Thesis for the degree of licentiate of engineering

Computational interaction models for automated vehicles and cyclists

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Cover: modeling the interaction between cyclists and automated vehicles at unsignalized intersection

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Abstract

Cyclists' safety is crucial for a sustainable transport system. Cyclists are considered vulnerable road users because they are not protected by a physical compartment around them. In recent years, passenger car occupants' share of fatalities has been decreasing, but that of cyclists has actually increased. Most of the conflicts between cyclists and motorized vehicles occur at crossings where they cross each other's path. Automated vehicles (AVs) are being developed to increase traffic safety and reduce human errors in driving tasks, including when they encounter cyclists at intersections. AVs use behavioral models to predict other road user's behaviors and then plan their path accordingly. Thus, there is a need to investigate how cyclists interact and communicate with motorized vehicles at conflicting scenarios like unsignalized intersections. This understanding will be used to develop accurate computational models of cyclists' behavior when they interact with motorized vehicles in conflict scenarios.

The overall goal of this thesis is to investigate how cyclists communicate and interact with motorized vehicles in the specific conflict scenario of an unsignalized intersection. In the first of two studies, naturalistic data was used to model the cyclists' decision whether to yield to a passenger car at an unsignalized intersection. Interaction events were extracted from the trajectory dataset, and cyclists' behavioral cues were added from the sensory data. Both cyclists' kinematics and visual cues were found to be significant in predicting who crossed the intersection first. The second study used a cycling simulator to acquire in-depth knowledge about cyclists' behavioral patterns as they interacted with an approaching vehicle at the unsignalized intersection. Two independent variables were manipulated across the trials: difference in time to arrival at the intersection (DTA) and visibility condition (field of view distance). Results from the mixed effect logistic model showed that only DTA affected the cyclist's decision to cross before the vehicle. However, increasing the visibility at the intersection reduced the severity of the cyclists' braking profiles. Both studies contributed to the development of computational models of cyclist behavior that may be used to support safe automated driving.

Future work aims to find differences in cyclists' interactions with different vehicle types, such as passenger cars, taxis, and trucks. In addition, the interaction process may also be evaluated from the driver's perspective by using a driving simulator instead of a riding simulator. This setup would allow us to investigate how drivers respond to cyclists at the same intersection. The resulting data will contribute to the development of accurate predictive models for AVs.

Keywords: automated vehicles, computational models, vulnerable road users, active safety systems, cyclists' interaction, driver models

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Contents

1 Introduction

1.1 Cyclists' crashes with motorized vehicles

Cyclists are one of the most commonly injured road users. In contrast to the share of driver fatalities, that of cyclist fatalities has been increasing in European countries in recent years [1]. Unlike road users in passenger cars, cyclists are not protected by a metal compartment around them. For that reason, cyclists are highly susceptible to severe injury in crashes with motorized vehicles.

According to Hellman et al. (2016), over 70% of cyclists' crashes occur where they share the path with motorized vehicles [2]. This is particularly problematic at unsignalized intersections, where users must come to an agreement in order to cross the intersection safely. In Sweden, priority rules dictate that cyclists usually have the right of way in this scenario; however, according to Svensson et al. (2010), in 42% of cases, drivers do not yield to cyclists [3].

1.2 Crash prevention methods for cyclists' interactions with motorized vehicles

The most important countermeasures to prevent cyclists' crashes with motorized vehicles are: 1) developing automated driving systems and vehicle safety systems, 2) infrastructure design, and 3) policy making.

Safety systems that benefit today's vehicles are categorized as either active or passive. Active safety systems try to prevent crashes, while passive safety systems aim to reduce crash consequences, such as injuries. Active safety systems are continuously looking for threats by predicting possible critical scenarios. The systems can intervene to try to prevent crashes either by warning the driver or by taking control of the car. Two examples of active safety systems that are commonly used in modern cars are forward-collision warning (FCW) and autonomous emergency braking (AEB) systems. The former issues a warning to the driver in the event of an imminent crash with an object in front. In the case of vehicles' interactions with cyclists at intersections, if drivers do not see the approaching cyclist, the FCW can warn them. The AEB activates if the driver does not respond to an issued warning; the system can stop the vehicle to prevent a crash [4].

Automated driving systems and automated vehicles (AVs) are being developed with the promise of removing human error in driving tasks. At higher levels of automation, all the driving tasks will be performed by the vehicle, including continuous decision-making in complex urban environments. The three main phases of automated driving functionality are sensing, prediction, and action [5]. The first phase is performed by the mounted sensors inside and outside the vehicle, which collect information about the surroundings. The second phase is based on the sensing data; the AV uses its prediction models and algorithms to decide how to proceed given the current situation. A substantial amount of research has been done on this phase [6, 7]. In the last phase, the vehicle acts on the decisions made in the second phase. For example, that the decisions include dealing with cyclists. For a successful implementation of AVs in urban areas, there is a need to define a safe and comfortable way of interacting with VRUs. Thus, it is important to investigate and extract cyclists' behavioral patterns (from a variety of data sources) when they interact with motorized vehicles, in order to develop predictive models for AVs to safely interact with cyclists at crossings.

Many researchers have pointed out the importance of infrastructure design for cyclist's safety. For instance, Wegman et al. (2010) enumerate different infrastructure measures for reducing cyclists' crashes, including dedicated cycling paths and special design requirements for roundabouts [8]. Boda et al. (2018) conducted a study on the interaction between motorized vehicles and cyclists at an intersection, in which they found that the drivers' response process was mainly influenced by the visibility of the cyclist [9]. In another study, Jensen (2016) gives some insights about how to increase cyclists' safety through better design of intersections and roundabouts [10].

Policymakers try to reduce the risk of crashes by imposing laws or giving recommendations to regulate the movement of road users. For instance, in Sweden motorized vehicles should give priority to crossing cyclists who are riding in dedicated, marked cycling lanes. Cyclists have a responsibility to pay attention to other road users when they approach unsignalized intersections as well. There are other ways to reduce the potential risks in encounters between cyclists and motorized vehicles. For example, some countries (e.g., Australia, New Zealand, Argentina, and Cyprus) have made helmets mandatory for cyclists [11]. In some other countries, school children learn safe and reliable cycling techniques as part of their educational program [12].

1.3 Behavioral models to improve safety

Predicting VRUs' intentions is crucial in order for AVs to have safe, trusted interactions with them in critical scenarios [7]. VRU-AV interactions can be challenging in mixed urban environments due to several reasons, like multiple interactions at a time or infrastructure design. The VRU may also have difficulty understanding the AV's intention, due to a lack of explicit communication and AV's low speed [13]. To overcome this challenge, researchers have proposed novel solutions, like using an external human-machine interface (eHMI) to communicate the VRU's future actions [14, 15]. eHMIs are particularly efficient in low-speed urban situations where the VRUs have time to read the messages on eHMIs [16]. Proposed eHMI designs for facilitating the interaction between VRUs and AVs include a display on the vehicle, a projection on the road, and a light strip [17]. However, it is the AV's responsibility to correctly predict the VRUs' intent during the interaction and safely react. While much research has been done on predicting pedestrians' intent in the course of interactions with motorized vehicles [18, 19], only a small amount has focused on predicting cyclists' intent in urban spaces—and even fewer have tried to develop computational models that predict that intent. The focus of this thesis is to investigate the factors affecting cyclists' yielding behavior at intersections and determine what visual cues are useful for predicting their intent—in a specific interaction scenario.

Active safety systems utilize algorithms to detect a threat. In-time activation of these safety systems requires that the algorithms be well tuned, to avoid unnecessary interventions (when the driver was already aware of the threat). If the safety system repeatedly intervenes unnecessarily, the driver will no longer trust the system and stop using it. This possibility imposes a high risk when the situation needs an intervention from the safety system [20]. In-time intervention by active safety systems may ensure crash avoidance and increased safety for the VRUs and all road users [21]. Road users' behavioral models can improve threat assessment algorithms to intervene earlier and in an acceptable manner for the driver [21]. The main objective of using road user behavioral models in active safety systems is to avoid all crashes, including crashes with cyclists [22], and make sure that the driver trusts the system's performance. In a cyclist-vehicle interaction scenario in an intersection, the system should be able to predict the intent of the cyclist and react if needed.

1.4 Behavioral cues for predicting road users' behavior

Recent studies have shown that visual information about VRUs is important for predicting their decisions. In fact, visual information about pedestrians, like body pose and head turn, has been shown to relate to the decisions they make [23, 24]. A few studies have also found a connection between visual information about cyclists and their decision making. For instance, Hemeren et al. (2014) showed videos of cyclists approaching an intersection to several participants and asked them which visual cues were more important for predicting whether the cyclists intended to go straight or turn left. They found that the cyclist's position (leaning or sitting up straight), head turn (toward their intended path), and speed were the most critical cues. In another study, Abadi et al. (2022) developed a neural network model to predict cyclists' intention to cross, using body and head orientation [25]. Another objective of this thesis is to extend this research by determining what visual cues are used by cyclists to communicate their decision to cross or yield to motorized vehicles at an intersection. Incorporating VRUs' visual information in predictive models may help AVs predict cyclists' intentions more accurately.

1.5 Interactions in traffic

Interactions among road users frequently happen in daily traffic, when users share space in the environment. With increasing traffic volume, more conflicts and interactions are happening between road users. Markkula et al. (2020) defined interactions as a situation in which the behavior of at least two road users is influenced by a sharing-space conflict [26]. Thalya et al. (2020) also defined an interaction as occurring when two or more road users share the road and try to communicate in order to probe the other's intent to navigate safely and comfortably [27].

One of the places where high-conflict interactions frequently occur is crossings where road users' paths intersect [28]. Hellman et al. (2016) found that over 70% of cyclists' crashes with motorized vehicles happen at crossings [2]. Crossings are either controlled by traffic signals or, in unsignalized intersections, by priority rules. Interactions at unsignalized intersections are usually more critical since they require communication and agreement between the road users to cross safely [28]. Further, depending on the intersection design, different interactions between motorized vehicles and VRUs may occur, as enumerated by Pokorny et al. (2017) [29].

1.6 Cyclists' interaction models

To date, only a few studies have quantitatively investigated the interactions between cyclists and motorized vehicles at crossings. These studies used four types of data: naturalistic driving (ND), test track (TT), simulator, and video. ND data are considered to have the highest ecological validity [30]. The downsides of ND data are the confounders in the environment and the impossibility of repeating the scenarios. The second type of data, TT data, uses constructed scenarios, which provide repeatability. The participants are not subject to real traffic, since they are driving on dedicated TTs, so the data are less ecologically valid compared to ND data. On the other hand, they still have real motion cues from the vehicles and the real environment around them, which makes TT data more ecologically valid than the third type, simulator data [31]. Simulators allow full control over the details of the tests and a safe environment to perform the scenarios. They are particularly useful for this thesis's subject because they remove the risk of collision between road users. In addition, they offer repeatability and generally lower costs compared to TT and ND data. However, it should be noted that simulator data have the lowest ecological validity of all types of data [32]. Two types of simulators can be used for evaluating interactions between cyclists and motorized vehicles, driving simulators and riding simulators. The last type of data that has been used in these studies is video data. Participants are exposed to videos of a certain conflict scenario and are asked about their reaction to it. This type of data lacks accurate sensor data and has low ecological validity. On the other hand, like studies using simulator data, these offer repeatability and a safe testing environment.

One of the first works observing cyclist-vehicle interactions was done by Silvano et al. (2016) [33]. The authors used ND data from a roundabout to observe the conflicts between cyclists and motorized vehicles [33]. They developed a two-stage framework for the interactions. In the first stage, their model determines whether a conflict is happening between the two road users; in the second stage, they model the driver's yielding behavior. They used binary logit models to determine the existence of a conflict and the driver's yielding decision. They found that the relative time to arrival at the intersection, the vehicle's speed, and the cyclist's distance to the conflict zone are the significant variables affecting the driver's decision to yield. The limitations of this work are that they lacked a complete trajectory of involved road users, and they did not use any information about the cyclists in their modeling.

Boda et al. (2018) observed drivers' interactions with cyclists on a TT [9]. They used both a TT and a driving simulator to model and validate the driver's response to the approaching cyclist at an unsignalized intersection. The independent variables consisted of the cyclist's speed, the vehicle's speed, and the configuration of arrival at the intersection in terms of relative distance. They modeled the lateral clearance between the vehicle and the bike at the time the gas pedal was released and again at brake onset. They also modeled the brake onset behavior in respect to the changes in independent variables and differences among the participants. They concluded that the drivers' response behavior is mainly influenced by the visibility (the time at which the cyclist becomes visible) at the intersection. In another work, Boda et al. (2020) developed a model for predicting driver behavior using two independent variables: optical looming control and projected post-encroachment time [34].

Simulators have gained popularity for investigating cyclists' interaction with motorized vehicles, primarily because of the advantages mentioned. However, most of the works that used simulators observed drivers' behavior while overtaking cyclists; very few studies evaluated drivers' interactions with cyclists at crossings. In one of the few, Bella and Silvestri (2018) evaluated the effect of different infrastructure designs on drivers' interactions with cyclists [32]. They used a driving simulator to test the effect of different infrastructure countermeasures (like raised islands and pavement color) on drivers' response in interaction with cyclists. When the countermeasures were in place, the drivers had better braking profiles, in terms of deceleration, compared to the baseline condition without countermeasures. The authors did not develop a predictive model for the interaction.

Another experiment was done by Velasco et al. (2021) on cyclists' interactions with automated vehicles. They showed videos of vehicles approaching an unsignalized intersection to participants wearing a virtual reality (VR) headset. The video was stopped at a critical moment, and participants (as cyclists) were asked if they would yield for the AV. The independent variables in this study consist of vehicle type (automated or conventional), gap size, vehicle speed, and who had the right of way. They found that the gap size and the right of way were the primary factors affecting the cyclists' decision whether to yield to the vehicles. Cyclists were less likely to yield if they had larger gap sizes and the right of way.

Despite the high frequency of cyclists' crashes with motorized vehicles at intersections (over 70% of all cyclists' crashes), not much research has been done to quantitatively analyze their interactions with motorized vehicles. Further, parameters that may explain cyclist's behavior (like demographics) have not received much attention in the literature, partly because of the lack of datasets containing such information. Evaluating cyclists' behavior-related parameters may help to understand different aspects of cyclist-vehicle interactions at unsignalized intersections.

At the present time, the main knowledge gap in cyclist-vehicle interactions is the lack of a detailed analysis of the cyclists' behavior. To be sure, a few studies have analyzed the interaction from the drivers' point of view, determining how the driver responds to the presence of the cyclist [34, 33]. However, to devise interaction models, it is important to understand how cyclists communicate their intent while interacting with vehicles and what their behavioral patterns are during the interaction. We did not find any previous research that used computational models incorporating cyclists' information or behavioral cues. Further, no previous work has evaluated their predictive models using ND data from intersections. In fact, previous research has only rarely used mathematical models to quantitatively analyze cyclist-vehicle interactions for application in active safety systems and AVs.

1.7 Aims and objectives

The main aim of this thesis is to contribute to safe interaction between AV and cyclists by investigating the factors that affect the interaction and developing predictive models.

The following research objectives of the overall Ph.D. will address the gaps identified in the previous research:

1. Investigating how cyclists communicate their intent while interacting with vehicles at unsignalized intersections.
2. Explaining and devising quantitative models to predict cyclists' behavior through their kinematics and appearance information.
3. Proposing behavioral models for automated vehicles to interact safely and comfortably with cyclists at intersections.

To address these objectives, we conducted three experiments: 1) field data collection from an intersection, 2) a riding simulator experiment and 3) a driving simulator experiment. Using the field dataset, we addressed Objectives

1 and 2 in the first experiment by developing data-driven models of the interaction between cyclists and vehicles. The second experiment also addressed Objectives 1 and 2 by analyzing data from a riding simulator. This thesis addresses Objectives 1 and 2 by investigating the interaction process between cyclists and motorized vehicles and developing descriptive models to find the influencing factors. Future work in this PhD will address Objective 3 by developing advanced predictive models for the intersection scenario.

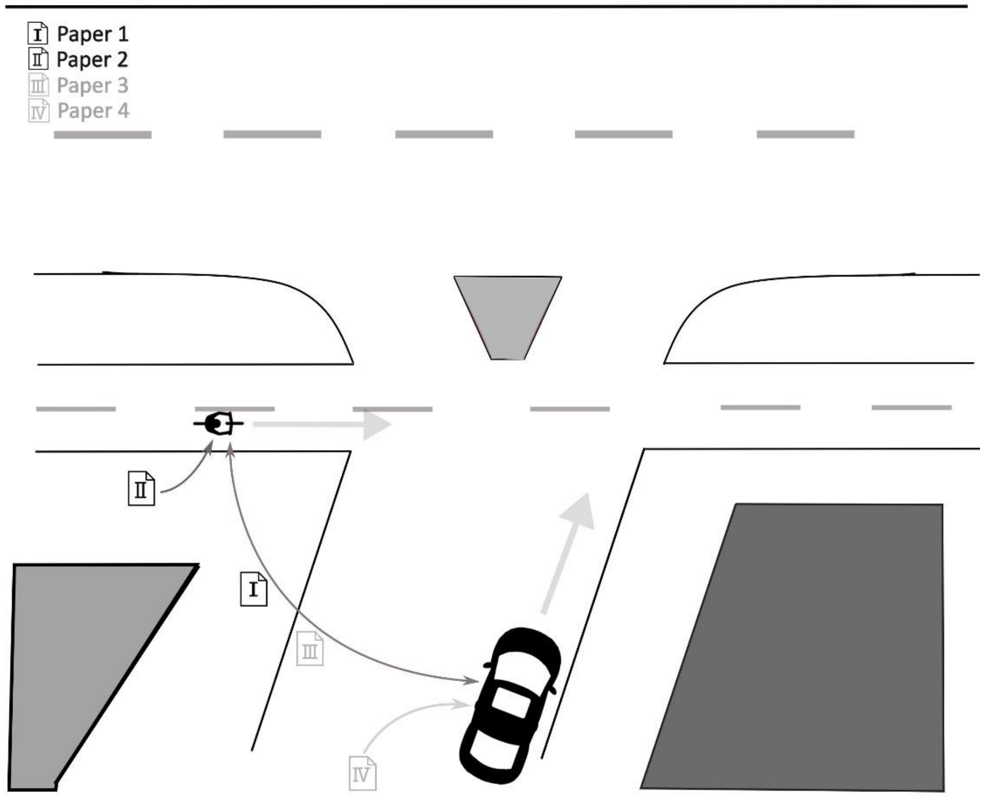

Figure 1- Overall picture of the PhD studies, showing the four planned papers and how they address the research objectives. PAPERS III and IV are future works that will be addressed to obtain the PhD degree after the licentiate.

2 Methodology

2.1 Cyclist-vehicle interactions: objective definition and assessment of crash risks

Interactions between motorized vehicles and cyclists occur in different forms, either in urban areas or on rural roads. In this thesis, a specific form of interaction scenario was investigated: it is one of the most common types of conflicts that leads to crashes in Sweden [2].

The scenario is an interaction at an unsignalized intersection between the following road users: 1) a driver in a motorized vehicle and 2) a cyclist. An intersection in Gothenburg (GPS coordinates: 57◦42′ 31.1″ N, 11◦56′ 22.9″ E) was selected for data collection and analysis. In 2016, there was a fatal crash between a student (cyclist) and a heavy truck at this intersection. The layout of the intersection and the moving direction of the involved road users is depicted in Figure 2: the cyclist approaches a three-way intersection and continues straight in a dedicated bike lane. The subject vehicle approaches the intersection from the right side of the cyclist and merges into the vehicle's lane. The vehicle cuts across the cyclists' path, and the two road users need to negotiate who crosses first.

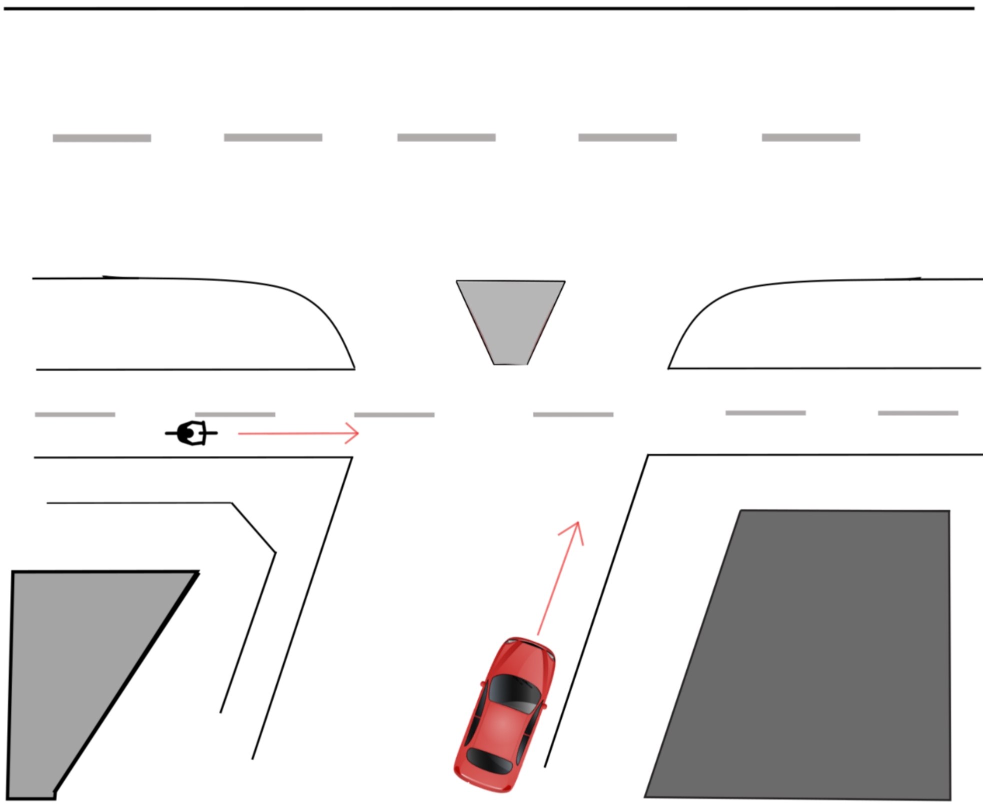

Figure 2- The intersection design and observed interaction scenario

This thesis investigated how a variety of factors affected the interaction between the driver and the cyclist. These factors comprised kinematic parameters like speeds and distances and cyclists' visual information like pedaling and head turn. Kinematic information has been used to model the behavior of drivers interacting with cyclists [34]; the factors that have been found to be important include cyclist speed, vehicle speed, and configuration of arrival (in terms of relative distance) at the intersection [9, 33]. Road users communicate with each other both explicitly and implicitly when they need to interact. Communication is explicit when it conveys a message deliberately (through gestures and eye contact, for example). Implicit communication is always present in road users' behavioral cues, such as a driver's way of driving [35, 36]. As mentioned in the previous part, road users' behavioral cues can be useful for predicting their intention in traffic [37]. The effects of kinematic factors and behavioral cues on interaction outcomes were investigated and modeled in this thesis.

2.2 Data sets

Different methodologies exist for data collection concerning the subject scenario in this thesis. These methods include ND data collection, field tests, TT experiments, and simulator experiments. Each data collection method has its inherent limitations and advantages. The main difference between the data types is the ecological validity; ND data has the highest ecological validity to investigate the road user's behavior. ND datasets are subject to issues like lower accuracy, higher data collection costs, and difficulties in finding interesting events. Due to the crash risk for the road users in the scenario in this thesis, field testing was not feasible. TTs also provide a realistic environment which can yield high-quality data for analysis. In addition, the controllability of TT tests is a great advantage for obtaining detailed aspects of driving behavior. However, the need for a lot of preparation to ensure that the TT resembles a real-world scenario is one of the disadvantages of this type of data. On the other hand, simulators are great tools for evaluating human behavior without subjecting participants to possible harm. Simulators also provide the chance to control the scenario and repeatedly test participants, for a lower cost than other data collection methods. The downside of simulator studies is that they have the lowest ecological validity of these four methodologies.

The feasible data collection methods for the scenario in this thesis are ND data, TT study, and simulator experiments. This thesis used ND data and riding simulator data. For the analysis and modeling of the interaction events between cyclists and vehicles in PAPER I, ND data were used, while for the analysis of the cyclists' behavior during the interaction with AVs, riding simulator data were used.

The data for PAPER I were gathered at an urban intersection in Gothenburg, Sweden. VISCANDO, a company specializing in traffic surveillance systems, collected the data. They utilized an AI-based sensor positioned on a high-rise building corner, aimed at the focal point of potential conflicts. The sensor recorded the movements of both cyclists and motorized vehicles, allowing the extraction of interaction events between these road users. The accuracy of these events was verified by cross-referencing with corresponding videos of interaction events. Kinematic parameters such as speed and distance were derived from the trajectory dataset, with supplementary information from cyclists' appearance incorporated from the videos. The videos that were used for recording cyclists' visual information were reduced due to GDPR (General Data Protection Regulations) regulations. Refer to Figure 3 for a visual representation of the intersection from the sensor's perspective.

Figure 3- Intersection from the mounted sensor by VISCANDO.

The data for PAPER II were acquired through a riding simulator (see Figure 4). Participants used a virtual reality headset to observe the environment and were tasked with traversing an intersection (designed to closely resemble the one from the ND data). The experiment comprised 12 trials per participant, evaluating the interaction shown in Figure 2. In this scenario, a cyclist rides straight in a bike lane, while a vehicle approaches from the right side. The subject vehicle was controlled to meet the cyclist at various times time at the intersection. Different sensors measured the cyclist's activities during the test. Cyclists maintained a maximum speed of 18 km/hr., while the vehicle had an initial speed of 25 km/hr. The trials varied in terms of the difference in time to arrival at the intersection (DTA) and cyclists' visibility conditions. The analysis also incorporated participants' questionnaire responses to provide additional insight into their behavior during the trials.

Figure 4- Bike simulator with virtual reality headset

2.3 Regression models

Generalized linear regression models have been used for the analysis and modeling of most of the data in this thesis. Logit models are a form of linear regression model with a specific link function [38]; they model the probability of an event occurring based on a set of independent variables. The log odds of an event's occurrence are related to a linear combination of one or more independent variables [39]. The logit function transforms the linear predictors onto a probability scale from 0 to 1. In this paper, the cyclist's decision whether to cross the intersection before the vehicle was modeled as a binary outcome. Different independent variables were considered to test the model, including both road users' kinematics (speed and distance), and the cyclist's demographic and visual information. The general form of a logit model is as follows:

$$P = \frac{\exp(a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots)}{1 + \exp(a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots)} \qquad (1)$$

Where

P = the probability that a case is in one category

b_1, b_2, b_3 = vector of parameters to be estimated

x_1, x_2, x_3 = independent variables affecting the decision to yield *a* = intercept

This thesis used the Python package *statsmodels* to obtain the model parameters. To balance the dataset based on the dependent variable, we used the SMOTE (Synthetic Minority Oversampling Technique) method. To calculate the model prediction accuracy, the Leave One Out Cross-Validation (LOOCV) method was used.

Linear mixed-effect models are statistical tools used to analyze data with both fixed effects (general trends applicable to all data points) and random effects (variations specific to certain groups or subjects). These models are particularly useful when the experiment has repeated measures. Linear mixed-effect models are an extension of simple linear models, that utilizes both fixed and random effects [40]. The logistic mixed-effect model was developed to predict the cyclists' yielding decision. The general form of a logistic mixed-effect model can be expressed as Equation 1, where P is the probability that a case is in one category, X the fixed-effect regressor matrix, β the vector of fixed effects, Z the random-effects regressor matrix, α the vector of random effects, and ε the observation error vector.

$$\log\left(\frac{p}{1-p}\right) = X\beta + Z\alpha + \varepsilon \tag{2}$$

To estimate the model parameters, we used the R package *glmer*. The two main independent variables in the model consisted of the DTA and visibility distance.

To model each individual cyclists' speed profile, we used an arctan function with four coefficients. The equation, which has three scaling factors and an offset factor, forms an s-shape which replicates the cyclist's speed during the approach to the intersection with respect to time. This model was used to compare the average cyclists' speed profiles across different trials. The following formula shows the general form of the equation:

$$Y = a * \arctan(\mathrm{b} * \mathrm{t} + \mathrm{c}) + d \tag{3}$$

The parameter fitting and evaluation were done using the MATLAB fitting function.

3 Summary of papers

The results of this thesis are presented in the two appended papers. The following section provides a summary.

3.1 PAPER I: How do cyclists interact with motorized vehicles at unsignalized intersections? Modeling cyclists' yielding behavior using naturalistic data

3.1.1 Background

Very little research has been done to quantitatively analyze and model the interaction between cyclists and motorized vehicles at intersections, although a large proportion of cyclists' crashes occur at crossings where they share the path with motorized vehicles. Accurate predictive models are needed to define a safe and comfortable way for AVs to interact safely with cyclists in this conflict scenario.

3.1.2 Aim

This paper aims to provide insights into cyclist-motorized vehicle interactions based on ND data. The interaction events were used to investigate the factors influencing cyclists' yielding behavior.

3.1.3 Methods

The ND data for this experiment were acquired from an unsignalized intersection in Gothenburg, Sweden. Fourteen days' worth of observations were searched to find relevant interaction events between cyclists and motorized vehicles. Relevant events were defined as those with a DTA within a certain range in the trajectory data. A total of 105 interaction events were extracted from the trajectory dataset; more information about them was added later by checking the corresponding sensory data. For each interaction event, kinematics (both road users' speeds and distances), cyclists' visual information (head turn and pedaling), and observed demographics were collected. Safety metrics like PET (post-encroachment time) were also measured to determine the criticality of the scenario. Logistic regression was used to quantify the effect of different parameters on the cyclist's decision to cross the intersection before the vehicle.

3.1.4 Results

Modeling results showed that both kinematics (road users' speed and DTA) and cyclists' visual information (head turn and pedaling) are significant predictors for cyclists' decision whether to cross the intersection first. The Leave One Out Cross-Validation (LOOCV) method showed an acceptable model accuracy of 83%.

3.1.5 Conclusions

It was found that not only kinematics but also the cyclists' visual information are useful for predicting whether cyclists will cross ahead of an oncoming vehicle. However, kinematics play a more important role. The findings of this study may be used in AV algorithms, which could supplement cyclists' kinematics with their visual information to predict whether they will yield.

3.2 PAPER II: Understanding the interaction between cyclists and automated vehicles at unsignalized intersections: Results from a cycling simulator study

3.2.1 Background

While other modes of transport experience decreasing fatalities, cyclists' fatalities have been increasing in recent years in Europe [1]. Although most cyclists' crashes occur at crossings, there is not much research analyzing the conflicts between cyclists and motorized vehicles. Understanding the cyclists' behavioral patterns will help to develop accurate predictive models to use in AVs, which will help AVs interact safely and comfortably with cyclists in conflict scenarios.

3.2.2 Aim

This paper aims to provide a descriptive statistical model of cyclists' behavior when interacting with automated vehicles at unsignalized intersections. In this regard, this paper aims to extract cyclists' behavioral patterns during the interaction using statistical terms.

3.2.3 Methods

A bike simulator was used to collect data from participants riding through an intersection similar to the one from the ND data collection. Twenty-seven participants were instructed to pass through the intersection several times. The environment was shown to the participants by a virtual reality headset. A car was shown approaching from the right side of the intersection (from the cyclist's perspective), and the participant needed to decide what to do. The effects of the DTA at the intersection and the field of view (FOV) distance on the cyclists' response process were investigated. Participants filled out a questionnaire after the experiment to record their experience regarding the interaction scenario. Data from the simulator's sensors and the questionnaire were used to determine how the cyclists interacted with the AVs and what factors influenced their decision making. A mixed-effect logistic regression model was used to determine the effects of the independent variables on cyclists' decision whether to cross the intersection first. Cyclists' speed profiles were modeled using an arctan function to compare the average profiles across different trials.

3.2.4 Results

Data from 25 participants were analyzed. Most cyclists followed a consistent sequence of actions as they approached the intersection, and this sequence was influenced by changes in the independent variables. Among the independent variables that were tested in the model, only the DTA affected the cyclists' decision to cross the intersection first. The sooner the cyclists arrived at the intersection relative to the car (higher DTA), the more likely they were to cross the intersection first. When cyclists' average speed profiles were compared, the results showed that the greater the FOV distance, the sooner the cyclists noticed the vehicle—with a smoother speed profile (in terms of deceleration rate). Participants mentioned in the questionnaires that the lack of communication and eye contact with the driver made them ride more cautiously.

3.2.5 Conclusions

The DTA was shown to have the most influence on the cyclists' behavior. On the other hand, their behavior was also affected by the fact that the vehicle was driverless, which caused them to act conservatively. Incorporating surrogate methods for communication with AVs may facilitate their acceptance by the cyclists in the future. Furthermore, more visibility benefits the cyclists to adapt their speed earlier and have smoother speed profiles. This finding holds significance for intersection design, confirming the importance of visibility to mitigate the severity of conflicts.

4 Discussion

4.1 Cyclists' interactions with motorized vehicles: influencing factors and behavioral patterns

Crossings are a common place for the occurrence of conflicts between motorized vehicles and cyclists. The subject intersection is unsignalized and governed by priority rules. According to Swedish traffic rules, the vehicle should give priority to the cyclist at this type of intersection (which has a dedicated cycling path), while cyclists should be aware of their surroundings and pass through the intersection carefully. However, in practice, motorized vehicles do not always give priority to cyclists, and both road users need to negotiate who crosses the intersection first.

Different conflict scenarios can occur between cyclists and motorized vehicles at crossings. The most common are 'vehicle turning right versus cyclist going straight' and 'vehicle going straight versus cyclist going straight' [41]. Different parameters can influence the outcome, including aspects of infrastructure design, road users' kinematics, demographics, and road users' characteristics. The three studies conducted in this thesis were intended to capture the effect of different variables on the interaction outcome between the cyclist and the vehicle. The finding that the variables affecting the outcome the most are DTA and visibility confirms the results of previous studies [9, 33]. We may conclude that the significant variables in these two studies are the most important parameters affecting the interaction. However, this conclusion needs to be confirmed by analyzing data from different locations.

Kinematics play a major role in the interactions between cyclists and motorized vehicles, as is evident from both previous results and those from the studies in this thesis [33, 42]. The developed logistic model in PAPER I uses three kinematic variables: cyclist speed, vehicle speed, and DTA. It is worth pointing out that the effect size of the kinematic variables in this paper was larger than the effect size of the variables related to the cyclists' visual information. Relying on kinematics alone, we can predict cyclists' decision making, but the prediction can be further improved by considering cyclists' visual information. In PAPER II, the DTA was found to significantly affect the cyclists' decision to cross the intersection first.

Road users use both implicit and explicit communication strategies to proceed with their path in traffic and interact with other road users. Current automated driving functions mostly rely on the kinematics of other road users to predict their future state. However, recent research has shown the potential of using cyclists' visual information in predicting their intent in traffic [23, 37, 25, 43]. Abadi et al. (2022) proposed a neural network model to estimate the cyclist's crossing intention using body pose and head orientation [25]. In another study, Hemeren et al. (2014) investigated what visual cues are more relevant for predicting a cyclist's future path. They found that cyclist's position, head turn, and speed are the most critical cues for predicting their future path [37]. Grigoropoulos et al. (2022) devised a predictive model that relies only on cyclists' visual information to predict their direction of movement at an intersection [43]. They achieved an acceptable level of accuracy at predicting cyclists' intent at an intersection, establishing the importance of cyclists' visual information in predictive models.

In both studies in this thesis, we also found that cyclists' visual information is relevant for predicting their yielding decision. For instance, our results confirm that head turn is an important signal for crossing decisions, as reported by Abadi et al. and Hemeren et al. (2014). While the primary focus of Grigoropoulos et al. (2022) and Hemeren et al. (2014) is the utilization of cyclists' visual cues to anticipate their travel direction at intersections, their research underscores the crucial role that cyclists' visual information plays in accurately predicting their decision-making process. PAPER I reports that cyclists' pedaling and head turn were significant for predicting who will cross the intersection first. The effect of these two variables conforms to prior expectations—specifically, if cyclists keep pedaling, it is more probable that they are going to cross the intersection before the vehicle. Moreover, if the cyclist turns their head toward the approaching vehicle, it is more likely that the cyclist will cross the intersection first. In PAPER II, the simulator data showed that participants had a consistent sequence of actions as they cycled toward the intersection. Knowing cyclists' behavioral patterns will help predict when they brake or stop pedaling during the interaction. Our studies show that adding extra information from visual cues to the predictive algorithms may lead them to make more accurate predictions of cyclists' behavior, helping improve the safety and comfort of interactions between cyclists and AVs.

Some studies have investigated the role of infrastructural modifications on the outcomes of interactions between cyclists and motorized vehicles. In one instance, Bella & Silvestri (2018) investigated how different countermeasures affect driver control during interactions with cyclists. They used a driving simulator to test the effect of some countermeasures (pavement color and raised islands) on the driver's behavior during the interaction [32]. They concluded that better visibility at the intersection meant that drivers made smoother maneuvers in terms of deceleration rate and slowed down earlier. Another study by Boda et al. (2018) found that the drivers' braking behavior was mainly influenced by visibility at the intersection [9]. Maximizing visibility at intersections would let road users adopt safer strategies for interacting with each other [9].

In this thesis (PAPER II), we observed the effect of visibility on the cyclists' response process at an unsignalized intersection. It was found that increasing the extent of the road that is visible to the cyclists may cause less severe interactions with other road users, since cyclists can spot them earlier and have more time to adopt a safe strategy for the interaction. The cyclists had smoother speed profiles because they decelerated more gradually in the trials with extended visibility. This result validates the findings of Bella & Silvestri (2018) regarding cyclists' earlier speed adjustment when provided with extended visibility. Furthermore, it underscores the significance of visibility by corroborating the research conducted by Boda et al. (2018) concerning the interplay between cyclists and motorized vehicles.

The national association of transportation officials (NACTO) recommends that intersection design should facilitate eye contact between street users, ensuring that motorists, cyclists, and pedestrians intuitively read intersections as shared spaces [44]. NACTO suggests that visibility can be achieved through a variety of design strategies, including intersection "daylighting," low-speed intersection approaches, trim vegetation, and height sigh distances. Gonzalez-Gomez et al. (2022) state that visibility is one of the four key factors affecting roundabout safety [45]. The other three are: approaching drivers, comprehensibility of traffic operations, and adequate space for the largest permitted vehicles.

Given the significance of visibility (highlighted in this study and prior research), urban planners have reason to leverage these findings to craft intersections that prioritize sufficient visibility, thus improving the safety of cyclists. Furthermore, AV developers can apply this knowledge to enhance the design of their systems, so that AVs exhibit more cautious behavior in intersections characterized by restricted visibility.

4.2 Differences of data types: challenges and opportunities

Two different types of data were used in this thesis for analysis and modeling, and each has its own strengths and weaknesses. In the first study, ND data was used to evaluate the interaction events. This type of dataset has the highest possible ecological validity and offers a great possibility to observe road users' behavior [31]. However, the number of events that could be used in this thesis was limited due to the limitations in data collection and resources. As a matter of fact, ND data are subject to many confounding factors as opposed to simulator data that may influence the interaction. To reduce the effects of extraneous factors, an effort was made in this thesis to extract clean interaction events from the ND dataset (with minimal influence from other road users). The next difference is the accuracy of the measurements among the two datasets: the simulator data was more accurate than ND data. The ND data was provided by a single sensor attached to a building, and as the distance from the sensor increased, the measurement accuracy decreased. In contrast, the simulator provided highly accurate data on different aspects of cyclists' behavior, like pedaling and braking.

Simulators provide a more controlled environment compared to ND data sets; this allows to collect data from participants by repeating the same scenario. In addition, we would have more relevant data from the same scenario. Especially in a conflicting scenario like the concerned scenario in this thesis, simulators are a useful tool to investigate human behavior without subjecting them to any harm. However, the extent that the environment in the simulator is ecologically valid should be evaluated in a different study. Even though data collection in simulators is more straightforward than the ND datasets, a significant amount of time should be dedicated to preparing a realistic scenario in the simulators.

In spite of these differences, trends in important factors that affect the interaction events were similar in ND data and simulator data. For instance, the DTA variable influenced the interaction outcome in similar ways in both datasets. However, road users' behavior differed in magnitude in these two datasets; the variety of influencing factors was higher in the ND dataset. This can be attributed to the differences in measurements, subject cyclists, and the environment. In addition, confounding factors, like the effect of other road users' presence, may influence the interaction outcome in the ND dataset. Obtaining the same trends in both datasets gives validity to the results, even though the two datasets have intrinsic differences.

4.3 Implications for traffic safety

Automated driving systems may benefit from the results of this thesis; in-time and accurate predictions about cyclists' behavior can be used to improve the systems' predictive algorithms, leading to safer and more comfortable performance in future traffic. The model developed in PAPER I is only the first step in incorporating cyclists' visual information to predict their intent during the interaction with AVs. AVs can sense and obtain both kinematics and visual information from their on-board sensors to predict cyclists' behavior in conflicting scenarios. Some work has recently been done on how to extract cyclists' visual information from video data that can facilitate the acquisition of this kind of information from in-vehicle sensors [25]. Providing cyclists' visual information for predictive algorithms would enable a safe and comfortable interaction between AVs and cyclists at unsignalized intersections and consequently increase the trust in AVS.

There is a body of research investigating designs of intersections and roundabouts that are safer for cyclists [46]. Most of this work emphasizes dedicated bike lanes and speed control for motorized vehicles [47, 48]. In one paper, Madsen et al. (2017) assessed the implications for cyclists' safety of various geometric configurations for biking tracks at intersections [49]. Visibility, addressed in this thesis, is one of the design elements. Although previous research has demonstrated that restricted visibility significantly increases the risk of accidents between cyclists and motorized vehicles at intersections, the complete impact of this factor remains insufficiently understood [50]. When cyclists and motorized vehicles converge at intersections, reduced visibility obstructs the ability of both parties to anticipate each other's movements and intentions, leading to potential conflicts and collisions. Boda et al. (2018) pointed out that visibility plays a major role in drivers' behavior when interacting with cyclists at unsignalized intersections [9]. In this thesis, we examined the role of visibility on cyclists' response process during that interaction. In PAPER II, it was shown how extended visibility may result in less severe interactions between cyclists and motorized vehicles. The findings of this thesis suggests that by modifying existing intersections and providing proper visibility, we can encourage less dangerous encounters between cyclists and motorized vehicles. Thus, this thesis has advanced the research one step further. Addressing the visibility aspect comprehensively through modifying intersections is a goal for the future which has the potential to significantly reduce the number of severe conflicts between cyclists and motorized vehicles and promote safer coexistence on the roads.

In terms of regulations and policy making, the responsible authorities can enhance cyclists' safety in different ways. According to this thesis (as well as prior literature), the speed of road users stands out as a significant factor influencing interactions between cyclists and motorized vehicles. One obvious response to this knowledge is controlling motorized vehicles' speed, which has a direct impact on other road users' safety as well [47]. Another is to launch educational programs, targeting both cyclists and drivers, to raise awareness about safe practices, right-of-way rules, and the importance of mutual respect. As reported in PAPER I, in 35% of cases vehicles crossed the intersection first even though cyclists had priority. In summary, reducing speed limits and promoting safe practices in traffic through educational programs can both help increase cyclists' safety.

4.4 Limitations

As noted, both datasets used in this thesis have limitations. The number of interaction events in the ND data was limited due to data collection challenges. In addition, finding and annotating interaction events in the ND data set was a time-consuming process that required significant human resources. Furthermore, video annotation in the ND data is subject to personal judgment; we tried to minimize this effect by using multiple annotators. Another limitation in the ND dataset was the accuracy of the data. ND data was collected from one sensor, causing the measured distances to be less accurate for faraway objects. Further, the ND dataset was collected from one location in one country, which makes it hard to generalize the results to the whole population.

The simulator data was collected in an artificial environment, making the interactions less realistic than those in the ND data. There is a need to evaluate to what extent the results from the bike simulator match reality. Unfortunately, some participants had to drop out due to motion sickness; not having motion cues in the bike simulator might be one of the causes. It's important to acknowledge that the data collection for the riding simulator took place during the pandemic, which inevitably had an impact on the number of participants who enrolled in the study. The bike simulator used for this thesis can be greatly improved for future research. In the future, resolving the mentioned issues in this thesis in the bike simulators may help to recreate a more realistic interaction scenario between cyclists and motorized vehicles.

The choice of model to describe the data was mainly limited by the available data. The developed models in this thesis used one instant in time to predict who crosses the intersection first. However, the complete interaction process is usually too complicated to be captured in a single moment; the decision whether to cross or yield is the result of a series of interactions between the two road users. Therefore, a continuous prediction model may be needed. Other variables can also play a role in the interaction outcome, like deceleration rates, which were not evaluated in this thesis due to poor data quality (PAPER I).

Another point is the specific scenario addressed in this study, a cyclist, and a vehicle at right angles, both going straight (Figure 2). Although the selected form of interaction is quite common and risky according to crash records, other forms of interaction also need attention, like a cyclist going straight encountering a vehicle turning right.

4.5 Future work

The models developed in this thesis may help AVs interact safely with cyclists. However, these models should be further developed and trained with other data sources to improve their generalizability. In addition, future work may focus on models that can predict cyclists' yielding decision in real time. Such a model can inform AVs continuously about the cyclists' decision and plan accordingly. The future work planned in PAPER III is to evaluate how different types of drivers interact with cyclists at unsignalized intersections, modeling the cyclists' yielding decision according to the driver type. Preliminary analysis of the ND data showed that expert drivers had riskier interactions with cyclists than non-expert drivers.

So far, the ND dataset has given a holistic view of the interactions between cyclists and motorized vehicles. The cycling simulator data, on the other hand, has given some insights into the cyclists' response process when they interacted with vehicles at the same intersection. What is lacking is the interaction from the driver's perspective. In PAPER IV, we will address this lack by recreating the same interaction scenario using a driving simulator to investigate the driver's behavior.

5 Conclusions

This thesis investigated the interactions between cyclists and motorized vehicles from two data sources. Factors that affect the interaction outcome consisted of cyclists' kinematics and visual information, although the kinematics play the primary role in the interaction process. In both studies, the DTA influenced who crosses the intersection first. The road user who arrives first at the intersection is more likely to cross first, and the likelihood increases with the size of the time gap between the two users. The modeling outputs in this thesis may be used by AV algorithms to predict cyclists' intent in real time at crossings.

From an infrastructure point of view, cycling safety at intersections can be improved in many ways. Dedicated bike lanes are a successful example. Specifically, unsignalized intersections can benefit from other types of modifications to enhance cyclists' safety, like better visibility as reported in this thesis. It was found that providing wider visibility at the intersection may lead to safer interactions between the cyclists and motorized vehicles. This recommendation has implications for city planners, who can increase VRU safety by modifying urban intersection designs accordingly.

This thesis suggests that adding cyclists' visual information to the input for AVs' predictive algorithms may improve their ability to predict the cyclists' future state. Results from the simulator study showed that cyclists followed a consistent sequence of actions as they approached the intersection. Applying this knowledge and improving predictive algorithms will increase the public's trust in AVs and ensure safe and comfortable encounters with cyclists at crossings.

According to the results of the simulator study, in AV interactions, cyclists may need a communication method such as eHMI to compensate for being unable to communicate with a human car driver. The eHMI can help cyclists understand the AV's intent in conflict scenarios. However, the type of eHMI that would be most effective should be investigated in another study.

The focus of this thesis was to describe the interaction process between cyclists and motorized vehicles in statistical terms. The models developed in this thesis should be further trained by larger data sources to increase the generalizability. Future works should focus on investigating drivers' behavior when they encounter cyclists at crossings. In addition, using ND data, we may investigate the interactions with cyclists based on different vehicle types like passenger cars, trucks, and taxis.

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