Ein Ansatz zur Charakterisierung des Fahrerverhaltens auf Basis naturalistischer Fahrdaten

An Approach to Rider Behavior Profiling based on Naturalistic Riding Data

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Zusammenfassung

Wodurch ähnelt ein Motorradfahrer dem anderen? Welche Charakteristika im Fahrerverhalten oder der daraus resultierenden Fahrzeugdynamik definieren einen bestimmten Fahrstil? Während für das Verhalten von Autofahrern verschiedene Modelle existieren, sind verlässliche Modelle für das Verhalten von Motorradfahrern noch selten. Im Rahmen des Projekts KIMoVe wurde eine naturalistische Fahrstudie (sog. Naturalistic Riding Study) mit N = 37 Testpersonen durchgeführt. Ziel ist es, Parameter zu finden und zu analysieren, die geeignet sind, das Fahrerverhalten Motorradfahrender zu charakterisieren und mögliche Cluster von Fahrern mit gleichen Verhaltensmustern zu finden. Diese Erkenntnisse werden in ein realistisches Fahrerverhaltensmodell in der Fahrsimulationssoftware SILAB® einfließen.

Jeder Teilnehmer absolvierte eine ca. 130 km lange Motorradtour mit einem Messmotorrad im öffentlichen Straßenverkehr. Die aufgezeichneten Daten enthalten CAN-Bus-Informationen, GNSS-Positionierung und ein 360°-Video, angereichert mit Fragebogen- und Interviewdaten. In der Nachbearbeitung werden die Daten mit kartenbasierten Informationen wie z.B. Geschwindigkeitsbegrenzungen ergänzt. Das Videomaterial wird u.a. verwendet, um die laterale Position des Motorrads auf der Straße zu bestimmen und so Informationen über die Wahl der Fahrlinie zu erhalten.

Ein automatisierter, kartenbasierter Segmentierungsalgorithmus wird verwendet, um einen Vergleich der Daten jedes Fahrers innerhalb derselben Kurve zu ermöglichen. Aus diesen Segmenten werden charakteristische Werte abgeleitet und ausgewertet, um (Un-)Ähnlichkeiten zwischen verschiedenen Fahrern in verschiedenen Kurven zu finden. Diese finden sich z.B. im sogenannten Wank-Phasen-Diagramm oder dem Geschwindigkeits-Schräglagen-Diagramm wieder (Feichtinger, 2021). Die vorliegende Arbeit soll tiefere Einblicke in die Analyse des Motorradfahrerverhaltens auf der Grundlage etablierter Theorien, wie z.B. Ajzen's Theory of Planned Behavior (Ajzen, 1991) geben. Es wird die Grundarchitektur eines neuen Fahrerverhaltensmodells (sog. Rider Behavior Model, RBM) vorgestellt und der Forschungsbedarf skizziert, der zur Parametrisierung dieses Modells in zukünftigen Arbeiten notwendig ist. Die potenziellen Anwendungsfelder derartiger Modelle sind vielfältig. Das genauere Verständnis von und die Modellierung des Fahrerverhaltens kann bspw. für die Individualisierung von Fahrzeugabstimmungen, die Fahrerzustandserkennung oder auch die Verkehrssimulation Verwendung finden und somit final zu einer erhöhten Fahrersicherheit beitragen.

Abstract

What makes one motorcycle rider resemble another? What criteria of riding behavior or resulting vehicle dynamics define a certain riding style? Various models on car driver behavior exist, but reliable models of powered two-wheeler rider behavior are still rare. Within the scope of the KIMoVe project, a naturalistic riding study with N = 37 riders was conducted to find and analyze parameters that are suitable for characterizing rider behavior and to find potential clusters of riders sharing behavioral patterns. This knowledge will shape a realistic rider behavior model within the SILAB® driving simulation software.

Each participant drove a measurement motorcycle on public roads for approximately 130 km. The recorded data includes CAN bus information, GNSS positioning and a 360° video, enriched with questionnaire and interview data. In post-processing, the data is complemented with map-based information such as speed limits. The video data is used to identify the motorcycle's lateral position within the road, therefore providing information on each rider's trajectory selection.

An automated, map-based segmentation algorithm is used to allow for a comparison of each rider's data within the same curve. From these segments, characteristic values are derived and evaluated to find (dis)similarities between different riders in different curves. These can be found, for example, in the so-called roll-phase diagram or the speed-lean angle plot (Feichtinger, 2021). This work shall provide deeper insights in the analysis of motorcycle rider behavior based on established theories, such as. Ajzen's Theory of Planned Behavior (Ajzen, 1991). The basic architecture of a new Rider Behavior Model (RBM) is presented and research needs that are necessary to parameterize this model in future works are outlined. The potential applications of such models are manifold. Beyond a better understanding and modelling of rider behavior, the outcomes may then e.g., be used to facilitate individual rider assistance system setting adjustments, rider monitoring or advanced traffic simulation and therefore contribute to enhanced rider safety.

An Approach to Rider Behavior Profiling based on Naturalistic Riding Data

1. Introduction

The disparity in accident and fatality rates between motorcycles and passenger cars remains a significant concern. While the overall trend in traffic fatalities has shown a decline, this reduction is not uniformly distributed across different vehicle types. According to the “Annual statistical report on road safety in the EU, 2024” (European Commission, 2024), in the past decade, motorcycle fatality rates in the EU have not decreased at the same pace (-10%) as those for passenger cars (-25%). In 2022 there were 3,361 motorcycle fatalities in the EU. About one third of which did not involve other vehicles and about one third of which occurred on urban roads. Data from 2021 shows that 92% of that year’s motorcyclist’s fatalities happened on dry roads (European Commission, 2021). These figures suggest that the riders themselves and their individual approach to the road is one important key to safety and preventing casualties.

If we want to investigate the rider's individual contribution to an accident (e.g., loss of control, distraction, choosing the wrong line), we can sometimes rely on accident reconstruction data. Fortunately for the riders, this data is sparse. Unfortunately for us, the data typically does not allow to make assumptions about the intentions of the riders that lead to their ultimately wrong actions. And even if we could make such assumptions, we would have no way of knowing whether these intentions were only temporarily mistaken, or whether they corresponded to the typical behavior of riders who had just been lucky enough to be on the road for a long time without being involved in a crash.

We therefore need to improve our understanding of how and why riders behave as they do in everyday riding situations. Such knowledge could not only help prevent accidents and fatalities, but could also be used, for example, to tailor advanced rider assistance systems (ARAS) to the needs of individual riders or to improve the realism of traffic simulations. In the passenger car domain, there is much more data and models available that relate to driver behavior or distributions of vehicle dynamics characteristics that are likely to be observed in regular driving (e.g., Fries & Fahrenkrog, 2021; Krajzewicz, Kühne, & Wagner, 2004).

For the motorcycle sector, there are many colloquial terms used to describe motorcyclists and to group them so that we can get an idea of their everyday riding 'type'. The following Table 1 is by no means exhaustive, but lists some of the potential characteristics that are often used to differentiate between riders. However, models describing rider behavior mainly concentrate on crash situations or are based on questionnaire data instead of vehicle dynamics data (e.g., Elliott, Baughan, & Sexton, 2007; Sakashita et al., 2014; Vlahogianni, Yannis, & Golias, 2014).

Table 1: Colloquial terms to describe riding styles.

RIDING STYLE:	**PURPOSE OF RIDING:**	**TYPE OF MOTORCYCLE:**	**FREQUENCY OF RIDING:**
Aggressive	Daily Commute	Cruisers	Daily Riders
Relaxed	Recreational	Sport Bikes	Weekend Warriors
Practical	Long-Distance Travel	Touring Bikes	Occasional Riders
Adventurous	Performance	Adventure Bikes	Professional Riders

Even if we accept these arbitrarily chosen characteristics as valid means of grouping motorcyclists into 'types', we still don't know exactly how a 'relaxed' rider will maneuver through a given scenario and how this might differ from a 'practical' rider. And we still don't know how a particular type of rider might be represented in accident statistics. It seems reasonable to assume that a performance-oriented aggressive rider is more likely to be involved in an accident. However, a recreational and occasional rider, on the other hand, may be less physically fit, may lack routine, may be more prone to making mistakes, and so may end up with a comparable or even higher risk.

This paper describes an approach to a modelling architecture that aims to predict the most likely behavior of a rider given a set of individual parameters and scenario conditions. A review of the postulated relations naturally requires larger amounts of data. This need will be highlighted here and the current status of our data collection and evaluation will be illustrated as a basis.

2. Theory development

The following section summarizes the general idea behind the Rider Behavior Model as shown schematically in Figure 1. In order to understand the structure and background, the model is to be built and explained step by step in the following section.

Let's think of a large empty space, where motorcyclists may ride, wherever they want. The vehicle's states are then only limited by a few technical capabilities (e.g., engine power, lean angle clearance, …) that set boundary conditions for observable states. Within those technical boundary conditions, the rider's capabilities of maneuvering the vehicle will have an impact on observable vehicle behavior. For example, an insecure rider might not exceed roll angles greater than some threshold value. An untrained rider might not exceed certain deceleration values. An exhausted rider might lack of the force needed at the handlebar to generate high roll rates. These riders' **capability** limits $\boldsymbol{C}$ are some first predictors to help make assumptions on the vehicle's trajectory, as there are no constraints given by the environment.

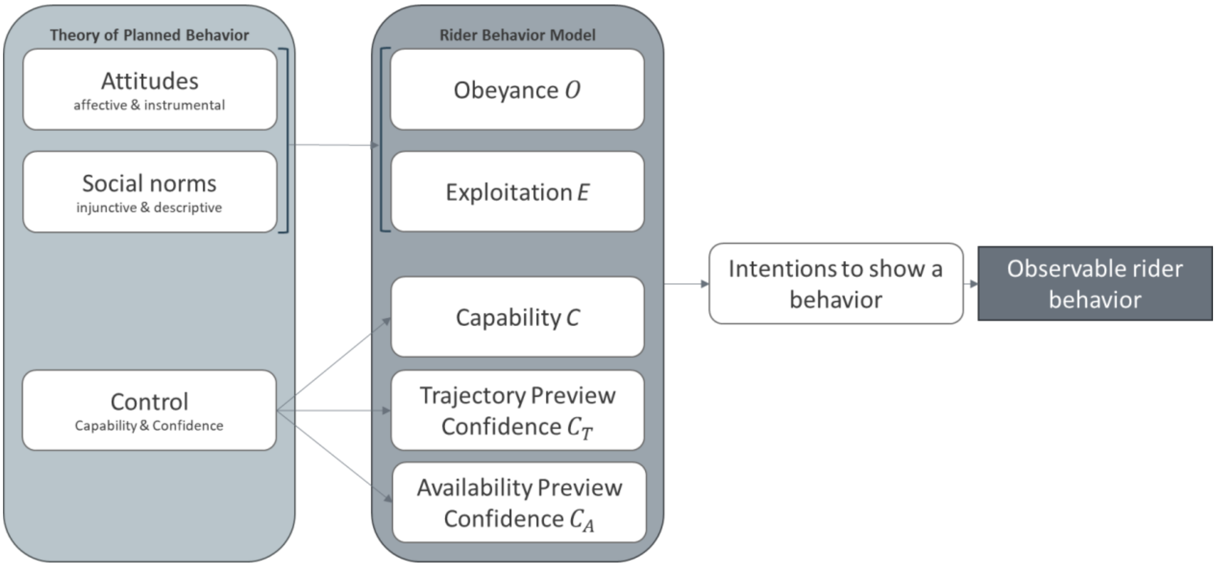

Figure 1: Key elements of the Rider Behavior Model (RBM).

It is also clear that these riders may not always use their abilities to these limits. We assume that it is a matter of personal (more stable trait variable) and temporal preference (rider state) to what extent riders will approach the limits of their ability. In the forthcoming, we will call this the rider's **exploitation $\boldsymbol{E}$.** We assume that both capability C and exploitation E are time-variant due to e.g., rider's fatigue or simply daily mood. Figuratively speaking, one could assume that a rider starting for a weekend trip in one's home territory has a different likelihood of showing higher amounts of exploitation than the same rider after eight hours of touring in an unknown territory.

Getting back to our experiment of thought: as we fill up the abovementioned empty space with a landscape and a road, the previously random trajectory becomes constrained. Now, the rider has to follow a track that is defined within certain limits. Knowledge of these boundaries may be available (think of one's home territory) or not (think of travelling abroad in an unknown territory). We assume that riders have a certain preview distance at their disposal. If the riders have full knowledge about the road width and curvature ahead, they can plan and execute the correct vehicle inputs in order to follow the road within the given limits and within their capabilities.

The top plot in Figure 2 shows a hypothetical road curvature over a preview distance. Ideally, the preview would be unobstructed and error-free. However, it is more likely that along the preview distance the rider's preview and therefore trajectory planning is subject to uncertainties. Some landmarks, such as trees along the road or a view down the valley where the road is going, can help to get a sense of the road ahead even at a distance.

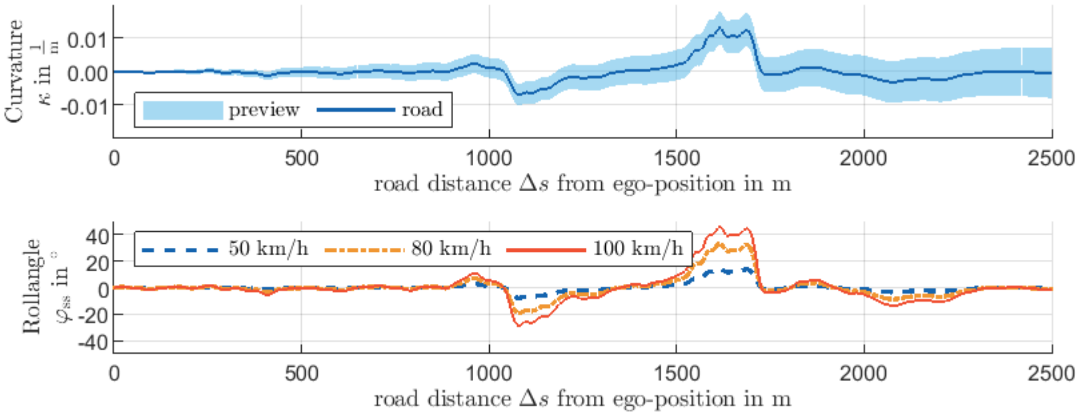

Figure 2: Hypothetical road curvature and preview error (top). Required roll angle at different speeds (bottom).

Yet, a good estimation of the curvature is key to set a proper vehicle speed in time. The lower plot shows, how the curve at a distance of about 1,600 m does only require a maximum roll angle of less than 20° when riding at 50 km/h, but even 30° or 45° at 80 km/h or 100 km/h respectively. If a rider will underestimate the curvature and target a higher velocity, this can easily lead to exceeding one's personal roll angle limit. As time (and distance) goes by, the rider will however gain confidence along the preview distance. We assume that this **confidence in the track preview $\boldsymbol{C_T}$** is essential for the rider's planning of their target speed and target trajectory. If riders are uncertain about the road ahead, they are likely to ride more slowly, giving them more time to learn about the oncoming road and more options for action in the event of a preview error.

Once the route has been determined, the next factor to limit the options for action is the availability of the route ahead. In real life, we must assume, that a given road will not always be fully available for a rider. Dirt, objects, potholes, other traffic participants, etc. will affect a rider's planned trajectory. Since such "disturbances" cannot be learned or plotted on a map, they must be detected by the rider in a timely manner while riding. As mentioned above, this recognition is subject to uncertainties. We therefore introduce the **track availability confidence $\boldsymbol{C_A}$**, which indicates how confident a rider is that the targeted route is accessible without obstacles.

Finally, there is another constraint on the rider's desired speed and trajectory: rules and regulations. These may be immanent as speed limits, right of way regulations, noise limits, or any other externally imposed restriction on the rider's free intentions. However, as with any road user, these rules may be subject to interpretation rather than a strict restriction on the behavior that can be observed. Therefore, we introduce the **obeyance $\boldsymbol{O}$** to describe the rider's motivation to obey rules and regulations more or less strictly.

The above-mentioned factors capability, exploitation, confidences and obeyance reflect motorcycle-specific operationalizations of the well-established Theory of Planned Behavior, introduced by Ajzen (1991). It incorporates his constructs of normative beliefs, subjective norms and control beliefs that form a behavioral intention, which leads to observable behavior. Our approach follows the idea that these factors are key elements of a cost-function that tries to maximize the **thrive $\boldsymbol{T}$**, which we assume as the level of success, self-affirmation, or pleasure, a rider experiences while performing their riding task.

To get a less vague idea of these factors, we can postulate two different examples. It is easy to see that all of the ratings described are subject to individual bias, which must be accounted for as an error in the model.

The examples show, how differently selected factors C, E, C_T and O can manifest into different kinds of rider behavior and therefore different targets for the velocity, lateral offset, roll angle and other dynamic quantities. However, we do not yet know, how – by means of a transfer function or probability distribution – each specific factor is defined and linked to these dynamic quantities.

Rider A is very experienced. She has good control over her bike and likes the thrill of riding fast. However, she is doing a tour in a foreign country in an unfamiliar isolated region. This could result in

- *high obeyance due to unknown foreign regulations*
- *(as) high exploitation (as possible) due to her motivation*
- *generally low trajectory preview confidence as she is riding in a foreign, curvy territory. Higher trajectory preview confidence only in close proximity and for areas with good visibility*
- *high availability preview confidence, as – in her experience – other traffic participants or obstacles are sparse in such isolated regions and there is no obvious reason for sudden changes of road quality, or similar*

Rider B just received his riding license. He needs his bike for commuting to school. This could result in

- *high obeyance, because he wants to keep his new license*
- *low exploitation, as he is still somewhat anxious and lacks the motor skills to control the motorcycle in challenging conditions*
- *low overall preview confidence, due to the lack of experience and cognitive skills (the riding task itself is still quite resource intensive and he cannot rely on a large pool of previous experiences in comparable conditions, etc.)*

Rider B puts a large weight on his confidence in the availability preview confidence. He chooses a trajectory that keeps other road users or obstacles at a distance. Since he is not yet very familiar with his bike, he reduces his speed. This gives him more time for his preview and he will only need small roll angles to match his riding ability.

Quantifying rider behavior

Behavior - literally - is the response of a system to various inputs. In our case, the system of interest is the rider. The inputs are manifold (visual, auditory, vestibular, haptic, etc., sketched orange in Figure 3). It is obvious that motorcycling is dominated by visual input. As of now, however, there exists no definitive answer as to which input has which effect on a rider. From a scientific point of view, one would ideally vary certain predictors in controlled conditions and observe the effects on rider behavior.

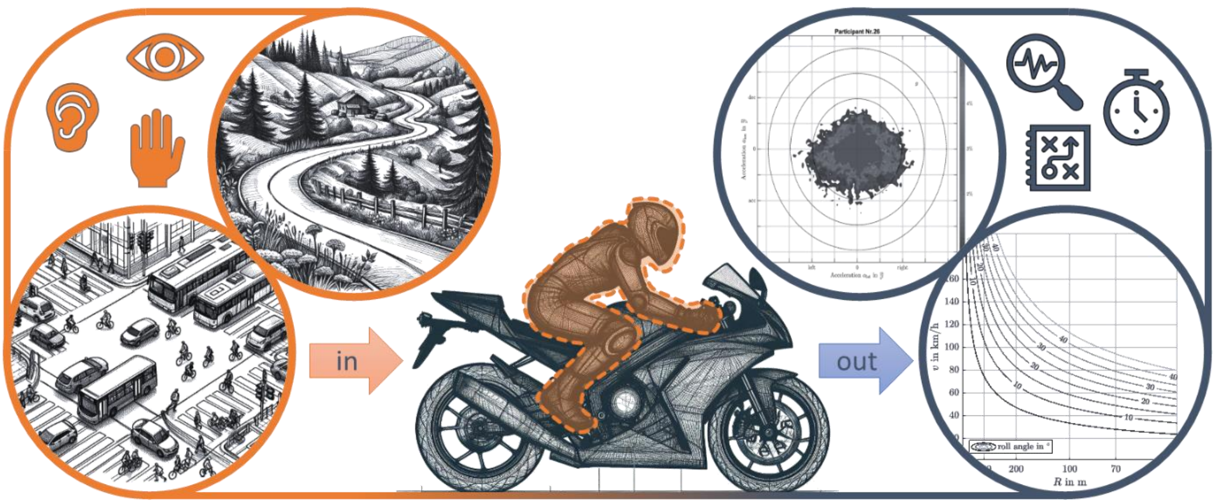

Figure 3: Deriving behavioral patterns from vehicle measurements

As direct effects such as changed muscular tension are complicated to measure and typically unspecific, one must instead rely on vehicle dynamics measurements that manifest these rider behaviors in measurable parameters (sketched blue in Figure 3). In the long term, IMU and GNSS data may be sufficient for this purpose. However, in order to model and parameterize the rider behavior model, it is helpful to use additional vehicle sensor information like throttle or brake inputs, engine revolutions, etc. and to collect video data for enabling scenario interpretation and in-lane tracking.

From the road to a target speed and roll angle

The trajectory of the road is best described by its curvature $\kappa(s)$ over its arc length s. Utilizing formulae for steady state motorcycle dynamics, it is clear that a given curvature will mandate a specific roll angle φ, when travelling at a certain velocity v:

$$\tan(\varphi) = \frac{a_y}{g} = v^2 \cdot \kappa$$

This relation is shown by the colored contour lines in Figure 4, that depicts the radius R of a curve (the inverse of the road curvature $R = 1/\kappa$) on the abscissa and the velocity v on the ordinate of the plot. If a motorcyclist is riding at about 100 km/h they will need about 20° of roll angle if the curves radius is at about 216 m (green dot in Figure 4).

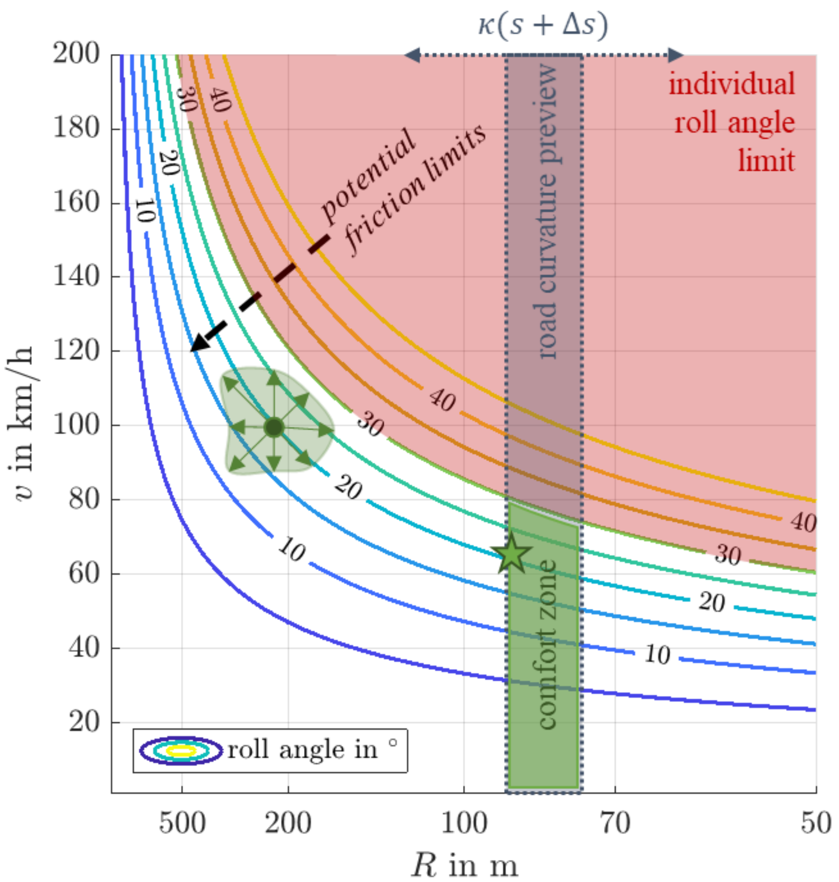

Figure 4: Potential combinations of v, R and phi. Capability limits. Curvature preview and comfort zone. Only one corner direction is depicted. The full plot should have a left and right side that are however symmetrical.

At this state, a rider will have a certain capability of accelerating longitudinally (i.e., throttle and brake) or laterally (i.e., increasing or decreasing the roll angle). This is indicated by small green arrows in the plot and is one potential manifestation of the capability C. A rider will have a certain preview about the oncoming road. At a distance Δs along the road, the rider may observe an increase in road curvature. However, since the road has a certain width, there is some room to adjust the exact curvature needed. This is shown as the wide, dashed blue strip. The street's course will mandate the rider to timely arrive within this corridor, if the rider wants to stay on the road. The position and width of the blue strip is relatable to the trajectory preview confidence C_T. It is now up to the rider's planning and motivation to target a specific suitable combination of velocity (ordinate) and roll angle (iso-lines) for the oncoming road curve. This target combination (green star in Figure 4) will lie somewhere within the curvature preview strip and typically below the rider's individual roll angle limit indicated as *comfort zone* (Scherer et al., 2021). Within this zone, the other model predictors, such as exploitation, may influence the final desired state.

Within the distance Δs the rider must now act to change from the current state (green dot) to the target state (green star). We assume that there are more or less likely paths, a rider will perform, depending on their individual attitudes, beliefs in social norms and their behavioral control, which are manifested in their capability, exploitation, preview confidences and obeyance.

3. Methods: Naturalistic Riding Study

To better understand rider behavior and to link it to potentially relevant predictors from the model, it is necessary to observe rider behavior under naturalistic conditions. Therefore, a naturalistic riding study was conducted with the aim of gathering rider behavior data still under rather controlled conditions. The motorcycle and the test route were kept constant in order to maximize the probability that observable differences are attributable to rider behavior. This procedure has been based on previous studies in this domain (Will et al., 2019).

Participant sample

The study has been approved by WIVW's group in charge for ethical assessment. The strict ethical guideline as defined in the standard operating procedures based on the Guidelines for Safeguarding Good Research Practice of the German Research Foundation (DFG) as well as the Code of Professional Ethics of the German Association of Psychologists (bdp) and the German Psychological Society (DGPs) has been followed.

A total of N = 37 riders participated in the study. Two riders were female. The sample covered a wide range of age and riding experience as can be seen in Table 2. All participants were holding a valid motorcycle driver's license class A.

Table 2: Participant sample characteristics.

	MEAN	***STANDARD DEVIATION***	***MINIMUM***	***MAXIMUM***
Age in years	45	14	22	68
Motorcycle mileage in the last 12 months in km	5,942	5,810	200	30,000
Motorcycle mileage in the lifetime in km	120,137	143,716	1,500	750,000

Study procedure

The data acquisition for this study took place between September and November 2023. All participants were welcomed and provided with an informed consent document containing all necessary information about the study. The participants then completed the Motorcycle Rider Behavior Questionnaire (MRBQ), a questionnaire on demographic data and a questionnaire tailored to the study purpose. The latter included Likert scales on items relating to specific behaviors (e.g., I pay attention to fuel consumption. I always obey the Highway Code. I always stay on my intended line in bends, etc.). The next step was to explain the measurement motorcycle and the test route. The instruction was to ride in their natural behavior at their own pace.

The test route started and ended at the WIVW facilities and covered a distance of approximately 130 km (Figure 5 left). It took about two hours to complete that course. The test route included different types of roads and environments, from urban to motorway, from worn out country roads to modern asphalt. All participants rode the same KTM 790 Duke measurement motorcycle equipped with a SILAB® based data acquisition system in a top case (Figure 5 right). GNSS data, CAN bus data (including 5-axis IMU) and video data from an Insta360 X3 were recorded. Route information was provided by a motorcycle navigation system and discussed with each participant prior to the ride.

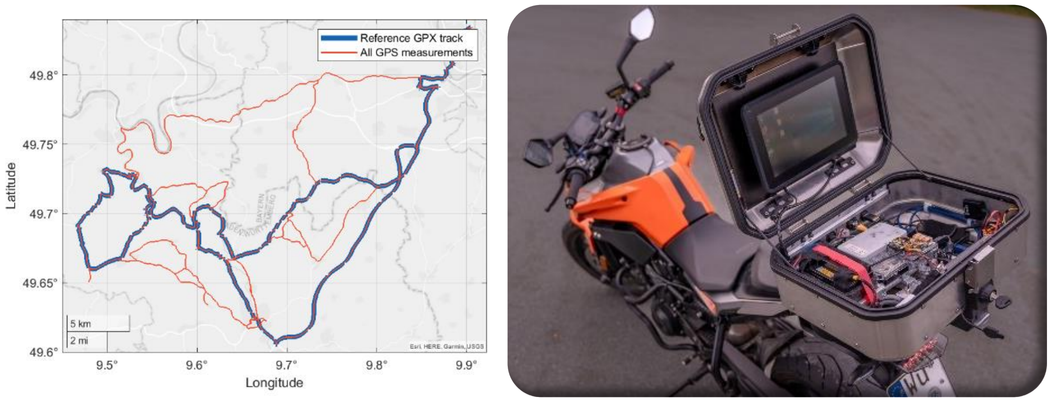

Figure 5: Target route of the naturalistic riding study & measurement motorcycle (KTM 790 Duke)

In a few cases, the participants did not take the target route because they misunderstood the information provided by the navigation system or because of road works that prevented the use of the desired roads. Figure 5 shows the target route (blue line) and each participant's (de-)tour tracks (dashed red lines). After completion of the test ride, the riders filled in a follow-up survey. This focused on their current wellbeing, motivation and how they had experienced the test ride (e.g., getting used to an unknown vehicle or disruptions during the ride). At the end of the appointment, all riders received an expense allowance for their participation.

Data Processing and Evaluations

The aforementioned study generated about 10 GB of ASCII-encoded measurement data files including GPS and vehicle BUS information as well as 4 TB of video data. In postprocessing, we added publicly available weather data of a weather station close to the target route, as well as the sun's azimuth and elevation with respect to the motorcycle's GPS position.

Wherever available, we added meta-data from open-street-maps (OSM, 2024), like speed limits or road conditions through a map matching query in the Valhalla routing engine (Valhalla, 2024). Missing data and outliers were manually added or corrected based on the available video data.

The synchronization of the video data is based on a pseudo-random binary noise sound-signal that was generated by SILAB (blue line in Figure 6) and provided to one channel of the camera's stereo microphone input. Via cross-correlation of the target signal and the volume of each video file, any video frame can be attributed to a specific sample of the measurement data.

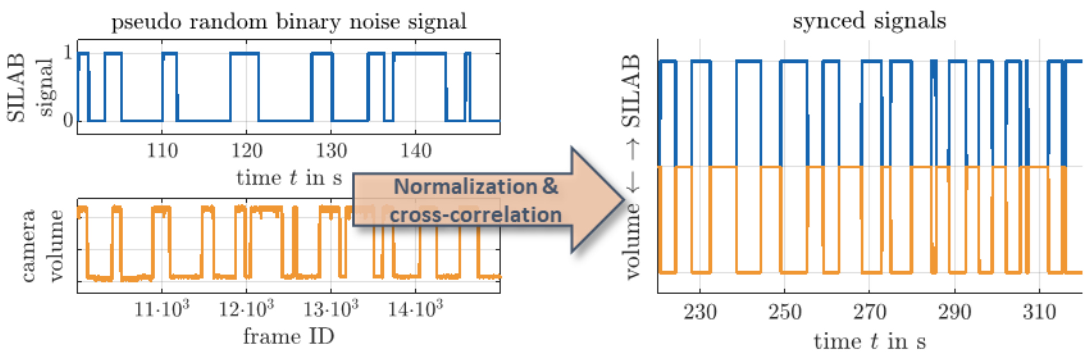

Figure 6: Synchronization of video frames and measurement samples via cross correlation of the sound signal.

The 360° camera was fixed on a steering mount and was placed vertically above the front wheel. The ego-lane positioning is based on a classical algorithmic approach, utilizing a canny-edge-filter and Hough-transformation to find road markings, while the ego position is determined by finding the frontmost position of the bright orange fender via a hue filter. As sketched in Figure 6, we estimate the road width at the ego position from the rectified and horizonted image that is provided from the camera export. Then, the normalized ego-position between the left road marking (-1) and right road marking (+1) is saved in the according data sample.

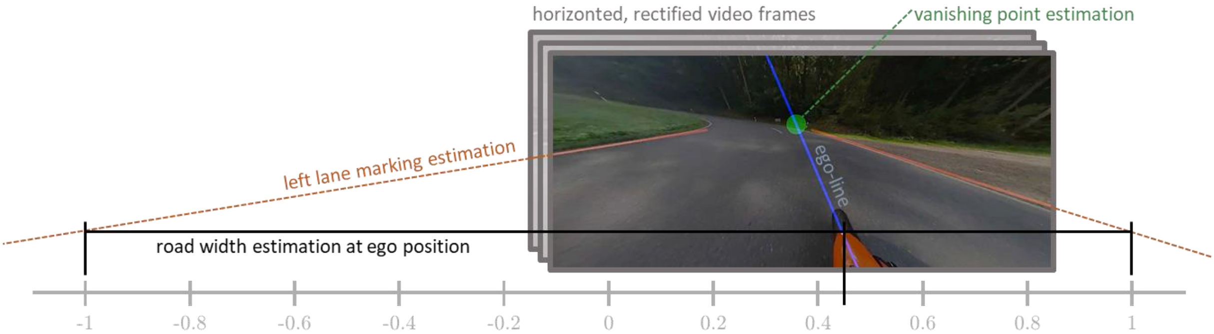

Figure 7: Algorithmic ego-lane-position tracking

In order to allow for the statistical evaluation of the riding data, we segmented all datasets as follows: The segmentation algorithm takes the map data of the target route as an input. From that data, the road curvature is estimated. Single segments are cut at every sign change of that curvature. Then, only such segments, that span over a minimum threshold distance (10 m) and cornering angle (10°) are kept for further investigation.

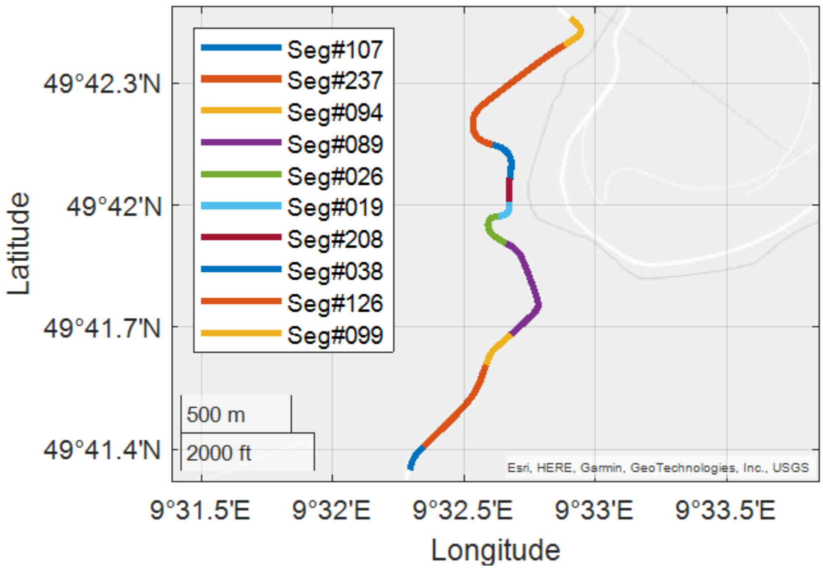

Figure 8: Detected curve segments for an exemplar section of the target route.

The process results in a set of $N_C = 256$ curve segments along the target route. To each of these segments, we assign the measured data of each participant by finding the closest match in the individual GPS trajectories. This allows to compare each individual rider's data at the same point on the road.

In a first evaluation effort, we targeted four analysis methods that have shown promising results in other studies. Firstly, we evaluated so-called ***g-g* histograms** that allow us to get an overview of the overall dynamics of a certain rider (Will et al., 2020). It is expected that they are indicative for e.g., components of the rider's capability or exploitation, as they show both acceleration limits as well as their empirical frequency during a ride. Secondly, we took interest into the so-called **roll-phase diagrams** that were introduced in Scherer et al. (2021) and show the motorcycle's roll rate over the roll angle for a specific cornering segment. This allows to easily observe the maximum roll angle and the steadiness of how this roll angle was achieved. It is expected, that they are indicative for e.g., capability factors, but also might show potential course corrections that could be a sign of errors in the rider's preview. Thirdly, we analyzed **speed-lean diagrams** (Feichtinger, 2021) for the cornering segments. They provide an easy insight, if and how a rider will brake into or accelerate out of a curve. Lastly, we evaluated the **ego-lane-positions** that resulted from the video material according to the abovementioned process.

4. Results

The main aim of the following results section is the presentation of data analysis concepts in relation to the Rider Behavior Model. This is achieved by selecting prototypical examples rather than evaluating the entire sample.

G-g-histograms

The two plots in Figure 9 show the horizontal longitudinal and lateral accelerations that two participants achieved during their ride. The color indicates the frequency with which a data sample was measured at a certain combination of longitudinal and lateral acceleration. The data contains only such samples that were measured on roads with official speed limits between 50 km/h and 100 km/h. As a result of, for example, track availability or different levels of obeyance, the observed speeds may cover a wider range.

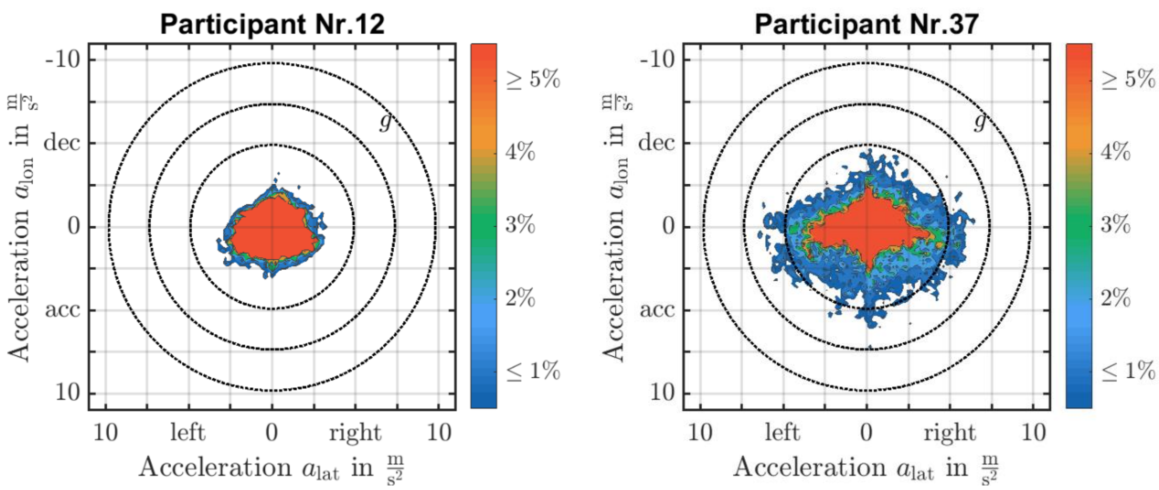

Figure 9: G-g-histograms of two different riders containing samples of all roads across the target route with speed-limits between 50 km/h and 100 km/h.

It can be seen that the two plots differ greatly in the area they cover. Participant 37 reaches much higher lateral accelerations than participant 12. This can be seen as an indicator of higher (roll angle) capabilities. At the same time, we see that - while participant no. 37 is capable of high roll angles - the rider does not approach these limits very often, which might indicate a smaller exploitation value. On the contrary, participant 12 seems to be less capable but more motivated to exploit the individual limits. Turning back to Figure 4, we assume, that the values and their cumulative frequencies observed for each rider can serve well to estimate the potential vertical movement of the ego state (green dot) along the roll iso-lines as well as the likelihood of approaching a certain maximum iso-line.

Speed-lean-diagrams

In addition to this information, the speed-lean-diagrams provide insight in how a rider might switch between the roll-iso-lines while adjusting the speed. Figure 10 shows a set of plots that all depict the identical cornering segment from different participants. In this case, the segment is a tight left curve that spans over almost 180°. The lines show the velocity on the abscissa and roll angle on the ordinate of each plot. A time information is provided through color coding of the lines, ranging from blue (first sample in the segment) to red (last sample in the segment). For better readability, the labels are only provided for one plot, but all plots are scaled identically.

In most occurrences, the lines show a 'V'-shaped pattern that is slightly tilted clockwise, with the signal running counterclockwise (from blue to red). It can be seen, how the roll angle increases, as the velocity decreases. The rate $\frac{dv}{|d\varphi|}$ seems to indicate a more "sportive" ride, as the rider will brake more heavily into a curve and accelerate more heavily out of the curve while simultaneously building up or decreasing the roll angle. Participant Nr. 16, for instance, shows a rather vertical 'I' shape that results from following traffic rather than riding freely. Participant Nr. 36 struggles with a leading vehicle as well, but overtakes it directly after the apex, which becomes well observable in the vertical decline and diagonal incline of the ‘V’. Furthermore, it can be seen, that smaller openings of the ‘V’ often align with wet roads. Only in few occurrences, the signal runs clockwise, indicating some kind of hesitation to accelerate out of the curve. For participant 5, this can be explained by worse track conditions (wet & shadowy) at the end of the curve compared to its entry (dry & sunny). At this stage, the interpretation shows the importance of the video data to avoid misleading explanations.

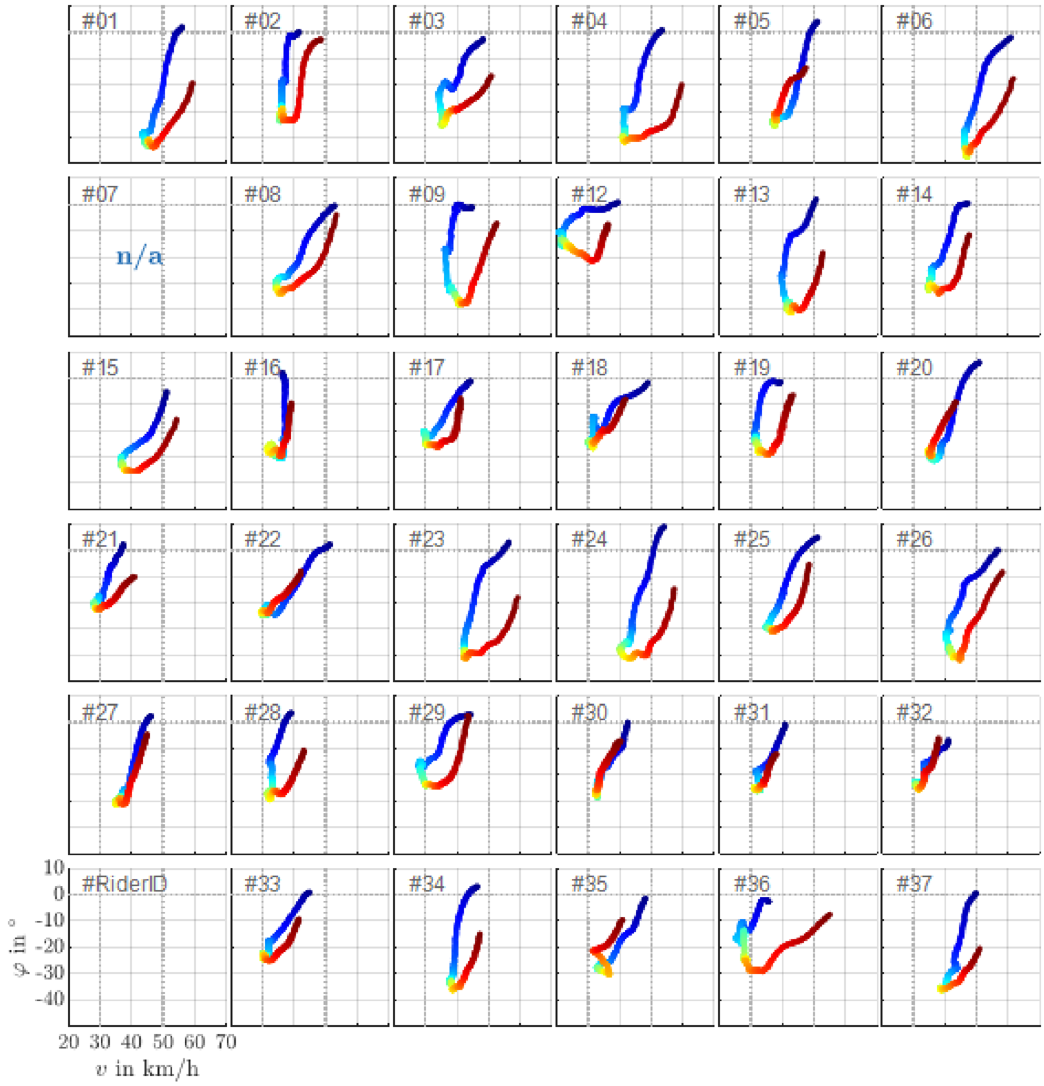

Figure 10: Speed-lean-diagrams from 34 riders for one identical corner segment

Evaluating these data for different classes of curves might allow a better estimation of the movement of the ego-state in Figure 4. We are therefore looking for patterns in the tilt and opening of the shapes during unbiased rides.

Roll-phase diagrams

The following set of plots shows data samples from the same cornering segment and generally follows the same layout presented in Figure 10. However, Figure 11 relates the roll angle to the roll rate rather than the vehicle speed.

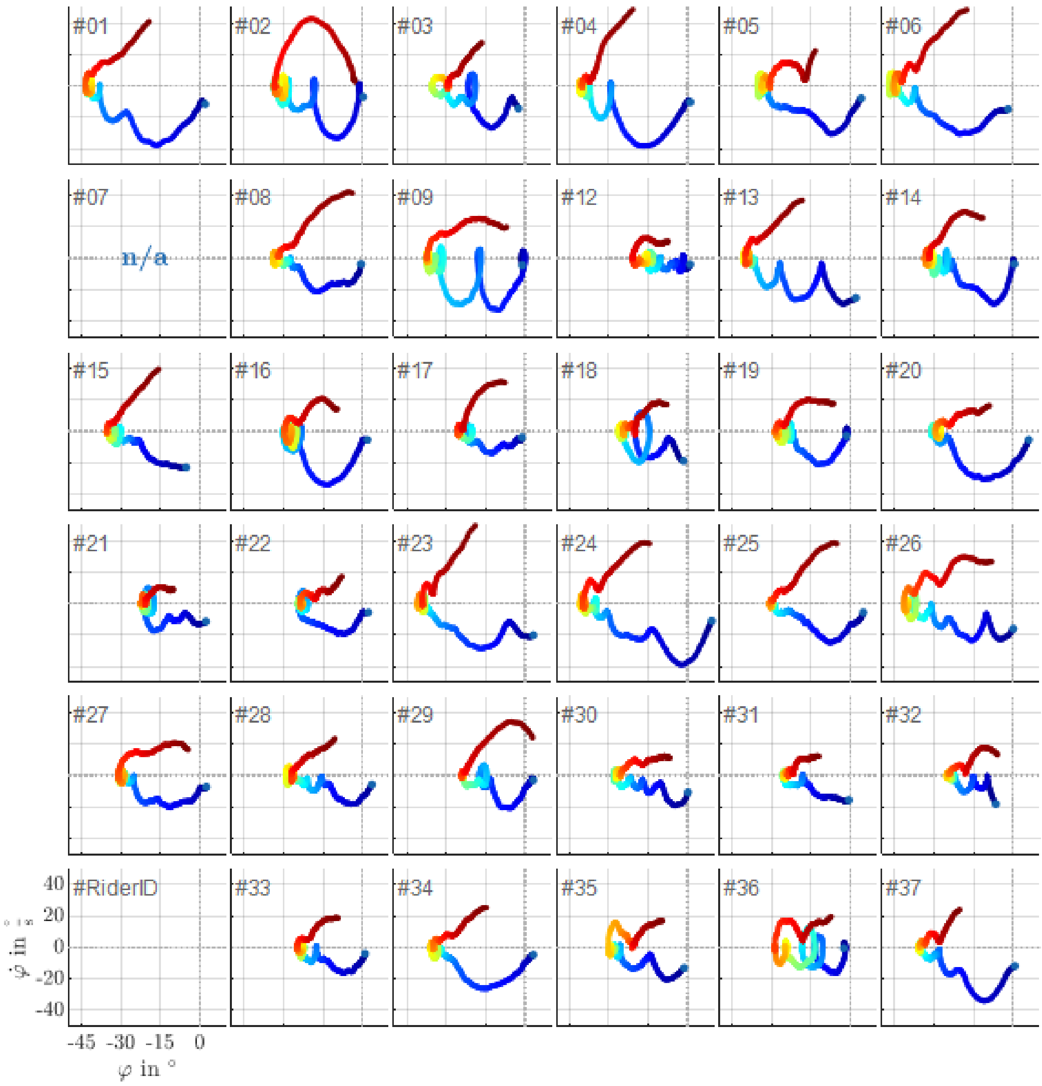

Figure 11: Roll-phase diagrams from 34 riders for one identical corner segment

The roll-phase diagram must always be read clockwise, as negative roll rates will always produce more negative roll angles and vice versa. The set of graphs immediately shows clear qualitative differences as some riders appear to be 'curling' towards their maximum roll angle. This shows how these riders will not target and achieve this maximum in a steady manner, but rather they will dip into the curve step by step, typically indicating some sense of insecurity or lack of deliberation. Extreme cases can be seen, for example, in participant no. 18, who not only stops, but actually reverses the rolling motion when turning in. Video analysis shows a clear course correction in this case, as the rider enters the curve much too early. Rider no. 36, who overtook at the apex of the corner, also shows several corrections, possibly influenced by the traffic ahead. Participant no. 29, who also shows positive roll rates in the run-up to the apex, makes a line correction due to oncoming traffic in the opposite lane. On the other hand, we find instances where the roll phase diagram is less curly and shows only a clear oval shape, indicating a more controlled cornering manoeuvre. It can be seen that different RBM model predictors can influence the occurrence of this diagram (e.g. track availability, capability, etc.).

Ego-lane-tracking

Lastly, we investigated the participants' lateral offset during cornering based on the previously described, camera-based ego-lane-tracking. Figure 12 shows the results of this method for 16 participants within an identical cornering segment. The vertical tick-lines show distances of 50 meters.

The segment is a quick left bend, but in the plots, each line is projected on a straight road for better readability of the lateral offset. We can see that every depicted rider shows a tendency to cut the corner. Especially participants no. 8 and 12 tend far towards the left side of the road. This distinct behavior is also observable in many other segments from rider 12.

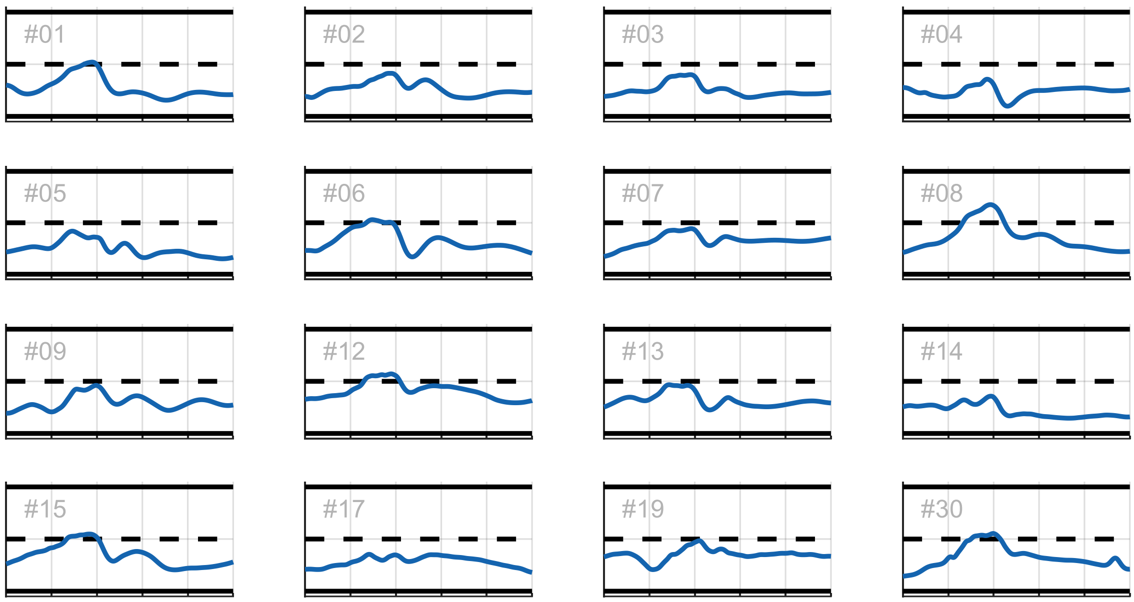

Figure 12: Ego-lane-tracking data based on algorithmic lane detection of a 360° camera

Participant no. 19 elaborates the entry into the bend by shifting to the outside before aiming for a late apex in the middle of the road, which is also clearly visible in the video file. It can be seen that the participants approach different end positions within their lane as they exit the corner. Participants no. 7 and 19 clearly tend towards the middle of the road, while e.g., participants no. 5 and 14 tend towards the right side of the road. Both riders no. 4 and 6 come close to the outside line of the road at the end of the bend and then quickly move back to the center line.

All these different manifestations of line crossing could be attributed to individual behavioral patterns. For example, crossing the center line might imply lower obeyance values for that rider. Course corrections might indicate issues with the rider's preview or - if the rider is known for seldomly needing course corrections - reactions e.g., to opposing traffic. Identifying these stable patterns is an important next step.

5. Discussion & Outlook

This paper presented an approach to a modelling architecture for a motorcycle Rider Behavior Model that is based on the four factors capability, exploitation, obeyance and preview confidence. The benefits of such a model are manifold, particularly in the context of increased safety for motorcyclists. In order to achieve this, it is essential to increase our knowledge and understanding of how and why a rider ends up in an accident, moving beyond reliance on accident data alone.

Accordingly, a naturalistic riding study was devised and executed, yielding a substantial quantity of telemetry-related, GNSS-, video- and meta-data. The primary objective is to reduce the data complexity and condense it into meaningful, interpretable values that facilitate statistical evaluation across different riders, road segments, and environments. It is only through the application of such values that it will be possible for either human or artificial intelligence to identify and correlate clusters, for example with subjective rider evaluations or other forms of annotation. It is evident that the presented study represents merely the initial phase of a prolonged journey to ascertain the optimal model structure and parameterization. The presented naturalistic riding study is limited in sample size and there are issues with requiring participants to use an unfamiliar motorcycle. Furthermore, the measuring setup (a heavy top case and a visible camera setup) and the mode of navigation might cause biased behavior among the participants. In a future study, it would be preferable to allow participants to choose their preferred mode of navigation and ride with their own familiar motorcycle.

The overall data evaluation is struggling with the lack positioning accuracy of standard GPS. We expect vast improvements in that area in a reasonable short amount of time. Even within the KIMoVe project, we aim to develop a telemetry device designed to precisely capture vehicle dynamics data by integrating high-precision GNSS for centimeter-level positioning accuracy. The device will also measure acceleration and roll angles along all three spatial axes, enabling efficient and precise data analysis through reliable data recording at high sampling rates and high-speed transmission.

The foreseeable improvements on localization sensor technology might eventually enable an in-lane tracking of the rider, meaning that the individual driving line will be evaluable. As of now, we try this by analyzing video data. The algorithmic approach presented above shows limitations, that we currently try to overcome with an AI-based approach utilizing Cross Layer Refinement Networks (CLRNet). However, with the learnings from this study, we'd reiterate on both hard- and software concepts for the camera setup. Aside from the in-lane tracking, the 360° camera prove valuable as it provided a multitude of information regarding both environment and rider, enabling us to bring reason to many of the previously shown curve evaluation plots. In order to increase the efficiency of this process, again, AI methods promise to be helpful, as they could annotate e.g. the existence of other traffic participants. Lastly, similar information might become available with the increased implementation of environmental sensors in modern motorcycles.

The selected segmentation algorithm is designed to facilitate location-synchronous data evaluation between different riders. Moreover, it enables the correlation of the location of the road's apex with that of the apex actually ridden. However, the entire process is contingent upon the accuracy of the map and GNSS data, which can be improved upon. Alternative approaches that perform the segmentation based on individual telemetry data may prove superior in terms of defined start- and end-points of a segment (e.g., at zero roll), but may present challenges when normalizing the data over a specific road segment.

Another area of interest is the relationship between subjectively assessed behavior and objectively observable behavior. A preliminary analysis of the data suggests potential issues with the self-assessment capabilities of some participants.

In order to gain a deeper understanding of the similarities and diversity of motorcycle rider behavior, it is essential to obtain more representative naturalistic riding data. This would in turn facilitate the identification of appropriate and promising countermeasures to the still high number of crashes. However, in order to identify outliers in riding behavior from normal behavior, it is first necessary to have a solid understanding of what normal riding actually is.

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Map data copyrighted OpenStreetMap contributors and available from https://www.openstreetmap.org

7. References

Ajzen, I. (1991). The Theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Elliott, M. A., Baughan, C. J., & Sexton, B. F. (2007). Errors and violations in relation to motorcyclists' crash risk. *Accident Analysis & Prevention, 39*(3), 491-499.

European Commission. (2021). *Facts and Figures Motorcyclist and moped riders.* Brussels: European Road Safety Observatory. European Commission, Directorate General for Transport.

European Commission. (2024). *Annual statistical report on road safety in the EU, 2024*. Brussels: European Road Safety Observatory, European Commission, Directorate general for Transport.

Feichtinger, C. (2021). *Racebike Dynamics* (Vol. 9). Graz: Verlag der Technischen Universität Graz.

Fries, A., & Fahrenkrog, F. (2021, 21-22 September 2021). *Validation and verification of the stochastic cognitive driver model.* Paper presented at the ACIMobility Summit, Braunschweig, Germany.

Krajzewicz, D., Kühne, R., & Wagner, P. (2004, 24-25 March 2003). *A Car Driver's Cognition Model.* Paper presented at the Proceedings of Intelligent Transportation Systems Safety and Security Conference, CD, ITS Safety and Security Conference, Miami, USA.

Sakashita, C., Senserrick, T., Lo, S., Boufous, S., De Rome, L., & Ivers, R. (2014). The Motorcycle Rider Behavior Questionnaire: Psychometric properties and application amongst novice riders in Australia. *Transportation Research Part F: Traffic Psychology and Behaviour, 22*, 126-139. doi:https://doi.org/10.1016/j.trf.2013.10.005

Scherer, F., Winner, H., Pleß, R., Will, S., Neukum, A., Stanglmayr, M., . . . Prokop, G. (2021). *Schräglagenangst* (Bundesanstalt für Straßenwesen Ed. Vol. F142). Bremen: Carl Schünemann Verlag,.

Vlahogianni, E. I., Yannis, G., & Golias, J. C. (2014). Detecting powered-two-wheeler incidents from high resolution naturalistic data. *Transportation Research Part F: Traffic Psychology and Behaviour, 22*, 86-95. doi:https://doi.org/10.1016/j.trf.2013.11.002

Will, S., Metz, B., Hammer, T., Pleß, R., Mörbe, M., Henzler, M., & Harnischmacher, F. (2020). Relation between riding pleasure and vehicle dynamics - Results from a motorcycle field test. *Applied Ergonomics, 90*, 1-9. doi:10.1016/j.apergo.2020.103231

Will, S., Mörbe, M., Metz, B., Henzler, M., Hammer, T., Matschl, G., & Harnischmacher, F. (2019). *Methodological Considerations about Motorcycle Naturalistic Riding Investigations - an On-road Study on Rider Fatigue*. Paper presented at the 8th International Symposium on Naturalistic Driving Research (NDRS), Melbourne, Australia.

OpenStreetMap contributors (2024).
Planet dump. Retrieced from https://planet.openstreetmap.org

Valhalla (2024).
https://valhalla.github.io/valhalla/