Model-Based Prediction of Two-Wheelers

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***Abstract*— The breakthrough of intelligent vehicles will also be determined by the safety gain they provide. In order to perform accident avoiding reactions at the earliest point in time possible, predictions about the future behavior of other traffic participants are needed. The most exposed share of traffic participants regarding this issue are single-track two-wheelers (1T2W): they share the road with cars and trucks but are not as agile due to their kinematics. Furthermore, they are faster than pedestrians but comparably vulnerable as those.**

In order to guarantee their safety, we make use of their movement restricting kinematics. We simulate three typical classes of 1T2W under conservative assumptions about their agility in order to generate a spatial region in which they have to be due to physics after a fixed prediction horizon of up to 1.5 seconds. The proposed approach was verified in experiments with real high-dynamic driving maneuvers.

***Index Terms*— prediction, safety, cyclist**

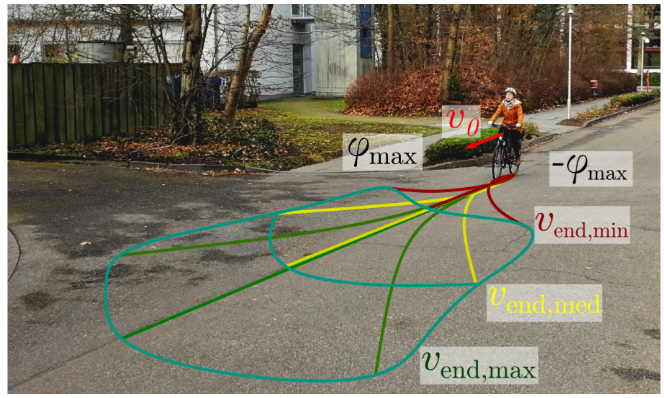

Fig. 1: A cyclist on an unstructured road. Possible trajectories for observation $o_t = (\varphi_t, \ddot{\varphi}_t, v_{x,t}, \dot{\psi}_t)$ are simulated with different parameter combinations $s_{i,j} = (v_{\text{end},i}, \varphi_{\max,j})$. The end points of the simulations determine the region (petrol) inside of which the cyclist has to be after a fixed time span.

I. Introduction

Increasing safety not only for vehicle occupants but also for Vulnerable Road Users (VRUs) is promised when arguing about the benefit of intelligent vehicles in urban traffic. Whilst close attention regarding traffic safety is payed to pedestrians, actually bicycles, motorcycles, and an increasing fleet of motorized scooters – subsumed as single-track two-wheelers (1T2W)[1] – make up nearly two thirds of VRU fatalities and casualties. Furthermore, the number of fatalities and injuries of two-wheelers tends to increase while the number of pedestrian fatalities and injuries tends to decrease in Germany [1].

In order to avoid accidents between automated vehicles and VRUs, it is required to correctly detect, track and predict them. Predicting VRUs is a particularly difficult task, because they obey traffic rules far less than two-track vehicles which in many cases can be predicted along lanes. In this paper, we propose a method to predict two-wheelers based on a dynamic model which is combined with worst-case assumptions about the kinematic variables. It results in boundary points of a geometric space where the 1T2W has to be due to physics after a defined period of time, often referred to as „reachable set".

In comparison to pedestrians, 1T2W are significantly faster and due to their kinematics [2]–[4] less flexible regarding quick changes of direction. In comparison to a two-track four-wheeler (e.g. car, bus, truck) for which the kinematic single-track model [5] (commonly referred to as bicycle model) approximately represents the dynamics, the 1T2W has only one degree of freedom (DoF)[2]. The rider or a controller can choose either the steering angle or the acceleration force, and has to adopt one to the other in order to keep the vehicle in a stable, upright position. With the kinematic single-track model as it is used for cars, speed and steering angle can be chosen independently to a great extent. Those disadvantages – 1 DoF, higher speed compared to pedestrian, combined with protection gear rather comparable to those of pedestrians than to the bodywork of a car – make two-wheelers the most vulnerable share of VRUs.

In our work, we refer to the vehicle model developed by Riekert *et al.*[5] as single-track model and to the models which include a roll angle as bicycle model.

The contribution of this work is to make use of a kinematic model of a generalized single-track two-wheeler in order to generate a geometric space where the 1T2W has to be inside of after a small prediction horizon of up to 1.5 seconds. Originally, this model was developed for control of autonomous riderless motorbikes by Zhang [6]. We describe two common models and evaluate our prediction on real world data recorded in an unstructured environment with three common parameter combinations: Cyclist, motorcyclist and motorized scooter. The approach can be used as a single-shot approach, if conservative assumptions about the current state of the 1T2W are made.

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[1] This scales to trikes (3T3W), cars (2T4W) and excludes self-balancing scooters such as Segways (2T2W).

[2] Technically, it has two DoF and one nonholonomic constraint for the roll angle, namely $|\varphi| < \varphi_{\max}$.

II. Related Work

While many researchers focused on VRU safety as a demarcated problem [7]–[10], only few publications tackle the problem of cyclist prediction. We did not find any publication tackling two-wheeler safety by making use of their unique kinematics.

Jia *et al.* [11] found the necessity of developing a specialized model for cyclist crash prediction from the viewpoint of a heavy goods vehicle after testing a collision avoidance system [12].

Zernetsch *et al.* [13] applied an artificial neural network (ANN) to the task of cyclist prediction and compared it against a Kalman Filter (KF) and a 1-D kinetic approach in which they fit the unknown parameters to recorded data of 566 cyclist tracks. Both the ANN and the kinetic model outperform the baseline KF for prediction horizons between 0.5 and 2.5 seconds.

Pool *et al.* [14] trained the parameters of a probabilistic single Gaussian and a Gaussian mixture linear dynamic system with data of 108 cyclists which they recorded with a mobile platform. They tuned the linear models based on 5 common driving directions (straight, half right, half left, right and left) of cyclists in their dataset. This dataset was also used by Saleh *et al.* [15] who trained a bidirectional recurrent ANN to predict future trajectory points of cyclists without an underlying vehicle model. In [7], Kooij *et al.* proposed a generic probabilistic prediction approach based on Switching Linear Dynamical Systems that can be fit to several types of traffic participants. They validated their approach with the example of pedestrian and cyclist prediction. Zernetsch *et al.* [10] used a dataset with 1,311 cyclist trajectories at an urban intersection in order to train an ANN to predict future waypoints with uncertainty. Xiong *et al.* [9] compared the predictions of VRUs with different recurrent ANNs in image coordinates. Pool *et al.* [16] presented a recurrent ANN that predicts the future position of cyclists as a 2D Gaussian. The model is trained with high level context information extracted from 51 cyclist tracks.

Further work was done in the classification of cyclist starting behavior at intersections [8], [17]–[20].

Besides the basic equilibrium of forces in longitudinal direction proposed by Zernetsch *et al.* [13], no approach makes use of the unique physical characteristics of cyclists. Furthermore, there is no generic safety approach that tackles all kind of 1T2W and we cannot find any publication that approaches the well-known problem of motorbike safety or the increasing problem of motorized scooter safety from the third party viewpoint of an intelligent vehicle.

III. Proposed Approach

A. Goal

In this work, we propose to use a kinematic model for 1T2W in order to obtain a novel safety approach customized for the most endangered group of traffic participants: cyclists, motorcyclists and motorized scooter riders. Due to the kinematics of a 1T2W, the area it can reach in a limited prediction time span Δt_{pred} of a few seconds is confined. With some assumptions about the possible maneuvers of the 1T2W it is possible to derive the boundaries of this area. An automated vehicle can then ensure safety similarly to the Responsibility Sensitive Safety (RSS) approach proposed in a white paper by Shalev-Shwartz *et al.*[21]. Position prediction is assumed to be a two-dimensional problem. Those 1T2W our approach is supposed to predict are assumed to drive normally[3] but not necessarily traffic rule compliant.

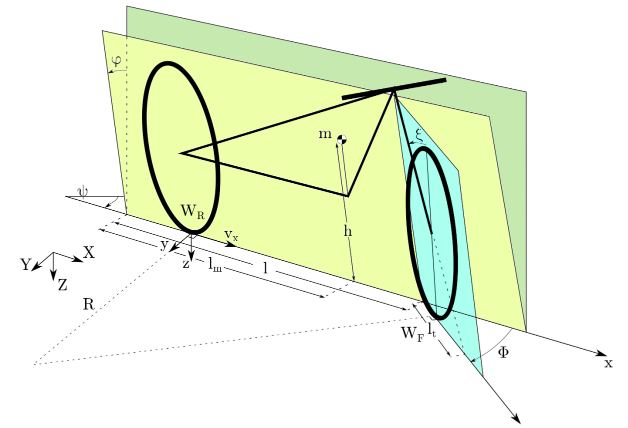


Fig. 2: Sketch of the mathematical model for single-track two-wheelers.

We consider an unstructured environment according to 3.7.2. in [21] in order to get the most conservative estimation of future positions. Let t_0 be the current point in time. Let $\mathcal{T}_{a,t_1}$ be a set of two-dimensional trajectories of a 1T2W and let $\mathcal{T}_{e,t_1}$ be the set of possible trajectories of the ego vehicle until $t_1 = t_0 + \Delta t_{\text{pred}}$. The planning module of the ego vehicle is aware of $\mathcal{T}_{e,t_1}$ and at time t_0 it has chosen a certain trajectory $\tau_{e,t_0} \in \mathcal{T}_{e,t_1}$ but it is not necessarily the same for each t_0. Following definition 21 in [21], the ego vehicle knows the occupied region $\mathcal{T}_{e,\text{brake},t_1}$ furthest away on the possible trajectories which it would still reach if it conducted an emergency braking maneuver at t_0. According to definition 22, a situation is safe, if

1) one of the traffic participants can come to a full stop in order to avoid a crash or
2) both can come to a full stop without crashing.

The most conservative estimate would be to not expect the cyclist to react to the ego vehicle, therefore the second case lapses and the first case can be formulated as $\mathcal{T}_{a,t_1} \cap \mathcal{T}_{e,\text{brake},t_1} = \emptyset$ and $\mathcal{T}_{a,t_1} \cap \mathcal{T}_{e,t_1} \neq \emptyset$. Our approach can be seen as a proposal on how to calculate $\mathcal{T}_{a,t_1}$ for single-track two-wheelers.

B. Generic Prediction Model for Single-Track Two-Wheelers

In literature, two kinematic models are frequently applied. The first was introduced by Getz [4], the second was developed by Zhang [6]. Both model the rider and the bike as a combined mass above and between both wheels (see

[3] I.e. non-acrobatically, even though the kinematic model would allow it.

Fig. 2). The state of each model can be described by two variables, roll angle φ between the plane in upright position and the frame of the bike, and velocity v_x of the rear wheel's ground contact point W_R. Neither of them is considering the wheels as bodies of a multi body system. The only effect of the wheels that is considered is the nonholonomic constraint given by the wheel-ground interaction: A wheel-ground contact point cannot move perpendicular to its velocity vector. The intersection of the lines perpendicular to the contact points W_R and W_F between wheels and ground determine the instant center of rotation if the roll movement is not considered.

The difference between both models is the consideration of a caster angle between the upright z-axis and the axis of the steering joint ξ. The kinematic equation derived by Getz [4]

$$h\ddot{\varphi} = g\sin\varphi + ((1 + h\dot{\psi}\frac{\sin\varphi}{v})v\dot{\psi} + l_m\ddot{\psi})\cos\varphi \quad (1)$$

solved for $\ddot{\psi}$ and sorted for $\dot{\psi}$ yields to

$$\ddot{\psi} = -\dot{\psi}^2\frac{h}{l_m}\sin\varphi - \dot{\psi}\frac{1}{l_m}v + \frac{h}{l_m}\frac{\ddot{\varphi}}{\cos\varphi} - \frac{g}{l_m}\tan\varphi \quad (2)$$

where ψ is the angle relative to a world fixed reference frame, h is the height of center of gravity (CoG) and l_m is the distance between W_R and CoG.

We find the equivalent equation for a kinematic model with caster angle ξ according to Zhang [6]

$$\begin{aligned} &\frac{l_m h\sigma}{l}\dot{v}_x\cos\varphi + h\dot{v}_y\cos\varphi + h^2\ddot{\varphi} \\ &+\Big(1 - \frac{h\sigma}{l}\sin\varphi\Big)\frac{h\sigma\cos\varphi}{l}v_x^2 \\ &-g\Big(h\sin\varphi + \frac{l_t l_m\cos\xi}{l}\sigma\cos\varphi\Big) \\ &= -\frac{l_m h}{l}v_x\dot{\sigma}\cos\varphi \end{aligned} \quad (3)$$

where $\dot{v}_{x/y}$ are the accelerations of W_R, l_t is the trail, $\sigma = l/R$ is the kinematic steering variable and l is the distance between W_R and W_F.

The side slip velocity v_y contributes to the kinetic energy in the Lagrangian and yields to the second term in eq. 3, which equals zero, since side slip is neglected. As in eq. 1, the steering angle σ shall be determined implicitly. Therefore, it is substituted with

$$\sigma = l\dot{\psi}\frac{1}{v_x} \quad (4)$$

which yields to

$$\begin{aligned} \ddot{\psi} =& \dot{\psi}^2\Big(\frac{h}{l_m}\sin\varphi\Big) \\ &+ \dot{\psi}\Big(\frac{g l_t\cos\xi}{h}\frac{1}{v_x} - \frac{1}{l_m}v_x\Big) \\ &+ \frac{1}{l_m}\Big(g\tan\varphi - h\frac{\ddot{\varphi}}{\cos\varphi}\Big) \end{aligned} \quad (5)$$

after some transformations. The terms are separated for constants (h, l_m, l_t, ξ, g) and time dependent variables (v_x, φ).

If an observation $o_t = (\varphi_t, \ddot{\varphi}_t, v_{x,t}, \dot{\psi}_t)$ is given, this differential equation can be evaluated by assuming the worst case steering maneuvers represented by $\varphi(t)$ and $v_x(t)$ for $t \in [0, \Delta t_\mathrm{pred}]$.

In order to get a differential equation that is only depending on derivatives of ψ, we define worst case speed and roll angle profiles. Therefore, we make similar deliberations like those used in Zernetsch *et al.* [13]. For each pair of observation o_t and parameter combination $s_{i,j} = (v_{\mathrm{end},i}, \varphi_{\mathrm{max},j})$ at time step t_a, we run a simulation with eq. 5 and obtain an end position $p_{t_a,i}$. For each simulation, a differentiable velocity profile and roll angle profile is designed. Instead of those profiles, a controller could be implemented. For a probabilistic treatment, an Unscented Kalman Filter (UKF) [22] can be used.

C. Boundary Models

1) Velocity Profile: The current speed of the 1T2W is assumed to be given. It can be estimated for all tracked vehicles. If our approach is used in a single-shot application, the speed can be measured with two radars which are mounted with a horizontal offset. The maximum absolute deceleration is determined either with the stiction margin or by geometry, therefore braking maneuvers in which the rear wheel (due to uplifting) or the front wheel (due to transition from stiction to dry friction) looses stiction are not considered. According to a literature survey [23][4] the usual braking deceleration with antilock braking system (ABS) at both wheels can be 0.642 - 0.842 g. Therefore, the maximum absolute deceleration is $a_\mathrm{brake} = -\min(g\frac{l-l_m}{h}, 0.7g)$ with $g = 9.81\frac{m}{s^2}$. To simulate a braking maneuver of the 1T2W, we assume a_brake until it stops starting from the current speed v_0 which leads to $v_\mathrm{decel}(t) = a_\mathrm{brake}t + v_0$.

For the acceleration, we assume convergence to an estimated end speed v_end which could be the physical limit of the 1T2W, that is around 40 km/h in case of a bicycle, 25 km/h for a restricted motorized scooter, or the current speed limit plus a safety margin of +20% of the speed limit for motorcycles. Furthermore, the maximum acceleration a_max is limited by the torque of the vehicle or the rider, respectively. The resulting speed profile in case of maximum acceleration is given as

$$v_\mathrm{accel}(t) = v_\mathrm{end}\cdot\tanh\left(\frac{a_\mathrm{max}}{v_\mathrm{end}}t - \mathrm{arctanh}\left(\frac{v_0}{v_\mathrm{end}}\right)\right). \quad (6)$$

2) Roll Angle: The current roll angle φ_0 is assumed to be given. It could be derived from a lidar point cloud, or it could be estimated directly from the trajectory of the 1T2W: The local curvature R can be estimated from the trajectory. With inserting the relation $\dot{\psi} = v_x/R$ into eq.

[4]This is a non-reviewed online secondary reference. For one of the primary references, see e.g. Dunn *et al.*[24].

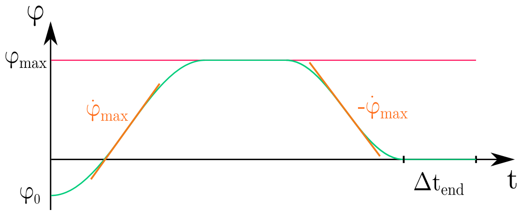


Fig. 3: Schematic roll angle profile between φ_0, $\varphi_{\max}$ and $0°$.

5 and assuming initial conditions for $\ddot{\psi}$ and $\ddot{\varphi}$, ϕ can be calculated numerically. However, in this work we focus on the prediction concept only.

Assuming φ_0 is given, we form a differentiable profile which consists of shifted cosines and straight lines. It connects the initial roll angle φ_0 with the maximum roll angle $\varphi_{\max}$. In order to increasing realism for simulations with a standstill, we introduce an end phase of $\Delta t_{\text{end}} = 0.3s$ for which the 1T2W keeps a roll angle of $0°$ in case of $v_{\text{end}} = 0$.

$|\varphi_{\max}|$ can be up to $45°$ for motorcycles. According to our measurements, bicycles have a roll angle of up to $27°$, motorized scooters can reach up to $25°$.

IV. Results and Evaluation

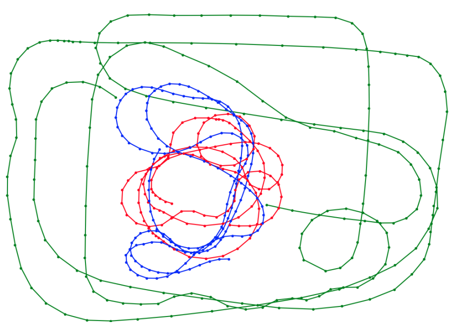


Fig. 5: Trajectories of cyclist (red), motorcyclist (green) and scooter (blue) on an empty square of size 60 m times 90 m. Dots highlight actual measurements.

A. Experimental Setup

TABLE I: Parameters used for simulation.

		Bicycle	**Motorbike**	**Scooter**
	Model	FIXIE Inc. Floater	Suzuki GSF600 '94	Voi Voiager 2
l	in m	0.82	1.15	0.70
l_m	in m	0.42	0.60	0.40
l_t	in m	0.20	0.40	0.15
h	in m	1.10	0.65	0.80
ξ	in °	15	25	5

For evaluation, we recorded a bicycle, a motorbike and a motorized scooter for 2-3 minutes on an empty, unstructured square as shown in Fig. 5. The riders were instructed to perform „extreme“ driving maneuvers, especially tight curves with a large roll angle, harsh braking and acceleration both during straight rides and curves. The three riders are not professionals but experienced. Therefore, we do not claim that they reached the physical limit of the ride nor of the wheels. Still we are confident that we obtained data of maneuvers which are considered extreme if performed in normal traffic.

We recorded the sequences with a Velodyne HDL64S2 mounted on a stationary platform. We labeled those three sequences with 2 Hz by making use of our 3D label tool PointAtMe [25]. In contrast to an IMU mounted to the ride, the annotator can label the actual roll angle from W_{R} to CoG. For the bicycle and the motorized scooter an IMU might yield to significant errors.

B. Results and Discussion

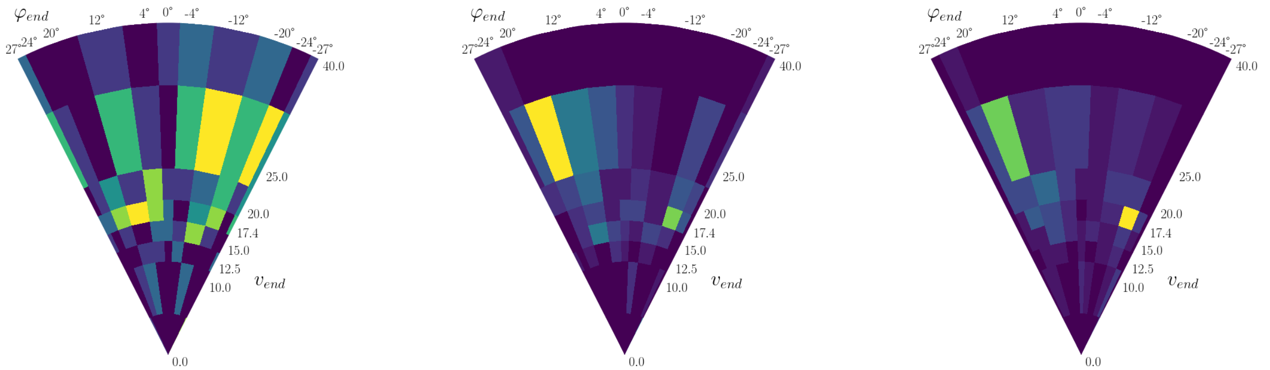
According to RSS, safety in a situation with an intelligent vehicle and a S2TW can be guaranteed, if the automated vehicle can avoid entering the future trajectories of the other traffic participant with a velocity $v_{\text{enter}} \neq 0$. In order to evaluate our approach we need to check if the 1T2W stays within the generated convex trajectory hull for all time steps. The hull needs to be generated for each time step, so the shape of this hull is unique for each observation o_{t_a}. For each corresponding observation $o_{t_a+\Delta t_{\text{pred}}}$ after the current observation, we now choose the simulated end position $p_{t_a,i,j}$ closest and add one counter to the corresponding bin $s_{i,j}$ in the histogram.

In Fig. 4 the results are visualized in circular histograms for three different prediction horizons. In simulation, the specified ticks on the axes of the histograms are used for v_{end} and $\varphi_{\max}$, respectively. The specific distribution in the center of each histogram does not correspond to the validity of the model but the specific distribution at the edge does. If the counters for edge cases are high (yellow), the simulation might be not conservative enough.

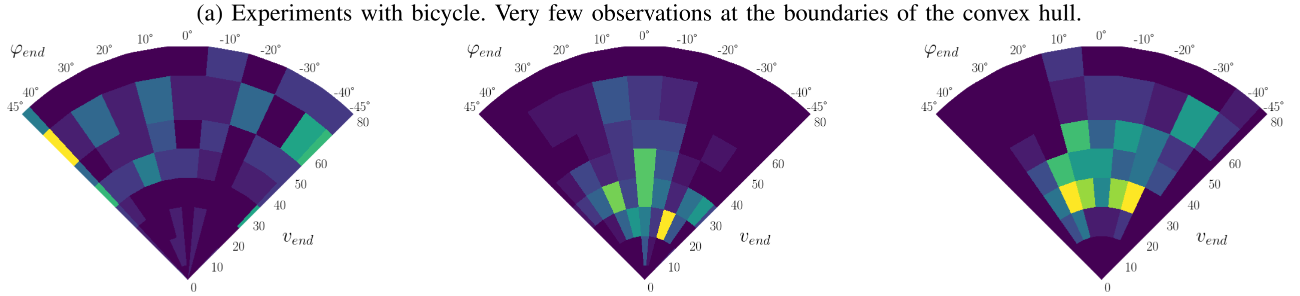
The result matches the expectations. The rear wheel of the ride is in the middle of the convex hull for nearly all observations. The few points which are outside have a distance to the convex hull of up to 0.15 m which is below the spatial expansion of a 1T2W. For $\Delta t_{\text{pred}} = 0.5s$ the convex hull is extremely small, therefore there are a couple of outliers outside of the hull. This might be due to the limitations of the model regarding its assumptions about fixed CoG, neglected radius of the tyre (flat disc assumption), neglected slip and due to uncertainties in the measurements and labeling process. For a prediction horizon of $\Delta t_{\text{pred}} = 0.5s$ many measurements are rather close to the boundaries of the histograms, especially to the roll angle boundaries. A specified parameterization adapted to the recorded data for each prediction horizon might lead to a more robust model.

C. Practical Application

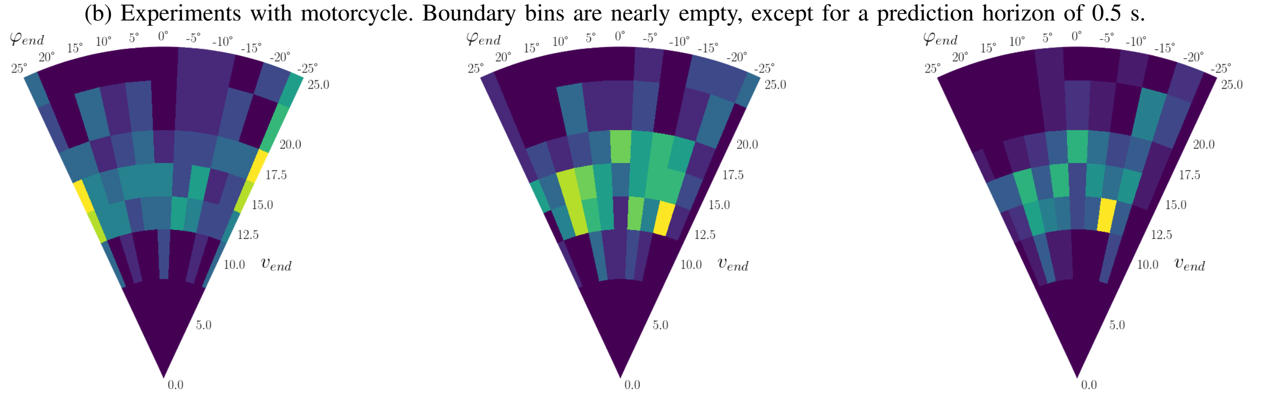
In a real world application like an autonomous mobile platform, the simulations have to be conducted in real time.



(a) Experiments with bicycle. Very few observations at the boundaries of the convex hull.



(b) Experiments with motorcycle. Boundary bins are nearly empty, except for a prediction horizon of 0.5 s.



(c) Experiments with electric scooter. Only for a prediction horizon of 0.5 seconds many observations in boundary bins.

Fig. 4: Radial histograms of recorded „extreme“ observations o_{t_a}. Each o_{t_a} is assigned to the bin $b_{i,j}$ closest to the simulated end point $p_{t_a,i,j}$. All combinations $s_{i,j} = (v_{\text{end},i}, \varphi_{\max,j})$ of the shown ticks are simulated for an observation o_{t_a}. Prediction horizons from left to right: 0.5, 1.0 and 1.5 seconds. Dark blue: 0 observations in bin, yellow: many observations in bin.

We are confident this is possible with an efficient implementation, but it might consume a wrongful amount of computational resources, especially, since more than one 1T2W might have to be predicted in crowded urban scenarios. Instead, we propose to use a small amount of 1T2W classes, e.g. racing bike, city bike, freight bike, motorbike, scooter and motorized scooter, and run the simulations with universal parameter combinations $s_{i,j}$ and initial conditions o_t – if such exist – in advance. In the mobile platform, lookup tables can then be used for direct access to the simulation results. Also, models could be trained with an arbitrary amount of simulated data if robustness of the model can be ensured.

For prediction horizons of more than 1.5 seconds, the prediction approach might not be useful anymore because the flexibility of a cyclist does not differ anymore from the single-track model used for cars. Especially in the first few moments our proposed approach is superior to the single-track model because it considers the effect of countersteering.

In general, it is proposed to use the presented approach as a delimiter of safety boundaries, e.g. for the unlimited output of a trained model in order to make it robust against outliers and post-process output which is physically impossible.

V. Conclusions and Future Work

In this paper, we propose a safety-guaranteeing prediction method for single-track two-wheelers (1T2W). Due to their movement-restricting kinematics, a reachable set can be generated by simulating the kinematic model of a parameterized two-wheeler. This is the first work known to the authors which makes use of the unique kinematics of a 1T2W. According to real world experiments, the model is able to predict the spatial outlines for most recorded extreme maneuvers, but it should not be used without a safety margin. We propose to make use of the corresponding differential equation in order to generate a prior which restricts the possible output of learned or parameterized model. As a next step, a probabilistic model specifically designed for the purpose of 1T2W prediction shall be developed and parameterized.

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