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LPV-based control for automated driving using data-driven methods

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Abstract: This paper presents a data-driven modeling approach and control design for automated driving purposes. The parameters of the control-oriented polytopic model is tuned using machine-learning algorithm in a Linear Parameter Varying (LPV) structure. The control of the automated driving is designed based on the LPV control synthesis method, with which the performances of the system are guaranteed. Through the automated driving system the steering intervention is performed, while the maximization of the longitudinal velocity in a predicted safety region is achieved. The operation and the effectiveness of the proposed control system is demonstrated through a comprehensive simulation example using the high-fidelity simulation software CarSim.

Keywords: autonomous vehicle control, data-driven modeling, LPV control design, decision tree

1. INTRODUCTION AND MOTIVATION

Nowadays, one of the main challenges of the automotive industry is the development of the self-driving autonomous vehicles. It requires new technologies and solutions, which guarantee the safe, efficient and economical traveling. It involves the cooperation of the different research fields such as sensing (both the vehicle and environment), communication (V2V, V2I), decision making and control.

The paper deals with the control task by providing an adaptable data-based approach, which is more suitable for autonomous vehicles. A large number of control design methods have already been developed and implemented. They are based on their physical models. Even though some of the used models have high complexity, they are not able to describe accurately the nonlinear dynamics of the vehicle and moreover, they make the control design more difficult, see e.g. Németh et al. [2016], Masouleh and Limebeer [2016].

Possible approaches can be the deep-learning and machine learning-based control systems. Neural network-based solutions were proposed by Hubschneider et al. [2017], Rausch et al. [2017]. In general, they can handle nonlinear behaviors of cars and provide acceptable performances. The main drawback of the data-driven learning solutions is that there are no theoretical backgrounds for stability analysis. Thus, their applications might have risk in real-life scenarios, e.g. in an extreme scenario.

The main purpose of the paper is to present data-driven modeling and control solutions for autonomous vehicles, whose stability and performances can be guaranteed. The structure of the control system is based on the LPV (Linear Parameter Varying) method, while its scheduling variables are selected by a machine-learning-based technique. Through the combination of these approaches, the nonlinear behavior of the vehicle can be taken into account and, at the same time, the stability and the performances of the controller are also guaranteed.

Some furhter approaches with similar purposes are found in the literature. For example, in Rosolia and Borrelli [2018] a Model Predictive Control based solution, whose terminal cost and terminal sets are determined by using an iterative approach, is proposed. A Model Free Control methods was proposed Fliess and Join [2013]. The advantage of this approach is that it does not require any preliminary knowledge of the system structure and it is able to handle highly nonlinear systems as well. A drawback of this method is that performance specifications are difficult to integrate into the system.

In the paper it is assumed that the structure of the physical model is considered to be known and its parameters are

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identified by an optimization algorithm in the operating points. It allows the designer to use the same formulation of the performances as in any LPV-based configurations. Furthermore, the scheduling variables of the LPV system is determined by a machine-learning algorithm (e.g. C4.5 decision tree algorithm), which uses big measured signals provided by the vehicle.

The main contribution of the paper is a data-driven method for the parameter tuning of a control-oriented model in LPV form, which is used in the robust control design. Although the proposed method is independent from the control applications in this paper the problem is formed in the context of automated driving. Another contribution of the paper is a control strategy, which has two features. First, the lateral steering control guarantees the performances of the path following functionality against the wide range variation of the vehicle dynamic scenarios. As a novelty of the paper, the robust control design is based on a data-driven polytopic LPV model, whose scheduling variable represents the variation of the conditions in the vehicle dynamics. Second, a maximization method of the longitudinal velocity is proposed. During the optimization, the velocity is selected to keep the predicted vehicle motion in a safety region. The operation of the proposed method is demonstrated through a complex scenario in the high-fidelity simulation software CarSim.

Structure of control system

The structure of the modeling and the control design is presented as follows. Figure 1 shows the main elements of the algorithm. They are divided into five subtasks: 1. *Prepocess of data*, 2. *Model identification*, 3. *Control design*, 4. *Velocity optimization* and 5. *Simulation environment*.

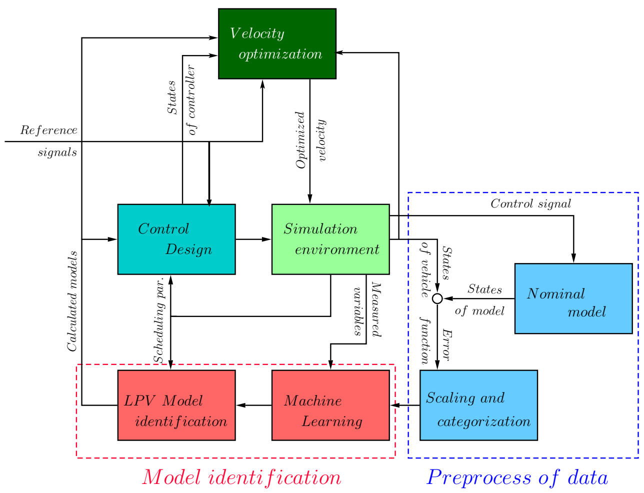


Fig. 1. Layers in the design process of the automated driving strategy

The 'Simulation environment' includes the high-fidelity simulation software CarSim. This software has two roles: 1. it is used to generate the training and test datasets for the machine-learning algorithm and 2. it is used to evaluate the proposed control system. The layer 'Prepocess of data' divides the generated dataset into training and tests for the machine-learning algorithm. It also includes the scaling and the categorization of the data. More detailed description of this layer is presented in Subsections 2.1 and 2.2. The 'Model identification' includes the computation of the scheduling parameters. Basically, it selects the most significant variables from the dataset, which have high impact on the dynamics of the vehicle. Moreover, the parameters of the LPV-based models are computed in this layer. This layer is presented in Subsections 2.3 and 2.4. The 'Control design' contains the control design steps of the lateral controller, which are described in Section 3. The goal of the layer 'Velocity optimization' is to compute the optimal longitudinal velocity for the vehicle, which can guarantee the safe and stable motion of the vehicle, detailed in Section 4. Finally, a comprehensive simulation is presented to show the operation and effectiveness of the proposed control system in Section 5.

2. DATA-DRIVEN MODELING OF THE LPV SYSTEM

In this section the modeling method in the LPV form is presented. The main steps of the modeling is the acquisition of the datasets, the labeling of the collected instances, the selection of the scheduling variables and the parameter identification of the LPV-based model.

2.1 Acquisition of data from simulations

In the data acquisition the simulations in CarSim software are performed to collect large number of signals. Several simulations have been generated with varying parameters in order to cover a wide range of the operation of the vehicle. The vehicle has been driven by the in-built driver at different fixed longitudinal velocities $10-20m/s$ in the simulations. During these simulations, the following signals have been measured and saved with the sampling time $T_S = 0.01s$: 1. longitudinal velocity (v_x), 2. angular velocity of the wheels ($\omega_{x,y}$), 3. yaw-rate ($\dot{\psi}$), 4. steering angle (δ), 5. accelerations (a_x, a_y), 6. side-slip angle (β). Note that the side-slip angle is only needed for the modeling process, during the operation of the vehicle is not required. Its advantage is that the onboard measurement of β can be avoided, which requires expensive sensors.

2.2 Labeling the collected instances

In the next step the instances are ordered into categories, which reflect on the nonlinear behavior of the vehicle. The categorization is carried out by computing the deviation of each instance from the physical model, which is considered to be the nominal model of the system. The physical model, basically, consists of two equations, see Rajamani [2005]:

$$I\ddot{\psi} = C_1\alpha_1 l_1 - C_2\alpha_2 l_2 \tag{1}$$

$$mv_x(\dot{\psi} + \dot{\beta}) = C_1\alpha_1 + C_2\alpha_2 \tag{2}$$

where α_i are the side-slip angles of the rear and front wheels, $\dot{\psi}$ denotes the yaw-rate, β represents the side-slip angle of the vehicle, m is the mass of the car, I is the yaw-inertia, C_i are the cornering stiffness of the front and rear wheels and l_i are geometric parameters of the vehicle.

For computing the response of the nominal model, the equations are formed into a state-space representation.

The state vector $x = \begin{bmatrix}\dot{\psi} & \beta\end{bmatrix}^T$, the input of the system $u = \delta$ and its matrices are denoted by A_p, B_p. Furthermore, this continuous representation is discertized using the sampling time $T_s = 0.01s$. The states of the discretized model are computed for each instance. The categorization of the instances relies on the deviation of the measured and the computed states. Therefore, the relative errors of these signals are determined as:

$$\dot{\psi}_e(t_i) = \frac{|\dot{\psi}_m(t_i) - \dot{\psi}_n(t_i)|}{\dot{\psi}_n(t_i)} \tag{3a}$$

$$\beta_e(t_i) = \frac{|\beta_m(t_i) - \beta_n(t_i)|}{\beta_n(t_i)} \tag{3b}$$

where $\dot{\psi}_m$ and β_m denote the measured outputs while $\dot{\psi}_n$ and β_n are the outputs of the nominal system. In the method categories have been predefined for the classification of the instances, such as n equidistant sections between 0 and 1. It is defined a function $\mathfrak{f}$, which associates the errors (3) with the categories. A given instance in t_i is labeled based on the following value

$$cat(t_i) = \max\Big(\mathfrak{f}\big(\dot{\psi}_e(t_i)\big), \mathfrak{f}\big(\beta_e(t_i)\big)\Big), \tag{4}$$

which means that label $cat(t_i)$ is selected based on the maximum of the errors.

2.3 Selection of the scheduling variables

In the previous subsection, the instances have been ordered into predefined categories ($cat(t_i)$). The categorization is based on the difference between the instances from a nominal model, which are calculated offline based on the collected data. The result of the categorization is a decision tree, which might be used during the operation of the vehicle online. Thus, in the followings a decision tree algorithm is used to determine the category of the current instance using solely the available onboard signals. The decision tree algorithms are able to catch highly nonlinear behavior by finding the correlation between the available signals and the output variable (in this case the category). The consequence of the decision tree is the value of the scheduling variable, which are contained by the leaves. Thus, the decision tree determines the category of a given instance ξ, which is used in the LPV system as a scheduling parameter.

In this paper, the C4.5 decision tree algorithm for categorization purposes is applied Hunt [1962], Quinlan [1993]. The basic idea behind the algorithms is to minimize the entropy of the training sets by creating new subsets (new conditions, nodes). It is achieved by putting the instances into the appropriate category.

2.4 Parameter tuning of the LPV system

In the parameter tuning of the polytopic LPV system the parameters of each linear systems are used. The linear systems are related to the resulting categories, from which the polytopic LPV system can be built up. The structure of the nominal model is preserved, which means that each linear systems have two states ($x_d = [\dot{\psi} \;\; \beta]$). The state-space representation is formed as:

$$\dot{x}_d = A_d(\xi)x_d + B_d u_d(\xi), \tag{5}$$

where

$$A_d(\xi) = \begin{bmatrix} a_{11}(\xi) & a_{12}(\xi) \\ a_{21}(\xi) & a_{22}(\xi) \end{bmatrix}, \quad B_d(\xi) = \begin{bmatrix} b_1(\xi) \\ b_2(\xi) \end{bmatrix},$$

and $a_{11}(\xi), a_{12}(\xi), a_{21}(\xi), a_{22}(\xi)$ and $b_1(\xi), b_2(\xi)$ are parameters, which must be determined. The control input of the system is the steering angle $u_d = \delta$.

The goal of the identification process is to minimize the errors between the measured states ($x_{m,j}(t_i)$) and the computed states ($x_{d,j}(t_i)$) for each time step. This leads to an optimization problem, in which the parameters $a_{11}(\xi), a_{12}(\xi), a_{21}(\xi), a_{22}(\xi)$ and $b_1(\xi), b_2(\xi)$ must be identified:

$$\min_{\substack{a_{11}(\xi), a_{12}(\xi), a_{21}(\xi), \\ a_{22}(\xi), b_1(\xi), b_2(\xi)}} \sum_{i=1}^{N} \sum_{j=1}^{2} \big(x_{m,j}(t_i) - x_{d,j}(t_i)\big)^2, \tag{6}$$

where j denotes the states of the system ($\dot{\psi}$ and β) This quadratic optimization problems can be solved for all fixed category xi, see Gill et al. [1981], Coleman and Li [1996]. Using the identified linear systems, the gridded LPV system can be built up.

3. LATERAL CONTROL DESIGN FOR AUTOMATED DRIVING

The goal of the control design is to guarantee the trajectory tracking of the vehicle, which requires the modeling of the lateral motion of the vehicle. Therefore, the presented control-oriented LPV model is augmented with two additional states: lateral velocity (v_y) and lateral position (y) using the following equation:

$$\begin{aligned} \dot{v_y} &= v_x(\dot{\psi} + \dot{\beta}) = \\ &= v_x\dot{\psi} + v_x(a_{21}(\xi)\dot{\psi} + a_{22}(\xi)\beta + b_2(\xi)\delta). \end{aligned} \tag{7}$$

The identified system is augmented as:

$$\dot{x} = A(\rho)x + B(\rho)u \tag{8}$$

and

$$A(\rho) = \begin{bmatrix} a_{11}(\xi) & a_{12}(\xi) & 0 & 0 \\ a_{21}(\xi) & a_{22}(\xi) & 0 & 0 \\ v_x(1 + a_{21}(\xi)) & v_x a_{22}(\xi) & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, B(\rho) = \begin{bmatrix} b_1(\xi) \\ b_2(\xi) \\ v_x b_2(\xi) \\ 0 \end{bmatrix},$$

where the augmented state vector of the system is $x = \begin{bmatrix}\dot{\psi} & \beta & v_y & y\end{bmatrix}^T$, $u = u_d$ and ξ, v_x are selected as scheduling variables, whose vector is $\rho = [\xi \;\; v_x]$.

The performance specifications, which must be guaranteed by the controller, are defined as follows.

- The main goal of the control design is to guarantee the trajectory tracking of the vehicle, which means that the error between the lateral position (y) and the reference signal (y_{ref}) must be minimized:
$$z_1 = y_{ref} - y, \qquad |z_1| \to min, \tag{9}$$
- Another important requirement is the tracking of the yaw-rate signal to achieve the smooth tracking of the road.
$$z_2 = \dot{\psi}_{ref} - \dot{\psi}, \qquad |z_2| \to min, \tag{10}$$
where the computation of $\dot{\psi}_{ref}$ can be found in Rajamani [2005].

- Since the control actuation has physical constraints, the intervention must be limited as:

$$z_3 = \delta, \qquad |z_3| \to min. \tag{11}$$

The defined performances are written into a vector $z = [z_1\ z_2\ z_3]^T$, which leads a performance equation:

$$z = C_1 x + D_{11} r + D_{12} u, \tag{12}$$

where C_1, D_{11}, D_{12} are matrices and r contains the signal y_{ref}. The dynamic equation of the vehicle motion (8) is extended with the performance equation:

$$\dot{x} = Ax + Bu, \tag{13a}$$
$$z = C_1 x + D_{11} r + D_{12} u, \tag{13b}$$
$$y_K = C_2 x, \tag{13c}$$

where $y_K = [y\ \dot{\psi}]$.

In the control design several scaling and weighting function are used to guarantee the presented performances. $W_{ref,1}$ and $W_{ref,1}$ are the scaling functions of the references signals. $W_{z,1}$, $W_{z,2}$ and $W_{z,3}$ are the weighting functions of the performances. While, the weighting functions $W_{w,1}$ and $W_{w,2}$ are to attenuate the noises of the measured signals.

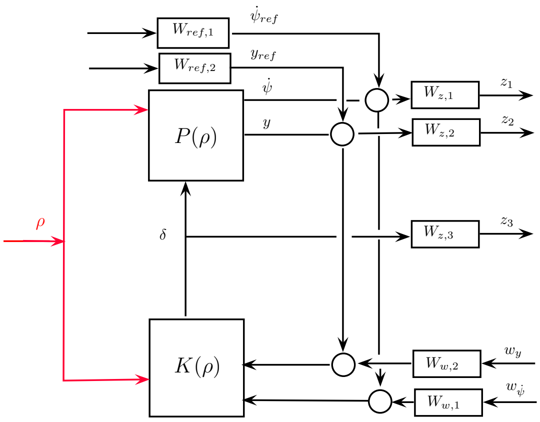


Fig. 2. Augmented plant for LPV control design

The quadratic LPV performance problem is to find the parameter-varying controller $K(\rho)$ in such a way that the resulting closed-loop system is quadratically stable and the induced $\mathcal{L}_2$ norm from disturbance and to performances is less than the value γ. The minimization task is the following:

$$\inf_{K(\rho)} \sup_{\rho \in F_\rho} \sup_{\|w\|_2 \neq 0, w \in \mathcal{L}_2} \frac{\|z\|_2}{\|w\|_2}, \tag{14}$$

where F_ρ bounds the scheduling variables. The yielded controller $K(\rho)$ is formed as

$$\dot{x}_K = A_K(\rho) x_K + B_K(\rho) y_K, \tag{15a}$$
$$u = C_K(\rho) x_K + D_K(\rho) y_K, \tag{15b}$$

where $A_K(\rho), B_K(\rho), C_K(\rho), D_K(\rho)$ are variable-dependent matrices.

The implemented structure with the lateral control system and the decision tree is illustrated in Figure 3.

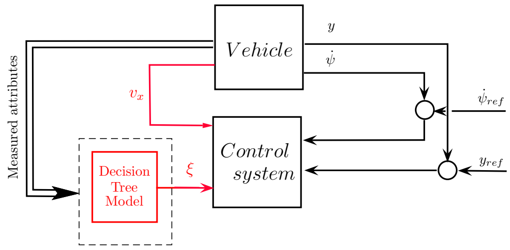


Fig. 3. Implementation of the lateral control system

4. VELOCITY OPTIMIZATION PROCESS FOR AUTOMATED DRIVING

The appropriate selection of the velocity profile has significant contribution on the performances of the vehicle. For example, when the vehicle takes a sharp bend at high velocity, the lateral forces can easily reach their peak values, which may result in significant performance degradation in terms of path following. Nevertheless, the unnecessarily slow motion of the vehicle is also unacceptable due to the increased traveling time. Therefore, it is requested to maximize the velocity of the vehicle, while the performance level and the lateral stability of the vehicle are preserved. It leads to an optimization problem, as it is presented in this section.

The concept of considering stable regions in the vehicle control design is also presented in Palmieri et al. [2012]. In the method of that paper the preferred regions are determined based on the physical model of the vehicle. The concept of the determination is to find the regions of the piecewise linear model in the state-space, where the oversteering and the nonlinear characteristics of the lateral dynamics can be avoided. The innovation of this paper is that the acceptable regions can be determined through the data-driven polytopic LPV model instead of the simplified nominal vehicle model. Using this method a more accurate representation of the acceptable regions can be provided.

The selection of the optimal velocity profile requests the lateral motion prediction of the controlled vehicle. The closed-loop system is formed using the data-driven LPV model and the presented controller as:

$$\dot{x}_{cl} = A_{cl}(\rho) x_{cl} + B_{cl}(\rho) r, \tag{16}$$

where $\dot{x}_{cl} = [\dot{x}\ \dot{x}_K]^T$ is the state vector of the closed-loop system and the matrices are composed as

$$A_{cl}(\rho_1) = \begin{bmatrix} A_{cl,11} & A_{cl,12} \\ A_{cl,21} & A_{cl,22} \end{bmatrix}, \tag{17a}$$

$$B_{cl}(\rho) = \begin{bmatrix} B(\rho) D_K(\rho) D_{21} \\ B_K(\rho) D_{21} \end{bmatrix}, \tag{17b}$$

where $A_{cl,11} = A(\rho) + B(\rho) D_K(\rho) C_2$, $A_{cl,12} = B(\rho) C_K(\rho)$, $A_{cl,21} = B_K(\rho) C_2$, $A_{cl,22} = A_K(\rho)$. For the prediction of the states of the closed-loop system, (16) is reformulated to a discrete-time model using the sampling time T (Tóth [2010]), which results in the model

$$x_{cl}(k+1) = A_{cl}(k) x_{cl}(k) + B_{cl}(k) r(k), \tag{18a}$$
$$y_{cl}(k) = C_{cl} x_{cl}(k), \tag{18b}$$

in which the compact notation $A_{cl}(k), B_{cl}(k)$ is used instead of $A_{cl}(\rho(k))$ and $B_{cl}(\rho(k))$, respectively. The measurement vector $y_{cl}(k)$ in (18) contains the states of the data-driven system, whose states must be predicted. C_{cl} is the related matrix for the selection of the states.

The prediction of $y_{cl}(k)$ is performed on the horizon n, such as

$$\begin{aligned}\boldsymbol{y_{cl}(k,n)} &= \begin{bmatrix} y_{cl}(k+1) \\ y_{cl}(k+2) \\ \vdots \\ y_{cl}(k+n) \end{bmatrix} \\ &= \begin{bmatrix} C_{cl}A_{cl}(k) \\ C_{cl}A_{cl}(k)A_{cl}(k+1) \\ \vdots \\ C_{cl}\prod_{i=k}^{k+n} A_{cl}(i) \end{bmatrix} x_{cl}(k) + \\ &+ \begin{bmatrix} C_{cl}B_{cl}(k) & \cdots & 0 \\ C_{cl}A_{cl}(k)B_{cl}(k) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ C_{cl}\prod_{i=k}^{k+n-1} A_{cl}(i)B_{cl}(k) & \cdots & C_{cl}B_{cl}(k) \end{bmatrix} \begin{bmatrix} r(k+1) \\ \vdots \\ r(k+n) \end{bmatrix} \\ &= \mathcal{A} + \mathcal{B}R \end{aligned} \quad (19)$$

where $\mathcal{A}$ contains the current states of the system with the varying system matrices, $\mathcal{B}$ is composed by the state matrices and R contains the reference signals. Moreover, it is necessary to consider that $\dot{\psi}_{ref}(k)$ and $y_{ref}(k)$ in $r(k)$ depend on $v_x(k)$. Thus, the modification of the longitudinal velocity can also result in the variation of the reference signal.

The purpose of the velocity profile design is to maximize v_x on horizon n. During the velocity maximization the system must be inside of the set, which is provided by each linear systems of the polytopic LPV representation. It is expressed through a constraint in the optimization problem, such as:

$$\xi|_{y_{cl}(k,n)} \leq \xi_{max}. \qquad \forall k \leq i \leq n. \quad (20)$$

where $\xi|_{y_{cl}(k,n)}$ denotes the categories in the predicted states and ξ_{max} is the maximum value of ξ.

Finally, the optimization problem of the longitudinal velocity profile is formed as

$$\max_{v_x(k+1)\ldots v_x(k+n)} \sum_{i=k}^{n} v_x(i) \quad (21)$$

subject to

$$\xi|_{y_{cl}(k,n)} \leq \xi_{max}. \qquad \forall k \leq i \leq n. \quad (22)$$

The result of the optimization is the velocity profile of the autonomous vehicle on the horizon n, which guarantees the safe motion of the vehicle.

5. SIMULATION RESULTS

In this section the operation of the proposed control system is presented through a comprehensive simulation example.

The number of the categories in the LPV modeling process is selected to 6. Using these categories several decision trees have been produced with different sizes, see Table 1. The columns of the table show the signals, which are used in the generation: the minimal number of instances per leaf, percentage of the correctly classified instances and the size (elements) of the tree. The 'minimal number of instances per leaf' is a design parameter of the tree, by which the size of the tree can be influenced. As it can be seen, there is a strong correlation between the size and the achieved accuracy of the tree, which means that a large decision tree is advantageous from the aspect of the categorization. However, in practice the large trees might not be applicable due to computational issues. Therefore, in general, a trade-off must be found between the accuracy and the size. In this case, even the most accurate tree has only 51 elements, hence it can be used in the followings.

Table 1. Relationship between the tree size and its correctness

Signals	Min. obj.	Corr. Class. Inst.	Size
$\delta, \dot{\psi}, a_y, v_x$	500	96.37%	51
$\delta, \dot{\psi}, v_x$	1000	95.82%	33
$\delta, \dot{\psi}$	2000	94.54%	19
δ, a_y	3000	93.21%	17
δ	5000	91.54%	13

Table 2 shows the confusion matrix for the selected tree. The confusion matrix represents the percentages of the correctly classified and mislcassified instances for each categories. As the table illustrates, the percentage of the misclassification is low and all of the misclassified instances is only one category away from the correct category. It indicates that the selected tree is appropriate to be used in the control system.

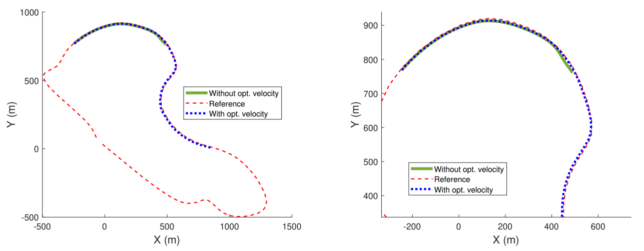
Table 2. Confusion matrix for the selected decision tree

$\xi=0$	$\xi=1$	$\xi=2$	$\xi=3$	$\xi=4$	$\xi=5$	
57.86	0.7	0	0	0	0	$cat=0$
0.6	27.2	0.5	0	0	0	$cat=1$
0	0.5	8.3	0.5	0	0	$cat=2$
0	0	0.24	3.87	0.24	0	$cat=3$
0	0	0	0.2	1.3	0	$cat=4$
0	0	0	0	0.24	1.54	$cat=5$

In the simulations, the vehicle is driven along a section of the Melbourne Grand Prix Circuit twice. In the first case, the passenger car is controlled by the proposed control system using the velocity optimization process. Whilst, in the second simulation, the vehicle is driven using the nominal velocity profile.

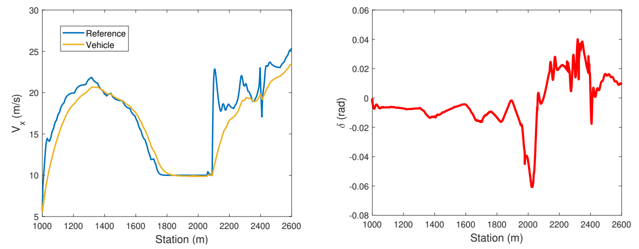
The path of the vehicle in both cases are shown in Figures 4. Figure 5(a) presents the calculated velocity profile as reference velocity and the realized velocity of the vehicle. As Figures 4 show, the vehicle, which tracks the predefined speed profile, is not able to follow the track, because it leaves the road in the first bend. In the other scenario the vehicle with the optimized speed profile has small lateral errors. In Figure 5(b) the steering angle is illustrated. As it shows, the steering angle varies between $[-0.06rad \ldots 0.04rad]$, which is a physically reasonable range for this signal.

The lateral position error is illustrated in Figure 6(a). It can be seen that the lateral error of the vehicle with optimized velocity profile is significantly smaller, its maximum is around $0.4m$. In contrast, the vehicle with the other



(a) Whole track (b) Highlighted bend

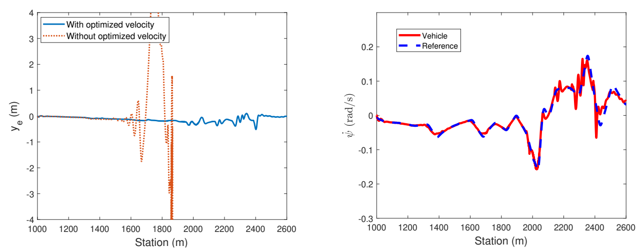
Fig. 4. Positions of the vehicles during the simulations



(a) Velocity profils (b) Steering intervention

Fig. 5. Longitudinal velocity and steering intervention

velocity profile leaves the road with high lateral error. Figure 6(b) shows another performance of the control system, such as yaw-rate tracking. As it illustrates, the proposed system is able to guarantee the tracking of the yaw-rate signal similarly to the lateral position.



(a) Lateral position error (b) Yaw-rate tracking

Fig. 6. Tracking errors in the performance signals

Finally, the variation of scheduling parameter xi is illustrated in Figure 7. This parameter is calculated through the proposed decision tree, which uses the variables $\delta, \dot{\psi}, a_y, v_x$. It can be seen that the maximum of this parameter is $\xi = 3$, which means that the vehicle does not exceed the upper bound ξ_{max} in the simulation. Therefore, the lateral stability of the vehicle during the scenario is guaranteed.

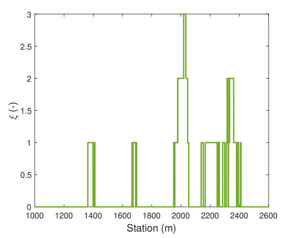


Fig. 7. Scheduling variable ξ

6. CONCLUSIONS

A novel data-driven control strategy has been proposed for autonomous vehicles. The main advantage of this approach is that the performances of the system can be guaranteed in a wide operation range, which is the consequence of the innovated polytopic data-driven model. The proposed velocity optimization method is able to guarantee that the unstable regions of the vehicle dynamics can be avoided, which improves the safety of the vehicle motion. Through the cooperation of the enhanced LPV controller and the velocity optimization method the formulated performances of the lateral dynamics can be guaranteed.

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