TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
2023, Vol. 2677(2) 1165–1178

DOI: 10.1177/03611981221110566
journals.sagepub.com/home/trr
SAGE

Robotic Competitions to Design Future Transport Systems: The Case of JRC AUTOTRAC 2020

Biagio Ciuffo[1], Michail Makridis[2], Valter Padovan[1], Emilio Benenati[3], Kanok Boriboonsomsin[4], Mamen Thomas Chembakasseril[5], Petros Daras[6], Viswanath Das[3], Anastasios Dimou[6], Sergio Grammatico[3], Ronny Hartanto[5], Malte Hoelscher[7], Yu Jiang[4], Suad Krilasevic[3], Shangrui Liu[4], Quang Nhat Nguyen Le[5], Cas Rosier[3], Pingbo Ruan[4], Zhensong Wei[4], Guoyuan Wu[4], Xuanpeng Zhao[4], and Zhouqiao Zhao[4]

Abstract

Vehicle automation and connectivity bring new opportunities for safe and sustainable mobility in urban and highway networks. Such opportunities are however not directly associated with traffic flow improvements. Research on exploitation of connected and automated vehicles (CAVs) toward a more efficient traffic currently remains at a theoretical level, and/or based on simulation models with limited reliability. Furthermore, testing CAVs in the real world is still costly and very challenging from an implementation perspective. A possible alternative is to use automated robots. By designing and testing both the low- and the high-level controllers of CAVs, it is indeed possible to reach a better understanding of the challenges that future vehicles will need to face. Robotic applications can effectively test these challenges within a wide variety of research communities—for example, via robotic competitions. Along this direction, the Joint Research Centre has organized the first European robotic traffic competition for automated miniature vehicles. Each team participated with four robots and was judged based on a set of indicators that assess the collective behaviors of the vehicles. Results show the suitability of the methodology with different teams proposing completely different approaches to deal with the challenge and thus achieving different results. Future competitions may further raise awareness about the possibility of using CAVs to improve traffic and to engage with a broader community to design systems that are really capable of achieving this goal.

Keywords

automated and connected vehicles, policy and organization, knowledge management, research and innovation management, and research methods

In the coming decades, road transport will undergo significant transformations thanks to the advent of new vehicle technologies and mobility solutions (*1*). Among others, vehicle connectivity and automation will probably change the way road transport is provided and used. It should not be a surprise that, although in their early stage of development and deployment, connected and automated vehicles (CAVs) are substantially attracting the attention of researchers.

Research on CAVs covers a wide range of aspects such as the development of new business models for transport operators, the driving logic and functionality of future vehicles, the interaction between CAVs and

[1]European Commission, Joint Research Centre (JRC), Ispra, Italy
[2]Institute for Transport Planning and Systems (IVT), ETH Zürich, Zürich, Switzerland
[3]Delft Center for Systems and Control, TU Delft, Delft, The Netherlands
[4]Center for Environmental Research and Technology, University of California, Riverside, Riverside, CA
[5]Rhine-Waal University of Applied Science, Robotics Lab HRSW, Kleve, Germany
[6]Information Technologies Institute, Centre for Research and Technology, Hellas, Thessaloniki, Greece
[7]Computer Science and Media Department, Leipzig University of Applied Sciences, Leipzig, Germany

Corresponding Author:
Biagio Ciuffo, Biagio.CIUFFO@ec.europa.eu

other road users, and the infrastructure and the design of the future automated road transport. This latter subject is particularly interesting as it entails the possibility to completely re-imagine road transport and its governance. As an example, some researchers are proposing that road design based on road partitioning with lanes could become obsolete with CAVs that would instead better navigate in a lane-free infrastructure (*2*). This type of research mainly involves the use of simulation models, by means of which it is possible to test several alternative ways CAVs operate with and without interaction with external control strategies. In general, there are two main types of investigations: one based on observations and a second based on numerical simulation. On top of that, different modelling approaches facilitate analytical research in both types of investigations.

Vehicle automation and connectivity will not arrive in a single functional component, but they will involve the integration of many different processes. The Advanced Driver Assistance Systems that are currently available in many commercial vehicle models include such processes that can give researchers, policy officers, and the public a good perspective of future automated vehicles. Perhaps the most studied component is the Adaptive Cruise Control, which monitors the distance from other vehicles ahead and regulates the longitudinal speed of the vehicle accordingly. Other examples include the Automated Emergency Braking, the Lane Change Assist, the Highway Chauffeur, and many others. Since fully automated vehicles (Level 3 and above) are currently not available, most research studies infer the impact of such systems in relation to traffic congestion, energy, and safety through experimental data and empirical observations (*3–6*).Such empirical investigations have limitations in regard to vehicles involved, road specifications, extrapolation to large networks, and many others. Furthermore, it is reasonable to assume that future automated vehicles will have much more evolved systems. Nevertheless, such analyses provide interesting insights and alerts on the possible benefits that people expect by the mass deployment of CAVs.

Another alternative is the use of simulation models in traffic studies, especially when the interaction among thousands of vehicles is to be tested. It has to be said that traffic models used so far describe the vehicle motion in a fairly simplified way (*7*, *8*) for two reasons: (i) the need to have computationally effective models able to simulate thousands of vehicles in reasonable time, and (ii) the impossibility to achieve a perfect representation of vehicle dynamics strongly influenced by the randomness intrinsic of the human driving (*9*, *10*). With the ever-increasing computation power and the driving task assigned to CAVs, the motivations for adopting simplified modelling approaches are not any longer in place and they actually risk affecting the results of studies aimed at designing new possible driving strategies for the future of vehicles (*11*). Furthermore, removing human behavior from the driving task widens the space of possible solutions to improve the efficiency of road transport and opening the topic up to research teams (e.g., focusing on industrial process optimization) and other communities (e.g., makers' groups) traditionally not involved in transport research. In order not to miss the opportunities that these openings offer to also democratize technological development, while at the same time ensuring that the new solutions proposed to improve road transport using CAVs have solid foundations, new approaches would also be needed.

The present paper discusses the first robotic competition designed and developed toward the impact of CAVs on traffic. The main idea was to add a third dimension between simulations and observations. Recently, there has been a flourishing of competitions (in the form of hackathons, datathons, etc.) to address a wide variety of technical and technological challenges (*12*). Organizing robotic competitions is in fact a possible approach to democratizing the development of automated and autonomous vehicles. In this case, the robots are small-scale automated vehicles representing a physical model of the actual vehicle. Physical models are governed by the same laws that govern the motion of conventional vehicles, which is a great benefit. Within robots, both the high-level control (also referred to as action planning) and low-level control logic need to be properly implemented to achieve a good performance. Consequently, research outcomes and results are more trustworthy than those with simulation models that usually only mimic the high-level controller of a vehicle and disregard the impact of software–hardware interaction in a CAV. The shortcoming of physical models is that they can still be too expensive and their development too inefficient to reproduce complex traffic scenarios involving hundreds or thousands of vehicles. Nevertheless, by designing networks of appropriate size, it is possible to test strategies to assess the impact on traffic efficiency with a limited number of vehicles.

In this light, this paper introduces AUTOTRAC 2020 (*13*), the first robotic competition for small-scale automated vehicles whose objective is to challenge the capability of CAVs to generate an efficient traffic flow. The paper is organized as follows. In the next section, a state-of-the-art concerning the use of physical models for traffic studies is provided. Then the structure and the rules of the AUTOTRAC 2020 competition are presented. The architecture selected by the three best teams is then introduced. A summary of the results is then presented before the conclusions of the work are outlined.

Robotic Applications in Transport Research

The use of robots in transport research is not new. There are several options for open-source or commercial robotic platforms for research and education available in the literature (*14–17*). In most cases, it is fairly easy to develop such robots, since the required parts are off-the-shelf or easy to manufacture. The CARMA program developed by the US Federal Highway Administration (FHWA), adopts scaled-down vehicles (referred to as CARMA 1tenth) to test new solutions before they are implemented on real vehicles (*18*).

Furthermore, MIT (*19*) and Cambridge University (*20*) took a further step and propose complete platforms for testing automated driving. Cambridge's approach proposes a platform hosting multiple robots, as well as a system providing the positions of the vehicles. MIT's approach comprises not only a robotic platform (Duckiebots) but also cities (Duckietowns) for testing more complex transportation tasks.

In addition to the robotic platforms, the University of Delaware also created the physical model of a whole city. This "Smart City" is used to test the algorithms developed in a realistic though scaled-down configuration (*21*). In contrast to the other solutions, this approach additionally contains a centralized server system capable of complex controlling tasks (*22*)—that is, using the model city as a way to implement a decentralized control framework.This framework is able to coordinate conflicting traffic situations by providing means of sharing information of critical zones between the vehicles. The behavior of this system is simulated and then successfully validated by experiments with scaled-down CAVs in the Smart City environment.

The use of scaled-down cities is however still rare. Indeed, moat researchers, use robots in a simpler way, focusing on specific vehicle properties. In Klančar et al. (*23*), for example, the authors propose a platooning algorithm relying only on sensor information relative to the vehicle in front, without inter-vehicle communication. The kinematic properties of the robotic system are modeled. A controller is designed to keep the robots in the platoon, to avoid obstacles as well as to be able to merge or leave the platoon. These theoretical proposals are confirmed by experiments with multiple Pioneer 3AT robots. These experiments highlight problems that are not present in simulation, such as tracking error and sensor noise, which are crucial problems whose effect can be magnified as the number of vehicles increase.

In Baarath et al. (*24*), the authors design a simple robot platooning system by developing a kinematic model of the robots and using a Proportional-Integral-Drivative (PID) controller to control their movement.The numerical simulations of the controller are verified by using a robot following a person. A similar approach is found in Besseghieur et al. (*17*), which also creates a mathematical model of the robots used (TURTLEBOT) to deal with the platooning problem. Based on that, a state-tracking controller is designed and the actual implementation of the robots, based on Robot Operating System (ROS), is described. Then, the reliability of this proposal is assessed with different experiments. Experiments show that even though there are tracking errors, they converge to zero after some time.

Of a similar nature, Hu et al. (*25*) propose a control scheme to maintain string-stability of a heterogenous and connected platoon. The authors propose a specific communication topology, as well as using a generic kinematic model capable of representing the heterogenous vehicle problem. The platooning problem is formulated and a control protocol is designed and simulated. To verify the feasibility of the approach, experiments are carried out with differential drive robots. Issues like communication delay in the robotic implementation of the model are shown, together with ad hoc solutions to minimize their impact. Because of the kinematic properties of the robots, the authors assume that the results can be generalized to real-world vehicles.

In Ikemoto et al. (*26*), the authors instead focus on the task of cooperatively merging platoons in scenarios such as ramps and intersections. Cooperative behavior is made possible by defining a periodical pattern for each road, where reaching the maximum allows vehicles to enter an intersection. As this pattern has a half-phase difference between the vehicles, the vehicles are safe to enter the intersection. These theoretical assumptions are verified in an experimental setting using robots.

A slightly different approach is instead used in Purcaru et al. (*27*), where the authors design a traffic-sign-detection algorithm, which is then verified using a robotic platform.

Finally, Tuchner and Haddad (*28*) focus on the formation phase of a vehicle platoon. A system based on the Interpolating Control is proposed, to control the longitudinal movement of the vehicles in the presence of uncertainty. To test the system under real-world conditions and in particular to consider aspects such as non-linearity and model uncertainty, the proposed approach is verified with robotic experiments. The experiments show that there is slight deviation from the simulation behavior, but the results stay well within the defined constraints.

All the aforementioned papers are in line with the scope of the present work. However, they still use robots in a single-dimensional way. By using robots, the authors believe that it is possible to involve a wider number of citizens in the design of future vehicles and transport systems. Makerspaces, Hackerspaces, Fab-Labs, and other forms of engagement in the technological development by normal people are flourishing nowadays (*29*). Often

considered as a driver for the "democratization of innovation" (*30*), the maker movement is about the people's needs to engage with objects in ways that make them more than just consumers (*31*). This aspect is particularly important as CAVs are showing a way to address transport externalities and as such, their design should include a strong citizens' engagement to ensure that the products that will be on the market not only reflect the objectives of their developers but also respond to the future needs of the people. By engaging the makers, in reality, we are taking an additional step by introducing a community with high out-of-the-box thinking propension to a field with enormous innovation potential.

Since makers have usually limited funds and remain out of the academic discussions and events, a possible way to engage them is via robotic competitions. Competitions also stimulate participants to give their best so as to achieve a top place and therefore they can provide an important stimulus to innovation in some field. A clear example of innovation driven by competitions is the DARPA Grand Challenge, which has stimulated significant progress in automated driving at the beginning of the century (*32*). Without the ambition and the budget of the DARPA challenges, nowadays several competitions for scaled-down CAVs take place every year. All of them however focus on the capability of a single robot to autonomously deal with challenging situations (obstacles, particular road layouts, routing, etc.) while none of them so far focused on the use of CAVs to achieve efficient road traffic flow. To fill this gap, in 2019, the European Commission Joint Research Centre (JRC) launched the AUTOTRAC 2020 robotic competition, whose main highlights are provided in the following sections.

Small-Scale Automated Vehicle Traffic Challenge 2020

The organization of the small-scale AUTOmated vehicle TRAffic Challenge (AUTOTRAC) 2020 (*13*) was funded by the JRC. As already mentioned, the competition objective is to engage the academic and makers' communities in a bottom-up way to propose possible technical approaches to improve traffic flow with the support of CAVs.

The competition was initially supposed to take place in the JRC Ispra premises in Italy from March 30th to April 1st, 2020. However, as a result of the COVID-19 crisis, it was initially moved to October 5th–7th and then it was realized that a physical event was not possible. The alternative solution was to ask the competing teams to run the scenarios of the competition in their premises following specific rules, capture in video the performance of their solution, and send it back to the JRC team for assessment. An ad hoc video processing software (the automated camera-based referee system [ACRS]) for the quantitative assessment of the performance of each team has indeed developed by the Centre for Research and Technology Hellas (CERTH) and could be used also in the case of the online event. The final event of the competition took place as an online event on June 17th, 2021, as part of the 7th International IEEE Conference on Models and Technologies for Intelligent Transportation Systems (*33*).

The competition consists of a multitude of challenges for the contestants, who were asked to tackle problems in the area of robotics, sensors, and traffic management. Each contesting team participates with four robot vehicles. The vehicles compete on two test tracks: one reproducing urban conditions and the other reproducing highway conditions. A set of performance metrics per scenario assesses the collective performance of the group of vehicles, in line with the goals of the competition. The ACRS monitors the behavior of the robot vehicles and determines the final score for the team.

The next section summarizes the set of rules with regard to participation and robot requirements. The complete set of competition rules were made available to the participants following their subscription to the challenge.

Participation and Robot-Vehicle Requirements

Each team participates with four robot vehicles. The contestants are free to choose their robotic platform, as long as it meets the specifications stated below. These requirements enabled the teams either to develop their own system, or to use a commercial platform. The main robot-vehicle technical requirements were set as follows:

1. Each vehicle must be fully automated. Any kind of interaction with the team members or any other remote entity during the competition is forbidden.
2. Each vehicle should be equipped with electric motors.
3. Energy must be supplied with batteries: a battery with a max voltage of 24V or LiPo 6S (22,2V).
4. Changing and charging batteries are allowed.
5. The vehicles must be based on a chassis with maximum dimensions of $250 \times 250 \times 250$ mm (width $\times$ length $\times$ height).
6. The vehicle's maximum weight should be 3 kg.
7. The sensor setup can be arbitrarily chosen by the teams. Laser sensors are allowed only up to Class 2 devices.
8. Reference standard for laser devices: IEC 60825-1: 2014

9. Only sensors for external lines/spaces recognition can exceed the dimensions of the vehicle by a maximum of 3 cm on all sides.
10. There is no limitation to the use of robotic platforms and sensors.
11. Each vehicle must be equipped with at least one camera for environment recognition.
12. It is possible to use smartphones or tablets (not PCs) beyond the maximum measurements and weight of the rules.
13. Each team is free to apply vehicle-to-vehicle connectivity between its vehicles. No WiFi network for such a reason will be provided by the JRC.

Competing Scenarios

The robots compete in two test scenarios: one corresponding to highway conditions, and the other to urban driving. Figure 1 illustrates the layout of the two test tracks.

The highway scenario takes place on the J-shaped track. Each team sets up all four vehicles in the track. The four vehicles should be positioned behind the red "START" line in platoon formation. Inter-vehicle distance is set to 5 cm. At their starting position, the vehicles have all wheels on a portion of the black track; only the sensors (extra 3 cm) can be on the white background. The vehicles should drive as fast as possible and, at the same time, they need to keep as close as possible to each other without creating or being involved in a crash (accident), for the whole duration of the test, which is 3 min. As an additional challenge for the teams, a tramline was also included in the scenario. Originally, the tramline was supposed to be used by a tram (provided by the JRC) moving on track on a regular schedule. The robots are requested to always give way to the tram. Given the difficulty to provide the tram and to ensure that it would have had equal operations for the different teams, the tramline only requested the vehicles to slow down below a certain threshold. At the end of the 3 min, the four vehicles had 1 min to park in the green space without touching. An additional score was given for each correctly parked vehicle. In Figure 1, the parking area is indicated by a green background. Each team has 10 min available to position the vehicles, start the test, complete it, and park the vehicles). Teams that do not manage to finish are not scored.

The urban scenario took place on the #-shape track. Each team sets up all four vehicles in the four different initial positions of the track. Each starting position is associated with a different color. The color is assigned to the vehicle. At their starting position, the vehicles are positioned with all wheels on the black track; only the sensors (extra 3 cm) can be on the white background.

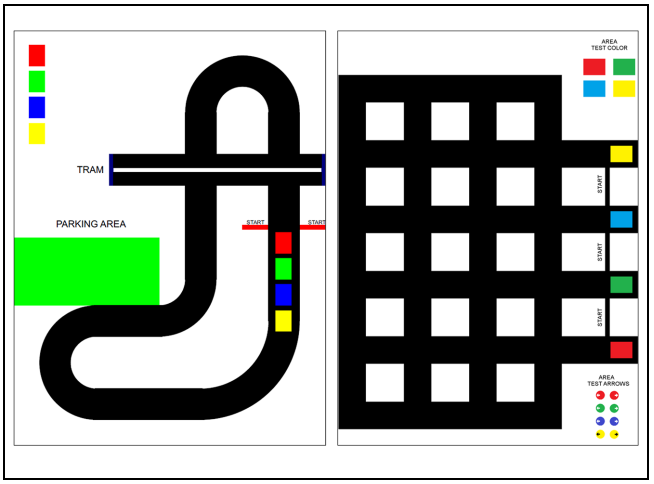

Figure 1. Network layouts for the Automated Vehicle Traffic Challenge competition. On the left the J-shaped track corresponds to highway conditions. On the right the #-shape track corresponds to urban conditions.

The car should be able to read and memorize its color at the beginning of the race. During the race, the color will not change. The vehicle should be able to recognize it through its sensors on the different traffic signs. When an action from the vehicle is expected (turn left or right), there is a traffic sign with the corresponding color at the intersection. There are signs only when the vehicle has to turn. If not, the car has to go straight. The vehicles should follow as quickly as possible the paths indicated by the signs of their assigned color without creating or being involved in a crash (accident), for the whole duration of the test, which is 3 min. Each team had 10 min available to position the vehicles, start the test, and complete it. The scoring of the teams depends on the factors described in the following section.

Performance Metrics

The scoring of each team participating in the competition is obtained by the aggregated points from the different performance metrics that reflect the requirements for the vehicles to safely and efficiently navigate over the two network layouts. In particular, the following metrics were adopted:

1. *Collision*. Each vehicle that manages to finish without collision is awarded 25 points. Each collision costs five points. No points are awarded with more than five collisions.
2. *Lane-keeping*. Each vehicle that manages to stay within the lane and finish is awarded 25 points. A vehicle will be considered out of lane when at least two wheels are outside the lane. Every time

a vehicle gets out of the lane, it loses five points. No points are awarded for more than five lane-keeping infringements.

3. *Parking (for highway track only)*. For the highway scenario each vehicle parked correctly is awarded 25 points. A correct parking means being inside the green area without touching other vehicles. Collision avoidance, lane-keeping, and parking are the three safety metrics used in the competition and they mainly focus on the individual behavior of the vehicles.
4. *Time gap (only for highway track)*. This metric is important to identify the fleet leading to the highest road capacity on highways (keeping the speed constant, the shorter the time gap, the more vehicles can cross a road section in a certain time interval and thus the higher the road capacity). For each of the three following vehicles, the ACRS records their instantaneous time gaps with a regular frequency and after the successful completion of the task by the team, it will report the following value:

$$TG_j = \sum_{i=1}^{3} \left\{ tg_{med} + tg_{perc90} + tg_{perc70} \right\}_{i,j}$$

where tg_{med} is the median time gap and tg_{perc90} and tg_{perc70} are the 90th the 70th percentiles in the time gap values distribution, i is the number of the vehicle, and j is the participating team. The final score is computed as follows:

$$\widehat{TG_j} = 1 - \frac{(TG_j - TG_{min})}{TG_{max} - TG_{min}}$$

where TG_{max}*and* TG_{min} are the minimum and maximum time gap values computed from all the teams that managed to complete the task. The final score $\widehat{TG_j}$ is in the range $[0, 1]$ and the total points for team j are determined by the product of $\widehat{TG_j} * 100$, a value in the range $[0, 100]$. Teams that do not manage to complete the challenge (all vehicles should complete their race) get no points for this challenge.

5. *Distance travelled.* A short time gap is a necessary but not sufficient condition for high capacity as vehicles could be extremely close to each other but proceed with very low speed. For this reason, a second efficiency related metric was introduced which is proportional to the average speed of the vehicles—namely, the overall distance travelled. To achieve highly efficient traffic flow, the teams had to compromise the need to keep the vehicles close enough and to proceed fast enough to cover sufficient distance. In the urban network layout, the distance travelled is the only efficiency metric as it needs to compromise with the need to avoid collisions. For each of the vehicles, the ACRS estimates their total distance travelled and if the vehicle finishes it reports the estimated distance travelled.

Table 1. Assessment Table (Scoring)

	Metric	Maximum points
Highway/urban scenario	Collision (CL)	100
	Lane-keeping (LK)	100
	Distance travelled (DT)	100
Highway scenario	Time gap (TG)	100
	Parking (PK)	100
	Tram speed reduction (TSR)	100

$$DT_j = \sum_{i=1}^{3} \{DT\}_{i,j}$$

where DT_j is the accumulated distance traveled by all vehicles I of Team j. The final score will be computed as follows:

$$\widehat{DT_j} = \frac{DT_j - DT_{min}}{DT_{max} - DT_{min}}$$

where DT_{max} *and* DT_{min} are the minimum and maximum distance travelled values computed between the teams that managed to complete the task. The final score $\widehat{DT_j}$ is in the range $[0, 1]$ and the total points for Team j are determined by the product of $\widehat{DT_j} * 100$, a value in the range $[0, 100]$. Teams that do not manage to complete the challenge (all vehicles should complete their race) get no points for this challenge.

It is worth underlining that other metrics could have been used to represent both traffic safety and efficiency. In this first competition, it was selected to focus on the aforementioned ones also because of the need to ensure their fast and robust computation by the automated referee system.

The final score for each team is computed by aggregation of the individual metric scores as summarized in Table 1. For the sake of transparency, we have to admit that this was not the best choice. By aggregating the different scores, we are de facto encouraging teams to pay more attention to the highway scenario than to the urban one, since the former assigns twice as many points as the latter. As will be shown in the remainder of the paper, this had no effect on the final results of the competition.

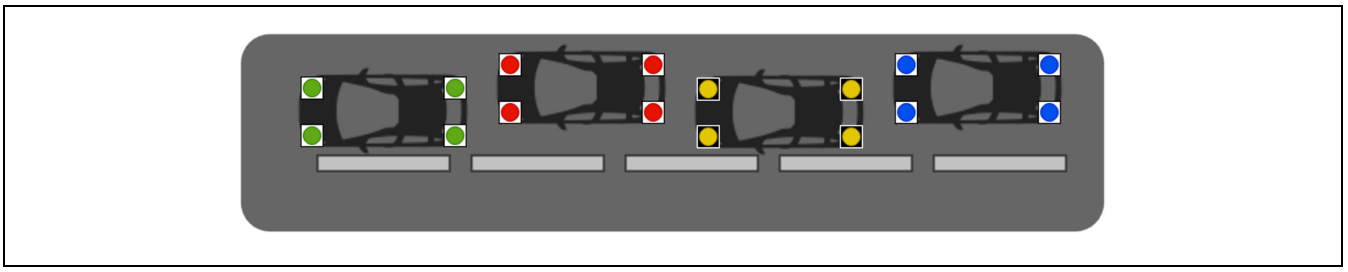

Figure 2. Schematic demonstration of the markers' positioning.

ACRS

The evaluation of the teams participating to AUTOTRAC was performed using an ACRS developed by CERTH, Greece. For this purpose, a marker-based single-camera setup was designed to track the vehicles and evaluate their performance. The camera employed is a Basler acA1920 155uc with a Conva 8-mm lens. It is a color camera with a resolution of 1920×1080 and videos were captured at 50 fps. The camera was mounted at 3.5 m from the tracks to ensure that they are fully visible in the produced stream. Each vehicle is equipped with four markers that are placed in the corners of the vehicle, as depicted in Figure 2. The markers have a different color for each vehicle: green, red, yellow, and blue. The markers were provided by JRC.

The video stream from the camera is processed by the ACRS software. The processing pipeline is initially localizing the vehicles. The markers are detected and subsequently the center of the vehicle and the outline of the car are computed. If a marker is not properly detected, its position is recovered by a reasoning engine that uses the previous position and the position of the other markers. Then, vehicles are tracked across frames, calculating the distance covered and their instant speed.

In parallel, a violation detection framework was developed to identify speed, lane, and parking violations, as well as collisions. The tracks were automatically modelled, identifying the boundaries of the road and the parking space (in the J-shaped track). A vehicle was given a penalty for trespassing the boundaries of the track. To alleviate the barrel effect of the camera and the inevitable perspective problems when the markers and the vehicle have a significant height, the boundaries were adaptively relaxed to prevent false violations. In regard to collisions, a combination of the route outline and irregular motion was used to detect them.

As showed in Figure 3, the ACRS provides real time results through a dedicated interface that visualizes the position and the speed of each vehicle, as well as the violations using semi-transparent color effects.

Moreover, it calculated the instant scores of each team by taking into account their performance and violations. Instead, metrics that involve all participating teams were calculated after the evaluation of all teams. A video of the participations, as well as a log of all measurements and events, was saved for auditing the final results.

Approaches Adopted by the Competing Teams

After the publication of the competition notice in July 2019, seven international teams submitted their application and accepted to participate in AUTOTRAC 2020 (Table 2). The participating teams are fairly heterogeneous in line with the competition's objectives (having both academic teams and independent groups of makers). In addition, from the four academic teams, only one was from transportation science, and thus also from this point of view, the multi-perspective approach could be ensured.

Unfortunately, as a result of the COVID-19 pandemic and the Nagorno-Karabakh conflict (for the Armenian Team) affected the possibility of teams members meeting and working on the development of the robots; only three teams could confirm their participation to the final event. This unfortunately affected the competition results and, in particular, it was not possible to witness the variety of solutions that teams of different natures could have brought. In the next sections, a brief introduction to the solutions proposed by the three teams participating in the final event is provided. This information is summarized in Table 3.

Team 1: ROSbot Team (TU Delft)

The team used multiple Husarion ROSbots (*34*). These robots are based on a four-wheeled model, where each wheel is independently driven by a DC Motor controlled via a Husarion CORE2-ROS with an Asus Tinkerboard. The following sensors were used by the vehicles: Orbecc Astra RGBD Camera, RPLidar A2, MPU 9250 IMU, and Wheel encoders.

As shown in Figure 4, lanes are detected via an RGB camera and Computer Vision techniques for edge detection (Sobel edge detection, Hough transformation). This enabled the robot to control its translational position on

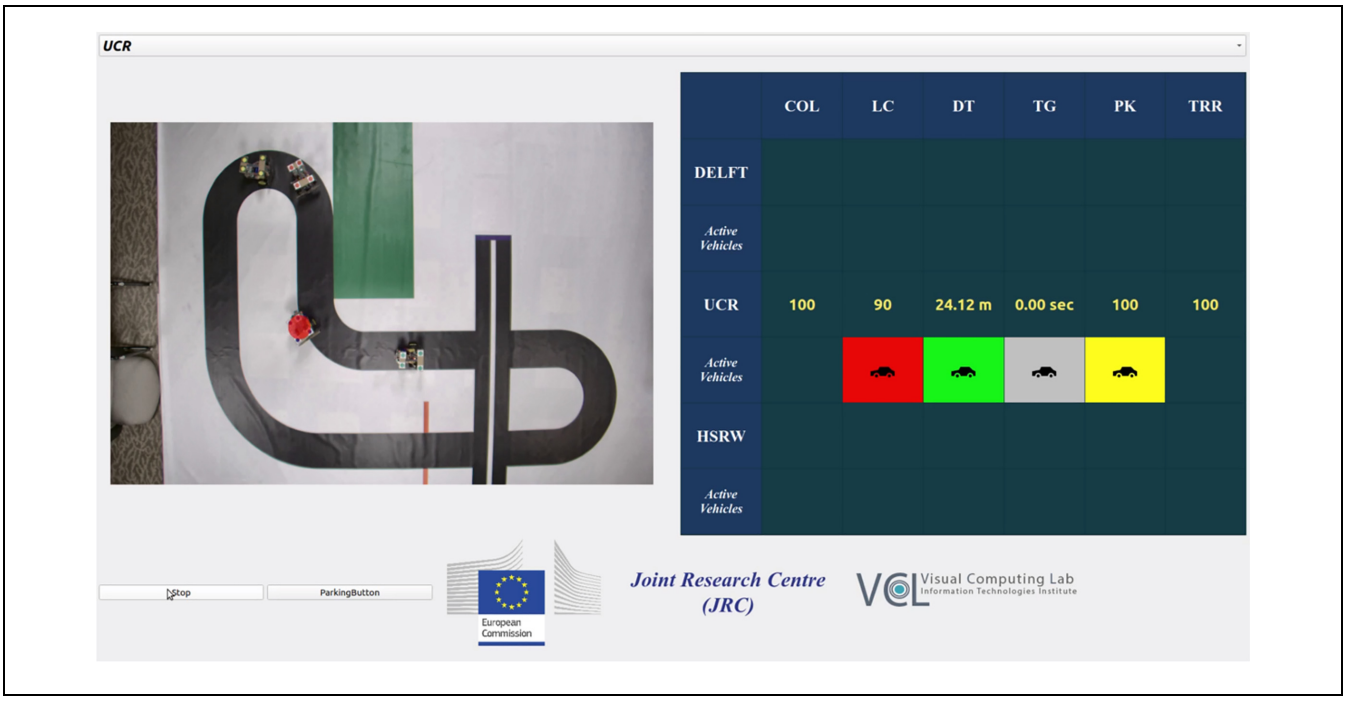

Figure 3. Graphical user interface of the automated camera-based referee system.
Note: COL = Collision; LC = Lane Keeping; DT = Distance Travelled; TG = Time Gap; PK = Parking; TRR = Tram Speed Reduction; DELFT = Technical University of Delft; UCR = University of California Riverside; HSRW = Rhine-Waal University of Applied Science.

Table 2. Competing Teams in the Automated Vehicle Traffic Challenge 2020 Robotic Challenge

Name	Acronym	Category	Nationality
Technical University of Delft	TU-Delft	Academia	The Netherlands
Rhine-Waal University of Applied Sciences Robotics Club	HSRW	Academia	Germany
University of California, Riverside	UCR	Academia	U.S.A.
ThreeSmart	ThreeSmart	Academia	Armenia
HTWK Smart Driving	HTWK	Makers	Germany
ItLUG Robotics Team	ItLUG	Makers	Italy
Kids Garage	KG	Makers	Belarus

the road (with a PD controller trying to keep the robot in the center).

The tram is detected by the first vehicle via LiDAR, which stops if it is not safe for the whole platoon to pass. Following vehicles solely base their speed on the leading vehicle (they stop if the first vehicle stops), which has a slightly slower speed than the following vehicles.

Junctions are detected using the same approach used for lane detection. Signs are detected based on shape (ellipse), color, and arrow direction. Right of way in the urban scenario is managed by robots publishing their approaching junction to a central managing node. If the junction is not reserved (that is the queue is empty), the robot might pass. If the queue is not empty, the robot slows down and waits for its turn. V2X communication is implemented via a private WiFi network.

Team 2: Rhine-Waal University of Applied Sciences Robotics Club (HRSW)

The team decided to design its own robotic platform using off-the-shelf components, as well as a custom 3D-printed chassis. It is based on the differential-drive model consisting of two independently controlled wheels as well as a passive trailing caster ball. In particular, the two driven wheels are propelled by independent motors (TT Motor), to provide translation and rotation controlling capabilities.

To increase the realism of the solution and also to use the four vehicles as their own research platform for future studies, the team decided to use different systems in their robots. In particular two different motor controllers were used, the Motorshield HAT (Pibot) and FeatherWing Motor Controller (Jetbot), as well as two

Table 3. Main Characteristics of the Robotic Platforms Developed by the Three Final Competing Teams

Team	Robot platform	Sensors	Methodologies employed	Designed operations	Communication
TU Delft	Husarion ROSbots	• LiDAR • Cameras • IMU • Wheel encoders	• Sobel edge detection • Hough transform • PID controller	• Lane detection • Translational position detection • Tram detection • Traffic sign detection • Leading vehicle detection • Junction detection • Right-of-way detection	WiFi
HRSW	Custom robotic platform	• Fish-eye cameras • Wheel encoders • Ultrasonic sensor • IMU	• NvidiaNet model • Ultrasound distance sensing • Haar cascade	• Lane detection • Translation control • Rotation control • Tram detection • Traffic sign detection • Right-of-way detection	Bluetooth
UCR	Custom robotic platform	• LiDAR • Fish-eye cameras • Speed encoders	• U-NET for semantic segmentation • ROI color recognition • PD controller • Ellipse detection via OpenCV ellipse fitting • Horn–Schmuck method	• Lane-keeping • Orientation control • Perception system used semantic segmentation • Tram detection • Traffic sign detection • Speed control • Leading vehicle detection • Direction recognition • Intersection recognition • Parking area recognition	WiFi

Note: HRSW = Rhine-Waal University of Applied Science; IMU = Inertial Measurement Unit; PID = Proportional-Integral-Drivative; UCR = University of California, Riverside.

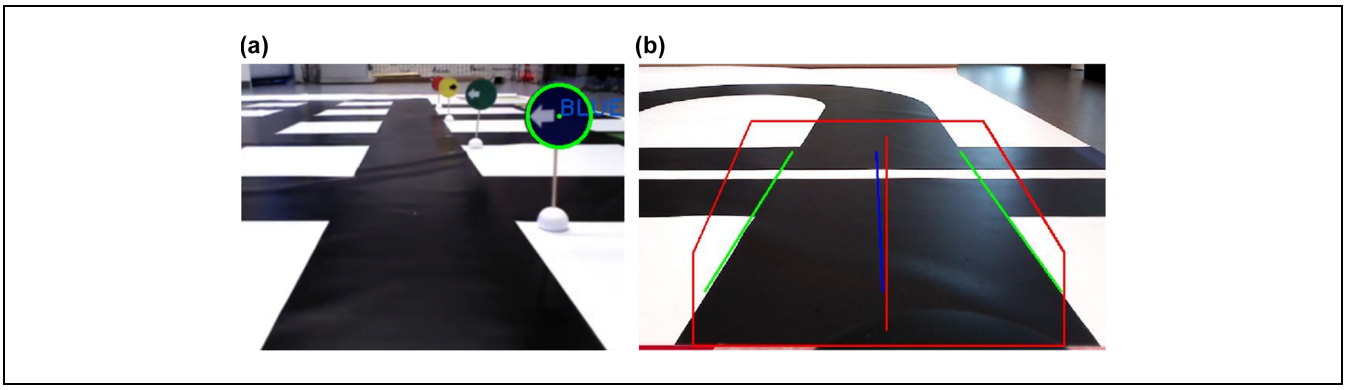

Figure 4. (*a*) Traffic sign and (*b*) lane detection for Team 1.

logical units, Nvidia Jetson Nano and Raspberry Pi 4. In regard to sensors, vehicles used fish-eye cameras, wheel encoders, ultrasonic sensors, and IMU.

Lane detection was performed via the Machine Learning Model (NvidiaNet). The tram is detected via distance sensing and color detection. Platooning is managed via ultrasound distance sensing and inter-vehicular communication. If the distance to the front vehicle is too small, the vehicle stops. If it is too large, a broadcast is done ordering the frontal vehicle to wait.

Traffic signs are detected via Machine Learning (Haar cascade). Right of way is according to the priority-of-right rule by detecting vehicles with markers on their right side. A visual example of traffic sign detection and lane navigation is provided in Figure 5.

Communication between vehicles is done via decentralized Bluetooth communication.

Team 3: University of California, Riverside (UCR)

The team initially used a customized Ackermann-steered radio-controlled (RC) vehicle. However, this architecture proved to be incapable of performing sharp turns in the #-shaped track. Thus, the architecture was redesigned to a differential drive robot based on off-the-shelf components.

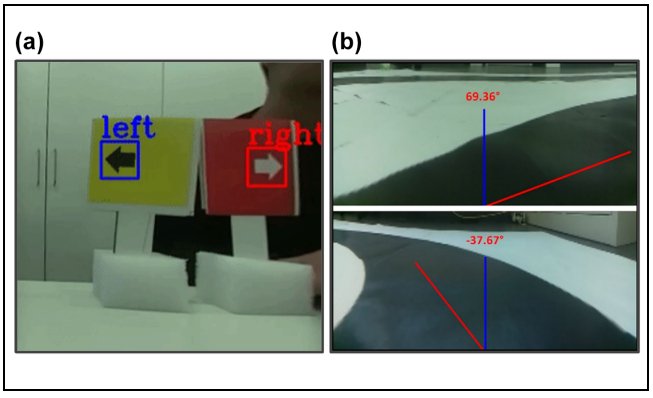

Figure 5. (*a*) Traffic sign and (*b*) lane navigation for Team 2.

The final solution consisted of two driven wheels as well as a trailing, passive wheel. The two driven wheels are propelled by independent motors (TT Motor), to provide translation and rotation controlling capabilities. In regard to sensors, speed encoders are used to measure the rotation of the respective motors, a one-dimensional LiDAR-Sensor is used for distance measurement of objects ahead of the robot and a 160-degree fish-eye camera provides a picture of the situation in front of the robot. In relation to logical units, the thorough control of the system is based on a Raspberry Pi 4B. V2X communication was implemented via a private WiFi network.

The camera-based perception system used semantic segmentation performed via Machine Learning (Deep Neural Network, adapted from U-Net). Lane-keeping was performed by finding the middle between the left and right side of the track, adding a waypoint. Orientation control was performed by the difference between the waypoint in the middle of the track and the current camera heading. Speed control was ensured via communication, or PD controller using LiDAR distance in case of communication loss. In particular, the leader has a state, which is taken by following vehicle after a fixed time. Different speed modes are used for straight/curves.

Traffic sign detection is performed via (i) Region-of-Interes (ROI) color recognition, (ii) ellipse detection via OpenCV ellipse fitting, and (iii) direction recognition by comparing pixels on the halves.

Intersection recognition is performed by transforming the segmented image to birds-eye view, extracting vertical and horizontal lanes (erosion) and combining intersections.

Tram recognition is performed by finding tram lane and checking for optical flow (Horn–Schmuck method), and passage happens only if all cars can pass. A visual example of traffic sign and lane perception and recognition is provided in Figure 6.

For #-shaped scenarios, a reservation system is implemented. First, the round reservation for the known future route is applied. After all vehicles find their loop, a reservation of intersection is implemented.

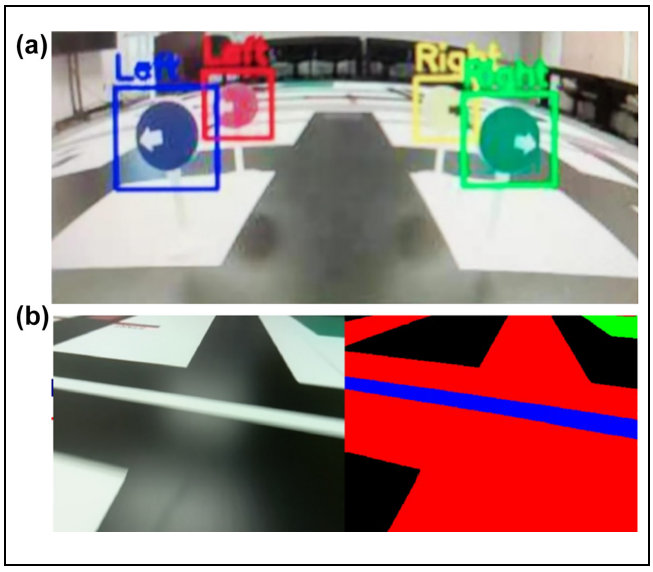

Figure 6. (*a*) Traffic sign and (*b*) camera-based perception for Team 3.

For parking, the recognition of parking area is performed in the last lap so that the vehicles can turn into the parking area. Once the vehicle has approached the first point within the parking area, it needs to turn toward the western end of the parking area, approach the end, turn northwards, and conclude the parking maneuver. All robots wait until the previous robot has finished parking.

Communication via Ros Nodes includes vehicle status, intersection reservation, parking indication, and time to tram.

Results

The ACRS used the videos from the three teams to determine the final score and appoint the winner. In the initial plans for AUTOTRAC, an additional race was planned on both scenarios with vehicles from different teams to have a benchmark representative of a scenario where heterogenous vehicles unable to communicate among themselves were deployed on the road. The benchmark would have then been used to quantify the improvement of the proposed solution in regard to traffic efficiency.

Unfortunately, the impossibility to have a physical final event jeopardized the possibility to have this benchmark scenario to be used in the scoring system. This was a missed opportunity because witnessing the traffic performance in the absence of communication would have been an interesting outcome of the competition.

The results from the ACRS are reported in Table 4. From the table, it is possible to see that the best-performing solution was the one proposed by TU-Delft, followed by those from UCR and HSRW. It is also possible to notice that the outcome was mainly driven by the outstanding performance on the J-shaped scenario in which the TU-Delft solution outperformed all the others. In contrast, UCR performed better than the other two teams in the #-shaped scenario. This result is particularly interesting because it shows how different motorway and urban navigations are for automated vehicles and that using the same approach in both cases will perhaps not be possible for real-world applications. This is understandable because traffic dynamics are considerably different in urban and highway scenarios, and, in particular, the role of the infrastructure to help traffic coordination

Table 4. Results of the Automated Vehicle Traffic Challenge 2020 Robotic Challenge

Scenario	Metric	Absolute scores			Normalized scores		
		TU-DELFT	UCR	HSRW	TU-DELFT	UCR	HSRW
J-shape	CL	100	100	100	0.167	0.167	0.167
	LK	90	25	100	0.150	0.042	0.167
	DT	73	100	0	0.122	0.167	0.000
	TG	100	33	0	0.167	0.055	0.000
	PK	100	75	100	0.167	0.125	0.167
	TSR	100	100	100	0.167	0.167	0.167
Total J-shape		563	433	400	0.939	0.722	0.667
#-shape	CL	100	100	95	0.333	0.333	0.317
	LK	90	45	95	0.300	0.150	0.317
	DT	0	100	26	0.000	0.333	0.088
Total #-shape		190	245	216	0.633	0.817	0.721
Total		1317	1111	1016	2.51	2.26	2.05

Note: CL = collision; LK = lane-keeping; DT = distance travelled; TG = time gap; PK = parking; TSR = tram speed reduction; UCR = University of California, Riverside; HSRW = Rhine-Waal University of Applied Science.

will certainly be more important in the urban case also in real life.

In relation to technological solutions adopted by the three teams, the results are difficult to generalize. The TU Delft vehicles were controlled via model-based feedback control, specifically, via proportional-integral feedback on the positional and angular states, the latter being calculated via integrated odometry, inertial sensors, and visual information. This approach is classic in automatic control theory and here outperformed non-model-based methods, essentially based on machine learning, on the highway scenario. We were unable to draw similar conclusions for the urban scenario, since the TU Delft vehicles were much slower at the intersections because of their significantly bigger size, resulting in the impossibility to simultaneously turn and move longitudinally.

These outcomes confirm the suitability of robotic competitions to draw inference about the evolution of road traffic in the presence of CAVs. They have indeed highlighted that to achieve an efficient traffic flow different approaches will need to be implemented in different types of road networks. They have also clearly showed that the effect of CAVs on traffic efficiency will heavily depend on the solutions (hardware and software) that the CAVs' developers will implement.

Apart from the competition results, it is also interesting to report that the three teams all confirmed the learning opportunity that the competition offered to the team members. Indeed, working on both hardware and software with the objective to achieve optimal performance for traffic and not for the single vehicle in different navigation scenarios is an extremely challenging multidimensional problem. This confirms the suitability of an open competition-based approach to foster the development of effective CAV-based solutions.

Concerning the remark previously made on the suitability of the proposed approach to aggregate the scores from all metrics; fortunately, the final rank would not be different if the scores would have been normalized by the maximum number of points of the two network layouts (thus by 600 for the J-shaped scores and by 300 for the #-shaped scores). For the next edition of the competition, yet to be planned, a revised scoring system will be introduced to ensure that it is the fairest and the most representative of an improved transportation system.

Conclusion

The JRC of the European Commission organized the first competition of small-scale robot vehicles focused on the CAVs' collective performance: AUTOTRAC 2020. The objective of AUTOTRAC 2020 is to challenge the capability of CAVs to generate an efficient traffic flow. Each team participated with four robots and was assessed based on a set of indicators rewarding the best resulting traffic dynamics. Three teams competed on two different road layouts: one corresponding to highway and the other to urban conditions. A set of performance metrics focused on rewarding good individual and collective vehicle behaviors has been proposed. In particular, the metrics referred to collision avoidance, efficient lane-keeping, minimal fleet time gap, efficient parking, and maximum distance traveled. The assessment was performed with an independent ACRS developed by the CERTH.

The final event of the competition was held in the form of an online event on June 17th, 2021, as part of the 7th International IEEE Conference on Models and Technologies for Intelligent Transportation Systems attracting significant attention. Hopefully, AUTOTRAC 2020 and its future editions will be able to raise awareness on the necessity to pay particular attention to the impact of CAVs to the system as a whole, rather than each user individually toward a better, safer, cleaner, and sustainable road mobility.

The results of the competition were very interesting with all participants managing to successfully finish the competition using different solutions in regard to robots, sensors, and logic. They showed that the efficiency of future traffic in the presence of CAVs will highly depend on the choices made by their developers. Furthermore, they showed that the impact of CAVs' implementations might be substantially different depending on the context. Solutions that will perform well in urban conditions will probably not generate efficient highway traffic and vice versa. This suggests the need by regulators to introduce clear traffic requirements on the vehicle operations (especially for highway applications) and to guarantee infrastructure-enabled vehicle coordination (especially in the urban context). Remarkably, all participants gave positive feedback on the overall AUTOTRAC experience, which brought new knowledge to their laboratories for future research.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: B. Ciuffo, M. Makridis, V. Padovan; data collection: A. Dimou, S. Grammatico, Q.N. Nguyen Le, G. Wu, Z. Zhao; analysis and interpretation of results: B. Ciuffo, M. Makridis, V. Padovan, A. Dimou; draft manuscript preparation: B. Ciuffo, M. Makridis, A. Dimou, S. Grammatico, Q.N. Nguyen Le, G. Wu, Z. Zhao. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The organization of the small-scale AUTOmated vehicle TRAffic Challenge (AUTOTRAC) 2020 was funded the European Commission Joint Research Centre in the framework of its internal Exploratory Research Programme.

ORCID iDs

Biagio Ciuffo https://orcid.org/0000-0003-3734-4264
Michail Makridis https://orcid.org/0000-0001-7462-4674
Emilio Benenati https://orcid.org/0000-0003-4875-4760
Kanok Boriboonsomsin https://orcid.org/0000-0003-2558-5343
Petros Daras https://orcid.org/0000-0003-3814-6710
Viswanath Das https://orcid.org/0000-0003-2382-1322
Sergio Grammatico https://orcid.org/0000-0002-6021-2350
Malte Hoelscher https://orcid.org/0000-0001-5350-4390
Yu Jiang https://orcid.org/0000-0003-1716-2834
Zhensong Wei https://orcid.org/0000-0003-3523-5689
Zhouqiao Zhao https://orcid.org/0000-0002-5286-3807

References

1. Alonso Raposo, M., B. Ciuffo, P. Alves Dias, F. Ardente, J. Aurambout, G. Baldini, C. Baranzelli, et al. *The Future of Road Transport - Implications of Automated, Connected, Low-Carbon and Shared Mobility*. EUR 29748 EN. Publications Office of the European Union, Luxembourg, 2019. https://publications.jrc.ec.europa.eu/repository/handle/JRC116644. Accessed July 28, 2021.
2. TrafficFluid. ERC Advanced Grant: Lane-free Artificial-Fluid Environment for Vehicular Traffic. https://www.trafficfluid.tuc.gr/en/home. Accessed July 28, 2021.
3. Makridis, M., K. Mattas, A. Anesiadou, and B. Ciuffo. OpenACC. An Open Database of Car-Following Experiments to Study the Properties of Commercial ACC Systems. *Transportation Research Part C: Emerging Technologies*, Vol. 125, 2021, p. 103047. https://doi.org/10.1016/j.trc.2021.103047.
4. Tiernan, T., P. Bujanovic, P. Azeredo, W. G. Najm, and T. Lochrane. *CARMA Testing and Evaluation of Research Mobility Applications*. Federal Highway Administration, U.S. Department of Transportation, 2019. https://doi.org/10.21949/1503647.
5. Knoop, V. L., M. Wang, I. Wilmink, D. M. Hoedemaeker, M. Maaskant, and E.-J. Van der Meer. Platoon of SAE Level-2 Automated Vehicles on Public Roads: Setup, Traffic Interactions, and Stability. *Transportation Research Record: Journal of the Transportation Research Board*, 2019. 2673: 311–322.
6. Ciuffo, B., K. Mattas, M. Makridis, G. Albano, A. Anesiadou, Y. He, S. Josvai, et al. Requiem on the Positive Effects of Commercial Adaptive Cruise Control on Motorway Traffic and Recommendations for Future Automated Driving Systems. *Transportation Research Part C: Emerging Technologies*, Vol. 130, 2021, p. 103305. https://doi.org/10.1016/j.trc.2021.103305.
7. Ciuffo, B., M. Makridis, T. Toledo, and G. Fontaras. Capability of Current Car-Following Models to Reproduce Vehicle Free-Flow Acceleration Dynamics. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 19, 2018, pp. 3594–3603. https://doi.org/10.1109/TITS.2018.2866271.
8. Fiori, C., V. Arcidiacono, G. Fontaras, M. Makridis, K. Mattas, V. Marzano, C. Thiel, and B. Ciuffo. The Effect of Electrified Mobility on the Relationship Between Traffic Conditions and Energy Consumption. *Transportation Research Part D: Transport and Environment*, Vol. 67, 2019, pp. 275–290. https://doi.org/10.1016/j.trd.2018.11.018.
9. Makridis, M., G. Fontaras, B. Ciuffo, and K. Mattas. MFC Free-Flow Model: Introducing Vehicle Dynamics in Microsimulation. *Transportation Research Record: Journal of the Transportation Research Board*, 2019. 2673: 762–777.
10. Anesiadou, A., M. Makridis, K. Mattas, G. Fontaras, and B. Ciuffo. Characterization of Drivers Heterogeneity and its Integration Within Traffic Simulation. *arXiv Preprint arXiv:2107.02618 [physics]*, 2021.
11. He, Y., M. Montanino, K. Mattas, V. Punzo, and B. Ciuffo. Physics-Augmented Models to Simulate Commercial Adaptive Cruise Control (ACC) Systems. *arXiv Preprint arXiv:2107.07832*, 2021.
12. Falk, J., G. Kannabiran, and N. B. Hansen. What do Hackathons Do? Understanding Participation in Hackathons Through Program Theory Analysis. *Proc., 2021 CHI Conference on Human Factors in Computing Systems*, Yokohama, Japan, 2021, pp. 1–16. https://doi.org/10.1145/3411764.3445198.
13. European Commission Joint Research Centre. JRC AUTOTRAC 2020. https://ec.europa.eu/jrc/en/event/other-event/jrc-autotrac-2020-how-future-road-transport-will-look. Accessed July 29, 2021.
14. Arvin, F., J. Espinosa, B. Bird, A. West, S. Watson, and B. Lennox. Mona: An Affordable Open-Source Mobile Robot for Education and Research. *Journal of Intelligent & Robotic Systems*, Vol. 94, 2019, pp. 761–775. https://doi.org/10.1007/s10846-018-0866-9.
15. Mondada, F., M. Bonani, X. Raemy, J. Pugh, C. Cianci, A. Klaptocz, S. Magnenat, J. C. Zufferey, D. Floreano, and A. Martinoli. The E-Puck, a Robot Designed for Education in Engineering. *Proc., 9th Conference on Autonomous Robot Systems and Competitions*, Vol. 1, Portugal, 2009, pp. 59–65.
16. Leeuw, W. D., M. Ricke, C. Rosier, T. Wielenga, and S. Grammatico. A Multi ROSbot Laboratory Setup for Experimenting Autonomous Driving Maneuvers. *Proc., 28th Mediterranean Conference on Control and Automation (MED)*, Saint-Raphael, France, 2020, pp. 532–537.
17. Besseghieur, K., R. Trębiński, W. Kaczmarek, and J. Panasiuk. Leader-Follower Formation Control for a Group of ROS-Enabled Mobile Robots. *Proc., 6th International Conference on Control, Decision and Information Technologies (CoDIT)*, 2019, pp. 1556–1561.
18. Federal Highway Administration (FHWA). CARMA Evaluation. https://highways.dot.gov/research/operations/CARMA-evaluation. Accessed March 8, 2022.

19. Paull, L., J. Tani, H. Ahn, J. Alonso-Mora, L. Carlone, M. Cap, Y. F. Chen, et al. Duckietown: An Open, Inexpensive and Flexible Platform for Autonomy Education and Research. *Proc., 2017 IEEE International Conference on Robotics and Automation (ICRA)*, Singapore, IEEE, New York, 2017, pp. 1497–1504. https://doi.org/10.1109/ICRA.2017.7989179.
20. Hyldmar, N., Y. He, and A. Prorok. A Fleet of Miniature Cars for Experiments in Cooperative Driving. *Proc. IEEE International Conference on Robotics and Automation (ICRA)*, Montreal, QC, Canada, IEEE, New York, 2019, pp. 1–7.
21. Stager, A., L. Bhan, A. Malikopoulos, and L. Zhao. A Scaled Smart City for Experimental Validation of Connected and Automated Vehicles. *IFAC-PapersOnLine*, Vol. 51, 2018, pp. 130–135. https://doi.org/10.1016/j.ifacol.2018.07.022.
22. Beaver, L. E., B. Chalaki, A. I. Mahbub, L. Zhao, R. Zayas, and A. A. Malikopoulos. Demonstration of a Time-Efficient Mobility System Using a Scaled Smart City. *arXiv Preprint arXiv:1903.01632*, 2019.
23. Klančar, G., D. Matko, and S. Blažič. Wheeled Mobile Robots Control in a Linear Platoon. *Journal of Intelligent and Robotic Systems*, Vol. 54, No. 5, 2009, pp. 709–731.
24. Baarath, K., M. A. Zakaria, M. V. Suparmaniam, and M. Y. bin Abu. Platooning Strategy of Mobile Robot: Simulation and Experiment. *MATEC Web Conferences*, Vol. 90, 2017, p. 01060. https://doi.org/10.1051/matecconf/20179001060.
25. Hu, J., P. Bhowmick, F. Arvin, A. Lanzon, and B. Lennox. Cooperative Control of Heterogeneous Connected Vehicle Platoons: An Adaptive Leader-Following Approach. *IEEE Robotics and Automation Letters*, Vol. 5, No. 2, 2020, pp. 977–984. https://doi.org/10.1109/LRA.2020.2966412.
26. Ikemoto, Y., Y. Hasegawa, T. Fukuda, and K. Matsuda. Zipping, Weaving: Control of Vehicle Group Behavior in Non-Signalized Intersection. *Proc., IEEE International Conference on Robotics and Automation, ICRA'04*, Vol. 5, New Orleans, LA, IEEE, New York, 2004, pp. 4387–4391. https://doi.org/10.1109/ROBOT.2004.1302408.
27. Purcaru, C., R. Precup, D. Iercan, L. Fedorovici, B. Dohangie, and F. Dragan. Nrobotic Mobile Robot Navigation Using Traffic Signs in Unknown Indoor Environments. *Proc., 2013 IEEE 8th International Symposium on Applied Computational Intelligence and Informatics (SACI)*, Timisoara, Romania, IEEE, New York, 2013, pp. 29–34. https://doi.org/10.1109/SACI.2013.6608982.
28. Tuchner, A., and J. Haddad. Vehicle Platoon Formation Using Interpolating Control: A Laboratory Experimental Analysis. *Transportation Research Part C: Emerging Technologies*, Vol. 84, 2017, pp. 21–47.
29. Rosa, P., F. Ferretti, Â. G. Pereira, F. Panella, and M. Wanner. *Overview of the Maker Movement in the European Union*. EUR 28686 EN. Publications Office of the European Union, Luxembourg, 2017. https://publications.jrc.ec.europa.eu/repository/handle/JRC107298.
30. Von Hippel, E. *Democratizing Innovation*. MIT Press, Cambridge, MA, 2005.
31. Dougherty, D. The Maker Movement. *Innovations*, Vol. 7, No. 3, 2012, pp. 11–14.
32. WIKIPEDIA. DARPA Grand Challenge. https://en.wikipedia.org/wiki/DARPA_Grand_Challenge.
33. European Commission Joint Research Centre. JRC AUTOTRAC Final Event. https://ec.europa.eu/jrc/en/event/other-event/autotrac-2020-final-event.
34. HUSARION. ROSbot 2.0 & ROSbot 2.0 PRO. https://husarion.com/manuals/rosbot/.