LPV-based Control Design with Guarantees: a Case Study for Automated Steering of Road Vehicles

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***Abstract*— This paper proposes a Linear Parameter Varying (LPV) based steering control design method, which contains data aided control elements, e.g., learning-based agents. The framework is based on a supervisory control structure, which contains a supervisor, a LPV controller and the data aided control element. The goal of this paper is to provide a safe steering control, with which the human steering intervention can be effectively imitated. Moreover, in the proposed framework the data aided control can be adapted to the actual requirements on driving style, without re-designing the LPV control. Thus, a general control structure with performance guarantees on path following constraints is provided, in which the data aided steering control element can be varied. The effectiveness of the proposed method through driver-in-the-loop scenarios is illustrated, in which different settings on the control system are analyzed.**

I. INTRODUCTION AND MOTIVATION

Due to rapid changes in the production of vehicle control elements, the flexibility of automated systems has high priority from the viewpoint of practical implementation. A novel requirement is to provide control design frameworks, which are able to provide safe vehicle motion, even with modified (e.g., upgraded) control elements. A solution on this design problem is the concept of plug and play control [1].

The motivation of plug ad play control schemes is to provide enhanced personalized driving performance for the drivers in partially automated vehicles (e.g., at Level 3). The aim of providing control systems for automated vehicles, whose operation is close to the human-driven vehicles, can improve the spreading of that technology. Paper [2] has proposed an experimental study, in which tests with human passengers have been performed for differentiating the motion of human-driven and automated vehicles (Level 2). It has been concluded that most of the passengers were not able to differentiate the vehicles, i.e., human-like motion of automated vehicles can strength trust and acceptance of autonomous driving. Nevertheless, another important demand against automated vehicles is to eliminate typical driving failures, e.g., safer and improved decision-making capability [3]. A recent technique for achieving safe human-like autonomous driving functionality is imitation learning [4], [5], [6]. The goal of this technique is to mimic human behavior, which methods have lots of variations in robotics and human-machine interactions [7]. In spite of promising method of behavioral cloning, a recent challenge is to provide safe motion of the vehicle under huge number of environmental conditions [8].

Adaptation to the variation of driving style can be guaranteed through data aided methods, e.g., learning techniques. Nevertheless, it can lead to different learning-based agents in the control loops of the vehicles. Guaranteeing robust performances for different agents in the vehicle control without individual design process in each vehicle is a crucial problem. In vehicle control context various partial results in plug and play control have been published, e.g., [9], [10]. Plug and play applications also exist for transportation systems [11] or for unmanned aerial vehicles [12]. Moreover, robust control methods in the context of human-machine shared driving can provide a safe and efficient way for control design [13].

The contribution of this work is a design method, which is based on the control theory of Linear Parameter Varying (LPV) systems. In the method the LPV-based control operates together with a data aided control element under a supervisory framework. The advantage of the method is that the data aided controller can be modified without the redesign of the LPV-based controller, and the resulted system provides guarantees on safe vehicle motion. Although the proposed supervisory control solution has some similarities to Model Predictive Control (MPC) methods, it also has some benefits. For example, the supervisor incorporates a quadratic optimization task, but it is simplified and it requires reduced computation effort. The dynamics of the system is not included as a constraint of the optimization problem, it is incorporated in the LPV control design task. Moreover, an advantage of the proposed framework is that the task of learning is not considered by the MPC problem. Therefore, training can be a separated offline problem, and the selection of the training method, agent structure is independent from the control problem. This independence provides a solution on the problem of considering different driving styles. On the level of robust LPV control design, the output of the data aided steering control is considered only as a bounded disturbance. Thus, this paper proposes a general structure

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with performance guarantees, in which the data aided control element can be varied.

The paper is organized as follows. In Section II the design method for steering control purposes is presented, such as the robust LPV control and the supervisor design. The learning process for imitating human driving characteristics in Section III is presented. The effectiveness of the method through simulation examples is demonstrated in Section IV, and finally, the paper is concluded in Section V.

II. Control design for achieving guarantees on performances

In this section the design of the LPV-based robust control and the supervisor is proposed. The structure of the control architecture, with its three main elements in Figure 1 is found, see also [14]. The feedback loop involves in the LPV-based robust controller. The data aided controller (u_L) is in an auxiliary loop with its own measurement y_L. The goal of the supervisor is to provide bounded signals $\rho_L \in \varrho_L, \Delta_L \in \Lambda_L$ with 1 dimension, which signals influence the control intervention u. Nevertheless, the supervisor is also out of the control loop, only its output in the control operation is involved. Using this control system structure, the steering

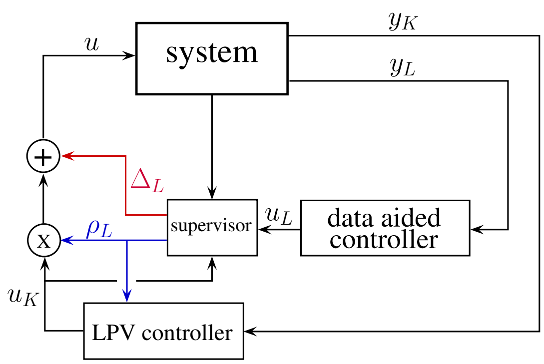

Fig. 1. Illustration on the architecture of the control system

control input u from the output of the robust controller u_K, using the outputs of the supervised are composed as follows [14]

$$u = \rho_L u_K + \Delta_L. \tag{1}$$

The goal of the supervisor is to provide ρ_L, Δ_L, with which u is as close as possible to u_L, and simultaneously, safety performances on the closed-loop system are guaranteed.

In this section the design of the robust LPV control and the supervisory algorithm is presented. The operation of the LPV control, together with the supervisor, provides guarantees on selected safety performance requirements. The design of the data aided controller is presented in the next section.

A. Design of the robust LPV control

The robust LPV control design for steering is based on the lateral dynamical vehicle model [15]. The state-space representation of the system is $\dot{x} = A(\rho)x + B_2 u$, where the state vector contains lateral velocity, yaw-rate and lateral position $x = \begin{bmatrix} v_y & \dot{\psi} & y \end{bmatrix}^T$ and the control input involves steering angle $u = \begin{bmatrix} \delta \end{bmatrix}$ in, and longitudinal velocity $\rho = v$ as scheduling variable is selected.

Formulation of u (1) in the state-space representation of the describing vehicle model is involved, such as

$$\dot{x} = A(\rho)x + B_2 \Delta_L + B_2 \rho_L u_K, \tag{2}$$

which means that Δ_L is a disturbance of the system and ρ_L can be handled as a scheduling variable.

Two performances on the level of LPV-based control design are formed due to safety reasons. First, lateral error of the vehicle from road the centerline y_{ref} must be limited, such as $z_1 = y_{ref} - y,, |z_1| \rightarrow min$. Second, saturation on control intervention must be avoided, because at the saturation effect of δ the performances of the systems can be degraded. Thus, $z_2 = \delta, |z_2| \rightarrow min$ performance requirement is formed. The performance vector $z_K = \begin{bmatrix} z_1 & z_2 \end{bmatrix}^T$ through the state-space equation of vehicle dynamics can be expressed as $z_K = C_2 x + D_{21} y_{ref} D_{22} u$, which can be reformulated through (1) as

$$z_K = C_2 x + D_{21} w + D_{22} \rho_L u_K, \tag{3}$$

where $w = \begin{bmatrix} y_{ref} & \Delta_L \end{bmatrix}^T$. Similarly, the formulation of measurement $y_K = y_{ref} - y$ is expressed as

$$y_K = C_1 x + D_{11} w + D_{12} \rho_L u_K. \tag{4}$$

The control-oriented state-space representation of the system from the dynamics, performances, measurements on the system is composed, such as

$$\dot{x} = A(\rho) + B_2 \Delta_L + B_2 \rho_L u_K, \tag{5a}$$
$$y_K = C_1 x + D_{11} w + D_{12} \rho_L u_K, \tag{5b}$$
$$z_K = C_2 x + D_{21} w + D_{22} \rho_L u_K. \tag{5c}$$

Due to the disturbances composed in w, closed loop stability and disturbance attenuation at the same time must be guaranteed [16]. The augmented plant for the design of the robust LPV control is illustrated in Figure 2. The

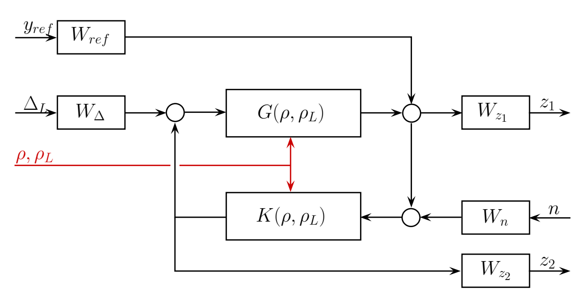

Fig. 2. Illustration of the augmented plant

system (5) is represented as $G(\rho, \rho_L)$ and the controller is $K(\rho, \rho_L)$. The reference signal y_{ref} is scaled with the function $W_{ref} = \frac{y_{ref,max}}{T_{ref}s+1}$. This representation reflects to the steady-state case at reference with $y_{ref,max}$ value. Time constant T_{ref} reflects to the dynamics of the reference signal. Weighing function on the tracking of reference signal is also applied, i.e., to improve z_1 performance. This weight is formed as $W_{z_1} = \frac{1/e_{max}}{T_e s+1}$, where the allowed maximum of the lateral error in steady-state is represented by e_{max}. The setting-time of the tracking is noted by T_e. Performance z_2 is also weighted, i.e., $W_{z_2} = \frac{1}{\delta_{max}}$ on δ is applied to limit its value. Weighting function on the disturbance is also applied, such as $W_\Delta = \Delta_{max}$ is applied to Δ_L.

Stability and performance level of the closed-loop system through the LPV design process are guaranteed [17], [18], [19]. In the design process the parameter-varying controller $\mathcal{K}(\rho, \rho_L, y_K)$ must be selected, with which quadratic stability of the closed-loop system is achieved. Moreover, the induced $\mathcal{L}_2$ norm from w to z must be under the predefined value γ. It leads to the minimization problem: following:

$$\inf_{\mathcal{K}(\rho_L, y_K)} \sup_{\rho_L \in \varrho_L} \sup_{\substack{\|w_K\|_2 \neq 0, \\ w_K \in \mathcal{L}_2}} \frac{\|z\|_2}{\|w_K\|_2}. \tag{6}$$

The formulated optimization task using an offline process is resulted, and the designed controller $\mathcal{K}(\rho, \rho_L, y_K)$ operates online in the closed-loop.

B. Formulation of the supervisory algorithm

The goal of the supervisor is to result in Δ_L, ρ_L, with which u can be as close as possible to u_L and predefined safety performance criteria are guaranteed. It leads to a constrained optimization process [20], in which the objective of the optimization is to minimize $(u - u_L)^2$, i.e., $(\rho_L \delta_K + \Delta_L - u_L)^2$ using (1). The constraint of the optimization reflects to the primary performance criteria, i.e., predicted lateral error through a predefined e_{max} scalar value must be limited. The prediction of the lateral error at preview time T_p is formed through the motion prediction of the vehicle:

$$\psi(k+1) = \psi(k) + v(k)\frac{\tan\delta(k)}{L}T_p, \tag{7a}$$
$$X(k+1) = X(k) + v(k)\cos(\psi(k+1))T_p, \tag{7b}$$
$$Y(k+1) = Y(k) + v(k)\sin(\psi(k+1))T_p, \tag{7c}$$

where k reflects to the actual signals and $k+1$ to the predicted vehicle states, such as X, Y position, L is the wheelbase of the vehicle. For providing discrete formulation of motion dynamics in (7), the sampling time is selected to be equal to T_p. In practice, the predicted lateral error $e(k+1)$ can be calculated through a search method, where the goal is to find minimum difference between $X(k+1), Y(k+1)$ and the coordinates of the set of forthcoming waypoints:

$$e(k+1) = \min_{i \in I_p} \sqrt{(X(k+1) - X_i)^2 + (Y(k+1) - Y_i)^2}, \tag{8}$$

where I_p represents the set of candidate waypoints. The predicted lateral error depends on $\delta(k)$, i.e., on $\rho_L \delta_K + \Delta_L$ through $X(k+1), Y(k+1)$.

The optimization problem of the supervisor is formed as

$$\min_{\rho_L, \Delta_L} (\rho_L \delta_K + \Delta_L - u_L)^2, \tag{9a}$$

subject to

$$e(k+1) \leq e_{max}, \tag{9b}$$
$$\rho_L \in \varrho_L, \tag{9c}$$
$$\Delta_L \in \Lambda_L. \tag{9d}$$

The solution of (9) requires the results of two optimization process, which are in a hierarchical structure. In the outer optimization loop the task is to minimize the objective $(u - u_L)^2$, and in the inner optimization loop, for all candidate ρ_L, Δ_L pairs the minimization task (8) must be solved.

Remark The selections of bounds ϱ_L, Λ_L have impacts on the LPV design process (see (6)) and on the supervisory optimization (9). Selection of high-range bounds lead to the possibility of increased difference $(u - u_L)^2$, but it leads to increased conservativeness of the LPV control. Tight bounds result in improved performance level of the LPV controller, but the entire performance level, which is determined by the data aided agent, is reduced. A selection process on ϱ_L, Λ_L can be found in [14].

III. Design process for achieving data aided steering control

In this section the achieving of data-aided steering control is presented. The aim of using data in case of this vehicle control problem is to achieve a control element, with which the steering characteristics of a human driver can be imitated. Therefore, a supervised learning process is applied, in which the agent is a neural network. This method requires desired input-label pairs and the parameters of the network are updated based on the loss between the desired label and the output of the network.

Data acquisition for training and validation

In this paper data on human steering intervention through Software-in-the-Loop (SiL) tools have been collected. In high fidelity vehicle dynamic simulator CarMaker a $25km$ long route has been imported with a desired path along the middle of it. The coordinates of the route have been recorded in an urban area of Budapest, Hungary in real life and thus, an urban virtual model for this environment has been created. During SiL simulation human drivers and CarMaker human driver models have driven along the route to generate driving data for training and validation process. In case of driver models, it has mimicked a human driver, its attributes, e.g. the extent it leaves the path during cornering, and the acceleration rates in each direction, can be parameterized.

The inputs of the neural network are the actual longitudinal velocity v, and moreover, the lateral distance to the path and the deviation angle (Figure 3) in 25 points along the $50m$ ahead of the vehicle. The output of the network is a steering wheel angle δ_L.

For training purposes, the collected data have been sorted into categories. Each category has values, where lateral

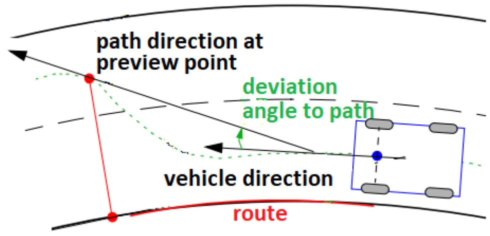

Fig. 3. Illustration on deviation in heading angle

distances are within $0.15m$ to each other, heading angles are within $1.2°$ and longitudinal velocities are within $0.7m/s$ to each other. The actuated steering angle in these categories has standard deviation, generally below 0.1, independently from the given category. These categories are used for balancing the dataset, i.e., the high amount of samples on straight motion is reduced, and thus, samples on turning motion are not underrepresented.

Parameters of the network and the training process

In this work, the neural network contains fully connected layers. The ideal network depth and the amount of neurons in it are determined with tests utilizing a wide range of values. This hyperparameter search carried out that increasing the number of neurons above 32 does not result in a notably higher performance level, and 4 hidden layers have been enough. Since the complexity of the neural network influences both the time of a training process and evaluation in the controller, the insufficient increase in the neuron number must be avoided. It yields the selection of 32 neurons in each hidden layer.

The loss function is the mean squared error of the neural network output and the corresponding true value in the training set.

The training process is performed in the PyTorch environment [21], the network parameters are optimized with the Adam method, which involves first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments [22]. The learning rate is initialized to 0.005 and decreased with multiplication by 0.85 after every 300^{th} epoch [23].

IV. Simulation Results

In this section the results of three different simulation scenarios are shown. First, the data aided controller is a neural network, which is able to steer the vehicle for achieving path following. Second, instead of a data aided control, human driver steering intervention is actuated within the LPV-based control framework. Finally, in the third example the steering inputs of the neural network and the driver are combined.

The structure of the SiL simulation setup is illustrated in Figure 4. The steering angle of the front wheels depends on the rotation angle of the steering wheel. Thus, in this setup δ is not realized on the front wheels of the vehicle directly, but the electric motor of the steering wheel is rotated to achieve δ on the wheels. Nevertheless, if the driver can decide to modify the angle of steering wheel, and thus, the driving is transferred. Torque T for the steering wheel actuator through a PID control from the difference of steering wheel angle and δ is computed.

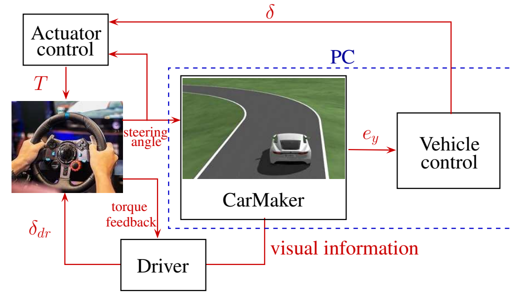

Fig. 4. Scheme of driver-in-the-loop with neural network simulation setup

A. Operation of the proposed control under different driving styles

Since the vehicle control method is based on learning from previously recorded driving, the developed method can be adapted to the individual drivers to achieve personalized driving characteristics. In the first simulation example the SiL environment of Figure 4 is used, but the physical steering system is emulated with the steering by driver model of the CarMaker. The advantage of this embedded model is that the different scenarios can be easier repeated, compared to the scenario when different human drivers rotate the steering wheel.

The training data is generated with two driver settings, in which model an aggressive driver with the limits of the G-G diagram with $[-6, 6]$ m/s^2 is represented, and a restrained one with $[-3, 3]$ m/s^2. Three cases are illustrated, in every case the driver model is the aggressive one. In the first case the aggressive driver without automatic control intervention drives the vehicles. In the last two cases the proposed LPV-based control strategy is applied using different neural networks: in second case with a neural network trained through data on a restrained driver, in third case through data on an aggressive driver.

In all cases the path following is guaranteed, see an exemplary a section of the $24km$ long urban track in Figure 5(a). The lateral errors on the whole track are in the same range $[-1.62, 1.49]$ m, while their standard deviations with respect to the only driver case are 0.20 m and 0.07 m for the restrained and aggressively trained nets, respectively. Figure 5(b) illustrates the lateral errors, where it can be seen that peak values in the second case are resulted. The reason for the higher deviation is the different behavior of the driver and the trained neural net. As it can be seen in Figure 5(d), the speed is lower with the restrained neural network, since it tries to keep the acceleration within the $[-3, 3]$ range, see Figure 5(c). Due to the behavior of the driver, aggressive human driver interventions with a restrained-style neural network decrease the tracking performance. Therefore, it is important that the behavior of the driver assistance system must be similar to the actual driver. Although, with the proposed LPV-based control structure the safe driving is ensured, independently from the differences in the driving styles.

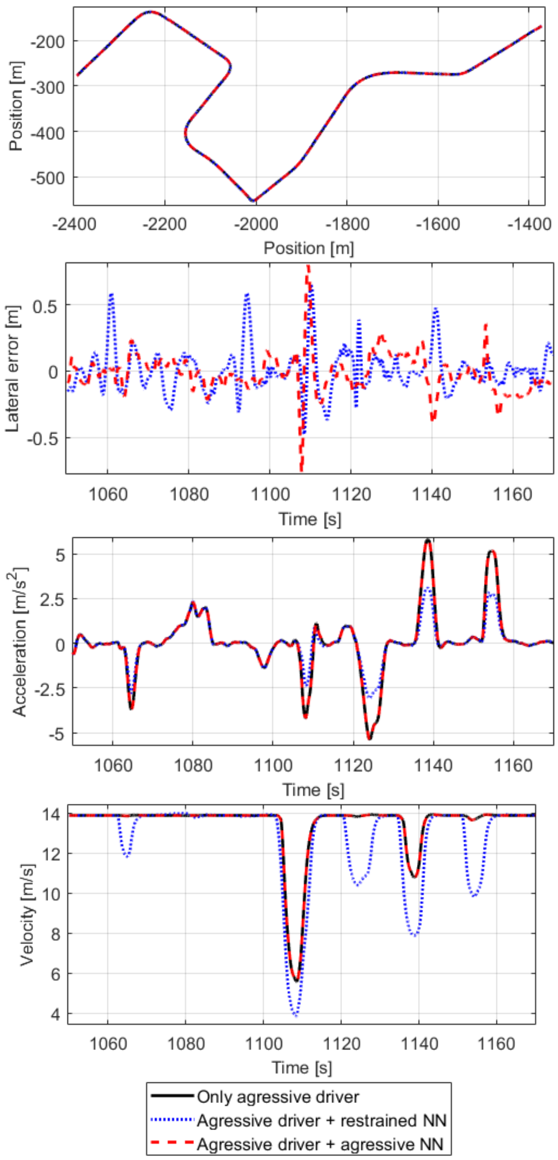

Fig. 5. Operation of the controller with various trained driving behavior

B. Action of the LPV control in an emergency situation

In this simulation case, a human driver is also in the loop, and thus, the proposed control architecture operated as a steering assistance. The goal of this setup is to handle driving situations, when the driver's hands on the steering wheel are not necessarily hold. The vehicle control provides steering angle $u = \delta$, but this steering angle through the driver δ_{dr} can be modified. The advantage of this control solution compared to the previous setup is that the driver has the ability to modify the trajectory of the vehicle, if the driver is not satisfied with its motion. Moreover, the functionality of driving transfer between the driver and the automated system through this setup can be tested, which is an important aspect of automated driving [24], [25].

In this scenario a traffic situation is carried out, where suddenly an obstacle on the road has appeared (Figure 6). This change in the desired path is too late for a human driver to react appropriately, and thus, intervention is needed from the proposed supervisory control architecture. At the start of the simulation, a clear road is ahead, but at around 4.5 s suddenly a parking vehicle moves back to the road, and thus, a steering intervention for avoiding collision must be found. A video on the scenario is available at `https://youtu.be/RVySk6bFDGQ`.

(a) Road section with parking vehicles

(b) Suddenly moving vehicle

Fig. 6. Illustration on the example with moving obstacle vehicle

Since the human driver does not have enough time to react in such a sudden situation, the steering wheel is kept straight by the driver. Since this intervention can lead to collision, additive torque to the steering system is given, which is illustrated along with the steering angles in Figure 7. It can be seen that u_K (LPV) differs from the driver intervention δ_{dr} (Driver), because in the LPV-based control design the driving style and characteristics of the driver are not involved. Nevertheless, u (Supervisor) is close to δ_{dr}, i.e., the steering control has the capability to assist effectively for the driver. Consequently, through the proposed control strategy the imitation of the driver in the assistance can be carried out.

The path of the vehicle can be found in Figure 8. Although, the slower steering actuation of the driver, the avoidance of the collision is guaranteed. Thus, the proposed control structure is able to operate effectively and safely with a driver-in-the-loop.

Furthermore, in Figure 7, it can be seen that the neural network u_L and the LPV controller u_K calculate sudden and significant intervention between $5s \ldots 6s$ to avoid the collision. Nevertheless, the signal of the neural network, u_L has low value to avoid collision in itself. Its reason is that this type of sample with sudden intervention in the training dataset is not found, and thus, the data-aided control is

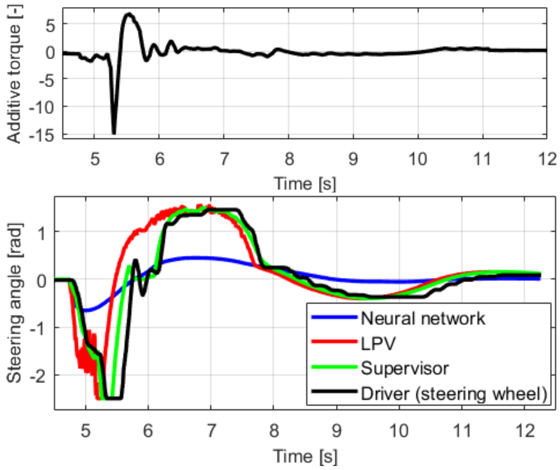

Fig. 7. Action of the steering system together with a human driver

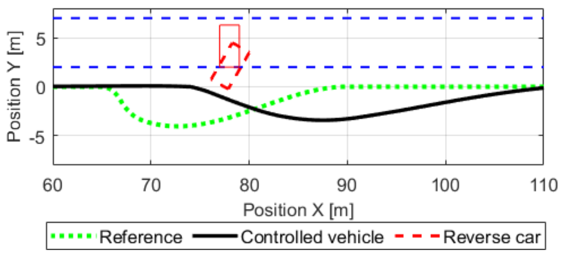

Fig. 8. Path following of the automated (w/o.) and assisted (w.) case (blue lines illustrate parking slots)

not trained under these situations. Therefore, an intervention purely with u_L can lead to a collision. This example shows that the LPV-based control with the supervisor is able to guarantee safe vehicle motion, through the increasing of the steering intervention, compared to u_L.

V. Conclusions

This paper has proposed a control system, in which a LPV-based control operates together with a neural network to achieve safe and human-imitated vehicle motion. It has been shown that different styles in steering of human driver through supervised learning-based controllers can be imitated. Moreover, through the proposed control design framework the control can be adapted to the human driver, while the safe motion of the vehicle is preserved. Safe operation of the control system through an advanced LPV control design and a supervisory algorithm has been guaranteed. The results of the paper through SiL simulations with driver-in-the-loop have been illustrated.

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