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Towards Black-Box Dynamics Modelling within Learning-based Nonlinear Model Predictive Control for Virtual Motorcycles

Francesco Bianchin [1], Enrico Picotti [2,*], Mattia Bruschetta [2]

[1] TUM School of Computation, Information and Technology, Technical University of Munich; francesco.bianchin@tum.de, ORCID 0009-0004-7916-467X
[2] Department of Information Engineering, University of Padova, Italy; {name.surname}@dei.unipd.it, ORCID 0000-0002-5356-610X; ORCID 0000-0003-0769-4191
[*] corresponding author

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Abstract:

In recent years, both academic and industrial effort has been devoted to developing Virtual Riding (VR) strategies, in line with the attempts towards virtual prototyping in the automotive business. The advantages of virtual prototyping include reduced costs, time-to-market, and increased safety. Nonlinear Model Predictive Control (NMPC) schemes have been utilized to achieve high-performance real-time control of the motorcycle system, while emulating a realistic riding behavior, as described, e.g., in Massaro (2011); Bruschetta et al. (2021). To apply NMPC techniques, a detailed model of the plant is necessary, and different dynamics models have been proposed in literature. However, the accuracy of physics-based motorcycle models that grant real-time feasibility of the NMPC remained questionable when compared to a realistic system behavior. Besides, they require specific measurements and identification procedures to be applied. In this sense, Learning-based NMPC (LbNMPC) framework, described in Hewing et al. (2020), could be a promising new direction. LbMPC is a broad research field that generally refers to the implementation of learning techniques into NMPC control schemes. Specifically, the *learning dynamics* sub-field covers the data-based adaptation of the NMPC prediction model. In this context, Gaussian Process Regression (GPR) resulted very effective in applicative scenarios, as shown in Kabzan et al. (2019); Carron et al. (2019); Picotti et al. (2023).

We propose an LbNMPC controller for a virtual motorcycle based on black-box dynamics modeling. Learning-based dynamics models of the accelerations have been obtained by GPR, where the targets are the yaw $\ddot{\psi}$ and roll $\ddot{\theta}$ accelerations in body frame, while longitudinal and lateral ones are computed by the nominal model described in Bruschetta et al. (2021). Two independent zero-mean GPs have been trained, defining the covariance matrix through the Squared Exponential kernel. To reduce the computational burden, a sparse GP approximation and a feature selection procedure have been applied. Regarding the former, the Variational Free Energy approach proposed in Titsias (2009) has been employed, while the latter has been implemented adapting the iterative incremental approach proposed in Rossi et al. (2006), using R^2 index to define the feature importance. The obtained black-box acceleration estimates are greatly consistent with the *real* ones, i.e. the simulated ones in the commercial high-fidelity simulation framework `VI-BikeRealTime`, as depicted in Fig. 1. The achieved R^2 values for yaw and roll are 0.82 and 0.90, respectively.

The LbNMPC obtained using the black-box model has been compared to the NMPC using the nominal physics-based model described in Bruschetta et al. (2021). The configuration of the controllers is the same, except for the prediction model within. The closed-loop behavior on a racetrack has been evaluated based on the tracking capabilities. In particular, lateral and angular displacement with respect to the given trajectory and the velocity error with respect to the given profile have been assessed. The LbNMPC achieved a significant reduction (between 48% and 83%) of all the indicators, as reported in Tab. 1 and depicted in Fig. 2, while involving an increase of 238% of the computational time. Indeed, the results demonstrate the benefits achievable by the LbNMPC approach, while still acknowledging the significant computational burden increment.

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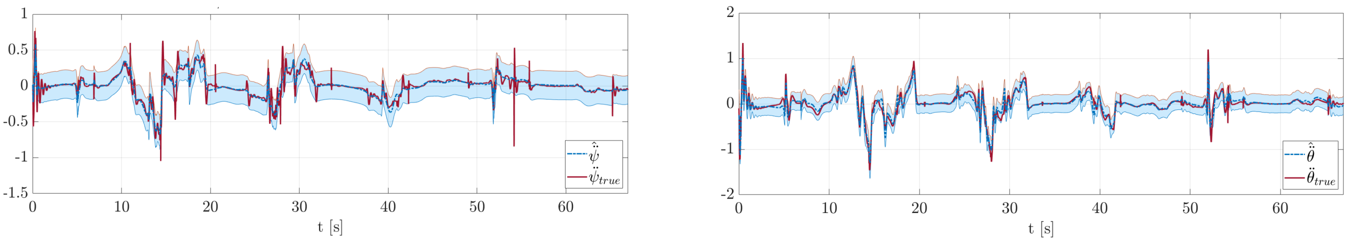

Figure 1. Black-box yaw and roll accelerations' estimation.

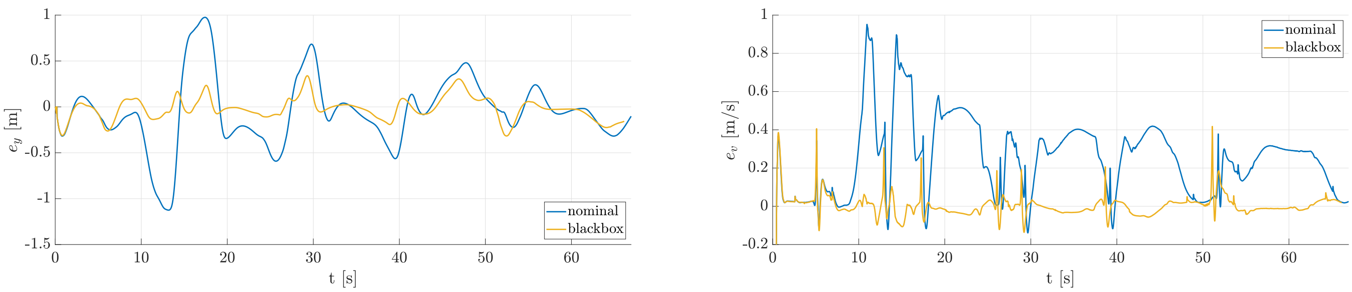

Figure 2. Lateral and velocity errors w.r.t. trajectory for nominal and black-box models.

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Table 1. Closed-loop results in terms of mean tracking performance and computational time.

	nominal	black-box
e_y $[m]$	0.277	0.0936 (-66.2%)
e_ψ $[deg]$	0.908	0.472 (-48.0%)
e_v $[m/s]$	0.268	0.0451 (-83.2%)
T_{solver} $[ms]$	6.57	22.84 (+248%)

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