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Transportation Research Procedia 72 (2023) 3545–3552

Transportation Research Procedia

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Transport Research Arena (TRA) Conference

Collision-free motion control with learning features for automated vehicles in roundabouts

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Abstract

Control design for safe and time-efficient motion of automated vehicles in roundabout scenarios poses various challenges, especially adaptation to the actual traffic scenario and coordination of the vehicles. This paper proposes the design of a hierarchical motion control with learning feature for roundabout scenarios. The control is designed on two levels, such as on cloud level and on vehicle level. The control on the cloud level is designed by using reinforcement learning (RL), with which the energy efficient motion of the vehicle is achieved. The vehicle level contains a robust controller and a supervisor, with which the collision avoidance of the vehicles is guaranteed. The proposed control on a Hardware-in-the-Loop environment with small-scaled indoor vehicles in augmented reality is implemented. The effectiveness of the control and the safe motion of the automated vehicles under multi-vehicle scenario are demonstrated. The provided scenario illustrates that safe, i.e., collision-free motion of all automated vehicles can be guaranteed.

Keywords: automated vehicles; learning features; roundabouts; collision-free motion; control design;

1. Introduction

Development of highly automated vehicles and intelligent traffic systems encourages the academic researchers to analyze the future control challenges of autonomous vehicles. Handling of complex traffic situations with fully autonomous vehicles and other participants - like human-driven vehicles - are known as current control design tasks. Collision avoidance, the minimization of traveling time or passenger comfort in traffic scenarios, such as crossing roundabouts, are basic constraints in the design of control strategies for autonomous vehicles. This paper focuses on

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10.1016/j.trpro.2023.11.746

that problem, i.e., crossing roundabouts under multi-vehicle traffic context. In Morsali et. al (2021) has been designed a geometrical set, based on support vector machine method, to calculate trajectories for autonomous vehicles for safe crossing of roundabouts. The control method defines collision regions to contribute to the increase of traveling comfort. In Wang et. al (2012) has been proposed a collision avoidance algorithm for autonomous vehicles to follow the trajectory based on state estimation. A warning function and the approach of force field has been built in the method for the vehicles to avoid conflict areas and crossing the roundabout in safety.

Roundabouts without traffic signals have also been deeply analyzed according to different aspects of the control of traffic and of autonomous vehicles. The motion and driving behavior of autonomous vehicles in complex traffic situations have been described and analyzed for the design of control algorithm for vehicles to cross roundabouts, contributing to safe traffic, see Nemeth et. al (2019). In Perez et. al (2011) has been designed a coordination scheme including trajectory planning and lateral control of vehicles in roundabouts. The proposed modular algorithm has been allowed to be tested in different situations. The behavior profiles of human drivers and a decision-making algorithm to coordinate autonomous vehicles in roundabout scenarios have been combined by Rodrigues et al. (2017). Based on drivers' behavior, a decision-making framework to guarantee the safe and efficient motion of automated vehicles in roundabouts has been proposed by Hang et. al (2021). In that work game theory approaches have been built in the presented framework while model predictive control is used for motion prediction of the vehicles. In Debada et. al (2017) has been designed a control strategy using virtual vehicles approach to consider maneuvers of and create cooperation with other vehicles. The proposed algorithm guarantee balance in waiting time and smooth circulating speed in urban roundabout scenarios.

In the control design of autonomous vehicles in complex traffic situations, the application of enhanced machine-learning-based methods has become widespread in the scientific research community. Several papers have been focused on learning approaches to be built in the presented coordination algorithms to guarantee more efficient passage of the vehicles through roundabouts. For example, in Deveaux et. al (2021) has been analyzed the driving risks, e.g., collisions, to be the base for the control of autonomous vehicles in roundabouts. Considering Time-To-Collision data, a machine-learning-based algorithm together with a supervisor predict the probability of exit motion of vehicles to guarantee safe urban traffic. In Konstantinidis et. al (2021) and in Chalaki et. al (2020) have been used multi-agent reinforcement learning methods for the control of highly automated vehicles in roundabouts. In Konstantinidis et. al (2021) all vehicles drive according to the same control policy having observed only the environment. On the other hand, Chalaki et. al (2020) has proposed a zero-shot transfer of autonomous vehicle policy to control vehicles in roundabouts while improve different performances like traveling time or speed profiles. A Q-learning algorithm for autonomous vehicles to cross the roundabouts safely has been proposed by Garcia et. al (2019). By the defined Qvalue function the vehicles follow the appropriate behaviors for maneuvering to drive through the roundabout without collision.

To summarize the existing results, the research activities have focused on the control methods of autonomous vehicles in roundabouts, and thus, several conclusions can be appointed. Firstly, numerous modern approaches have been proposed yet, it is necessary to design control method to be used for autonomous vehicles to drive complex maneuvers in various traffic scenarios. Secondly, several learning approaches have been defined for the coordination of autonomous vehicles in complex roundabout scenarios. Nevertheless, control algorithms - guaranteed safety conditions for the vehicles in crossing a roundabout - are needed to be developed. Furthermore, it is necessary to design additional communication and control architectures, e.g. cloud-based solutions, for the widespread implementation and application of CAV technologies in case of roundabout traffic situations.

This paper proposes a hierarchical control for automated vehicles, with which their safe and efficient motion in roundabouts under multi-vehicle environment can be guaranteed. The proposed hierarchy contains a vehicle level control and a cloud level control. The aim of the cloud level control is to achieve enhanced control performances using the high computation capacity of the cloud. Thus, reinforcement learning on the cloud level for achieving minimum energy consumption of the vehicles is implemented. Moreover, on the vehicle level the safety requirement, i.e., collision avoidance, is guaranteed. The advantage of the solution is that safe performance specifications even at the degradation of the communication in the network can be guaranteed. Significant novel content of this work is the implementation of the method using indoor test vehicle environment with cloud connection.

The paper is organized as follows. The hierarchical control structure with the design on the vehicle level and on the cloud level is presented in Section 2. The focus of Section 3 is the demonstration of the effectiveness of the method under Hardware-in-the-Loop (HiL) implementation. Finally, the paper in Section 4 is concluded.

2. Hierarchical control for automated vehicles with performance guarantees

The architecture of the hierarchical control with each levels is illustrated in Fig. 1(a). The goal of the control is to provide single motion input $u(k)$ for a given individual vehicle, i.e., longitudinal acceleration command $a_1(k)$, with which the vehicle moves along its route. $u(k)$ is computed by the supervisor, such as $u(k) = u_K(k) + \Delta(k)$, where $u_K(k)$ is the output of the robust controller on the vehicle level. $\Delta(k) \in \widehat{\Delta}$ is an additional term of the control input and $\widehat{\Delta}$ is the finite domain of $\Delta(k)$. In the control architecture, $u_L(k)$ is a candidate control input, which is suggested by the RL-based controller. The value of $\Delta(k)$ is a result of an optimization process in the supervisor, which minimizes the difference between $u(k)$ and $u_L(k)$ and guarantees collision avoidance between the automated and the other vehicles (Nemeth et. al (2021)).

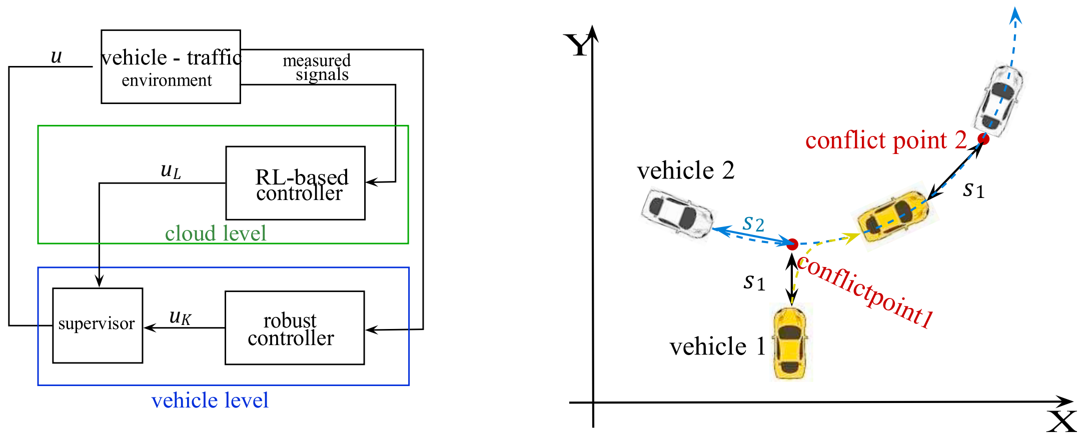


Fig. 1. (a) Illustration of the control architecture; (b) Vehicle interactions in roundabout.

The constraint between the vehicles through a method of conflict points is formulated. Roundabout can be handled as a complex scenario with intersection and vehicle following tasks, i.e., safe motion requires the modification of the conflict point during the motion of the vehicle, see Fig. 1(b). In case of entering into the roundabout the conflict point can be defined as the crossing of the vehicle routes. After entering into roundabout, automated vehicle must follow preceding vehicle. In this case, the actual position of the preceding vehicle is the continuously varying conflict point. The aim of the constraint is to keep safety distance s_{safe} between automated and other vehicles, e.g., further automated vehicles or human-driven vehicles: $s^2{}_1(k+1) + s^2{}_2(k+1) \geq s^2{}_{safe}$, where $k+1$ represents the next time step.

Thus, the constrained optimization problem of the supervisor for n number of vehicles is formed as

$$\min_{\Delta(k)} \left(u(k) - u_L(k)\right)^2, \tag{1a}$$

subject to

$$\left(s_{1,i}(k+1, u(k))\right)^2 + \left(s_i(k+1)\right)^2 \geq s^2_{safe}, \forall i \in [1, n], \tag{1b}$$

$$\Delta(k) \in \hat{\Delta}. \tag{1c}$$

The solution of the optimization problem (1) is $\Delta(k)$, from which the control input $u(k)$, as the sum of $u_K(k)$ and $\Delta(k)$ is resulted.

The computation of $u_L(k)$ is resulted by a neural network, which has been trained through a reinforcement learning process. The model for the learning process contains the supervisor, the robust controller and the vehicle-traffic environment. Due to the incorporation of the supervisor and the robust controller, the avoidance of the collision during the training process of the agent in every episode is guaranteed. The goal of the neural network is to improve the economy performance of the automated vehicle, i.e., the minimization of u. Moreover, it is also recommended to learn the decisions of the supervisor, which means that $(u(k) - u_L(k))^2$ is recommended to minimize. Thus, the reward function $r(k)$ is composed as follows:

$$r(k) = -Q1u^2(k) - Q2(u(k) - u_L(k))^2, \tag{2}$$

where Q_1 and Q_2 positive values are design parameters, which scale the importance of each term in $r(k)$.

The goal of the reinforcement learning process is to maximize reward (2) during the episodes. In this work deep deterministic policy gradient (DDPG) for the training process of the agent is carried out. It is a model-free, off-policy reinforcement learning method (Lillicrap et. al (2016)) in an actor-critic structure, which computes an optimal policy that maximizes the long-term reward. The observations, i.e., measured signals of the neural network are $s_{1,i}(k)$ value, $u(k-1)$, $u_L(k-1)$ and $u_K(k)$. The output of the RL-based controller is $u_L(k)$, which is a candidate control input for advising purposes.

3. Implementation of the motion control algorithm

The goal of this section is to propose the effectiveness of the algorithm through its implementation on small-scaled test vehicles. In the demonstration a Hardware-in-the-Loop (HiL) environment has been used, in which augmented reality (AR) and multiple indoor vehicles are contained. The goal of the presented example, i.e., motion of automated vehicles in a roundabout scenario, is to show the safe motion of the automated vehicles, which use the proposed control algorithm. The roundabout example in Fig. 2 is illustrated. The roundabout has anticlockwise circulation and three entrance/exit connections. The safety performance requirement against the vehicles is to keep at least $s_{safe} = 1m$ distance from each other.

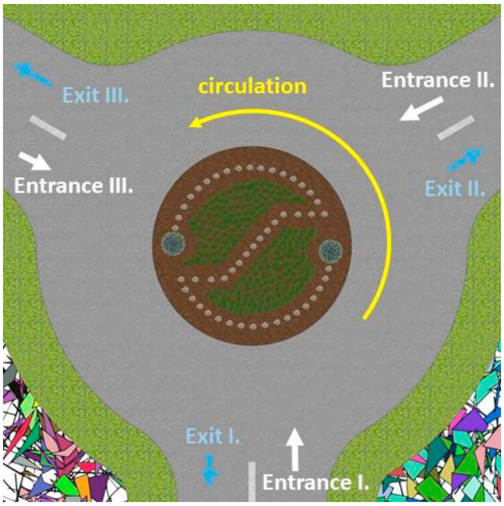


Fig. 2. Illustration of the roundabout example.

In the example three automated vehicles are involved, two of them are real physical small-scaled vehicles and one of them is virtual vehicle in the AR. The scheme of the HiL architecture is illustrated in Fig. 3. The positions of the physical vehicles through OptiTrack motion capture system are measured and this information via ROS network is transferred. In the architecture the motions of the virtual vehicles on a PC, as a node of the ROS network, are simulated. These motions in the AR on a tablet are visualized. On the tablet the Android-based Unity environment with Vuforia AR engine is used, with which the pose of the tablet, related to a fixed marker on the floor is estimated. From the viewpoint of control implementation, the RL-based control on the cloud is found, and the robust control with supervisor on the physical vehicles (or on the PC for virtual vehicles) are installed. The lateral motion of the physical vehicle based on their lateral error from the centerline through a PID controller is influenced.

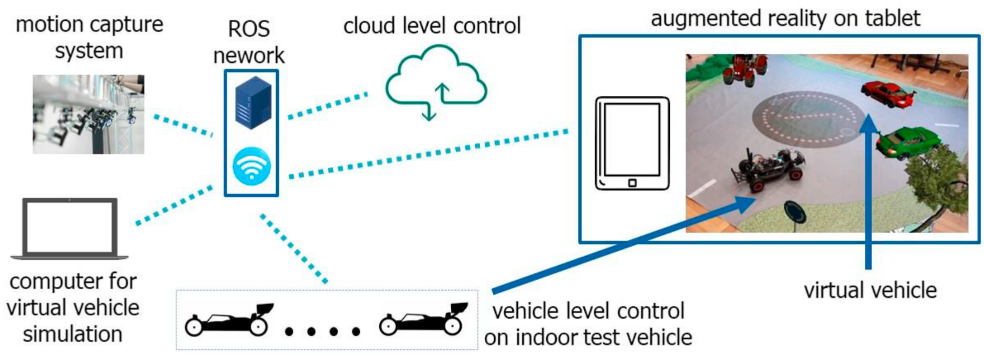
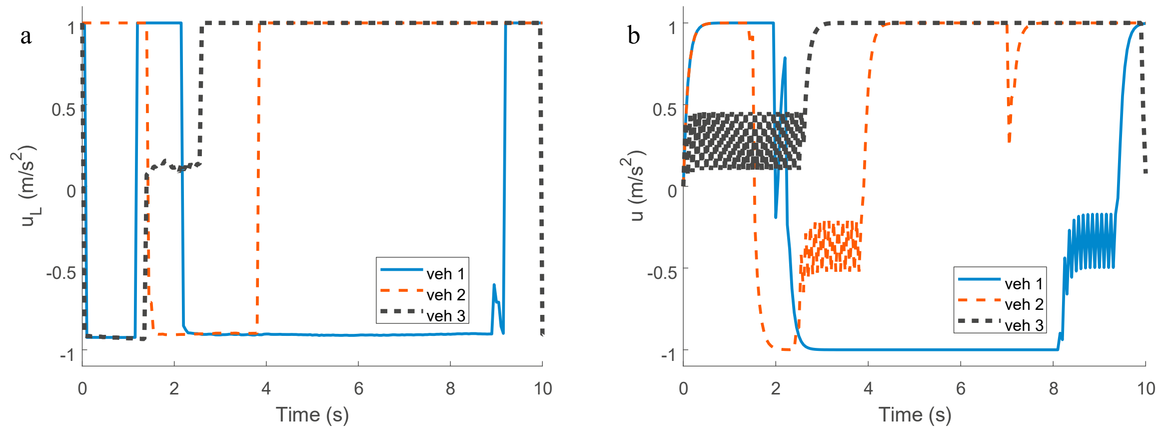


Fig. 3. Scheme of the HiL architecture with multiple vehicles.

Some scenes of the simulation scenario are illustrated in Fig. 4. At the beginning of the scenario vehicle 1 and vehicle 2 are in conflict, see Fig. 4(a). Although vehicle 1 decides to enter into the roundabout at Entrance I., but the distance between vehicle 1 and vehicle 2 is kept above s_{safe}, see Fig. 5(d) around 1.5s. The avoidance of the collision the achieved by the reduction of u_2 (see Fig. 5(b)), which induces the reduction of v_2, as it is shown in Fig. 5(c). In Fig. 4(b) the conflict of vehicle 1 and vehicle 3 is shown, which results in the speed reduction of vehicle 1, see Fig. 5(c) after 2s. For a short time between 2s...4s, until vehicle 2 does not leave the roundabout at Exit II. (see Fig. 4(c)), all of the vehicles move together. In this phase of the scenario, s_1 and s_2 have small values, but s_{safe} has been kept, see Fig. 5(d). At the last part of the scenario, vehicle 1 follows vehicle 3 and both vehicles leave the roundabout at Exit I. The motion of the vehicles together with the characteristics of s_1 (see Fig. 5(d)) demonstrate that the proposed motion control algorithm is able to guarantee safe vehicle following and the handling of vehicle interactions.

Finally, it is suggested to compare the signals of u_L and u for each vehicle, see Fig. 5(a)-(b). The objective of the supervisor is defined by (1), i.e., the difference between u and u_L must be minimized, while the constraints of the optimization are kept. It can be seen that the characteristics of u and u_L for all vehicles are close to each other. Nevertheless, the difference between u and u_L guarantees the safe motion of the automated vehicles.

Fig. 4. (a) Vehicle 1 enters into the roundabout; (b) Vehicle 3 enters into the roundabout; (c) Vehicle 2 leaves the roundabout; (d) Vehicle 3 leaves the roundabout



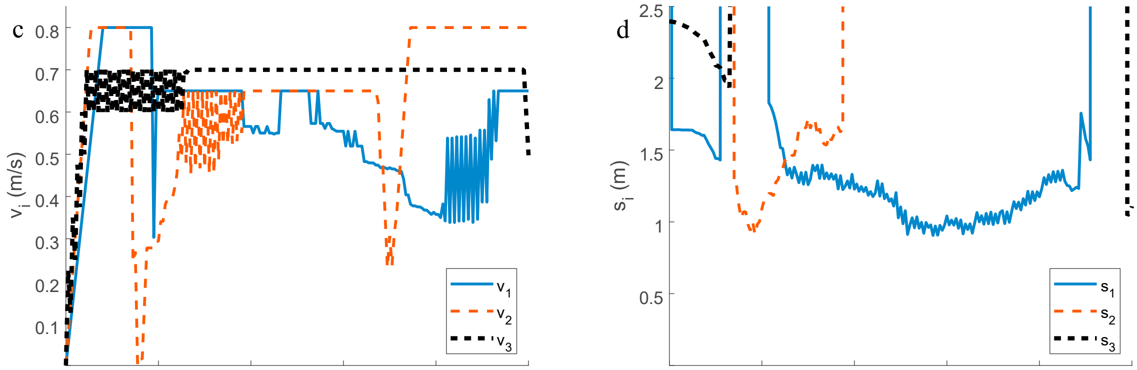


Fig. 5. (a) Candidate input from cloud; (b) Acceleration input;
(c) Speeds of the vehicles; (d) Distances from the actual conflict point

4. Conclusions

The paper has proposed a hierarchical algorithm for the motion control of automated vehicles to guarantee their safe crossing of roundabouts. The presented method has been implemented for four-wheeled indoor test vehicles and has been tested in multi-vehicle environment. As a contribution, the designed hierarchical control strategy with learning features guarantees the driving of the vehicle through the roundabout without collision. Furthermore, the control algorithm, including the reinforcement learning method on the cloud level, contributes to reducing control energy of the vehicles, i.e., better environmental performances are guaranteed.

For future work, the extension of the presented hierarchical control for automated vehicles driving in multi-lane roundabouts and complex urban traffic scenarios is considered. For this purpose, a systematic method is needed to be applied for the determination of conflict points between the vehicles. Thus, the learning of the RL-based control may become more complex, because of the multiple features of the control design task, i.e., by the increasing complexity of the reward function and number of observation.

Acknowledgements

The research was supported by the European Union within the framework of the National Laboratory for Autonomous Systems (RRF-2.3.1-21-2022-00002). The paper was partially funded by the National Research, Development and Innovation Office under OTKA Grant Agreement No. K 135512.

The research of Zs. Farkas was supported by the Hungarian Government and co-financed by the European Social Fund through the project “Talent management in autonomous vehicle control technologies” (EFOP-3.6.3-VEKOP16-2017-00001).

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