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LPV control design based on ultra-local model for trajectory tracking problem

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Abstract:
Model Free Control (MFC) is a novel technique to overcome some modeling and control challenges of highly nonlinear systems. The MFC control strategy consists of two parts, i.e., ultra-local model-based control and state feedback control. This paper proposes the robust Linear Parameter-Varying (LPV) method for design the state feedback control part of the strategy. In the design of robust LPV control the effect of the ultra-local model, formed as a disturbance, is involved. The contribution of this extension to the original concept of MFC design is that a desired performance of the closed-loop system can be achieved. The effectiveness of the presented control strategy is demonstrated through a trajectory tracking problem of autonomous vehicles using the high-fidelity simulation software, IPG CarMaker.

Keywords: ultra-local model, trajectory tracking, autonomous vehicles, LPV control

1. INTRODUCTION AND MOTIVATION

The control of highly nonlinear systems has also been a challenging task due to their complexity, which made the modeling process difficult. In the last decades, several methods have been developed, which aimed to handle such systems. These solutions, in general, are based on a mathematical model of a system using physical laws. However, the accuracy of these models can be low, especially in the presence of fast-changing nonlinear dynamics. The accuracy of the model has a crucial impact on the performance of the resulted control system. Robust control methods such as $\mathcal{H}_\infty$ Doyle et al. [1994], LPV Mohammadpour and Scherer [2012] can handle certain variations in the behavior of the system and even unmodelled dynamics, however, the resulted controller highly depends on the percentage of the uncertain part of the system.

In the last decade, a novel control concept was introduced by Michel Fliess et al. see Fliess and Join [2009], which was called Model Free Control (MFC). The main idea behind this concept is to continuously model the dynamics of the considered system using a so-called ultra-local model. The ultra-local model is computed from the control signal applied in the previous time step and from a certain derivative of the measured signal. Moreover, in the original concept, this ultra-local model is extended with a conventional controller e.g. PID, which aims to guarantee certain performances of the control system, such as tracking of a reference signal. The impact of the ultra-local model and the conventional control on the controlled system is balanced by a free parameter, which is generally denoted by α.

Recently, several papers have been published on the MFC-based control methods and its applications. For example, an automotive-oriented application can be found in Baciu and Lazar [2020], in which a longitudinal velocity controller is proposed, which is made in two steps. Firstly, the pole placement method is investigated, then a fine-tuning method is shown, by which the performances can be increased. The vertical motion of the vehicle can be also controlled by an ultra-local model-based approach. In Mustafa et al. [2019] a model-free adaptive fuzzy logic controller is proposed for active suspension systems. Moreover, the ultra-local model-based approach is also tested in an Unmanned Aerial Vehicle. Using the proposed method, the performances of the Vertical Take-Off and Landing maneuver, compared to a PD controller, can be increased Chekakta et al. [2019]. A full model-free control structure has been designed for micro air vehiclesBarth et al. [2020].

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Using the control structure, the position tracking, velocity, and attitude control are solved during the flight.

Although there are several successful applications, the ultra-local model-based control still hides some drawbacks, which must be solved for controlling certain systems. As Polack [2018] points out, the implementation of this control method can be challenging due to the time delays and the estimation errors. Another issue is related to the tuning of the conventional control. Since the ultra-local model is used as a feedback of the system, it creates a closed-loop system, which results in a change in the dynamics of the system. Therefore, during the tuning phase of the conventional controller, the closed-loop system must be taken into account in order to guarantee the stability and the required performances of the overall control system. The third open question is related to the tuning of the free parameter α since there is no elaborated method to compute it.

In this paper, a modified ultra-local model computation is used, which is called an error-based ultra-local model. This model consists of two ultra-local models: 1. computed from the measured signals, 2. determined by the references signals using a nominal model of the control system. Then, an extended state-space representation is presented, which describes the dynamics of the interconnected system. This state-space representation serves as a basis of robust control design, which has two main goals: 1. to ensure the required performances of the control system, 2. to guarantee the stability of the overall control system. The efficiency and the operation of the proposed method are demonstrated through a vehicle-oriented control problem: trajectory tracking. In addition, a α tuning method is applied for this given application of ultra-local model-based control.

The rest of the paper consists of the following chapters: The error-based ultra-local model is presented in Section In section 2. The applied nominal model and the formulation of the extended state-space representation is detailed in 3. The robust control design for the trajectory tracking problem is presented in 4. Finally, Section 5 summarizes the contribution of the paper.

2. STRUCTURE OF ERROR-BASED ULTRA-LOCAL MODEL

Original ultra-local model

The original Model Free Control concept and the ultra-local model was proposed by Fliess and Join [2009]. The ultra-local model is used to describe the dynamics of a nonlinear system such as:

$$\dot{x} = f(x, u), \tag{1}$$

where the state-vector is x with n elements, u denotes the control signal, which consists of 1 element for the sake of simplicity. The ultra-local model is valid for a short period of time, then its update using the measured signals, see Fliess and Join [2013], d'Andrea Novel et al. [2010]. The ultra-local model can be computed as:

$$y^{(\nu)} = F + \alpha u, \tag{2}$$

where $F \in \mathbb{R}$ represents the ultra-local model, $y^{(\nu)}$ denotes the ν^{th} derivative of the output signal. The exact value of ν varies depending on the considered system and the control purposes. α is the tuning parameter of the control system. Then, the ultra-local model can be determined as:

$$F = y^{(\nu)} - \alpha u. \tag{3}$$

Using the ultra-local model, the control signal can be computed as:

$$u = \frac{-F + y_{ref}^{(\nu)}}{\alpha} + \mathcal{K}(e, \hat{x}), \tag{4}$$

where $\mathcal{K}(e, \hat{x})$ represents the conventional controller, which aims to eliminate the steady-state tracking error using the tracking error e and the estimated states $\hat{x}$.

Error-based ultra-local model

As mentioned, the original structure has some drawbacks regarding the implementation. Therefore, a novel formulation is proposed, in which two ultra-local model is considered. The first one is based on the measured signals, while the second one uses the references signals provided by a nominal model. The new structure, called error-based ultra-local model is computed as:

$$y^{(\nu)} = F + \alpha u, \tag{5a}$$

$$y_{ref}^{(\nu)} = F_{nom} + \alpha u_{nom,ref}, \tag{5b}$$

$$\underbrace{y^{(\nu)} - y_{ref}^{(\nu)}}_{e^{(\nu)}} = \underbrace{F - F_{nom}}_{\Delta} + \underbrace{\alpha u - \alpha u_{nom,ref}}_{\alpha\tilde{u}}, \tag{5c}$$

$$e^{(\nu)} = \Delta + \alpha\tilde{u}, \tag{5d}$$

where F and F_{nom} are the ultra-local models, u and $u_{nom,ref}$ are the applied and the reference control inputs, y and y_{ref} represent the measured and the reference outputs. Since the goal of the control design is to keep ν^{th} derivative of the error value zero, i.e., $e^{(\nu)} \to 0$, the control input u is computed as:

$$u = \underbrace{-\frac{\Delta}{\alpha}}_{u_1} - \underbrace{\mathcal{K}(e, \hat{x})}_{u_2}. \tag{6}$$

where u_1 is the control input provided by the error-based ultra-local model, u_2 denotes the control input computed by the applied controller. More detailed description on the error-based ultra-local model can be found in Hegedus et al. [2022].

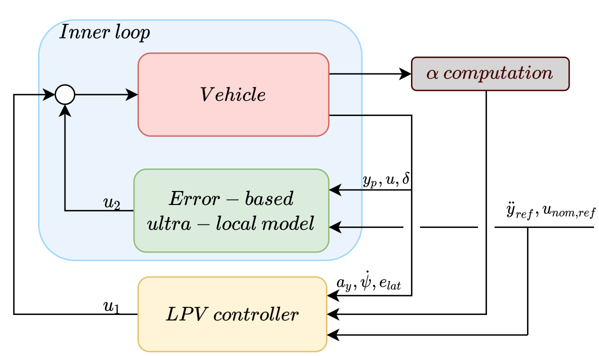


Fig. 1. Architecture of the control system

In the followings, a vehicle-oriented application is presented, whose goal is to show the operation and the efficiency of the proposed control method. In Figure 1 the structure of the whole control system is illustrated. Firstly, the nominal model is detailed, then the extended state-space representation is presented. Using the extended representation, an LPV-based control is designed, which ensures the required performances and the stability of the closed-loop system.

3. COMBINED MODELING OF THE SYSTEM AND THE ULTRA-LOCAL MODEL

Firstly, the nominal model is presented, which in this case is based on the single-track dynamical bicycle model. This model describes the lateral dynamics of the vehicle and consists of the following equations, seeRajamani [2005]:

$$I_z\ddot{\psi} = \left(\delta - \beta - \frac{\dot{\psi}l_1}{v_x}\right)C_1 l_1 - \left(\beta + \frac{\dot{\psi}l_2}{v_x}\right)C_2 l_2, \tag{7a}$$

$$mv_x(\dot{\psi} + \dot{\beta}) = \left(\delta - \beta - \frac{\dot{\psi}l_1}{v_x}\right)C_1 + \left(-\beta + \frac{\dot{\psi}l_2}{v_x}\right)C_2, \tag{7b}$$

$$\ddot{y}_p = v_x(\dot{\psi} + \dot{\beta}). \tag{7c}$$

where v_x and $\dot{y}_p$ are the longitudinal and lateral velocities of the vehicle, m is the mass, I_z denotes the yaw-inertia, β represents the side-slip angle, $\dot{\psi}$ is the yaw-rate, l_1 and l_2 are geometric parameters, C_1 and C_2 are the cornering stiffness of the front and rear axles, δ is the steering angle, which is the input of the model. The presented model can be transformed into a parameter-dependent state-space representation as:

$$\dot{x}_v = A_v(v_x)x_v + B_v(v_x)u_v, \tag{8}$$

$$A_v(v_x) = \begin{bmatrix} -\frac{l_1^2C_1+l_2^2C_2}{I_z v_x} & -\frac{l_1C_1-l_2C_2}{I_z v_x} & 0 \\ \frac{-l_1C_1+l_2C_2}{mv_x} - v_x & -\frac{C_1+C_2}{mv_x} & 0 \\ 0 & 1 & 0 \end{bmatrix}, \tag{9a}$$

$$B_v(v_x) = \begin{bmatrix} \frac{l_1C_1}{I_z} \\ \frac{C_1}{m} \\ 0 \end{bmatrix}. \tag{9b}$$

The state vector consists of $x_v = [\dot{\psi},\, \dot{y}_p,\, y_p]^T$. $u_v = [\delta]^T$ is the control input and the scheduling parameter is v_x.

3.1 Extended state-space representation

In order to include the effect of the error-based ultra-local model, the presented state-space representation of the lateral dynamics is extended using the following assumptions:

- The measured output: lateral position (y_p)
- The derivative is set to $\nu = 2$, which is computed through an ALIEN filter Polack [2018].
- Parameter α is computed by using an optimization process, see Subsection 3.3.
- $u_{nom,ref}$ is computed as described in Appendix A.
- The controller is neglected ($\mathcal{K}(e, \hat{x})$=0).

The signals of the error-based ultra-local model are treated in the following way: $\ddot{y}_{ref} = \ddot{\psi}_{ref}$, and $u_{nom,ref} = \delta_{ref}$ are external disturbances of the extended state-space representation. $\ddot{y}_p$ is computed from y_e through a derivative filter. $u = \delta$ is also taken into account using a filter algorithm. Both filters are modeled as a first-order system such as:

$$G_{f,i}(s) = \frac{s}{T_i s + 1}, \tag{10}$$

where T_i is a design parameter. State-space representation of the filter for $u = \delta$: $A_{f,1} = [\frac{-1}{T_1}]$, $B_{f,1} = [\frac{1}{T_1}]$, $C_{f,2} = [1]$. State-space representation of the filter for $\ddot{y}_p$: $A_{f,2} = [\frac{-1}{T_2}]$, $B_{f,2} = [\frac{1}{T_2}]$, $C_{f,2} = [1]$. Then, the extended state-space representation is formed as:

$$\dot{x}_e = A_e(\rho)x_e + B_e(\rho)u_e + B_{e,w}(\rho)w_e, \tag{11a}$$

$$A_e(\rho) = \left[\begin{array}{c|c|c} A_v & B_v & -B_v/\alpha \\ \hline 0_{1\times3} & A_{f,1} & -B_{f,1}/\alpha \\ \hline B_{f,2}A_v^{1\times3} & 0_{1\times1} & A_{f,2} \end{array}\right], \tag{11b}$$

$$B_e(\rho) = \begin{bmatrix} B_{v,1} \\ \hline B_{f,1} \\ \hline 0_{1\times1} \end{bmatrix}, \quad B_{e,w}(\rho) = \left[\begin{array}{c|c} B_v/\alpha & -B_v \\ \hline B_{f,1}/\alpha & -B_{f,1} \\ \hline 0_{1\times1} & 0_{1\times1} \end{array}\right], \tag{11c}$$

$$\tag{11d}$$

where $u_e = [\delta]$, $x_e^T = [\dot{\psi},\, \dot{y}_p,\, y_p,\, u,\, \ddot{y}_p]$, $w_e^T = [\ddot{y}_{ref}, u_{nom,ref}]$ and $A_v^{2\times3} = e^T A_v$, $e^T = [0, 1, 0]$. $B_v = [\frac{l_1C_1}{I_z},\, \frac{C_1}{m},\, 0]^T$, $\rho = [v_x, \alpha]$. In the next subsection a robust control design is presented using the extended state-space representation.

3.2 LPV control design

The goal of the control design is to eliminate the steady-state tracking error in this way ensuring accurate trajectory tracking while guaranteeing the stability of the control system. The polytopic, LPV system has two scheduling parameters: $v_x = \{10 - 20m/s\}$ and $\alpha = \{20 - 100\}$. The required performances are formulated as:

- *Minimization of the lateral error* The control system must guarantee the accurate trajectory tracking of the vehicle, which means minimizing the error between the reference and the measured lateral positions:
$$z_1 = y_{ref} - y_p, \quad |z_1| \to min, \tag{12}$$
- *Minimization of the intervention* Since the system system has its own limitations, the designed controller must minimize the intervention:
$$z_2 = \delta, \qquad |z_2| \to min. \tag{13}$$

The plant is augmented with weighting functions to guarantee the predefined performances as illustrated in 3.2. $W_{z,1}$ and $W_{z,2}$ are to weight the control signal and the tracking error. Since the measurements include noises, $W_{w,1}$, $W_{w,2}$ and $W_{w,3}$ are used to attenuate their negative effects. $W_{u_{nom,ref}}$ and $W_{\ddot{y}_{p,ref}}$ weights the external signals from the ultra-local model. Finally, $W_{ref,1}$ scales the reference signal.

The augmented state-space representation can be written as:

$$\dot{x}_e = A_e(\rho)x_e + B_e(\rho)u_e + B_{e,w}(\rho)w_e, \tag{14a}$$

$$z_e = C_{e,1}(\rho)x_e + D_{e,1}(\rho)u_+, \tag{14b}$$

$$y_e = C_{e,2}(\rho)x_e + D_{e,2}(\rho)w_{e,2}, \tag{14c}$$

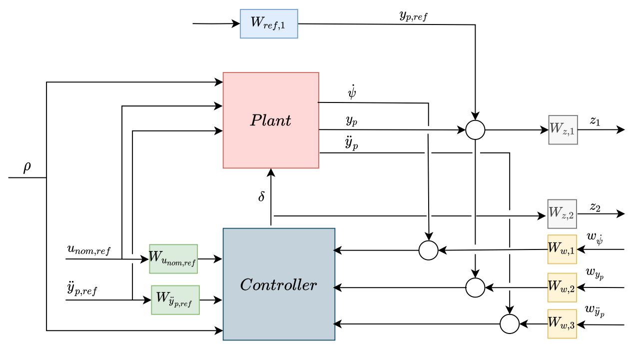


Fig. 2. Augmented plant

where the measured states of the system: $C_{e,1}x_e = [\dot{\psi}, y_p, \ddot{y}_p]$. While, $w_{e,2}$ contains the noises of the measured signals.

The control design task leads to a quadratic optimization problem, whose solution is the controller $K(\rho)$, which guarantees that the closed-loop system is quadratically stable. In addition, the yielded controller must guarantee that the induced norm $\mathcal{L}_2$ between the performances and the disturbances is less than a given value γ.

$$\inf_{K(\rho)} \sup_{\rho \in F_\rho} \sup_{\|w\|_2 \neq 0, w \in \mathcal{L}_2} \frac{\|z\|_2}{\|w\|_2}, \tag{15}$$

where F_ρ bounds the scheduling variables. The computed controller $K(v_x, p_1)$ is formed as

$$\dot{x}_K = A_K(\rho)x_K + B_K(\rho)y_K, \tag{16a}$$

$$u = C_K(\rho)x_K + D_K(\rho)y_K, \tag{16b}$$

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

3.3 The tuning parameter α

The control input is composed of the LPV controller and the error-based ultra-local model. The main role of the design parameter α is to make a balance between the two components of the control input. Briefly, if $\alpha \to \infty$ mainly the results of the baseline controller are taken into account, and the effect of the ultra-local model-based part is suppressed. On the other hand, if $\alpha \to 0$ the impact of the error-based ultra-local model part is increased during the determination of the control input. While potentially the performances of the control system can be increased using the results of the ultra-local model, the closed-loop system may not have the desired performance or even lose its stability, if the balance is not chosen appropriately, and the value of α is set to low.

It can be concluded that the parameter α gives the reliability of the nominal model at the given operating point of the system. This means that in the case when the deviation between the nominal model and the system increases, the parameter α can be decreased in order to increase the impact of the error-based part. The determination of the α value is a challenging task since it cannot be calculated analytically. In several papers, the mentioned parameter is considered to be a constant value while in this paper it is varied using the states of the system. Moreover, using the augmented system, the determined α gives the scheduling variable of the LPV system.

3.4 The determination of the actual value of α

In this paper, the algorithm is tested on a trajectory tracking problem. During the vehicle control, the parameter α is varied in order to increase the performances of the tracking. Since α cannot be computed analytically, the tuning method is performed through a data-driven solution. The main idea behind the α calculation is to use a directly measurable state of the vehicle, which characterizes the given operating point well. Generally, the nonlinear effects of the vehicle become more significant as the lateral acceleration and the yaw-rate increase. This means, that at higher acceleration values the reliability of the nominal model decreases.

In this paper, the actual parameter α is determined using the lateral acceleration of the vehicle. It has been mentioned that as the deviation between the nominal model and the real system increases, the parameter α can be decreased to achieve a higher performance level. Therefore, α is calculated using the following form, which is recomputed at every time step:

$$\alpha_{act} = \alpha_0 - \gamma a_y, \tag{17}$$

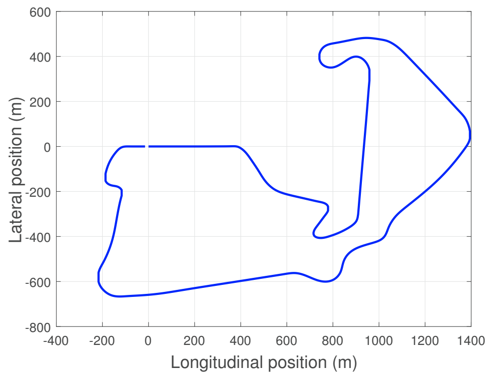
where γ scales the lateral acceleration value and α_0 gives a nominal value of α. The scaling factor γ and the nominal value for α are determined by a data-driven analysis, in which the goal is to reduce the tracking error in various driving scenarios. More details for the tuning method can be found in Hegedus et al. [2022].

4. SIMULATION EXAMPLE

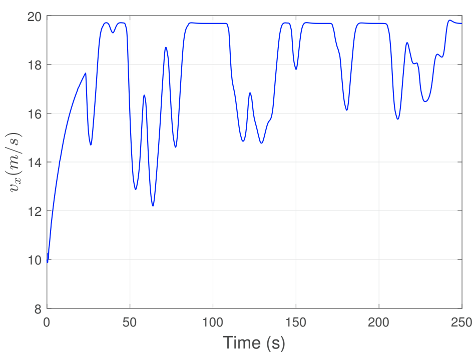
In the following, a comprehensive simulation example is presented to demonstrate the operation and the effectiveness of the proposed control strategy. During the simulations, three different controllers are tested and the results are compared to each other. Firstly, the proposed method is implemented. Secondly, the LPV controller is tested only at one operation point, at the nominal value of the design parameter (α_0), which is determined by the optimization process and the nominal value of α is set to 100. Finally, a $\mathcal{H}_\infty$ controller is designed, by which the uncertainties are handled during the control design. The simulation examples are performed in CarMaker, vehicle dynamics simulation software, and the reference track is the Yas Marina race track, which is shown in Figure 3(a). Moreover, the velocity profile depicted in Figure 6(b), which is determined using the built-in driver model of CarMaker.

In Figure 4, the lateral errors of the controllers are presented. It can be seen that all of the implemented controllers remain stable during the test scenario. However, the best tracking performance is provided by the proposed LPV-based solution as the highlighted section shows in figure 4. The differences between the two LPV controllers are not remarkable during the rest of the test scenarios. This phenomenon can be explained by the fact, that the vehicle mainly travels close to the nominal α value. However, with the decrease in the reliability of the nominal model (this part is highlighted in the figure), the tracking performances are significantly better using the proposed method.

Figure 4 shows the control inputs of the vehicle. It can be seen that the impact of the ultra-local model increases



(a) Reference path



(b) Velocity of the vehicle

Fig. 3. The reference track and longitudinal velocity of the vehicle

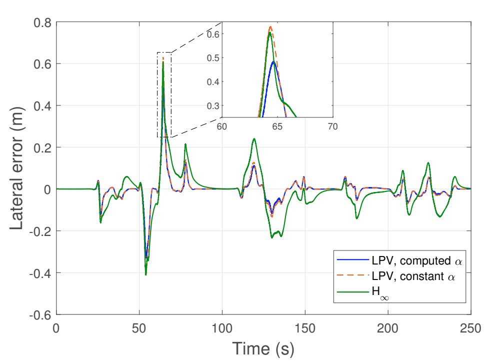


Fig. 4. Lateral errors during the test scenarios

when the deviation between the nominal model and the system increases. The blue line represents the results of the LPV controller, while the ultra-local model-based part is given by red. Both control signals are of almost the same magnitude

Finally, the lateral acceleration is presented and also the computed actual value of α is shown in Figure 6.

Figure 6(a) that the maximum value of the lateral acceleration exceeds 9 m/s^2, which means that the vehicle is close to its physical limits but the stable motion of the vehicle is still guaranteed. Moreover, the nominal value of the design parameter (α_0) is 100, and as the lateral acceleration increases, the value of α decreases. It can be concluded that using the proposed method, the stable

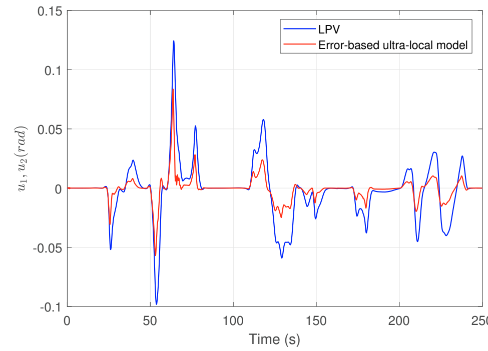
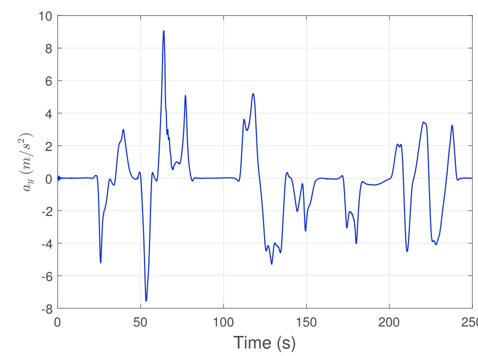
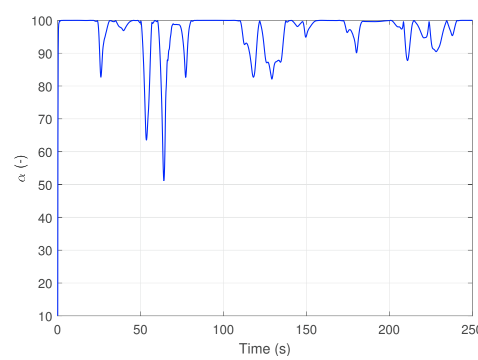


Fig. 5. Control inputs during the test scenarios



(a) Lateral acceleration of the vehicle



(b) Actual value of α

Fig. 6. The parameter α and the measured lateral acceleration of the vehicle

motion of the vehicle can be guaranteed even at the highly nonlinear range of the vehicle. Moreover, using the error-based ultra-local model, the tracking performances of the control system can be increased.

5. CONCLUSION

In this paper a novel control strategy has been presented, which combined the advantages of the robust control and ultra-local model-based solutions. The uncertainties and the nonlinearities of the considered system has been handled by the ultra-local model while the stability of the closed-loop system was guaranteed by the LPV controller. The free parameter of the ultra-local model (α) has been handled as a scheduling parameter of the extended system, therefore the variation of it could not destabilize the system. The operation and the effectiveness of the proposed control algorithm has been demonstrated through a complex test scenario using the high-fidelity simulation software, CarMaker.

Appendix A. DETERMINATION OF THE REFERENCE SIGNAL

In the followings, the calculation of the nominal control input ($u_{nom,ref}$) is detailed. Based on the nominal model of the system, the input signal is determined using a dead-beat like control algorithm. The basis of the mentioned method is a discrete state space representation of the nominal system (7), which can be formed as:

$$x_d(t+1) = \Phi x_d(t) + \Gamma u_d(t), \qquad \text{(A.1a)}$$

$$y_d(t) = \xi^T x_d(t), \qquad \text{(A.1b)}$$

where the state vector is: $x_d^T = [\dot{\psi} \quad \dot{y}_p \quad y_p]^T$ and Φ, Γ, ξ^T are matrices, which are computed from the continuous model using the sample time $T_s = 0.02s$. The output of the system is the lateral position, $\xi^T = [0 \quad 0 \quad 1]^T$. Moreover, the whole system depends on one external signal, the longitudinal velocity of the vehicle, which is taken into account during the determination of the state space representation. The vehicle motion can be predicted and the goal is to guarantee the tracking of the reference trajectory. Using (A.1) the lateral position of the vehicle is predicted along the predefined time horizon (n):

$$y_p(k,n) = \begin{bmatrix} y(k+1) \\ y(k+2) \\ \vdots \\ y(k+n) \end{bmatrix} = \underbrace{\begin{bmatrix} C\phi \\ C\phi^2 \\ \vdots \\ C\phi^n \end{bmatrix}}_{\mathcal{A}} x(k) + \qquad \text{(A.2)}$$
$$+ \underbrace{\begin{bmatrix} C\Gamma & 0 & \cdots & 0 \\ C\phi\Gamma & C\Gamma & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ C\phi^{n-1}\Gamma & C\phi\Gamma & \cdots & C\Gamma \end{bmatrix}}_{\mathcal{B}} \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+n-1) \end{bmatrix}.$$

In this case, the input vector of the system is defined as:

$$\mathcal{U} = [u(k), u(k+1)...u(k-1+n)]^T = \underbrace{[\omega_1, \omega_2 ... \omega_n]^T}_{\Omega} u_n \qquad \text{(A.3)}$$

where ω_i gives the weight for the i^{th} input signal. Moreover, the values of the weight vector is determined in a descending way. Using (A.2) and (A.3), the reference signal for the vehicle can be computed as:

$$u_{nom,ref} = \mathcal{B}^{-1}\Omega^{-T}(y_p(k,n) - \mathcal{A}x(k)) \qquad \text{(A.4)}$$

where, ($y_p(k,n)$) denotes the reference lateral position and $x(k)$ gives the actual states of the vehicle. During the calculation of the error-based ultra-local model the nominal control input is determined using (A.4).

Appendix B. COMPUTATION OF LATERAL ERROR

During the computation of the lateral error, the motion of the vehicle is predicted in order to increase the tracking performances. Based on the actual states of the vehicle, the predicted error value can be computed as:

$$x_e(t+T_p) = R(x_p, y_p) - (x(t) + v(t)cos(\psi(t))T_p) \qquad \text{(B.1)}$$

$$y_e(t+T_p) = R(x_p, y_p) - (y(t) + v(t)sin(\psi(t))T_p) \qquad \text{(B.2)}$$

where, T_p denotes the length of the prediction and R is the reference position at the given state of the vehicle. In this paper, the value of the prediction is set to $T_p = 0.25s$.

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