SZÉCHENYI EGYETEM
UNIVERSITY OF GYŐR

2nd Conference on Sustainability – COS '24

DOI: 10.62897/COS2024.2-1.160

IMPLEMENTATION OF AUTOMATED CONTROL ON TEST VEHICLE FOR SAFE MOTION IN ROUNDABOUTS

Bence Jekl[a], Mihály Kopasz[a], Zoltán Antal[a], Balázs Németh[a,*], Péter Gáspár[a,b], Dániel Pup[b], Ernő Horváth[b]

[a] HUN-REN Institute for Computer Science and Control, Kende utca 13-17, 1111 Budapest, Hungary
[b] Széchenyi István University, Egyetem tér 1, 9026 Győr, Hungary
* balazs.nemeth@sztaki.hun-ren.hu

This paper presents an innovative solution for testing automated vehicle (AV) control systems in real roundabout scenarios. The main difficulty of testing solutions is that they require safety manoeuvres with multiple vehicles, which is costly and time-consuming. The application of Augmented Reality (AR) can provide a solution to this problem, as a large number of virtual vehicles can be easily simulated and visualised without the need for further physical test vehicles. The aim of this paper is to present the test environment using the example of a hierarchical control strategy.

1. Introduction and motivation

The design of control for a safe and time-efficient motion of AVs in roundabout scenarios presents several challenges, particularly in adapting to the actual traffic scenario and coordinating the vehicles. Collision avoidance between participants, whether a human-driven vehicle or an autonomous vehicle, of the traffic situation stands in the center of proposed control strategies aiming the safe crossing of roundabouts. The most important three open problems based on the survey of Campi et al. (2024) are as follows: (1) traffic management in roundabouts with AVs poses the problem of vehicle ordering and motion profile design; (2) the development of accurate driver models, the assessment of AVs' behavior and driving comfort, and the exploration of advanced learning schemes and cooperative decision-making algorithms are crucial for addressing these challenges. (3) Additionally, the use of dynamic driving simulators and empirical studies can provide valuable insights into the behavior of AVs, connected AVs or Cooperative, Connected AVs in roundabouts. Masi et al. (2020) propose a control strategy to ensure collision-free navigation through one- and two-lane roundabouts by autonomous vehicles while adhering to priority constraints. Azimi et al. (2014) have developed a vehicle-to-vehicle communication and control method for autonomous vehicles to ensure safety in complex traffic scenarios, such as roundabouts. Wang et al. (2012) have designed a control algorithm that estimates vehicle states for trajectory tracking, addressing the challenge of collision avoidance in roundabouts. The interactions between vehicles are modeled using a game-theoretic approach, which is employed in the decision-making algorithm. Debada et al. (2016) have proposed a distributed control method comprising reactive and predictive strategies for determining priorities, aimed at coordinating autonomous vehicles as they navigate roundabouts.

In spite of the high number of theoretical results, there are only a few papers that deal with the verification of the designed algorithms based on real-vehicle implementations on roundabout scenarios. Wang et al. (2022) have proposed an interaction-aware safety evaluation framework for the AVs, with which a high number of scenarios can be generated for control evaluation purposes. Németh and Gáspár (2023) also provide a testing method for vehicle control in general interactions, but it is limited to small-scale test vehicles. Vinayak et al. (2023) also demonstrate an implementation but that focuses on the lateral control system. Thus, it shows that there is a gap between the applied testing solutions and the theoretically achieved results, i.e., the results must be verified under real test scenarios.

This paper presents the implementation of a hierarchical motion control strategy with learning functionality for roundabout scenarios. The control is designed with two levels: one with a learning-based agent and one with a model-based control. The learning-based agent is created using reinforcement learning, while the model-based control is designed using robust PID control techniques. These two levels are coordinated through a supervisor in order that collision avoidance is ensured. The study demonstrates the effectiveness of the method through implementing it on test vehicle Nissan Leaf, that is the main novelty of the paper, because the presented control strategy has not been tested under real vehicle yet. The test scenario is realized together with the parallel running of virtual vehicles, i.e., the test vehicle has to adapt to surrounding vehicles. The provided scenarios illustrate that the automated vehicle can move safely without collisions and similarly, the time-efficient motion can be achieved.

2. Architecture of the hierarchical control strategy

The fundamentals of the hierarchical control strategy can be found in Németh and Gáspár (2023). The aim of the control strategy is that a model-based control and a learning-based control work together under a supervisor. The learning-based control is able to provide high-performance motion due to the reinforcement-lerarning-based (RL) training process, although the stability of the algorithm cannot be achieved. Stability and avoiding performance loss are guaranteed by the model-based control, but that leads to low performance due to its simple structure. The aim of the supervisor is to combine the outputs of the two controls. It means that the candidate signal of the learning-based control u_L is preferred is stability can be preserved with u_L. But, if stability or performance loss are resulted by u_L, then the control signal is limited by the robust domain around the output of the model-based control u_K. The final control input of the system is he output of the supervisor, that is formed as , where is the result of the quadratic optimization within the supervisor. The control strategy together with its formulas are detailed in Németh and Gáspár (2023).

The illustration of the control system implementation on an algorithmic level can be shown in Figure 1. The “ROS data in” and “ROS data out” blocks represent the communication between the Matlab model and the Nissan Leaf test vehicle. The Simulink model’s input is the Leaf’s actual position, and its output is the required steering angle and velocity. The other output is the environment vehicle’s position and yaw values, which are sent to a smartphone through a TCP/IP protocol. The phone is attached to the windshield of the test vehicle, and it is running a Unity app in order to display other vehicles on the picture of its camera in real-time. Although the paper deals with speed profile design, a comment is added to the lateral control. The desired steering angle is calculated with a PID controller, whose input is the lateral error of the test vehicle, calculated based on the predicted position, calculated with the use of the yaw angle.

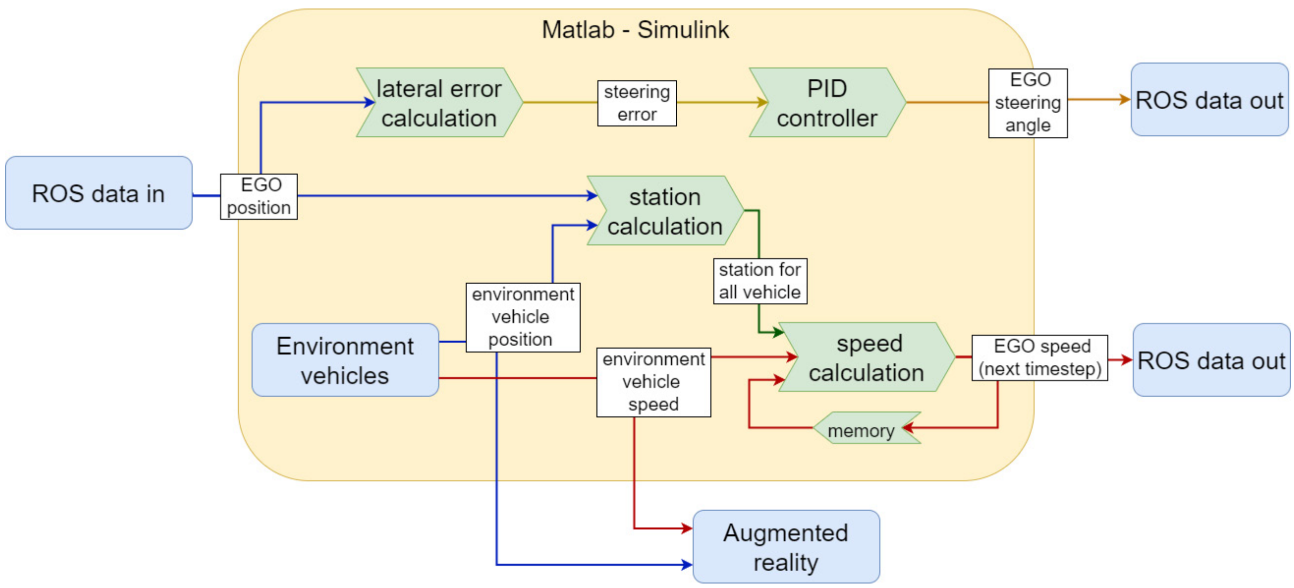

Figure 1: The working principle of the system

Figure 2 shows the scheme of the speed calculation algorithm. The block "optimization" contains the quadratic optimization of the supervisor, i.e., the value of Δ is calculated based on the vehicles' station and velocity, on the u_K and u_L acceleration values. The EGO data calculation algorithm is determining the main output, based on the Δ acceleration and the EGO vehicles's velocity from the previous time-step.

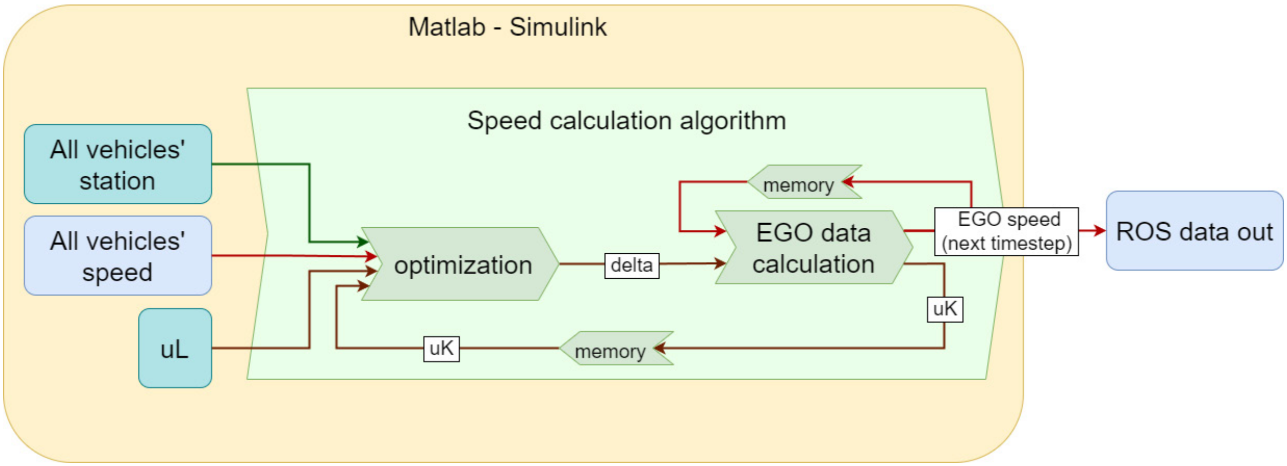

Figure 2: Speed calculation algorithm

The candidate acceleration command u_L is the output of the RL agent, see Figure 3. In this research project it is implemented using Matlab Simulink Reinforcement Learning Toolbox. The trained agent is designed based on the Deep Deterministic Policy Gradient (DDPG) method within an actor-critic structure. In this work the training requested the performing of 500 episodes for achieving high cumulative reward. Its inputs are the observation signals from the environment and the calculated reward. The observed data are the vehicles' stations and velocity values. The reward is calculated based on the total distance driven from the beginning of the simulation and based on the difference between the actual acceleration and the u_L value.

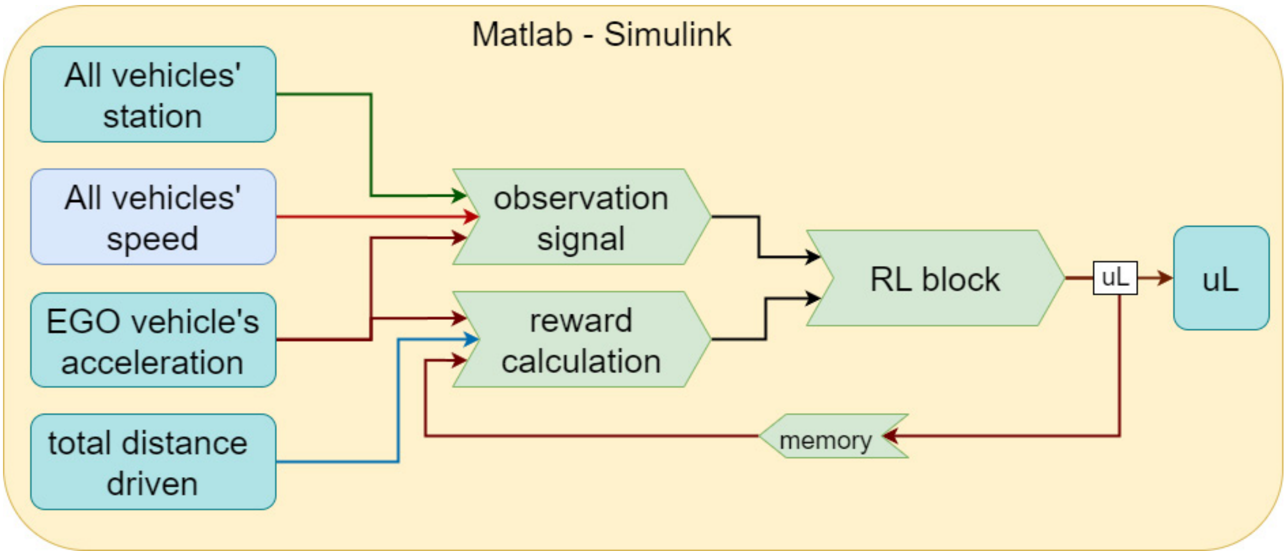

Figure 3: The calculation of the learning-based acceleration

3. Demonstrations

The presented algorithm was tested using Nissan Leaf test vehicle on a test track, where a roundabout was built up using cones. Although the operation of the algorithm has been tested under lots of different entering-exiting scenarios, i.e., the parameters of the roundabout is not fixed during the tests. In this paper only one representative example is presented in order to show the effectiveness of the AV control operation. It consisted of a 1 lane roundabout with a radius of 10 m. It had 3 incoming and 3 outgoing roads, located 120° angular rotations after each other. The center lines of the roads and their IDs are shown in Figure 4. The environment vehicles were generated by MATLAB, and their routes were pre-set before the simulation started. Their position was used to calculate the station value, which was their distance to the next conflict point on their route, shown with green crosses in Figure 4. The AV's station value is also calculated and forwarded to the speed calculation algorithm, which outputs the EGO vehicle's desired velocity for the next time step. The description of the details of the test vehicle with AV functionalities can be found in Horváth and Pozna (2021). The demonstration set-up for illustrating virtual vehicles in AR can be found in Németh et al. (2023).

The demonstration also contained virtual AVs for simulating the environment. Their routes were also randomized, and their velocity profiles were set to constant velocity values. The goal for the AV was to drive safely to the roundabout, i.e. give way to other vehicles in the roundabout, and to maintain a safe distance from other vehicles, which were driving slower before the AV, during the whole test. The sides of the roads were marked with traffic cones in order that the pathway was made visible. The requirements against the test AV were to steer on the pre-defined route and move with the velocity computed by the presented own-developed control algorithm.

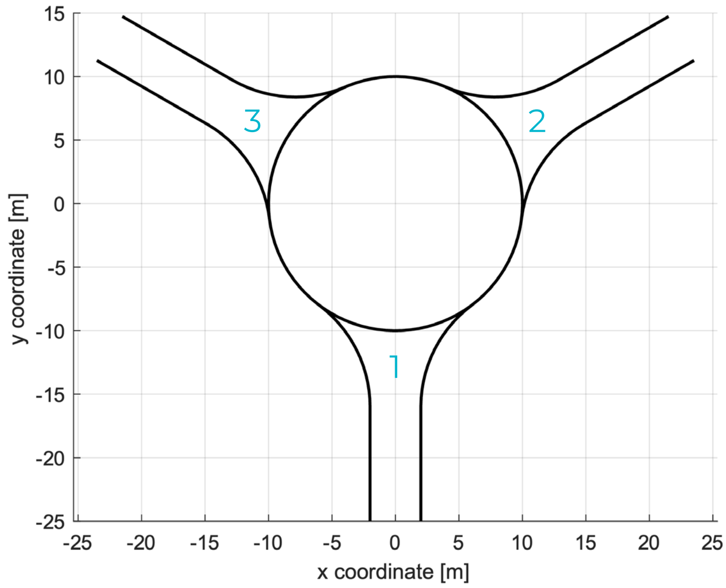

Figure 4: The scheme of the roundabout in the test field

3.1. Results

The performed tests showed that the test AV was able to follow the reference path, which is illustrated in Figure 5. During this scenario, the test AV vehicle was driven into and out of the roundabout using the road with ID 1. The simulation started from a standing position, i.e., the initial velocity of the AV was 0 m/s. The vehicle accelerated immediately after the start of the test. The maximum of the lateral error during path tracking was 0.83 m. This value was achieved when the test AV was entered into the roundabout. This is considered to be acceptable, because the lane of the roundabout is wide enough to tolerate this tracking error, i.e. the AV was not left the lane.

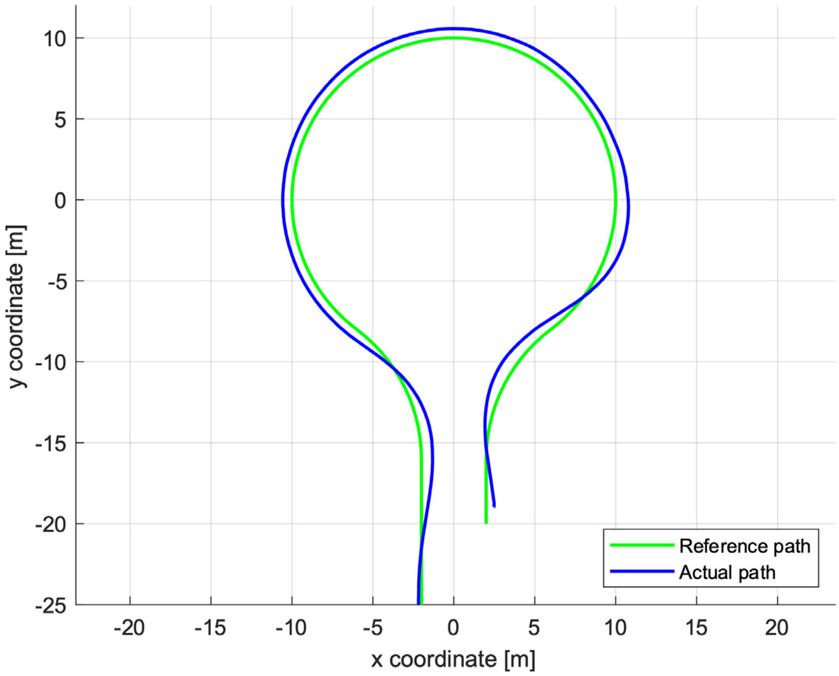

Figure 5: The path of the AV

The velocity profile of the test AV can be found in Figure 6. After the initialisation of the test AV velocity, the reference velocity of 0.25 m/s was achieved for approaching the roundabout entrance. The reason for accelerating to this low velocity was that one of the virtual vehicles arrived at Entrance 1; see the left image in Figure 7. Thus, the algorithm highlighted energy efficiency instead of insufficient acceleration and deceleration commands. The test AV was driven off at around 16 seconds after the simulation started. After that, the AV accelerated to reach the maximal allowed speed, 10 km/h. This was a safe speed to drive in the roundabout. After 43 seconds of the test, the vehicle caught up with a virtual vehicle in the roundabout and decreased its velocity to hold a safe distance behind it. Since that virtual vehicle had the same route to drive out from the roundabout as the test AV, it had to be followed; see the right image in Figure 7.

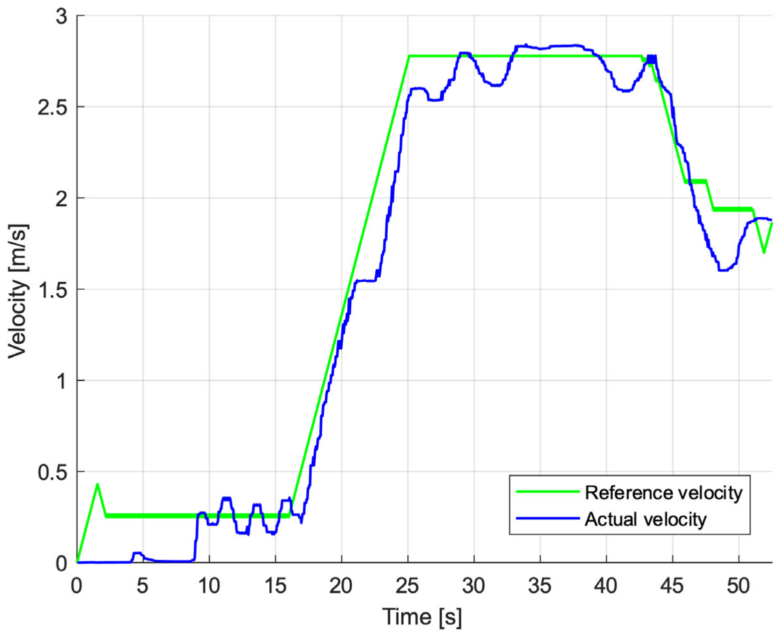

Figure 6: The velocity profile of the AV during the test

Figure 7: Illustrations of the virtual vehicles' motion on the test track using real-time AR environment

Figure 8 shows the distance between the test AV and the closest virtual vehicle in the environment. This metric has high important from the viewpoint of safety, such as to avoid collision. If this value was above 30m, it was not illustrated in Figure 8. It can be seen that the minimum value of the distance was 18 m when the test AV was driven into the roundabout, i.e., the approaching manoeuvre was safe, see 16s in Figure 8. Moreover, when the test AV approached the virtual vehicle in the roundabout, it moved closer to the preceding vehicle. In order to keep a predefined distance, the test AV started to brake when it was closer than 13.5 m, which resulted in an energy-efficient motion profile, see Figure 6. Nevertheless, the distance between the vehicles was never below 6.4 m, which is considered to be safe.

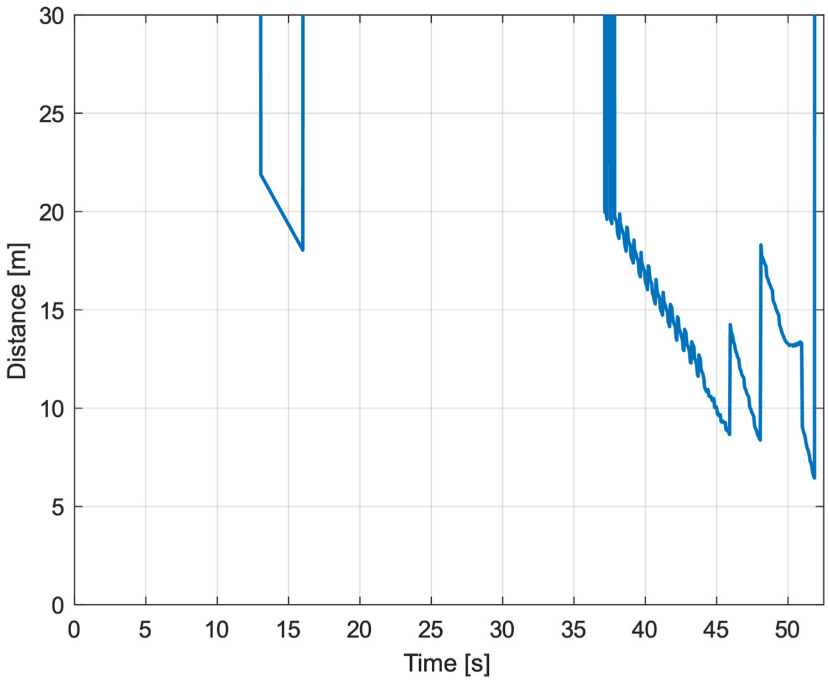

Figure 8: The distance to the closest virtual vehicle in the environment

4. Conclusion

The presented test result shows that the AV is able to move with a safe and energy-efficient velocity profile, and the proposed learning-based algorithm can be implemented. The presented investigation shows that the initial test of the algorithm was successful, which provides a basis for performing further tests in ZalaZone Automotive Proving Ground. The algorithm and the demonstration setup contribute to sustainability from two viewpoints. First, the energy-efficient nature of the learning-based method provides a solid basis for working out a general motion profile generation algorithm under complex urban driving scenarios. Second, the demonstration setup has reduced the cost of testing AV functionalities in real time. Its reason is that it does not require the involvement of further test vehicles, but the motion of virtual vehicles can be illustrated in the physical environment in real-time.

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 research was also supported by the Foundation R&D Program of the Széchenyi István University within the Research into artificial intelligence-based technologies and systems framework.

References

- Azimi, R., Bhatia, G., Rajkumar, R. R. and Mudalige, P. "Stip: Spatio-temporal intersection protocols for autonomous vehicles," in 2014 ACM/IEEE International Conference on Cyber-Physical Systems (ICCPS), 2014, pp. 1–12.
- Campi, E., Mastinu, G., Previati, G., Studer, L., and Uccello, L. "Roundabouts: Traffic Simulations of Connected and Automated Vehicles—A State of the Art," in IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 5, pp. 3305-3325, May 2024.
- Debada, E., Makarem, L., and Gillet, D. "Autonomous coordination of heterogeneous vehicles at roundabouts," in 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016, pp. 1489–1495.
- Horváth, E., and Pozna, C. R., "Clothoid-based Trajectory Following Approach for Self-driving vehicles," 2021 IEEE 19th World Symposium on Applied Machine Intelligence and Informatics (SAMI), Herľany, Slovakia, 2021, pp. 251-254,
- Masi, S., Xu, P., and Bonnifait, P. "A curvilinear decision method for two-lane roundabout crossing and its validation under realistic traffic flow," in 2020 IEEE Intelligent Vehicles Symposium (IV), 2020, pp. 1290–1296.
- Németh, B., Gáspár, P. "Hierarchical motion control strategies for handling interactions of automated vehicles," in Control Engineering Practice, vol. 136, 105523, 2023.
- Németh, B., Farkas, Zs., Antal, Z., Fényes, D., Gáspár, P. "Collision-free motion control with learning features for automated vehicles in roundabouts", in Transportation Research Procedia, vol. 72, 2023, pp. 3545–3552.
- Vinayak, A., Zakaria, M.A., Baarath, K., Peeie, M. H., and Ishak, M.I., "A Novel Triangular-Based Estimation Technique for Bezier Curve Control Points Generation on Autonomous Vehicle Path Planning at the Roundabout Intersection," Journal of Intelligent & Robotic Systems, nol. 109, no. 89, 2023.
- Wang, L., Huang, W., Liu, X., and Tian, Y. "Vehicle collision avoidance algorithm based on state estimation in the roundabout," in 2012 Third International Conference on Intelligent Control and Information Processing, 2012, pp. 407–412.
- Wang, W., Zhang, S., and Peng, H. "Comprehensive Safety Evaluation of Highly Automated Vehicles at the Roundabout Scenario," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 20873-20888, Nov. 2022.