Motorcycle-specific trajectory prediction based on vehicle dynamics, rider inputs and behaviour information for future assistance systems

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***Abstract*—Future motorcycle assistance systems, being it functions that warn or intervene in critical situations or that enhance riding comfort and safety during normal operation, need knowledge of rider intention by means of the upcoming trajectory or manoeuvre. In previous work, the authors presented a motorcycle specific trajectory prediction algorithm for cornering using a roll angle prediction model based on a Recurrent-Neural-Network (RNN) architecture. This approach accounts only for the lateral component of the future motorcycle dynamics but nevertheless shows great improvements over the state-of-the-art constant yaw rate motion model. In this paper, the effect of the longitudinal component of trajectory prediction is investigated. We present the impact of adding a velocity prediction component to the roll angle model as well as the performance of combined longitudinal and lateral trajectory prediction models. All prediction models showcased solely rely on measurements of vehicle dynamics, rider inputs and rider behaviour, neither environmental sensing nor map information are used. The performance evaluation of the prediction models is carried out using an extensive test data set from a self-conducted riding study. Manoeuvre-specific analysis provides an additional insight into the behaviour of the machine-learned prediction algorithm. The consideration of longitudinal dynamics in the prediction leads to distinct improvements over sole lateral prediction, especially in riding situations with limited "look ahead time". This is found by evaluating the maximum prediction time with acceptable position accuracy. The findings demonstrate the potential of motorcycle-specific algorithms for trajectory prediction and thus motivate the development of future motorcycle assistance systems that rely on more accurate knowledge of rider intention.**

Keywords—trajectory prediction, motorcycle dynamics, rider behaviour

I. Introduction

Rider of powered two-wheelers (PTW) belong to the most vulnerable road users, as they account for 21 % of the fatalities in road traffic worldwide [1]. The main reason for this lies in the inherent low passive safety of PTW, both in case of single accidents as well as in collision with other traffic participants. This circumstance is one main driver for the development of Motorcycle Stability Control (MSC) systems as well as Advanced Rider Assistance Systems (ARAS). While MSC ensures the stability and controllability of a PTW in highly dynamic riding situations, e.g., during emergency braking, ARAS functions help to actively mitigate or avoid critical riding situations in the first place. Especially the latter functions are often entitled predictive safety measures which emphasizes that they rely on assumptions about the future development of a traffic situation. ARAS functions that are currently available on PTW, like FCW (Forward Collision Warning), are typically using a radar sensor to identify and interpret the actions of surrounding traffic participants. In addition to that, ARAS needs information about the future behaviour of the ego-vehicle that is actively controlled by the rider – this information is called rider intention in general. Depending on the application, rider intention can be expressed as a continuous trajectory of one or more future vehicle dynamic states (e.g., the future relative position on the road) or as specific class of manoeuvre lying ahead.

Rider intention detection is an open field of research in the domain of motorcycle safety systems. The authors investigate the use of motorcycle-specific algorithms that utilize measurements of rider inputs in the steering system and rider behaviour in terms of upper body and head movement for rider intention detection. A first study evaluated the physical effects of steering and upper body inputs on the lateral dynamics of motorcycles [2]. Afterwards, a riding data set was recorded on open roads in order to analyse rider behaviour in realistic riding situations. This data set was used to train an RNN-based roll angle trajectory prediction algorithm. With this approach, the authors investigated the importance of the chosen rider input and behaviour signals for the prediction of lateral dynamics [3]. The promising prediction performance of the RNN-motorcycle-specific algorithm motivates its use for the prediction of longitudinal dynamics too. This and different approaches of combined longitudinal and lateral dynamic prediction algorithms for PTW are investigated in this paper.

The state of research in the field of trajectory prediction for PTW is described in section II. Afterwards, chapter III introduces the trajectory prediction algorithms that are compared. Chapter IV explains the metrics used for the performance evaluation of the prediction algorithms. The performance of the different models is compared in Chapter V, followed by summary and outlook in Chapter VI.

II. State of the Art

The Connected Motorcycle Consortium [4] investigated state-of-the-art algorithms for PTW-trajectory prediction in a recent whitepaper. Their work is motivated by the C-ITS technology (Corporate Intelligent Transport Systems) that enables connected vehicles to exchange information about their ego-intentions and therewith theoretically enables highly effective collision warning and avoidance functionality. A motorcycle multi-body simulation is used to analyse different turning scenarios at an intersection. Multiple constant heading or curvature motion models are analysed for the maximum achievable prediction time with reasonable accuracy; this metric is called “evaluation index (EI)” and it is explained in section IV in more detail as it is used in this paper too. As expected, turning of a motorcycle poses the biggest challenge for trajectory prediction as the EI falls to 1 s during the manoeuvre. At the same time, the authors state that an EI of 6.5 s would be required for the realization of a C-ITS warning function in a left-turn scenario.

Scherer [5] presents a heuristic rider model for curve riding of motorcycles that is based on mathematical functions. The model relies on the hypothesis that a motorcycle rider takes similar curves in a similar manner, which is driven by individual style, skill, and preferences. Hence, the function parameters are obtained by rider individual identification. The heuristic model is meant to be used for both riding style analysis as well as trajectory prediction. It is developed based on data from a riding study on an enclosed test track. Only few dynamic states of the bike are needed for the function evaluation, but the prediction requires knowledge about the shape of the curve lying ahead. A proof of the prediction concept on a larger set of curves on open roads is not available so far.

Neural network (NN) based models are state-of-the-art in research and development of autonomous driving applications, where the future behaviour and/or position of surrounding traffic participants is of interest [6]. Inspired by these research activities, the authors applied an RNN-based NN to the task of ego-motorcycle trajectory prediction in their previous work [3]. A NN-model realizes regression of the dynamic state of roll angle over the future 4 s of riding that is then transformed into a trajectory of future relative position based on a constant velocity assumption. This approach leads to big improvements over state-of-the-art constant yaw rate motion models, e.g., the number of situations with an EI smaller than 2 s is reduced by over 90 %. The present paper presents the continuation of this approach.

The three approaches presented have in common that rider intention is expressed by a trajectory of riding states, calculated by different types of regression models. This kind of approach has the advantage that (in theory) any kind of riding manoeuvre can be modelled. In contrast to manoeuvre prediction models, no a-priori knowledge of riding situations in the data is needed; this supports the generalization capability of the approaches [6].

III. Trajectory Prediction Algorithms

This paper compares the four different configurations of trajectory prediction algorithms given in Table I that rely on a common RNN-based NN-architecture. All algorithms have a relative position trajectory as final output. They are named according to the differing output state variable(s) of the NN(s) applied. The “roll angle” algorithm is very similar to the approach of the previous work [3] where a NN predicts a roll angle trajectory that is then transformed into relative positions based on a constant velocity assumption. The subsequent section briefly introduces the common NN-architecture used in all configurations.

TABLE I. Configuration of the RNN-based trajectory prediction algorithms

Name of prediction configuration	**NN output → optional processing**	**Input features**
“Roll angle”	φ → position transformation with constant velocity	Roll angle, roll rate, pitch angle, pitch rate, yaw rate, longitudinal acceleration, lateral acceleration, vertical acceleration, forward velocity, front brake pressure, steering torque, steering angle, steering rate, rider upper body lean angle, rider upper body lateral offset, rider head yaw angle
“Roll angle + velocity”	1st NN: φ, 2nd NN: v_x → position transformation	
“Roll angle & velocity”	φ, v_x → position transformation	
“Relative position”	x, y (relative position)	

To calculate a state prediction at a single point in time, the unimodal regression model interprets 16 input features over a time history of 1.6 s / 2.0 s that are discretized every 0.02 s / 0.2 s in two parallel LSTM-layers (Long Short-Term Memory, most common type if RNN-layer). All prediction configurations use the same set of input features listed in Table I; those are motorcycle internal measurement signals of dynamic states, rider inputs, body, and head movement. The inputs are divided into “high dynamic” and “low dynamic” signals to ensure better performance of the RNN-layers; whereas the first group of signals needs fine discretization to be interpretable by any RNN-layer, this discretization would hinder the recognition of patterns for low dynamic signals. The two LSTM-layers interpret the features timewise and reduce dimensionality. Their joint output is processed in a subsequent MLP (Multi-Layer Perceptron) that is made up of two linear layers, dropout regularization, and a final output layer. The output is a state prediction over the upcoming 4 s of driving, sampled in 20 prediction points. The model hyperparameters were deduced by optimization of the “roll angle” prediction configuration. Fig. 1 shows the described NN-architecture and the dimensionality of information that is processed for a single prediction. A green arrow indicates the intrusion of the initial value of the predicted state (at current time of prediction) to the NN’s output. Thus, the NN is trained to predict only relative changes to the initial state which helps to achieve smoother predictions.

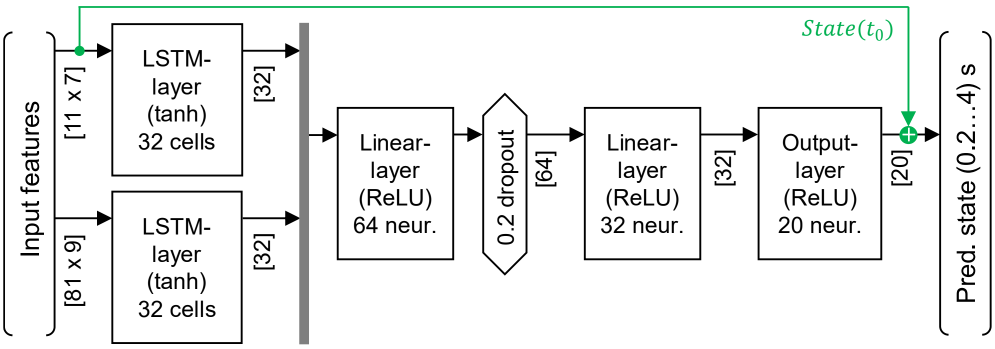

Fig. 1. Block diagram showing the common NN-architecture for the prediction of a state trajectory.

It was decided that all configuration that are compared in this paper use the described common set of input features due to the reduction of complexity. For the same reason, the hyperparameters are kept constant to the values from the initial optimization made with the “roll angle” model. The configuration “roll angle + velocity”, in the second row of Table I, means that a second, standalone NN is used for velocity prediction in addition to the “roll angle” prediction model. It is trained by altering the target state in the NN’s output and accordingly the intrusion of the initial value to velocity. The configurations in the lower two rows of Table I feature a single NN that predicts the values of two state variables at once. In order to do so, the sizes of the neural layers are doubled to account for the increased output dimension of 40.

All configurations that don’t have the “relative position” trajectory as direct output of the NN require additional processing to calculate it based on roll angle φ_i and forward velocity $v_{x,i}$. At first, a simplified kinematic model is established to calculate the path curvatures κ_i at all prediction points i; the equations are presented below. It is based on a quasi-static assumption about the lateral dynamics and considers tire width R_t and centre of gravity height of the motorcycle-rider system h_{CG}. Variable e_i describes the distance between the tire-road contact point and the centre of gravity. Additional simplification arises from neglecting the effects of rider movement, road banking angle and steering angle. The ground truth future positions are transformed from ground truth roll angles and velocities using the same formulas, so that the simplifications don’t cause a bias in the performance evaluation.

$$\kappa_i = \frac{-9{,}81 \tan(\varphi_{c,i})}{{v_{x,i}}^2}$$

$$\varphi_{c,i} = \arccos\left(\frac{{h_{CG}}^2 - 2\, h_{CG}\, R_t - e_i^2}{-2\, R_t\, e_i}\right) \cdot \mathrm{sgn}(\varphi_i)$$

$$e_i = \sqrt{(h_{CG} - R_t)^2 + 2(h_{CG} - R_t) R_t \cos(\varphi_i) + {R_t}^2}$$

The trajectories of relative future positions (x_i, y_i) of the motorcycle are calculated from path curvature κ_i and forward velocity $v_{x,i}$ assuming a path of constant curvature between the discrete prediction points. This is reflected by the following equations, where ψ_i indicates the relative heading angle of the motorcycle.

$$\psi_i = \psi_{i-1} + \Delta t_i\, v_{x,i-1}\, \kappa_{i-1}$$

$$x_i = x_{i-1} + \frac{\sin(\psi_i) - \sin(\psi_{i-1})}{\kappa_{i-1}}$$

$$y_{\mathrm{i}} = y_{\mathrm{i\text{-}1}} - \frac{\cos(\psi_{\mathrm{i}}) - \cos(\psi_{\mathrm{i\text{-}1}})}{\kappa_{\mathrm{i\text{-}1}}}$$

In addition to the RNN-based prediction algorithms, the state-of-the-art approach of constant curvature and velocity prediction is evaluated for the sake of comparison to a baseline (it is named "simple"). It is realized by taking the current roll angle and velocity value at the time of prediction as constant over the 20 prediction points in the above equations.

IV. Trajectory Prediction Metrics

All models compared in this paper are trained and tested on identical data that is taken from a 74 h and 4900 km large set of open-road riding with a fully equipped test bike (KTM 1290 Super Adventure S, 2018). The riding data was recorded by 21 different riders on varying routes in the southwest of Germany. This ensures high diversity in riding situations and riding style. The focus of the riding test was on the rural road environment but riding in towns and on the highway are present too. Due to the very different nature of two-wheeler stability in low-speed, riding situations that feature velocities lower than 30 km/h are not considered. Prediction performance metrics are evaluated on a test data set comprising 7 % of the riding data.

While the trainings of the NNs in the different configurations rely on minimization of the MSE (Mean Squared Error) of the predicted state variables directly, the trajectory prediction performance is tested on uniform and interpretable metrics that are evaluated from the predicted relative positions (x, y). The distance d in meter between ground truth (marked with *) and prediction is discriminated into a longitudinal and lateral component with respect to the ground truth heading ψ^* at each point on the prediction horizon. This is realized using the following formulas.

$$d = \sqrt{(x - x^*)^2 + (y - y^*)^2}$$

$$d_{\mathrm{Lon}} = \cos\left(\arctan\left(\frac{y - y^*}{x - x^*}\right) - \psi^*\right) d \ \mathrm{sgn}(x - x^*)$$

$$d_{\mathrm{Lat}} = \sin\left(\arctan\left(\frac{y - y^*}{x - x^*}\right) - \psi^*\right) d \ \mathrm{sgn}(x - x^*)$$

Distance errors are condensed into a single number by calculating the RMSE (Root Mean Squared Error) over all N test situations and all 20 prediction points per test situation according to the following equation.

$$\mathrm{RMSE}(d, d^*) = \sqrt{\frac{1}{\mathrm{N}} \sum_{1}^{N} \left(\frac{1}{20} \sum_{i=1}^{20} d_{\mathrm{i}}^{\,2} \right)}$$

Based on the lateral distance d_{Lat} between ground truth and prediction, an EI number can be derived for every test situation – as done in the CMC's investigation [4]. It describes the maximum prediction time that can be achieved in a riding situation with respect to a defined accuracy threshold in the lateral distance to ground truth. The threshold is set to an absolute lateral error $|d_{\mathrm{Lat}}|$ of 2 m. The left diagram in Fig. 2 shows ground truth (black) and predicted (blue) position trajectories in an exemplary test situation. The absolute lateral and longitudinal position error are presented over prediction time on the other axes in pink. As indicated by the arrow, the EI is 2.2 s in this situation.

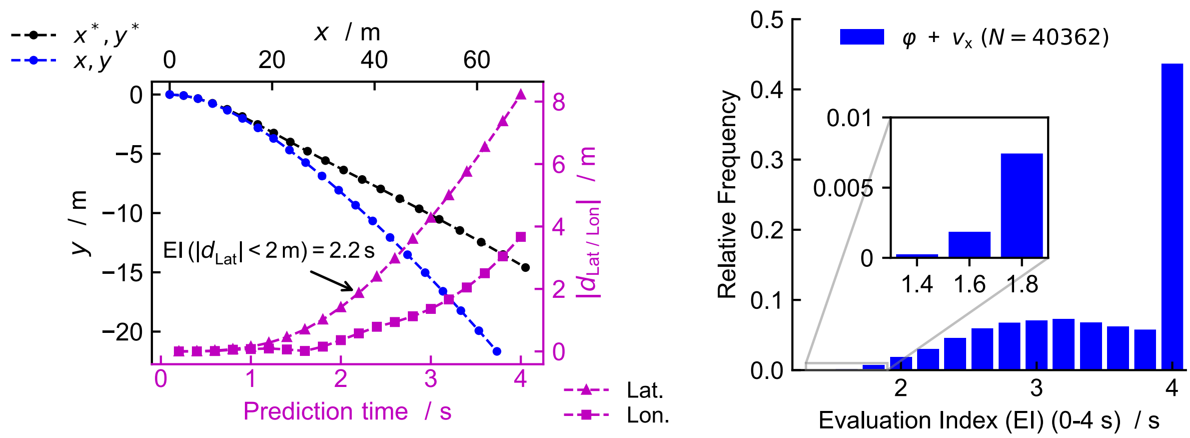

Fig. 2. Left: predicted and ground truth position trajectories, and distance errors in an exemplary situation. Right: histogram of EI values in all test situations.

The EI values of all test situations can be summarized calculating the average or by visualization in a histogram as presented in the right diagram in Fig. 2. A higher average EI indicates a more accurate prediction. In the histogram in Fig. 2, one sees that the EI equals the maximum prediction time of 4 s in more than 40 % of the riding situations. Furthermore, the EI helps to identify situations that are difficult to predict and form a lower performance boundary of the algorithm. The share of test situations with an EI below 2 s ($n(\mathrm{EI} < 2s)$) is analysed as additional metric accordingly, it should be minimal.

In addition to evaluations over the whole test data set, prediction performance is separately analysed in different riding situations which gives more insights into the strengths and weaknesses of the algorithm. The data is labelled into lateral dynamic manoeuvre segments for that purpose. The concept of segmentation of the ride according to the roll dynamics (roll angle and roll rate) is inspired by Magiera [7]. The three transient manoeuvre segments of roll-in (typically at curve entry), roll-out (typically at curve exit), and roll-over (e.g., in lane changes or following curves) are distinguished from the two quasi-stationary segments of straight riding and constant cornering using a state machine. This concept is illustrated by the coloured zones in the roll dynamic diagram in Fig. 3.

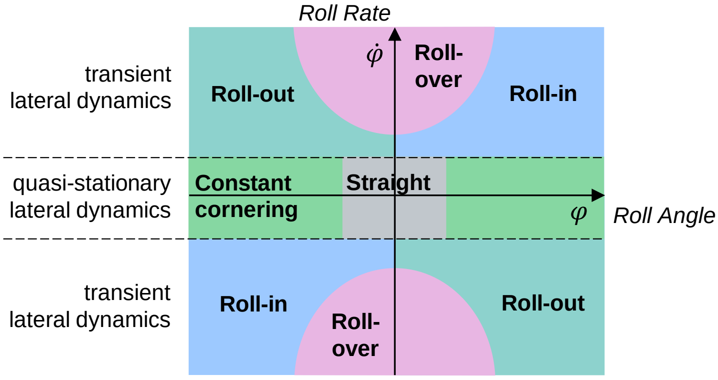

Fig. 3. Concept of five lateral dynamic manoeuvre segments (bold names) illustrated in the roll dynamics diagram.

V. Prediction Performance of Different Configurations

Table II lists the RMSE metrics for longitudinal and lateral distance error, the average EI value, and the relative share of test samples with an EI lower than 2 s. The "roll angle" algorithm is the only prediction configuration that solely considers lateral dynamics in the NN-model; this equals the setup in the previous work [3] and is therefore underlined. The best performing values in each metric and the according best prediction configuration of "roll angle + velocity" are highlighted in bold letters. From all NN-models that cope with both longitudinal and lateral prediction (the lower three rows in Table II), the "relative position" configuration clearly shows the lowest performance in all metrics. While this direct position prediction achieves better RMSEs than the "roll angle" configuration, it performs worse in both average EI and share of situations with EI lower than 2 s.

TABLE II. Model Performance in Different Metrics

Prediction configuration	**RMSE (d_{Lat}) / m**	**RMSE (d_{Lon}) / m**	**Average EI / s**	**$n(EI < 2s)$ / %**
Simple	3.86	3.73	2.99	12.46
Roll angle	2.07	3.36	3.42	1.35
Roll angle + velocity	**1.95**	**2.13**	**3.44**	**0.95**
Roll angle & velocity	2.00	2.30	3.43	1.00
Relative position	2.04	2.44	3.39	1.97

The bar plots in Fig. 4 visualize the lateral and longitudinal distance RMSEs of the different prediction configurations and the "simple" baseline algorithm. Percentages indicate the relative improvements that are achieved compared to the "roll angle" configuration that only considers prediction of lateral dynamics (referred to as reference "Ref."). Up to 36.6 % improvement in longitudinal RMSE are achieved when replacing the constant velocity assumption ("roll angle") with the RNN-based velocity prediction ("roll angle + velocity"); although the roll angle prediction part of both configurations is identical, adding the velocity prediction causes an improvement of 5.8 % in the lateral RMSE too. This is due to a cross-effect that occurs in the transformation from roll angles and velocities into positions, where any longitudinal error propagates into a lateral error (and vice versa) going along the prediction horizon.

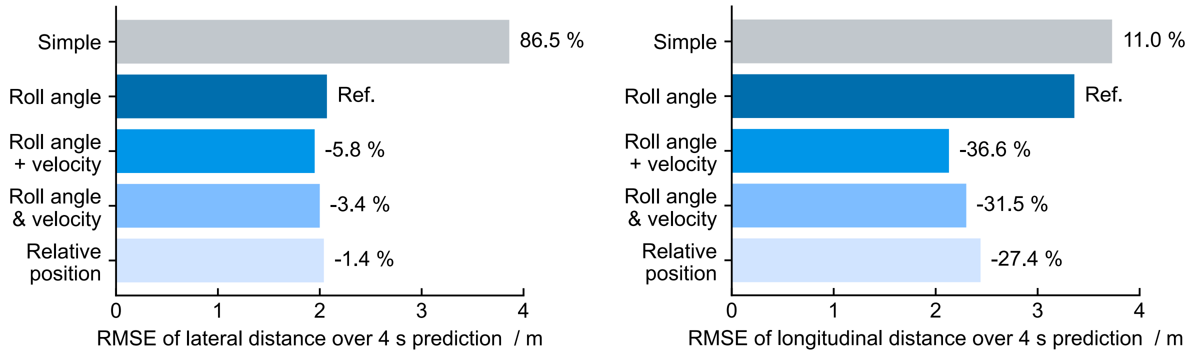

Fig. 4. Lateral and longitudinal distance RMSE on test data (x-axes), evaluated for different model configurations (y-axes). Realtive change over “roll angle” prediciton configuration indiacted in percent.

It comes by surprise that the separation of longitudinal and lateral dynamics prediction in two NNs (“roll angle + velocity”) achieves better prediction results than the two combined models that use a single large NN (“roll angle & velocity”, “relative position”). There seem to be no synergies with a combined model that can provide a performance improvement. Another explanation is that separate NNs can better specialize on the given prediction task during the model training. A second finding is that the combined “roll angle + velocity” configuration outperforms the direct “relative position” prediction model even though it requires an additional processing step to get relative positions as output. This indicates that there are more distinctive patterns in roll angle and velocity trajectories that a NN can learn and imitate compared to relative position trajectories.

The performance on test data of the best configuration of “roll angle + velocity” is analysed in more depth. Fig. 5 shows lateral and longitudinal distance RMSEs separated for the different manoeuvre segments that were introduced in section IV. In addition, the percentages indicate the relative improvement of the “roll angle + velocity” configuration compared to the “simple” constant yaw rate and velocity algorithm.

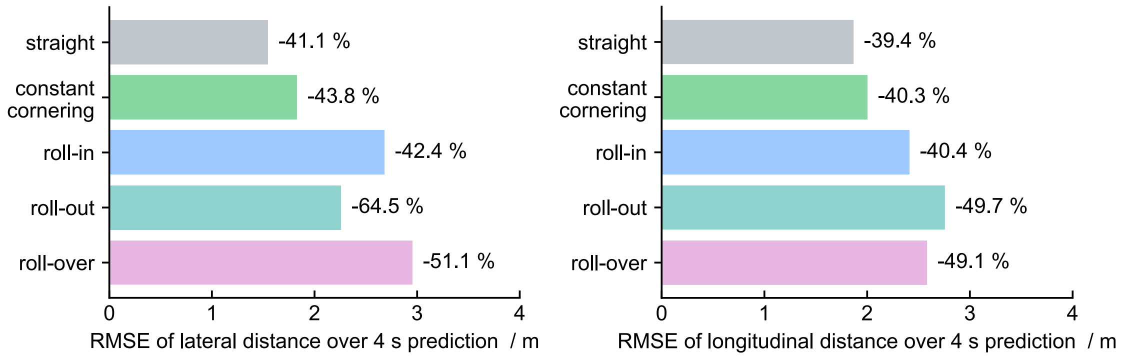

Fig. 5. Lateral and longitudinal distance RMSE of the “roll angle + vx” configuration on test data (x-axes), evaluated for different manoeuvre segments (y-axes). Relative change over the “simple” algorithm indicated in percent.

In general, riding manoeuvres with higher lateral dynamics (roll-in, roll-out, roll-over) have higher absolute lateral and longitudinal distance RMSEs. While this is unquestionable for the lateral error, the reason for the longitudinal error might be that cornering is one major cause for changing the velocity of a motorcycle. Roll-over manoeuvres are the most difficult ones to predict with regard to the lateral error whereas for the longitudinal error these are roll-out manoeuvres. It is imaginable that changing the roll angle from one curve to another (roll-over) and acceleration out of curves (roll-out) pose riding situations where the lateral / longitudinal dynamic states are changing very quickly and there is a huge set of possible behaviours (roll angles / velocities that are intended by the rider).

The percentages of improvement in Fig. 5 show where the RNN-based trajectory prediction approach achieves the highest gain over the state-of-the-art. The lateral position RMSE benefits the most in roll-out manoeuvres with a 64.5 % reduction; since most corners end by riding in a straight line, the rider intention during a roll-out can be imitated by the NN more easily. For the longitudinal prediction accuracy, highest improvements of over 49 % are achieved in roll-out and roll-over manoeuvre segments. The relative improvements in all other manoeuvre segments but roll-out are very similar between lateral and longitudinal RMSE. This shows that the RNN-based prediction approach, that was initially designed for roll angle trajectory prediction, can successfully be applied to velocity trajectory prediction too.

VI. SUMMARY AND OUTLOOK

The suitability of an RNN-based prediction model for PTW-specific trajectory prediction was known from a previous investigation that focussed on lateral dynamics (roll angle) prediction only. This approach achieves that the feasible prediction time (EI metric) falls below 2 s in only in 1.35 % of all representative test situations. In the paper at hand, the same RNN-based prediction architecture was applied to the task of longitudinal dynamics prediction as well. Three configurations of prediction models, that address both longitudinal and lateral dynamics, are investigated and compared to the previous results and the state-of-the-art algorithm of constant yaw rate and velocity. It turns out that the best motorcycle trajectory prediction is achieved by adding an additional, separate NN for velocity prediction to the roll angle prediction NN; this is superior to the direct prediction of relative position in a single NN and to the combined velocity and roll angle prediction in a single NN. While the longitudinal distance error improves by 36.6 % compared to the lateral-only prediction, there is also an additional improvement of 5.8 % in the lateral error. The share of test situations with less than 2 s feasible prediction time (EI metric) lowers to only 0.95 %. Finally, the investigation of prediction performance for different lateral dynamic manoeuvre segments proves that the RNN-based prediction approach is well suited for the task of longitudinal prediction too, as the relative improvements over the state-of-the-art algorithm are in similar range for longitudinal and lateral errors.

Future improvement potential for the prediction of longitudinal dynamics lies in the selection of different input features like selected gear, clutch, engine speed or throttle position. Furthermore, the optimization of the NN architecture for velocity prediction could bring additional gains. Overall, the presented improvements of trajectory prediction for motorcycles allow future assistance systems a better understanding of rider intention. This offers potential for the development of ARAS that act safer, more comfortable, and enjoyable. The work on RNN-based motorcycle trajectory prediction also gives an idea of the high potential of data-driven algorithms for motorcycle safety in general.

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