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A Model-Based Online Reference Prediction Strategy for Model Predictive Motion Cueing Algorithms

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Abstract: Interactive driving simulation has become a key technology to support the development and optimization process of modern vehicle components and driver assistance systems both in academic research and in the automotive industry. However, the validity of the results obtained within the virtual environment depends essentially on the adequate reproduction of the simulated vehicle movements and the corresponding immersion of the driver. For that reason, specific motion platform control strategies, so-called *Motion Cueing Algorithms* (MCA), are used to replicate the simulated accelerations and angular velocities within the physical limitations of the driving simulator best possible. In this paper, we present a novel model-based approach to predict oncoming vehicle motion at runtime. For that purpose, a virtual driver model as well as a simplified vehicle dynamics model are introduced to estimate the future driver inputs and the resulting vehicle trajectories according to the current driving situation. This additional system knowledge enables control algorithms designed on the idea of *Model Predictive Control* (MPC) to exploit their potential more efficiently. The performance of the proposed prediction strategy is evaluated on the basis of measurement data from a real test run in comparison to an ideal prediction and a constant reference, using a hybrid kinematics motion system as an application example.

Keywords: Online Reference Prediction; Motion Cueing; Model Predictive Control; Driver Model; Interactive Driving Simulation; Dynamic Motion Platform Control.

1. INTRODUCTION

As a consequence of the constantly increasing multifunctionality and interconnectivity of modern vehicle components and Advanced Driver Assistance Systems (ADAS), automobile manufacturers and developers are facing new technological challenges in recent years. Furthermore, topics such as e-mobility and autonomous driving bring new competitors from the information technology sector onto the market, so that shorter development cycles with simultaneously enhanced product complexities are necessary in order to maintain competitiveness. To overcome those challenges, interactive driving simulators represent an essential tool to complement the conventional development process, based on physical prototypes and on-road tests, by virtual test procedures. In that context, model-based prototyping methods using driving simulations offer the benefit of time and cost savings, as well as safe and reproducible test environments with high flexibility. For example, varying weather and lighting conditions can be directly adapted to the test requirements in the simulated environment, which supports i.a. the development of modern headlamp systems significantly (Rüddenklau et al., 2019). Moreover, interactive driving simulation provides access to human-centered studies such as marketing, driver training and acceptance research (Hartwich et al., 2018).

Disregarding from the particular analysis purpose, the validity of the results obtained in a simulator study is closely linked to the driver's degree of immersion. Hence, it is necessary to provide the human perception system with all required motion information, so-called *Motion Cues*. In addition to the acoustic, visual, and haptic stimuli, also the vestibular Motion Cues, more precisely inertial motion in terms of the translational accelerations and angular velocities of the simulated vehicle, have to be reproduced via the dynamic motion system of the driving simulator. Therefore, as shown in Fig. 1, specific Motion Cueing Algorithms are applied to transform the inertial motion of the vehicle dynamics simulation into admissible control signals within the physical limitations of the motion system and thus create a driving impression that is as realistic as possible.
Commonly, filter-based MCA, known as *Washout Algorithms*, are applied for this task. These consist of a sequence of frequency divisions using appropriate filters to

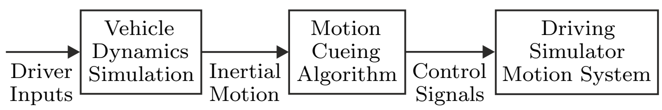

Fig. 1. Topology of Interactive Driving Simulation.

extract the high-frequency components of the translational accelerations and angular velocities, while sustained low-frequency signal parts are reproduced by the gravitational force, which is referred to as *tilt coordination* technique (Nahon and Reid, 1990).

In recent years, research has focused on optimization-based Motion Cueing strategies according to the principle of Model Predictive Control (Garrett and Best, 2013; Ellensohn et al., 2018). Compared to Washout Algorithms, MPC-based MCA offer the advantages of a better correlation with the reference signals, since there is no additional phase shift due to implemented filters and thus generate a higher degree of immersion. Moreover, hard constraints, such as physical limitations of the motion system and human perception thresholds, can be explicitly taken into account by the control algorithm, enabling an optimal planning of the motion trajectory. According to Beghi et al. (2012) with knowledge of future reference signals, it is possible to exploit the available workspace more efficiently. However, in contrast to conventional control tasks, an exact knowledge of the reference trajectory is in the context of interactive driving simulation equivalent to the assumption that the driver behavior and the resulting vehicle reaction are known in advance. Since this clearly depends on the current driving situation, as well as on the driver himself, model predictive MCA usually assume a constant reference trajectory based on the current accelerations and angular velocities (Grottoli et al., 2018). Although this intuitive prediction strategy enables active driving simulations with a human *Driver-in-the-Loop*, the potential of the predictive controller is obviously not fully exploited. In previous studies of Bruschetta et al. (2017), a reference prediction based on recorded data from test drives on a racetrack is introduced. Here, the current translational accelerations and angular velocities of the vehicle dynamics simulation are kept constant over a short time horizon. For all further time steps within the prediction horizon, the recorded reference from the test drive is selected. If an unexpected driver behavior is detected, the recorded reference is smoothly scaled down to zero. In addition, an artificial neural network that was trained to predict the future vehicle motion at runtime is presented by Mohammadi et al. (2016). Although this approach leads to a less conservative planning of the motion trajectory compared to a constant reference definition, the potential of the motion system is not fully utilized. Thus, there is still no generally admitted approach to estimate reliable reference trajectories for generic driving situations yet.

For that reason, we propose in the present work a novel model-based prediction strategy to exploit the potential of optimization-based MCA more efficiently and therefore provide a better reproduction of the vestibular Motion Cues. A key feature of this approach represents the implementation of a virtual driver model based on established control algorithms. While the prediction of the pedal actuation by the driver is estimated via a linear extrapolation of the current inputs, the future steering inputs are approximated using the *Exact Linearization* technique. This nonlinear control approach includes both available route information and the actual driving state and thus enables a lateral control up to the stability limit of driving dynamics. In combination with a simplified vehicle dynamics model, the driver model is implemented in an iterative prediction algorithm in order to determine the future driver inputs as well as the resulting vehicle reactions depending on the current driving situation within a defined time horizon. By means of measurement data from a real test drive, the resulting control quality of the proposed prediction strategy is compared against a constant reference signal and an ideally known trajectory, which serves as a benchmark in this study.

2. MODEL PREDICTIVE MOTION CUEING ALGORITHM

In addition to the implemented future reference prediction, the quality of the vestibular stimuli reproduction is primarily influenced by the MPC-based control strategy itself. This results from previous research and is described in detail by Biemelt et al. (2018). For that reason, only the basic idea of the algorithm illustrated in Fig. 2 is subsequently discussed.

According to the well-known MPC paradigm, an optimal control problem is numerically solved over a receding time horizon at each calculation cycle. Subsequently, only the first element of the optimal control variable is applied to the process and the procedure is reiterated. For this, the dynamic behavior of the simulator motion system is described as

$$\begin{aligned} \dot{x}(t) &= A \cdot x(t) + B \cdot u(t) \\ y(t) &= f(x(t)). \end{aligned} \tag{1}$$

In this *Wiener model*, the linear state differential equation describes the dynamics of all five controlled actuators with the state vector $x \in \mathbb{R}^{15}$, which contains the angles, the angular velocities and the angular accelerations of each actuator. The associated reference angles are combined in the input vector $u \in \mathbb{R}^5$, while the output equation includes the nonlinear direct kinematics of the driving simulator in order to describe the acting accelerations and angular velocities at the driver's head position. Since the considered motion system of the ATMOS driving simulator, which is described in detail by Al Qaisi and Trächtler (2012), does not support any yaw motion, the output vector is defined as $y = \left[a^T \;\, \omega^T\right]^T \in \mathbb{R}^5$. However, especially the integration of the direct kinematics increases the complexity of the optimization problem to be solved by the MPC and thus also the required computational effort. To overcome this and meet the real-time requirements, the output equation of (1) is approximated by a first order *Taylor series* in each time step. This leads to the constrained optimal control problem

$$\begin{aligned} \underset{\Delta u(0),\ldots,\Delta u(N-1)}{\text{minimize}} \sum_{k=1}^{N} \|y(k) - r(k)\|_Q^2 + \sum_{k=1}^{N} \rho(k) \\ + \sum_{k=0}^{N-1} \|\Delta u(k)\|_R^2 + \|u(N-1)\|_S^2 \end{aligned} \tag{2}$$

subject to

$$\begin{aligned} x_{lo} \le x(k) \le x_{up},\ k \in [1, N] \\ u_{lo} \le u(k) \le u_{up},\ k \in [0, N-1]\ , \end{aligned}$$

where the first and third summand of the cost function consider the control error and the change rate of the actuating variables with the weighting matrices $Q \in \mathbb{R}^{5\times 5}$ and $R \in \mathbb{R}^{5\times 5}$ within the prediction horizon. As the limits

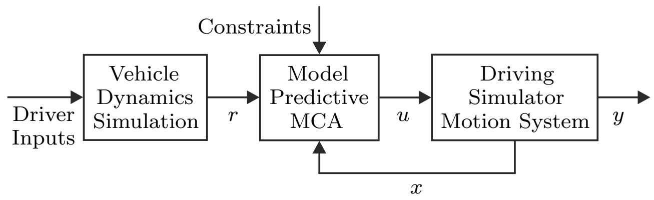

Fig. 2. Scheme of the MPC-Based Control Algorithm.

of the actuators are included as constraints in the optimization problem, it is guaranteed that the planned motion trajectory can be realized by the driving simulator. In addition, the penalty term $\rho(k)$ limits the overall rotation rate of the motion system to the human perception threshold. This enables the MCA to simulate sustained accelerations via the gravity without being distinguishable for the driver. Furthermore, the last summand in (2) represents a terminal cost to return the system to its initial position after performing the movement. Since the control algorithm is executed with a cycle time of $T_{MPC} = 25\,ms$, the prediction horizon is chosen to $N = 40$ discrete time steps in order to realize a receding time horizon of one second. Assuming an a priori known reference trajectory $r \in \mathbb{R}^{5N}$, the described algorithm offers significant improvements over conventional Washout Algorithms regarding the control quality, as it was shown by Biemelt et al. (2019) using various driving maneuvers.

3. MODEL-BASED ONLINE REFERENCE PREDICTION

In order to exploit the potential of the MPC-based MCA described in Section 2 best possible, we subsequently present a novel approach to estimate the future reference trajectory at runtime. Therefore, a concept prementioned by Biemelt et al. (2018) is adopted, which extends the structure shown in Fig. 2 by a model-based prediction strategy, resulting in the scheme illustrated in Fig. 3. The online prediction is composed of a virtual driver model

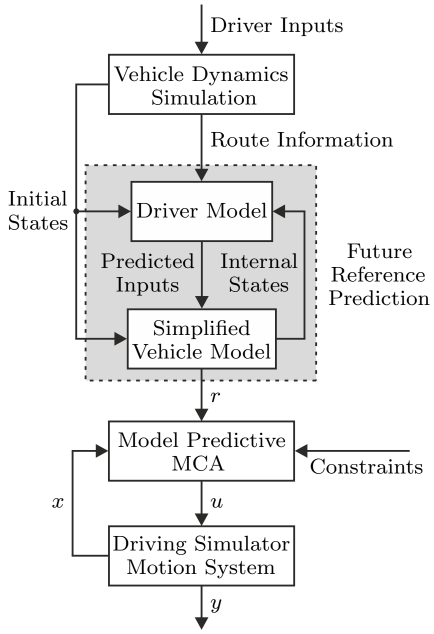

Fig. 3. Model-Based Future Reference Prediction.

and a simplified vehicle model that are initialized with the corresponding state variables from the vehicle dynamics simulation in the beginning of each prediction sequence. Thus it is ensured that the future reference signals are estimated in accordance with the current driving situation. Consecutively, available information on the route and the internal states of the simplified vehicle model are utilized to determine the expected driver inputs, more precisely the pedal actuation as well as the steering input. From these predicted inputs, the resulting motion of the vehicle model is obtained. By repeating this closed loop procedure iteratively, the reference signals for all time steps within the prediction horizon are determined. In the following, the basic components of the proposed approach are discussed in detail.

3.1 Simplified Vehicle Dynamics Model

It is obvious that even an ideal Motion Cueing Algorithm will not create a realistic driving impression if the applied vehicle dynamics model does not ensure a plausible driving behavior. Hence, besides the MCA, the vehicle dynamics simulation itself crucially influences the resulting degree of immersion during an interactive driving simulation. That is why the *Automotive Simulation Models* (ASM) tool suite developed by dSPACE is used for this task in the present work. This commercial multibody model features all relevant subsystems of a real vehicle such as engine, powertrain, axle kinematics, and electronic control units and is therefore well-established in automotive applications (Patil et al., 2012). However, it is easy to see that, because of its complexity, this model is not suitable for an iterative prediction of future reference trajectories since the resulting computational effort is not compatible with the real-time requirements of the MPC.
For this reason, the prediction is performed using a simplified vehicle model of reduced order, which on the one hand can be calculated efficiently, and on the other hand describes the relevant system dynamics of the ASM reference vehicle model with adequate accuracy. More specifically, a nonlinear single-track model is applied, which was extended by models of the powertrain, the brake system and tire models in order to determine the longitudinal and lateral dynamics within the prediction horizon. Here, the extended subsystems are modeled and parameterized analogously to the ASM, while the system dynamics are simplified as much as possible without affecting the prediction accuracy significantly. The corresponding system equations are determined according to the kinematic relations in Fig. 4. These are not further specified at this point, as it represents a standard approach from vehicle modeling. Since the plane single-track model does not offer a description of the vertical dynamics nor the roll and pitch velocities, these quantities are derived from the acting longitudinal and lateral accelerations as well as the road excitations with an appropriate spatial model, which is evaluated subsequently to the single-track model.
The overall simplified vehicle model according to Fig. 3 therefore contains 21 internal state variables, which are initialized in each prediction cycle with the state variables of the ASM vehicle dynamics simulation. Based on the property that the internal states of the reduced order vehicle model are clearly determined for any times $t > t_0$, if the initial states at time t_0 and the input variables for

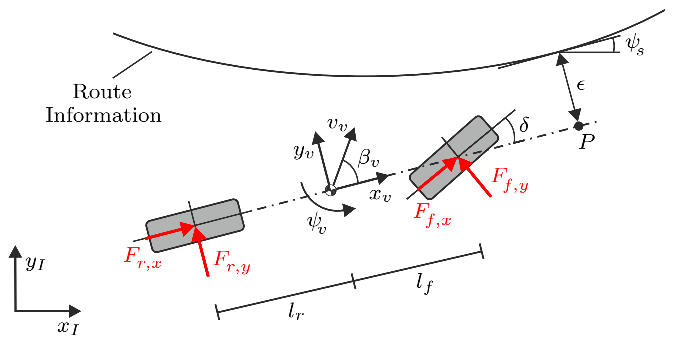

Fig. 4. Simplified Vehicle Dynamics Model.

$t > t_0$ are known, the reference vector $r(k)$ of the optimal control problem (2) can be determined with the required accuracy as a function of the predicted inputs from the driver model for each time step $k \in \mathbb{Z}$ with $1 \leq k \leq N$.

3.2 Prediction of Longitudinal Driver Inputs

Driving a vehicle can be interpreted as a control task in which the human driver acts as the controller. It therefore seems reasonable to estimate the future driver inputs based on the current driving situation for a future time horizon using a control algorithm that is considered as a driver model. While this concept achieves good results in estimating lateral driver inputs, as described in the following section, practical application has shown that the pedal actuation by a human driver is hard to generalize. Imagine a situation where the simulated vehicle is driving towards a speed-limitation. Although it can be assumed that the driver will reduce the vehicle's speed, the exact timing and intensity of the brake process depends on the particular driver type and a multiplicity of external influences, such as the visual range.

Hence, we propose a linear extrapolation of the driver inputs for predicting the future positions of the accelerator pedal $p_A(k)$ and the brake pedal $p_B(k)$. For this, the corresponding difference quotients

$$\begin{aligned} \frac{\Delta p_A}{\Delta t} &= \frac{p_A(0) - p_A(-1)}{T_{MPC}} \\ \frac{\Delta p_B}{\Delta t} &= \frac{p_B(0) - p_B(-1)}{T_{MPC}} \end{aligned} \tag{3}$$

based on the known current and last driver inputs $p(0)$ and $p(-1)$ are kept constant for each prediction cycle of the MCA. With respect to the application, the driver model thus assumes that the driver continues his current inputs with a constant rate of change within the considered time horizon of one second. This method provides a good approximation of the real driver inputs for short prediction intervals, while the quality of prediction clearly decreases for long time periods. However, it should be noted that any estimation of future driver inputs is affected by errors, as human driving behavior can never be predicted exactly. It was observed that with this method, a satisfying prediction of the pedal actuation can be achieved, which results in an adequate tracking of the longitudinal accelerations by the MPC-based MCA (see Section 4).

3.3 Prediction of Lateral Driver Inputs

In contrast to the previously described estimation of the pedal actuation, available information about the future route enables a precise prediction of the oncoming steering inputs using a control algorithm in the driver model. This is based on the assumption that the human driver in the simulator attempts to follow the given route best possible. That can generally be expected, since the route is usually specified prior to the interactive driving simulation depending on the research question.

Therefore, a method for lateral control of vehicles is applied in the context of this work that enables a stable control up to the limits of driving dynamics. It is based on a nonlinear control algorithm according to the principle of Exact Linearization, which was initially described by König et al. (2007). Here, the lateral dynamics of the simplified vehicle model as shown in Fig. 4 are defined by the differential equations of the slip angle β_v and the yaw angle ψ_v as

$$\begin{aligned} \dot{\beta}_v &= -\dot{\psi}_v + \frac{1}{m \cdot |v_v|} \cdot (F_{f,y} + F_{r,y}) \\ \ddot{\psi}_v &= \frac{1}{J} \cdot (F_{f,y} \cdot l_f - F_{r,y} \cdot l_r) \end{aligned} \tag{4}$$

with the mass m and the moment of interia J being vehicle parameters. These equations can be derived from the conservation of momentum of the single-track model using a small angle approximation. Since this represents a standard modeling approach, which is explained in detail by Schramm et al. (2014), the derivation is not further discussed at this point.

To ensure a sufficiently accurate description of the lateral dynamics up to the traction limit, the degressive behavior of the lateral forces is approximated by nonlinear arc tangent functions:

$$\begin{aligned} F_{f,y} &= c_{f,1} \cdot arctan\,(c_{f,2} \cdot \alpha_f) \\ F_{r,y} &= c_{r,1} \cdot arctan\,(c_{r,2} \cdot \alpha_r) \end{aligned} \tag{5}$$

By parameterizing $c_{i,1}$ and $c_{i,2}$ adequately, the relevant tyre characteristics of (5) are consistent with the complex tyre models of the vehicle model from Section 3.1. The variables α_i denote in this context the sideslip angles, which can be expressed by the steering angle δ, the slip angle β_v, and the yaw velocity $\dot{\psi}_v$.

Moreover, it is necessary to consider the limited bandwidth of the vehicle's steering system that is approximated by the first order differential equation

$$\dot{\delta} + \omega_s \cdot \delta = \omega_s \cdot u \tag{6}$$

with the cutoff frequency ω_s and the driver's steering input u.

Since the basic idea of the proposed prediction strategy assumes an ideal driver behavior, an expression of the lateral deviation ϵ from the specified route is required. For this purpose, the time related change of the lateral deviation $\dot{\epsilon}$ is described as follows from geometric aspects according to Fig. 4:

$$\dot{\epsilon} = |v_v| \cdot sin\,(\psi_v + \beta_v - \psi_s) + l_p \cdot \dot{\psi}_v \cdot cos\,(\psi_v - \psi_s) \tag{7}$$

Here, the parameter l_p describes the distance of a vehicle fixed reference point P from the center of gravity, which provides a damping influence on the resulting control behavior (Alloum et al., 1995). Under the assumption that the driving direction $\psi_v + \beta_v$ and the route direction ψ_s

do not differ significantly at any time, which is the task of the lateral controller, (7) can be simplified to

$$\dot{\epsilon} = |v_v| \cdot (\psi_v + \beta_v - \psi_s) + l_p \cdot \dot{\psi}_v \ . \tag{8}$$

By combining (4)-(6) and (8), the nonlinear state space description of the simplified vehicle model's lateral dynamics results as

$$\begin{aligned} \dot{x}(t) &= f(x(t)) + g_u \cdot u(t) + g_z \cdot \psi_s(t) \\ y(t) &= h(x(t)) \end{aligned} \tag{9}$$

with the corresponding state vector

$$x(t) = \begin{bmatrix} \psi_v(t) & \dot{\psi}_v(t) & \beta_v(t) & \epsilon(t) & \delta(t) \end{bmatrix}^T \in \mathbb{R}^5. \tag{10}$$

The scalar output variable y represents the lateral deviation ϵ, while the route direction ψ_s is included as a disturbance in the system (9). Thus, this control-affine system is of order $n = 5$ and has a relative degree of $\vartheta = 3$, enabling the *Input-Output Linearization* technique to be applied in order to minimize the lateral deviation (Henson and Seborg, 1990). For this purpose, the time derivatives of the output variable are determined up to the relative degree ϑ, using *Lie Operators* for reasons of clarity:

$$\frac{\mathrm{d}^3\epsilon(t)}{\mathrm{d}t^3} = L_f^3 h(x(t)) + L_{g_u} L_f^2 h(x(t)) \cdot u(t) - |v_v| \cdot \ddot{\psi}_s(t) \tag{11}$$

Based on this expression, the following compensation term is derived to ensure that the transfer behavior of a new system input $\tilde{u}$ to the control variable ϵ yields the linear system dynamics of a triple integrator:

$$u(t) = \frac{1}{L_{g_u} L_f^2 h(x(t))} \left(-L_f^3 h(x(t)) + |v_v| \ddot{\psi}_s(t) + \tilde{u}(t) \right) \tag{12}$$

Since the lateral dynamics system (9) thus provides a linear input-output behavior, a control law of the form

$$\begin{aligned} \tilde{u}(t) &= -k \cdot [\epsilon \ \ \dot{\epsilon} \ \ \ddot{\epsilon}]^T \\ &= -k \cdot \begin{bmatrix} h(x(t)) \\ L_f h(x(t)) - |v_v| \cdot \psi_s(t) \\ L_f^2 h(x(t)) - |v_v| \cdot \dot{\psi}_s(t) \end{bmatrix} \end{aligned} \tag{13}$$

is applied to ensure a desired pole configuration of the closed loop system. This specifies the performance of the lateral dynamics controller and consequently the steering characteristics of the virtual driver model.

The proposed approach is characterized by an intuitive tuning, a reliable control up to the traction limit, as well as a low computational effort and is therefore well suited for the implementation in an iterative prediction strategy. In this context, the algorithm can be interpreted as disturbance control that attempts to compensate initial lateral offsets induced by the human driver at the beginning of each prediction sequence.

3.4 Resulting Iterative Prediction Algorithm

In order to estimate the future reference trajectory r according to Fig. 3 at runtime, an iterative prediction algorithm was developed in the context of this contribution. For this, the overall closed loop system, consisting of the simplified vehicle dynamics model and the virtual driver model, is initialized every $25\,ms$ with the current state variables from the vehicle dynamics simulation. The resulting initial value problem is subsequently solved, using the *Euler method* to evaluate the future internal state and reference variables within the prediction horizon N. Here, an internal step size of $1\,ms$ is used to ensure the stability of the numerical integration, causing a considerable computational effort. However, the required compliance with the real-time requirements was achieved by an efficient implementation in this work, using an AMD Opteron CPU @ $2.8\,GHz$.

Subsequently, the predicted reference signals are scaled with constant factors in the postprocessing, since an exact reproduction is usually not feasible due to the motion system's limited workspace. But in contrast to a constant reference trajectory, the proposed prediction strategy exploits the workspace more efficiently, which enables a lower signal scaling and thus a more immersive driving impression. As the model-based determined references are nevertheless affected by prediction errors, a reduction in the weighting of the control deviations through the prediction horizon is applied. Therefore, the weighting matrix Q in the optimization problem (2) is exponentially decreased in each future time step k as

$$Q(k) = Q_0 \cdot \zeta^{k-1} \tag{14}$$

with $\zeta = 0.99$ for all $k \in [1, N]$. This modified weighting is used for both online prediction and constant reference to ensure a consistent basis for evaluation described in the next section.

4. RESULTS AND DISCUSSION

In the following, the resulting control quality of the MPC-based MCA in combination with the proposed prediction strategy is evaluated. The online prediction is for this purpose compared to the conventional approach of constant reference signals, as well as an ideally known reference trajectory. The latter is obviously not realizable during active driving simulations with a human Driver-in-the-Loop and serves only as a benchmark in this context. As a basis for evaluation, test drives were carried out by an experienced simulator driver, who was instructed to follow a defined route while respecting the given speed limits. Measurement data of the translational accelerations and angular velocities taken with an inertial measurement unit at the driver's head position are used to analyze the respective control performances.

Fig. 5 shows the resulting longitudinal acceleration and pitch velocity tracking. It becomes evident that the control algorithm yields an adequate reproduction of the longitudinal acceleration from the vehicle dynamics simulation with all prediction strategies, which proves the robustness of this approach. However, in contrast to the constant reference approach, the use of the online prediction shows a significantly higher agreement with an ideally known reference, especially when there are rapid changes in the acceleration, for example at the times $t = 6$ seconds and $t = 58$ seconds. Moreover, the use of a constant reference trajectory causes larger time delays over the entire measuring period, which have already been observed by Grottoli et al. (2018). The corresponding pitch velocities contain in all cases low-frequency disturbances that can be explained by a necessary rotation of the motion system to reproduce sustained accelerations using the tilt coordination technique. By introducing the penalty term in the cost function of (2), these can be successfully limited to the acceptance threshold of $0.1\,rad/s$ relative to the

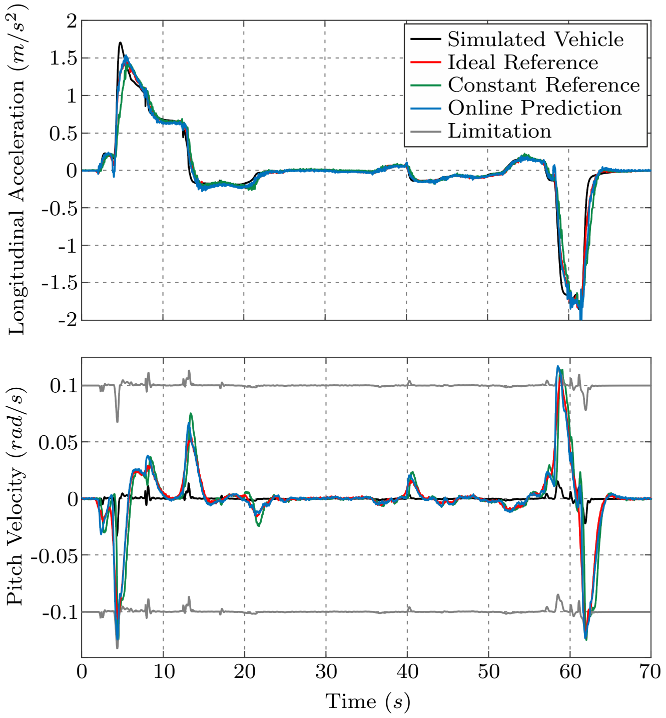

Fig. 5. Longitudinal Acceleration and Pitch Velocity Tracking.

reference value, regardless of the selected reference trajectory approach. It is worth mentioning in this context that the MPC thus accepts control errors in the tracking of longitudinal accelerations in order to avoid the rotation of the motion system being detectable for the human perception system. Equivalent results can be derived from Fig. 6, which illustrates the measured lateral accelerations and the associated roll velocities. Also in this case is the acceleration reference from the simulated vehicle tracked

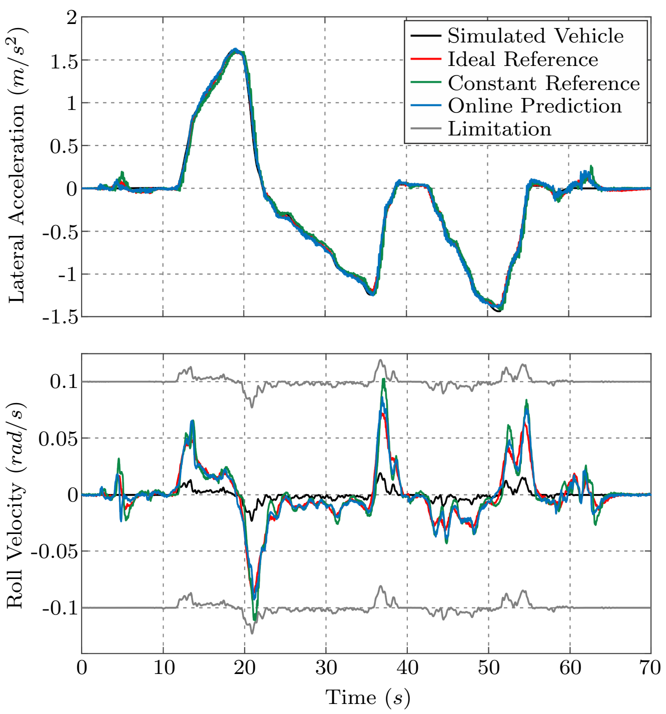

Fig. 6. Lateral Acceleration and Roll Velocity Tracking.

very well by all three algorithms. Furthermore, the difference between online prediction and a constant reference is less significant, since moderate lateral accelerations were examined during the test drive. Due to the results of the longitudinal acceleration reproduction, it is to be expected that in more aggressive driving maneuvers, such as a double lane change at high speed, the online prediction strategy will enable a better tracking. Nevertheless, even in this moderate maneuver there is a noticeable time delay when using a constant reference trajectory, indicating that the potential of the MPC approach is not optimally exploited. The roll velocity error is again successfully limited to the defined threshold value when using all algorithms, for which reason it is assumed that these deviations are not perceived by the driver. Concluding, the vertical accelerations measured in the test drives are shown in Fig. 7. Here it can be seen that the particular method for specifying the reference trajectory only has a minor influence on the reproduction of vertical accelerations, since the signals only differ insignificantly. All three approaches exhibit low-frequency deviations from the reference acceleration, which are caused by the motion system's coupled degrees of freedom and cannot be completely compensated. However, these unpreventable errors are mostly below the human perception threshold, so that they do not affect the quality of the motion rendering in a negative way.

In order to objectify those results, a suitable valuation metric is applied that was described in detail by Biemelt et al. (2019). It is based on defined quality criteria using the performance indicators λ_1 and λ_2. While λ_1 provides a measure of the average normalized control error, the indicator λ_2 describes the perceived control quality, including well-established models of the human vestibular organs,

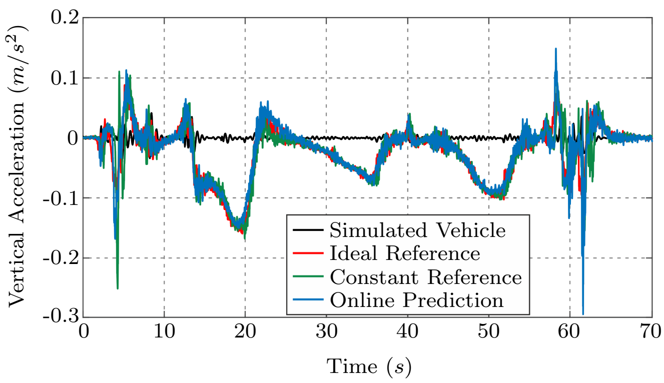

Fig. 7. Vertical Acceleration Tracking.

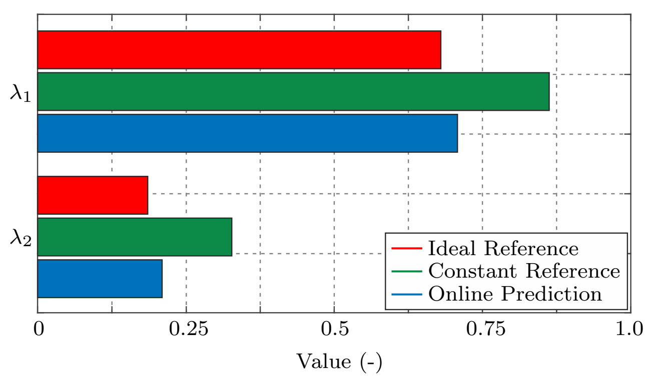

Fig. 8. Performance Indicator Based Evaluation.

as well as perception thresholds. Consequently, the closer those performance indicators are to the origin, the better is the reproduction of the simulated vehicle movements by the driving simulator. The graphical analysis of the performance indicators according to Fig. 8 illustrates the benefits of the proposed online prediction strategy over a constant reference trajectory, since smaller performance indicators are achieved. Furthermore, it should be noted that both quality indicators are only slightly larger when the online prediction is used than with an ideally known reference signals. This proves the high prediction quality of the described approach and thus allows a more realistic driving impression, which is a major benefit for interactive driving simulation.

5. CONCLUSION AND FUTURE WORK

In this paper, the development of a model-based prediction approach to estimate future reference trajectories for model predictive Motion Cueing Algorithms was presented. In contrast to existing methods, the presented algorithm is based on a simplified vehicle model, as well as a virtual driver model, to approximate future driver inputs and the resulting vehicle reactions depending on the current driving situation. By including algorithms from nonlinear control theory, a stable lateral control up to the limits of driving dynamics is ensured. The added value for the interactive driving simulation was proven on the basis of measurement data from real test drives, which demonstrated a satisfying control quality. Thus, it could be verified that the potential of optimization-based control algorithms can be exploited almost optimally by integrating additional model knowledge in the reference prediction algorithm.

The future work will deal with the subjective validation of these observations. In this context, appropriate subject studies will be conducted in order to rate the resulting degree of immersion by human drivers. Besides, the virtual driver model will be improved so that the driver behavior can be reproduced even more accurately. This includes, in addition to interaction with other traffic participants, adequate prediction strategies for driving situations in which the future route cannot be clearly determined, e.g. at intersections, or if the driver obviously acts contrary to the predicted behavior.

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