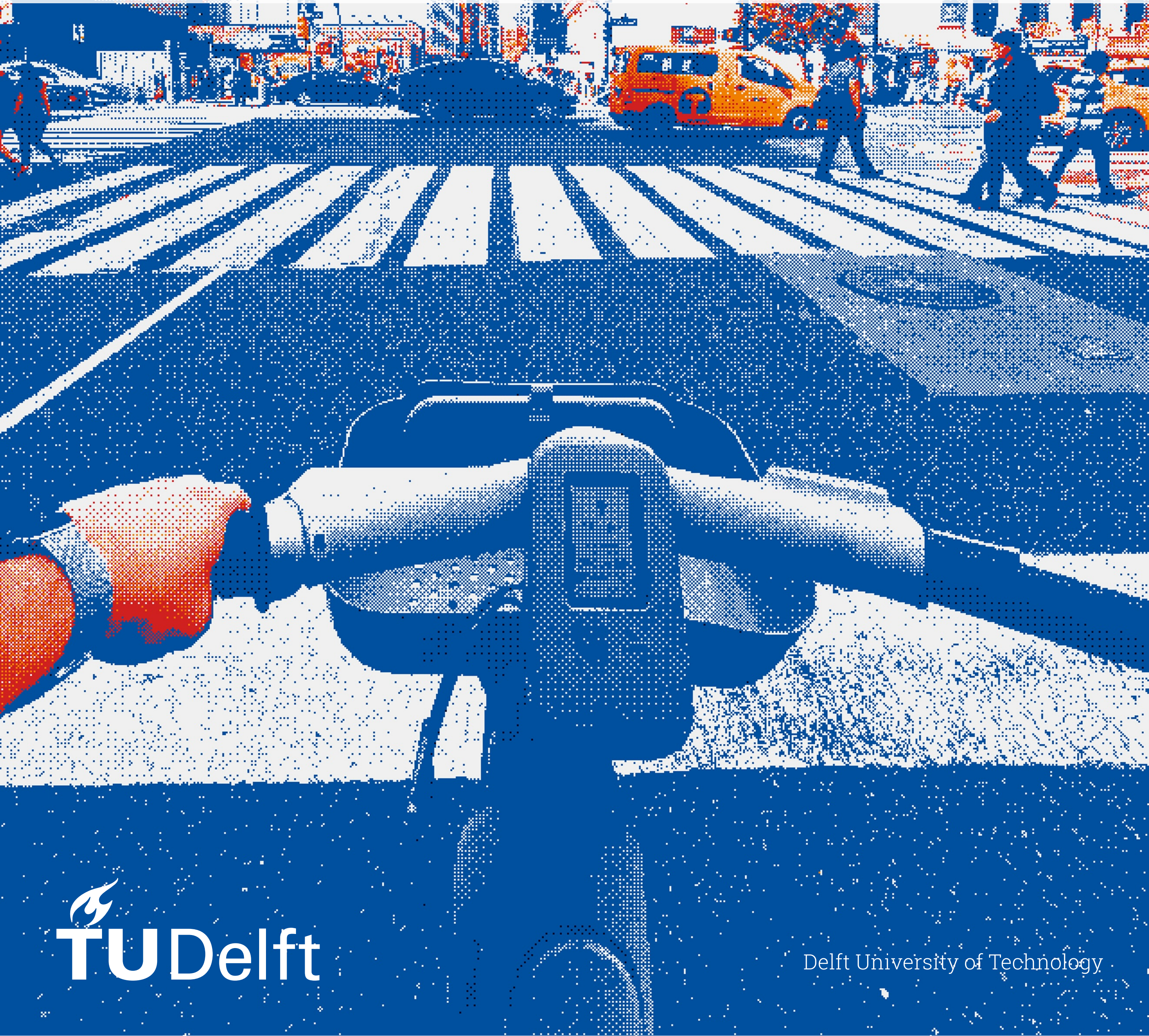
Modeling of Microscopic Cyclist Behavior with Path-Planning Algorithms

TIL5060 TIL Thesis

Hsuan-An Chu



TU Delft

Delft University of Technology

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by

Hsuan-An Chu

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Summary

In this thesis, an exploration into the potential use of path-planning algorithms in modeling cyclist behavior is made, and a novel model utilizing such algorithms, incorporating the commonly found overtaking behavior on bike paths, is developed and assessed.

The investigation started with a literature review on the existing behavioral interpretations and findings of bicycle riding, where the cyclists' interaction with the environment and other cyclists is found to be at different task levels of the riding process. Based on the findings, further analysis into how existing techniques replicate the different layers of behavior is made and assessed. During the assessment, this research determined that path-planning algorithms could best be used to replicate the physical steering behavior of cyclists. An investigation into the inner workings of path-planning algorithms is also done, resulting in the final four-layer conceptual framework based on the two-layer operational framework of bicycle riding, adapting the process into mental (perception, goal orientation) and physical (path planning, movement) layers.

With the adapted modeling framework, a model is developed, verified, and assessed with face-validation against real-world trajectory data. The development and verification step provides insights into the inner workings of the model, showcasing how the four layers of the framework are realized, and how the changing of used parameters would affect the intermediate output between the model layers. The face validation consists of two scenarios: a physical steering and pedaling-focused scenario of chicanes, which is a series of bottlenecks, and an overtaking scenario that focuses on the mental process of overtaking decisions. The results showcased that the developed model can create plausible steering and pedaling behaviors in the chicane scenario. However, the model showed lower accuracy and consistency in predicting the mental overtaking maneuvers.

The assessment result of the developed model showcased the strength of path-planning algorithms in augmenting the existing model with the physical steering capability of the cyclists. The limited accuracy in the overtaking scenario highlights the importance of capturing the mental process of bicycle riding. Future work could further refine the mental layers of the framework, specifically the goal orientation process. The adapted modeling framework also provides a new direction and foundation for further work on the path-planning additions and improvement of bicycle behavioral modeling.

Preface

A few years ago, I remember seeing a YouTube video of a competition about people cycling against the wind, and I thought it was a pretty silly idea. Fast forward to today, and I've been to the Oosterscheldekering, ridden a classic Dutch omafiets (Without the wind, of course), and am now finishing a Master's thesis on the topic of bicycle riding. It's safe to say that without coming to the Netherlands, I never would have chosen this topic.

The idea for this thesis was sparked by some of the most insightful courses I've attended during my studies. Victor, Maria, and Andreas's traffic modeling class sparks my interest in traffic operations. From there, Irene and Saeed's lectures on intelligent vehicles introduced me to the world of motion and path planning. Professor Alexander's advanced simulation course provided me with the foundation in agent-based modeling, and finally, Dorine and Winnie's course on active transport modes threaded all these ideas together. Without these classes and lecturers, the concept for this thesis wouldn't exist.

Of course, this project would not have been realized without my supervision team. I'm grateful to Alexandra for her frequent guidance and support, and to Winnie and Frederik for their vital feedback and tips when I needed them most. Without them, this project may as well be just a scribble in my notebook. I also want to give a huge thanks to the friends and colleagues I've met during my study, whether they are from Taiwan, the Netherlands, China, Indonesia, India, Turkey, Germany, Italy, or Kenya. Without their support and collaboration, I wouldn't have reached the end of my study.

Outside of my studies, I want to thank my friends from high school, university, and concert bands for keeping up with me, even across time zones. A special thanks goes to my mentor from my undergraduate studies for the initial encouragement and suggestion to attend a graduate programme. And finally, the biggest thank you of all goes to my family. Their encouragement and unconditional support have been the foundation of this expedition across the Eurasian continent.

Hsuan-An Chu
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Introduction

Bicycles have been an increasingly popular mode of transportation among the general public and policymakers in recent years. The mode's growth can be attributed to its well-established benefits in personal and environmental well-being (Mueller et al., 2018; Chen et al., 2022), and additionally, the mode's affordability, reliability, and low to non-existent external costs (Gatersleben and Appleton, 2007). Additionally, with the mode's continuous innovation, such as the development of e-pedelecs and cargo bicycles, cycling is expected to grow as new types of bicycles provide longer range and cargo transporting capabilities that substitute travel that was only possible with public transportation and cars (Riggs, 2016; Kroesen, 2017). However, the increased popularity of the mode come with increasing challenges in the planning, designing, and operating of bicycle infrastructures, as the mode has drastically different dynamics than automobiles.

Compared to automobile traffic, bicycle traffic is highly different in both physical and behavioral characteristics, such as the mode's vehicle size, need for balancing, self-propelled nature, and operational flexibility, which leads to the mode's more lateral and unrestricted utilization of the infrastructure, such as overtaking within the same lane, and curb riding. Additionally, cycling infrastructure often intersects and shares spaces with automobiles, pedestrians, and other road users. Such a difference in the movement and the operational environment of the bicycle riding creates challenges in the interpretation of the cyclists' riding behavior, sparking interest in the modeling of bicycle riders for two distinct disciplines of research: the field of traffic and robotics. The traffic engineering and research aims to provide insight into the evaluation of the efficiency and safety of bicycles, while the field of robotics aims to integrate intelligent systems such as robots and intelligent vehicles into the human population. Due to the similar objective, these two fields naturally exhibit similar parallels in the modeling techniques.

Early iterations in the modeling techniques include the discretizations of physical space and human action. Creating the so-called Cellular Automata (CA) approach in the modeling and predicting human behavior (Nagel and Schreckenberg, 1992; Meyer and Filliat, 2003). There are also attempts at describing human motion using Newton's laws of motion and vehicle properties, yielding the velocity-based (Best and Norton, 1997) and the force-based approach (Helbing and Molnar, 1995). Throughout the years, with more advancement in computational and data collection techniques, this has led to more sophisticated techniques such as the game theoretic approach found in Hoogendoorn et al. (2003), the discrete choice approach of Antonini et al. (2006), and more recently the machine learning based approach (Alahi et al., 2016). All these mentioned techniques have been found to be adapted and augmented for use in the modeling of bicycles, including CA (Li et al., 2013), Velocity-based (Brunner et al., 2024), Force-based (Ni et al., 2023), discrete choice (Gavriilidou et al., 2019a), and game theory-based (Hoogendoorn et al., 2021).

However, there still remains a modeling approach that has not yet been adapted for bicycle use. The sampling path-planner approach Broz (2004), such an approach is said to be better in long-term prediction and modeling when compared to physics-based approaches, and better generalization capability when compared to data-driven methods (Rudenko et al., 2020). Besides these alleged benefits, the research on sampling-based path planners is a relatively mature field in the field of robotics, and the rapid development of the planning algorithm has enabled the incorporation of vehicle kinematics, which is how the vehicles respond given the handling input of acceleration and steer. Such additions could be of good use in the modeling of bicycle riding behavior, considering the complex handling properties of the bicycle.

With these potential benefits, this research aims to explore the possibility of the incorporation of sampling-based path planners in the use of bicycle behavior modeling. As an example, this research will attempt to recreate the commonly found overtaking behavior, as it is a major contributor affecting the lateral distribution on a bicycle path (Castro et al., 2025). An attempt to model the microscopic riding behavior of the cyclists using a sampling-based path planner could yield two major benefits. First, an attempt to model the microscopic riding behavior of cyclists with the use of path-planning algorithms will be made, which will be a brand-new modeling approach. Moreover, bridging the gap between the field of traffic modeling, sampling-based path planning, and human motion trajectory prediction. Opening up more possibilities for new modeling techniques and crossover research between the fields, which could potentially accelerate the modeling development and yield new innovations.

1.1. Research questions

Based on the findings from the initial investigation. This research has identified a gap in the use of planning-based approaches, which could be of good use in bicycle behavior modeling. To fill in this gap, this research aims to develop a conceptual model incorporating sampling-based path-planning algorithms that could replicate bicycle riding and the commonly found overtaking behavior. Framing the research question of: ***To which extent can characteristics of bicycle riding be accurately captured with a model that incorporates path-planning algorithms?*** This main research question could be answered with the completion of the following sub-questions.

1. **How can the process of bicycle riding and overtaking be interpreted using existing frameworks?**
2. **Based on the explanations/frameworks, where could path-planning algorithms be used?**
3. **What framework modifications, components, and parameters are needed to model the microscopic behavior of cyclists with the incorporation of path-planning algorithms?**
4. **What are the observed strengths and weaknesses of the developed model?**

1.2. Research methodology

With the aim of answering the main and sub-questions, this research will develop a microscopic bicyclist behavior model that incorporates path-planning algorithms. The development of the model will follow the Microsimulation Model Development and Application Process (Dowling et al., 2004) from the Federal Highway Administration of the United States (FHWA), which is considered a major traffic authority in the world. The scope of this research has been adjusted to focus more on the subject of model development, reflecting the research questions. The literature review step would cover the first research question regarding the observed characteristics and interpretations of bicycle riding and overtaking, along with how the previously mentioned existing modeling method fits those explanations. Based on the findings, the research is also expected to find adjustments and placement for the path planning algorithms, which covers the second research question, and part of the third research question. Then, the modeling investigation would go into detail with the development step, where the model's different components and parameters will be determined, and their effects showcased in the verification step, completing the third research question. This research exchanges the steps of calibration and application of the model for a face validation step that better fits the fourth research question, providing insights into how the developed model behaves, the observed strengths and weaknesses, and potential future modifications needed for the model. The adapted development process consists of the following steps, and it is illustrated in figure 1.1.

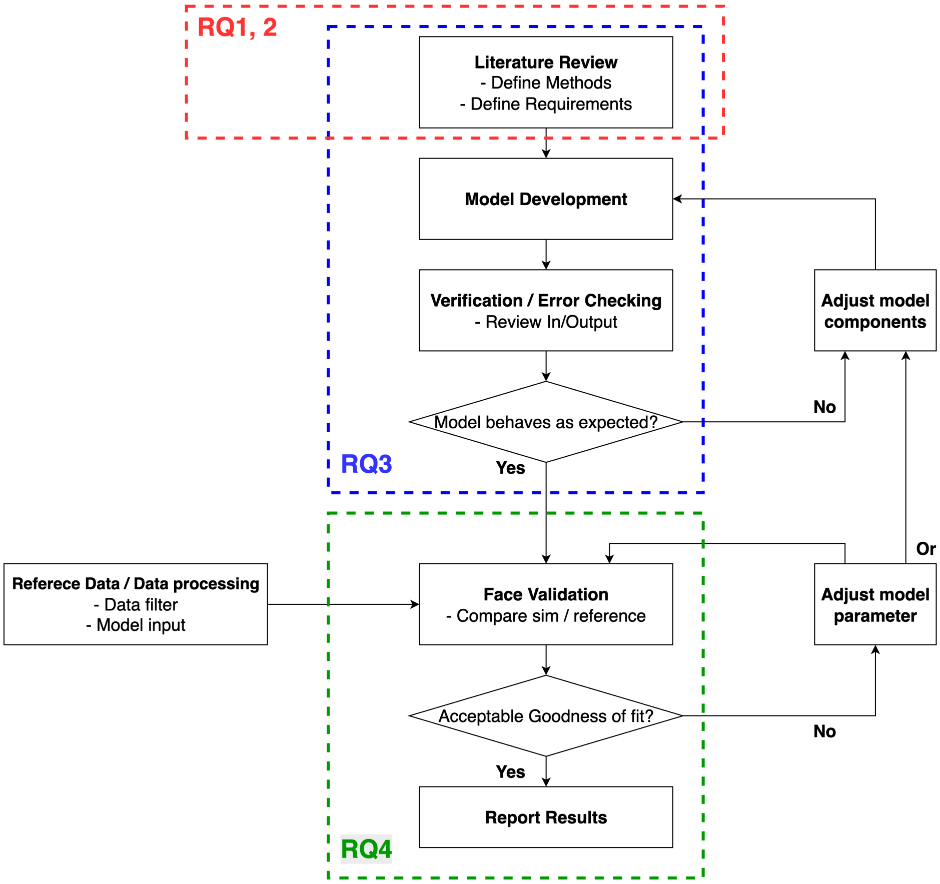

Figure 1.1: Model development process of this research

The literature review is presented in the following chapter 2, which contains further investigation into bicycle riding findings, existing modeling techniques, path planning algorithms, and initial framework modifications. Chapter 3 would continue on the framework modifications, providing more concrete inner workings, as well as the process of verification and face validation of the model. The result of the verification and face validation process will be showcased and discussed in chapter 4, and a conclusion of the research at chapter 5.

2
Literature review

In this literature review, this research elaborate on the investigation of existing techniques in modeling cyclist behavior that is briefly covered in the introduction. The investigation this time will be related and compared with the use of an existing framework. After the comparison, this research aims to explore the possible parameters and framework adaptation needed for the incorporation of a path-planning algorithm into the existing modeling framework. This is done by first investigating the properties of path-planning algorithms, then attempting to link such findings to a cyclist modeling context, collecting the desired parameter values, and making adjustments to the existing framework.

This literature review was first conducted with a database search on both Scopus and Google Scholar. For the cyclist behavioral research, starting keywords include a combination of: *Microscopic, Cyclist, Bicycle, Modeling, Behavior, Simulation*. While for literature related to the trajectory planning and predictions, starting keywords include a combination of: *Path, Motion, Planning, A*, Dijkstra, RRT*. The search results are then examined, and if suitable literature is found, such as Gavriilidou et al. (2019a) or Karaman and Frazzoli (2011), this research will use the literature as a basis for forward and backward snowballing. The references and citations of the literature are examined, and additional keywords found in the literature are also used as a supplement for the database searches.

2.1. Microscopic bicycle behaviors

With this section, this research will first examine how the process of riding a bicycle is explained, and how different part of the bicycle riding process is categorized. After the investigation, this research will investigate the previously defined scope of overtaking behavior based on the explanation and categorization, which could also be used for the later part of the modeling process.

2.1.1. Cyclist behavioral framework

The actions of riding a bicycle, when categorized using the definition of car driver task levels (Michon, 1985), span across tactical and operational behaviors, which consist of maneuvering and automated split-second actions. However, the behavior of bicycle riding differs from other wheeled traffic types because of the mode's self-propelled nature and the need to balance the vehicle upright. The need for these physical efforts put a different toll on the mental and perception process of cyclists (Boele-Vos et al., 2017). This means the maneuvering process while bicycle riding is closely related to the physical traits of the rider, so it should be more closely linked together. Thus, a combination of the definition of pedestrian and automobile was used to describe these behaviors, leading to the 2-layer operational framework of Gavriilidou et al. (2019a). Consisting of 2 layers, the operational mental and the operational physical layers. The mental layer focuses on the path choices within the routes, which would consist of different behavior decisions, such as overtaking, yielding, stopping at the red light, turning gap acceptance, and queuing, while the physical layer focuses on the process of steering and pedaling of the bicycles. Based on this modeling framework, this research will then dive into how bicycle behaviors for these two operational layers of behavior are explained and observed from the previous research. The investigation will focus on the previously defined scope in the introduction, which is the commonly found overtaking behavior.

2.1.2. Overtaking process

The mental layer of behavior is responsible for handling the path choice within the route/environment. To make those path choices, the mental layer relies on the input of environmental attributes, which include both physical objects and other road users.

The presence of such environmental objects can be explained using the field of safe travel concept (Gibson and Crooks, 1938) or sometimes referred to as a comfort zone (Lee et al., 2020). The field of safe travel makes assumptions that vehicle operators create a psychological environment where they can safely move based on their assumption of the vehicle's ability, without hindering other scene objects and the population. Due to the different dimensions and the need to balance bicycles, cyclists require a differently shaped boundary compared to automobiles. This has led to the proposal of a psychological boundary proposed in Twaddle (2017) based on the existing diamond shape of the physical modeling of Falkenberg et al. (2003), and the dimension of which is observed in the observation study of Meijer et al. (2019) in Amsterdam, the Netherlands.

Another factor that is related to how cyclists process environmental attributes is the perceptual properties of the cyclist, as this limits how far cyclists would interact with the given environmental conditions. Stülpnagel (2020) conducted a real-world riding experiment in Freiburg im Breisgau, Germany, where a cyclist's gaze pattern while riding is collected. The results have shown that at an average riding speed of 4.8 m/s, the gaze length across the riding environment is at a range of 22 meters, which is roughly equivalent to a time headway of 4.5 seconds. Such values are also similar in range to the interaction range of 4 to 5 seconds headway with other cyclists, which is estimated in the observation study of Hoogendoorn and Daamen (2016) in Delft, the Netherlands, and the observation study Mohammed et al. (2019) in New York City, USA.

The study of Mohammed et al. (2019) has also investigated the mechanism of overtaking for cyclists. The study has confirmed the early assumption (Botma and Papendrecht, 1991) of both a threshold value for both space and speed that dictated the overtaking behavior, which ranges from 0.5 to 2.3 m/s across multiple observations throughout the world (Khan and Raksuntorn, 2001; Falkenberg et al., 2003; Mohammed et al., 2019; Castro et al., 2025). These mechanisms cover the mental layer of the behavior as it makes decisions on how the cyclist will navigate the field of safe travel. The execution of the maneuver choices will rely on the physical layer of behavior, which is steering and pedaling.

The steering process of the bicycle relies on the capabilities of both the bike and the human. Early investigations for this topic focus more on the physical kinematics and the limitations of an unmanned bicycle itself (such as the one found in Yavin, 2006), but the riding process is also heavily influenced by both the rider's perceived capability to balance and steer. It is not until later days that data related to the human control of the bike, such as the human input's turning angles, frequency, and leaning angles, have been investigated using real-world riding measurements (Moore et al., 2010; Moore, 2012; Alizadehsaravi and Moore, 2022).

The pedaling motion of the cyclist is said to be following a similar behavioral description to that of automobiles, where riders would adjust their behavior based on their frame of reference, comparing the speed difference between themselves and their desired speeds, or the speed of the selected leader, making adjustments to the final output. The major difference between the behavior of the cyclists and automobiles is the self-propelled nature of the bicycles, so it is said that the pedaling motion of the cyclist is best described using the assumption of minimizing efforts, where the cyclist only decelerates to a necessary amount needed to avoid collision, minimizing the need to re-accelerate to a suitable speed (Andresen et al., 2014). In the same research, an experiment was conducted in Wuppertal, Germany, which derived a model that follows the assumption, yielding a good representation of the pedaling behavior.

After the thorough investigation of bicycle behavior explanations and characteristic findings. This research aims to review the various types of models that have been developed throughout the year, and how they achieve the mentioned mental and physical layers of the behavior in the next section.

2.2. Microscopic bicyclist behavior models

In this section, the various attempts at modeling bicyclist behavior will be reviewed, including techniques that stem from the 2 different origins, automobiles and pedestrians. The categorization of these models takes note of the categorization of Twaddle et al. (2014) with the addition of utility-based models, which have not yet been developed at the time of the study. The categorization is based on how the final movement, or the physical layer of movement, is achieved. The review will include a comparison of how the various model types achieve the previously mentioned mental and physical processes.

2.2.1. Cellular Automata (CA) model

Cellular Automata (CA) model, originally developed by Nagel and Schreckenberg (1992) for highway automobile traffic, is a discrete-time and space model that provides a fast and simple way of modeling car following behavior. Vehicles inside the model travel through a raster of cells. Following the simple logic that a vehicle can only exist in one cell, the agents adjust their speed and acceleration based on this rule. Gould and Karner (2009) then adapted this modeling approach for bicycle infrastructures by reducing the cell size to 2.1×1.4 meters, combined with lane changing and overtaking logic under wider or multi-lane situations. The model has shown comparable results when compared to field data in heterogeneous speed conditions. Attempts at modeling mixed traffic flows have also been made, utilizing smaller cells and different occupation amounts at the cells based on the vehicle size (Yao et al., 2009).

Since the movement of the rider is determined by a series of decision logic of discretized cells, this type of model is able to incorporate the mental decision process of making decisions, such as the various attempts found in modeling overtaking behavior (Li et al., 2013; Zhao et al., 2013). However, the models are still relatively limited since they can only simulate homogeneous traffic conditions with bicycle-only traffic. Later models address the issue by making the cells smaller, and each vehicle can occupy a set of cells at the same time based on the vehicle size (Yao et al., 2009). However, due to the assumption of discrete longitudinal and lane-based movement, the model is not able to reproduce an accurate representation of the steering and pedaling behavior of the cyclist. Proposals on modeling the steering behavior, with the use of trajectories shaped cells, have been found in literature (Vasic and Ruskin, 2011), but it remains at a conceptual phase.

Overall, it can be said that the CA models are a mental layer-driven approach that covers more of the decision-making process of bicycle riding.

2.2.2. Longitudinally continuous models

Contrary to the Cellular Automata models. Longitudinally continuous models operate in a non-discrete one-dimensional space. The bicycle variant of these models is derived from well-established car-following models. It typically uses one of the three types of car-following models: Gazis-Herman-Rothery models (Chandler et al., 1958), safety distance models such as Newell's car-following model (Newell, 1961), and psycho-physical models such as the one following Wiedemann's car-following principle (Wiedemann et al., 1974). These models are developed through observation and various assumptions about vehicular traffic. When no leading vehicle is present, the vehicle then tries to maintain its desired speed. Later revisions of the longitudinally continuous approach have taken bicyclists' effort conservation into account, such as the Necessary Deceleration Model (NDM) of Andresen et al. (2014).

However, these car/bicycle-following models all operate under the assumption of single-file traffic, that no overtaking can occur within a lane. Thus, it is harder to model the larger-than-normal lateral movement of a bicyclist. A separate lateral component is required to more accurately simulate the riding behavior of bicyclists in these types of models. Common approaches include the discretization of lateral spaces within a lane into strips, combined with a discrete choice model to select the strips and a continuous approach based on riders minimizing their time to collision (TTC) with other road users (Falkenberg et al., 2003). The lane-based approach exhibits similar limitations to the CA models, while the conflict-driven approach does not encode any mental decision process.

In recent years, more complex decision logic has been added to cover both the mental and physical layer behavior of bicyclists, such as the model developed by Brunner et al. (2024). The model consists of three layers: Maneuver planning, Movement planning, and the Acceleration layer. In the Maneuver layer, the model observes and classifies the surrounding bicyclists in a consideration range based on their desired speed and a set overtaking threshold. Based on those classifications, a desired lateral position is obtained. After obtaining the desired lateral position, the movement layer then determines the movement direction and the hypothetical desired lateral speed based on a set safety range for the surrounding bicyclists. Lastly, the acceleration layer calculates the acceleration using a longitudinally continuous model. After the computation of longitudinal acceleration, it can be combined with the desired lateral position and acceleration to obtain the actual speed of the agent. Through these three layers, both lateral and longitudinal movement and overtaking decisions are modeled. While this approach does incorporate both layers of behavior of the cyclist, it does not offer a direct representation of the steering behavior during bicycle riding, but only a lateral velocity-based constraint.

With these investigations, it can be said that the longitudinally continuous models are a physical layer, pedaling-focused type of modeling approach that requires further augmentation in the mental and steering behavior aspect of bicycle riding.

2.2.3. Force-based models

Force-based models are a group of model that operates in discrete-time and continuous-space. Agents' movement inside these models is not bound to a certain axis, they are omnidirectional under the influence of several attractive and repulsive forces, shown in figure 2.1.

The original force-based model, the Social Force Model, was first proposed by Helbing and

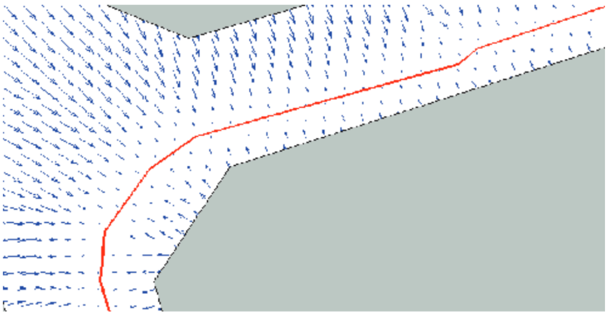

Figure 2.1: Force vector and trajectory of a force-based model by Schönauer et al., 2012

Molnar (1995) to describe the dynamics of pedestrians based on their psychological tendencies. The models adapted for use in modeling cyclists assume that the operational dynamics of bicyclists are similar to those of pedestrians. With it having a stronger attractive and repulsive force to the destination and other in-scene objects, this type of approach is versatile and could be easily modified to accompany heterogeneous traffic flow consisting of automobiles and bicycles (Li et al., 2011), or bicycles and pedestrians (Yuan et al., 2019). Early adaptation of the force-based approach operates under a physics-based environment. Thus, no decision-making process is implemented for the agents. Actions such as stopping for right-of-way are not present, which is opposite to the usual behavior in real-world traffic (Schönauer et al., 2012).

Thus, various attempts have been made to simulate the process of decision-making through the addition of more force components or manipulating the intermediate position of attraction forces with the help of a decision layer. Schönauer et al. (2012) uses game theory to determine the maneuver with maximum utility from a set of intermediate points, effectively simulating the yielding behavior for different modes of traffic. Liang et al. (2018) developed a purely physical approach through the use of a psychological-physiological force. The model contains individual force components that are responsible for the perception range and reaction range of the bicyclists, the Collision Avoidance Force, and the Contact Force. The former force is responsible for the preemptive maneuver of objects within perception range, with the latter force component responsible for close proximity movements under emergency or in high-density flows. When vector components from these two force fields are aggregated, movements comparable to the mental decision logic and process of real-world bicyclists can be observed. Ni et al. (2023) augmented a force model with environmental context cues. The agents could perceive multiple interactive road users. Then, through the use of a Bayesian Network, the agent could choose a suitable behavior from alternatives, building up an intermediate destination that corresponds to the selected behavior. These behaviors are then executed by a force-based component to complete the movement process. With these augmentations, force-based models cover the mental layer of the bicycle riding process.

The physical layer behavior of pedaling has also been investigated, with different force components used to change the state of movement, such as the one found in Liang et al. (2012). The model has two operation modes in free-flow and congested states based on the bicycle-following behavior of real-world bicyclists. The physical behavior of steering, however, remains a less discussed topic, with the implementation using intermediate goals to imitate the riding trajectories (Schönauer et al., 2012; Ni et al., 2023). It is not until Schmidt et al. (2024) that a proposal to make the trajectory kinematically compliant is found, but it still remains in the process of development.

Overall, the forced model can be said to be similar to longitudinally continuous models, where it requires an addition to model the mental layer of behavior, and the modeling of steering behavior in the physical layer is not directly tackled.

2.2.4. Utility-based models

There are also models developed based on the decision-making nature of human behavior. The so-called utility-based models operate on the premise of utility maximization or effort minimization when making decisions. The interaction with the environment and other agents could be modeled as a differential game, where a game is solved in a non-cooperative or cooperative manner continuously. These type of game theory models originates from the realm of pedestrian modeling (Hoogendoorn and HL Bovy, 2003), then later adapted for the use of bicyclist modeling (Hoogendoorn et al., 2021). Another type of model that is similar in working is the model that optimizes a set of reward policies or logic, which is often simply referred to as the agent-based models. These types of models were also originally used to model pedestrian interaction (Hussein and Sayed, 2017), which later on were developed for cyclist use with the addition of a longer optimizing period, capturing interaction of cyclists and other vehicles (Alsaleh and Sayed, 2021; Mohammed et al., 2022). These types of models often utilize kinematic variables as an optimization constraint, modeling both the pedaling and steering behavior of the cyclist.

There are also models that utilize a discrete choice approach, where it is assumed that the agent would choose the best action or decision in a stepwise manner with the use of a discretized action cone. This approach is first found in Antonini et al. (2006) for pedestrians, then later adapted to bicyclists by Gavriilidou et al. (2019a), which incorporates a second decision layer for goal orientation. This layer allows the agents to perceive and select a queuing position or decision, such as yielding or crossing. The action and goal orientation layers communicate with each other, making adjustments to the decision. This cycle is executed until the agent has reached their desired position. This modeling approach allows agents to make decisions and changes to their desired queue position and routes.

2.2.5. Evaluation of current bicyclist modeling techniques

After the investigation of various microscopic bicycle modeling techniques and their recent development, which are discussed in the previous subsections, this section will provide an evaluation of how the models include the stated 2-layer behavior of the model, which is shown in table 2.1.

Table 2.1: overview of how the reviewed model handled

Model Types	Decision (Mental)	Pedaling (Physical)	Steering (Physical)
CA	Yes	Discrete	No*
Longitudinal Continuous	- (Hybrid apprach)	Continuous	No
Force	- (Hybrid approach)	Continuous	No*
Discrete Choice	Yes	Discrete	Limited (From data)
Agent based (Reward driven)	Yes	Continuous	Yes
Game theory	Yes	Continuous	Yes

* Proposed but not yet implemented

Upon initial inspection, only the game-theoretic and the reward driven agent-based approach offers all the desired mental and physical properties that are required for the modeling of microscopic operational cyclist behavior, where the model not only able to handle the problem of decision directly through different strategies of different utility maximization approaches, it also tackles the problem of steering, pedaling directly using kinematic equations or variables. While other models all contain some shortcomings that require different layers of augmentation to achieve similar feature sets that the game theoretical approach has, such as the use of a logic or decision layer to handle different decision processes, which is found in the force model of Schönauer et al. (2012), and the longitudinal continuous model of Brunner et al. (2024).

Another major difference comes from the ability to capture the steering behavior of the physical layer, which again, is only currently handled in the game theoretic framework of Hoogendoorn et al. (2021) and the Markov Decision Process agent-based model of Alsaleh and Sayed (2021). The steering behavior is also partially handled in the discrete choice approach of Gavriilidou et al. (2019a), which could generate movement with respect to the vehicle kinematic constraints based on the data used, but it does not tackle the kinematic properties directly. Though it is still early to determine whether the incorporation of vehicle kinematics could yield benefits in the realm of bicycle traffic modeling, a trend of modeling with considerations of handling dynamics has started to emerge. Such as the use of a trajectory-shaped cell in the CA models (Vasic and Ruskin, 2011) and the proposal of kinematic models additions to the force model of Schmidt et al. (2024) that is currently in development.

The use of sampling-based path planning algorithms could, in theory, serve as an augmentation to existing models that do not incorporate kinematically constrained steering behavior. Such as the longitudinally continuous models, which currently utilize only lateral acceleration constraints. The addition of which is expected to provide a more accurate trajectory output, while also enabling the use of a longitudinally continuous model in a more complex environment that requires heavy navigation. In the next section, this research aims to offer an introduction to sampling-based path planners and investigate how sampling-based path planners could be used to model the physical layer behavior of bicycle steering.

2.3. Sampling-based path planners

The problem of path planning originated from the need to find a path or motion for a robot to move from point A to point B. This problem was originally formulated as a search through the known configuration space, which is called Search-based planning, with the use of path finding algorithms like Dijkstra (Dijkstra, 1959) and A* (Hart et al., 1968) through an imposed grid. However, the grid formation requires prior knowledge of the configuration of the search space, which is not easily generalizable to new or dynamic environments. This led to the development of sampling-based path planning algorithms.

The sampling-based path planning algorithms consisted of 2 major types of methods: the graph-based and tree-based methods. The use of sampling, connection, and optimization steps allows these types of algorithms to adapt to different spaces and tasks. Graph-based methods, such as the Probabilistic Roadmap Planner (PRM, Kavraki et al., 2002), which samples the entire environment first, then connects a viable path through the environment, this type of graph-based planner is also called the multi-query planners, as the planned graph is based on the environment, and it could be used for different agents on the scene. Thus, it is considered useful in more static and repetitive environments like factories or warehouses (Orthey et al., 2023). Another major type of the model is Tree-based or single query methods, which plan a path in reference to the position of the agents, most notably the rapidly exploring random trees (RRT, LaValle, 1998). These types of planners are considered relatively efficient and could be suitable for more dynamic environments, as the path could be rapidly re-planned. Later iteration of the model focused more on the optimality of the path, such as the optimal RRT and PRM star(RRT*, PRM*, Karaman and Frazzoli, 2011), and also adaptation to fit an unbounded solution space, such as the ST-RRT of Grothe et al. (2022), which uses a dynamic goal and search region and could be used to simulate the visual range of intelligent vehicles and human perception, shown in Figure 2.2.

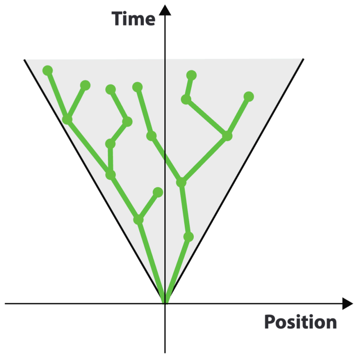

Figure 2.2: Illustration of a unbounded search by Orthey et al. (2023)

Sampling-based path planners are also easily adaptable to incorporate various dynamics. The sample then wire nature of the algorithms means various constraints and costs can be embedded in the algorithm when wiring a path, such as turning constraints and action costs. This makes for a simple point-based kinematic model, such as the one found in RG-RRT of Shkolnik et al. (2009). Other, more sophisticated kinematic models, such as Dubin's Car (Balluchi et al., 1996), are also found in other implementations. The incorporation of a kinematic generates a more feasible path while planning. Lastly, these planners provide solutions and optimality guarantees when the goal is well-defined, which makes the quality of the given path stable when there is sufficient computation time. The optimality guarantees also facilitate the incorporation of different planning strategies, such as effort minimization and utility maximization, which could be of use for modeling cyclists. These characteristics, as well as the prevalence of sampling-based planners in the field of robotics and intelligent vehicles, mean there are a lot of potential tools and methods to explore when converting sampling-based planners for the use of bicycle modeling. Besides these desirable characteristics, the research of tree-based planners remains an active field (Muhsen et al., 2024), and any major advancement in speed or planning techniques breakthrough could aid in a model that utilizes such algorithms.

2.4. Conclusion and Conceptual framework

In this chapter, the modeling framework of Gavriilidou et al. (2019a) is first investigated, which offered explanation of bicycle riding behavior based on the difference in the task level between cyclists and automobiles, which splits the operational behavior into 2 parts: a mental layer that is responsible for handling the path choice within the route/environment, and a physical layer that executes the path with steering and pedaling. The problem of path choices could be related to many riding decisions, such as yielding, stopping, turning gap acceptance, queue positions, and in the scope of this research, overtaking. Various aspect and explanations that are present in the process of overtaking is also visited for use in the latter part of the modeling in this research.

This research has also assessed the found attempts at modeling microscopic bicycle behaviors using the 2-layer operational framework of Gavriilidou et al. (2019a). During the investigation, this research has found that the ability to incorporate realistic steering with respect to the bicycle kinematics has long been proposed, but it is of rarity. The use of sampling-based planners could be a great augmentation to the existing models, especially longitudinally continuous models, which focus mainly on the pedaling behavior of the physical layer.

In the latter section of this chapter, a brief introduction to the 2 major varieties of the sampling-based path planner and how they are adjusted to fit the different needs is provided, and it has been found that the tree-type path planners are more suitable for use in the modeling of driving or riding behavior, as they offer the adaptation to solve unbounded and kinematic problems. With this information, this research is now able to conclude on how the knowledge gathered from the previous section could be used and adapted to enable the incorporation of path planning algorithms in the modeling of cyclist operational behavior.

To initiate the path-planning algorithms, a bounded search region and the boundaries of obstacles are required. The bounding of the search region can be related to the known limited perceptual range and interaction, meaning that information outside the range can be negated, and the boundaries of objects on the scene can be processed using the assumption of a field of safe travel, where bicycle riders create an environment physiologically based on their assumption and ability to traverse the environment safely. Using the theory, the psychological boundary can be translated into an obstacle within a planning problem, where a planned path should not interfere with the set limit.

With the set boundaries, which are the interaction of the cyclists, a dynamic goal is still required to set up a planning problem. The problem of goal placement can be explained using the observed overtaking behavior of the cyclist, where, based on a threshold for both the speed and the available space, the cyclist would choose to follow or overtake to reach their long-term goals. After the determination of the planning boundary and goal, the path planning algorithm could start, and the path could be planned with the known human riding inputs as a kinematic constraint, generating a path, which is a series of steering inputs. Lastly, since the planned path only generates a steering output. The pedaling should ideally be modeled using a longitudinal continuous model that best fits the effort conservation tendencies that are commonly assumed because of the bicycle's self-propelled nature.

Based on these findings, this research has also concluded on the following modeling requirements for the later development of the model:

- The developed model has to incorporate both the operational mental and physical layers of behavior.
- The developed model has to navigate based on the field of safe travel, following personal boundaries and vehicle kinematics.
- The developed model should incorporate the known overtaking and behavioral mechanisms found in the literature review
- The developed model should follow the effort conservation tendencies commonly assumed in bicycle riding.

With these derived requirements in mind, this research has also made an adaptation to the 2-layered operational framework of Gavriilidou et al. (2019a). The original mental layer, which handles path choices within the route, will be made based on the given environment attributes. The layer is adapted to be a two-step process, where a reachable planning domain is first created based on the field of safe travel concept, and a step for goal placement for the initiation of the planning algorithms. This approach transforms the process of bicycle riding into a dynamic planning problem of changing goals and bounds. This research calls these two processes perception and goal orientation, as the process creates a perceived reachable space and places a goal.

The physical layer, where the steering and pedaling are handled in the original model, is also split into two. The planning algorithm is used to tackle the steering inputs. The planner could search the reachable space and construct a feasible trajectory to the goal, given the current speed, based on the physical characteristics or kinematics of the vehicle. Then, a separated component is used to recreate the pedaling motion, adjusting the riding speed, and traveling along the planned kinematically feasible and reachable paths. This research calls these two actions path planning and movement, as indicated by their functions.

Based on these relations and function definitions, the final four model layers are formed. Shown in figure 2.3, in conjunction with the original framework.

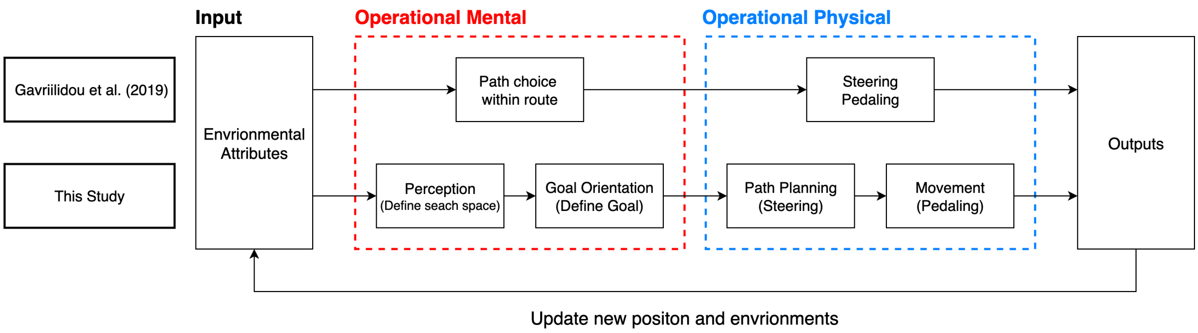

Figure 2.3: Modeling framework with respect to the two-layered framework of Gavriilidou et al. (2019a)

3
Methodology

In this chapter, information regarding the development, verification, and face validation is provided. The development of the model will build upon the framework, requirements, and knowledge gathered from the literature review. Starting from a draft model structure, then dives more deeply into the different layers of the developed model. In the latter part of the chapter, the process from verification to face validation is provided, which contains information about the simulation data, scenario, and the benchmarking procedure.

3.1. Model Development

Based on the requirement and adapted conceptual frameworks from the previous chapter, this research will start the model development process. A draft of the model structure and workings is first needed to ensure the model does not violate the framework and requirements. Besides these requirements, this research aims to utilize as many observable parameters and variables as possible to increase interpretability and connection to the real world. The development of the model is conducted in the programming language Python, with only external libraries that aid in numerical and data processing.

3.1.1. Model Structure and Logic

Based on the adapted four-layer process and the defined modeling requirements, an initial of how these layers of the model will work in sequence to reproduce the movement of individual bicyclists is first conceptualized, with their purpose, relations, and the input and output of each of the layers in the model, and how the layers interact with each other are first drafted which is shown in table 3.1 and graphed in figure 3.1.

After the draft of the purpose, intermediate outputs, and information flow for the model. This research further conceptualizes how the model's layer would produce the intermediate outputs and how the simulation will be conducted. The simulation is expected to be conducted in a step-wise manner, with the simulated agents following the same logic process at each time tick, where the updated speed and position of the modeled cyclists will be the initial condition of the next time step/tick, and the full process on how the model will replicate the movement of the cyclist is illustrated in the figure 3.2, and will be describe in the following:

1. The perception layer creates a search domain based on the visual interaction range, and the expanded psychological boundary of the peripheral cyclists and obstacles, creating a field of safe travel.

Table 3.1: Purpose and the output of the model layers

Model layer / Modules	Purpose	Output
Perception	Acquire a list of cyclists and process obstacle buffer within the consideration region	List of other agents
Goal orientation	Get potential leader and goal	Goal(x, y) (For path-planning), Leader info (For movement)
Path-planning	Constructing a path from the current position to the goal	Path
Movement	Adjust speed and travel along the path	New speed and new position for the timestep

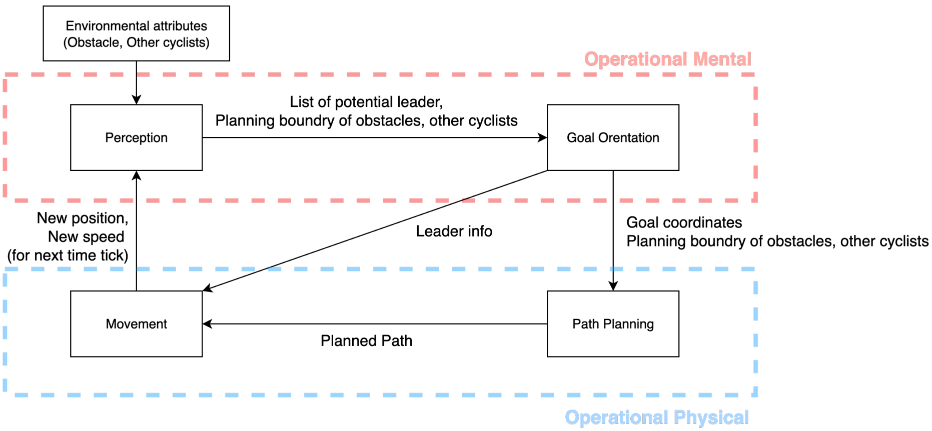

Figure 3.1: Flow of intermediate outputs for the developed model

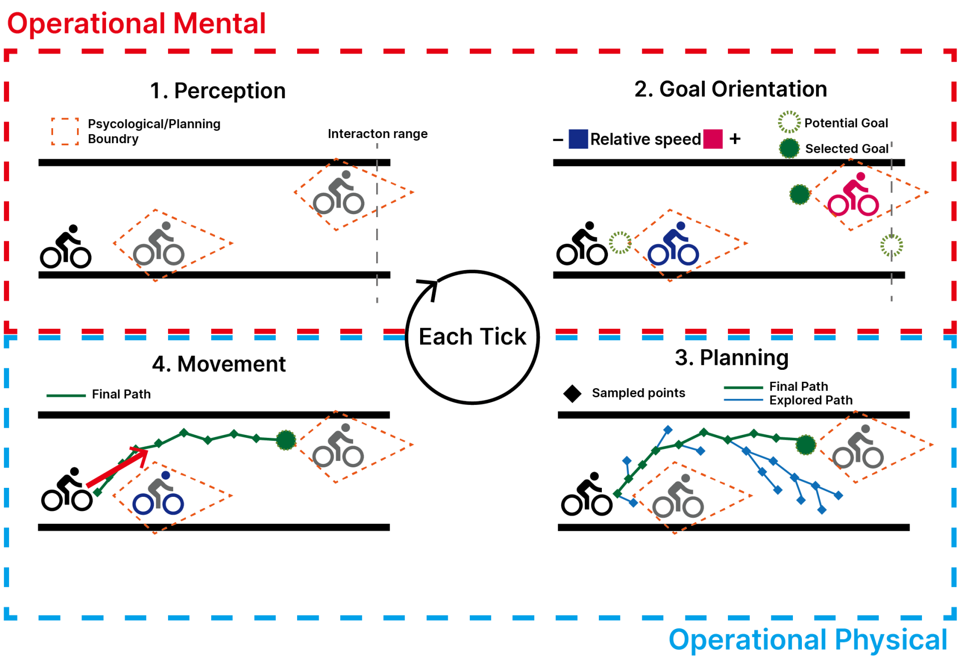

Figure 3.2: Logic of the developed model

2. The goal orientation layer selects its goal based on the available lateral space and the relative speed of the peripheral cyclists. (In the figure, the ego agent deemed the cyclist in front of it too slow and decided to overtake and follow another faster cyclist.)
3. The path planning layer starts to sample the surroundings and expands the tree of paths based on the set goal with respect to the turning capability of the cyclist.
4. the movement layer executes the movement along the generated path and travels the distance based on the speed and calculated acceleration based on the bicycle following behavior. The update to the new position completes a time step of the simulation, and the process starts again for the next time tick.

Additional details that facilitate the completion of this modeling logic will be provided in the following sections.

3.1.2. Perception layer

The perception layer is the first part of the model. This part of the model is responsible for processing environmental attributes such as the presence of other agents and obstacles into a bounded search space for the path planning algorithm. This action is similar to human perception, where, during a limited range of interaction with other cyclists, and range of visual focus for the environment is present.

Within the interaction range, the physical and psychological presence of other cyclists is processed, following the shape of the diamond proposed in literature (Falkenberg et al., 2003), which fits the dimensions of the real personal space found in the observation (Meijer et al., 2019). The diamond-shaped boundary is added with an extra set of length and width, which is the width of the ego agent transcribed onto the other cyclist. This ensures the true edge of the cyclist would not collide when the center point of the cyclist is at the edge of the boundary. A subset list of preceding cyclists is also collected during this step for later use in the goal orientation step, as the cyclists in this dimension fit the interaction region found in the literature (Hoogendoorn and Daamen, 2016). Parameters that are present in this layer of the model, along with some of their description, are presented in the following table 3.2.

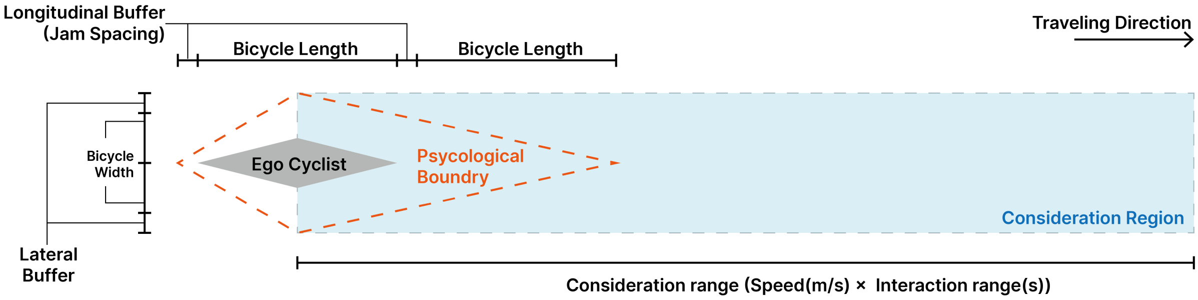

Figure 3.3: Implementation and dimensions of the perception process

After the definition of the search space and the presence of other simulated agents with the perception component, a discrete and feasible goal is needed for the planning algorithms to plan towards.

3.1.3. Goal orientation layer

The Goal orientation layer is responsible for setting a discrete goal in the search space, which the path planning algorithm will be initiated with. A simple logic and threshold-based approach is developed according to the literature finding of Mohammed et al. (2019). An illustration and

Table 3.2: Parameter values of the perception layer

Parameters	Unit	Description
Cyclist Length	m	-
Cyclist Width	m	-
Longitudinal Buffer	m	Same as jam spacing (Standstill distance)
Lateral Buffer	m	-
Interaction Range	Seconds	Time headway, for both environment and other cyclist

flow chart for determining the planning goal and agent behavior is shown in figure 3.5 and 3.4, where a list of cyclist agents captured in the consideration region of the perception layer is considered as leader candidates, the candidates' respective position and speeds is then checked to see if there exists any possibility of overtaking based on relative speed difference and space needed beyond the lateral clearances, and a goal is placed with respect to the decision. This check is done sequentially from the closest potential leader until there is no potential leader inside the consideration range. This execution sequence ensures that no actions will violate these constraints. If there exist no potential or viable leaders, the agents would enter an unconstrained state, where they would have a goal based on their desired lateral position. The use of a desired lateral position gives the simulated agent a long-term goal to follow, which could also be used to imitate the skewed lateral position distribution of the natural observation. The parameters that are present for this goal orientation process and their descriptions are shown in the following table 3.3.

Table 3.3: Parameter values of the goal orientation layer

Parameters	Unit	Description
Speed difference threshold	m/s	Speed difference required to initiate overtake
Lateral clearance threshold	m	Lateral clearance required to initiate overtake
Desired lateral position	[y]	Long term desired lateral position of the cyclist

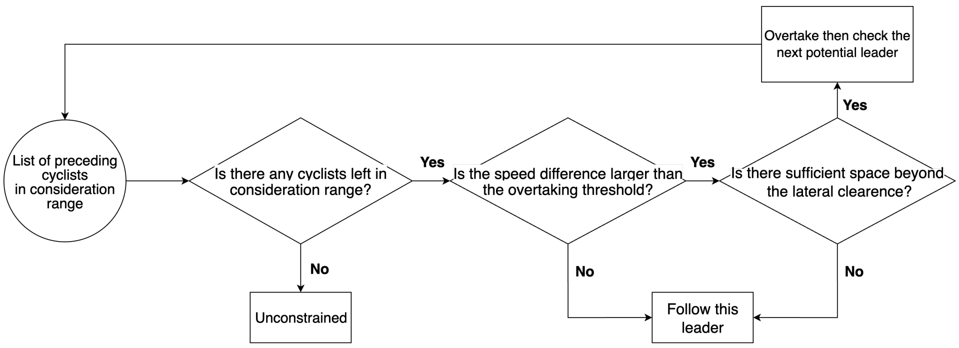

Figure 3.4: Flow chart of the goal orientation logic

3.1.4. Path planning layer

After defining the search space and goal, a path-planning algorithm can be initiated. For the purpose of this research, an algorithm with a solution and optimality guarantees is needed for

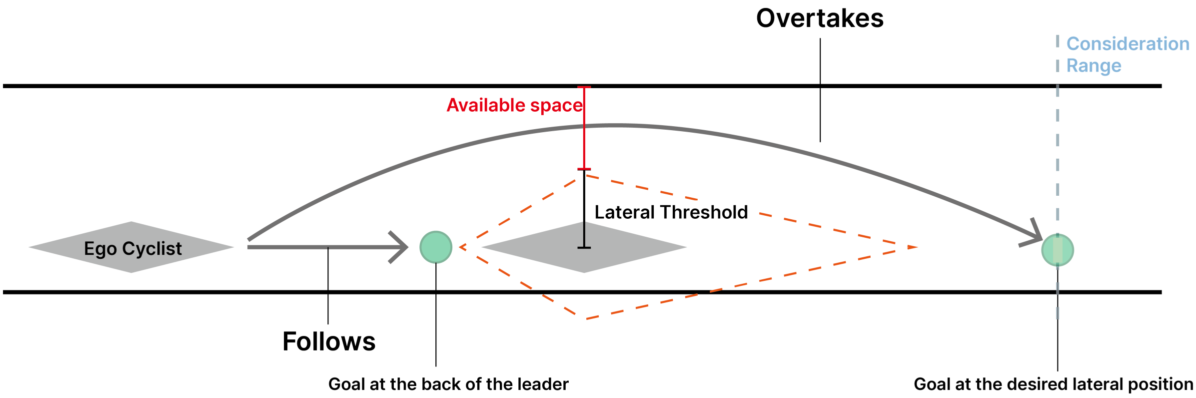

Figure 3.5: Illustration of the goal orientation process

the requirement of effort conservation. Additionally, the planning process should also contain the ability to comply with the turning constraint. To fulfill both requirements, a combination of techniques found in the algorithm RRT* (Karaman and Frazzoli, 2011), combined with the reachability constraint of the Reachability Guided RRT (RG-RRT, Shkolnik et al., 2009) that uses link sizes that represent the speed vector, combined with an angular constraint.

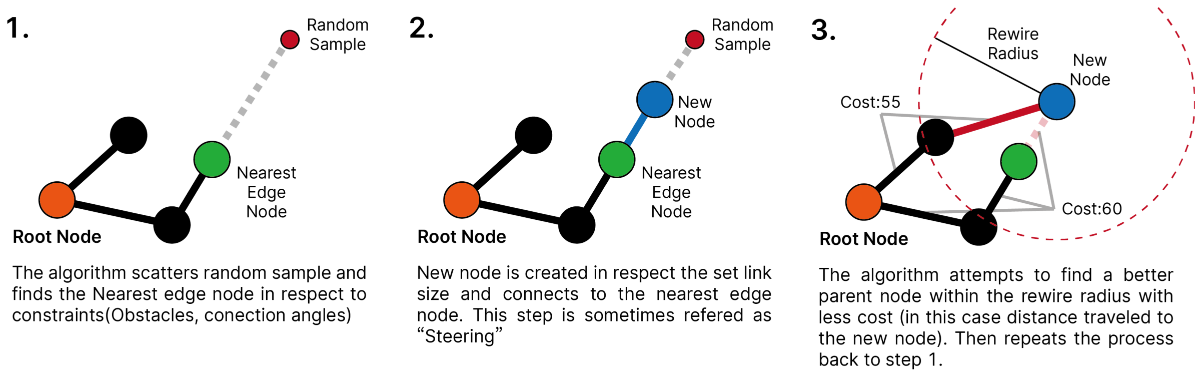

Figure 3.6: illustration of the RRT* algorithm

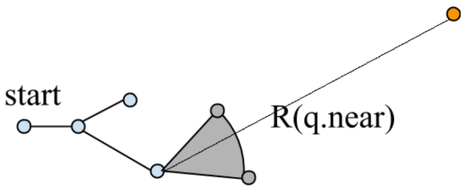

Figure 3.7: Constrained steering region (indicated in grey) of RG-RRT. From Elbanhawi and Simic (2014)

Showcased in figure 3.6, the algorithm first randomly places a new sample and finds the nearest node to the random sample. The algorithm then creates a new node based on the reachability constraint, which is bounded by the set path length and angle constraints (Illustrated in figure 3.7 as the grey region). After the new node is created, the algorithm then checks if the new node is within the radius and with respect to the reachability constraint of the path length in the existing tree. If the connection is valid, the algorithm then checks if there is a parent node of lower traversal cost compared to the current connection. If there is a better connection, the node will rewire to the new parent. This process is repeated when a new node has reached a certain radius around the goal. The respective parameters that will be present for the algorithm used for the implementation are shown in table 3.4.

Table 3.4: Parameter values of the path planning layer

Parameters	Unit	Description
Link size	m	Scales dynamically based on cyclists' speed and simulation resolution ensuring goal convergence and kinematic constraint
Rewire radius	Linksize	Larger radius creates more optimized path under the same iteration, at the expense of computational time
Angle constraint	Deg/s	Angle limit per node connection

3.1.5. Movement layer

The movement layer governs the final execution of the path. Since the path generated through path planning algorithms only encodes a static environment, there is a need for a separate layer to control the speed of the agent to avoid collisions in the longitudinal axis. Since a kinematically feasible path is already obtained during the planning process, a velocity-based or longitudinally continuous model is used for this task.

The car following model, Necessary Deceleration Model (NDM, Andresen et al., 2014), is used for this implementation. It operates under the assumption that bicyclists are effort minimizers, which fits the modeling requirements. The original formulation of the NDM was developed for use in single-file traffic. Thus, some adjustments and additions were made to the model for use in a continuous lateral space. The NDM formulation used in the model is shown in equation 3.2 through 3.6. The NDM model activates different acceleration (acc), and deceleration components(dec_1, dec_2), based on the spacing (s) and speed difference (Δv) of the leading cyclist. The final output of the deceleration is contained by the physical ability to slow down the bike (b_{max}). Respective parameters that are present are shown in the following table 3.5 along with their description.

$$d(v) = s_0 + l \tag{3.1}$$

$$acc = \begin{cases} \frac{v_0 - v}{\tau}, & \text{if } \; s > d(v) \\ 0, & \text{if } \; s \leq d(v) \end{cases} \tag{3.2}$$

$$b_{nec} = \begin{cases} \frac{(\Delta v)^2}{2(s-l-s_0)}, & \text{if } \; s - l - s_0 > 0 \\ b_{ease}, & \text{otherwise} \end{cases} \tag{3.3}$$

$$dec_1 = \min(b_{nec}, b_{max}) \tag{3.4}$$

$$dec_2 = \begin{cases} \frac{b_{max}}{(l-d(v))^2} \cdot (s - d\,(v))^2\,, & \text{if } s \leq d(v); \Delta v \leq \epsilon \\ 0, & \text{otherwise} \end{cases} \tag{3.5}$$

$$dec = \min(dec_1 + dec_2, b_{max}) \tag{3.6}$$

Compared to the original implementation, this implementation employs a fixed safety distance $d(v)$ and adds a new component b_{ease} when the lower fraction of b_{nec} becomes negative, which will not happen when the traffic formation is in a single-file environment. The added b_{ease} combined with a lower value of ϵ (also found in Brunner et al. (2024)) produces less sudden brakes when switching between leaders and close-quarter following, such as when a faster or

Table 3.5: Parameter values of the movement layer

Parameters	Unit	Description
Stand still distance (s_0)	m	Component of safety distance $d(v)$
Relaxation time (τ)	sec	Component of acceleration
Escape constant (ϵ)	m/s	Threshold value for fast leaving leader
Cycle length (l)	m	Component of safety distance$d(v)$
Max deceleration (b_{max})	m/s^2	Maximum deceleration limit
Easing deceleration (b_{ease})	m/s^2	Added during development, a smaller deceleration similar to coasting

slower vehicle decides to merge into the front or the back of another vehicle, which could lead to a sudden spike of a deceleration in the original implementation.

After acquiring the acceleration and deceleration with NDM, the final radius of possible movement is derived using a simple displacement function based on Newton's second law (3.8).

$$\text{Final Acceleration} \quad a = acc + (dec_1 - dec_2) \tag{3.7}$$

$$\Delta x = v \cdot \Delta t + \frac{1}{2} \cdot a \cdot \Delta t^2 \tag{3.8}$$

After deriving the movement radius(Δx), it can be used to solve the intersection of a given path, where the intersection will be the next position of the bicycle agent, illustrated in figure 3.8. This employment of a movement radius allows for the omnidirectional movement capability as well as some smoothing benefit. Since the planned path from the path planning layer is kinematically compliant, the output lateral movement will also be of reasonable velocity.

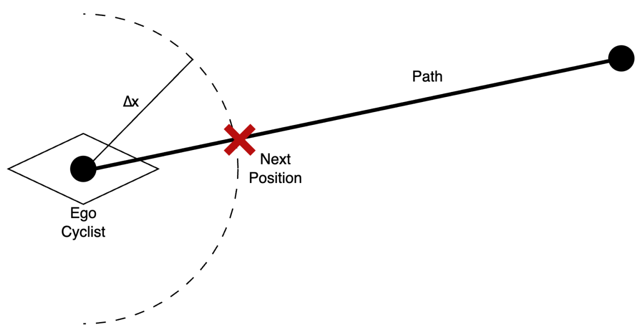

Figure 3.8: Illustration of movement radius

3.2. Verification approach

To conduct verification for the developed model, the governing inputs, which are the parameters or variables that have the greatest effect on the intermediate output of the model, are required. The intermediate output of the model is first described in the previous table 3.1of subsection 3.1.1, and the determined governing input for each layer of the developed model, along with their effects, is presented in the following table 3.6.

Table 3.6: Main governing inputs and their effect on the model

Model layer / Modules	Governing inputs	Effects
Perception	Speed (m/s)	Change of consideration range, Change in the potential leader list
Goal orientation	Speed threshold (m/s), Space threshold (m)	Change in overtaking decision, Change in placed goal
Path-planning	Start[x, y], Goal[x, y] Obstacle, Cyclist boundries	Change in planned path
Movement	Speed (Current, Desired), Leader info (Speed, position)	Change in acceleration, topspeed

The aim of the verification step is to examine these intermediate outputs across the four layers of the model, as these intermediate results serve as the parameters and main inputs for the layer's following steps. Upon initial investigation, these intermediate outputs are considered to be "Observable," meaning that they have a real physical meaning, and can be directly related to the physical world. Since these output values can be easily examined or graphed, this research deems that an observation-based approach to check if these intermediate outputs are consistent with the assumptions is sufficient.

Another goal of this verification is to provide information on how the model interacts with the intermediate output and the input change. Thus, the verification will be done in a synthetic scenario of a bicycle path that is 2 meters in width, with 2 other agents on scene, traveling at a constant speed of 2 and 3 m/s, showcased in figure 3.9. This would provide a consistent environment for the plotting and observation of the expected intermediate outputs, showcasing the inner workings of the developed model.

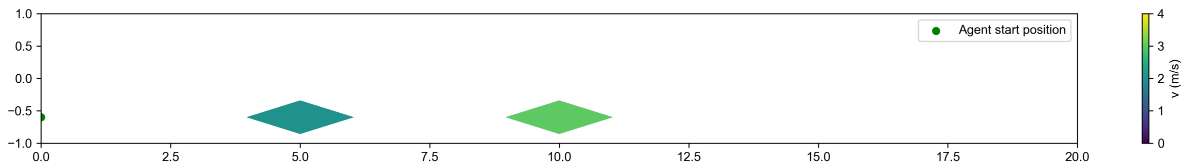

Figure 3.9: Synthetic environment of verification

The modeled agent would start at the position of $x = 0$, while the agents traveling at 2 m/s and 3 m/s will start at the position of $x = 5$ and $x = 10$, respectively. All agents will start at the lateral position of $y = -0.6$, which makes the remaining available lateral space 1.1 meters wide when the physical dimensions of the cyclists are accounted for. This is done to ensure no rounding errors that could impact the consistency of the results, which is expected to occur when the Lateral gap threshold is set to a value of 1.

Through the adjustment of the main inputs shown in table 3.6, the intermediate outputs of the model should behave in accordance with the change. For this verification, a set of different scenarios is designed to check if the intermediate outputs are consistent with the expectations. The set parameters for the agents are showcased in the following table 3.7, which will remain constant without specification, and their expected outputs and behavior are showcased in table

3.8.

Table 3.7: Agent parameter values for the verification

Parameters	Value	Unit	Description
Cyclist Length	1.95	m	Design vehicle of CROW (2016)
Cyclist Width	0.5	m	Design vehicle of CROW (2016)
Longitudinal Buffer	0.2	m	From Andresen et al. (2014)
Lateral Buffer	0.25	m	From Meijer et al. (2019)
Interaction Range	4	s	From Hoogendoorn and Daamen (2016)
Speed difference threshold	-	m/s	Main input of Goal orientation
Lateral gap threshold	-	m	Main input of Goal orientation
Rewire radius	2	Linksize	Set during development
Angle constraint	120	deg/s	From Alizadehsaravi and Moore (2022)
Stand still distance (s_0)	0.2	m	From Andresen et al. (2014)
Relaxation time (τ)	1.73	s	From Andresen et al. (2014)
Escape constant (ϵ)	0.5	m/s	From Brunner et al. (2024)
Cycle length (l)	1.95	m	Design vehicle of CROW (2016)
Max deceleration (b_{max})	5.5	m/s^2	From Andresen et al. (2014)
Easing deceleration (b_{ease})	0.3	m/s^2	Set during development

Table 3.8: Verification inputs and expected results

Model layer / Modules	Main input	Unit	Value	Expected output
Perception	Speed	m/s	2	List of 1 cyclist
			4	List of 2 cyclist
Goal Orientation (Speed 4 m/s)	Speed threshold Gap threshold	m/s m	0.6 1	Overtake all cyclists
			1.2 1	Overtake 1 cyclist
			0.6 1.5	Overtake no cyclists
Path-Planning	Goal	[x, y]	From goal orientation	Smooth path to goal, No boundary violation
Movement (OT threshold 1.2 m/s)	Current Speed, Desired Speed	m/s	5	No speed adjustment
			4	Decelerate and follows

For the perception layers, the consideration region is a multiplication of speeds and the set parameter of headway values. By adjusting the input speed values, the size of the consideration will change, which dictates the final output list of cyclists. A slower speed would result in a smaller consideration region, leading to a lower number of cyclists in the generated list, while a higher speed value would result in the opposite.

After examining the output of the perception layer, the adjustment of the different overtaking thresholds in the goal orientation step is investigated. A lower speed and lateral gap threshold would enable the agent to overtake more. The returned goal and leading cyclist from this step should change in response to these values. These returned goals will also be used for the verification of the path-planning layer, where the planned path will be examined to see if the algorithm could indeed find a path to the goal without violating any set constraints, such as the boundary and turning rates.

The last layer of the model to examine is the movement step. For this step of the model, the output speed should respond to the decisions made and the path planned in the previous steps. If an overtaking decision is about to occur, the agent should remain uninterrupted, reaching or maintaining its desired speed. If an overtake is deemed not viable, the agent should adjust its speed and follow the front-running cyclist.

The intermediate outputs of the model will be recorded and graphed for visual observations. If the model outputs are consistent with the previously mentioned expected changes, the verification step can be considered a success. Meaning that all parts of the developed model behave in accordance with the modeling concepts, and it can be further tested in the face validation phase.

3.3. Face validation approach

In the face validation step, attempts to utilize the developed model to recreate individual cyclists in real-world scenarios will be made, and the accuracy of the recreation will be assessed. This is done by using real-world datasets (in the case of this research, the large-scale cyclist experiments conducted in Rotterdam, the Netherlands, by Gavriilidou et al., 2019b). The data from the real-world datasets will be extracted, with some serving as the inputs and parameters for the developed model, and others serving as the ground truth. The true observations from the datasets are then compared to the simulated/estimated outputs from the developed models.

3.3.1. Face validation data

The real-world datasets used for this face validation procedure are the Large-scale cycling experiment conducted by Gavriilidou et al. (2019b), which provides a variety of cyclist trajectories, composed of different traffic compositions and different cycling situations, including scenarios that contain only regular, manually propelled bikes, which is of interest in this study. The experiment was conducted in an indoor venue in the city of Rotterdam, the Netherlands. During the experiment, the position of the cyclist is recorded using overhead cameras at a time resolution of 25 frames per second. The trajectories of the cyclists are extracted by using a software developed by Duives (2016), which automates the process described in Hoogendoorn et al. (2003), that tracks the red cap worn by the experiment participants (Shown in figure 3.10).

With the extracted cyclist positions, combined with the timestamp of the video feed, the cyclist's trajectory points are gathered. With these trajectory points and the timestamps from the camera footage, the position of the cyclist could be interpolated to fit the time resolution scales of the simulations. Showcased in the following figure 3.11

By using this approach of interpolating positions, this research is able to generate control agents that replicate the cyclists of the real world inside the simulation, which move in a consistent manner in accordance with the simulation's time scale. This approach also negates

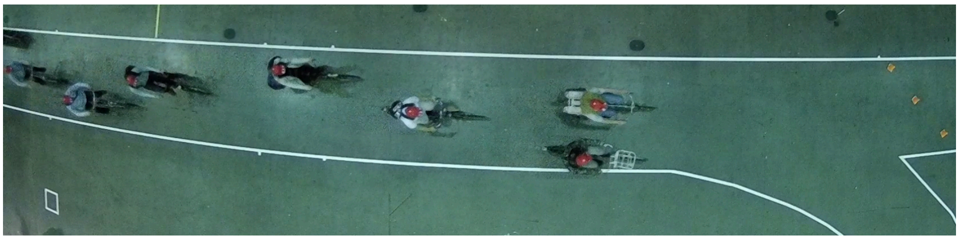

Figure 3.10: Experimental snapshot of Gavriilidou et al. (2019b), showcasing the red cap for tracking participant trajectories

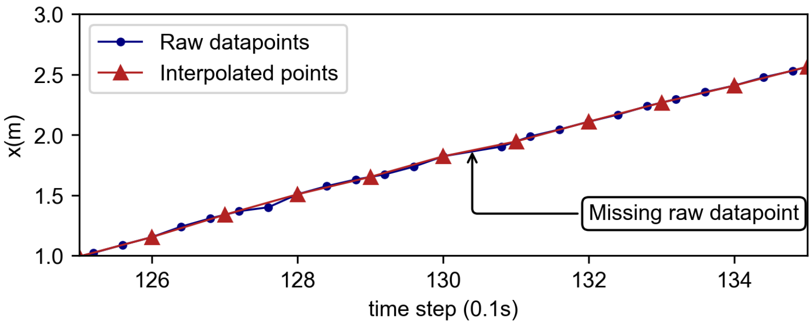

Figure 3.11: Raw data points and the interpolated positions of the observation data

the sometimes inconsistent data time spacings shown in the figure, which is caused by the overlap or measurement error, providing smoothing benefits. The speed of the cyclist is also derived using the interpolated position and time scales, which results in a more consistent estimate compared to this research's attempts to derive speed directly from the raw trajectory points and timestamps, which result in near or infinite speed estimation values, because of the measurement errors and time stamp fluctuations.

3.3.2. Scenarios and simulation setup

For this face validation process, a total of two simulation scenarios are chosen with the aim of examining the different layers of the model. The first scenario is the Chicanes scenario, focusing on the steering and pedaling behavior, which is the result of the path and movement part of the model. The second scenario is the overtaking scenario, where the decision-making performance of the model and how it affects path and movement, and finally the steering and pedaling output of the model is examined.

Simulation setup

To assess the performance of the developed model in a microscopic manner. This research will simulate the modeled agent individually, along with the cyclist agents that are recreated from the real-world observations. Shown in figure 3.12, the cyclists outlined in grey are the control agents. All control agents present on the scene will be recreated using the observation data, and they will travel in the same position and speed as the observations. While the one agent outlined in the red dotted line will be simulated based on their respective starting positions and initial inputs, it will be simulated by the developed model, shown in table 3.9.

With the simulation environment and input defined, the simulation is conducted in a time resolution of 10 time ticks per second. The positions and the decisions made by the model are updated in this time resolution, which roughly equates to the lowest human response time (Baars and Gage, 2013), meaning that the resolution of the actions and reactions of the sim-

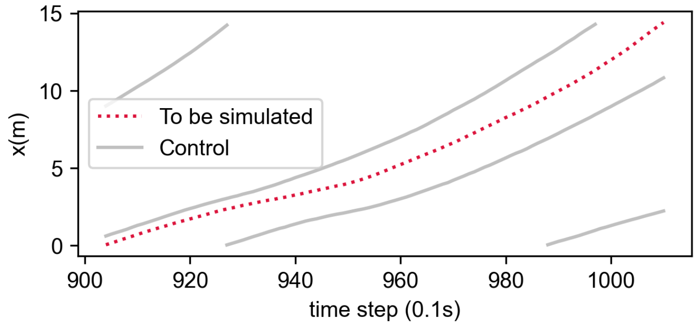

Figure 3.12: Simulation environment for a simulated agent

Table 3.9: Starting input of the simulated agents

Agent Inputs	Unit	Descriptions
Initial Position	[x, y]	Initial position of the agent
Initial Speed	m/s	Initial speed of the agent
Desired Speed	m/s	Mean speed of the agent
Desired Lateral position	[y]	Last recorded lateral position the agent

ulation agent should roughly equate to a human rider. This time tick resolution has also been tested beforehand and found to be enough to avoid any collision that may occur during the state change between the simulation ticks.

Chicanes

The Chicanes scenario (Sometimes referred to as a Meander, shown in figure 3.13) is a special type of bottleneck that requires the cyclist to navigate two sets of narrow gaps that are placed edge-to-edge to the riding path. The chicanes in the real-world experiment consist of two 0.75m gaps that are placed 2m apart from each other. For this scenario, a 15m section that consists of the approach and the exit before and after the chicane is selected, which is when the cyclists start to be found moving towards the chicane (shown in figure 3.14).

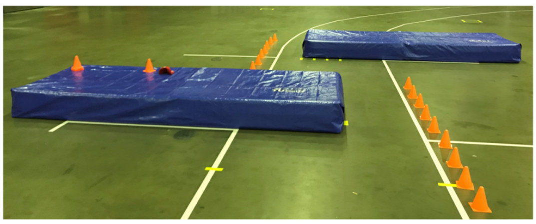

Figure 3.13: Photo of the chicane set up of Gavriilidou et al. (2019b)

The navigation-heavy and close to single-file nature of the chicane bottleneck leads to more varied behavior of speed and steering adjustments that are related to the path-planning and movement layer of the model, which makes this scenario a suitable choice for the face validation of the developed model's physical layer.

This scenario consists of a total of 92 cyclists' observations, which will all be simulated. The parameters used in the simulation of this scenario are showcased in the following table 3.10.

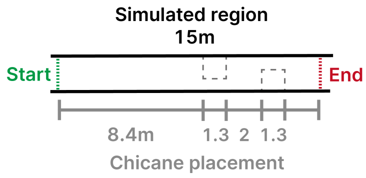

Figure 3.14: Dimension of the simulated environment

The used parameters are a mix of data from the observations and the behavioral findings mentioned during the literature review.

Table 3.10: Agent parameter values for the simulation of chicanes scenario

Parameters	Value	Unit	Description
Cyclist Length	1.8	m	Mean value from Gavriilidou et al. (2019b)
Cyclist Width	0.6	m	Mean value from Gavriilidou et al. (2019b)
Longitudinal Buffer	0.2	m	From Andresen et al. (2014)
Lateral Buffer	0.25	m	From Meijer et al. (2019)
Interaction Range	4	s	From Hoogendoorn and Daamen (2016)
Speed difference threshold	0.5	m/s	From Li et al. (2013)
Lateral gap threshold	1	m	From Mohammed et al. (2019)
Rewire radius	2	Linksize	Set during development
Angle constraint	120	Deg/s	From Alizadehsaravi and Moore (2022)
Stand still distance (s_0)	0.2	m	From Andresen et al. (2014)
Relaxation time (τ)	1.73	s	From Andresen et al. (2014)
Escape constant (ϵ)	0.5	m/s	From Brunner et al. (2024)
Cycle length (l)	1.8	m	Mean value from Gavriilidou et al. (2019b)
Max deceleration (b_{max})	5.5	m/s^2	From Andresen et al. (2014)
Easing deceleration (b_{ease})	0.3	m/s^2	Set during development

One thing to take note of is the value of the speed difference threshold for overtaking. There is no overtaking observed during the initial examination of the data from this scenario. Thus, a value from the literature is selected, considering the average speed of the scenario, a relatively high value that leads to a lower amount of lateral interactions.

Overtaking

The overtaking scenario is a scenario where the participants are given the opportunity to decide if they want to overtake during the 30m straight running section of the experiment track. This 7-minute run consists of 226 observed trajectories, out of which a total of 23 overtakers and 27 overtakings are observed. An example of 1 overtaker with 1 recorded overtake is shown in figure 4.6, where the overtake should satisfy the two conditions: an observed overtake where the cyclist exchanges position with another cyclist on the longitudinal axis, and at least a bicycle width of lateral movement on the lateral axis.

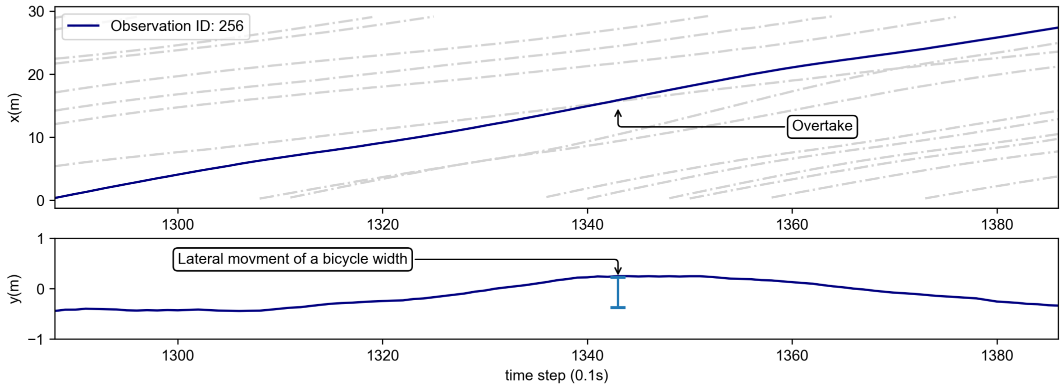

Figure 3.15: Example of 1 labeled overtaking

In this scenario, an attempt will be made to recreate these overtakes, which will require the tuning of parameter values for the goal orientation layer. A simple estimation is done by comparing the average speed of the overtakers and the one being overtaken. The final estimate for this value is a difference of 0.31 m/s, which is lower than the lowest one found in literature (0.5 m/s), but still plausible considering the context of the scenario and the lower and more homogeneous conditions of the indoor experiments. The final parameters used in the simulation are shown in the following table 3.11, where only the modified parameters are compared to the previous scenario (Table 3.10). The used parameter mostly equate to the ones used in the chicane scenario, with the exception of the overtaking thresholds.

Table 3.11: Modified parameter values for the overtaking scenario when compared to table 3.10

Parameters	Value	Unit	Description
⋮	⋮	⋮	⋮
Speed difference threshold	0.31	m/s	Estimated from observation
⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮

All of the 23 labeled overtakers will be simulated to examine if the psychological part of the developed model could replicate real-world observations.

3.4. Performance and Goodness of fit measures

After the simulation, the capability of the developed model to replicate real-world observations will need to be assessed.

For the chicane scenario, which focuses on the physical aspect of pedaling and steering of bicycle riding, the performance of which is best done by examining the trajectory of the modeled agent to the observations, in both time and space. The performance of the output trajectories will be benchmarked using the average absolute error of displacement for the 2 simulated spatial axes, the calculation for such measures is shown in the following equation 3.9 and

3.10.

$$\text{Displacement Error } x \text{ axis} = \frac{1}{T}\sum_{t=1}^{T}|x_{sim,t} - x_{obs,t}| \tag{3.9}$$

$$\text{Displacement Error } y \text{ axis} = \frac{1}{T}\sum_{t=1}^{T}|y_{sim,t} - y_{obs,t}| \tag{3.10}$$

Where across the simulated time frame (T) the absolute error for the observation at each time tick ($x_{sim,t}$, $y_{sim,t}$) will be compared to the observed position ($x_{obs,t}$, $y_{obs,t}$) of the actual cyclist at the given tick. This measure would provide an idea of how the generated trajectory deviates from the observation.

Another benchmark used is that the outputs of the model will first be examined, as it is one of the major components of the time trajectories. If a significant error exists in the speed outputs, it can also be said that a large amount of error will also exist in the time trajectories. The error across all the observations will be assessed using the goodness-of-fit measure of Root Mean Squared Percentage Error (RMSPE), as it is a metric that is more sensitive to larger errors across the observations, and such a measure is also commonly used in the literature, which could be of reference to assess the model's accuracy. The calculation of the RMSPE is shown in the following equation 3.11.

$$\text{RMSPE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{v_{sim,t} - v_{obs,t}}{v_{obs,t}}\right)^2} \times 100\% \tag{3.11}$$

Where the squared error of the speed measurement of the simulated agent at a time tick ($v_{sim,t}$) will be compared to the observed speed ($v_{obs,t}$) at the given time, is averaged, and then square-rooted across the simulation time frame. These two measures, supplemented with visual observation of the turning position and rate of lateral movement of the simulated trajectory, would give an idea of how accurate the model is at replicating the cyclists' pedaling and steering behavior.

The assessment of the overtaking scenario will also utilize the measures used in the previous scenarios, with the addition of the inspection for the modeled overtaking outputs. This can be done with a simple assessment using percentage errors.

$$\frac{\text{Simulated OT}}{\text{Observed OT}} \times 100\% \tag{3.12}$$

This error value can be benchmarked against the previous attempt in modeling overtaking behaviors such as Zhao et al. (2013) and Ni et al. (2023). Noted that because of the lower amount of overtaking observations (27) as a base, the fluctuation in the normalized output would be large, thus it could only provide a relative idea of the model's performance when benchmarked against the others. After comparing the prediction accuracy, this research will also supplement with a visual observation of the trajectories, combined with the previously mentioned performance measures, investigating whether the modeled overtakes are similar in position, and in the amount of lateral movements. Such an investigation would give an idea whether the model could really replicate the real-world overtaking both for the mental and physical layer of behaviors.

4
Result

4.1. Verification results

The verification setup for each of the model layers and their respective results showcased in the following table 4.1

Table 4.1: Verification inputs and expected results

Model layer / Modules	Main input	Value	Expected output	Result
Perception	Speed	2 m/s	List of 1 cyclist	Passed
		4 m/s	List of 2 cyclist	Passed
Goal Orientation	Speed threshold Gap threshold	0.6 m/s 1 m	Overtake all cyclists	Passed
		1.2 m/s 1 m	Overtake 1 cyclist	Passed
		0.6 m/s 1.5 m	Overtake no cyclists	Passed
Path-Planning	Goal (From goal orientation)	[x, y]	Smooth path to goal	Passed
Movement (OT threshold 1.2 m/s)	Current Speed, Desired Speed	5 m/s	No speed adjustment	Passed
		4 m/s	Decelerate and follows	Passed

A basic summary of the result will be provided in this section, while the full verification result, including the illustrations, is showcased in Appendix A. Based on the input value change, the perception layer has returned a different consideration range, which resulted in the change of the returned potential leader lists. The goal orientation layer has also made respective decisions that comply with the modeling logic. Based on the goal, the path-planning layer has also returned a smooth and achievable path, and the movement layer is able to travel on the path and make respective pedaling adjustments related to the movement of the selected leader.

With these results, it can be determined that all model layers are showcasing well-expected behaviors within all the set scenarios. Meaning that the model is now ready for use in the next step of face validation with real-world datasets.

4.2. Face validation results

In this section, the previously stated two simulation scenarios are constructed using the processed real-world observation data as references. The first chicane scenario aims to focus on the physical properties of the model, which is the replication of the steering and pedaling behavior of the cyclists. As stated in the previous chapters, the simulation of the cyclist is done on an individual basis, where in the environment, beside the simulated agents, all other agents remain in accordance with their observed path and speed. The result of the simulation will be shown in the following subsections.

4.2.1. Scenario Chicane

In the chicane scenario, when comparing the 92 simulated agents against their respective observations, the recorded absolute displacement error for the generated trajectory is 0.84 m and 0.23 m for the x and y axes. The resulting Root Mean Squared Percentage Error for the speed output is 17.9%.

For further interpretation of the result, this research also plotted the time trajectory output across the 2 spatial axes for a single simulated agent. The simulated agent is expected to output a plausible result for both the x and y axes across the simulated time frame. Besides the trajectory output across time, the output should also translate well onto the trajectory across the simulated space. The time trajectory output is shown in the following figure 4.1, and the space trajectory output is showcased in the following figure 4.2. To provide further evidence for the model's output, the space trajectory of 8 other randomly sampled agents is also plotted, which is shown in figure 4.3.

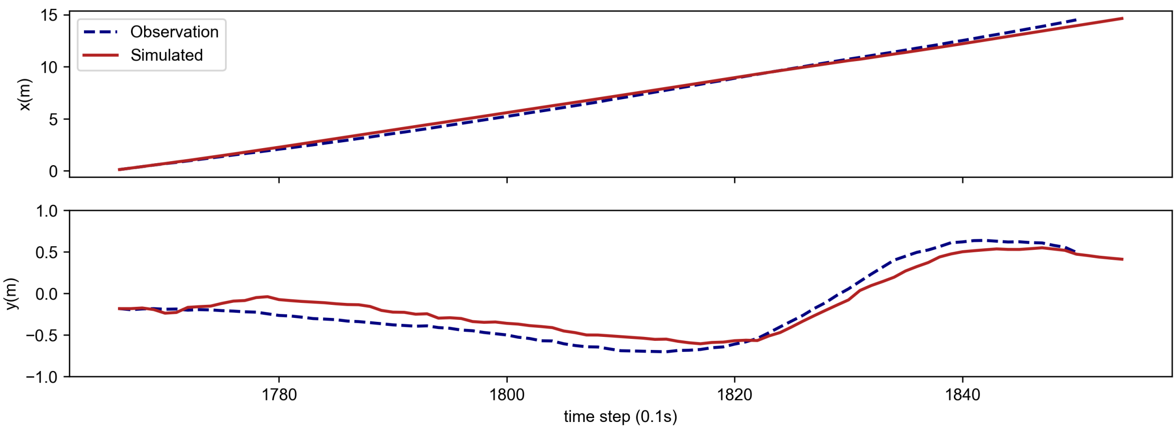

Figure 4.1: Time trajectory of the x and y axes for a simulated agent in the chicane scenario

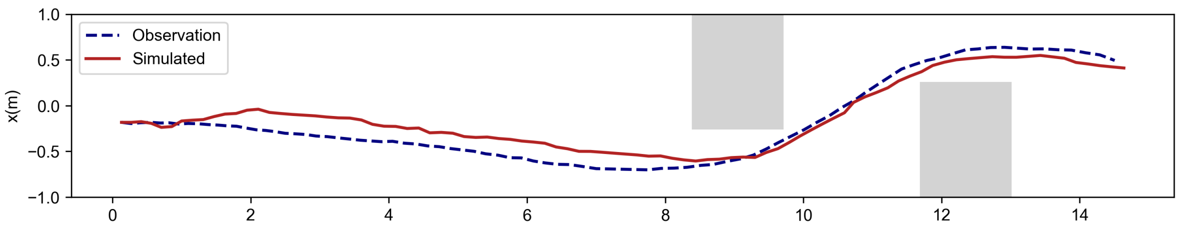

Figure 4.2: Space trajectory of the agent in figure 4.1

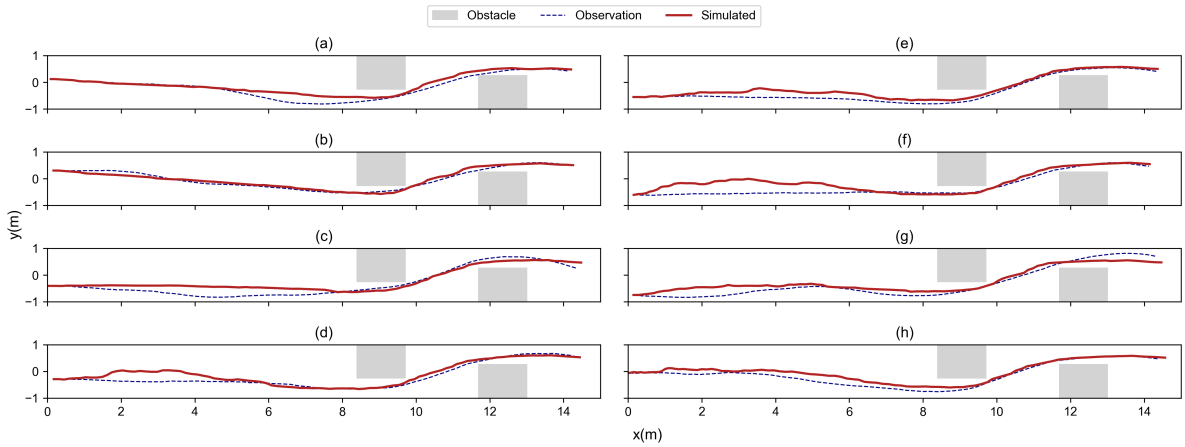

Figure 4.3: Space trajectory output of 8 other agents

For the result of the displacement output, the model is able to generate relatively accurate estimate of the position of the individual cyclists across the simulation time frame. The resulting absolute longitudinal and lateral displacement output is less than half of the set bicycle length and width, meaning that the estimated position of the cyclist is well within the plausible personal zone of the cyclist in the observation data.

The result for the simulated longitudinal and lateral displacement can also be confirmed by the RMSPE value of the speed outputs, which is within the viable range of 5.2 to 22.4% for a longitudinal continuous model found in literature (Zhu et al., 2018). Since speed is one of the major contributors to the movement across time, such a result could indicate that there are no major deviations in the time trajectory estimate, which is also evident in figure 4.1 and 4.2, where the slight desired speed change before and after the chicane, which the model currently does not incorporate, does not lead to a huge deviation between the temporal and spatial trajectories, showcasing similar turning rates, and positions across time and space.

The additional 8 spatial trajectories of figure 4.3 also further solidify the result, where the model's output trajectories can be said to be capturing most of the physical traits, such as the amount of lateral movement, turning positions, and turning trajectories. However, there are still some minor exceptions where the model deviates more from the observation, such as the observation found in subplot (a) and (g), where the observation employs a different strategy, which the cyclists align with the chicane earlier, and ride closer to the edge of the chicane obstacle, which lead to larger deviations before and on the exit of the obstacles, such difference in behaviors could be due to the heterogeneity in the mental perception of obstacles. With the performance of these observations, it could be said that the model could generate a plausible replication of the physical layer behavior of pedaling and steering, and with further tuning and perhaps the incorporation of more heterogeneity, the model could yield even better results.

4.2.2. Scenario Overtaking

After examining the physical capability of the developed model, the model's performance in capturing the mental layer of the process is investigated. A total of 23 labeled overtakers is simulated. The simulation of these overtakers should result in a total of 27 overtakes. A successful overtake is marked when the simulated agent is able to overtake the same cyclist that the observation cyclist has overtaken. The model has been able to recreate 19 out of the 27 overtakes, which roughly equates to a prediction accuracy of 70.3%. For the performance measure of the physical layer, the model has reported an absolute displacement error of 1.54 m and 0.38 m for the x and y axes, and an RMSPE of 24% of speed across the simulation time frame.

Both a successful and failed attempt of overtaking is showcased in the following figure 4.4 and 4.5, for the interpretation of the result. During the examination of the results, there also exist instances where the model has created an overtaking maneuver that is not present in the observation, which is also plotted in figure 4.6,

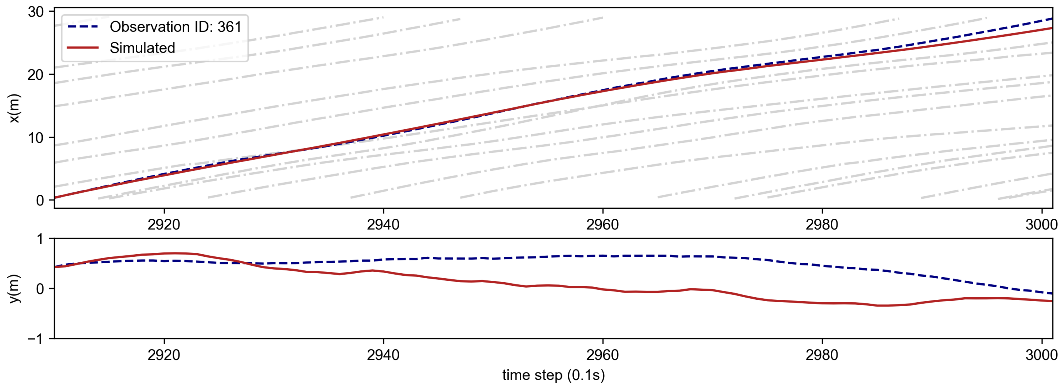

Figure 4.4: Example of 1 successfully modeled overtake

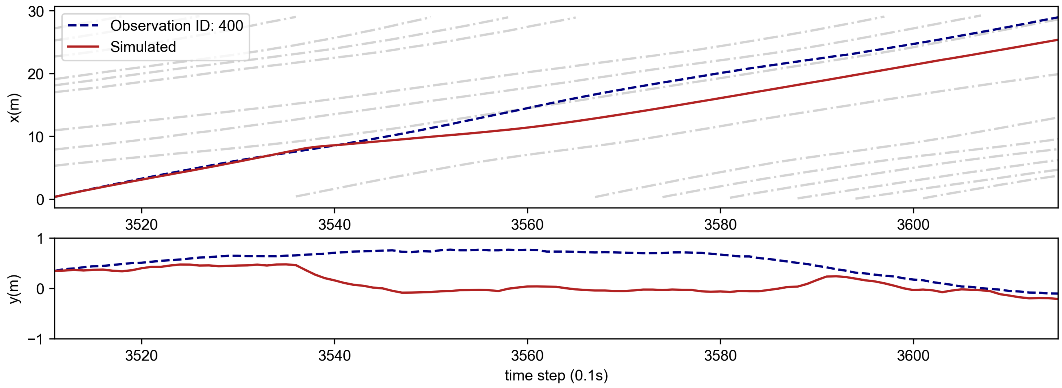

Figure 4.5: Example of a failed overtake modeling attempt

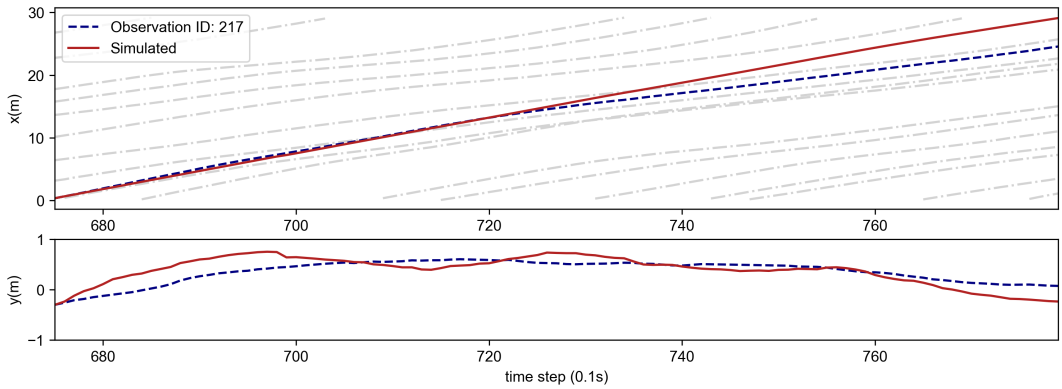

Figure 4.6: Model creating nonexistent overtaking maneuver

The model has reported a lower percentage in the prediction of overtakes compared to the other attempts found in the literature such as recorded 89.8% of the Zhao et al. (2013) and the 91.7% of Ni et al. (2023), though could not be directly compared because of the different environments and the the lower base number of observation of this research, the prediction accuracy of this research's model can still be deemed to be relatively low.

Besides the lower recorded accuracy, there also exist big inconsistencies in the successfully modeled overtake, such as the difference in lateral trajectories that can be seen in figure 4.4, where the model decided to merge in earlier than the observations. There are also inconsistencies found in the longitudinal axis of the simulation, leading to the extra overtaking maneuver in figure 4.6, where the simulated agent overtakes an additional cyclist, which is not present in the observation. These inconsistencies are further solidified by the higher displacement and speed error values. Due to both the lower accuracy and the inconsistent trajectory outputs, it is not possible to say that the developed model recreates mental behaviors that are plausible compared to the real-world observations.

Since the model utilizes 4 consecutive layers, and the performance of the physical layer has been examined in the previous section, the investigation of the cause of these inconsistencies starts from the first perception layer, which is responsible for the sensing and handling of boundaries for other cyclists. Based on the output trajectories, the perception layer does showcase results that are comparable to the reservation, such as the initial lateral movement of figure 4.4, and the amount of lateral movement that is present in the figure 4.5. Thus, this research attributes that the errors in the prediction may come from the goal orientation layer, where a wrongly placed goal may cause the early merging, and an incorrect leader selection could lead to the extra or no overtaking that is presented in the figure.

4.3. Discussion

Upon the inspection of these results, the developed model has generated relatively good results in the scenario of chicanes, which focuses on the physical layer behavior of steering and chicanes. With the use of the path-planning algorithms as the steering component, the simulated agent is able to generate a similar range and change of lateral motion when compared to most of the observations, supported by the low lateral displacement error values. The implemented NDM model, which is responsible for the pedaling behavior of the physical layer, is also able to generate a good speed estimation based on the starting conditions of the individual, meaning that the generated time trajectory estimation should also be of good quality. However, there are also some situations in which the model deviates more from the observation, where the trajectory (a) and (g) of 4.3. The model failed to replicate the larger counter steer or steering during the first turn of the chicane and the closer to the boundary of the subsequent turn, which violates the buffer constraint of the model. This research attributes such a difference to the heterogeneity of turning strategies, balancing needs, as well as the difference in acceptable buffer space when individuals encounter such obstacles. With the addition of such heterogeneity, the model is expected to yield better results in the physical layer of the behaviors.

The validation of the mental process of the model, however, exhibits different outcomes compared to the previous scenario. The model not only exhibits lower accuracy in the prediction of overtaking when compared to previous attempts found in the literature, but is also inconsistent in the predictions, sometimes generating non-existent overtakes when compared to the observation. The failure to predict overtaking also propagates down to the physical layer, as the modeling processes are in sequence to each other, leading also to the large deviation of displacement errors across both axes. Based on the trajectory outputs, this research attributes such an error to the goal orientation layer, which handles goal placement and leader selection in conjunction. Since the observed trajectories and decisions contain errors potentially in both of these selections, which causes deviation in both the overtaking decision and trajectory outputs, this research deems that a more sophisticated or decoupled approach should be implemented to improve ht result, and this research does not expect further tuning of the parameters used in the goal orientation layer could yield significant results. Therefore, the face validity of the model remains at a physical level.

5 Conclusion

This research was started with the novel idea that a path planner often found in the field of robotics and intelligent vehicles, which could be used to replicate human movements. After the initial background search, the lack of models using such techniques is indeed true. Then, a literature search was conducted on the existing modeling framework, and also on how existing modeling techniques fit with respect to the different layers of the existing modeling framework. After the literature review, the possibility of using path-planning algorithms as a steering component in the physical layer is found. Following these findings, this research attempted to make framework adjustments that could model the commonly found overtaking behavior of cyclists with the incorporation of path-planning algorithms. This research later developed a model that fits the modified framework and examines the performance of the model through the attempt to recreate real-world observations. The main finding of the research will be presented in the following section of this chapter.

5.1. Conclusion

The main findings for this research are closely linked to the previously defined research questions. Through answering these questions, the main findings of this research are summarized and concluded.

First, on the topic of the first research question: **How can the process of bicycle riding and overtaking be interpreted using existing frameworks?** This research has conducted reviews on the observed characteristics of bicycle riding and overtaking behavior using the interpretations of a 2-layer operational framework. The framework consists of the physical layer behavior of pedaling and steering, which have been investigated in multiple observation studies. The physical layer is also governed by the mental layer of decisions, which, in the case of overtaking, is found to be controlled by a lateral and speed threshold. These decision variables or environmental attributes are, in turn, governed by the perpetual process of the cyclists, which can be explained using the field of safe travel concept.

For the second research question of: **Based on the explanations/frameworks, where could path-planning algorithms be used?** This research examines the previous attempt at modeling such behavior using the interpretation of the 2-layer operational framework of the previous questions, and has found that models that incorporate steering kinematics have long been proposed, but are still considered to be of rarity. Path-planning algorithms could potentially be used as a dedicated way to model steering behavior in combination with the longitudinally continuous model that focuses on the pedaling part of the riding behavior.

With these findings, this research extends the answer to the third research question: **What framework modifications, components, and parameters are needed to model the microscopic behavior of cyclists with the incorporation of path-planning algorithms?** Continues on with the literature review process, how the algorithm is adapted to facilitate its use on an unbounded problem, the incorporation of the turning dynamics of a vehicle, and the need for placement of the dynamic goal is known. In combination with behavioral aspects found in the previous questions, this research makes an adaptation to the existing two-layered framework. The adapted framework consists of 4 sub-layers. The first perception layer creates a bounded search using the field of safe travel concept in combination with the known bicycle gaze and interaction range. The second goal orientation layer places a goal based on the known overtaking mechanism of the cyclists. Then, the physical layer, which consists of the planning layer and movement layer, initiates the path planning process, creating a path in accordance with the kinematic constraint and optimality criterion. Then the final movement is executed with the incorporation of a well-known bike following dynamic. The model then gets more concrete throughout the development, combining with the verification process, the full inner workings of the model are shown.

After the development and verification, a face validation is conducted, which will answer the fourth question of: **What are the observed strengths and weaknesses of the developed model?** The face validation uses parameters from both the literature and observations from the available dataset. The process consists of two scenarios, one that focuses more on the physical layer behavior of steering and pedaling, and one that includes examining the mental layer behavior of the model. The result of the face validation shows that the model is able to generate plausible steering and pedaling behavior in the physical layer. However, such claims could only hold when there exists less interaction that is governed by the mental layer, as the mental layer lacks both accuracy and consistency in the prediction of the overtaking behavior found in observation.

Thus, on the main topic of: **To which characteristics of bicycle riding can be accurately captured with a model that incorporates path-planning algorithms?** The answer to which will remain on the physical level of behavior. A combination of path-planning algorithms and a longitudinally continuous model is, in fact, capable of capturing the physical capability of steering and pedaling of the cyclist. However, such behavior of the physical layer is governed by the mental decision process of the cyclist. The face validation result has highlighted that the failure to model the intention of the cyclist would have a great impact on the final output of the generated behavior. At its current form, the developed model would only work well in an environment that contains only physical interaction with the environment.

With these findings, this research has made contributions in two aspects, as stated in the introduction. This research has provided a new modeling approach in capturing the physical steering part of the microscopic cyclist behavior using path planning algorithms, and provided some initial performance analysis, and where the approach could be improved through face validation. Another aspect of the contributions lies in the investigation made during the literature review, where necessary adaptations for the use of path planning algorithms in cyclist modeling are explored, opening up the future possibility for more types of models and additions.

5.2. Recommendation

Based on this research's findings and some experiences during the research period, this research determines that there are two main aspects that could yield significant benefits for the enhancement of this modeling technique. The first of which, based on the face validation findings, is the incorporation of more behavioral aspects. One of the major shortcomings of this research comes from the inaccuracies in capturing overtaking behaviors. This research suggests that it could be caused by the goal orientation layer of the model, rather than the parameter values used. The developed goal orientation layer, while functional, proved to be too simplistic to consistently predict the interactions. The goal orientation process is one of the more important aspects for both cycling research and for models utilizing path planning algorithms, as the algorithm requires the presence of a goal to initiate and optimize to. This research suggested the use of a potentially discrete choice-based approach for the enhancement of the model. Another accuracy enhancement could come from the use of different optimizing strategies, such as the addition of lean or steering effort for the planning algorithms. With the incorporation of these costs into the optimization step, previously outlining trajectories found in the chicane scenario is expected to be more accurately captured.

Another aspect that is out of the scope for this research, but could yield significant improvement, is the computational efficiency of the model. The model currently employs the use of basic RRT* models combined with kinematic constraints found in the RG-RRT, which require the use of higher iteration counts to gain convergence of a path. This makes the computation times objectively high. During the face validation step, the Python implementation of the model recorded on average 33 milliseconds to process a time tick. While it is currently running faster than real time under the smaller-scale face validation scenario of this research, more complicated scenarios found in real-world engineering scenarios are expected to increase the computation time drastically. With more complex scenarios, increasing the computational speed of the model is a must, as it allows for rapid iterations during the calibration steps. The field of path planning algorithms is constantly improving in terms of convergence speed. Thus, future research could attempt to incorporate more efficient variants of the path-planning algorithms, increasing computational efficiency. With both improvement in accuracy and speed, the models utilizing path planning algorithms could gain more relevance in the field of traffic modeling and engineering.

Bibliography

Alahi, Alexandre, Kratarth Goel, Vignesh Ramanathan, Alexandre Robicquet, Li Fei-Fei, and Silvio Savarese (2016). “Social lstm: Human trajectory prediction in crowded spaces”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 961–971.

Alizadehsaravi, L. and J.K. Moore (2022). “The effects of a steer assist system on bicycle postural control in real-life safety challenges”. English. In: *Proceedings of the 10th International Cycling Safety Conference*. Technische Universität Dresden.

Alsaleh, Rushdi and Tarek Sayed (2021). “Markov-game modeling of cyclist-pedestrian interactions in shared spaces: A multi-agent adversarial inverse reinforcement learning approach”. In: *Transportation research part C: emerging technologies* 128, p. 103191.

Andresen, Erik, Mohcine Chraibi, Armin Seyfried, and Felix Huber (2014). “Basic driving dynamics of cyclists”. In: *Simulation of Urban Mobility: First International Conference, SUMO 2013, Berlin, Germany, May 15-17, 2013. Revised Selected Papers 1*. Springer, pp. 18–32.

Antonini, Gianluca, Michel Bierlaire, and Mats Weber (2006). “Discrete choice models of pedestrian walking behavior”. In: *Transportation Research Part B: Methodological* 40.8, pp. 667–687.

Baars, Bernard and Nicole M Gage (2013). *Fundamentals of cognitive neuroscience: a beginner’s guide*. Academic Press.

Balluchi, Andrea, Antonio Bicchi, Aldo Balestrino, and Giuseppe Casalino (1996). “Path tracking control for dubin’s cars”. In: *Proceedings of IEEE International Conference on Robotics and Automation*. Vol. 4. IEEE, pp. 3123–3128.

Best, Robert A and JP Norton (1997). “A new model and efficient tracker for a target with curvilinear motion”. In: *IEEE Transactions on Aerospace and Electronic Systems* 33.3, pp. 1030–1037.

Boele-Vos, MJ, JJF Commandeur, and DAM Twisk (2017). “Effect of physical effort on mental workload of cyclists in real traffic in relation to age and use of pedelecs”. In: *Accident Analysis & Prevention* 105, pp. 84–94.

Botma, Hein and Hans Papendrecht (1991). “Traffic operation of bicycle traffic”. In: *Transportation Research Record* 1320.

Broz, Frank (2004). “Better motion prediction for people-tracking”. In: *Proc. of the International Conference on Robotics and Automation (ICRA), New Orleans, USA*.

Brunner, Johannes S, Ying-Chuan Ni, Anastasios Kouvelas, and Michail A Makridis (2024). “Microscopic simulation of bicycle traffic flow incorporating cyclists’ heterogeneous dynamics and non-lane-based movement strategies". In: *Simulation Modelling Practice and Theory* 135, p. 102986.

Castro, Guillermo Pérez, Fredrik Johansson, and Johan Olstam (2025). "Empirical study of bicycle traffic characteristics relevant for microscopic simulation". In: *Journal of Cycling and Micromobility Research* 3, p. 100054.

Chandler, Robert E, Robert Herman, and Elliott W Montroll (1958). "Traffic dynamics: studies in car following". In: *Operations research* 6.2, pp. 165–184.

Chen, Wu, Trine Agervig Carstensen, Ranran Wang, Sybil Derrible, David Rojas Rueda, Mark J Nieuwenhuijsen, and Gang Liu (2022). "Historical patterns and sustainability implications of worldwide bicycle ownership and use". In: *Communications Earth & Environment* 3.1, pp. 1–9.

CROW (2016). *Ontwerpwijzer fietsverkeer*. C.R.O.W kenniscentrum voor verkeer vervoer en infrastructuur.

Dijkstra, Edsger W (1959). "A note on two problems in connexion with graphs". In: *Numerische mathematik* 1.1, pp. 269–271.

Dowling, Richard, Alexander Skabardonis, Vassili Alexiadis, et al. (2004). *Traffic analysis toolbox, volume III: Guidelines for applying traffic microsimulation modeling software*. Tech. rep. United States. Federal Highway Administration. Office of Operations.

Duives, Dorine (2016). "Analysis and Modelling of Pedestrian Movement Dynamics at Large-scale Events". English. Dissertation (TU Delft). Delft University of Technology. ISBN: 978-90-5584-208-7.

Elbanhawi, Mohamed and Milan Simic (2014). "Sampling-based robot motion planning: A review". In: *Ieee access* 2, pp. 56–77.

Falkenberg, Georg, A Blase, T Bonfranchi, L Cosse, W Draeger, P Vortisch, L Kautzsch, H Stapf, and A Zimmermann (2003). "Bemessung von Radverkehrsanlagen unter verkehrstechnischen Gesichtspunkten". In: *Berichte Der Bundesanstalt Fuer Strassenwesen. Unterreihe Verkehrstechnik* 103.

Gatersleben, Birgitta and Katherine M Appleton (2007). "Contemplating cycling to work: Attitudes and perceptions in different stages of change". In: *Transportation Research Part A: Policy and Practice* 41.4, pp. 302–312.

Gavriilidou, Alexandra, Winnie Daamen, Yufei Yuan, and SP Hoogendoorn (2019a). "Modelling cyclist queue formation using a two-layer framework for operational cycling behaviour". In: *Transportation research part C: emerging technologies* 105, pp. 468–484.

Gavriilidou, Alexandra, Maria J Wierbos, Winnie Daamen, Yufei Yuan, Victor L Knoop, and Serge P Hoogendoorn (2019b). "Large-scale bicycle flow experiment: setup and implementation". In: *Transportation research record* 2673.5, pp. 709–719.

Gibson, James J and Laurence E Crooks (1938). "A theoretical field-analysis of automobile-driving". In: *The American journal of psychology* 51.3, pp. 453–471.

Gould, Gregory and Alex Karner (2009). "Modeling bicycle facility operation: cellular automaton approach". In: *Transportation research record* 2140.1, pp. 157–164.

Grothe, Francesco, Valentin N Hartmann, Andreas Orthey, and Marc Toussaint (2022). "St-rrt*: Asymptotically-optimal bidirectional motion planning through space-time". In: *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, pp. 3314–3320.

Hart, Peter E, Nils J Nilsson, and Bertram Raphael (1968). "A formal basis for the heuristic determination of minimum cost paths". In: *IEEE transactions on Systems Science and Cybernetics* 4.2, pp. 100–107.

Helbing, Dirk and Peter Molnar (1995). "Social force model for pedestrian dynamics". In: *Physical review E* 51.5, p. 4282.

Hoogendoorn, Serge and Winnie Daamen (2016). "Bicycle headway modeling and its applications". In: *Transportation research record* 2587.1, pp. 34–40.

Hoogendoorn, Serge, Alexandra Gavriilidou, Winnie Daamen, and Dorine Duives (2021). "Game theoretical framework for bicycle operations: A multi-strategy framework". In: *Transportation Research Part C: Emerging Technologies* 128, p. 103175.

Hoogendoorn, Serge and Piet HL Bovy (2003). "Simulation of pedestrian flows by optimal control and differential games". In: *Optimal control applications and methods* 24.3, pp. 153–172.

Hoogendoorn, Serge P, Winnie Daamen, and Piet HL Bovy (2003). "Extracting microscopic pedestrian characteristics from video data". In: *Transportation Research Board Annual Meeting*. Vol. 9. National Academy Press, pp. 1–15.

Hussein, Mohamed and Tarek Sayed (2017). "A bi-directional agent-based pedestrian microscopic model". In: *Transportmetrica A: Transport Science* 13.4, pp. 326–355.

Karaman, Sertac and Emilio Frazzoli (2011). "Sampling-based algorithms for optimal motion planning". In: *The international journal of robotics research* 30.7, pp. 846–894.

Kavraki, Lydia E, Petr Svestka, J-C Latombe, and Mark H Overmars (2002). "Probabilistic roadmaps for path planning in high-dimensional configuration spaces". In: *IEEE transactions on Robotics and Automation* 12.4, pp. 566–580.

Khan, Sarosh I and Winai Raksuntorn (2001). "Characteristics of passing and meeting maneuvers on exclusive bicycle paths". In: *Transportation research record* 1776.1, pp. 220–228.

Kroesen, Maarten (2017). "To what extent do e-bikes substitute travel by other modes? Evidence from the Netherlands". In: *Transportation Research Part D: Transport and Environment* 53, pp. 377–387.

LaValle, Steven (1998). "Rapidly-exploring random trees: A new tool for path planning". In: *Research Report 9811*.

Lee, Oliver, Alexander Rasch, Arend L Schwab, and Marco Dozza (2020). “Modelling cyclists’ comfort zones from obstacle avoidance manoeuvres”. In: *Accident Analysis & Prevention* 144, p. 105609.

Li, Maosheng, Feng Shi, and Dafei Chen (2011). “Analyze bicycle-car mixed flow by social force model for collision risk evaluation”. In: *3rd International Conference on Road Safety and Simulation*, pp. 1–22.

Li, Zhibin, Wei Wang, Pan Liu, John Bigham, and David R Ragland (2013). “Modeling bicycle passing maneuvers on multilane separated bicycle paths”. In: *Journal of Transportation Engineering* 139.1, pp. 57–64.

Liang, Xiao, MAO Baohua, and XU Qi (2012). “Psychological-physical force model for bicycle dynamics”. In: *Journal of Transportation Systems Engineering and Information Technology* 12.2, pp. 91–97.

Liang, Xiao, Meiquan Xie, and Xudong Jia (2018). “New microscopic dynamic model for bicyclists’ riding strategies”. In: *Journal of Transportation Engineering, Part A: Systems* 144.8, p. 04018034.

Meijer, Riske, Esra Van Dam, Henri Bouma, Jan Baan, and Sander E van der Hurk (2019). “Measurement method for objective cyclist behavior parameters”. In: *Traffic injury prevention* 20.sup3, pp. 16–20.

Meyer, Jean-Arcady and David Filliat (2003). “Map-based navigation in mobile robots:: Ii. a review of map-learning and path-planning strategies”. In: *Cognitive Systems Research* 4.4, pp. 283–317.

Michon, John A (1985). “A critical view of driver behavior models: what do we know, what should we do?” In: *Human behavior and traffic safety*. Springer, pp. 485–524.

Mohammed, Hossameldin, Alexander Y Bigazzi, and Tarek Sayed (2019). “Characterization of bicycle following and overtaking maneuvers on cycling paths”. In: *Transportation research part C: emerging technologies* 98, pp. 139–151.

Mohammed, Hossameldin, Tarek Sayed, and Alexander Bigazzi (2022). “Microscopic modeling of cyclists on off-street paths: a stochastic imitation learning approach”. In: *Transportmetrica A: transport science* 18.3, pp. 345–366.

Moore, Jason K, Mont Hubbard, AL Schwab, JDG Kooijman, and Dale L Peterson (2010). “Statistics of bicycle rider motion”. In: *Procedia Engineering* 2.2, pp. 2937–2942.

Moore, Jason Keith (2012). *Human control of a bicycle*. University of California, Davis.

Mueller, Natalie, David Rojas-Rueda, Maëlle Salmon, David Martinez, Albert Ambros, Christian Brand, Audrey De Nazelle, Evi Dons, Mailin Gaupp-Berghausen, Regine Gerike, et al. (2018). “Health impact assessment of cycling network expansions in European cities”. In: *Preventive medicine* 109, pp. 62–70.

Muhsen, Dena Kadhim, Firas Abdulrazzaq Raheem, and Ahmed T Sadiq (2024). “A Systematic Review of Rapidly Exploring Random Tree RRT Algorithm for Single and Multiple Robots”. In: *Cybernetics and Information Technologies* 24.3.

Nagel, Kai and Michael Schreckenberg (1992). "A cellular automaton model for freeway traffic". In: *Journal de physique I* 2.12, pp. 2221–2229.

Newell, Gordon Frank (1961). "Nonlinear effects in the dynamics of car following". In: *Operations research* 9.2, pp. 209–229.

Ni, Ying, Yixin Li, Yufei Yuan, and Jian Sun (2023). "An operational simulation framework for modelling the multi-interaction of two-wheelers on mixed-traffic road segments". In: *Physica A: Statistical Mechanics and its Applications* 611, p. 128441.

Orthey, Andreas, Constantinos Chamzas, and Lydia E Kavraki (2023). "Sampling-based motion planning: A comparative review". In: *Annual Review of Control, Robotics, and Autonomous Systems* 7.

Riggs, William (2016). "Cargo bikes as a growth area for bicycle vs. auto trips: Exploring the potential for mode substitution behavior". In: *Transportation research part F: traffic psychology and behaviour* 43, pp. 48–55.

Rudenko, Andrey, Luigi Palmieri, Michael Herman, Kris M Kitani, Dariu M Gavrila, and Kai O Arras (2020). "Human motion trajectory prediction: A survey". In: *The International Journal of Robotics Research* 39.8, pp. 895–935.

Schmidt, C.M., A. Dabiri, F. Schulte, R. Happee, and J.K. Moore (2024). "Essential Bicycle Dynamics for Microscopic Traffic Simulation: An Example Using the Social Force Model". English. In: *Proceedings of the 5th Symposium on the Dynamics and Control of Single-track Vehicles*.

Schönauer, Robert, Martin Stubenschrott, Weinan Huang, Christian Rudloff, and Martin Fellendorf (2012). "Modeling concepts for mixed traffic: Steps toward a microscopic simulation tool for shared space zones". In: *Transportation research record* 2316.1, pp. 114–121.

Shkolnik, Alexander, Matthew Walter, and Russ Tedrake (2009). "Reachability-guided sampling for planning under differential constraints". In: *2009 IEEE International Conference on Robotics and Automation*. IEEE, pp. 2859–2865.

Stülpnagel, Rul von (2020). "Gaze behavior during urban cycling: Effects of subjective risk perception and vista space properties". In: *Transportation research part F: traffic psychology and behaviour* 75, pp. 222–238.

Twaddle, Heather (2017). "Analysis and modelling of the operational and tactical behaviour of bicyclists". In: *UR: BAN Human Factors in Traffic: Approaches for Safe, Efficient and Stress-free Urban Traffic*. Springer, pp. 325–345.

Twaddle, Heather, Tobias Schendzielorz, and Oliver Fakler (2014). "Bicycles in urban areas: Review of existing methods for modeling behavior". In: *Transportation research record* 2434.1, pp. 140–146.

Vasic, Jelena and Heather J Ruskin (2011). "A discrete flow simulation model for urban road networks, with application to combined car and single-file bicycle traffic". In: *Computational Science and Its Applications-ICCSA 2011: International Conference, Santander, Spain, June 20-23, 2011. Proceedings, Part I 11*. Springer, pp. 602–614.

Wiedemann, R., Universität Karlsruhe. Institut für Verkehrswesen, and U. Köhler (1974). *Simulation des Strassenverkehrsflusses*. Schriftenreihe 8-10. Karlsruhe, Baden-Württemberg, Germany: Institut für Verkehrswesen der Universität Karlsruhe.

Yao, Danya, Yi Zhang, Li Li, Yuelong Su, Sihan Cheng, and Wenda Xu (2009). "Behavior modeling and simulation for conflicts in vehicles-bicycles mixed flow". In: *IEEE Intelligent Transportation Systems Magazine* 1.2, pp. 25–30.

Yavin, Y (2006). "The derivation of a kinematic model from the dynamic model of the motion of a riderless bicycle". In: *Computers & Mathematics with Applications* 51.6-7, pp. 865–878.

Yuan, Yufei, Bernat Goñi-Ros, Tim P van Oijen, Winnie Daamen, and Serge P Hoogendoorn (2019). "Social force model describing pedestrian and cyclist behaviour in shared spaces". In: *Traffic and Granular Flow'17 12*. Springer, pp. 477–486.

Zhao, De, Wei Wang, Chenyang Li, Zhibin Li, Pengming Fu, and Xiaojian Hu (2013). "Modeling of passing events in mixed bicycle traffic with cellular automata". In: *Transportation research record* 2387.1, pp. 26–34.

Zhu, Meixin, Xuesong Wang, Andrew Tarko, and Shou'en Fang (2018). "Modeling car-following behavior on urban expressways in Shanghai: A naturalistic driving study". In: *Transportation research part C: emerging technologies* 93, pp. 425–445.

A
Verification Results

In this appendix, the full result of the verification step is shown. The verification will be conducted based on the steps in inputs showcased in section 3.2, where the intermediate output of the developed model is compared against the assumptions and expected behaviors.

A.1. Perception

The verification of the perception layer consists of 2 scenarios, which are showcased in the following table A.1 with varying speed inputs. The output result should respond with the change.

Table A.1: Verification inputs and expected results

Model layer / Modules	Main input	Unit	Value	Expected output
Perception	Speed	m/s	2	List of 1 cyclist
			4	List of 2 cyclist

Table A.2: Result output of the perception layer

Main input	Unit	Value	Outputted consideration boundry (xmin, xmax, ymin, ymax)	Returned list length
Speed	m/s	2	(0, 8, -1.35, 0.15)	1
		4	(0, 16, -1.35, 0.15)	2

The output result is showcased in table A.2. For clearer illustration, the result of the outputs is also graphed onto figure A.1 and A.2.

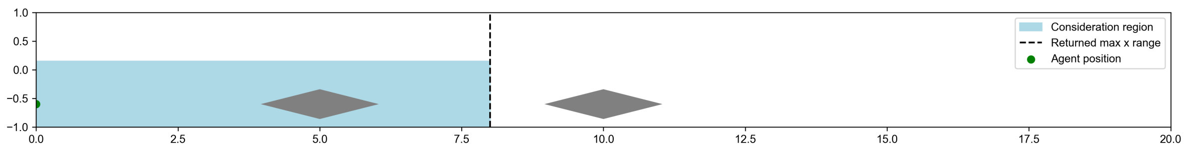

Figure A.1: Intermediate output when the speed is set at 2 m/s

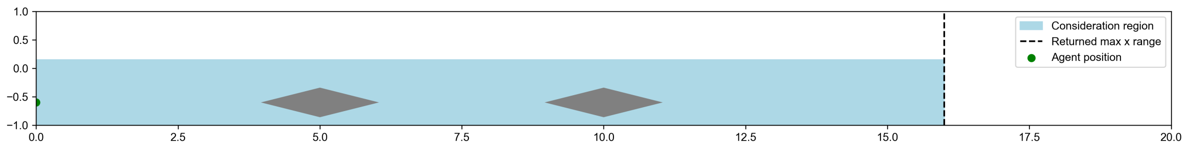

Figure A.2: Intermediate output when the speed is set at 4 m/s

The perception module have showcased expected behavior both in the table and figures, with the change of speed, the length of the consideration region changes accordingly. Covering a different amounts of other agents and changing the length of the returned list of potential leaders.

A.2. Goal orientation

For the goal orientation layer, the returned leader and goal should adjust based on the set overtaking conditions, which is showcased in table A.3.

Table A.3: Inputs and expected results for goal orientation

Model layer / Modules	Main input	Unit	Value	Expected output
Goal Orientation	Speed threshold Gap threshold	m/s m	0.6 1	Overtake all cyclists
			1.2 1	Overtake 1 cyclist
			0.6 1.5	Overtake no cyclists

Table A.4: Inputs and expected results for goal orientation

Main input	Unit	Value	Returned leader (x, y, v)	Returned goal (x, y)
Speed threshold Gap threshold	m/s m	0.6 1	(1000, 0, 10)	(16, -0.6)
		1.2 1	(10, -0.6, 10)	(8.75, -0.6)
		0.6 1.5	(5, -0.6, 2)	(3.75, -0.6)

The goal orientation module has showcased expected return values. With the unconstrained cyclists getting a leader position that is far enough not to hinder any speed adjustments. The situations that the goal orientation module has chosen to follow have also returned the correct leader and goal position, which will be the goal for the verification of the path-planning layer.

A.3. Path planning

For the verification of the path planning layer, the goal coordinates obtained in the previous step will be used. The intermediate output for this step of the model should be a smooth, continuous path that connects from the starting position to the goal region, while not violating any set boundary and angle constraints. The path output is shown in the following figure A.3 through A.5 respectively.

All of the three goal inputs have returned a viable path that connects the start and the goal

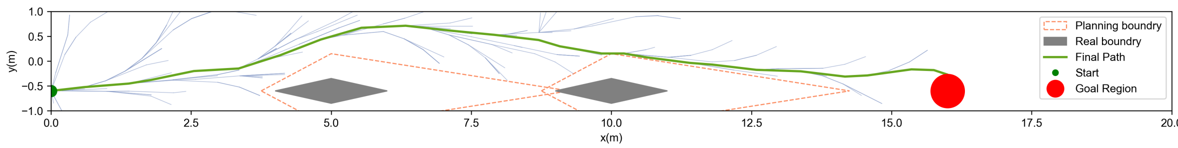

Figure A.3: Path output when the goal is at (16, -0.6)

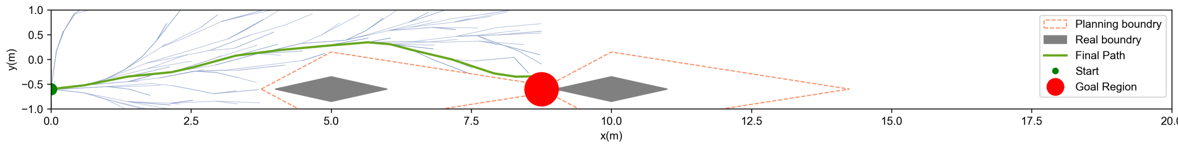

Figure A.4: Path output when the goal is at (8.75, -0.6)

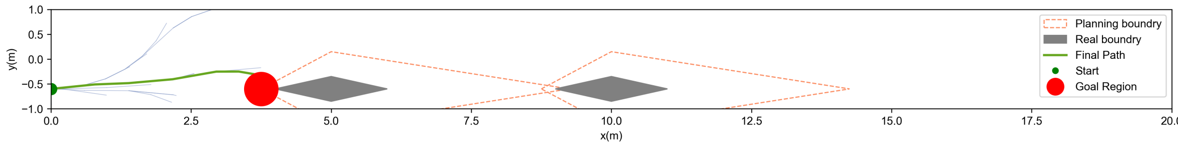

Figure A.5: Path output when the goal is at (3.75, -0.6)

with no obvious boundary or kinematic violation. Indicating that the path-planning part of the model is working as intended.

A.4. Movement

With all other parts of the model verified, the movement layer can finally be tested, as it relies on the leader and path inputs from the previous part of the model. The input and expected result of the movement layer are shown in the following table A.5.

Table A.5: Verification inputs and expected results

Model layer / Modules	Main input	Unit	Value	Expected output
Movement (OT threshold 1.2 m/s)	Current Speed, Desired Speed	m/s	5	No speed adjustment
			4	Decelerate and follows

If all parts of the model are working well. Considering a riding speed of 5 m/s and an overtaking speed threshold of 1.2 m/s, this would lead to a behavior that overtakes all other cyclists. While a set speed of 4 m/s would lead to speed adjustment and following behavior. The final movement output for the model is showcased in the following figures A.6 and A.7, where both inputs have generated trajectories have showcase the expected behaviors.

From the initial perception inputs to the final movement outputs, the developed agents have showcased well-expected behaviors that are in line with the modeling concepts. The developed agent should be well-equipped for the next face validation, where attempts to use the model to replicate observations from the real-world datasets will be made.

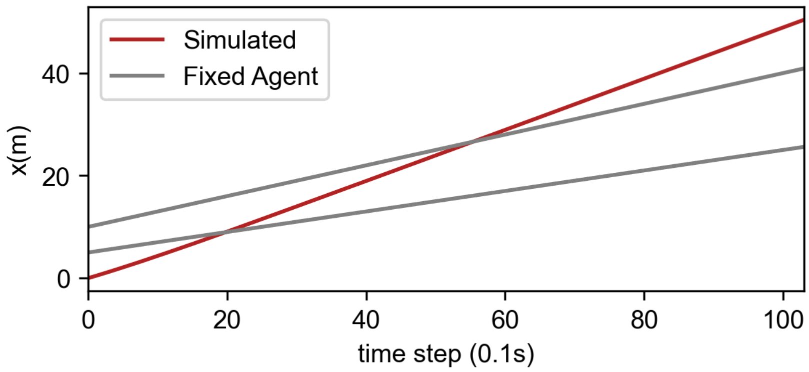

Figure A.6: Trajectory output when the agent's desired speed is set to 5 m/s

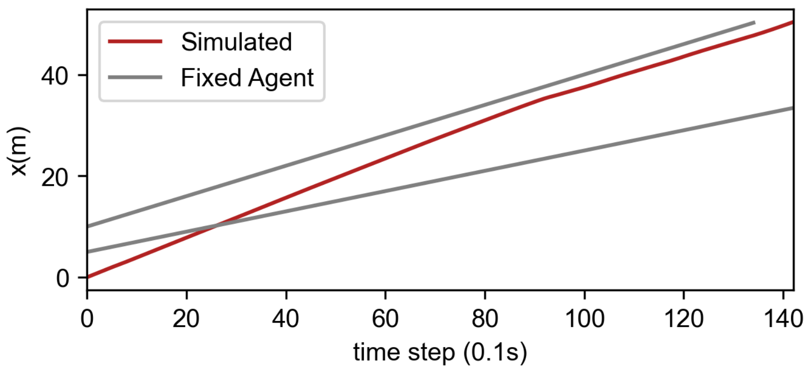

Figure A.7: Trajectory output when the agent's desired speed is set to 4 m/s