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Linear Parameter Varying and Reinforcement Learning Approaches for Trajectory Tracking Controller of Autonomous Vehicles

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Abstract

This research focuses on controlling the motion trajectory of autonomous vehicles by using a combination of two high-performance control methods: Linear Parameter Varying (LPV) and Reinforcement Learning (RL). First, a single-track motion model is researched and developed with coordinate systems to determine the car's motion trajectory through signals from GPS. Then, the LPV control method is used to design a controller to control the car's motion trajectory. Reinforcement learning method with detailed training procedures is used to combine with the advantages of LPV controller. Finally, the simulation results are evaluated in the time domain through the use of specialized CarSim software, which clearly demonstrates the superiority of the research method.

Keywords

autonomous vehicles, trajectory tracking, linear parameter varying, reinforcement learning, CarSim software

1 Introduction

With the outstanding development of science and technology today, autonomous vehicles have been researched and developed, bringing many conveniences to people, reducing traffic congestion, and significantly reducing traffic accidents (Yurtsever et al., 2020). Along with these advantages and with most autonomous vehicles using green energy, they are greatly welcomed by drivers and encouraged and supported by the governments. With this development trend, autonomous vehicles are receiving increasing investment from automobile companies and research centers around the world, turning the autonomous vehicle market into a potential market for investors.

To achieve safe mobility with little or no driver intervention, sensors, controllers, algorithms, machine learning systems and processors must be meticulously coordinated and organized. First, information about the vehicle and surrounding environment is collected by a network of main vehicle sensors such as GPS, IMU, encoders, cameras, LIDAR, and other sensors (Min et al., 2019; Sukkarieh et al., 1999; Van Wyk et al., 2019). This data is processed to indicate the location, speed of the vehicle and obstacles. After processing, a module creates a trajectory and sends it to the vehicle's controller to control speed, acceleration, steering angle, stability and braking appropriately (Corno et al., 2020; Falcone et al., 2007; He et al., 2019; Kang et al., 2018; Ren et al., 2023). These operations are based on the vehicle's current position, a calculated sequence of references, along obstacle avoidance algorithms, thanks to which the autonomous vehicle ensures smooth and safe movement while traveling on the road. RL (Reinforcement Learning) is a branch of Machine learning, a controller integrated with RL has the ability to collect information and to learn through trial and error using

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feedback from its actions. Thanks to these capabilities, RL is increasingly widely applied in autonomous vehicle control to equip self-driving vehicles with higher intelligence and adaptability to the environment (Elallid et al., 2022; Gómez Ruiz et al., 2024). When equipped with RL algorithms such as the Deep Neural Network (DNN) and Deep Reinforcement Learning (DRL), autonomous vehicles have the ability to navigate when changing lanes with predefined routes (Liao et al., 2020). Models based on Q-learning, Q-network and Deep Deterministic Policy gradient (DDPG) algorithms can learn to handle unforeseen situations and need adaptability on the road (Ye et al., 2019; Zhang et al., 2022). This adaptability is a very important and necessary factor in handling situations ranging from complex interactions during traffic to adaptation to unexpected weather conditions. This ability is continuously learned and updated while interacting with the environment to help autonomous vehicles ensure safety and efficiency when operating in different conditions and emergencies while traveling (Wang et al., 2018), e.g. in obstacle avoidance (Gong et al., 2019), and in longitudinal control when changing lanes.

However, the RL method applied to control the motion trajectory of autonomous vehicles still faces difficulties in some cases, for example in the case of noisy sensors. Another control method applied to autonomous vehicles is the Linear Parameter-Varying (LPV) control method. LPV control theory is especially effective in dealing with complex nonlinear systems (Mohammadpour and Scherer, 2012). The LPV technique is capable of representing various nonlinear systems with arbitrary slow or fast changes of parameters (Briat, 2014). Besides, thanks to the ability to extend some linear concepts to nonlinear systems such as $H\infty$, sensitivity shaping, D-stability, it helps its application in nonlinear systems in vehicles (Sename et al., 2013). When LPV is integrated into the autonomous vehicle controller, it is capable of autonomous driving control with time-varying speed and external disturbances (Li et al., 2021). Therefore, the advantages of the LPV method can overcome the RL method mentioned above, so this study aims to combine the above two methods to control the motion trajectory of autonomous vehicles. Specifically an LPV supervised RL based trajectory tracking control approach is introduced with the purpose to ensure vehicle stability in case of sensor interference, such as GPS signal interference. The main novelty of the present paper is the supervised control architecture, in which the RL based trajectory tracking controller is supervised by a robust LPV trajectory tracking controller, with the aim to deal with possible sensor noises in the GPS system. Thus, in case of interference in the GPS signal is detected, the RL based trajectory tracking of the autonomous vehicle is overtaken by the LPV controller. By this means, the otherwise exceptional RL controller which cannot handle disturbances and noises in a robust and stable manner is substituted by the LPV controller, which has an in-built stability margin to deal with such instances.

The paper is organized as follows: Section 2 describes a single track bicycle vehicle model. Section 3 presents the LPV controller synthesis for the vehicle trajectory tracking. Section 4 details the trajectory tracking RL controller for the autonomous vehicle. Section 5 demonstrates the simulation results in CarSim software (Mechanical Simulation Corporation, 2010) simulation environment through high-speed test scenarios. Finally, concluding remarks are presented in Section 6.

2 Modeling of vehicles for trajectory following

The bicycle model, serving as a cornerstone in vehicle simulation and dynamics analysis, provides a simplified representation of a vehicle's lateral motion and steering behavior, supporting research in high-level control design and trajectory planning, notably in the field of autonomous vehicles. In this model, which is graphed in Fig. 1, the vehicle's front and rear axles are represented as point masses, with state variables including position, orientation, velocity, and steering angle δ.

Equations of motion capture the interplay of forces and moments affecting the vehicle, while a simplified steering model relates the steering angle δ to the rate of change of the yaw angle ψ. Researchers leverage the bicycle model to test and refine control algorithms, facilitating the development of autonomous vehicle systems and robotics applications. While the model has its limitations, it offers a practical and efficient framework for initial testing and analysis before transitioning to more complex and detailed vehicle models. The dynamic equations in the lateral direction are shown in Eq. (1) (Kiencke and Nielsen, 2015):

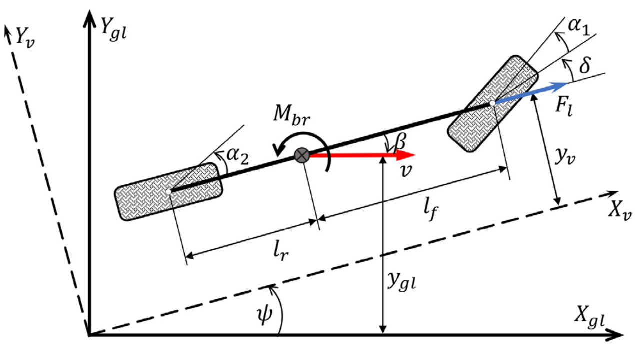


Fig. 1 Single track bicycle model

$$\begin{cases} J\ddot{\psi} = c_1 l_f\left(\delta - \beta - \dot{\psi} l_1 / \dot{\xi}\right) - c_2 l_r\left(-\beta + \dot{\psi} l_2 / \dot{\xi}\right) \\ m\dot{\xi}\left(\dot{\psi} + \dot{\beta}\right) = c_f\left(\delta - \beta - \dot{\psi} l_f / \dot{\xi}\right) + c_r\left(-\beta + \dot{\psi} l_r / \dot{\xi}\right), \\ \ddot{y}_v = \dot{\xi}\left(\dot{\psi} + \dot{\beta}\right) \end{cases} \quad (1)$$

where β is the side-slip angle, J is the yaw inertia of the vehicle, m is the mass of the complete vehicle, l_f and l_r are respectively the distances from the front and rear axles to the Center of Gravity (CG), c_f and c_r are respectively the front and rear tire cornering stiffnesses, which are identified in (Szabó, 2012). Meanwhile $\ddot{\xi}$ and y_v are respectively the longitudinal and lateral accelerations, which are measured by sensors.

In the realm of autonomous vehicle research, the goal of trajectory tracking design is paramount, with a specific focus on the coordinated utilization of the coordinate axes within the bicycle model. This objective centers on the development of advanced control algorithms and systems that enable autonomous vehicles to adhere to predefined trajectories while navigating complex real-world scenarios precisely. These systems must consider the vehicle's state variables, employing a coordinate system that typically encompasses longitudinal and lateral directions. The seamless coordination and control of the vehicle's motion along these axes are essential for ensuring that the vehicle accurately follows its intended path while adhering to safety standards, adapting to dynamic environments, and optimizing operational efficiency. This interdisciplinary pursuit in trajectory tracking design is pivotal for enhancing the capabilities and safety of autonomous vehicles in various contexts, spanning from path planning to real-time motion control.

Therefore, in Fig. 1, the coordinate transformation conversion between the world coordinate system (X_{gl} and Y_{gl}) and the vehicle's own rotating coordinate system (X_v and Y_v) is necessary. That is, the coordinate system attached to the vehicle will rotate by the yaw angle ψ. Here, the reference road coordinates $x_{gl,r}$ and $y_{gl,r}$ are introduced for the predefined trajectory of the vehicle. Hence, the lateral position of the reference road in the coordinate system of the vehicle can be calculated by Eq. (2):

$$y_{v,r} = -\sin(\psi)\, x_{gl,r} + \cos(\psi)\, y_{gl,r} \,. \quad (2)$$

Consequently, by utilizing the real-time vehicle position data obtained from the onboard GPS positioning system, it becomes possible to calculate the lateral deviation from the predetermined reference trajectory.

3 LPV controller design

It can be seen in Eq. (1) that the vehicle model depends on the forward velocity $\dot{\xi}$ and the inverse of the forward velocity. Moreover, when the vehicle is in motion, the forward velocity is one of the constantly changing parameters, and it depends on the driver and the motion condition of the vehicle. Here, the forward velocity $\dot{\xi}$ is chosen as a scheduling parameter. The dynamic Eq. (1) can be rewritten in the LPV state-space representation as in Eq. (3) with the varying parameter $\rho = \dot{\xi}$.

$$\dot{x} = A(\rho)x + B_1(\rho)w + B_2(\rho)u \,, \quad (3)$$

where the matrices $A(\rho)$, $B_1(\rho)$, and $B_2(\rho)$ are expressed in the following form:

$$\begin{cases} A(\rho) = A_0 + A_1\rho + A_2\dfrac{1}{\rho} \\ B_1(\rho) = B_{10} + B_{11}\rho \\ B_2(\rho) = B_{20} + B_{21}\rho \end{cases} . \quad (4)$$

The state vector of the system $x = \left[\dot{\varphi}\beta\,\dot{y}_v y_v\right]^t$ is selected to include the yaw rate, side-slip angle, lateral velocity and position of the vehicle.

In Fig. 2, the given $H\infty/LPV$ control structure includes the nominal model $G(\rho)$, the controller $K(\rho)$, the performance output z, the control input u, the measured output y, the measurement noise n.

According to Fig. 2, the concatenation of the nonlinear model (3) with the performance weighting functions has a partitioned representation in the following way:

$$\begin{bmatrix} \dot{x}(t) \\ z(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} A(\rho) & B_1(\rho) & B_2(\rho) \\ C_1(\rho) & D_{11}(\rho) & D_{12}(\rho) \\ C_2(\rho) & D_{21}(\rho) & D_{22}(\rho) \end{bmatrix} \begin{bmatrix} x(t) \\ w(t) \\ u(t) \end{bmatrix}, \quad (5)$$

with the $w(t) = [Rn]^T$ exogenous input, the control input $u(t) = [\delta]^T$, the measured output vector $y(t) = [\,\dot{\xi}\, y_v]^T$ by

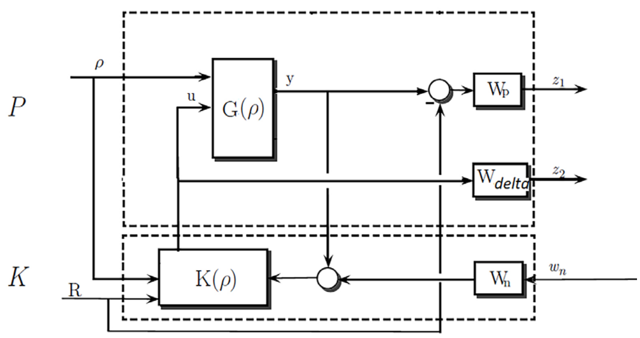


Fig. 2 Closed-loop interconnection structure

which $z(t) = [z_1\, z_2]^T$ performance output is defined. Here, $z_1 = |y_{v,r} - y_v|$ is the lateral deviation from the designed path. The aim of the control problem is to minimize the value of z_1, i.e. $z_1 \to 0$ (optimization criterion). Meanwhile, the second output performance is selected as follows: $z_2 = [\delta]^T$. The main goal of this idea is to reduce the steering angle while ensuring appropriate trajectory tracking, that is, to avoid the saturation of the actuator. The choice of the performance output is very important, and affects the effectiveness of the controller design.

The weighting functions W_n and W_δ represent respectively the sensor noises of the system (in this case the noisy GPS positioning signal), the activation of steering intervention and avoiding actuator saturation. With T_1 and λ design parameters, these weighting functions are chosen as first-order proportional form:

$$\lambda \frac{1}{T_1 s + 1}. \tag{6}$$

The weighting function W_p representing the performance signals ensuring the velocity and path tracking of the autonomous vehicle, is chosen in the following form:

$$W_p = \lambda \frac{\alpha_2 s^2 + \alpha_1 s + 1}{T_1 s^2 + T_2 s + 1}, \tag{7}$$

where $T_{1,2}$, $\alpha_{1,2}$ and λ are design parameters. Note, that these design parameters are selected for shaping the weighting functions in a manner to realize the expected behavior of the closed-loop system. As an example, W_p weighting function can be considered as penalty function, thus the shaping is designed to suppress the performance signals in the desired frequency range. On the other hand, W_δ is shaped in a manner to allow bigger steering angle for smaller frequencies and to avoid saturation of the steering system. The selection of the design parameters are chosen in an iterative manner, adjusting necessary parameters after the analysis of the closed-loop system.

The LPV controller $K(\rho)$ minimizes the induced L_2 norm of the closed-loop LPV system $P_{CL(\rho)} = LFT(P(\rho),K(\rho))$, with zero initial conditions, i.e.:

$$\sum_{CL}(\rho)_{2\to 2} = \sup_{\substack{\rho\in P \\ \bar{v}\le\dot{\rho}\le\underline{v}}} \sup_{\substack{w\in\mathcal{L}_2 \\ \|w\|_2\neq 0}} \frac{\|z\|_2}{\|w\|_2}. \tag{8}$$

The existence of a controller that solves the parameter dependent LPV γ performance problem can be expressed as the feasibility of a set of Linear Matrix Inequalities (LMIs), which can be solved numerically (Gáspár et al., 2004; Gáspár et al., 2005a; Gáspár et al., 2005b). The control goal is to find an LPV controller $K(\rho)$, which minimizes the induced L_2 norm of the closed-loop LPV system $P_{CL(\rho)} = LFT(P(\rho),K(\rho))$, with zero initial conditions. The induced L_2 norm from the disturbance ω to the performances z remains smaller than a predefined γ, as detailed in (Wu et al., 1996). Here, the γ value achieved is 1.112.

The closed-loop system achieves robust performance, as both robust stability and nominal performance requirements are satisfied. As an example, in Fig. 3 singular value plots are depicted for a selected $\rho = 27.7$ m/s value used in the simulation example.

4 Design of LPV supervised reinforcement learning control

A deep Q-learning network (DQN) agent has been applied, while the reinforcement learning environment consists the two-wheeled bicycle model, which represents the ego vehicle dynamics. The goal of the training is to realize trajectory tracking for the autonomous vehicle by applying an appropriate steering angle. A $T_s = 0.02$ s sample time has been used for the training process, while the output of the trajectory tracking control is the steering angle of the vehicle. In order to consider the physical limitations of the ego car, the steering angle δ has to be in the range of [−37 37] deg. The trajectory of the road is given by the simulation road presented in Section 5. The initial condition for the lateral deviation is set to 0.2 m, while the relative yaw angle −0.1 rad has been chosen.

The training model for the ego vehicle has been built in the following manner:

- The steering action δ from the agent to the environment is selected from −37 degrees to 37 degrees.
- Observations from the environment are defined as follows:
  - Lateral deviation: e_y
  - Relative yaw angle: e_ψ

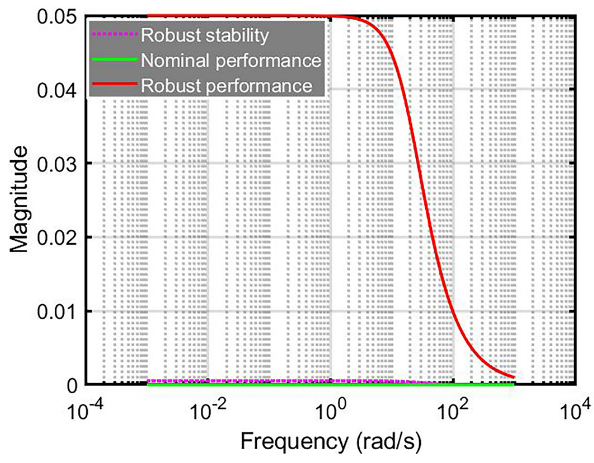


Fig. 3 Singular value plots

- Derivative of lateral deviation: $\dot{e}_y$
- Derivative of relative yaw angle: $\dot{e}_\psi$
- Integral of lateral deviation: $\int e_y$
- Integral of relative yaw angle: $\int e_\psi$.

The calculated reward r_t given at each time step t is chosen as $r_t = 20e_y^2 + 20\delta^2$, where the episode reward is the cumulative value of r_t. An example of the training process is shown in Fig. 4. Note, that during the training a fixed velocity of 100 km/h has been set, however, in case of varying velocities the reward function should scale the lateral error with the velocity, i.e. bigger errors should be allowed for higher velocities. Moreover, vehicle stability measures could also be added to the reward function to guarantee safety, for example by applying very big weights in case stability index based calculation shows instability. However, as generally trajectory tracking error and vehicle instability caused by skidding or roll-over are connected, these measures were neglected in the training process.

The aim of the LPV supervised control architecture is to guarantee stability of the vehicle using the RL controller even in the case of disturbances or sensor noises, which are assumed to be detected as detailed in (Brás et al., 2015). In normal operating conditions the vehicle steering system is operated by the RL agent, while in case of a detected sensor noise the robust LPV controller overtakes the control action, as depicted in Fig. 5. Note, that the two designed controllers operate in parallel, with the LPV controller designing a steering angle δ_{LPV}, whereas the RL agent calculates δ_{RL}. The following simple decision logic is applied for choosing the steering input of the autonomous vehicle:

$$\delta = \begin{cases} \delta_{RL}, & \text{without noise} \\ \delta_{LPV}, & \text{with noise} \end{cases} . \tag{9}$$

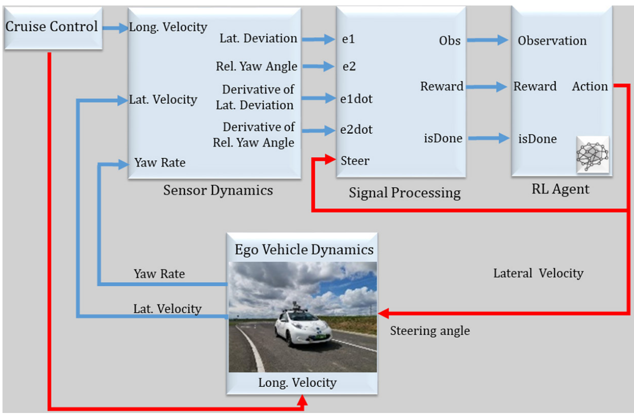


Fig. 4 Reinforcement learning training process

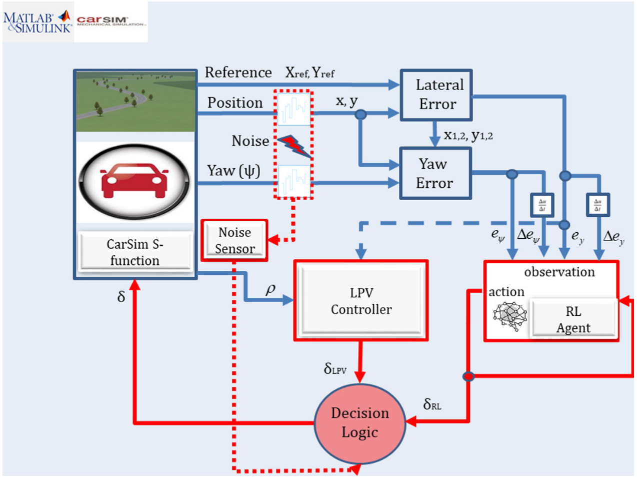


Fig. 5 LPV supervised RL controller (MathWorks, 2021)

5 Simulation results

To demonstrate the operation of the introduced reinforcement learning based supervised control design, real-life simulation scenarios have been tested with and without the designed supervised control method in the absence or presence of sensor noise associated with the GPS positioning system. The geometric and dynamic parameters of the chosen simulation vehicle are illustrated in Table 1. Note, that the same parameter values have been applied for the LPV control design described in Section 3 and for the RL training process detailed in Section 4.

The simulations have been evaluated with a constant velocity of 100 km/h on a curvy highway road given in CarSim software environment as depicted in Fig. 6.

5.1 Reinforcement learning control

During the base simulation case, the steering of the autonomous vehicle is operated by the trained RL agent. Here, sensor noise of the GPS system is not assumed, thus in this fault free case trajectory tracking is performed as expected with minimal lateral error, see Fig. 7 (b). Here, the maximal lateral

Table 1 Autonomous vehicle parameters

Parameter	Value	Unit
Vehicle mass (m)	1742	kg
Yaw moment of inertia (J)	1523	kgm^2
Distance from C.G to front axle (l_1)	1.161	m
Distance from C.G to rear axle (l_2)	1.539	m
Tread front (b_f)	1.54	m
Tread rear (b_r)	1.535	m
Height of COG (h_{COG})	0.438	m
Cornering stiffness front (c_1)	70	kN/rad
Cornering stiffness rear (c_2)	55	kN/rad
Aerodynamic drag co-efficient (c_w)	0.3431	–
Front contact surface (A)	1.6	m^2

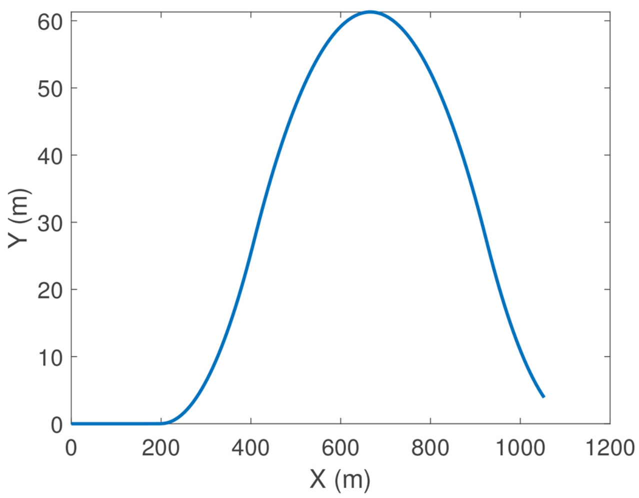


Fig. 6 Highway route X-Y plane

error never exceeds 2 cm. The corresponding steering wheel angle calculated by the RL controller is shown in Fig. 7 (a).

Note, that both the yaw rate depicted in Fig. 7 (c) and the lateral velocity shown in Fig. 7 (d) remains in a comfortable range for the passengers of the automated vehicle.

5.2 Reinforcement learning control with sensor noise

In the next simulation case a sensor noise for the navigation system has been added, as depicted in Fig. 8. Thus, a band-limited white noise signal with a maximal amplitude of 0.3 m has been introduced to the position of the vehicle between 5–11 s. As it is shown in Fig. 9, the defined GPS noise destabilizes the autonomous vehicle. The lateral error from the designed path depicted in Fig. 9 (b) quickly exceeds 2 m, while the steering input of the autonomous vehicle begins to oscillate, see Fig. 9 (a). As a result, both the yaw rate depicted in Fig. 9 (c) and the lateral velocity shown in Fig. 9 (d) exceeds critical levels as the autonomous vehicle skids out of the lane.

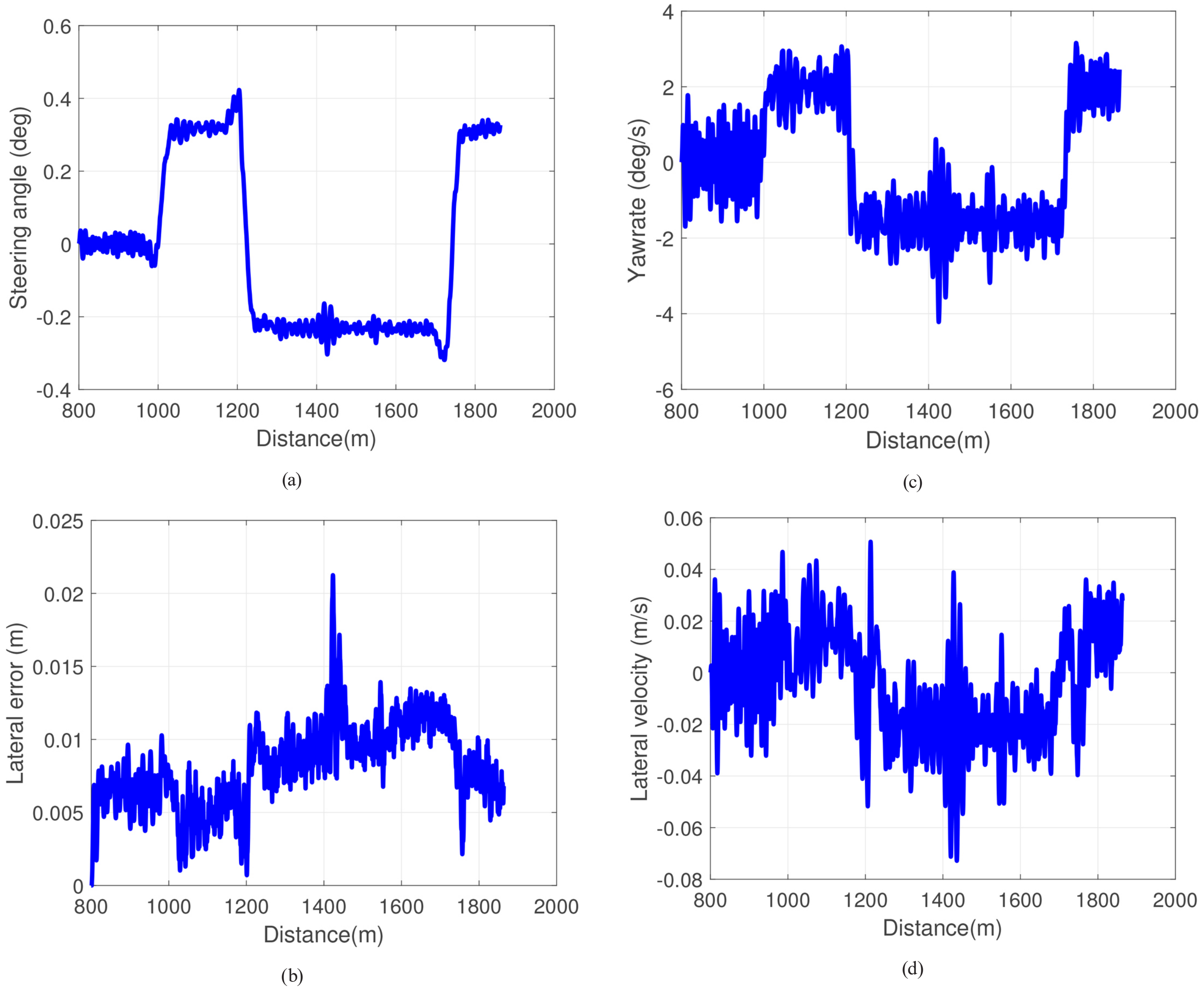


Fig. 7 RL simulation results without noise, a) Steering wheel angle, b) Lateral error, c) Yaw rate, d) Lateral velocity

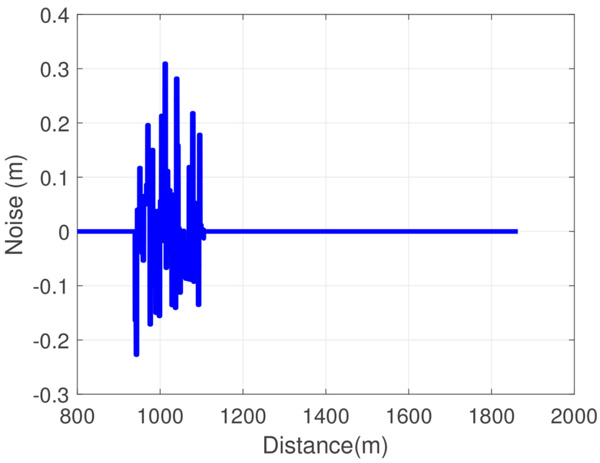
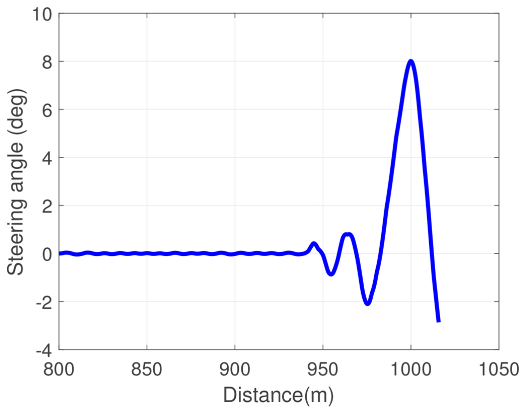
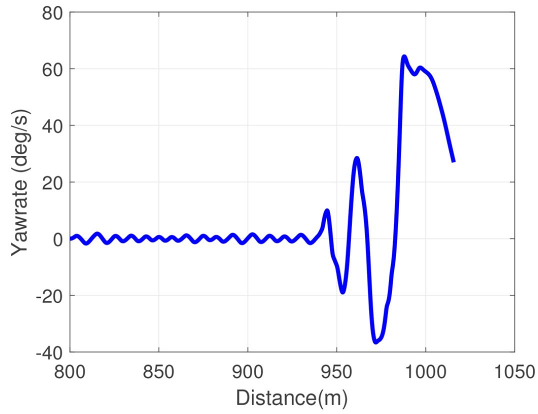


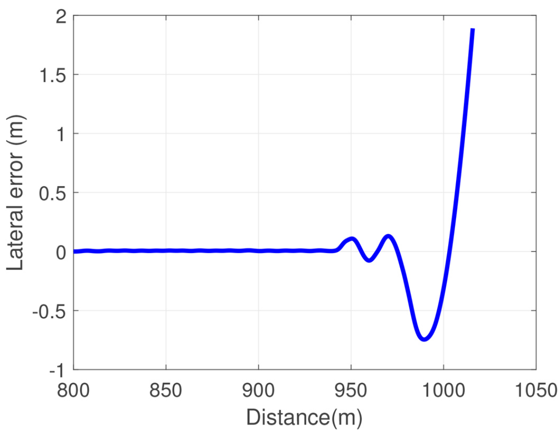
Fig. 8 Sensor noise



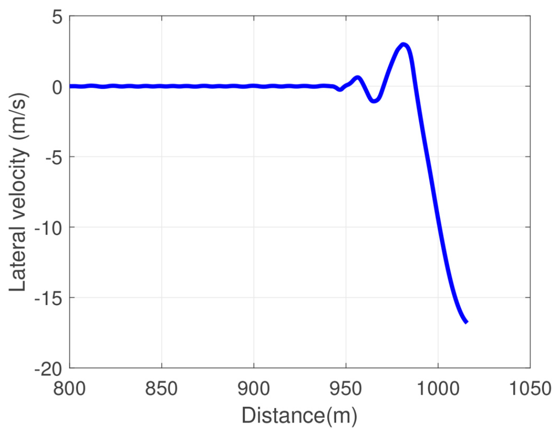
(a)



(c)



(b)



(d)

Fig. 9 RL simulation results with noise, a) Steering wheel angle, b) Lateral error, c) Yaw rate, d) Lateral velocity

5.3 Supervised RL control with sensor noise

Lastly, the simulation scenario has been selected where the autonomous vehicle uses the LPV supervised control architecture described in Fig. 4. Thus, in case the sensor noise of the GPS is detected, the trajectory tracking control of the autonomous vehicle is taken over by the LPV controller from the RL agent. Hence, although the lateral error of the vehicle shown in Fig. 10 (b) increases compared to the fault free case, it does not exceed 0.25 m, which is acceptable for high speed cornering with noisy GPS signals, as well as the slightly oscillating steering wheel angle, see Fig. 10 (a). Note, that both the yaw rate depicted in Fig. 10 (c) and the lateral velocity shown in Fig. 10 (d) increases as the sensor noise appears, however, quickly decreases as the GPS signal is normalized, thus the stability of the autonomous vehicle can be preserved.

6 Conclusion

The paper proposed a supervised control method in which an LPV controller supervises the trained reinforcement learning agent to realize stable trajectory tracking of the autonomous vehicle even under the effect of sensor noises. Thus, in case faulty or noisy GPS signal is detected, the operation of the steering is governed by the LPV controller, while in normal conditions by the reinforcement learning agent. The proposed supervised control method has been validated by simulations performed in CarSim software environment. In future work, sensor noise detection and controller selection and switching method will be further developed.

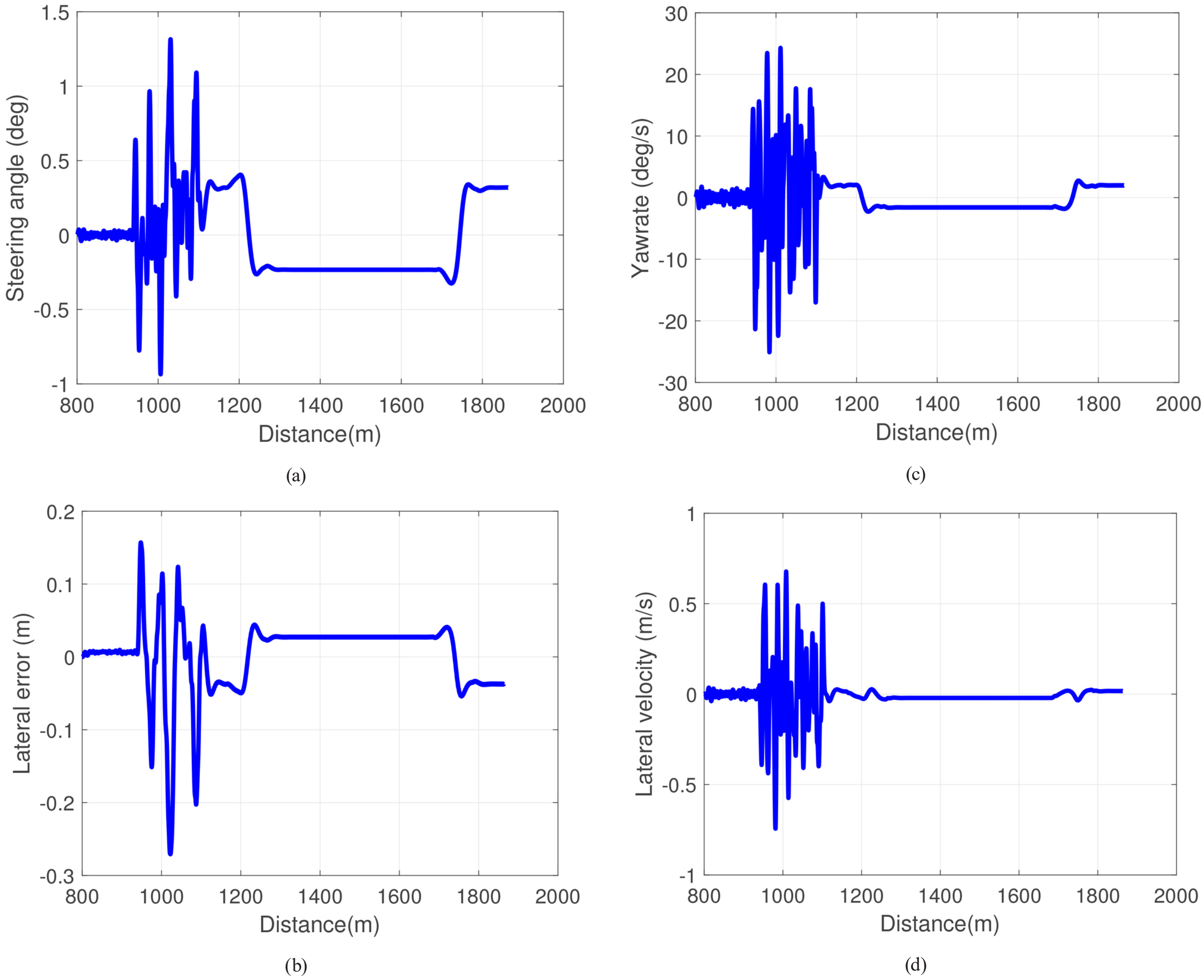


Fig. 10 Supervised RL simulation results with noise, a) Steering wheel angle, b) Lateral error, c) Yaw rate, d) Lateral velocity

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