact with a parked vehicle. Some literature discusses the impact of using handheld devices such as mobile phones [181, 218]. However, no simulation model produces such behavior in simulation. Other literature focuses on how parked vehicles impact the pedestrian flow [107, 117], but no method to model how pedestrians interact with the vehicles currently exists. There exists a visual attention model for parked vehicles in [82] which can be extended with trajectory generation. However, appropriate trajectory datasets are required. In addition to everyday objects, pedestrians interact with other rare objects while crossing. For example, pedestrians may use unicycles [16] or scooters [212, 31] while crossing the road. Enumerating all such objects and interactions with them is a taxing task.

- *There are other kinds of interactions that are not well discussed in the literature*. For example, pedestrians can fight each other on city streets [61, 62] or highways [60]. Unknown interactions make it more difficult as one has to discover such interactions first before modeling.

To summarize, the current literature only exhaustively explores some of the data available for analysis. Therefore, the models are heavily biased towards niche cultures and often completely ignore unique behaviors. Many known unknowns and unknown unknowns are yet to be discovered and modeled when it comes to variability in behavior.

5.4 Modeling Controllability

The controllability property ensures that test plans can be created to target specific pedestrian behaviors. For example, when validating autonomous driving against drunk pedestrians, a pedestrian behavior model must be able to explore possible behaviors and trajectories of drunk pedestrians only. Furthermore, it is also desirable to control specific micro-behaviors, such as whether the pedestrian can fall down or stop in the middle of the road to produce extremely rare and dangerous situations. With the controllability of the pedestrian model, test methods can navigate through the variability of the model with a well-defined purpose.

To support controllability, pedestrian agents must be controllable through some configuration options, such as speed or a set of possible micro-behaviors. Controllability works in two layers. At the higher layer, one can configure which behaviors pedestrians can show during the simulation. For example, the configured pedestrian can be drunk, wander on the road, and make sudden stops. At the lower layer, one can control the parameter that modifies the properties of a behavior. For example, one can control how long a drunk pedestrian stands still on the road before starting to move again.

Controllability serves several objectives to facilitate testing:

- **Test coverage:** To ensure that autonomous driving can deal with possible pedestrian behaviors on roads, it is essential that test cases can deterministically cover a wide range of possible pedestrian behaviors. A random search-based approach can explore all possible behaviors. However, it also produces repeating or similar test cases, making the search very costly. With control parameters, test designers can carefully control the parameters to search for unique test cases faster.

- **Targeting specific behaviors:** Producing scenarios with specific types of behavior requires control of the behaviors. For example, to thoroughly test against impulsive stops, the probability of stopping should be configurable.

- **Composing archetypes:** Pedestrian behaviors have correlations with each other and modify one another. With behavior controllability, one can create plausible archetypes by choosing a set of active behaviors that have a higher correlation with each other. The ability to compose archetypes supports the reusability of different behaviors for different types of pedestrians. For example, both adults and kids can sprint on the road, or a group can have some members intoxicated.

- **Producing critical scenarios:** In adversarial search methods, the goal is to evolve scenarios in such a way that the vehicle under test faces increasingly dangerous situations, [98, 141, 239, 242]. Such methods can be applied to behavior space to search for dangerous behavior in different situations. It is indeed a hard problem to tell which behavior is more dangerous. For example, a sober person crossing a roundabout may be much more dangerous than a drunk person on a 4-way straight road. Such search methods empirically measure the relative risk associated with pedestrian behavior.

5.4.1 Challenges & Research Gaps

- *Fine-control of pedestrian agent depends on agent modeling method.* Some methods cannot easily facilitate controllability. For example, neural networks are an effective data-driven approach [120, 2, 246, 259, 144, 68, 80, 184, 224] for pedestrian trajectory generation. However, fine control of the agent behavior is very difficult to achieve in neural-network-based models.

- *Search space complexity increases with the number of control parameters*. So, it is important to reduce the number of correlations to make the testing method tractable. Many pedestrian properties are highly correlated with each other. For example, rotation capacity is constrained by the speed of the pedestrian. So, the maximum possible rotation parameter can be derived from the speed parameter. However, finding such a correlation requires microscopic behavior research. The existing literature has some findings on how age, gender, or culture is related to pedestrian speed [222, 116, 96, 240, 139, 257]. However, more discoveries are needed at different archetype levels for generative modeling.

5.5 Modeling Approach

5.5.1 Combinatorial vs Archetypes

Each pedestrian is a composition of a set of behaviors (e.g., stop, flinch, run) with personalized limitations. For example, a child can be quick but cannot run as fast as an adult. One modeling approach is the random combination of behaviors with a random selection of parameter ranges. Another modeling approach is to combine behaviors that are compatible with each other and carefully select parameter ranges to represent some archetype. Both approaches have their advantages and disadvantages.

5.5.1.1 Combinatorial

By having a collection of behavior models, it's possible to combine them randomly to generate a large set of pedestrian models. While this can be easy to implement, it has some severe disadvantages.

Pros:

- Can represent unseen trajectories. For example, if there is ever an elderly person who can run fast, the combinatorial approach can produce such pedestrians.
- New behaviors can be added to the behavior collection, and less effort in making the combinations

Cons:

- Can produce unrealistic pedestrians. For example, a child may run at the speed of an adult.
- Testing method needs to deal with combinatorial explosions. Frequent testing may be prohibitively inefficient.

5.5.1.2 Archetypes

Chapter [4] defines archetypes such as the wanderer who tends to walk on the road along the lanes. Each archetype has its own set of possible behaviors and a specific range of behavior parameters. While this is very promising, it requires a heavy workload.

Pros:

- Models are very realistic as each archetype has its fixed set of behaviors learned from the real world.
- Testing methods have a much smaller search space of behaviors as the number of possible combinations is limited.
- Supports coverage and scenario-based testing. For example, one test suite can contain testing against children only.
- Archetypes are tangible assets and can contribute greatly to the community of practitioners and consumers of autonomous driving.

Cons:

- Requires expert human knowledge.
- Requires exhaustive research in discovering behavior inter-dependencies.
- Model can become extremely complex.

5.5.2 Predictive vs Generative Models

Generative modeling differs from probabilistic predictive modeling in that probabilistic predictive modeling tasks produce the most probable trajectories. Re-purposing a predictive model for generation leads to the exhibition of common behaviors only. However, effective testing requires both common and rare scenarios.

Predictive models based on neural networks or sequence probability optimization create a sequence of pedestrian positions [120, 2, 259], optionally along with body pose [224, 131], over a short period of seconds. While creating the sequence, the models are optimized to produce sequences with the highest joint probabilities of the data points. One can sample low-probability trajectories from existing predictive models. Unfortunately, low probability trajectories include long-tail and unrealistic cases and explode in numbers. However, these are potent learning methods given adequate data.

Generative models based on physics and rules allow the introduction of rare cases [145, 248, 156]. However, there are two catches. First, the physics models have a set of independent variables and are parameterized, which needs to be calibrated against them. Having a strict system of variables leads to failure when the scene context does not have values for the variable or has more traffic participants than the model considers. For example, the collision avoidance model, which only considers two traffic agents, may produce unexpected results when there are more than two agents in conflict. Second, rules create branches in behavior. So, it faces challenges in management when the model grows deep with hundreds of branches. Even with such disadvantages, these models can be crafted using rare data and human expertise.

5.5.3 One model vs Multi-model Approach

As the pedestrian behavior space is sparse, building a single model using both classical rule-based approaches and modern machine-learning-based approaches is difficult. Rule-based models quickly become large and difficult to manage. Machine learning-based approaches require representative data for every behavior and type of pedestrian. In addition, controlling one rule-based model is difficult because it may have a large number of control parameters, and one machine-learning-based model is difficult as it may not offer enough control parameters.

To address the drawbacks and gather the benefits of both approaches, the literature has explored multi-model approaches where different decisions, maneuvers, routes, and interactions are learned in different micro-models. At any point in a scenario, the active micro-models define the pedestrian trajectory and behavior. To correctly select micro-models, the pedestrian state is modeled as a finite state machine (FSM) [156, 249, 128]. Each state has a mapping to the relevant micro-models. For example, in [156], the pedestrian crossing decision is made in the *waiting* state, and the motion plan is made in the *crossing* state.

5.5.4 Evaluation of Models

Generative models are hard to evaluate because they have several roles to play:

- *Reproducing real-world scenarios:* With the same initial state, the generative model may not produce the same trajectory for pedestrians seen in a dataset exactly. This is because, it also has to produce the diversity from the initial state.

- *Producing realistic trajectories:* In predictive models, realism is measured by comparing generated trajectories with real trajectories using distance metrics such as Average Displacement Error (ADE) and Final Displacement Error (FDE). However, the generative model often only have micro-behavior models which produces new trajectories. So, it is essential that the micro-behavior models are evaluated separately as a very good generative model will not perform well on ADE or FDE.

- *Producing long-tail scenarios:* One of the main purposes of the generative models is to produce scenarios which are very rare or even non-existent in the real world datasets. But such scenarios are not impossible. Evaluation of such long-tail behaviors requires human evaluation or using metrics such as "Perplexity", [130].

This work suggest taking a multi-model approach for pedestrian simulation models. However, multi-model approaches require human expertise and effort, and prone to errors. Whether the correctness of the models is important depends on why the models are being used. For training of neural-network-based models, correctness is not essential. However, for testing, the correctness is important as testing cases must represent the real world behaviors accurately.

Chapter 6

Adversarial Jaywalker Modeling for Simulation-based Testing of Autonomous Vehicle Systems

The following chapter was originally published as *Adversarial Jaywalker Modeling for Simulation-based Testing of Autonomous Vehicle Systems* in IEEE Intelligent Vehicle Symposium (IV), Aachen, Germany, 2022. This was the initial effort to create a robust pedestrian model, and the underlying idea was to use a compositional social forces model where a finite state machine controlled progression among a series of different pedestrian behaviors, where each behavior is a separate social force model.

6.1 Abstract

We present an approach for creating adversarial jaywalkers, autonomous pedestrian models which intentionally act to create unsafe situations involving other vehicles. An adversarial jaywalker employs a hybrid state-model with social forces and state transition rules. The parameters (for social forces and state transitions) of this model are tuned via reinforcement learning to create risky situations faster with synthetic yet plausible behavior. The resulting jaywalkers are capable of realistic behavior while still engaging in sufficiently risky actions to be useful for testing. These adversarial pedestrian models are useful in a wide range of scenario-based tests for autonomous vehicles.

6.2 Introduction

Predicting pedestrian trajectories (position, velocity, etc.) is one of the core tasks of Autonomous Vehicle (AV) systems. This task is challenged by several hurdles in the perception of pedestrian movements. First, a pedestrian can change their direction of travel and speed quickly because of their intention and interaction with other road users [193]. Second, different pedestrians show different kinds of behavior in a given situation due to internal factors such as distraction, age, gender, and external factors such as the presence of other pedestrians, vehicles, signals, weather, etc. [221, 152, 188, 191]. Third, the validation of trajectory prediction algorithms is crippled by the scarcity of real-world data.

To reduce the cost and risks of testing AV systems on the road, researchers use several simulation methods to develop and test AV algorithms. One promising approach is modeling pedestrian behavior instead of generating synthetic data, a common approach. In this behavior modeling approach, during the test, the pedestrian behavior is generated dynamically based on the situation at hand [258, 251, 250, 66, 104, 162, 129]. The main advantage of such a behavior-model-based approach is that pedestrian behavior can often be generated in different environments (road structures, traffic participants, etc.). However, there are two challenges in behavior modeling for simulation: most behavior modeling is done in other domains such as traffic accident analysis, and simulation models lack rich pedestrian behavior.

We propose a hybrid multi-state social-force-based model similar to [250] for jaywalkers. Jaywalking is defined as crossing the road in the middle of a block (without a crosswalk or un-signalized intersection) or crossing along a crosswalk violating signals. People jaywalk for several reasons: urgency (e.g., fire evacuation), whim, reduced walking distance, etc. In a social-force-based model, different factors, vehicles, and other pedestrians exert forces on a pedestrian which decide their speed and direction of travel (see Helbing et al.[115]). Chen and Yang have extended Helbing et al.'s single state model, which is a crossing state, to a multi-state model to formulate behavior while waiting, finishing, and stopping in addition to basic crossing behavior [66, 250]. Zeng et al. introduced crossing area forces to keep pedestrians inside crosswalks in [258]. In a hybrid approach (social forces + manually-crafted rules), we can both introduce rules that control transitions among behavior and calibrate force intensities with available data. When any behavior pattern is missing in the data, we can develop custom rules to produce those patterns.

Existing social-force-based models have yet to achieve a rich set of behaviors and a high level of non-determinism. For example, [258] uses a gamma distribution from [260] to estimate the desired speed of a pedestrian based on crosswalk entering speed, crosswalk length, and signal timing. Hence, the pedestrian velocity varies only within a narrow band due to the small range of variation coming from the gamma distribution in a context. Moreover, in the case of jaywalking behavior, which may not have any signal factor in the context, the speed model does not work. In addition to capturing the speed profile of pedestrians, we also need to find edge cases in speed that make pedestrian trajectory prediction harder. So, we propose an adversarial jaywalker model which learns adversarial policies, such as speed distribution, that are more unpredictable and lead to more dangerous situations.

In addition to social-force-based models, another popular approach is machine-learning-based models. While supervised-learning-based models can learn behavior without specific mathematical modeling, they suffer from poor generalization due to non-representative datasets [162, 224]. Another approach is self-supervising learning, *(see [185] for such models*).

The goal of our research is twofold. We develop a jaywalker model considering behavior patterns and factors from different sources. We also develop adversarial strategies to intentionally create a problematic situation for the ego vehicle where it must react strongly to avoid an accident involving the pedestrian.

6.3 Jaywalker Modeling

A key element of our simulation approach is to use one or more jaywalkers driven by a behavior model. In this part, we first identify the goals of our model, then formulate the set of tasks and categorize them into three layers. The jaywalkers in our research settings need to satisfy multiple goals:

- *Human-like behavior:* Generated trajectories must be possible in real-world situations. That is, the pedestrian model exhibits human-like behavior. This criterion ensures the internal validity of our test framework.
- *Adaptability to adversarial behavior:* In our simulation, the jaywalker acts as an adversary, choosing actions that will deteriorate the current situation. To support this, the model needs to be manipulable by adversarial algorithms.
- *Allowing a rich set of behaviors:* Jaywalkers must have the ability to display a wide range of crossing pedestrian behaviors such as crossing midblock, crossing at a crosswalk, crossing in the presence of obstacles and other pedestrians, changing destination while crossing, and so on. So, the model needs to be architected in a modular way to support adding new behavior easily.

- *Behavior variation:* We need to have the opportunity to turn on and off different high-level behaviors (e.g., cautious, distracted, risk-taker, child, etc.) and alter their relative strengths. One of the core issues with existing models is that they model a single type of pedestrian, usually a rational one with a limited and deterministic set of possible trajectories given a situation. We wish to model a broader range of behavior.

- *Allowing accidental factors:* Some factors can drastically influence the behavior of a pedestrian while crossing. An example is dropping a belonging while crossing. These factors can lead to unexpected consequences.

In general, there are two ways of modeling the jaywalker behavior, rule-based (or physics-based) and data-driven, along with hybrid approaches that combine the two. In a rule-based approach (e.g. *social force and other rule-based models in [151, 258, 251, 66, 250, 104]*), we can divide all the decision making activities into *strategic, tactical, and operational* levels. Each level models the activities using knowledge-based or data-driven approaches. This approach helps us fill in the gaps in behavior datasets with our knowledge and lets us evolve the model with clear goals. In a data-driven approach, everything is learned from data by a machine learning process (*e.g., the MDP-based model in [162]*). The main advantage of this approach is it can capture the whole state represented by data, which is often too difficult in knowledge-driven approaches. Inspired by the hybrid approaches (*e.g., the multi-modal hybrid model in [129]*), we will create our model combining both knowledge and data. We define the terms *factor* and *force* before jumping into the details of our modeling methodology:

Factor: A factor is a tangible or intangible element that influences how pedestrians act on the road. Factors can influence some behavior or initiate new sub-behaviors. Examples of factors include age and gender of a pedestrian, presence of police on the road, etc. For a comprehensive list of factors, see [192, 188].

Force: In the base Social Force Model, a factor creates a repulsive or attractive force on the pedestrian. An example of a repulsive force is the force from an oncoming vehicle and an attractive force from the destination. Different factors have different models of forces, [258]. In our model, a factor can have its own force, or it can influence the force by another factor.

In a walking state, an example of the force equation with three factors looks like this:

$$F = w1 * F_a + w2 * F_b + w3 * F_c \tag{1}$$

where F_a, F_b, F_c are forces exerted by factors a, b, and c respectively. The weight parameters $w1, w2, w3$, in our model, are controlled by the urgency model (*Section 4*) which can increase or decrease the forces.

Pedestrians are modeled using a finite-state machine, where each state is a different behavioral condition (waiting, walking, etc.), [Section 6.3.1]. When the pedestrian is in motion within a given state, the motion is controlled by a set of force models based on the factors active in that particular state. The strategic level can be viewed as a process by which the parameters and forces in the model are given their initial values (which may turn on/off certain factors). The tactical level can be viewed as focused on managing the transition between states. Finally, the operational state is concerned with the execution of behaviors within each state via a social-force model.

To develop the rich set of behaviors, in addition to the factors and tactical models proposed in the current literature for simulation, we propose a novel set of factors, described in Section 6.3.1, and tactical models gleaned from pedestrian behavior research in different domains (traffic analysis, psychology, etc.). Novel models include urgency, risk, and destination models. Next we elaborate our model structure by describing the state model and our novel factors, Section 6.3.1, and each of the decision levels (strategic, tactical, & operational in Sections 6.3.2, 6.3.3, and 6.3.4 respectively):

6.3.1 States

Each state has its dedicated operational model (*see Section 6.3.4*), which can be modeled in isolation. An operational model is essentially a force model with a set of active factors, and optionally some rule-based behavior. For example, the waiting state may have a force model that makes a jaywalker falter in the start zone, while the walking state may not have any faltering behavior at all. The states, (*depicted in Figure 6.1*) are:

1. Initializing: planning to cross. In this state, the source and destination zones and internal factors of the simulation model are chosen.

2. Waiting: The pedestrian waits at the start zone.

3. Crossing: The pedestrian is moving inside the crossing area.

4. Frozen: The pedestrian is inside the crossing area, but stops moving momentarily. It is activated by the freezing factor. The frozen state is critical as the pedestrian is inside a lane and forced to move as soon as possible.

5. Survival: The pedestrian goes into this state when there is a near-accident situation. The model finds a safe zone where pedestrian quickly moves to save themselves.

6. Finished: The pedestrian reached destination zone.

Novel factors: We propose two factors, in addition to existing factors from existing social-force-based models, that are crucial in generating a rich set of pedestrian behavior.

1. A freezing factor: freezes the pedestrian when they are shocked (state *crossing* $->$ *frozen*). The freezing factor has a timeout. After the timeout, the state is resumed to *crossing*. The freezing factor is an abstract factor that can model all the factors that make a pedestrian stop while crossing. Examples of factors abstracted by the freezing factors include dropping a belonging, panicking, etc.

2. Intermediate destination factor: This factor is handy while crossing a multi-lane road or walking along a road while crossing. While crossing, the pedestrian

Fig: Jaywalker State Model

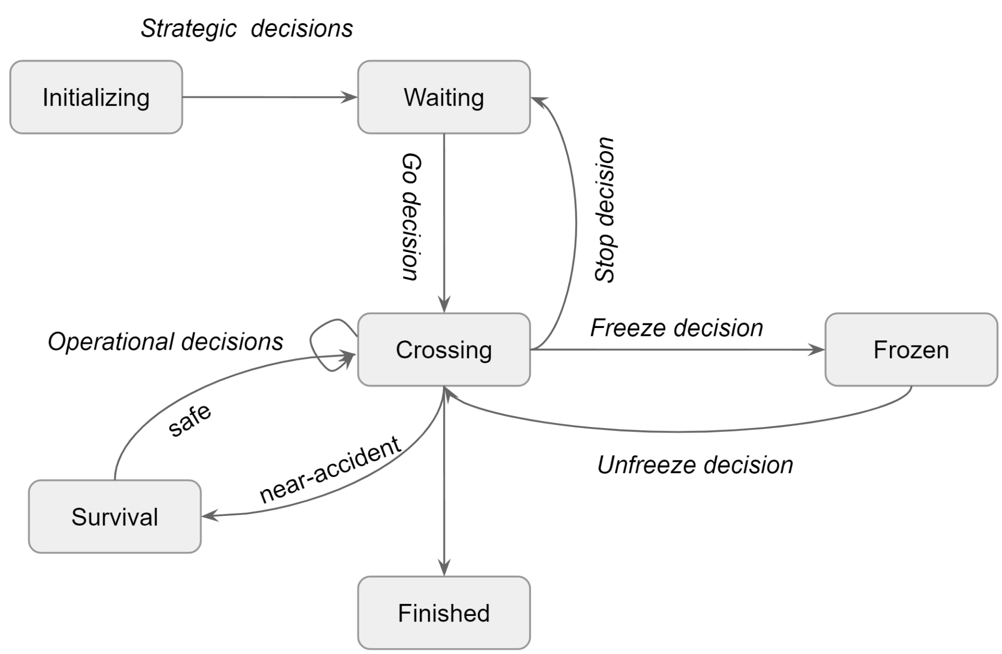


Figure 6.1: The six states of the jaywalker model categorize the set of behaviors that a jaywalker can exhibit.

towards the local destination, and when reached, the state changes from *cross* to *waiting*.

6.3.2 Strategic Level

At this level, we formulate the high-level goals for the model, which take the form of the initialization of forces and parameters in the state transition graph. Essentially this step allows us to configure the jaywalker's overall behavior (distracted, risk-taker, cautious, etc.) The purpose of modeling at this level is:

1. Identifying the source and destination zones.

2. Identifying the pedestrian's internal factors that change behavior in the lower levels. For example, distraction varies the pedestrian's attention to oncoming vehicles greatly.

3. Identifying the factors that can be abstracted away. For example, advertisements would be abstracted away at a lower level, but we still want some way to make the jaywalker behave as if they were distracted by an advertisement.

4. Choosing factors that, even present in the environment, can be ignored by the pedestrians.

5. Choosing the strength of force for each factor.

6. Deliberate introduction of factors such as talking to a phone and listening to music.

6.3.3 Tactical Level

The purpose of tactical level decisions is to model deliberate actions (discrete choices) by modeling discrete behaviors as individual states and transitions in the state transition graph. Compared to the strategic level, which focuses on configuring a jaywalker, the tactical level focuses on how an already configured jaywalker behaves. For example, the strategic level may create a risky jaywalker, but when a risky jaywalker starts crossing the road is modeled at the tactical level. The transitions are similar to transitions of multi-state models in [250, 104, 129]. The tactical level is broken into a set of decision models.

1. **Destination model:** does two things: (a) deliberate change in destination, (b) create local destinations that will eventually get the pedestrian to their primary destination. An example of a local destination is the island between two adjacent lanes where pedestrians may stop temporarily.

2. **Crossing area model:** creates a virtual crosswalk area for the jaywalker. It also determines the source zone and the destination zone. Pedestrians can start from any point in the source zone and stop at any point in the destination zone.

3. **Stop/Go model:** makes deliberate stop/go decisions from a waiting state based on a gap acceptance model.

4. **Urgency Model:** Urgency model modifies the speed and risk level of the pedestrian. In an urgent situation, a risk-averse person may suddenly become a risk-

taker.

5. **Risk Model:** The risk model encompasses multiple decision making processes. Each model changes its behavior according to a global risk level.

6. **Interaction Model:** models interactions with other pedestrians. Basically, it chooses whether to apply an attraction force or repulsive force on another person.

7. **Survival Model:** models evasive actions taken by a pedestrian in case of a near-accident situation.

6.3.4 Operational Level

We model the involuntary actions or automatic responses at the operational level through a multi-state social forces approach. These act as a realization and enactment of the behaviors defined by each state in the state transition graph. The purpose of this level is:

1. Keeping the operational model as simple as possible so that upper-level behavior can easily influence operational decisions by (a) switching forces by different factors on and off and (b) increasing or reducing forces for a factor by changing the force parameters.

2. Allowing force parameters to be calibrated by data.

3. Keeping operations in each state separate.

6.3.5 How the adversarial strategy uses the model

One can run simulations with a jaywalker model in different environment configurations indefinitely and wait for emergent critical scenarios. Unfortunately, that translates to a random search approach and is not efficient. To control the level of randomness, we propose an adversarial strategy that can search for possible challenging scenarios faster. The purpose of the adversarial search is:

1. Learn how to configure the jaywalker behavior parameters that result in more risky situations.
2. Find possible and plausible risky situations given an environment effectively.
3. Adapt the strategy with new AV algorithms automatically.
4. Ensure that changes in behavior do not violate the laws of physics and limitations of human movement capabilities.

We intend to achieve the adversarial nature by three high-level operations using Deep Reinforcement Learning:

1. Selecting/deselecting factors.
2. Choosing a risky option in case of a tactical/strategic decision.
3. Modifying the factor forces (this changes speed and direction and abides by the laws of physics) within the allowable range.

Our approach is different from [185], where a distribution over initial location of a pedestrian is learned by reinforcement learning. We focus on learning behavior configuration instead. However, our rich jaywalker model can also be used in their settings replacing the pedestrian models they use. For example, we can deselect some factors forcing the pedestrian to be distracted or not noticing some other traffic participant.

6.4 Current Results

We implemented the Destination model, Stop/Go model, and Survival Model in our current phase of research. We ran our model in the CARLA simulation engine, [86]. First, we discuss the implementation details for the models and then evaluate the simulation results.

6.4.1 Destination model

This model is active in the *Crossing* state. Currently, the destination model accepts the final destination as a parameter and creates a force towards the destination using the approach from Helbing et al., [115]. The force equation is

$$\vec{F_\alpha^0} = \frac{1}{\tau_\alpha}(v_\alpha^0 \vec{e_\alpha} - \vec{v_\alpha}) \tag{2}$$

Where τ_α is a relaxation time to achieve desired velocity from the current velocity. v_α^0 is the desired speed of the pedestrian. $\vec{v_\alpha}$ is the current velocity and $\vec{e_\alpha}$ is the desired direction towards the destination and given by:

$$\vec{e_\alpha} = \frac{(\vec{location}(destination) - \vec{location}(pedestrian))}{distance}$$

where the locations are in the 3-D world coordinate system of the CARLA simulator, distance is the euclidean distance between the pedestrian and the final destination. Intermediate destinations are in progress.

6.4.1.1 Stop/Go Model

The Stop/Go model decides when the pedestrian starts crossing the road. The model makes the state transition from *Waiting* to *Crossing*. Whether a pedestrian starts crossing the road depends on multiple factors such as the perceived gap (in time) with the oncoming vehicles, speed of the oncoming vehicle (some pedestrians do not cross while the vehicle is approaching even when there is enough gap), road width, age, gender, etc. According to [193], gap estimation gets poorer with increasing vehicle speed. Also, younger people are faster in estimating the gap with oncoming vehicles. This estimated gap is called the perceived gap and often differs from the actual gap. Logistic regression-based acceptance models with different factors are developed in [15, 264, 137]. In [67], a Generalised Linear Mixed Model (GLMM), and in [134], a Neural Network is used for gap acceptance modeling. The main input parameter of all the models are the perceived gap between the pedestrian and an oncoming vehicle. However, no models (*except for some proposed noise models such as [19]*) can map actual gaps to the perceived gap to the best of our knowledge. In our Stop/Go Model, we also model the perceived gap. Our current model is:

$$Gap_{perceived} = w * Gap_{actual} \tag{3}$$

where w is a weight parameter chosen by the user as there is no data to calibrate it. By default, we set it to 0.9. So, the perceived gap is longer than the actual gap to generate risky situations even when the pedestrian is not a risk-taker. We avoided a noise model for the perceived gap because we intend to exploit the weight parameter for adversarial search.

In our current research setting, we have one vehicle and one jaywalker, and our current Stop/Go model uses Brewer et al.'s gap acceptance model, [15], with our perceived gap model. The coefficients of the gap acceptance model are: beta0 = 6.2064 and beta1 = -0.9420. To model different risk levels, we multiply the probability of the Go decision by the Brewer model with the weight factor of the risk level. Currently, we have four risk levels: cautious, normal, risky, and extreme. A normal jaywalker follows the Brewer Model's probability distribution. A cautious jaywalker reduces the probability by 20%, while the risky profile increases the probability by 100%, and the extreme one never waits.

6.4.1.2 Survival Model

This model aims to generate behavior shown by a pedestrian in a near-accident situation with the on-coming vehicle. Pedestrians may show evasive behavior when the on-coming vehicle is near, even when the vehicle is yielding. In [258], the authors propose an on-coming vehicle force to model the evasive action. However, the repulsive force created by the force-field around the vehicle can push the pedestrian in directions that are not essentially realistic and fails to capture the most common evasive actions accurately [Figure 6.2]. In addition, this model makes the evasive action deterministic, which is easier to predict. When pedestrians face danger, they either rewind to a previous location or cross the road faster as they already have a planned trajectory. They do not follow an arbitrary direction as their focus and field of view are limited around the vehicle. So, we approach the problem in a completely different way. In such situations, the pedestrian chooses to rewind or move forward. If they rewind, they go back to a past location (which depends on how close they are to the conflict point), and if they move forward, they speed up. We implemented the rewinding method.

The model makes the state transition from *Crossing* to *Survival* when the perceived gap is close to the time the pedestrian takes to cross the lane. The state is resumed to *Crossing* when there is no chance of collision.

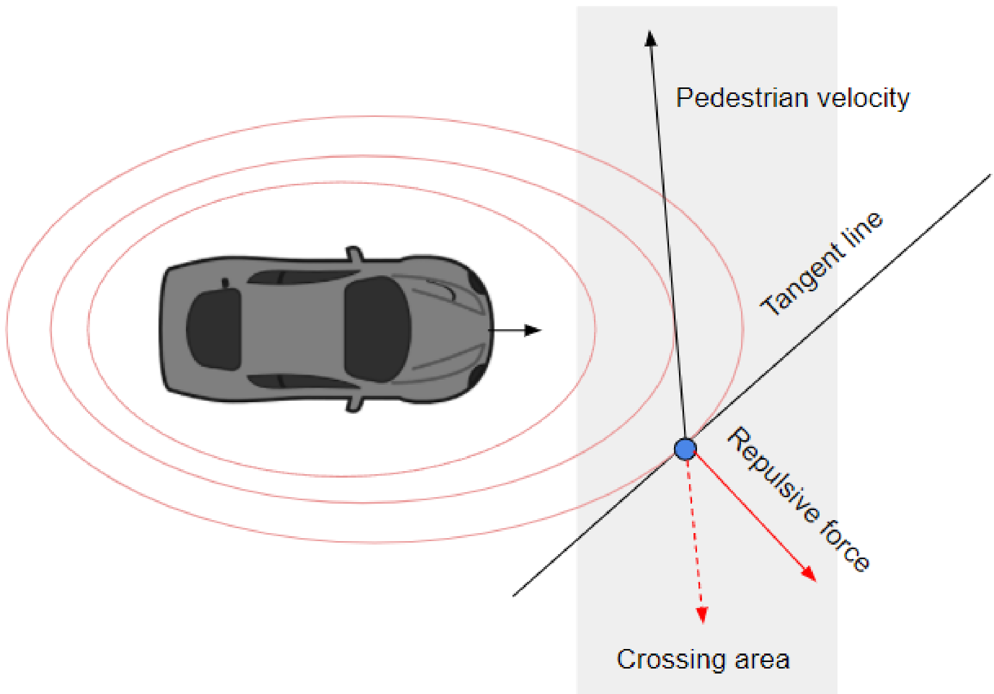


Figure 6.2: The red circles show the force field created by the oncoming vehicle. In [258], a repulsive force is applied on the pedestrian represented by the blue circle. The force is orthogonal to the tangent line on the force field. The intensity and direction of the force depend on the relative location of the pedestrian and the vehicle. The solid red line is the repulsive force proposed by the model in [258], and the dashed red line is our proposed force for rewinding.

6.4.2 Simulation results

The setting, (Figure 6.3), has one jaywalker and one vehicle on a two-lane road, with each lane being 3 meters wide. The jaywalker's source and destination points were set on sidewalks on the opposite sides of the road. We used a basic reactive vehicle agent from the CARLA package for our initial experiment. The vehicle only has emergency stop and collision avoidance maneuvers. It starts from a random location, 10 meters away from a fixed central location or the center location (three different start points). The destination location is the same for all the 30 simulation runs (episodes).

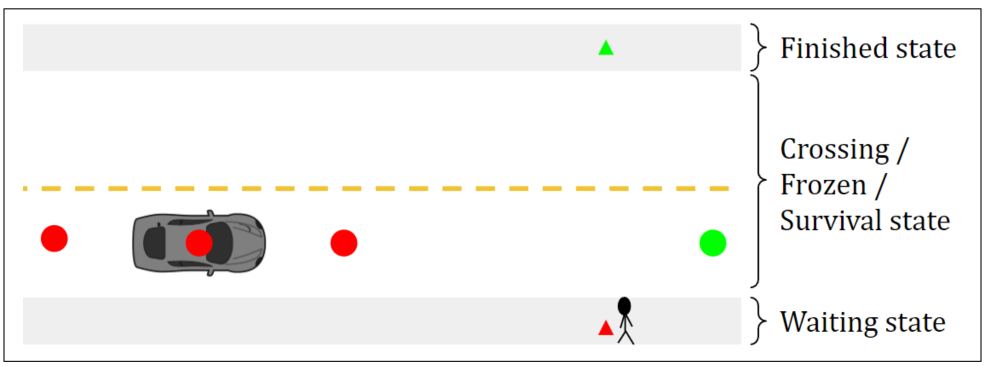


Figure 6.3: The red circles are start points and the green circle is the destination point of the vehicle. The jaywalker starts at the red triangle and tries to reach the green triangle. Inside the lanes, any of the crossing, frozen, and survival states may be active. Waiting and finished states can be active in the sidewalks (gray zones).

In Figure 6.4(a), the minimum distance the jaywalker travels from the source to the destination is 12 meters. However, due to our survival model, sometimes they may stop and go back depending on how close they are to the conflict point. We observed that a walker might walk up to 20 meters to cross a 12-meter path. Figure 6.4(b) shows the distribution of speed. We set $2ms^{-1}$ as the maximum speed in the simulation. A positive speed means the jaywalker is moving towards the destination, and a negative speed indicates movement in the opposite direction (retreating due to a chance of collision).

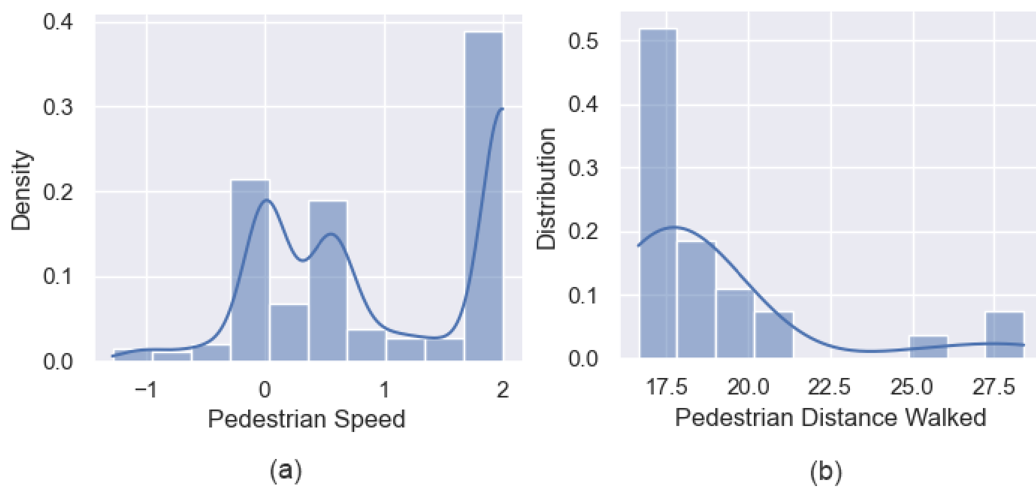


Figure 6.4: (a) Distribution of distance (in meters) covered by the pedestrian with the same source and destination locations, (b) Distribution of pedestrian speed in ms^{-1}. Negative speeds indicate backtracking.

A sample speed history of an episode is shown in Figure 6.5. However, not all the episodes trigger the survival model. In Figure 6.6, we show the displacement in y-axis against time-steps. In some episodes, the walker never stops and goes back. In addition, we see that the survival mode is activated at different positions across the different episodes. This sometimes means the walker stops and backtracks early, sometimes late. Also, the distance they backtrack varies.

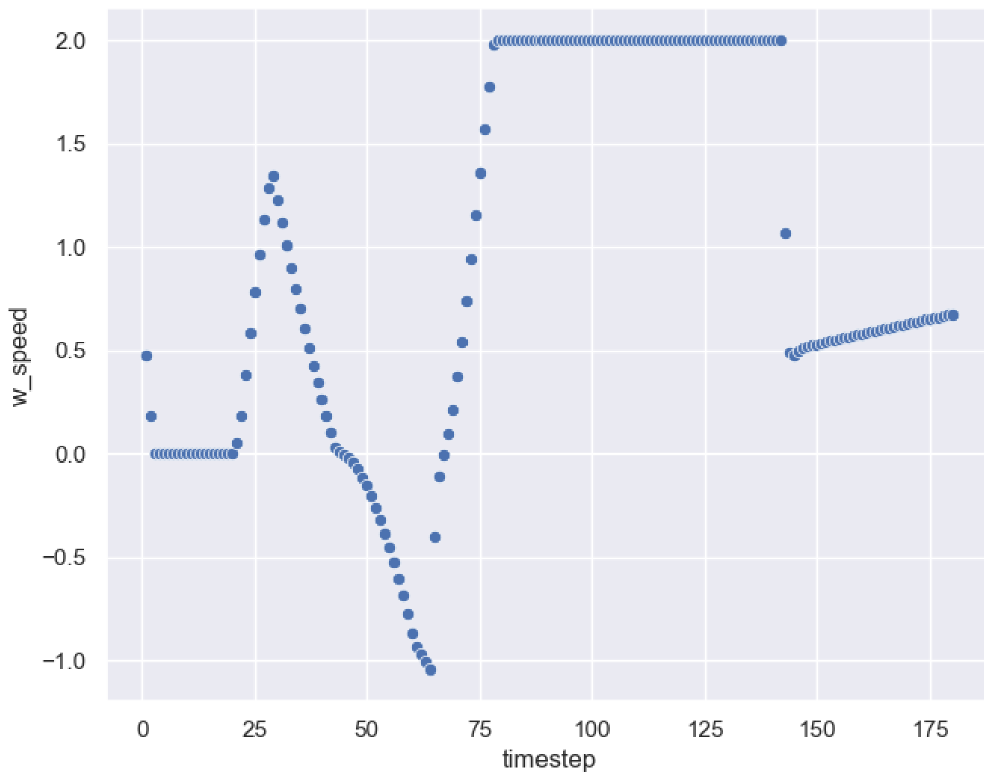


Figure 6.5: Pedestrian speed history during an episode. Time-steps (x-axis) are 0.007 seconds long, so, 100 time-steps equal to 0.7 seconds. Pedestrian speed w_speed is on y-axis and in ms^{-1}

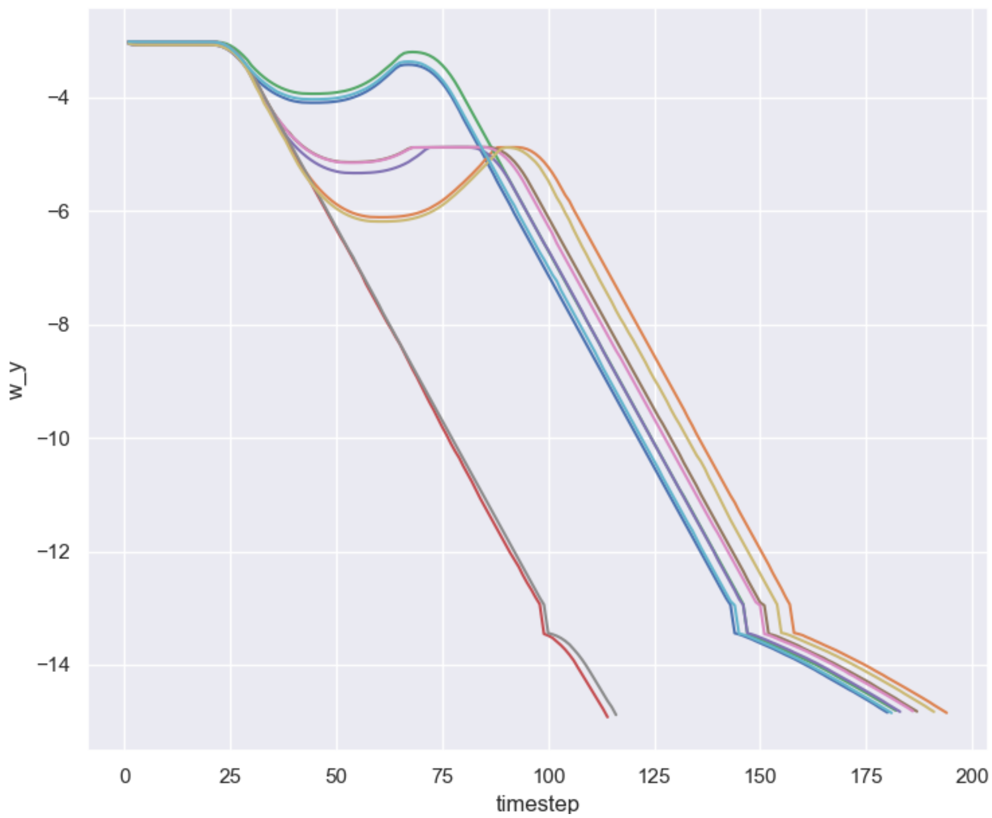


Figure 6.6: History of pedestrian displacement along y-axis in meters. We see the survival mode is trigger in time-step [30, 90] zone. Different color for different trajectories/episodes of simulation.

6.5 Conclusion

This paper presents a hybrid state machine plus social-force-based jaywalker model to generate jaywalker behavior in simulation. In this ongoing research, we gather knowledge from pedestrian behavior analysis from multiple domains such as traffic analysis, behavior analysis, simulation models, personal experiences, etc. We capture and model the micro-behavior patterns. We also shared our current progress with the modeling tasks. Our goal is to challenge the trajectory prediction algorithms that autonomous vehicle systems use with a jaywalker model with a rich behavior set.

Chapter 7

RePed: Adaptive Pedestrian Agent Modeling for Scenario-based Testing of Autonomous Vehicles through Behavior Retargeting

The following chapter was originally published as *Adaptive Pedestrian Agent Modeling for Scenario-based Testing of Autonomous Vehicles through Behavior Retargeting* in IEEE International Conference on Robotics and Automation (ICRA), Yokohama, Japan, 2024. This work proposes a novel method to ensure pedestrian agents exhibit the behaviors required by the test plans, even in changing situations in simulation.

7.1 Abstract

This work proposes a new representation of pedestrian crossing scenarios and a hybrid modeling approach, RePed, that facilitates transferring microscopic behavior models from behavior research to higher-level trajectories. With this, real-world trajectory-based scenarios can be augmented with a diverse set of human crossing maneuvers, producing a wealth of new scenarios and addressing the scarcity of rare case data that existing works struggle to deal with. Leveraging the controllability of this modeling approach, perturbation-based augmentation can be applied to enrich scenarios further. In addition, the representation is rooted in the ego vehicle's coordinate system with a logical representation of roads. This design enables scenario retargeting to various road structures, traffic conditions, and ego vehicle behaviors. Thus, it strongly supports scenario-based testing by forcing pedestrians to produce certain situations in simulation even when the ego Vehicle tries to evade them.

7.2 Introduction

Pedestrians do the darndest things. Consider the jaywalking pedestrian in the left-most panel of Figure 7.1, from the Pedestrian Situated Intent (PSI) 2.0 dataset [186]. In this scenario, a vehicle is cruising along the second lane in a four-lane one-way road. The pedestrian is in the lane immediately to its right. The scenario starts at *step 1* with the pedestrian approximately 15 meters away and walking towards the vehicle's lane,

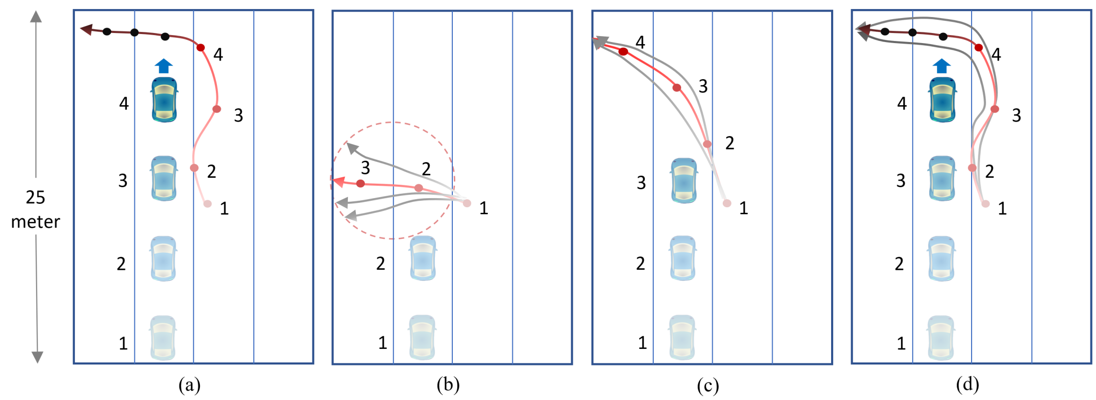


Figure 7.1: A real-world scenario and three modeling approaches. (a) In a 4-lane uni-directional road, the vehicle drives at 20 mph, shown at four interesting time steps (1-4). The pedestrian walks in a wavering fashion and suddenly crosses in front of the vehicle (dots at the same time steps). (b) Existing simulation models have low expressiveness and limited spatial and temporal variance, yielding simple behaviors. (c) Goal-based planners and Social-Force-based methods do not allow controllability and reproducibility of events. (d) Our modeling approach captures the original behavior and allows adaptability.

showing crossing intent by *step 2*. However, they change their decision and start to move away, leading the driver to think they will not cross the road. The cautious human driver slows down a tiny bit, anticipating the potential for a dangerous situation (*step 3*). Suddenly, the pedestrian changes direction, approaches the vehicle's lane, and starts crossing (*step 4*) within a fraction of a second. Luckily, the pedestrian safely crosses the road without getting hit or making the vehicle stop.

Though this kind of pedestrian scenario is rare, it does happen, and most human drivers have had to handle unexpected pedestrian behavior. Hence, autonomous vehicles must also safely handle these rare pedestrian scenarios. Now, imagine an ego vehicle is driving instead of the human one. Different ways of handling this situation can lead to varying outcomes. In the first variation, at step 3, the ego vehicle might speed up, assuming the pedestrian will not cross, leading to a dangerous situation at step 4. In the second variation, the ego vehicle moves much faster to pass the pedestrian before they begin crossing, avoiding any collision. In the third, the ego vehicle moves to the empty left-most lane, where the pedestrian might never challenge them. As we can see, due to possible variations in the ego vehicle's driving strategy, it is hard to ensure that they experience the near-miss event at step 4 like the human driver. From this, we identify *two different problems* in achieving the goal of testing the scenario against the ego vehicle at the *target situations in steps 3 and 4*: (a) reproducing the scenario and (b) adapting the scenario.

Existing literature addresses these two problems separately, resulting in either suboptimal performance in reproduction or limited adaptation capability. Figure 7.1b illustrates a machine learning-based approach that takes past trajectories of all the actors around the pedestrian and generates the future trajectory of the pedestrian. However, these methods cannot express dramatic long-term spatial and temporal variance due to the scarcity of rare scenario training data. In addition, it is hard to control the behavior of such models, making reproducibility harder to achieve. Figure 7.1c shows potential solutions to both problems involving Goal-based planners and Social-Force-Based behaviors, which can produce a simplified version of the pedestrian trajectories towards the destination point. However, they overlook the exciting events in between. An alternative approach involves creating a trajectory follower model that compels pedestrians to replicate the exact trajectory from a rare scenario. Nevertheless, this approach precludes the adaptability of the pedestrian against any change in the scenario, such as vehicle speed, vehicle lane, lane width, and the presence of other traffic participants.

We introduce a pedestrian scenario retargeting method, **RePed**, that can represent rare pedestrian scenarios and systematically adapt them to various test situations. This adaptation includes adjustments for varying vehicle speed, lane changes, and differences in lane count and width (*depicted in Figure 7.1d*). Our approach overcomes the expressivity limitations of current methods via a hybrid modeling approach that can utilize the best parts of the existing approaches. It allows reproducibility, adaptability, and controllability of the pedestrian behavior model.

The adaptability of our model ensures that ego vehicles are challenged by the target situations even when the ego vehicle's trajectory changes and the scenario tries to drift away during testing. The adaptability is achieved through a set of retargeting methods, which has a broader application to other types of traffic participants. The controllability of our model yields more advantages in addition to ensuring reproducibility and further variability using perturbation techniques. Search-based methods in scenario-based testing can use our proposed control parameters to create a search space to cover the possible range of variety, such as the minimum and maximum speed range of the vehicle under test.

We review relevant literature in Section 7.3 and outline our methods in Section 7.4. The simulation results of our behavior retargeting methods are presented in Section 7.5, while Section 7.6 explores the limitations and outlines future research prospects.

7.3 Related Work

Testing of autonomous driving in simulation involves creating a set of agents such as vehicles, pedestrians, and bicycles that mimic the real-world behavior of human road users. The testing process aims to identify critical scenarios (see [126]) where the ego vehicle behaves unexpectedly. On one end, testing methods replay real-world scenarios where the behavior of all the traffic participants is pre-determined except for the vehicle under test (the ego vehicle) [153, 112, 220]. However, it's often desirable to create variations of a scenario to stress-test the ego vehicle or adapt the behavior of other actors to the changing behavior of the ego vehicle [113]. On the opposite end, some methods have actors show completely random behavior by sampling from a set of predefined actions, and testing methods search for critical scenarios over a huge search space [98, 141], which can lead to unrealistic scenarios [85]. Realistic behaviors exhibit structured inter-dependencies, significantly reducing the search space. The exploration of this trade-off between extremes is an active area of research in scenario generation methods (*see comprehensive surveys in [85, 12, 150, 194, 265]*).

With realistic behavior models of traffic participants including pedestrians, scenario-generation methods get more freedom in creating random valid situations. Unfortunately, extensive exploration of pedestrian behavior is hindered by the complexity of human behavior and the scarcity of recorded data on rare events. Refer to [155] for a comprehensive literature review of pedestrian behavior modeling for AV testing. On another note, crowd behavior literature does not address individual-level diversity and richness and does not aim to capture rare behavior in road crossings, [74, 93, 179, 252].

This work is closely related to individual-level pedestrian crossing modeling, a crucial source of test scenarios for AV testing, [65]. The modeling problems during road-crossing can be categorized into three areas: (a) physical constraints, (b) maneuvers, and (c) crossing trajectory. Physical constraints define the boundaries of pedestrian movement such as speed, direction change, and reaction time. Maneuvers include speeding up, avoiding collision, retreating, and hand-signaling. Crossing trajectories involve movement plans using physical constraints and maneuvers. Some methods are good at modeling physical constraints [221, 152, 260, 254, 70], some at maneuvers

[114, 145, 248, 258, 17, 138, 159, 267], and some at producing long-term trajectories, [111, 224, 120, 2, 246, 259, 144, 80, 68, 184, 163, 140].

Physical constraint-based models require high-level trajectory and maneuver planners to be used as simulation models. Manuever-based models require high-level trajectory planners. Methods adept at modeling maneuvers are often employed in generating long-term trajectories, but they tend to produce less diverse trajectories due to tight coupling with interaction modeling. For instance, in the Social-Force-based approach, [114], high-level trajectory is generated by an attractive destination force. However, it is easy to model physical constraints and maneuvers with a limited amount of data and transfer the behavior enabling existing work outputs directly reusable. This motivates us to improve their trajectory generation process.

Various trajectory generation methods exist. Supervised learning and sequence modeling can create long trajectories but aren't suitable for road crossing scenarios, [83]. Another approach focuses on pedestrian pose trajectories using Generative AI, [224]. However, these machine learning-based methods struggle to model rare trajectories, transfer behaviors across settings, and are challenging to control for scenario search. Reinforcement learning-based methods such as [163, 63, 187, 241] learn specific outcomes defined by reward functions, limiting diversity and rare scenarios. Non-machine learning-based methods use path search in free areas, [111].

Recognizing the limitations of existing methods, we propose a hybrid approach that blends high-level pedestrian trajectories with low-level microscopic maneuvers. This approach has the potential to inject variability and diversity at both levels. By enabling the transfer of behavior across different scenarios, adapting to the ego vehicle's actions, and exposing control parameters, our proposed method empowers scenario generation techniques to craft novel yet realistic scenarios with a greater degree of flexibility.

7.4 Methodology

Our approach represents pedestrian trajectories using two main techniques. At a coarse level, the path of a pedestrian is modeled as a navigation path (NavPath) moving from one navigation point (NavPoint) to another in order. Fine-grained behavior is determined by a Behavior Primitive, which controls the pedestrian position from second to second. The process of creating a test scenario from a pedestrian behavior video involves (a) determining a set of NavPoints consistent with the observed pedestrian locations and (b) determining one or more Behavior Primitives that match observed pedestrian behaviors. We describe the representation of the Navigation Path, Behavior Primitives, the role of the Behavior Matcher in augmenting the Navigation Path, retargeting during the test, and how scenarios are adapted in simulation.

7.4.1 Navigation Path (NavPath)

A **NavPath**, comprised of **NavPoint**s, is a sparse pedestrian trajectory in the ego vehicle's coordinate system. Each pedestrian in a scenario is described as a NavPath. Key NavPath characteristics include:

- Represents only coarse directional movement, abstracting away micro-level behavioral variation.
- Tied to the vehicle coordinate system, so, if the vehicle reference frame moves, it also moves.
- Can be somewhat imprecise, allowing for flexibility in scenario crafting.

The Navpath's goal is to record behavior changes (which occur at NavPoints) and travel direction in pedestrian movement. These elements challenge ego vehicle prediction models. This representation plays the central role in representing diversity in pedestrian paths and behavior, whether manually crafted or automatically derived from real-world data or trained models.

Figure 7.2 illustrates the structure of a NavPath. A NavPath contains a set of NavPoints, each with associated behavioral and location properties. The NavPath itself also contains properties for pedestrian information, such as crossing direction (left-to-right or right-to-left) relative to the ego vehicle's travel axis (see Figure 7.3).

A NavPoint defines a pedestrian's state concerning the vehicle at a specific time. Key properties are *LaneId* (0 for ego lane, negative/positive for left/right lanes), *Lane Section* (LEFT (L), MIDDLE (M), RIGHT (R)), *Distance to Ego* (on ego vehicle's axis), and *Original Speed. For details, refer to Appendix 5.*

NavPoint properties achieve three goals: (1) retargeting for diverse road structures and ego vehicle locations, (2) translating behaviorally significant locations based on

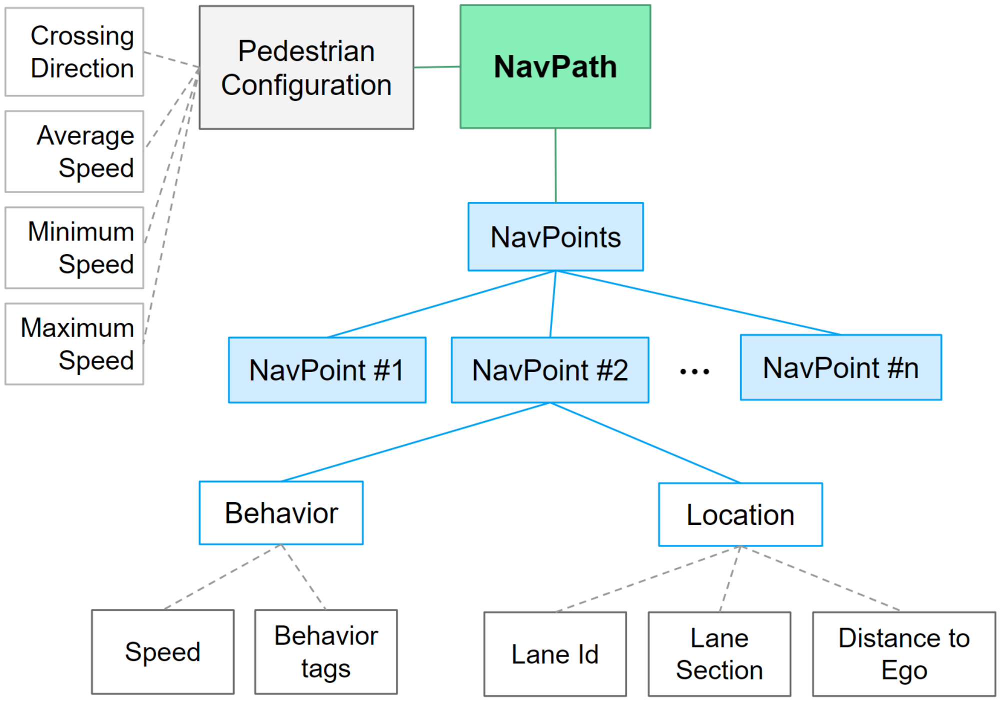


Figure 7.2: Structure of the Navigation Path

ego vehicle behavior, and (3) allowing fuzzing techniques while retaining the link to the ego vehicle's behavior.

7.4.2 Behavior Primitives (Behavior Tags)

Behavior primitives represent unique microscopic pedestrian behaviors (maneuvers) that happen sequentially on a trajectory. Each primitive has microscopic spatial and temporal variation based on pedestrian age, background, mental state, weather, road structure, and other traffic participants. This work proposes a few fundamental behavior primitives, emphasizing the unpredictability observed in the PSI 2.0 dataset,[186]:

- **Evasive Stop:** A complete halt within a roadway while crossing (*see Figure 7.5*).

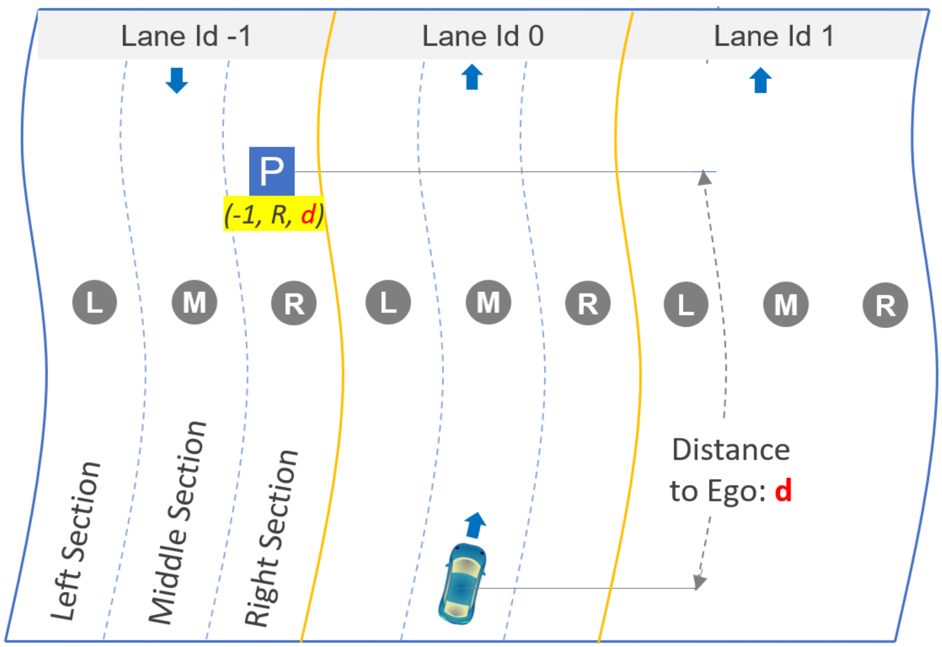


Figure 7.3: In this three-driving-lane road, NavPoint *P* has Lane Id: -1, Lane Section: R (right), and distance: d.

- **Evasive Flinch:** Resembling Evasive Stop, this maneuver includes a brief backward movement, occurring involuntarily and rapidly creating two situations (*see Figure 7.4*).

- **Evasive Retreat:** The pedestrian voluntarily steps back to safety from an approaching vehicle, a process that can take seconds (*see Figure 7.4*).

- **Evasive Speedup:** The pedestrian increases speed to avoid the approaching vehicle. (*see Figure 7.5*)

- **Evasive Slowdown:** The pedestrian reduces speed to let the vehicle pass, often leading to near-collision scenarios (*see Figure 7.5*).

Each behavior primitive is defined based on existing literature (*see Section 7.3*) and is characterized by its own set of controllable parameters.

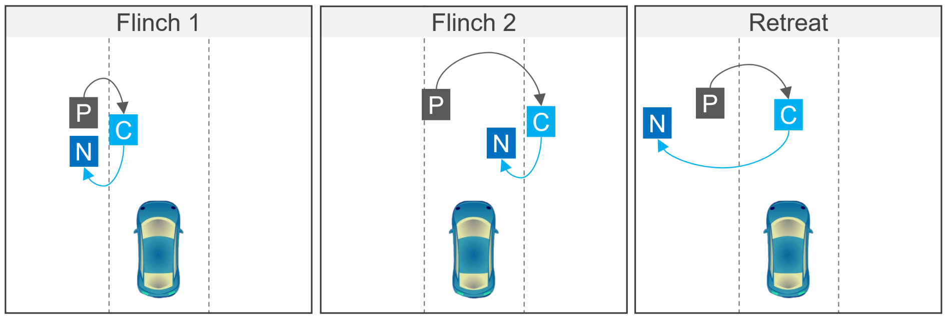


Figure 7.4: Flinch maneuver can place the pedestrian out of the way or in front of the ego vehicle. Retreat follows a longer path with voluntary movement. *P, C, and N* are previous, current, and next pedestrian locations respectively.

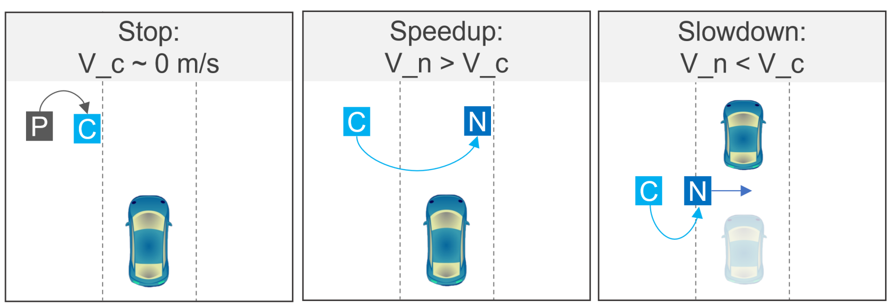


Figure 7.5: Evasive stop happens when the pedestrian speed is nearly 0. Speedup or Slowdown is characterized by acceleration/deceleration to avoid accidents.

7.4.3 Behavior Matcher

The Behavior Matcher matches a portion of the NavPath with a Behavior Primitive representing observed behaviors in the video. It augments the sparse trajectory defined by a NavPath with possible maneuvers. We have developed constraint-based pattern-matching methods for each behavior primitive, where each NavPoint is evaluated against all the matcher methods. *Detailed current set of constraints available at the link in Appendix 4.*

Given the current NavPoint N_{curr}, previous NavPoint N_{prev}, next NavPoint N_{next}, a future NavPoint N_{future}, distance between X, Y on ego travel axis $dLon(X, Y)$ in meters and on the lateral axis $dLat(X, Y)$ in lane sections, lateral side of Y with respect to X $side(X, Y)$, the summary of the constraints for each primitive is set forth below :

- **Evasive Stop:** speed(N_{curr})<Evastive Stop Threshold (defaults to 0.1 m/s).
- **Evasive Flinch:** N_{prev} and N_{next} are on the same side of N_{curr} and
  - $dLat(N_{next}, N_{curr})$<Lateral Threshold (defaults to one lane section width)
  - $dLon(N_{prev}, Ego)$<Longitudinal Threshold (defaults to 0.5 meters).
- **Evasive Retreat:** There exists a N_{future} such that $dLat(N_{curr}, N_{future}) >$ Lateral Threshold (defaults to two-lane section width) and :
  - N_{prev} and N_{future} are on the same side of N_{curr}.
  - $dLon(N_{future}, N_{prev}) <$ Longitudinal Threshold (defaults to 0.5 meters).
- **Evasive Speedup:** There N_{future} in front of the ego such that $speed(N_{future}) < speed(N_{curr})$ and
  - $side(Ego, N_{curr}) \neq side(Ego, N_{future})$

  - Angle between $direction(N_{curr}, N_{future})$ and $direction(N_{first}, N_{last}) < 90°$
  - There is no NavPoint between N_{curr} and N_{future}

- **Evasive Slowdown:** There exists N_{future} such that $speed(N_{future}) < speed(N_{curr})$ and
  - $side(Ego, N_{curr}) == side(Ego, N_{future})$
  - Angle between $direction(N_{curr}, N_{future})$ and $direction(N_{first}, N_{last}) < 90°$

7.4.4 Retargeting

Our current retargeting methods accommodate some key changes in ego behavior and road structure:

- **Lane Count:** We can retarget a m-lane scenario to a n-lane one using relative NavPaths.
- **Lane Width:** NavPoints handle lane width variations seamlessly (*due to logical lane sections*).
- **Ego Lane Change:** During simulation, ego vehicle lane changes are accommodated by re-planning.

- **Ego Speed Change:** Pedestrian speed is adjusted to meet the relative *distance-ToEgo* constraint during ego vehicle speed changes.

7.4.5 Simulation Process

See Figure 7.6 for an overview of the scenario realization process in simulation. The pedestrian is reactive and adaptive.

Steps in Simulation:

1. The Behavior Matcher (BM) consumes a NavPath and tags each NavPoint with Behavior Primitives (BP).

2. The tagged NavPath, Road, Ego vehicle, and its spawn location are given to the simulator as the inputs.

3. An *initial trajectory plan* for pedestrians is made based on road structure and ego vehicle's position and lane, with lateral perturbations in NavPoint locations.

4. As pedestrians approach NavPoints, activated BPs guide their movement, estimating time to the next destination while preserving spatial constraints with respect to the ego. Previous NavPoints are discarded.

5. If the ego changes lanes, then the pedestrian's *trajectory is re-planned* based on the remaining NavPoints.

The implementation architecture is available in Appendix 1, and the process and mathematical models of NavPoint realization are available in Appendix 5.

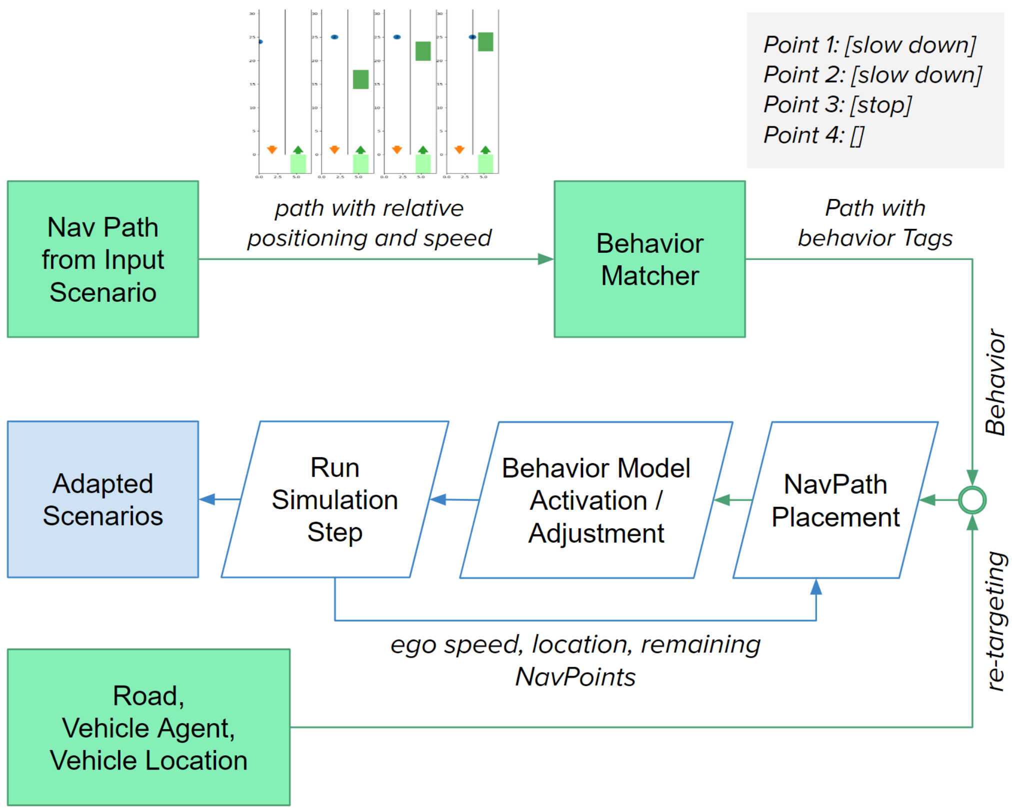


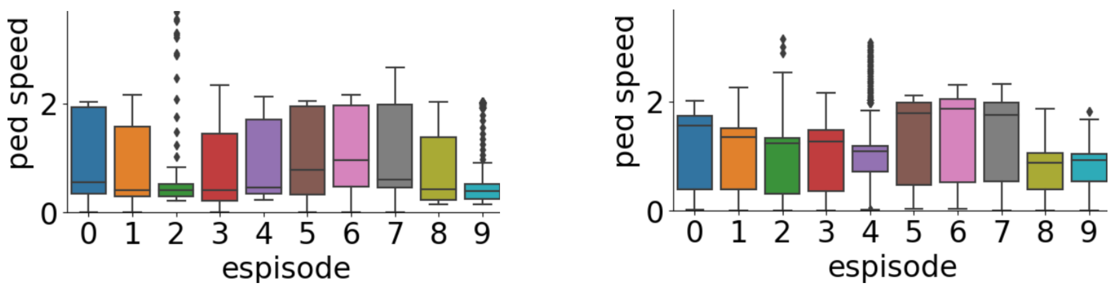
Figure 7.6: The test simulator takes two sets of inputs: Pedestrian navigation paths with behavior tags and vehicle agent, location, and road maps. Before the testing begins, the Behavior Matcher (7.4.3) tags the navigation points with Behavior Primitive Types (7.4.2). During a simulation loop, models for different primitives are activated or deactivated based on the proximity to specific NavPoints and NavPoints are translated based on ego-vehicles location, and road structure.

7.5 Evaluation

The validity of retargeting is explored by (a) examining the range of generated pedestrian velocities to ensure they are within plausible ranges, and (b) examining the distribution of pedestrian speeds vs. ego vehicle speeds. We explore scenarios that were generated via the translation of *PSI 2.0 Video #0015* into a NavPath with the stopping behavior modeled using Evasive Stop. The video shows a pedestrian coming to a stop in the middle of the road, allowing a vehicle (avg. speed 19 km/hr) to pass. To explore different scenarios, we *retargeted this video to two different road configurations*: a 2-lane road and a 4-lane road where the ego vehicle changes lanes. In both cases, the pedestrian starts crossing from the left sidewalk, and the ego vehicle starts in the right lane closest to the center of the road. In the four-lane configuration, the ego vehicle makes a lane change to the right-most lane, thereby moving away from the pedestrian. Each configuration was run in simulation for 100 episodes, with *ego vehicle speed varying in each run*, uniformly sampled in the range of [10, 30] km/h. NavPoint locations are also *laterally perturbed* by adding a noise value to their location. *We skipped the detailed evaluation of variability and diversity of maneuver models as retargeting is our main contribution.*

7.5.1 Pedestrian Speed Distribution

Figure 7.7 shows pedestrian speed data (sampled 25 times a second) for the first 10 (of 100) simulation runs for each road configuration. The median pedestrian speed



(a) 2-lane road

(b) 4-lane road + lane change

Figure 7.7: Pedestrian speed (in ms^{-1}) distribution of first ten episodes (trajectories) in each retargeting settings.

is moderate and speed distribution resembles real-world after retargeting, (*see [180]*). However, several runs in the 2-lane road have moments exceeding 2 m/s, and the 4-lane road has moments exceeding 2.5 m/s, which is a running speed. The fast speeds in the 4-lane scenario are due to the pedestrian needing to quickly catch up to the ego vehicle which has switched lanes away from the pedestrian.

7.5.2 Retargeting against Ego Speed

Figure 7.8a shows a series of joint distributions of vehicle speed vs. pedestrian speed. *Pedestrian successfully adapts to vehicle speed changes*. As pedestrian speed increases, the distance required to stop increases, and the pedestrian starts stop maneuver earlier, figure 7.8b. *The y-axis variation is due to lateral perturbation in NavPoint location in lane sections and destination force model* by Helbing, [114]. Figure 7.8c shows the stop duration. The variation happens due to the vehicle's speed trajectory, which impacts the Evasive Stop's duration. Figure 7.8d shows the variation in distance between the pedestrian and the vehicle when the pedestrian makes a stop. The variation along the y-axis occurs due to the pedestrian agent's time-gap estimation, *which exemplifies the variability introduced by maneuver models*.

7.5.3 Retargeting against Roads and Ego Lane Change

Figure 7.9 shows, for both 2-lane and 4-lane configurations, the distribution of pedestrian speeds, the variation of pedestrian speed over time, and the pedestrian speed at the moment the pedestrian decided to begin stopping for Evasive Stop. *The stopping statistics in figure 7.9b show that the pedestrian model successfully adapts when the vehicle makes a lane change*. Due to the lane change, the Evasive Stop tends to activate later (most stop activation times are greater than 300 frames). To accommodate the lane change, we can see an increase in pedestrian speed in general as they have to travel further. As this re-planning is done while the simulation is in progress, the pedestrian sometimes runs to catch up, (*see Figure 7.7*). The pedestrian failed to catch up in 1 episode.

7.5.4 Scenario Expressiveness

In the current implementation of the simulator, we have successfully represented all scenarios within the PSI 2.0 dataset with single pedestrians on straight and curved roads. However, since this dataset has midblock crossings only, additional work is required to represent intersection scenarios because inside intersections the notion of lanes changes.

7.6 Limitations and Future Work

This study focused on Behavior Primitives and the Behavior Matcher using PSI 2.0 data. Future research could enhance scenario expressiveness by utilizing alternative datasets such as the Waymo Open Dataset [225], NuScenes [18], or *behaviorally rich YouTube Dashcam Videos* such as [182]. Future expressiveness tasks:

- Expanding Behavior Primitives with new ones such as *dropping and picking up items while crossing and gestures perceivable by drivers [267, 159]*.
- Implementing vehicle collision avoidance models for near-collision situations. However, the vehicle repulsive force model such as [258] performs poorly in out-of-distribution situations. We suggest a set of models based on reachability sets, [111], or rules, [174].

Another direction would be automatic NavPath extraction from dense trajectories or videos. Interestingly, NavPath works smoothly even when the trajectories are broken, which is common in trajectory extraction from videos (s*ee [262]*). Future work should explore it more.

Lastly, future work should explore retargeting methods for road structures not addressed in this work such as intersections, where nearly fifty percent of accidents happen [99]. incorporating various traffic participants, occlusions, and obstacles by extending the NavPath representation.

7.7 Conclusion

In conclusion, this paper introduces a novel hybrid modeling approach for addressing the challenges in pedestrian behavior modeling and scenario-based testing against pedestrians for autonomous vehicles. It offers a unique contribution to the field by combining the strengths of existing pedestrian behavior modeling approaches to achieve scenario reproduction, adaptability, and controllability.

Our approach excels in reproducing real-world pedestrian crossing scenarios, ensuring the rigorous testing of autonomous systems against rare and complex events. Furthermore, its adaptability allows for modifying pedestrian behavior in response to changing scenarios, making it a valuable tool for testing under diverse conditions. The controllable nature of our model provides the added benefit of introducing variability through perturbation techniques, enabling a wide range of test scenarios. Future research can explore its application to various traffic participants and further refine its implementation, offering a promising avenue for continued advancements in autonomous vehicle development and testing.

7.8 Appendix

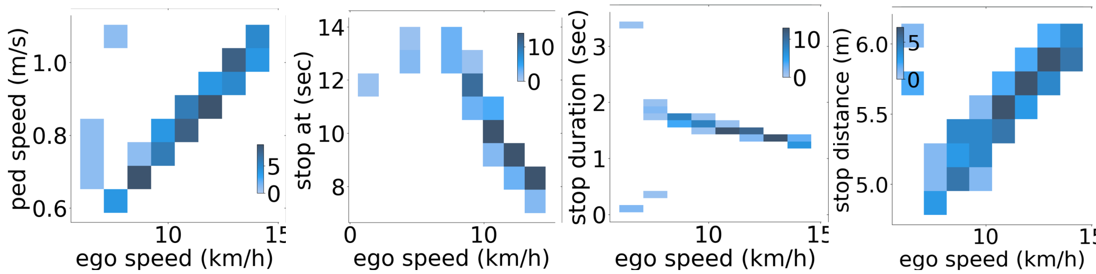
1. https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model.md - Model Architecture

2. https://github.com/adhocmaster/carla-jaywalker-experiments - Python Implementation for CARLA

3. https://github.com/adhocmaster/carla-jaywalker-experiments/tree/main/data/navpath - NavPath Dataset

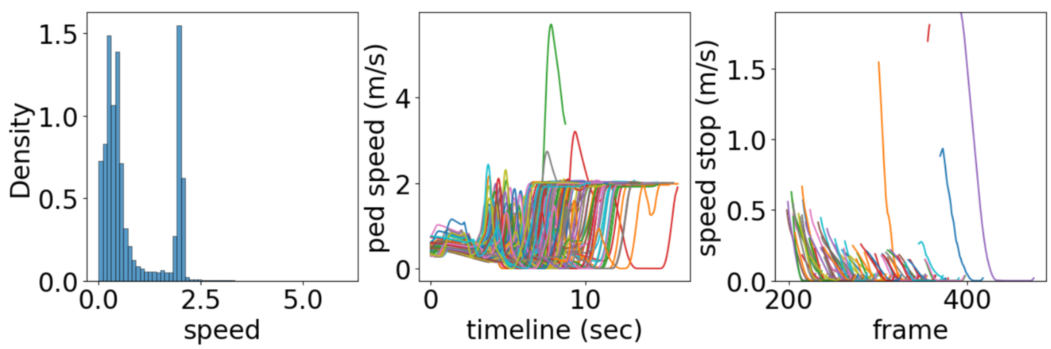
4. https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model-behavior.md - Behavior Primitives & Matcher

5. https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model-navpath.md - NavPath & Navpoint

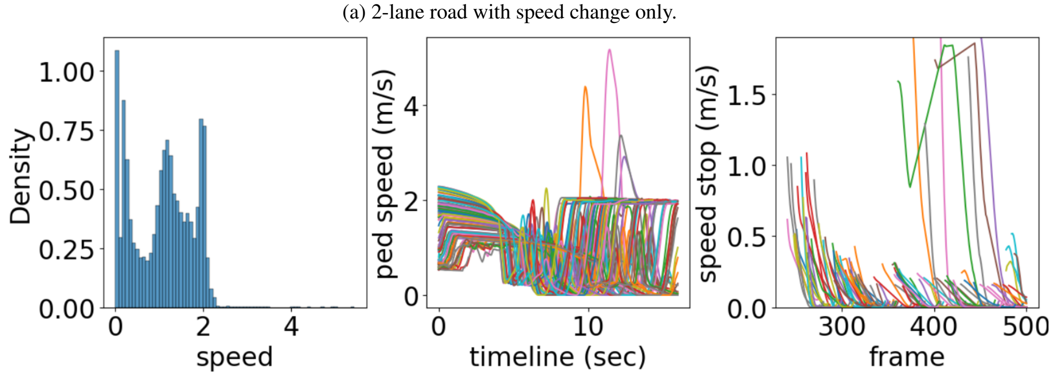


(a) (b) (c) (d)

Figure 7.8: Joint distribution of pedestrian (a) speed and vehicle (ego) average speeds, (b) stop-start time and vehicle speed at that time, (c) stop distance and vehicle average speed, and (d) stop duration and vehicle average speed, in 2-lane scenarios.



(a) 2-lane road with speed change only.



(b) 4-lane road with speed and lane change.

Figure 7.9: Distribution of pedestrian speed *(left)*, speed trajectories *(middle)*, speed and frame at the moment of Evasive Stop activation *(right)*.

Chapter 8

HyGenPed: A Hybrid Procedural Generation Approach in Pedestrian Trajectory Modeling in Arbitrary Crosswalk Area

The following chapter was originally published as *HyGenPed: A Hybrid Procedural Generation Approach in Pedestrian Trajectory Modeling in Arbitrary Crosswalk Area* in 35th IEEE Intelligent Vehicles Symposium (IV), Jeju Shinhwa World, Jeju Island, Korea, 2024. This work aimed to efficiently generate pedestrian routes given a polymorphic shared space on the road as pedestrians are free to take various routes in the real world.

8.1 Abstract

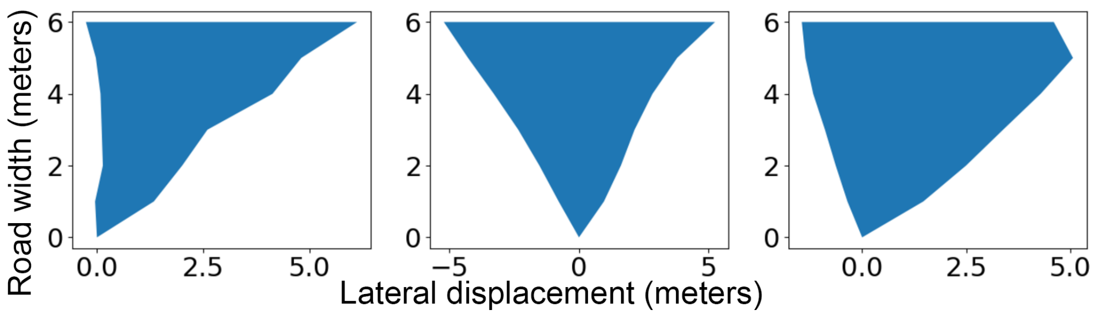
We propose a new method to create plausible pedestrian crossing trajectories that cover a given arbitrarily shaped crosswalk area for simulation-based testing of autonomous vehicles. This method addresses the crossing area coverage problem where the trajectories produced by the generative methods do not cover the entire area that pedestrians may possibly walk on. The actual area covered by pedestrians often differs from marked crosswalks on the road. Furthermore, in the case of jaywalking, the area can take a variety of shapes based on the road structure and surrounding places of interest. Our method is a constructive process that generates trajectories conditioned on an area defined with polygons. We demonstrate that the method can generate trajectories that cover a wide range of crossing areas, including ones from the InD dataset.

8.2 Introduction

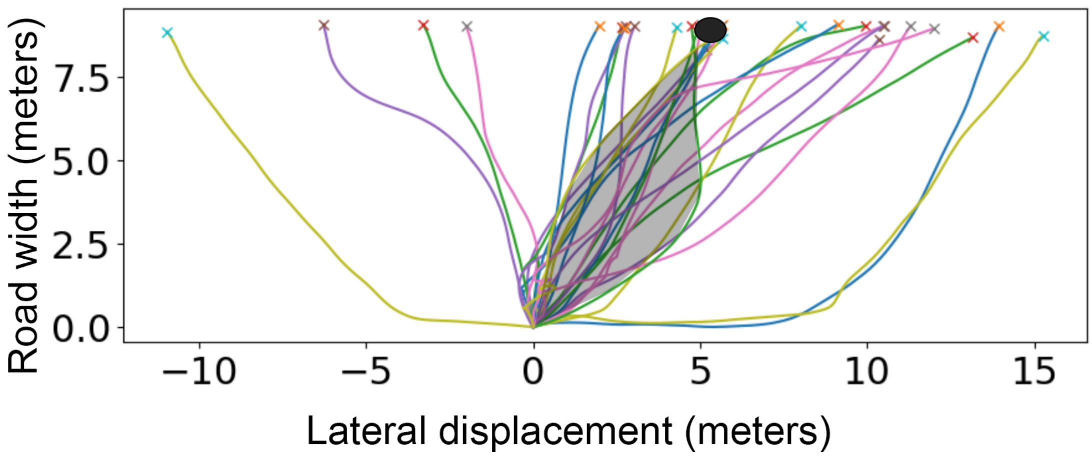
In simulation-based testing of autonomous vehicles, trajectory generators generate the position of dynamic actors such as vehicles, pedestrians, and bicycles on the simulation timeline to create test scenarios for the ego vehicle. Such testing aims to find scenarios that the ego vehicle may fail to handle (*see [126, 85, 12, 150, 194, 265]*). Therefore, it is necessary that the generators can generate diverse trajectories, cover all the possible situations, and generate them at a microscopic level. There are three spatial coverage challenges for pedestrian trajectory generators: (a) between a source and a destination point, there can be different paths a pedestrian can take; (b) from a source point, the pedestrian can reach different destination points on the other side of a road, (c) the space available for pedestrians to use can use can vary based on road structure. *Figure 8.1a* shows the trajectory envelopes of three different six-meter-wide road segments in the InD Pedestrian Dataset [14], which contains road user trajectory data from four intersection areas in Germany. While standard crosswalks are two to three meters wide, pedestrians often go beyond the crosswalk area and have lateral displacement larger than the crosswalk width. In mid-block scenarios, the lateral displacement is even wider.

Existing generative methods for pedestrian crossing trajectories do not tackle the coverage problems simultaneously either because of the lack of data or the expressiveness of the methods. We propose a hybrid approach where a high-level route plan is procedurally generated to ensure the coverage of shared road space and integrate an extended Social-Force-based model [114] to generate a motion plan. The route plan tackles the spatial coverage problems, and the motion plan tackles the gait challenges (e.g., speed, acceleration). We integrate existing works for motion planning.

In addition to solving the coverage problems, this work proposes a minimal set of control parameters to guide the generation of high-level routes, keeping the expressiveness very high. One can handcraft every point on the route at one extreme; at the other extreme, one has no control over the points. We choose several control parameters that guide the overall shapes of the routes (see Section 8.4).



(a)



(b)

Figure 8.1: (a) Trajectory envelopes for 6-meter wide roads from different road segments of location #2 in the InD dataset, [14]. In the left and right segments, the pedestrians cover five meters on the lateral axis, but in the middle, they cover ten meters. (b) shows the pedestrians' trajectories towards the north end of a nine-meter segment. The shaded area highlights the envelope of a start and destination pair.

This work contributes:

- A *hybrid pedestrian trajectory modeling* approach that facilitates route planning and motion planning in isolation.
- A *route planner* that solves spatial coverage problems of the pedestrian.

- A *set of control parameters* to guide the generation of pedestrian trajectories.

The remainder of this chapter is organized as follows: Section 8.3 discusses the existing simulation models and their capabilities. Section 8.4 discusses the route and motion planners. Section 8.5 shows the coverage against the InD dataset and the route planner's expressive range. Section 8.6 discusses the potential improvement and usage of the approach.

8.3 Literature Review

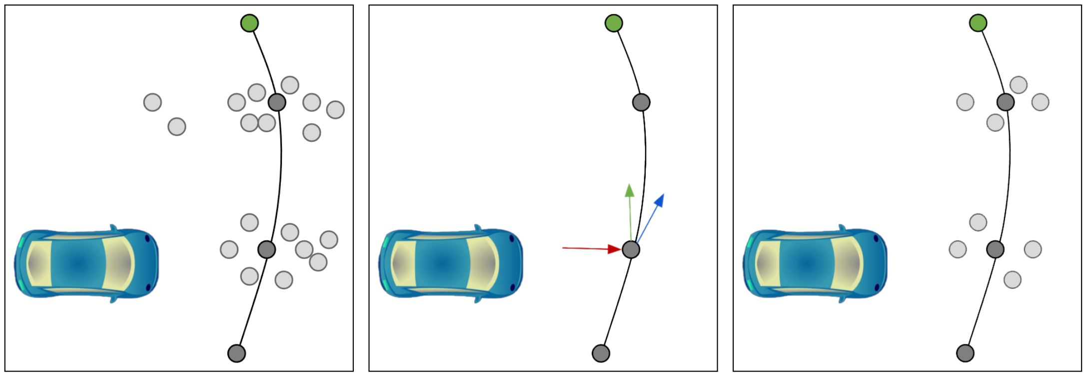
Microscopic pedestrian trajectory generators capture the crossing behavior of individual pedestrians. At a high level, the methods can be classified into three groups: (a) search-based, (b) physics-based, and (c) supervised-learning-based (*see Figure 8.2 for examples*).

In the search-based methods, a trajectory is planned for the pedestrian, often avoiding collisions and solving contextual constraints by choosing points in free places in future timelines. They often have rules to avoid collisions and decide pedestrian movement in time in a discrete spatial representation of the world. Some search-based methods generate near-optimal paths for multiple robot agents to avoid collisions and to achieve the shortest distance traveled, [5, 118, 81, 253]. Others focus on avoiding collisions with vehicles and modeling pedestrian-to-pedestrian interactions with a set of rules, [214, 263, 138, 17]. There are two main issues with existing search-based methods: (a) they lack objective functions to create diversity because of rich human behavior, (b) they do not address the coverage challenges.

In physics-based models such as Helbing's Social-force-based model, [114], pedestrians experience attractive and repulsive forces from the external world, which drives the pedestrian. The physics-based models generalize well against unseen situations, are highly interactive, and can create diversity in behavior with gait parameters such as speed, relaxation time, and force weights. However, physics-based models require modeling forces for all the possible factors and do not capture internal mental states such as distraction. In addition, ensuring route diversity with a noise model in the resulting force is challenging.

In supervised learning approaches, [2, 120, 246, 144, 184, 80, 224], the model learns pedestrian crossing behavior directly from trajectory datasets. Such methods are good at learning all the external and internal influences that drive a pedestrian. However, they fail in out-of-distribution scenarios, and they do not expose any controllable parameters to create different types of pedestrians. In summary, existing methods cannot ensure coverage of walkable areas and adaptability to a variety of scenarios at the same time.

Our work is similar to the STREETs model, [214], where a route plan with a sequence of waypoints is created for each pedestrian. These waypoints are locations that pedestrians intend to visit once. However, the STREET model focuses on crowd movement in town centers, and waypoints such as buildings and facilities are points of interest. They use a shortest-path algorithm to create such a route plan. Regarding road



(a) (b) (c)

Figure 8.2: Pedestrian trajectory generated by different approaches. (a) search-based methods explore the collision-free area around the pedestrian and make a motion plan. (b) physics-based models generate forces on the pedestrians to drive them on the road. (c) supervised learning-based models learn trajectory distribution from datasets.

crossings, we have only one intended waypoint for a pedestrian: the destination. The STREETs model suggests a straight line between the source and the destination point for road crossings. However, the real-world trajectories can be spatially diverse even when the source and destination remain the same (*see Figure 8.1b*).

There are a few promising hybrid approaches in [157, 103, 128]; but they lack a generative process to create diversity. Refer to [155] for a comprehensive review. Our proposed method creates a random sequence of waypoints in a user-defined area using constraints that keep the plan plausible.

8.4 Methodology

Our pedestrian simulation model works in two different phases: (a) the route-planning phase and (b) the motion-planning phase (*see Figure 8.3*). This section will first discuss the route-planning phase and then the motion-planning phase.

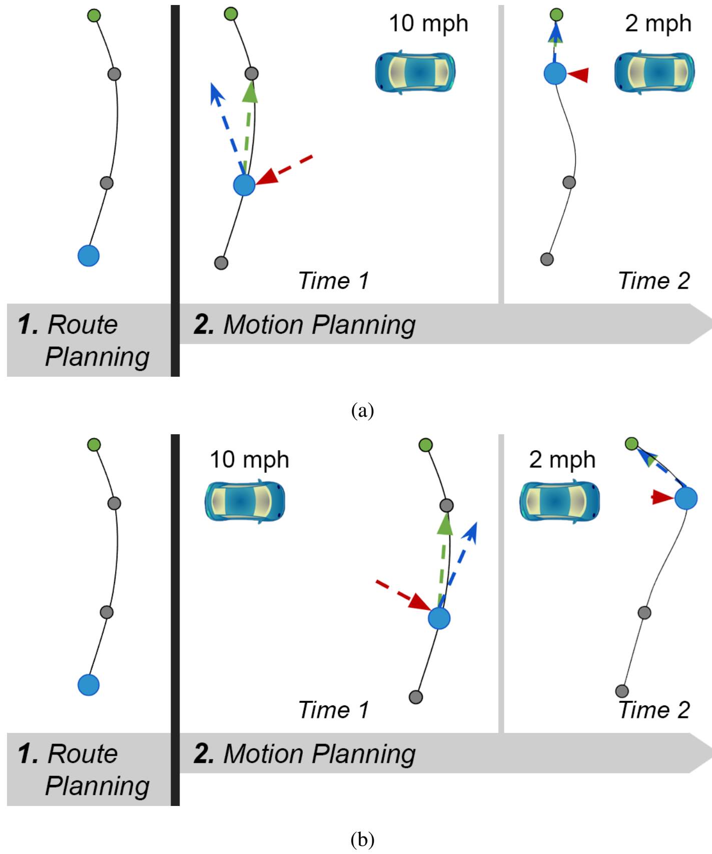


Figure 8.3: Two phases of simulation. First, the route planner creates a set of waypoints for high-level navigation. Second, force-based maneuver models define the trajectory in the motion planning phase. The route plans are the same in (a) and (b). However, they produce two different trajectories due to the direction of the oncoming vehicle. The blue circles represent the pedestrian's position, the green circles represent the destination, and the gray circles represent the waypoints of the route plan. Red arrows represent the repulsive force from the vehicle, green arrows are the attractive force towards the next waypoint, and blue arrows are the resultant force.

8.4.1 Route Planning Phase

The route planner takes a crosswalk or trajectory envelope as a polygon, a start point, a goal side, the number of waypoints between the start and goal side, and, optionally, the destination point on the goal side as the inputs. The planner generates a destination point if the user gives none. It produces trajectories with the following characteristics:

- Begin at the start point.
- Bounded inside the crosswalk polygon.
- Constrained angular shift from the crosswalk vertical axis and pedestrian heading.
- End close to the destination point (optional).
- Randomness (produces a variety of trajectories given the same input)

The method is a constructive search where the next waypoint of the pedestrian is determined based on the position and heading of the previous two waypoints (*see Algorithm 1*). The heading of the current waypoint facilitates the generator to enforce the physical limitation of human turns, and the angular shift constraints can define different types of pedestrians. *Figure 8.4* illustrates the input and outputs.

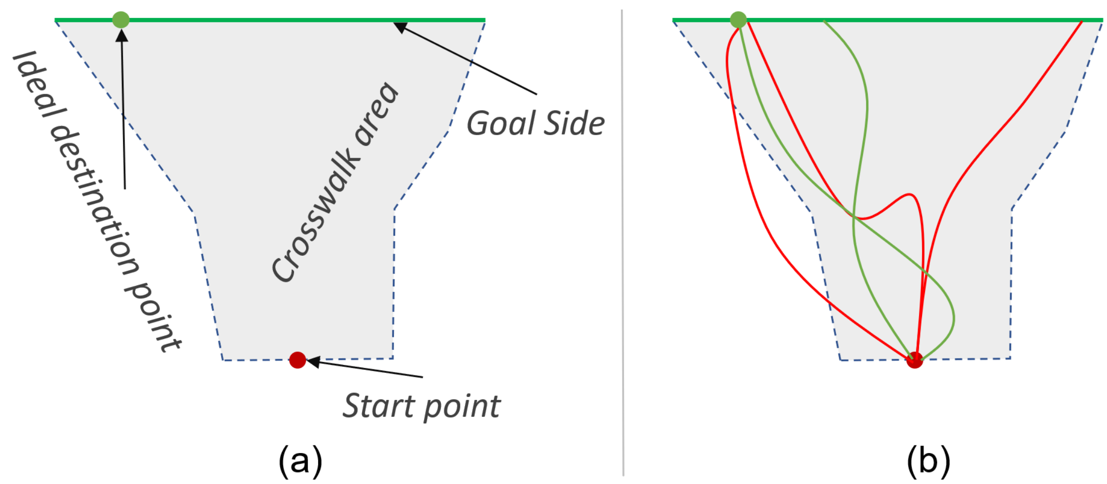


Figure 8.4: (a) The inputs to the route planner. (b) The red trajectories violate the constraints of validity and are discarded. The green ones are valid outputs.

Generation Steps

1. The method takes the crosswalk polygon, A, the destination side of the crosswalk, $goal$, the start point, S, optional destination point, D, the number of waypoints between the start and goal, nW, maximum heading difference with the final destination, α, maximum heading difference between consecutive waypoints, β, and lateral direction change probability, p.

2. The method initializes the route with the starting point S as the first waypoint. If D is given, it initializes the final destination point, D_{final} to D. Otherwise, D_{final} is set to the closest point on the goal line. $preDirection$ is the lateral direction (*-1 for left, +1 for right*) of the pedestrian in the last waypoint and is initialized based on the slope between the start and the final destination. After the initialization, the method generates nW intermediate waypoints through *the*

*main loop from **step** #3 to #6*.

3. **Main Loop Start,** nW **times:** It takes the latest waypoint as W_{pre1} and the second latest as W_{pre2}. W_{pre2} is null for the first intermediate waypoint.

4. Generate n evenly distributed points on line segment $\overline{\mathrm{W_{pre1}D_{final}}}$, *where* n *is the remaining number of waypoints to be generated*. From these points, the first two intermediate points, A, and B, are chosen starting from S *(Algorithm 1 from line #11 to #12)*.

5. Then a search block *(From Algorithm 1, line #14 to Algorithm 1, #37)* keeps generating candidate points for the next waypoint. The search ends when a candidate satisfies all the constraints. The process has two steps:

   (a) **Generation of a candidate,** C**:** C is randomly chosen inside A and B, and rotated randomly by $\{-90°, 90°\}$ around A based on the lateral direction change probability, p. With a low p, the next waypoint's rotation angle has a higher probability of being the same as the previous waypoint's rotation angle. *(From Algorithm 1, line #16 to Algorithm 1, #23)*. (*See figure 8.5*).

   (b) **Validation of the candidate,** C: First, C is discarded if it is *not* inside the crosswalk area. Otherwise, two heading constraints are checked (*See figure 8.6*). The pedestrian direction of travel at C, $direction_C$, must not be off by more than:

      i. α from the direction to the destination. This is the **destination heading**

constraint.

ii. β from the direction of the previous waypoint, W_{pre1}. This is the **gait rotation constraint**.

(From Algorithm 1, line #25 to Algorithm 1, #36).

6. Then the candidate, C is added to the plan, $waypoints$. - **Main Loop End**

7. After the intermediate waypoints are generated, the final destination point is added to the route.

Two devices guide the random generation of waypoints to lead to the destination. First, the next candidate is sampled on the line connecting to the current waypoint and the destination (*destination line*), (*see Figure 8.5*). Second, the destination heading constraint keeps the candidate going too far from the destination line. These devices introduce a bias for the candidates to be moving towards the destination (*see the distribution of the waypoints in Figure 8.11*).

8.4.2 Motion Planning Phase

The job of the motion planning phase is to exhibit a wide range of human behavior, interact with other traffic participants, and ensure the gait constraints of the human body. Our aim in the motion planning phase is to, given a route plan, explore all the possible situations that emerge due to the dynamic nature of the situation and the diversity of human behavior. *Figure 8.7* shows three possible different realizations of a

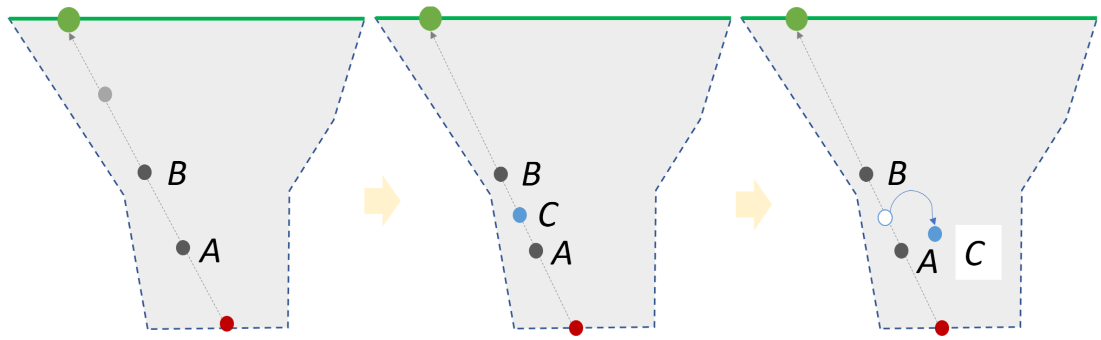


Figure 8.5: Generation of the candidate for next waypoint. The red circle is the source point, which is the latest waypoint, W_{pre} of the route plan. The green circle is the destination, D_{final}. A and B are the first two evenly distributed points between W_{pre1} and D_{final}. C is the generated candidate.

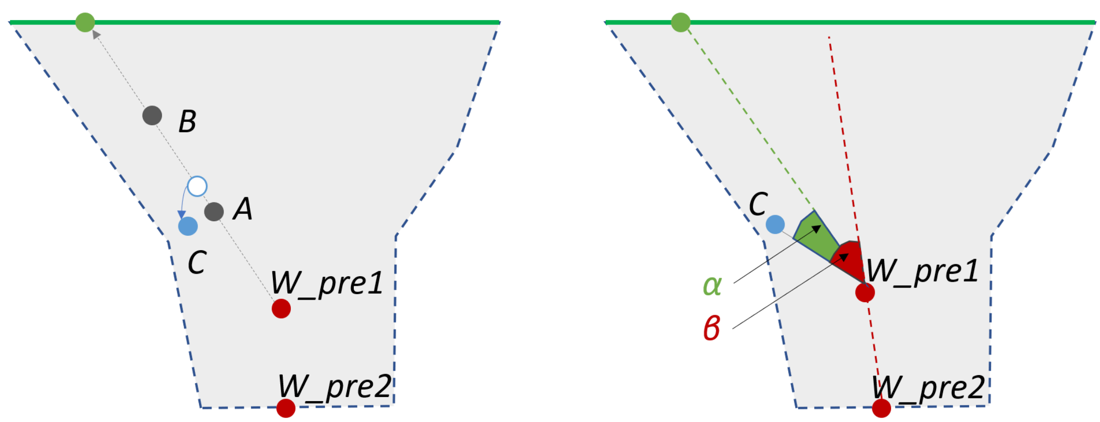


Figure 8.6: Controlling the drift by two heading constraints on the candidate, C (*generation illustrated in Figure 8.5*). W_{pre1} and W_{pre2} are previous two waypoints on the current route plan. The destination heading constraint ensures C has a deviation with the destination, green angle, less than α. The gait rotation constraint ensures the pedestrian does not change direction by more than β between consecutive waypoints.

Algorithm 1 Route planner

function GENERATEROUTE($A, goal, S, D, nW, \alpha, \beta, p$)

  $waypoints \leftarrow [S]$ ▷ start, S, added to the plan

  $D_{final} \leftarrow Destination(goal, S, D)$

  $DestinationSlope \leftarrow slope(\overline{\mathrm{SD_{final}}})$

  $preDirection = sign(slope)$

  for $i \leftarrow 1, nW$ **do**

    $W_{pre1} \leftarrow waypoints.Last(1)$ ▷ last waypoint

    $W_{pre2} \leftarrow waypoints.Last(2)$ ▷ second last

    $n = nW - i + 1$ ▷ remaining waypoints

    $pointsOL \leftarrow LinePoints(\overline{\mathrm{W_{pre1}D_{final}}}, n)$

    $A, B \leftarrow pointsOL[1, 2]$

    while $True$ **do** ▷ breaks on a valid point

      /**********Generate candidate, C*********/

      $C \leftarrow$ random point on $\overline{\mathrm{AB}}$

      $CDirection \leftarrow preDirection$ ▷ direction

Algorithm 1 Route planner (continued)

if $random\_choice([True, False], p)$ **then**
    $CDirection \leftarrow CDirection * -1$
end if
$angle \leftarrow CDirection * 90$
$C \leftarrow rotate(s, C, angle)$
/***********Constraints Checks**********/
if $C.notInside(A)$ **then** $continue$
end if
$\Delta Heading_\alpha \leftarrow \angle CW_{pre1}D_{final}$
if $i == 1$ **then**
    $\Delta Heading_\beta \leftarrow 0$
else
    $\Delta Heading_\beta \leftarrow 180 - \angle CW_{pre1}W_{pre2}$
end if

if $(|\Delta Heading_\alpha| \leq \alpha)$
    $\&\ (|\Delta Heading_\beta| \leq \beta)$ **then** $break$
end if
end while

Algorithm 1 Route planner (continued)

```
        preDirection ← CDirection
        waypoints.Add(C)                                   ▷ C accepted
    end for
    waypoints.Add(D_final)
    return waypoints
end function
function DESTINATION(goal, source, d)
    if d == null then
        return closest point on goal from source
    end if
    return d
end function
function LINEPOINTS(line_segment, n)
    return n evenly distributed points on line_segment
end function
```

route plan during the simulation.

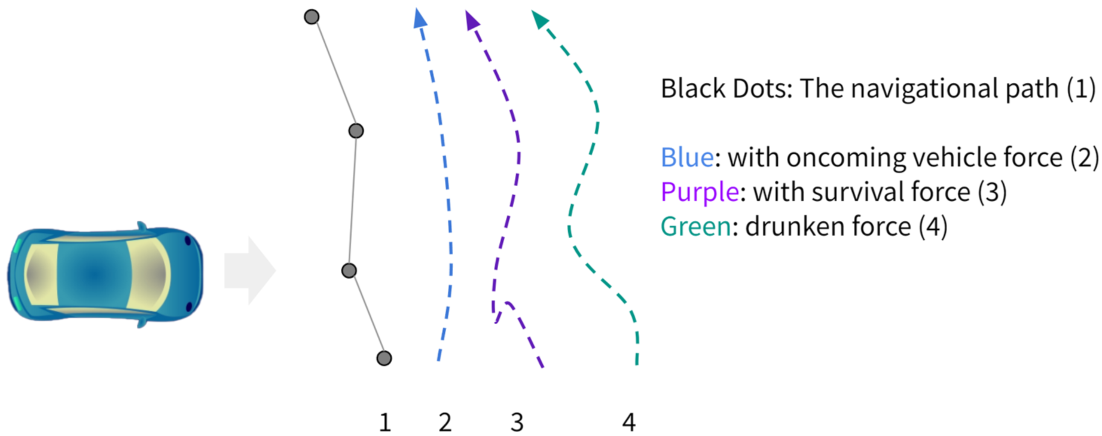


Figure 8.7: Realization of the route plan based on the motion models used during the simulation.

During the simulation, we drive the pedestrian towards the next waypoint with Helbing's destination force, [114]. In addition, we use three maneuver models from our motion planning research to interact with the on-coming vehicle: (a) the on-coming vehicle force model, (b) the survival model, (c) the drunken model, [156, 106]. *Figure 8.8* shows our hybrid planner navigates through the route with velocity updates from the motion planners.

8.5 Evaluation

We evaluate the route planner to answer the following questions:

- How much of the given crossing area is covered by the pedestrian trajectories?

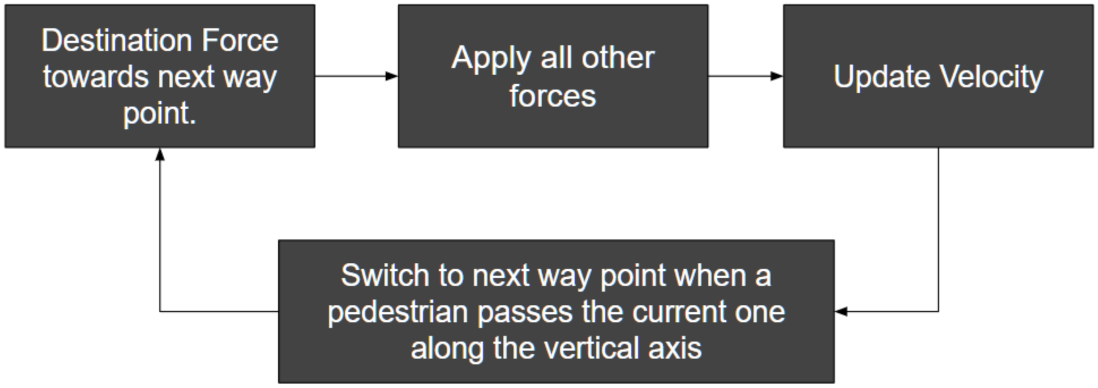


Figure 8.8: Simulation loop of the hybrid model. Force models are applied on pedestrians with next waypoint as the destination.

- How diverse are the trajectories regarding paths given a source and destination point?
- How do different parameters control the generator output shapes and coverage?

In our experimental settings, we have five trajectory envelopes of width 5-9 meters from the InD Dataset [14], with destination heading constraint, $\alpha = 60°$, gait rotation constraint, $\beta = 45°$, and a lateral direction change probability of $p = 0.2$. These parameters are kept constant unless otherwise specified. A Python implementation is available [1].

8.5.1 Spatial Coverage of the Crossing Area

In this analysis, we find answers to (a) how many waypoints and (b) how many trajectories we need to generate to cover the given crossing polygon. *Figure 8.9* shows

[1]https://github.com/adhocmaster/carla-jaywalker-experiments

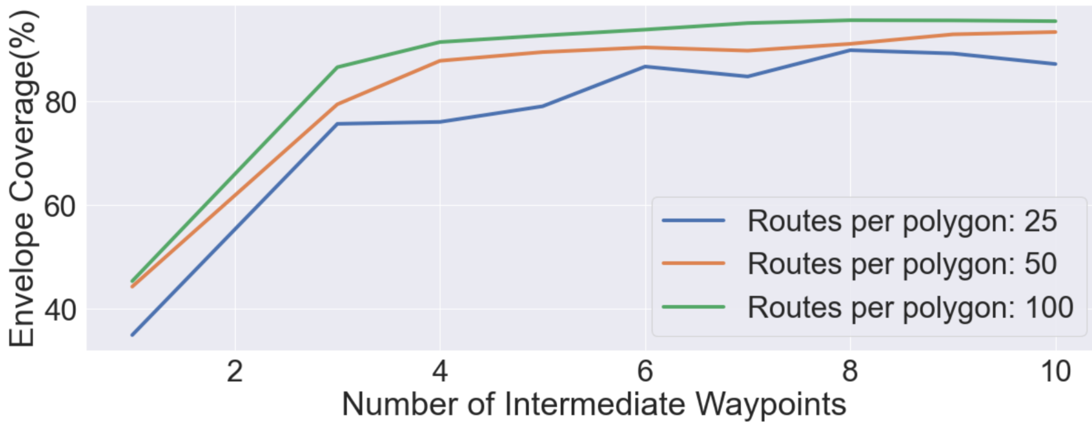
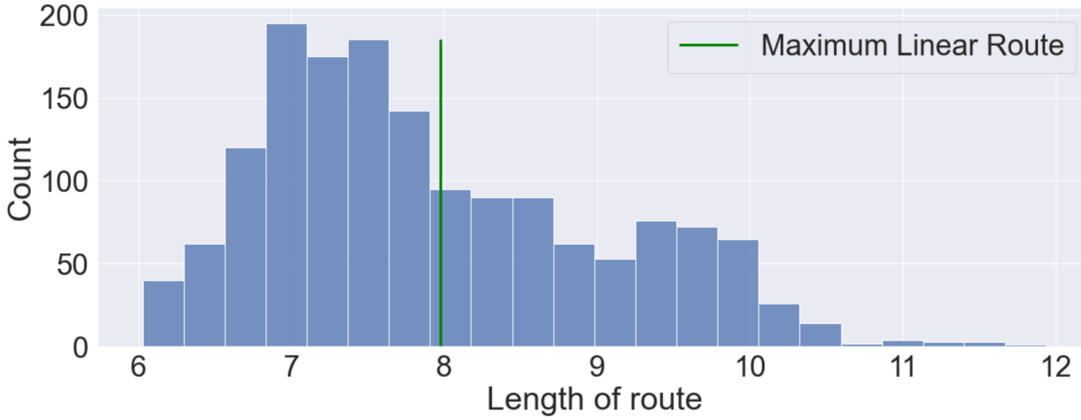


Figure 8.9: Impact of number of intermediate waypoints and number of route plans per start point on the trajectory envelope. X-axis has the number of intermediate waypoints between the start and the goal-line. Y-axis shows the percentage area of covered by the generated trajectory envelope and input area polygon.

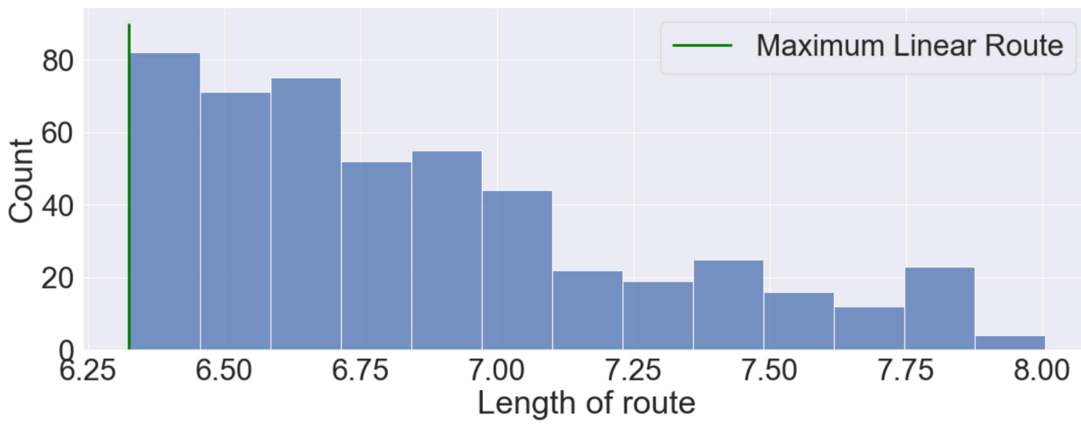
the spatial coverage based on two variables: (a) number of waypoints between the start and the goal-line, nW, and (b) number of routes generated for each polygon. With a hundred routes per polygon, we can achieve nearly 95% coverage. However, this does not imply that it ensures a representative set of routes.

8.5.2 Route Length Diversity Analysis

We use expressive range analysis (*see [219]*) to demonstrate the generation capabilities. *Figure 8.10* shows the frequency distribution of length of the generated route plans in a six-meter wide envelope with one and five different destination points. The minimum and maximum linear route lengths are six and eight meters, respectively. In *Figure 8.10b*, nW and destination point are held constant. Due to the interplay of lat-



(a) Five different destination points, $nW \in [1, 10]$



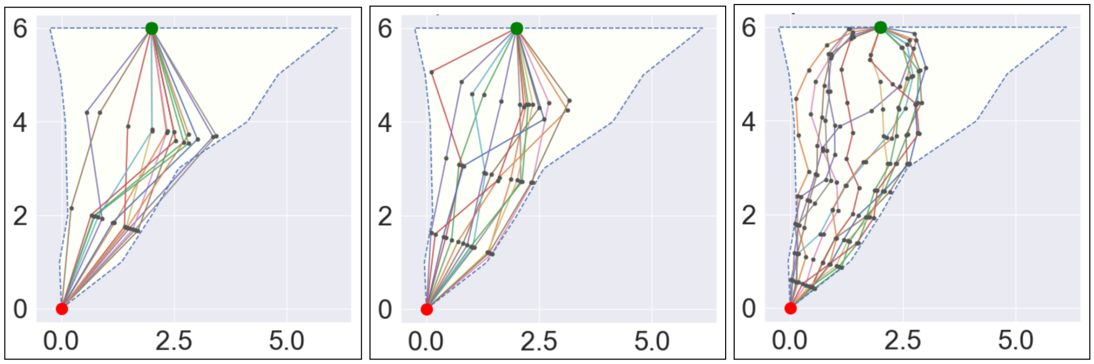
(b) One destination point, $nW = 3$

Figure 8.10: Frequency distribution of route length in a six-meter wide polygon from InD Dataset. The green line shows the length of the maximum linear route.

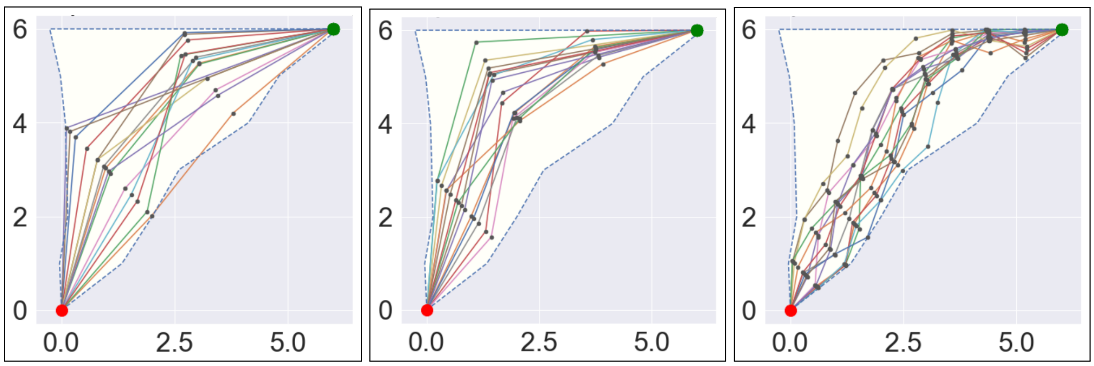
eral direction change probability and candidate sampling method, we still achieve a high diversity in length.

8.5.3 Shape Analysis

We change nW across columns and the destination point across rows in experiments on a six-meter wide envelope (*Figure 8.11*). More waypoints generate more variety in



(a) $nW = 2$ (b) $nW = 3$ (c) $nW = 10$



(d) $nW = 2$ (e) $nW = 3$ (f) $nW = 10$

Figure 8.11: Generated route plans. The red dots are the start point, the green dots are the destination points, and the black dots are the waypoints of a route. The first row has the destination point at (2,6) and the second at (6,6).

their envelope. However, a lower number of waypoints allows the motion planner more control. The location of the destination point does not have much influence on the shapes.

8.6 Future Work and Usage

In this section, we first discuss how the route planner can be improved and then how it can be further used to integrate sophisticated motion planners.

Statistical modeling can learn the design parameters of the route planner. For example, the maximum change in heading between subsequent waypoints can be measured from data. The direction change probability parameter can be extended to be a conditional parameter on other factors, such as desired pedestrian speed and distance from the destination, which may strongly correlate with the pedestrian's ability and intention to change direction during the crossing.

Any motion planner that takes a start and destination point can be integrated without modification to the approach. However, to use methods that generate future portion of trajectories without considering the destination point, such as deep-learning-based methods including [2, 120, 246, 144, 184, 80, 224], one needs retraining with destination conditioning or search for the candidate which terminates nearest to the destination point instead of most probable trajectory.

8.7 Conclusions

This work presents a hybrid approach in generative pedestrian modeling for the simulation-based testing of autonomous vehicles on city streets. With route planning and motion planning isolated from each other, it is possible to improve the expressiveness of the generative models as one can incorporate different models for each part. The proposed route planning method can take care of spatial coverage problems and produce real-world trajectory envelopes. The proposed integration approach shows promising results with rule-based and force-based models and allows the incorporation of machine learning models. Finally, the approach exposes control of the pedestrian model to the tester to selectively create different kinds of behaviors and trajectories.

Chapter 9

Future Work

This work unveils several possible directions for future research in pedestrian behavior ontology and its application, and simulation models with rich pedestrian behaviors and scenarios including rare ones. Continued research in ontology is necessary to ensure that autonomous vehicles are well-tested against a standard set of pedestrian behaviors on the road. This standardization of behaviors will support research and development collaboration across autonomous driving companies and research communities and communication among stakeholders of autonomous driving. Continued research and collaboration in simulation models are necessary due to the large set of unique behaviors that pedestrians show on the road across the globe. The modeling methods include rule-based systems to model rare behaviors that require human expertise, effort, and time. Therefore, open research in simulation models will serve the whole industry and the people.

9.1 Pedestrian Behavior Ontology

Chapter [3] presents the current state of the pedestrian behavior ontology for road crossings. Currently, the work is at an early stage and has several limitations which require attention. The major directions in future works are geographical, cultural, and seasonal differences in pedestrian behaviors, and co-relations among different behaviors. These directions are necessary to model when and where one can expect to face certain kinds of behaviors and how one can stitch together different behaviors to create holistically plausible pedestrian simulation models.

9.1.1 Geographical Differences

Geographical location and structure have a direct relationship with what an opportunist pedestrian can do beyond rational behavior. For example, a roundabout can be large enough to encourage pedestrians to cross across it to save time and energy [235, 234], or a walking path connected to the mid-block of a road can encourage jaywalking [34]. Modeling the relationship between geographical features and pedestrian behaviors can facilitate the test-case generation for different road structures for which one does not have any real-world data. It also helps autonomous driving algorithms to develop anticipatory methods to predict possible scenarios with pedestrians.

9.1.2 Cultural Differences

Culture plays an important role in how much risk a pedestrian takes and what kind of traffic violations one makes [222, 116, 149]. In [149], authors showed behavioral differences in pedestrians across different countries. Surprisingly, safety designs such as an underpass to reduce jaywalking may be more effective in China and less effective in Kenya. As autonomous driving needs to deal with cultural differences the way a human driver does, it is important to extensively study the differences and include them in the ontology.

9.1.3 Seasonal Differences

Seasons of the year and seasons of festivals or events change how pedestrians use the road. On a snowy road, a pedestrian can slip and fall down on the road while crossing [56] or can haul a sled carrying children [35]. During festivals such as Eid-Ul_Adha in countries such as Bangladesh, pedestrians often walk on and cross the roads with animals [109]. Events such as competitive sports, music concerts, and protests change the traffic dynamics and pedestrian behaviors on the road. Capturing these changes is important as pedestrian behavior in the same geographical location can suddenly change.

9.1.4 Correlation in Behaviors

One can think of a pedestrian behavior model in a given situation as a set of micro-behaviors that are compatible with each other. Not all the micro-behaviors can play together. For example, a pedestrian who is ignoring the approaching vehicle does not show evasive maneuvers even when they run the risk of collision. These correlations are important to reduce the infinite test space of pedestrians to a plausible and tractable space, yet containing an acceptable coverage of pedestrian crossing behaviors.

9.2 Simulation Models

Based on the study on pedestrian behaviors on the road, the following behavior models need attention from the broader research and development community for several reasons. First, some behaviors are very dangerous and extremely unexpected, while contributing to a considerable number of accidents. Second, some behaviors have not been addressed in the existing literature at all, but exist in traffic accident data. Autonomous driving needs to deal with known pedestrian behaviors. Third, different methods are required to model these behaviors due to the lack of sufficient data and evidence. While the recent trend is to use neural networks to learn models through data, rule-based methods need to be explored again to model these essential behaviors.

9.2.1 Impaired Models

According to NHTSA, about 57 percent of all pedestrians who die in road accidents have impairments *Figure [1.5]*. However, we have yet to develop simulation models that exhibit walking manners and behaviors reflecting different types of impairment. Based on fatal accident analytics some major impairments are:

- Under Influence: Pedestrians can be under the influence of drugs, medication, or alcohol which affects their cognitive capabilities required to cross roads safely. *Section [4.2]* shows how intoxicated pedestrians may behave on the road. This type of impairment contributes most to fatal accidents and needs to be well-addressed in simulation-based testing.

- Cane, Crutches, and Physically Impaired: Many accidents happen because pedestrians cannot move in their natural manner due to sudden changes in physiology. There is a chance that they plan normally but are not able to follow the plans as their walking capabilities are compromised.

- Blind, Low Vision, and Deaf: These disabilities reduce the ability to perceive traffic dynamics. Their behavior might be different from the pedestrians intentionally ignoring approaching vehicles. So, more work is needed to understand their behavior.

- Blackout: While this seems to be very rare, a surprising number of pedestrians faint on the road and succumb to death. Currently, there are no models for such pedestrians.

9.2.1.1 Group Models

A group of pedestrians usually moves like a single body. However, as shown in Section 4.7, a group can show a diverse and unique set of behaviors. While several works discussed group dynamics, the current models are very limited and often model a group as a single body. Therefore, more work is needed to capture different types of groups and their behavior. Based on the literature on group behaviors and shapes in [173, 71, 154, 256] and this work the key characteristics of robust group models are:

- The group can disperse at any time, creating multiple new groups while crossing [35, 204].
- The group can be fluid, meaning that some members may change their speed relative to others, changing the shape of the group. In [197], the kids outrun their guardians when crossing making the group much longer.
- When a group disperses, the members can make completely different decisions and follow different trajectories.
- The group members can interact with each other, which can lead to wrong intent estimation.
- A broken group can re-group while on the road [173, 154, 256, 71].

9.2.1.2 With Parked Vehicle Models

The pedestrian behaviors around a parked vehicle are different than crossing. Pedestrians interact with parked vehicles in different ways and often while being in the driving lane. The essential features of a model representing how pedestrians interact with stopped vehicles on the road are:

- Entering and exiting of a parked vehicle on the driving lanes [25].

- Walking around a parked vehicle [198].
- Loading and unloading objects on the driving lane [198].
- Changing tires on the driving lane [229].

9.2.1.3 Distracted Models

There has been some modeling work on distracted pedestrians. However, there are counter-examples of the existing models and many examples are not modeled at all. For example, in [152] the model claims that pedestrians wearing headphones cross the road more quickly. But that is the aggregated result. In [208], the pedestrian walks slowly. And speed is not the only differentiating aspect of a distracted pedestrian. *Section [4.3]* shows some key behaviors of the distracted pedestrians which have not been modeled yet. Because of distractions several other situation emerges where:

- The pedestrian can leave objects and group members behind [35, 209].
- The pedestrian can temporarily enter a driving lane with approaching vehicle resulting in accidents or near-misses [36, 124].
- The pedestrian can ignore all the traffic while crossing [208].

9.2.2 Occluded Models

Pedestrians can appear from any occluded area, especially in the city streets. Some occlusion scenarios are common and some are very rare. The pedestrians can be:

- Occluded by roadside objects such as trees.
- Occluded by a stopped vehicle.
- Occluded by a moving vehicle [125] on another lane.
- Occluded by the leading vehicle on the same lane in highway [125].

9.2.3 Kids Models

Modeling kids is different from modeling adults because:

- They have different heights and sizes which may make them harder to detect.
- They often do not understand the traffic rules. So, even if their walking manner is normal, they can make strategic errors while on the road.

9.2.4 Physical Models

The physical models mainly capture maneuvers and involuntary motion patterns which are completely based on the laws of physics.

9.2.4.1 Tripping Model

This model should capture the events where the pedestrian trips over or falls down on the road. In [56, 92, 57]. Presence of road objects, ice, potholes, or curbs can lead to pedestrians tripping while crossing. The dynamics of tripping or falling down also varies. Pedestrian can slide on the road, or recover by moving into some direction quickly. More research is needed on the dynamics and modeling of such behaviors.

9.2.4.2 Crawler Model

Rarely the pedestrian crawls on the road [89, 90, 92]. It may happen after the pedestrian falls on the road and not able get up. Pedestrians can crawl on the knees or on the belly.

- Crawling starts with walking on foot.
- Crawling may end with getting up again.
- Crawling can also have momentary stops.

9.3 Rare Behavior Models and Long-tail Scenario Generation

The proposed behavior models from this dissertation can greatly improve the generation of realistic long-tail scenarios based on simple scenarios from the real world. A scenario spans a period where traffic participants can show different behaviors. Current state-of-the-art driving algorithms are evaluated against datasets that mostly cover basic driving scenarios and are not tested against rarely-seen (long-tail) situations [108]. In [108], authors proposed augmentation of real-world scenarios with new agents for various participants including jaywalkers during simulation. However, the jaywalker behavior is still very simple, crossing the road without any rare behavior. Adding the diversity of behaviors from this dissertation can significantly develop the quality and diversity of long-tail scenarios generated from simple real-world scenarios. In addition, HyGenPend **Chapter [8]** can also generate rare route plans for the jaywalker agents, making the scenarios more challenging for the vehicle under test.

In addition to generating long-tail scenarios from simple real-world scenarios, RePed, **Chapter [7]**, also proposes a novel method to represent and augment real-world long-tail scenarios, and ensure that the expected dangerous situations emerge even when the ego vehicle behavior or road structure changes. Exiting literature attempts to ensure the emergence of expected pedestrian behavior by setting their initial location in the simulation world, [108, 242]. But once a pedestrian starts walking, it cannot adapt to changing situations on the road. RePed makes the pedestrian adapt while crossing. This adaptation method can be integrated with scenario generation methods to facilitate the test goals.

The micro-behavior models and the route-planner from HyGenPed, **Chapter [8]**, can also be used to improve the generation capabilities of Large Language Model (LLM) based generation methods where human editors can manipulate the agents in the scenarios using natural language, [245]. It is further elaborated on in *Section [9.4]*.

9.4 Explainable Scenarios

Explainable scenarios are necessary for humans to interpret scenarios and test results. One challenge in scenario generation for autonomous driving is that it is difficult to interpret the scenarios without human effort. Methods generate millions of dangerous scenarios, but it is not easy to tell whether these scenarios cover the diversity of pedestrians on the road.

This work suggests the incorporation of the micro behavior models in scenario generation methods as the method can easily keep a record of which behaviors took part in a scenario. As every behavior has an activation period and an interpretable name, it's easy to characterize millions of scenarios based on pedestrian behaviors. In this way, the test reports become interpretable and clear about what behaviors the autonomous driving has been tested against.

However, as there are other traffic participants in the scenarios, one needs more information to completely interpret the scenarios. Recently, Large Language Model (LLM) has been explored to generate and explain driving scenarios without human effort. This work can contribute to LLM-based driving systems in two different ways:

- Explain-only methods: Some methods are used to only explain scenarios, [64]. In such cases, manually generating data for fine-tuning or prompt exemplars is a costly task. The behavior matcher from RePed, **Chapter [7]** can identify unique micro-behavior patterns in pedestrian trajectories and create a natural-language-based description that can support LLMs to generate more accurate explanations.

- Scenario-generation methods: LLMs has also been used to generate scenarios, [73, 102, 245]. All the pedestrian behavior and scenario generation methods in this dissertation can significantly improve LLMs capability to generate explainable long-tail scenarios. In the most common setting, LLMs generate high-level instructions (*in the behavior space*) for agents, and agents need to have planners and behavior models that can act (*the trajectory space*) according to instructions. For example, when the LLM tells a pedestrian agent to retreat stop during simulation, the agent needs the capability to retreat. Using the micro model for retreat not only enables the agent to retreat but also makes the pedestrian trajectory interpretable.

Chapter 10

Conclusion

10.1 Summary

In this dissertation, we explored the necessity, requirements, and methods for pedestrian behavior modeling to make autonomous vehicles safer on the road. Throughout the journey, we learned about the diversity and unpredictability of human pedestrians on the road. We demonstrated several methods to test autonomous driving against rare pedestrian behaviors and scenarios in simulation.

First, we explored why pedestrian behavior modeling is necessary. 77 percent of fatal pedestrian accidents happen in non-intersection portions of the streets and 80 percent, in dark lighting conditions. Most accidents happen when human drivers cannot see or expect pedestrians. It is exacerbated by human drivers being intoxicated, aggressive, distracted, or drowsy. Though autonomous driving can detect pedestrians better, it needs to be tested thoroughly against numerous pedestrian behaviors and types. We hope an improved understanding of the range of pedestrian behaviors can lead AV makers to better document how their vehicles perform safely in a range of unusual situations, thereby increasing public and regulator confidence in this technology. To improve the understanding of pedestrians:

- This research aims to identify different kinds of pedestrians (The Dangerous Pedestrian Archetypes) which directly address public concerns. Often, the findings are astonishing. While crossing the road, a mother can be so distracted that she may leave her little kids behind on the road, or a drunk person can run towards the approaching vehicle and jump onto the hood. The archetypes makes it easier to communicate concerns and safety reports.

- This research aims to identify all the possible pedestrian acts on the road and develop an ontology for pedestrian crossing behaviors. The ontology contains all the rare behaviors, even when the behaviors cannot be attributed to specific archetypes. It reveals the research gaps in pedestrian behavior modeling and helps researchers and AV makers develop methods for coverage-based testing and reporting.

Second, we defined the properties of a robust pedestrian simulation model for AV testing. This simulation model must capture the diversity of pedestrian behaviors and support the test goals. To support the test goals, models need to produce behaviors and scenarios that the test plans expect. We elaborated on how the models can adapt and be controllable for that purpose. In addition, we also explored different approaches, from classical physics-based models to modern neural-network-based models, to develop a rich pedestrian model. To make a rich and controllable model, one has to go beyond machine-learning-based methods due to the lack of high-quality data and rare scenarios.

Third, we demonstrated how a finite-state-machine can be used to create a rich pedestrian model by composing behaviors in each state. In each state, different behaviors can be modeled using different methods and each behavior can be separately controlled to produce specific behaviors required by test goals. This work has a great potential in long-tail scenario generation where pedestrian agents, with rare behaviors, can be injected into existing scenarios to produce new and potentially critical scenarios.

Fourth, this work proposes RePed that ensures that autonomous vehicles under test cannot easily escape the desired situation during testing. RePed adapts the pedestrian agents so that specific events, such as a near-miss, happens even when the ego changes speed, or lanes, or drives in a different road structure. In addition, RePed offers an easy *language* to describe scenarios that can be reconstructed in simulation, and a *"Behavior Matcher"* method that can analyze trajectories and identify possible behaviors in natural language.

Fifth, HyGenPed allows us to generate a diverse set of route plans in any shape of shared space on road efficiently. Pedestrians can take various paths given the same shared space and shared space can also change dynamically based on traffic and obstacles. HyGenPed ensures the generated routes covers most of the area to challenge autonomous drive with pedestrians in all the possible positions.

Pedestrian behaviors are complex, and it is prohibitively difficult to model all of them using one method. This research encourages creative recipes and directions for future work to produce exciting and dangerous pedestrians and scenarios to strengthen autonomous driving in simulation.

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Appendix A

External Resources

This dissertation includes long-term research projects. The updated data and source codes can be found in the following URLs.

A.1 Pedestrian Behavior Ontology

- Annotation Tool Source Codes: https://github.com/AugmentedDesignLab/ped-behavior-annotator
- Ontology Behaviors: https://pedanalyze.readthedocs.io
- Ontology Datasets: https://github.com/AugmentedDesignLab/ped-behavior-annotator/tree/main/Dataset

A.2 Pedestrian Behavior Models

- RePed and HyGenPed Source Codes: https://github.com/adhocmaster/carla-jaywalker-experiments
- RePed Rare Scenario Dataset: https://github.com/adhocmaster/carla-jaywalker-experiments/tree/main/data/navpath
- Micro-behaviors and Behavior Matcher: https://github.com/adhocmaster/carla-jaywalker-experiments/blob/main/docs/adaptive-soft-model-behavior.md
- Video Demonstrations: https://www.youtube.com/watch?v=cj4ZpiOuGls&list=PLInS8yn6W0vQWolHXn6L6jVCi46cO2DPk