Quantified Cycling Safety: Towards a Mobile Sensing Platform to Understand Perceived Safety of Cyclists

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Figure 1: We propose to extend data collection methods about cyclists by including body movements, such as head rotations and physiological data. With this we aim to collect and analyze data about hazardous road situations prior to accidents with the goal to improve cycling safety (in contrast to post-hoc police accident reports and cyclists' self-reports).

Abstract

Today's level of cyclists' road safety is primarily estimated using accident reports and self-reported measures. However, the former is focused on post-accident situations and the latter relies on subjective input. In our work, we aim to extend the landscape of cyclists' safety assessment methods via a two-dimensional taxonomy, which covers data source (internal/external) and type of measurement (objective/subjective). Based on this taxonomy, we classify existing methods and present a mobile sensing concept for quantified cycling safety that fills the identified methodological gap by collecting data about body movements and physiological data. Finally, we outline a list of use cases and future research directions within the scope of the proposed taxonomy and sensing concept.

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CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**; • **Computer systems organization** → *Embedded systems*.

Keywords

Cyclist safety taxonomy, on-body sensing, head movements, perceived road safety

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1 Introduction

Over the past years, the interest in cycling as means of transportation for both recreational purposes and daily commuting has increased remarkably [20, 31]. However, even today accident reports [6, 11, 21] still show that cyclists represent a vulnerable road user group at risk. Cycling is often perceived as a dangerous activity, especially in urban areas without a dedicated cycling infrastructure.

Cycling safety is typically reflected in accident reports submitted by the police [21] or it is assessed based on cyclists' subjective responses [2]. Although the latter one provides data without necessarily encountering an accident and the former one reports a dangerous situation post-hoc, both of them rely on subjective assessments of the involved context and parties, such as police staff and officers, cyclists, and other road users. To complement this, in the last decade in-situ observations have started to look objectively at cyclist behavior for example through video recordings [33]. In addition, naturalistic cycling studies started to investigate cycling behavior in the wild using instrumented bicycles, for example, by collecting location/GPS, brake force, inertial measurement, and video data [7, 13, 16, 38]. In our work, we go beyond these established methods by exploring quantified cyclist data sources, e.g., physiological data and body movements, to better understand the perceived safety of cyclists with the goal to improve traffic safety.

The aspect of perceived safety for the cyclist is challenging for many reasons. For one, perceived safety can substantially differ from what objective numbers reflect. For example, an uncontrolled T-intersection can be considered less dangerous based on accident reports, but cyclists might spend a significant amount of time making a crossing decision due to the feeling of danger or uncertainty. The second challenge is the work-intensive evaluation of perceived safety for cyclists. For instance, camera-based observation can provide a correlation with objective factors such as distance to overtaking vehicles, or interviews with cyclists can report on their experiences and name problematic locations [22]. However, these techniques mostly focus on a fairly restricted area and it is tedious to generate a generalized overview.

In this paper, we contribute a two-dimensional taxonomy for assessing cyclists' safety based on (a) the data source (internal vs. external) and (b) the associated type of measurement (objective vs. subjective). Based on this taxonomy, we propose a mobile crowdsourcing approach that aims at identifying dangerous locations which do not (yet) show up in accidents reports but potentially prevent people from using the bike. Our approach fills an identified gap in our taxonomy. Our envisioned crowdsourced dataset based on this approach can inform the selection process for in-depth investigation methods (to improve road segments). In addition, it may serve as input for active cooperative assistance systems between vehicles and bicycles to improve biking safety. We leverage the sensing capabilities of the increasingly dense body-area network to derive information on perceived safety and user behavior from sensor information that can be collected using commodity hardware such as smartwatches or earables [18]. We expect this to serve as input for the design of cycling infrastructure and assistive systems with the overall goal to increase traffic safety and to improve well-being on the road. Finally, we outline a number of use cases applicable for this particular approach and discuss future research directions within the scope of the proposed taxonomy.

2 Background & Related work

In this section we outlined three main pillars of related work which we use to build upon: (1) cyclists assistance systems, (2) perceived safety in urban environments, and (3) mobile crowdsourcing.

2.1 Cyclists assistance systems

In prior work, researchers designed cyclist assistance systems that primarily focus on the data (to be) provided from *external sources* such as other road users broadcasting their position and velocity using vehicle-to-X technology (Car2X, i.e., communication between a car and other vehicles, infrastructure, road users, etc.), or from *internal sources* such as physiological data from sensors placed on the cyclist's body or the bicycle itself [17, 41].

Data collected from external sources can typically be used to provide warnings [23], navigation instructions [19, 25], or traffic behavior recommendations [24]. Communication between other traffic members and infrastructure objects, e.g., traffic lights, is foreseen to be facilitated via Car2X technology [28] using for instance 5G technology. From the perspective of human-computer interaction, this data is typically simulated in controlled experiments in bicycle simulators. One example, however, also demonstrates possibilities of collecting data about environment and providing a feedback to cyclists. For example, Schropp et al. [39] demonstrate a helmet with a head-worn camera to locate and attribute surrounding objects and bone conduction headphones to represent spatial audio notifications.

To collect data from internal data sources researchers employed for instance a method of augmenting existing cycling accessories such as helmets to collect physiological data. Andres et al. [4] augmented a helmet with an EEG system to observe cyclists' neural activity on-the-go and determine when they enter a state of peripheral awareness. Another example includes an augmentation of a bicycle with RGB-D cameras to recognize cyclists' head position and hand gesture to remind child cyclists about safety gestures [26].

This separation between external and internal sources based on the existing methods of data collection assisted us in defining two dimensions in the proposed taxonomy for assessing cyclists' safety, which we describe in details in Section 3. Additionally, in this work, we focus on the human-centered data collection for cyclists and aim to take a step further and explore correlations between implicit head movements and perceived safety.

2.2 Perceived safety in urban environments

Overall, the concept of traffic safety refers to measures which aim to prevent road users from being killed or seriously injured in traffic accidents. The term of perceived safety has different meanings depending on the social context. In the context of urban environments, Carolin Jansson described perceived safety as "a person's subjective feeling" and "an individual's experience of the risk of becoming a victim of crime and disturbance of public order" [15]. However, one has to make a clear distinction between crime-related and traffic safety, with the focus of our work being on the latter aspect. The definition of perception in urban environment provided Ewing and Handy [10] as "the process of attaining awareness or understanding of sensory information" motivates us to explore sensory information of individual cyclists and implicit head movements in attempt to quantify perceived safety in urban environments.

2.3 Mobile Crowdsourcing

The approach of traditional crowdsourcing is to break large tasks into small individual pieces that can be distributed to a large number of human workers to be completed, even without much contextual knowledge [14]. With the prevalence of smartphones equipped with numerous sensors and data connections, mobile crowdsourcing ties the tasks to be executed to a geospatial location [3], and potentially, even a time or timeframe. Monitoring traffic[1] [27] or road conditions is a popular example of mobile crowdsourcing [9, 37].

Additional information on a certain route, e.g., scenic views, might be even more important for cyclists than for car drivers [35] or bus tours [36]. Route-sharing platforms such as Biketastic [34] extend the route information available by adding sensor data on speed, roughness, noise levels, or perceived driving experience [30]. To which detail this additional information can be pushed was explored in Bikenet [8] with a very dense Bike-Area-Network of sensors, including magnetometers to determine the amount of cars driving around, or air quality sensors. A number of the sensors the authors had to install on their research bike is now readily available on commercially available bikes.

Similar to the automatic detection of potholes [9, 29], we aim to determine perceived safety through sensor data from readily available mobile hardware and keep the human in the loop to also assess subjective impressions. For example, a user might assess the quality of the road as poor, even though the automatic detection based on accelerometer data might not react yet [37]. While we also work on sensor data alone, measuring physiological responses inherently integrates the subjective perception of the user.

One problem in mobile crowdsourcing is to achieve an even spatial distribution of completed tasks as it is more likely for a mobile crowdworker to complete a task in a popular area than somewhere remote [32, 40]. This can be addressed by increasing the remuneration for tasks that are in places not well covered, or by using a mobile workforce that already has a good geospatial coverage [1]. More specifically, as mailmen often use a bicycle as means of transportation in urban areas, the approach of using the workforce of the local mail service presented by Acer et al. [1] can potentially also be applied here.

3 A Taxonomy of Methods to Assess Cyclist Safety

By comparing prior work on perceived cycling safety, we identified two dimensions along which existing approaches can be assessed. These complementary dimensions form our taxonomy of methods to assess cyclists' safety (see Figure 2): (1) data source (internal/external) and (2) type of measurement (objective/subjective). The first dimension *"Data source"* is split into *internal*, e.g., body movements, physiological data, and *external data sources*, e.g., traffic cameras, car sensing, GNSS, infrastructure, data sources. Methods positioned on the internal side aim to collect data from an egocentric perspective of a cyclist and while external methods provide data from sources unrelated to cyclists' activities. The second dimension *"Type of measurement"* covers *subjective* and *objective* aspects of the data is measured and assessed. The subjective part includes sources with cyclists', road users', or police officers' subjective estimations while objective methods rely only on quantitative assessments of input data (e.g., from sensors). The proposed dimensions are based on the idea on the qualitative and quantitative nature of data in

[1] for instance using services like Waze (https://www.waze.com/, last access: 2021-02-20)

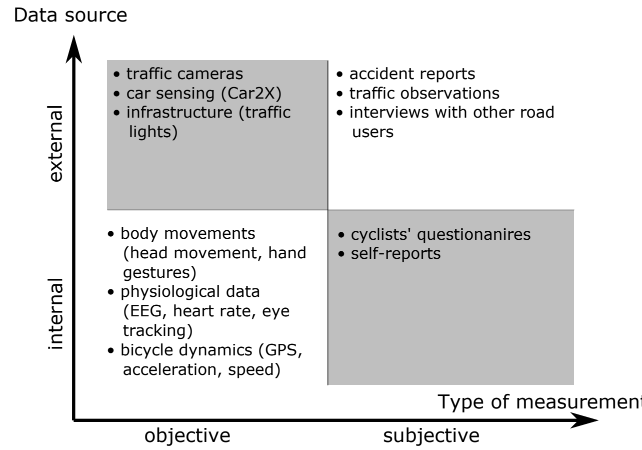

Figure 2: Two-dimensional taxonomy of methods to assess cyclists' safety: data source (internal/external) and type of measurement (objective/subjective).

general and an ego cyclists' perspective, which relies on the data from the outside world (external) and to cyclists and their bicycles (internal) (see Subsection 2.1). We expect that our proposed design space helps future researchers and engineers and assist them in developing technologies and choosing the right methodology for assessing cyclist safety from different perspectives (see Figure 2). In particular, it can lead to new technological advances of tracking cyclists' and bicycle's movements, augmenting helmets with additional physiological sensors, or raise attention in improving road infrastructure, which we lack as an external and quantifiable data source. The quadrants of the proposed taxonomy help to extend the list of methods already presented in the diagram, given that this is a growing and expanding field. We showcase the utility of our proposed taxonomy by presenting a concept in the following section, which is based on body movements and physiological data, and which fills a gap in our design space.

4 Concept: Body Movement & Physiological Data Collection

Smartphones and smartwatches are examples of mobile and wearable devices that many of us use on a daily basis. So-called earables could form a next generation of wearable sensor: These earables are earbuds that do not only provide audio output but also deliver rich sensor input from an inertial measurement unit (IMU) [18]. While IMUs on headphones – so far – were mostly used as custom hardware for audio-augmented reality research, more an more commercial earbuds can report 6 degrees-of-freedom (DOF) from accelerometer and gyroscope data (Google Pixel Buds [12]), and some even 9-DOF, including absolute orientation using a magnetometer (Apple AirPods Pro [5]). In the cycling context, such wearables will allow collecting sensor data to measure the amount of relative head rotation, e.g., as an indicator how much a cyclist looks around. When using earables with an integrated 9-DOF IMU that returns absolute orientation, we can measure the difference between the smartphone in the pocket of the cyclist as a reference for the driving direction and the earbuds. This helps to determine in which direction the cyclist looked, eventually getting an indication which potential elements of interest (e.g., approaching cars or pedestrians) require additional attention. In combination with geolocation, this can be used to create a heat map of where cyclists turn their heads the most. We expect that the number of head rotations correlates with perceived road safety (or level of difficulty of a traffic situation). In combination with other measurements (e.g., speed and acceleration) we expect this information to enable urban planners to identify road segments which require special attention and maybe even remodeling to improve cycling safety.

4.1 Automated mobile crowdsourcing of subjective impressions

Mobile crowdsourcing is a powerful tool to quickly aggregate data with geospatial references. From a user's perspective, the simplest form is a mode of operation that works on sensor data alone and does not require specific attention, such as inferring traffic conditions from GNSS positions [27] or detecting potholes from accelerometer data [9]. However, as mentioned before, the user's perception might differ from an algorithmic interpretation [37]. Including the human in the loop by asking for subjective assessment to complete a certain task does not need to be complex. For instance, it might be sufficient to answer questions, such as "Is the sidewalk clean at this intersection?" or "Is the bench next to you damaged?" [1]. However, this requires active user input which might increase the remuneration needed to achieve an acceptable task completion rate.

Our approach is to collect objective sensor data, which automatically measures the cyclists' physiological responses caused by their individual interpretation of the driving scene. The increasing density of the body area network formed by wearable devices and the increasing amount of sensors in these wearables (e.g., pulse oximeter or IMU) enable us to get more information that can be collected without user-interaction. In the interest of privacy, the interpretation of these body signals should happen on the user's device and only be made available in anonymous and aggregated form. As automatic detection might lead to inconclusive results, a confirmation of results by the user should be considered.

We envision our proposed concept to be particularly useful in situations requiring tedious environmental assessment, which might lead to difficulties in making crossing and turning decisions. In the following section, we outline a couple of use cases in details.

5 Use cases

We derived five use cases based on the accident reports [6, 11, 21] that we considered as challenging for cyclists in terms of decision making and which might require measures to improve perceived safety (see Figure 3). While situations D and E are considered the most dangerous ones for cyclists based on accident reports [6, 11, 21], we also consider situations A-C, which include a comparable level of difficulty, but are typically missed in statistical reports. We present them in details in the following:

Use Case A: To simplify a left turn at a traffic light-protected intersection, some cities implement small waiting areas on the side of the bike lane in order to avoid cyclists having to cross a car lane as in Use Case C). Cyclists in these areas are supposed to cross the streets together with pedestrians. Since they remain closer to the circulating traffic, we assume cyclists in the waiting areas will still turn their head more often to stay aware of the traffic compared to cyclists waiting at the regular halting line just a few meters away. This shows that we also need to take into account whether the cyclist is stationary or moving when interpreting sensor data.

Use Case B: In a situation of obstacles on a shared bus & bike lane, e.g., when a bus stops, the cyclist has to pass the obstacle by entering the car lane temporarily. This requires checking the upcoming traffic from behind prior to the manoeuvre.

Use Case C: Prior to turning left, a cyclist has to change her position within a lane (or even change lanes), which requires turning back to check the traffic behind. After arrival at the appropriate part of the lane, the cyclist has to check for traffic coming from upfront in presence of traffic lights, or even traffic from the left, right, and front in case of an uncontrolled intersection.

Use Case D: A cyclist enters a street by turning left when leaving home. Given the lower priority of the cyclist off-road compared to vehicles on the road, she has to check both left and right traffic directions before entering her lane.

Use Case E: A cyclist is turning left at an uncontrolled intersection. In this situation the cyclist has to check both the traffic from the right to give way and needs to wait until upcoming traffic from the front has passed.

The use cases listed above do not cover all possible situations where our proposed concept is expected to support a detailed analysis, but they showcase exemplary scenarios which can provide a better understanding of perceived safety. Once our prototypical system is implemented, we plan to create routes composed of these use cases in future evaluations to assess our hypothesis of increased head movements as an indication of decreased perceived safety.

6 Future Research Directions

Future research should delve into the exploration and extension of the proposed taxonomy of methods for assessing cyclists' safety, improvements and implementation of the proposed head movement concept, and development of further technical solution. In the following we outline future research directions based on the work presented in this paper.

6.1 Where do we go with the cyclists' safety taxonomy?

We believe that our proposed taxonomy helps in building a more comprehensive picture regarding the data collection focused on cyclists' safety. Unlike common subjective measures, e.g., accident reports and self-reports, the taxonomy points out the necessity of objective data collection and a quantified look at cyclist safety. The quantitative data collection should help identifying hazardous road situations before accidents occur and, therefore, avoid accidents and injured cyclists. Similar to navigation platforms such as Waze and Google Maps which already showcased the benefits for improving services through crowdsourced data collected from readily available sensors with low effort, our proposed crowdsourcing method will help in getting a bigger picture through naturalistic studies and in-the-wild data collections. Admittedly, the primary value of

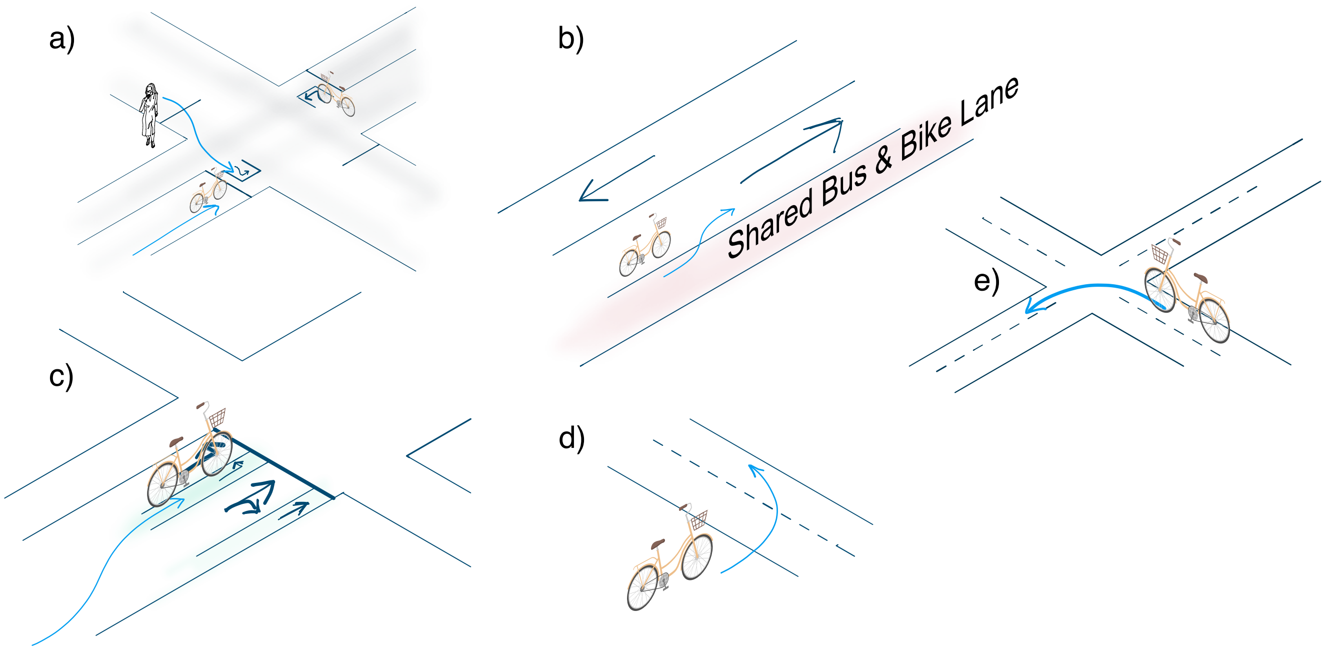

Figure 3: Typical situations with cyclists at risk and a higher amount of head rotation that can be an indicator of unsafety. a) The special left-turn waiting area is close to the ongoing traffic. Thus, waiting cyclists want to stay aware of the traffic. b) An obstacle such as a stopping bus on a shared lane requires the cyclist to merge into traffic on a car lane. c) To reach the dedicated left-turn bike lane the cyclist has to cross a car lane. d) To enter a road by crossing two car lanes the cyclist needs to be aware of traffic in two directions. e) Turning left at an intersection is risky because the car drivers might overlook the cyclist.

the provided taxonomy lies in the awareness of researchers, road planners, and authorities towards safe, green, and sustainable cities.

6.2 Future of the head movement concept

Following the proposed taxonomy and the proposed crowdsourcing approach, we plan to implement a prototype and run a series of experiments with cyclists to test our concept and assess our hypothesis related to the correlation between head movements and perceived road safety. We plan to start with studies in bicycle simulators to ensure safety conditions and collect preliminary empirical evidence for the idea that a decrease in perceived safety leads to increased head movement. With this approach, we extend the technical opportunities of unsupervised data collection for naturalistic studies. Moreover, due to our lightweight approach and easy scalability of the setup, we consider data collection from a series of road situations in field studies, covering different road infrastructures of many cities, weather conditions, and cycling cultures. Cyclists typically avoid roads with a high perceived risk, meaning that if we think about the collection of head movement data as a mobile crowdsourcing task, the most dangerous places for bikers will likely remain blind spots on the map. The risk on a certain road could also be measured by evaluating how large the compensation needs to be for a cyclist to drive along a certain road.

6.3 Future technical solutions

In this work, we showcased one possible technical solution of collecting internal data about cyclists from an objective perspective. The proposed taxonomy allows us to spot gaps in the field of cyclist safety research. This holds especially for collecting data from various physiological sensors, e.g., EEG, heart rate monitors. For example, an increased heart rate might indicate a decreased perceived safety, and EEG data can provide an indication of peripheral awareness [4], where decreased peripheral attention might lead to decreased safety. With future development of Car2X technology, we envision not only receiving safety relevant information from other vehicles and infrastructure, but also sending the cyclists' state and behavior to other road users as an additional safety indicator. Thus, the additional data collected (e.g., body movements and physiological data) can serve as input for novel assistance systems. As an example, we envision an assistance system which informs the driver of a silent electric car about the presence of a cyclist ahead that did not turn his head and, thus, might not be aware of the approaching electric car.

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