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Editorial

Advances in Automated Driving Systems

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1. Introduction

Electrification, automation of vehicle control, digitalization and new mobility are the mega trends in automotive engineering and they are strongly connected to each other. Whereas many demonstrations for highly automated vehicles have been made worldwide, many challenges remain to bring automated vehicles on the market for private and commercial use.

The main challenges related to automated vehicle control are:

1. Reliable machine perception; accepted standards for vehicle approval and homologation;
2. verification and validation of the functional safety especially at SAE level 3+ systems;
3. legal and ethical implications;
4. acceptance of vehicle automation by occupants and society;
5. interaction between automated- and human-controlled vehicles in mixed traffic;
6. human–machine interaction and usability;
7. manipulation, misuse and cyber-security;
8. but also the system costs for hard- and software and development effort.

These challenges mainly relate to the complex interaction between the human occupants, the automated vehicle and the environment the vehicle is operated in (see Figure 1). The main system components and the related challenges are elaborated in the following:

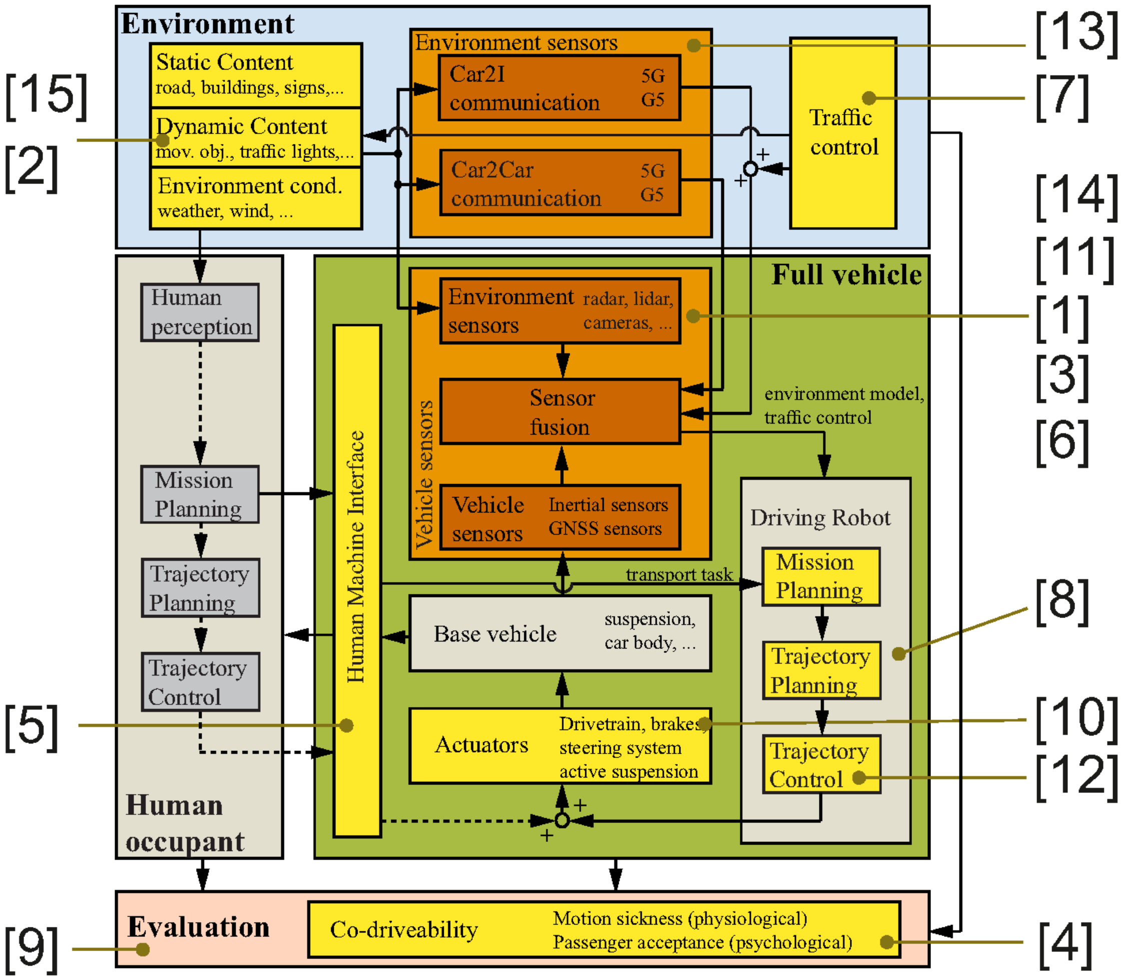

Figure 1. Traffic system in automated driving. The figure shows the complex interaction of the main system components in automated driving systems and how the articles of the Special Issue are thematically classified.

1.1. Environment

The environment, comprised of the static and dynamic content, as well as the ambient conditions, roadside infrastructure and traffic control systems are essential aspects in driving automation. It provides information to the driver with lane markings and traffic signs that were initially developed for human perception. However, requirements of the future road infrastructure need to consider opportunities and limitations of perception sensors.

1.2. Perception

Machine perception, highlighted in orange in Figure 1, is traditionally vehicle-based. Here, many challenges arise because of the increasingly complex algorithms to process raw sensor data into a reliable digital environment that allows planning of the vehicle trajectory. In addition, environmental conditions such as rain, fog or lighting conditions can deteriorate the machine perception, leading to enhance machine perception with data fused from different sensors.

Due to the high cost for the components and their integration in the vehicle, increasingly sensors located in the roadside environment communicate with the automated vehicle. They shall provide additional information about the static contents such as the road network, roadside infrastructure and buildings, as well as the dynamic content such as moving objects. For the vehicle-to-X communication (V2X) we see different technologies such as dedicated short range communication and mobile communication to allow for data exchange of a huge amount of data at minimum delay, while maintaining data security and privacy.

1.3. Vehicle Guidance

Visualized in grey, the driving robot (right side of Figure 1) increasingly performs tasks of the human driver (left side), consisting of mission and trajectory planning and control. The mission planning is something that is an intrinsic human task but widely supported by machine navigation systems. Here, external traffic control systems located in the road infrastructure or cloud-based services can additionally support to optimize transportation tasks by re-routing. However, the most difficult task is the trajectory planning using the horizon offered by the field of view of the human or machine perception. Instead of the traditional approach, namely to deterministically program driving tasks such as for adaptive cruise control, modern methods of artificial intelligence (AI) offer a data driven approach to handle complex and maybe even situations not being experienced before. Nevertheless, the safety validation of AI base trajectory planning is a not solved issue. Vehicle control, usually handled by traditional methods of automation and control, aims to minimize the error in planed and driven trajectories. Here, they need to cooperate with vehicle dynamics control (VDC) systems. Implementing intelligence in the road infrastructure allows for advanced traffic control that maybe even perform trajectory planning as the most delicate step in vehicle control.

1.4. Base Vehicle

The vehicle, depicted in green in Figure 1, is based on a traditional vehicle but enhanced with actuators, which will evolve from classical steering, power train and braking systems to advanced X-by-wire systems offering new levels of vehicle control.

1.5. Human Machine Interface

The human–machine interface (HMI) is a delicate component that needs to be designed carefully in order to improve the already high level of reliability in human vehicle control. Literature reports that billions of kilometers need to be driven with an automated vehicle in order to prove statistical significance of a superior behavior of a driving robot. As long as we have the human driver as an operator that needs to perform tasks in vehicle guidance, such as observation of the environment and fallback in case of system failure, the HMI is essential to avoid distraction or inappropriate behavior of the human driver.

1.6. Evaluation

Formerly the evaluation of driving behavior focused on the driver, and included criteria related to controllability, disturbance behavior, observability and parameter insensitivity. These criteria could be evaluated in a manageable amount of testing on proving grounds, often with open-loop maneuvers to exclude human vehicle guidance. In addition, human impression of the driving behavior and comfort was rated with different subjective and objective methods, leading into an evaluation of drivability of the vehicle. In driving automation, the driver increasingly transforms into a passenger, so we need to take into account the human as a co-driver or even a passenger, so rating becomes more of a co-drivability feature. Additional focus has to be put on other aspects such as perceived trust, safety and acceptance of the human occupant, which happens on a psychological level. However, the physiological aspect also has to be taken into account; for example, motion sickness as experienced often from passengers.

However, the sheer infinite amount of possible driving scenarios call for innovative methods for evaluating not only the safe behavior of an automated vehicle, but also a high rating of co-drivability.

2. Articles of the Special Issue

This Special Issue deals with recent advances related to the technological aspects of the aforementioned challenges:

- Machine perception for SAE L3+ driving automation;
- trajectory planning and decision making in complex traffic situations;
- X-by-wire system components;
- verification and validation of SAE L3+ systems;
- misuse, manipulation and cybersecurity;
- human–machine interaction, driver monitoring and driver intention recognition;
- road infrastructure measures for introduction of SAE L3+ systems;
- solutions for interactions of vehicles human and machine controlled in mixed traffic.

The collection includes 15 articles that deal with the aforementioned challenges. In Figure 1, the thematic classification of the different articles related to the different system components is illustrated. Not surprisingly, it illustrates that many studies are focused on reliable human perception.

Article [1] deals with a methodology to quantify the performance of sensor models in virtual validation and verification (V & V) of automated driving functions, an important step towards reduction of on-road testing. The effect of automation on traffic flow during the transition phase in mixed traffic was investigated by [2]. Article [3] deals with the quality of ground truth annotation data to improve the transfer of on-road testing results into simulation. The evaluation of perceived trust was examined in [4], demonstrated in a driving simulator study. The topic of drowsiness classification in the context of driving automation was investigated in [5]. In simulation of Automated Driving (AD) functions, modelling of camera sensors is often carried out with physical modelling; however, research in [6] presented an alternative with phenomenological modeling. Article [7] introduced a conflicted management framework, especially focusing on aiming at managing urban and peri-urban traffic. The potential of implementing AI into vehicle guidance, demonstrated on the safety of ACC, was investigated in [8]. Article [9] deals with insufficiencies during the decomposition of testing of ADAS functions from the system to lower levels, and defining rules for testing of modules to dispense with system tests. Improvement of vehicle control for wheel loaders was investigated in [10] using a deep learning-based prediction model of the throttle valve. The difficulties in reliable detection of pedestrians is addressed in [11], based on convolutional neural network algorithms applied on images manipulated with inverse gamma correction. Vehicle control at handling limits was investigated in [12], introducing a model-predictive controller that is able to initiate and maintain steady-state drifting. Article [13] deals with a functional prototype of a cooperative perception system aiming at future cloud-based services of automated driving functions, focusing on motorway use. A field study dealing with the capability of a market-introduced traffic sign recognition system was conducted in [14], revealing deficits by misreading of signs. A method to introduce automated driving functions in traffic flow simulation for virtual V & V was introduced by [15], based on a co-simulation framework between multi-body and traffic flow simulation.

As the Special Issue is dedicated to this topic, future research will continue in the development of the individual system components and their complex interaction, constantly rising the level of autonomy while providing an acceptable behavior for the individual and the society, superior compared to human vehicle guidance.

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