Model-Based Prediction of Two-Wheelers

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***Abstract*— The breakthrough of intelligent vehicles will probably 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 (ST2W): they share the road with cars and trucks but are not as agile due to their kinematics. Futhermore, they are faster than pedestrians but equally vulnerable as those. In order to guarantee their safety, we make use of their movement restricting kinematics. We simulate three typical classes of ST2W under conservative assumptions about their agility in order to generate a spacial region in which they have to be due to physics after a fixed prediction horizon of up to 1.5 seconds. In experiments with real data, the proposed approach indeed creates a convex hull in which the recorded rider stays during the sequence.**

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

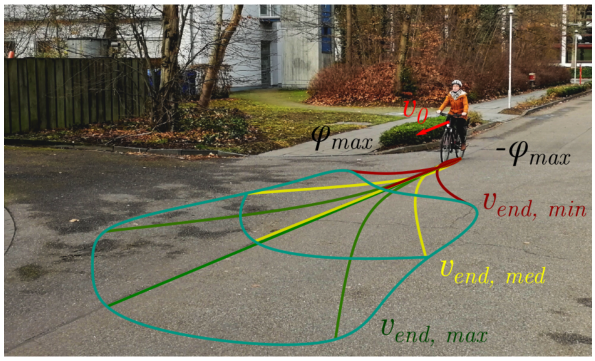

Fig. 1: A cyclist on an unstructured road. Possible trajectories are simulated with different parameter combinations $p_i = [v_{end,i}, \varphi_{max,i}]$. The end points of the simulations determine the region (petrol) where the cyclist has to be inside of after a fixed time span.

I. Introduction

Increasing safety not only for vehicle occupants but also for Vulnearable 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 - concised as single-track two-wheelers (ST2W)[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 particularily difficult task, because they obey traffic rules far less than two-track vehicles which in many cases can be predicted lane-based. 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 ST2W has to be due to physics after a defined period of time.

In comparison to pedestrians, ST2W 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 ST2W has only one degree of freedom (DoF). The (motor-) cyclist or 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 to a great extent independently of each other. 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 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 ST2W has to be inside of within 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 ST2W are made.

II. Related Work

While many researchers focused on VRU safety as a demarcated problem [7]–[10] and on pedestrians in particular [11]–[16] by generating position predictions, only few publications tackle the problem of cyclist prediction. We did not

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[1]This explizitly excludes self-balancing scooters such as Segways.

find any publication tackling two-wheeler safety by making use of their unique kinematics.

Jia *et al.*[17] found the necessity of developing a specialized model for cyclist crash prediction from the viewpoint of a heavy goods vehicle after testing a collision avoidence system [18].

Zernetsch *et al.* [19] applied an artificial neural network (ANN) to the task of cyclist prediction and compared it against a Kalman Filter (KF) and an 1-D kinetic approach in which they fit the unknown kinematic 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.* [20] 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 the dataset. This dataset was also used by Saleh *et al.*[21] 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 the approach with the example of pedestrian and cyclist prediction. Zernetsch *et al.*[10] used a dataset with 1311 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.*[22] 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 VRU starting behavior at intersections [8], [23]–[26].

Besides the basic equilibrium of forces in longitudinal direction proposed by Zernetsch *et al.* [19] no approach makes use of the physical characteristics of cyclists. Furthermore, there is no generic safety approach that tackles all kind of ST2W and we cannot find any publications that approach the well-known problem of motorbike safety or the increasing problem of motorized scooters 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 ST2W 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 ST2W, 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 ST2W 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.*[27]. Position prediction is assumed to be a two dimensional problem. Those ST2W our approach is supposed to predict are assumed to drive normally[2] but not necessarily traffic rule compliant.

We consider an unstructured environment according to 3.7.2. in [27] 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 ST2W and let $\mathcal{T}_{e,t_1}$ be the set of possible trajectories of the ego vehicle until $t_1 = t_0 + \Delta t_{pred}$. 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 [27], the ego vehicle knows the occupied region $\mathcal{T}_{e,brake,t_1}$ furthest away on the possible trajectories which it would still reach if it conducted an emergency braking maneuver. 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 $\mathcal{T}_{a,t_1} \cap \mathcal{T}_{e,brake,t_1} = \emptyset$ 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 ST2W.

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. The state of the models can be described by two variables, roll angle ϕ between the plane in upright position and the frame of the bike, and steering angle ψ. 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 non-holonomic constraint: a wheel cannot move perpendicular to its velocity vector. The intersection of the lines perpendicular to the contact points between wheels and ground determine the instant center of rotation if the roll angle is not considered.

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

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

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

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

where ψ is the angle relative to a world fixed reference frame, h is the height of center of gravity (CoG), l is the

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

distance between the contact points of both wheels to the ground and v is the speed of the rear wheel.

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

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

where $v_{x/y}$ are the accelerations of the rear wheel contact point, l_t is the trail, b is the horizontal distance between rear wheel and projected centre of mass and σ is the kinematic steering variable. The side slip velocity $\dot{v}_y$ 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

$$\sigma = l\dot{\psi}\frac{1}{v_x} \tag{4}$$

which yields to

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

after some transformations. We separated the terms for constants (h, b, l_t, ξ, g) and time dependent variables (φ, v_x).

Those differential equations can be evaluated by assuming the worst case steering maneuvers represented by φ and v_x.

C. Boundary Models

In order to get a differential equation that is only depending on ψ, we define worst case speed and roll angle profiles. Therefore, we make similar deliberations like those used in Zernetsch *et al.* [19]. For each pair of observation o_t at timestep t and parameter combination $p = [v_{end}, \varphi_{max}]$, we run a simulation with eq. 5. After calculating the next ψ_{i+1}, every other quantity can be calculated by evaluating the equations given in [6]. For each simulation, a differentiable velocity profile and roll angle profile is designed. Instead of a roll angle profile, a controller could be implemented.

1) Velocity Profile: The current speed of the ST2W 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 violation of friction condition) looses stiction are not considered. According to a literature survey [28][3] 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

$$|a_{brake}| = \min\left(g\frac{l-b}{h}, 0.7g\right). \tag{6}$$

with g being the gravitational acceleration. To simulate a braking maneuver of the ST2W, we assume a_{brake} until it stops starting from the current speed v_0

$$v_{decel}(t) = -a_{brake}t + v_0. \tag{7}$$

For the acceleration, we assume convergence to an estimated end speed v_{end} which could be the physical limit of the ST2W, 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

$$v_{accel}(t) = v_{end}\cdot\tanh\left(\frac{a_{max}}{v_{end}}t - \operatorname{arctanh}\left(\frac{v_0}{v_{end}}\right)\right). \tag{8}$$

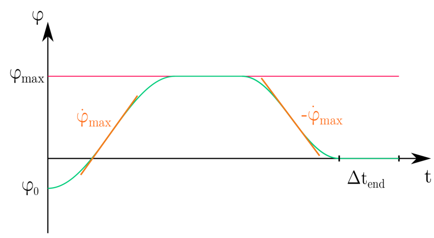


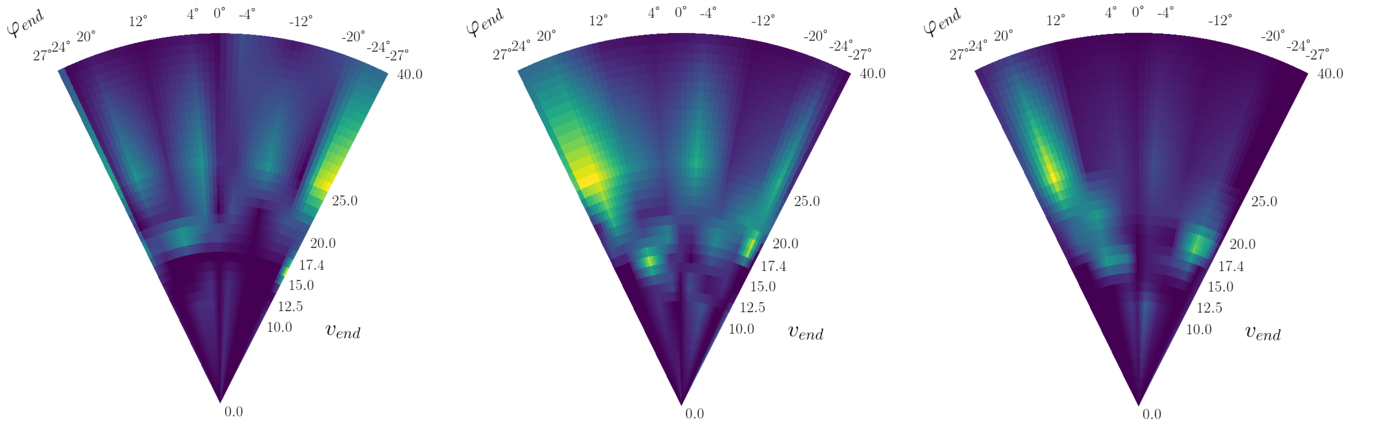
Fig. 2: Schematic roll angle profile between φ_0, φ_{max} and 0^o.

2) Roll Angle: The current roll angle φ_0 is assumed to be given. If the point cloud and the bounding box of a ST2W is given, the points roughly form a plane, if the 2D bounding box and the corresponding image is given, then the roll angle could be derived from an optical axis of symmetry. However, in this work we focus on the prediction concept only.

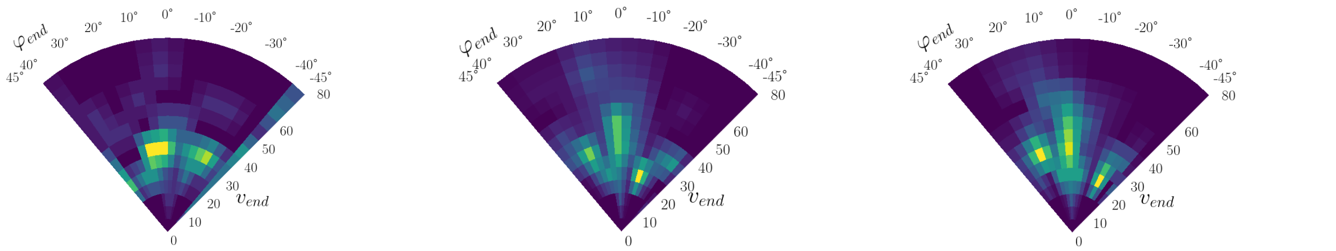
Assuming φ_0 is given, we form a differentiable profile which consists of shifted cosines and straight lines. It connects the initial roll angle φ_0 with the maximum roll angle φ_{max}. In order to increasing realism for simulations with a fullstop, we introduced an end phase of $\Delta t_{end} = 0.3s$ for which the ST2W keeps a roll angle of 0^o in case $v_{end} = 0$ in.

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

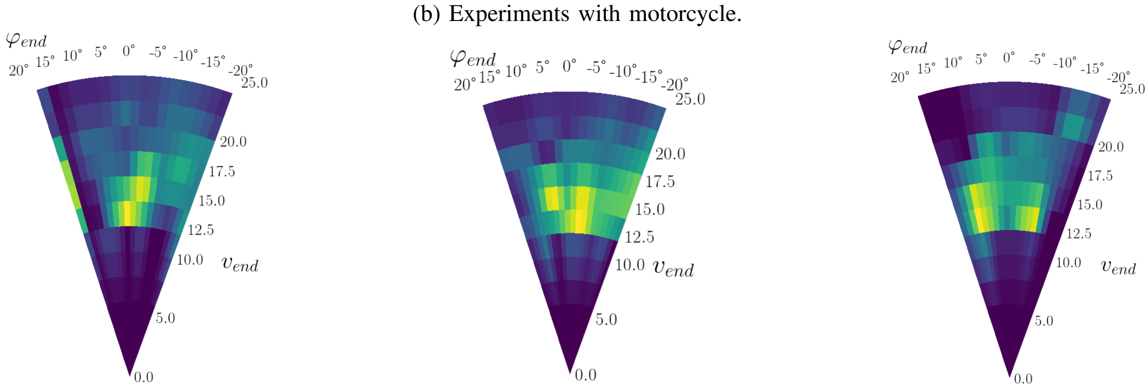
[3]This is a non-reviewed online secondary reference. For one of the primary references, see e.g. Dunn *et al.*[29].



(a) Experiments with bicycle.



(b) Experiments with motorcycle.



(c) Experiments with electric scooter.

Fig. 3: Radial heatmap of recorded two-wheeler appearences in „extreme" trajectory. Only combinations of the shown ticks are simulated. Ocurrencies in grid cells are then linear interpolated. Prediction horizons from left to right: 0.5, 1.0 and 1.5 seconds.

IV. Results and Evaluation

For evaluation, we recorded a bicycle, a motorbike and a motorized scooter for 2-3 minutes on an empty, unstructured square. The rider was instructed to perform „extreme" driving maneuvers, especially tight curves with a large roll angle, harsh brakes and accelerations both during straight rides and curves. The rider is not a professional but experienced. Therefore, we do not claim that he reached the physical limit of the ride nor of the wheels. Still we are confident that we obtained values which are considered extreme if performed in normal traffic.

We recorded the sequences from a stationary platform with a Velodyne HDL64S2. We labeled those three sequences with our 3D label tool PointAtMe [30]. In contrast to an IMU mounted to the ride, the annotator can label the actual roll angle from contact point of rear wheel with ground to the center of mass. For the bicycle and the motorized scooter an IMU might yield to significant errors.

According to RSS, safety in a situation with an intelligent vehicle and a single-track two-wheeler can be guaranteed, if the automated vehicle can avoid entering the future trajectories of the other traffic participant with a velocity $v_{enter} \neq 0$. In order to evaluate our approach we need to check if the ST2W stays within the generated convex trajectory hull for all timesteps. The hull can be generated for a specific time step.

In Fig. 3 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 φ_{max}, respectively.

The result matches the expectations. The rear wheel of the ride is within the region of the convex hull in nearly all measurements. For $h = 0.5s$ the convex hull is extremely small, therefore there are a couple of outliers outside the the convex hull. This might be due to the limitations of the model regarding its assumptions about fixed center of mass, 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 $h = 0.5s$ the maximum is rather close to the boundaries, especially to the roll angle boundaries. A specified parameterization for each prediction horizon might yield to a more robust model.

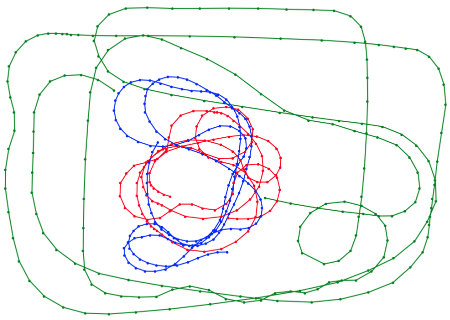


Fig. 4: Trajectories of cyclist (red), motorcyclist (green) and scooter (blue) on a square of size 60 m x 90 m.

A. Practical Application

In a real world application like an autonomous mobile platform the simulations have to be conducted in real time. 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 ST2W might have to be predicted in crowded urban scenarios. Instead, we propose to use a small amount of ST2W classes, e.g. racing bike, city bike, freight bike, motorbike, scooter and motorized scooter, and run the simulations with universal parameter combinations - 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 model is superior to the single-track model because it models the effect of countersteering.

In general, it is proposed to use the presented approach as a delimiter of safety boundaries, e.g. for the output of a trained model in order to make it robust against outliers.

V. Conclusions and Future Work

In this paper, we propose a safety-guaranteeing prediction method for single-track two-wheelers (ST2W). Due to their movement-restricting kinematics, a reachable set can be generated by simulating the kinematic model of a parameterized two-wheeler. Compared to the reachable set of the single-track model, the generated region is significantly smaller. This is the first work known to the authors which makes use of the unique kinematics of a ST2W. According to real world experiments, the model is able to predict the spatial outlines of 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 models. As a next step, a probabilistic model specifically designed for the purpose of ST2W prediction shall be developed and parameterized.

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