

THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

**Automated Driving Maneuvers
- Trajectory Planning via Convex Optimization in the
Model Predictive Control Framework**

by

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Automated Driving Maneuvers

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Front cover:

A convex quadratic program is formulated within the model predictive control framework to generate an appropriate, safe, and smooth lane change trajectory for the ego vehicle.

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To my family and friends

Abstract

Highly automated vehicles have the potential to provide a variety of benefits e.g., decreasing traffic injuries and fatalities while offering people the freedom to choose how to spend their time in their vehicle without jeopardizing the safety of themselves or other traffic participants. For automated vehicles to be successfully commercialized, the safety and reliability of the technology must be guaranteed. A safe and robust trajectory planning algorithm is therefore a key enabling technology to realize an intelligent vehicle system for automated driving that can cope with both normal and high risk driving situations.

This thesis addresses the problem of real-time trajectory planning for smooth and safe automated driving maneuvers in traffic situations where the ego vehicle does not have right-of-way i.e., yielding maneuvers e.g., lane change, roundabout entry, and intersection crossing. The considered problem of generating an appropriate, safe, and smooth trajectory consisting of a sequence of longitudinal and lateral control signals is formulated as convex optimal control problems in the form of Quadratic Programs (QP) within the Model Predictive Control (MPC) framework in a manner that allows for reliable, predictable, and robust, real-time implementation on a standard passenger vehicle platform.

The ability of the proposed trajectory planning algorithms to generate appropriate, safe, and smooth trajectories is validated by simulation studies and experiments in a Volvo V60 performing automated lane change maneuvers on a test track. The contribution of this thesis is thereby considered to be a building block for Advanced Driver Assistance Systems (ADAS) regarding yielding maneuvers e.g., lane change, and eventually highly automated vehicles.

Keywords: Advanced Driver Assistance Systems, Autonomous Driving, Automated Driving, Lane Change, Trajectory planning, Model Predictive Control, Optimization.

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Last but not the least, I like to thank my wonderful family and friends, who motivate me to fulfill my ambitions.

*Julia Nilsson
Göteborg, 2016*

List of publications

This thesis is based on the following four publications:

Paper A J. Nilsson, P. Falcone, M. Ali, and J. Sjöberg, “Receding Horizon Maneuver Generation for Automated Highway Driving,” *Control Engineering Practice*, vol. 41, pp. 124-133, August, 2015.

Paper B J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Longitudinal and Lateral Control for Automated Yielding Maneuvers,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1404-1414, May, 2016.

Paper C J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Lane Change Maneuvers for Automated Vehicles,” Accepted for publication in *IEEE Transactions on Intelligent Transportation Systems*, 2016.

Paper D J. Nilsson, J. Fredriksson, and E. Coelingh, “Trajectory Planning with Miscellaneous Safety Critical Zones,” Submitted for possible conference publication, 2017.

In addition to the papers included in this thesis, the author of the thesis have also written the following publications:

J. Nilsson and J. Sjöberg, “Strategic Decision Making for Automated Driving on Two-Lane, One-Way Roads Using Model Predictive Control,” *IEEE Intelligent Vehicles Symposium*, pp. 1253-1258, June, 2013, Gold Coast, Australia.

J. Nilsson, M. Ali, P. Falcone, and J. Sjöberg, “Predictive Manoeuvre Generation for Automated Driving,” *IEEE Conference on Intelligent Transportation Systems*, pp. 418-423, October, 2013, The Hague, The Netherlands.

- J. Nilsson**, “On Decision-Making and Control for Automated Highway Driving,” Licentiate Thesis R003/2014, ISSN 1403-266X, Chalmers University of Technology, February, 2014, Gothenburg, Sweden.
- J. Nilsson**, Y. Gao, A. Carvalho, and F. Borrelli, “Manoeuvre Generation and Control for Automated Highway Driving,” *IFAC World Congress*, pp. 6301-6306, August, 2014, Cape Town, South Africa.
- J. Nilsson**, M. Brännström, E. Coelingh, and J. Fredriksson, “Longitudinal and Lateral Control for Automated Lane Change Maneuvers,” *American Control Conference*, pp. 1399-1404, July, 2015, Chicago, IL, USA.
- J. Nilsson**, J. Fredriksson, and E. Coelingh, “Rule-Based Highway Manoeuvre Intention Recognition,” *IEEE Conference on Intelligent Transportation Systems*, pp. 950-955, September, 2015, Las Palmas de Gran Canaria, Canary Islands, Spain.
- J. Nilsson**, J. Silvlin, M. Brännström, E. Coelingh, and J. Fredriksson, “If, When, and How to Perform Lane Change Maneuvers on Highways,” Accepted for publication in *IEEE Intelligent Transportation Systems Magazine*, 2016.

Furthermore, related patent applications have been submitted as following:

- J. Nilsson** and M. Ali, “Manoeuvre Generation for Automated Driving,” Patent pending, European Patent Office, Application no. 13184034.0, September, 2013.
- H. Lind, E. Coelingh, M. Brännström, P. Hardå, and **J. Nilsson**, “Method for Transition Between Driving Modes,” Patent pending, European Patent Office, Application no. 14163798.3, April, 2014.
- M. Brännström and **J. Nilsson**, “Method of Trajectory Planning for Yielding Manoeuvres,” Patent pending, European Patent Office, Application no. 14186538.6, September, 2014.
- J. Nilsson**, M. Ali, and M. Brännström, “Lane Change with Limited Field of View,” Patent pending, European Patent Office, Application no. 15176443.8, July, 2015.
- J. Silvlin, M. Brännström, **J. Nilsson**, and M. Ali, “Method and System for Gap Selection,” Patent pending, European Patent Office, Application no. 15189538.0, October, 2015.

J. Nilsson and M. Brännström, “Method and System for Evaluating Inter-Vehicle Traffic Gaps and Time Instances to Perform a Lane Change Manoeuvre,” Patent pending, European Patent Office, Application no. 16156686.4, February, 2016.

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Part I
Introductory chapters

Chapter 1

Scope

The U.S. Census Bureau estimates that the average American spends more than 100 hours every year commuting to work, which is more than the typical two weeks' vacation time of 80 hours [1]. In a society where time is a commodity, it is questionable if people should spend their time performing repetitive and mundane driving tasks rather than having the freedom to choose how to spend their time in their vehicle.

Perhaps not surprisingly, many drivers are sometimes engaging in secondary tasks which are not remotely related to the actual driving task. Activities e.g., text-messaging, phone-calls, and internet browsing, cause a large part of all drivers to ever so often take their eyes and minds off the road, risking the safety of both themselves and those around them [2]-[3]. Each year traffic accidents are estimated to cause over 1.2 million deaths and 50 million injuries worldwide [4] which to a large extent is correlated to driver inattention and errors [5].

In order to increase traffic safety and driver convenience, both academia and industry have become dedicated to the development of intelligent vehicle systems. Advanced Driver Assistance Systems (ADAS) e.g., Adaptive Cruise Control (ACC), Lane Keeping Aid (LKA), and collision warning with auto brake have been shown to improve drivers' comfort and safety [6]-[8]. It is therefore expected that further developed automated functionality will continue to enhance driver comfort and overall traffic safety by offering people the possibility to freely choose to e.g., work, relax or even have a snooze, rather than driving the vehicle (as illustrated in Figure 1.1), without jeopardizing the safety of themselves or other traffic participants.

For automated vehicles to be successfully commercialized, the safety and reliability of the technology must be guaranteed. As such, a reliable and robust trajectory planning algorithm is among others a key enabling technol-



Figure 1.1: Automated driving has the potential to allow drivers the freedom to choose how to spend their time in their vehicles without risking the safety of themselves or other traffic participants [9].

ogy to realize a safe and dependable intelligent vehicle system for automated driving that can cope with both normal and high risk driving situations

1.1 Problem description

To extend the capability of ADAS and eventually progress to highly automated vehicles, the intelligent vehicle system must be able to make appropriate self-regulatory decisions regarding the vehicle's actions i.e., plan appropriate trajectories which allow the vehicle to adapt its behavior to the current traffic situation. As an illustrative example, consider the traffic situation which is schematically represented in Figure 1.2. In the depicted traffic situation, the ego vehicle i.e., the vehicle which is controlled by an intelligent vehicle system, is driving in the same lane as the preceding vehicle, S_1 , and the trailing vehicle, S_2 , while two surrounding vehicles, S_3 and S_4 are driving in the left adjacent lane. If the ego vehicle should perform a left lane change maneuver in the described traffic situation, the intelligent vehicle system must consider whether the maneuver should be performed ahead of S_3 , in the inter-vehicle traffic gap between S_3 and S_4 , or behind S_4 , as well as plan the corresponding trajectory.

Similarly, when considering other maneuvers where the ego vehicle must adapt its behavior to the surrounding traffic situation and does not have right-of-way i.e., yielding maneuvers e.g., entering a roundabout or crossing an intersection, it becomes evident that these types of maneuvers can also

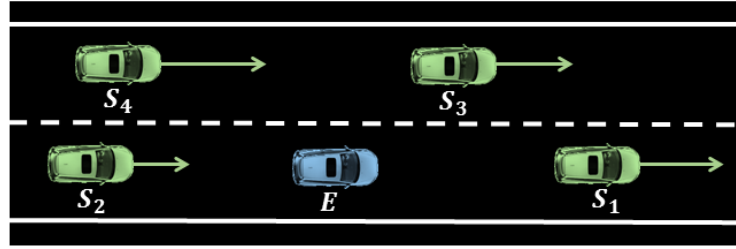


Figure 1.2: Vehicles traveling on a one-way two-lane road. The ego vehicle, E , is shown in blue and the surrounding vehicles, S_1 , S_2 , S_3 , and S_4 , are displayed in green. The arrows represent the predicted paths of S_i , $i = 1, \dots, 4$.

be considered as trajectory planning problems with the purpose of positioning the ego vehicle in an appropriate gap between some surrounding traffic participants or objects. The intelligent vehicle system must thus have the ability to determine which trajectory that is most appropriate with respect to issues concerning e.g., the required control signals to execute the maneuver and the overall safety of the maneuver. This is a challenging trajectory planning problem since it involves both longitudinal and lateral movement in the presence of surrounding traffic participants which are also in motion. Furthermore, to be applicable to passenger vehicle ADAS or highly automated vehicles, the algorithm must have the ability to deal with the conflicting demands of limited computational resources, planning in a dynamic and uncertain environment, and generating provable safe trajectories, while abiding traffic rules and regulations, as well as satisfying the ego vehicle's physical and design limitations.

To enhance the automated functionality of ADAS and eventually progress to highly automated vehicles, this thesis thus addresses the following real-time trajectory planning problem of automated driving maneuvers where the ego vehicle does not have right-of-way i.e., yielding maneuvers e.g., lane change, roundabout entry, and intersection crossing:

If the ego vehicle should perform an automated yielding maneuver e.g., lane change, determine in which gap between some traffic participants or objects, and at what time instance the maneuver should be performed, and calculate a feasible maneuver (if such exists) in terms of a longitudinal and a lateral trajectory, i.e., the control signals, which allow the ego vehicle to position itself in the selected gap at the desired time instance. Furthermore, the maneuver should be planned such that the ego vehicle maintains safety margins to all surrounding traffic participants and objects, respects traffic rules and regulations, as well as satisfies physical and design limitations.

1.2 Prerequisites

To successfully commercialize ADAS for automated yielding maneuvers e.g., lane change, and eventually progress to highly automated vehicles, the trajectory planning algorithm in the intelligent vehicle system must be reliable, predictable, and safe, without relying on driver-in-the-loop interaction or a lead vehicle. In addition, the algorithm should be operational in real-time as well as being economically viable and consequently realizable using as much as possible of existing sensor and actuation technologies without the assumption of Vehicle-to-Vehicle (V2V) communication or infrastructure modifications. The trajectory planning algorithms presented in Paper A-D in Part II of this thesis are thereby developed under the following set of assumptions:

- A1 The ego vehicle is equipped with sensor systems which measure its position on the road as well as e.g., the relative positions and velocities of surrounding traffic participants and objects.
- A2 The ego vehicle is equipped with prediction systems which estimate the motion trajectories of surrounding traffic participants and objects over a time horizon.
- A3 The ego vehicle is equipped with low-level control systems capable of following the planned trajectory.

Examples of the assumed low-level control system, the necessary sensor technology, and the assumed prediction systems are given in [10], [11], and [12]-[14], respectively. Furthermore, uncertainties resulting from the sensor and prediction systems can be taken into account by e.g., increasing the safety margins which the ego vehicle must maintain to the surrounding traffic participants and objects over the prediction horizon in relation to the confidence level of the assumed systems. A simplified schematic architecture of

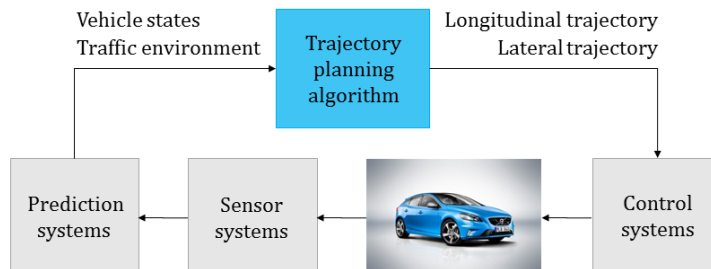


Figure 1.3: Schematic architecture of an intelligent vehicle system for automated driving.

the proposed intelligent vehicle system for automated driving is illustrated in Figure 1.3.

1.3 Contribution

The trajectory planning algorithms presented in Paper A-D in Part II of this thesis all share the following common benefits:

- Optimization of the ego vehicle’s longitudinal and lateral control signals, i.e., trajectory, without the assumption of an explicit reference trajectory.
- Optimization of the ego vehicle’s longitudinal and lateral control signals i.e., trajectory, while accounting for constraints to allow for safe and smooth maneuvers in various traffic situations.
- Optimization of the ego vehicle’s longitudinal and lateral control signals i.e., trajectory, formulated as convex optimization problems in the form of Quadratic Programs (QP) within the Model Predictive Control (MPC) framework, which provides a structured approach to express system objectives and constraints to allow for reliable, predictable, and robust, real-time implementation on a standard passenger vehicle platform.

The contribution of this thesis i.e., the proposed trajectory planning algorithms presented in Paper A-D, is thereby considered to be a building block for ADAS regarding automated driving maneuvers in traffic situations where the ego vehicle does not have right-of-way i.e., yielding maneuvers e.g., lane change, roundabout entry, and intersection crossing, and eventually highly automated vehicles. Further details regarding the scientific contribution of each individual paper are provided in Chapter 5.

1.4 Outline

This thesis consists of two parts, where Part I provides a context and background for Part II which includes Paper A-D that constitute the core of this thesis. Part I includes the following six chapters which can be read independently of each other:

Chapter 1 Scope

The first chapter introduces the topic and contribution of the thesis and gives an overview of the thesis outline.

Chapter 2 Intelligent vehicle systems for passenger vehicles

The second chapter contains a short outline of the development of automated vehicle technology from the initial idea in the late 1930s until today, and provides a brief overview of how the advances of intelligent vehicle systems have been introduced to passenger vehicles in the form of various ADAS.

Chapter 3 Trajectory planning

The third chapter provides a brief introduction to commonly used methods for trajectory planning, comments on their applicability to passenger vehicle ADAS and highly automated vehicles, and motivates the choice of MPC as the preferred trajectory planning framework in Paper A-D.

Chapter 4 Theory and tools

The fourth chapter gives a short overview of the methodologies and concepts i.e., MPC, convex optimization, QP, and reachability analysis which are utilized in Paper A-D.

Chapter 5 Summary and contribution of Paper A-D

The fifth chapter offers a summary of Paper A, Paper B, Paper C, and Paper D and clarifies the scientific contribution of each paper as well as the contribution to each paper by the author of the thesis.

Chapter 6 Concluding remarks and future research directions

The sixth chapter contains concluding remarks and a short discussion on future challenges and research directions.

Part II includes the following four papers:

Paper A J. Nilsson, P. Falcone, M. Ali, and J. Sjöberg, “Receding Horizon Maneuver Generation for Automated Highway Driving,” *Control Engineering Practice*, vol. 41, pp. 124-133, August, 2015.

Paper B J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Longitudinal and Lateral Control for Automated Yielding Maneuvers,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1404-1414, May, 2016.

Paper C J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Lane Change Maneuvers for Automated Vehicles,” Accepted for publication in *IEEE Transactions on Intelligent Transportation Systems*, 2016.

Paper D J. Nilsson, J. Fredriksson, and E. Coelingh, “Trajectory Planning with Miscellaneous Safety Critical Zones,” Submitted for possible conference publication, 2017.

Intelligent vehicle systems for passenger vehicles

Automated vehicles have been a vision for the academic and industrial community since the idea was first brought to general attention at the Futurama exhibit in 1939 [15]. The quest to develop vehicles that can control themselves and allow people to be safely driven to their desired destination at their own leisure, has however proved to be a daunting mission. Nevertheless, the last decades have witnessed tremendous achievements in automated technology for passenger vehicles as further outline in sections 2.1-2.2.

Given the intense development of intelligent vehicle systems for automated functionality in passenger vehicles, it is clear that highly automated passenger vehicles is a plausible notion in the near future. If successfully implemented, this technology will give drivers the option of handing over the control and the responsibility to the vehicle under certain conditions. Thus allowing people the freedom to safely choose how to spend their time in their vehicle while having the option of taking back control and enjoy driving whenever they want.

The US National Highway Traffic Safety Administration (NHTSA) has defined five levels of automation as explained in Table 2.1 [16] in the end of this chapter. From the definitions it can be seen that most of the current commercially available passenger vehicle ADAS reaches Level 1 automation, but their capability is continuously pushed into the Level 2 boundaries and partly automated functionality is now a reality. In the research community Level 3 automation is a fact and the ambition to reach Level 4 automation is unending. It is however important to remember that although Level 2 automation is legal since it does not change the basic assumption that a licensed driver is responsible, there is currently no legal framework except

for testing in certain jurisdictions for unsupervised automated vehicles i.e., Level 3 and Level 4 automation. Hence, as the boundary between human and machine control shifts, it becomes significantly important to address and clarify the legal and liability concerns regarding the responsibility of vehicle control.

2.1 Automated vehicles

Since the Futurama exhibit in 1939, a number of research programs in industry and academia all over the world has been conducted in order to realize the vision of safe and efficient vehicles that can control themselves without human intervention. Several national and international projects e.g., the development of the Navlab vehicle by the Carnegie Mellon University, USA [17], the European EURÉKA project PROMETHEUS [18], the advanced safety vehicle program in Japan [19], and the PATH project in the USA [20], were launched with the purpose of pushing the limit for the capabilities of automated vehicles.

In August 1997, the results of e.g., the PATH project were showcased in Demo '97 organized by the US National Automated Highway System Consortium (NAHSC). Demo '97 was held on I-15 in San Diego, California and was to that date one of the most comprehensive highway-based demonstrations. In various automated highway scenarios, where scenario control and vehicle management were accomplished by either an entirely timed and scripted program, by GPS and location-based triggering, or by situation-based triggering, the demonstration showcased the key technologies of distance keeping using radar, lidar, video, and inter-vehicle communications, as well as lane following via roadway embedded magnets, roadway laid radar-reflective stripes, or visible lane markers detected with vehicle-mounted cameras [21]-[23]. Demo '97 has since been followed by a number of demonstrations around the world showcasing both cooperative and non-cooperative automated vehicles.

2.1.1 Cooperative automated driving

The SAfe Road TRains for the Environment (SARTRE) project demonstrated in 2012 a platoon consisting of a manually driven lead truck, followed by one truck and three passenger vehicles as illustrated in Figure 2.1. In a platoon, the lead vehicle driven by a professional driver takes responsibility for the platoon consisting of following vehicles in semi-autonomous control mode that allows them to follow the preceding vehicle and imitate its longitudinal and lateral control signals. As such, vehicles can automatically follow



Figure 2.1: The SARTRE road train [9].

one another, which is expected to allow for safer and more environmental efficient transportation, while giving drivers leisure to e.g., operate a phone, reading a book, or watching a movie [24].

Vehicle platooning was also the theme of the Grand Cooperative Driving Challenge (GCDC) in 2011, where the challenge consisted of both urban and highway platooning scenarios, with a main focus on the ability to perform longitudinal control of the vehicles [25]-[26]. In May 2016 a new edition of the GCDC further expanded the scope of the challenge by requiring the vehicles to be laterally controlled and demonstrate the ability to merge platoons and to join a road via a T-intersection without driver intervention [27].

VisLab Intercontinental Autonomous Challenge (VIAC) in 2010 demonstrated the ability of automated lane keeping, waypoint-following or following of a lead vehicle, in a three month expedition from Italy to China [28]-[29]. During VIAC the automated vehicles were able to drive in unmapped and unknown scenarios, while managing any kind of obstacles at low speeds. Due to the lack of digital maps, a leader-follower approach was used to manage most of the trip, but when the follow vehicle could not view the lead vehicle, it followed coarse GPS waypoints broadcasted via radio connection by the lead vehicle, or followed the lane by using information provided by a vision-based lane markings detection system. In the follow up project Public Road Urban Driverless-Car Test (PROUD) the VIAC experience was transferred to performing automated driving on open public roads near Parma, Italy in July 2013 by utilizing an openly licensed map enriched with information about the traffic situations to be managed e.g., pedestrian crossings [30].

2.1.2 Non-cooperative automated driving

An intense development of automated vehicles was triggered by aspiring challenges advertised by the Defense Advanced Research Projects Agency (DARPA) [31]-[32]. The DARPA Grand Challenges (GC) took place in the off-road environment of the Mojave Desert, USA. In the first GC in 2004, no entry finished the race, opening up for a second chance in 2005. The second GC had a somewhat shorter route with more densely defined waypoints but had otherwise the same conditions as in 2004. As such, the second time around five teams completed the course whereas the vehicle “Stanley” developed by the Stanford racing team won the race. The main technological contributions of the challenge were regarding robust hardware and software for perception, localization, and path planning with corresponding trajectory tracking, in unknown terrain [33]-[34].

In the 2007 Urban Challenge (UC) the contestants were required to automatically execute a series of navigation missions through a simplified urban environment consisting of roads, intersections, and parking lots, while obeying traffic rules, and interacting safely and correctly with surrounding traffic participants. Of the 89 teams who entered the competition, 11 teams participated in the final event, where 6 teams completed the race that was won by the entry “Boss” developed by the Tartan racing team, consisting of researchers and professionals from Carnegie Mellon University, General Motors Corporation, Caterpillar, and Continental [35]-[37].

The DARPA UC demonstrated that vehicles can indeed be made to drive themselves in a semi-structured dynamic urban environment. However, it is important to remember that the challenge was performed in a specially designed test area that allowed for some simplifying assumptions e.g., all vehicles could be expected to follow the rules of the road, cyclist and pedestrians were non-existent, and the velocity was limited. The participants were also given clear directions of which scenarios and traffic situations that could be expected as well as a route definition file of the area to be traversed. Nevertheless, the substantial incentive that the DARPA challenges gave for pushing the boundary of state-of-the-art automated vehicles, resulted in immense research contributions within all areas of automated driving. An important aspect is that in both the GC and UC the automated vehicles did not rely on a lead vehicle and were thereby forced to make their own driving decisions rather than imitating the behavior of a preceding vehicle.

Subsequent projects by some of the teams who participated in the DARPA challenges have resulted in numerous prototype automated vehicles e.g., the Google car [38] and the MadeInGermany vehicle [39] that can be seen driven in normal traffic conditions in the streets of e.g., San Francisco and Berlin.

The project Stadtpilot which is a follow up project of Braunschweig University, demonstrated automated driving maneuvers e.g., lane keeping, adaptation of distance and speed to the traffic flow, and traffic light interaction, on the public city ring road of Braunschweig in the midst of regular traffic in October 2010 with a maximum velocity of about 60 km/h [40]-[41].

The BMW Group Research and Technology has been testing automated vehicles on Germany's highways since spring 2011, with the first automated trip without driver intervention between Munich and Ingolstadt successfully performed on June 16th 2011 [42]. Since then, thousands of kilometers have been driven on the highways around Munich, Germany, by prototype automated vehicles in real traffic with speeds up to 130 km/h [43].

In August 2013, a Mercedes Benz S-Class S 500 Intelligent Drive drove the historic Bertha Benz Memorial Route from Mannheim to Pforzheim, Germany, in an automated manner. The automated vehicle was equipped with close-to-production sensor hardware and relied solely on vision and radar sensors in combination with accurate digital maps to obtain a comprehensive understanding of complex traffic situations. To complete the route, the automated vehicle had to handle traffic lights, pedestrian crossings, intersections, and roundabouts in real traffic. It had to react on a variety of traffic participants and objects including parked, preceding, and oncoming vehicles, bicycles, pedestrians, and trams, thus testing the employed vision algorithms for object recognition and tracking, free space analysis, traffic light recognition, lane recognition, as well as self-localization in a non-structured and unpredictable environment [44].

Volvo Car Group has proclaimed a company ambition to achieve "Leadership within autonomous driving by pioneering customer offers" [45]. For instance, the project "Drive Me - self-driving cars for sustainable mobility" which will involve 100 automated passenger vehicles is a means to this end [46]. The project is a joint initiative between Volvo Car Group, the Swedish Transport Administration, the Swedish Transport Agency, Lindholmen Science Park, Autoliv, Chalmers University of Technology, and the City of Gothenburg while endorsed by The Swedish Government. As such, the Drive Me project is an unique venture since it involves all the key players of legislators, transport authorities, a major city, a vehicle manufacturer, and real customers which will utilize the 100 cars in everyday driving conditions on approximately 50 kilometers of selected roads in and around Gothenburg.



Figure 2.2: Advanced Driver Assistance Systems e.g., Adaptive Cruise Control, Lane Keeping Aid, Road Sign Information, and Blind Spot Information System [9].

2.2 Advanced driver assistance systems

Due to several technical and legal reasons as well as economic aspects, highly automated vehicles are not yet a reality for commercially available passenger vehicles. Nonetheless, today's market offers numerous ADAS e.g., as illustrated in Figure 2.2, that have the ability to assist the driver in various ways in order to relieve the stress of the driver, and provide a safer and more environmental efficient mode of transport [47].

2.2.1 First generation ADAS

Initially ADAS were based on proprioceptive sensors, e.g., accelerometers, gyroscopes, and potentiometers, i.e., sensors which measures the internal state of the vehicle, e.g., wheel velocity, acceleration, and rotational velocity. These enable the control of vehicle dynamics with the goal of following the trajectory requested by the driver in the best possible way. One of the first ADAS based on proprioceptive sensors was the Anti-lock Braking System (ABS) with serial production from 1978. The ABS limits the wheel slip to prevent the wheels from locking when the driver brakes [48]-[49]. Years later in 1995, the introduction of Electronic Stability Control (ESC), marked a further milestone in the development of ADAS. The ESC system detects if the vehicle begins to skid and assists the driver in maintaining control of

the vehicle by applying an individual braking force on one or more of the wheels which affects the yaw rotation of the vehicle in order to keep it in a stable operating region [50]-[51]. In 2002, Roll Stability Control (RSC) was introduced in order to keep the vehicle from rolling over during hard cornering maneuvers on flat roads by applying an individual braking force on one or more of the wheels [52].

2.2.2 Second generation ADAS

The second generation of ADAS is based on exteroceptive sensors i.e., sensors which acquire information from outside the vehicle e.g., ultrasonic, radar, lidar, video, and Global Navigation Satellite Systems (GNSS) receivers. These sensors provide information about e.g., the road ahead, the presence as well as the status of other traffic participants, and the vehicle's position in the world, rendering the possibility to develop ADAS which provides information and warnings to the driver, and enhance the comfort and safety of driving.

To mention a few examples, in 1995 Mitsubishi introduced ACC which is a function that uses lidar or radar sensors to measure the distance, velocity, and azimuth of preceding vehicles to improve the longitudinal control of traditional Cruise Control (CC) systems. When the roadway is free, ACC functions as a conventional CC i.e., by maintaining the ego vehicle at a desired set speed, but when a preceding vehicle is detected, the ACC system adjusts the velocity of the ego vehicle in order to follow the preceding vehicle at a safe driving distance. ACC systems are primarily designed as a comfort enhancing system for driving on highways or in similar driving conditions [53]. In 2002 Honda introduced a LKA system to the Japanese market which combines ACC with lane keeping support based on lane detection by video sensor, in order to enhance lateral control and thereby aid the driver to remain in the intended lane [54]-[55].

Further combining the functionality of ACC and LKA, BMW offers a "Traffic Jam Assistant" system which maintains a desired distance to the preceding vehicle as well as incorporates active steering support to keep the vehicle within the lane at speeds up to 60 km/h [56]. In 2016, Volvo S90 introduced a "Pilot Assist" system that automatically accelerates, brakes, and steers the ego vehicle in order to keep it within the lane and maintain a set distance to the preceding vehicle in that lane, at speeds up to 130 km/h. Even closer to automated driving, since 2015 Tesla Motors Model S offers an "Autopilot" system which allows the ego vehicle to automatically steer down the highway, change lane, and adjust speed in response to traffic flow, all the while under the supervision of the driver [57].

To protect against rear-end collisions on open roads or highways, Mer-



Figure 2.3: Parking assistance system for automatic reversing into a parking space [9].

cedes Benz has developed the “Collision Prevention Assist” system which supports the driver to maintain a safe distance to preceding vehicles and applies braking power if the risk of collision is imminent and the driver does not brake sufficiently [58]. Since 2008 Volvo Car Group offers the “City safety” system which is a low speed collision mitigation and avoidance system primarily aimed towards queue type collisions [59]. City Safety is currently standard on all Volvo models to warn the driver of hazardous situations and brake the ego vehicle if necessary to avoid or mitigate a collision with other vehicles, cyclists, pedestrians and, in some cases, even large animals on the road ahead.

Parking assistance systems as e.g., illustrated in Figure 2.3, entered the market in the mid 1990s. Initially, these systems had merely a warning function to help prevent collisions when driving into and out of parking spaces. Later, these systems were extended by rear view cameras to better assist the driver with more detailed information, and nowadays video data of the vehicle’s surroundings have been upgraded from a simple rear view to one that spans an entire 360° [60].

The introduction of electronically controllable steering allowed for developing parking assistant systems which are capable of laterally controlling the ego vehicle during parking maneuvers. In 2003 Toyota Motor Company introduced an intelligent parking assist system which steers the ego vehicle into a designated parking space. Over the years, the capability of this system expanded from parallel to perpendicular parking. In April 2015, it

was announced that the new BMW 7 Series will be able to maneuver in or out of parking spaces or garages without anyone at the wheel. It will thereby become the world's first series-produced passenger vehicle with this feature [61].

It can be expected that further automated functionalities will gradually enter the market as technology and society progress. As such, the automated driving task needs to be broken up into basic functional components that can be technically implemented at a certified level of maturity on the correct level of autonomy. To ensure the safety of any automated function, it must comply with ISO-26262 which is the primary functional safety standard for automotive systems. As such, ISO-26262 covers the management of functional safety, safety life-cycle, and safety assessment according to the Automotive Safety Integrity Level (ASIL) which is determined by a Hazard Analysis and Risk Assessment (HARA) [62]-[63].

Table 2.1: Levels of automation [16].

Level 0: No-automation (classic driving)

The driver is in complete and sole control of the primary vehicle controls (brake, steering, throttle, and motive power) at all times, and is solely responsible for safe operation of the vehicle. The vehicle may be equipped with certain driver support systems e.g., forward collision warning, lane departure warning, and blind spot monitoring but these systems do not have control authority over any of the primary vehicle controls.

Level 1: Function-specific automation (assisted driving)

Automation of one or more specific control functions, e.g., ACC, LKA, and automated parallel parking. The vehicle's automated system may assist or augment the driver in operating one of the primary controls i.e., either steering or braking/throttle controls but the driver has overall control and is solely responsible for safe operation.

Level 2: Combined function automation (partly automated, supervised driving)

Automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions, e.g., a system consisting of ACC in combination with LKA. The driver is responsible for monitoring the roadway and safe operation and is expected to be available to take over control at all times and on short notice.

Level 3: Limited self-driving automation (highly automated driving)

Automation enables the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions. The vehicle is designed to ensure safe operation during the automated driving mode. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time.

Level 4: Full self-driving automation (fully automated driving)

Automation is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Responsibility for safe operation rests solely on the automated vehicle system.

Trajectory planning

For automated vehicles to be successfully commercialized, the safety and reliability of the technology must be guaranteed. As such, a robust trajectory planning algorithm is among others a key enabling technology to realize a dependable intelligent vehicle system for automated driving that can cope with both normal and high risk driving situations.

A vehicle trajectory is defined as a path with time stamps which contains not only the geometric position, but also the velocity and acceleration information. The challenge of developing a reliable and robust trajectory planning algorithm is due to the problem of generating smooth and dynamically feasible trajectories which allow the ego vehicle to interact with other traffic participants, e.g., vehicles, cyclists, and pedestrians in such a way that ensures the safety of all traffic participants while abiding traffic rules and regulations as well as accounting for the vehicle's physical and design limitations, in real-time with the restricted computational resources of a standard passenger vehicle platform.

In the literature, various approaches to trajectory planning for automated vehicles are presented e.g., [64]-[72]. The most common techniques include but are not limited to methods that can be divided into four groups namely graph search e.g., [73]-[78], randomized sampling e.g., [79]-[84], curve interpolation e.g., [85]-[92], and numerical optimization e.g., [93]-[102], which are further explained in sections 3.1-3.4 respectively.

3.1 Graph search

The basic idea of graph search algorithms is to explore a state space with the purpose of finding the best trajectory from a start position to a goal position.

As such, the state space is divided into graph nodes or grid cells which are assigned values depending on e.g., obstacle and goal proximity. The graph search algorithm e.g., Dijkstra, A*, or D* can thereby explore the state space by utilizing a heuristic value function in order to find the most appropriate trajectory for the traffic situation. A proper value function which effectively estimates the cost from any node/cell in the graph/grid to the goal node/cell is thus essential for effective trajectory planning.

Graph search algorithms for trajectory planning have been successfully implemented and shown to generate collision-free trajectories for automated vehicles in various traffic situations. However, it may be challenging to formulate a heuristic value function that is suitable for various traffic situations and scenarios. In addition, graph search algorithms are traditionally developed for planning problems that have one fixed goal position, which is not always the case for on-road trajectory planning. Furthermore, the planned trajectory may be jerky and thus requires additional smoothing by e.g., Spline or Bézier curve interpolation. Moreover, graph search algorithms may require significant computational resources since the number of graph nodes or grid cells grows exponentially with the dimension of the state space e.g., position, heading angle, velocity etc. and as such they might require too much computational resources to be executable in real-time on a standard passenger vehicle platform.

3.2 Randomized sampling

In difference to graph search algorithms, randomized sampling-based algorithms do not rely on an explicit representation of the state space in terms of a graph or a grid. Instead, sampling-based trajectory planning algorithms e.g., Rapidly exploring Random Tree (RRT) and the Probabilistic Roadmap Method (PRM) build a graph representation by randomly sampling the configuration space. As such, a newly sampled configuration point is added to the graph if there exist a feasible trajectory which connects that point to an already existing node in the graph. Furthermore, by only adding a new node to its nearest neighbor, sampling-based algorithms are able to generate the shortest feasible trajectory which connects the initial position to the goal position.

Randomized sampling-based algorithms have the capability to generate trajectories for complex maneuvers that accounts for advanced kinematic and dynamic motion constraints. However, similar to the graph search algorithms they might suffer from high demands on computational resources due to the dimension of the configuration space. In addition, the solution trajectory

of sampling-based algorithms may be sub-optimal, jerky, and not curvature continuous.

3.3 Curve interpolation

Interpolation entails constructing a new set of data points within the range of a discrete set of previously known data points i.e., reference points. Hence, given a set of reference points which e.g., describes a road map, curve interpolation algorithms generate a new set of data points i.e., a trajectory, which allows the ego vehicle to traverse the road map from a start position to a goal position.

There are numerous methods for interpolation where some of the most common approaches for curve interpolation algorithms include but are not limited to:

Lines and circles

Interpolation between reference points is defined by straight and circular segments.

Clothoid curves

Interpolation between reference points is defined by Fresnel integrals rendering it possible to generate trajectories with linear changes in curvature which allows for smooth transitions between straight and curved segments.

Polynomial curves

Interpolation between reference points is defined by a polynomial function rendering it possible to respect constraints on e.g., position, velocity, and heading angle in the reference points which are interpolated.

Bézier curves

Interpolation between reference points is defined by parametric Bernstein polynomials and rely on control points to define the shape of the segment.

Spline curves

Interpolation between reference points is defined by piecewise parametric polynomials which allows for smooth transitions between segments.

In order to generate a safe and feasible trajectory, curve interpolation algorithms commonly evaluate a set of possible curves i.e., trajectories, based

on e.g., the risk of colliding with surrounding traffic participants, vehicle dynamics, trajectory smoothness etc. Curve interpolation algorithms thereby allow for planning a trajectory to traverse a given set of reference points while accounting for the dynamic traffic environment, vehicle dynamics, and trajectory continuity. However, all curve interpolation algorithms depend on a given set of reference points which might be challenging to define appropriately. Furthermore, curve interpolation algorithms do not provide any formal means to guarantee the optimality of the solution trajectory.

3.4 Numerical optimization

In numerical optimization, a trajectory is generated as the solution of a constrained optimal control problem. Hence, numerical optimization methods for trajectory planning aim to minimize a cost function subject to a set of constraints. The set of constraints might incorporate conditions related to vehicle dynamics, collision avoidance, and system limitations to ensure safe and smooth trajectories. If the constrained optimal control problem is solved online in receding horizon, i.e., if the problem is formulated over a shifted time horizon based on e.g., new available sensor measurement information at every time instance, the numerical optimization scheme is commonly referred to as Model Predictive Control (MPC) [103]-[104].

The main advantage of resorting to numerical optimization or MPC for trajectory planning is the easy integration of information and constraints resulting from e.g., traffic predictions or road geometry, and that collision avoidance is guaranteed, provided that the optimization problem is feasible. However, vehicle dynamics and collision avoidance constraints generally result in nonlinear and/or mixed-integer inequalities, which may lead to prohibitive computational complexity that prevents the real-time execution of the trajectory planning algorithm. To reduce the computational burden a particular optimal control trajectory planning algorithm is therefore generally tailored to a certain application, or assumes a given reference trajectory, or only allows for a short prediction horizon, or linearize the non-linear system in certain operating regions by e.g., assuming constant longitudinal or lateral vehicle control.

3.5 Why model predictive control?

As described in sections 3.1-3.4 there are various approaches to trajectory planning for automated vehicles, which all have their benefits and draw-

backs, but where the main compromise usually entails the trade-off between required computational resources, solution optimality, and ability to generate smooth collision-free trajectories which are appropriate for various maneuvers in different traffic situations. Furthermore, many of the commonly used trajectory planning methods lack formal stability analysis and verification methods and thereby rely heavily on extensive simulation and experimental testing for validation.

Since a safe trajectory is essential to successfully commercialize automated vehicles, a trajectory planning method which guarantees collision avoidance is advantageous. Hence, approaches based on numerical optimization are attractive for trajectory planning for automated vehicles since the methods provide a means to formally guarantee the reliability, predictability, and robustness of the trajectory planning algorithms. For this reason, in addition to its ability to orderly handle system constraints in receding horizon, MPC is an appropriate methodology to apply for control design of ADAS and intelligent vehicle system for automated driving.

The trajectory planning algorithms in Paper A-D in Part II of this thesis are all developed within the MPC framework in a manner that allows for reliable, predictable, and verifiable, real-time implementation. Furthermore, the proposed trajectory planning algorithms do not assume a reference trajectory, considers both the longitudinal and lateral control aspects of trajectory planning, and allows for a realistic prediction horizon. Hence, the proposed algorithms are able to deal with the conflicting demands of limited computational resources, planning in a dynamic and uncertain environment, and generation of safe and smooth trajectories in various traffic situations while abiding traffic rules and regulations as well as satisfy the ego vehicle's physical and design limitations.

Chapter 4

Theory and tools

The trajectory planning algorithms presented in Paper A-D in Part II of this thesis utilizes MPC, convex optimization, QP, and reachability analysis to formulate and solve the trajectory planning problem of automated driving maneuvers in traffic situations where the ego vehicle does not have right-of-way i.e., yielding maneuvers, described in Section 1.1. Hence, sections 4.1-4.3 provides a short introduction to each of the methodologies.

4.1 Model predictive control

The trajectory planning problem of automated driving maneuvers can be formulated as follows

$$\min_{\text{trajectory}} \text{ cost function,} \quad (4.1a)$$

subject to

$$\text{vehicle dynamics,} \quad (4.1b)$$

$$\text{physical and design constraints,} \quad (4.1c)$$

$$\text{collision avoidance constraints,} \quad (4.1d)$$

where the cost function (4.1a) reflects the control objectives e.g., allowing the ego vehicle to maintain a desired velocity while minimizing the required acceleration and jerk, the constraints (4.1b) and (4.1c) guarantee that the generated trajectory accommodates vehicle dynamics and some physical and design constraints e.g., retaining the ego vehicle within the road boundaries, while the constraint (4.1d) ensures a safe collision-free trajectory. The solution of (4.1) thereby corresponds to the most appropriate trajectory expressed as an optimal control sequence in terms of e.g., the ego vehicle's longitudinal and lateral position on the road, velocity, and acceleration.

In order to account for a dynamic and uncertain traffic environment that changes over time, the concept of Receding Horizon Control (RHC) is very useful. In contrast to fixed horizon control, in RHC only the first element of the optimal control sequence i.e., trajectory, generated as the solution to the optimal control problem (4.1) is applied to the system i.e., ego vehicle. Then the optimal control problem (4.1) is resolved based on the current state of the ego vehicle and its surrounding traffic environment. Thereby, RHC accounts for unexpected events in the surrounding traffic environment at each time instance. The main idea of RHC can thus be summarized as follows:

1. Measure the state, \mathbf{x} , e.g., the ego vehicle's longitudinal and lateral position on the road, velocity, acceleration, and relative distance and velocity to surrounding traffic participants, at the current time instance, t .
2. Solve the optimal control problem (4.1) for the current state, \mathbf{x} , to obtain the optimal control sequence, \mathbf{U} , e.g., the ego vehicle's longitudinal and lateral position on the road, velocity, and acceleration.
3. If there exists no feasible solution to the optimal control problem (4.1), then proceed to plan a backup trajectory.
4. If a feasible solution to the optimal control problem (4.1) exists, then apply the first element of \mathbf{U} to the system i.e., ego vehicle.
5. Wait for the new sampling time instance $t + 1$, then go to step 1.

If the optimal control sequence is computed by solving the optimization problem online, RHC is usually referred to as MPC. The general formulation and notation of a MPC problem is

$$\min_{\mathbf{U}_t} J(\mathbf{x}_{t|t}, \mathbf{U}_t) = \|\mathbf{P}\mathbf{x}_{t+N|t}\|_p + \sum_{k=0}^{N-1} \|\mathbf{Q}\mathbf{x}_{t+k|t}\|_p + \|\mathbf{R}\mathbf{u}_{t+k|t}\|_p, \quad (4.2a)$$

subject to

$$\mathbf{x}_{t+k+1|t} = f(\mathbf{x}_{t+k|t}, \mathbf{u}_{t+k|t}), \quad k = 0, \dots, N-1, \quad (4.2b)$$

$$\mathbf{x}_{t+k|t} \in \mathcal{X} \subseteq \mathbb{R}^n, \quad \mathbf{u}_{t+k|t} \in \mathcal{U} \subseteq \mathbb{R}^m, \quad k = 0, \dots, N-1, \quad (4.2c)$$

$$\mathbf{x}_{t+N|t} \in \mathcal{X}_f, \quad \mathbf{x}_{t|t} = \mathbf{x}(t), \quad (4.2d)$$

where $\mathbf{x}_{t+k|t}$ is the state vector at time instance $t + k$, predicted at the current time instance t , over the finite discrete time horizon, $N \in \mathbb{N}^+$, called the prediction horizon, based on the current state $\mathbf{x}_{t|t} = \mathbf{x}(t)$. The predicted state $\mathbf{x}_{t+k|t}$ is obtained by applying the optimal control sequence $\mathbf{U}_t = [\mathbf{u}_{t|t}^T, \dots, \mathbf{u}_{t+N-1|t}^T]^T$ to the system dynamics (4.2b). In (4.2a), $\mathbf{P} \in$

$\mathbb{R}^{n \times n}$, $\mathbf{Q} \in \mathbb{R}^{n \times n}$, and $\mathbf{R} \in \mathbb{R}^{m \times m}$ are weighting matrices with appropriate dimensions to penalize the final state \mathbf{x}_N , state vector \mathbf{x} , and control input \mathbf{u} , respectively. The admissible sets of states and control inputs are respectively denoted by \mathcal{X} , \mathcal{X}_f , and \mathcal{U} , where \mathcal{X}_f denotes the final set of admissible states. If $p = 1$ or $p = \infty$, $\|\dots\|_p$ denotes the p -norm while if $p = 2$, $\|\dots\|_2$ is generally considered to be the squared 2-norm.

Hence, in the MPC planning framework a trajectory is found as the solution of a constrained optimal control problem (4.2) over a finite time horizon. In particular, a cost function is minimized subject to a set of constraints including e.g., the vehicle dynamics, system limitations, and conditions introduced to avoid collisions with surrounding traffic participants and objects. The constrained optimal control problem is solved in receding horizon, i.e., at every time instance the problem is reformulated and solved over a shifted time horizon based on new available sensor measurement information. Further details concerning the MPC methodology are provided in [103]-[104].

4.2 Convex optimization and quadratic program formulation

For a yielding maneuver e.g., lane change, to be safe, the planned trajectory should allow the ego vehicle to maintain safety margins to all relevant surrounding traffic participants and objects. As an illustrative example, consider the traffic situation that is schematically depicted in Figure 4.1, in which the ego vehicle is driving on a one-way two-lane road with four surrounding vehicles. In the described traffic situation, a safe lane change maneuver entails that the ego vehicle does not enter safety critical regions defined by e.g., a time gap and minimal lateral distance which the ego vehicle must maintain to each surrounding vehicle. However, as indicated in Figure 4.1 the black region outside the safety critical regions is non-convex i.e., every pair of data points within the black region cannot be connected by a straight line segment for which each data point is also within the black region. As such, imposing collision avoidance constraints by e.g., nonlinear and/or mixed-integer inequalities to ensure that the ego vehicle remains outside the safety critical regions results in a non-convex trajectory planning problem (4.1) which generally requires too much computational resources to be appropriate for real-time implementation on a standard passenger vehicle platform.

There exist some standard non-convex optimization problems which can be transformed into convex optimization problems through a change of state variables i.e., \mathbf{x} , and manipulations on the cost function (4.1a) and set of constraints (4.1b)-(4.1d). However, generally it is very difficult to trans-

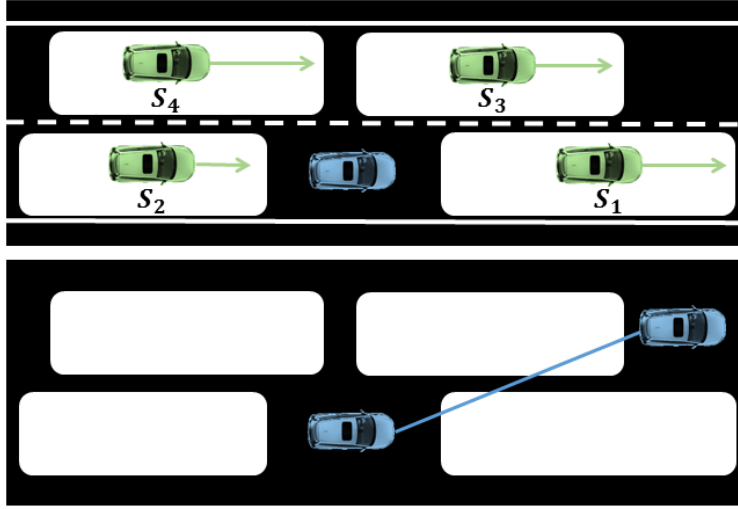


Figure 4.1: *Top:* Vehicles traveling on a one-way two-lane road. The ego vehicle is displayed in blue and the surrounding vehicles, S_1 , S_2 , S_3 , and S_4 , are displayed in green. The white boxes around each surrounding vehicle represents safety critical regions which the ego vehicle should not enter.

Bottom: The black region outside the safety critical regions is non-convex.

form a non-convex optimization problem into a convex optimization problem. Nonetheless, if a convex problem formulation can be obtained e.g., as presented in Paper A-D in Part II of this thesis, it is very valuable since convex optimization problems can be efficiently solved with low computational resources [105]. The reason why convex optimization problems can be efficiently solved is that in convex optimization problems, local optimizers i.e., solutions, are also global optimizers. Hence, when solving convex optimization problems, the computational process can be terminated when any optimal solution is found without the risk of choosing a local optimal solution. Further details regarding convex optimization are given in [106].

If the sets \mathcal{X} , \mathcal{U} , and \mathcal{X}_f in (4.2c)-(4.2d) are convex, the system described by (4.2b) is linear, and the cost function (4.2a) is quadratic, then the MPC problem (4.2) can be equivalently rewritten as a standard QP

$$\min_{\mathbf{w}} J(\mathbf{w}) = \frac{1}{2} \mathbf{w}^T \mathbf{H} \mathbf{w} + \mathbf{d}^T \mathbf{w}, \quad (4.3a)$$

subject to

$$\mathbf{H}_{\text{in}} \mathbf{w} \leq \mathbf{k}_{\text{in}}, \quad (4.3b)$$

$$\mathbf{H}_{\text{eq}} \mathbf{w} = \mathbf{k}_{\text{eq}}, \quad (4.3c)$$

with $\mathbf{w} \triangleq [\mathbf{u}_{t|t}^T, \dots, \mathbf{u}_{t+N-1|t}^T, \mathbf{x}_{t|t}^T, \dots, \mathbf{x}_{t+N|t}^T]$. The QP problem (4.3) is a

special type of mathematical optimization problem which is convex if the matrix \mathbf{H} is symmetric and positive semi-definite.

4.3 A note on reachability analysis

In order to determine whether the ego vehicle can position itself in a certain gap between some traffic participants or objects, at a certain time instance, the concept of reachability analysis can be utilized. Reachability refers to the ability of a system e.g., the ego vehicle, to get from point a to point b . Or in other words, by utilizing reachability analysis it is possible to determine whether there exists a trajectory i.e., a control sequence in terms of e.g., the ego vehicle's longitudinal and lateral position on the road, velocity, and acceleration, which allows the transition between point a e.g., E 's current position, to point b e.g., a certain inter-vehicle traffic gap.

More formally, the one-step robust reachable set for the initial states $\mathbf{x}_{t|t} \in \mathcal{X}$ of the system described by (4.2b) subject to (4.2c)-(4.2d), is defined as

$$\text{Reach}_f(\mathcal{X}) \triangleq \{\mathbf{x} \in \mathbb{R}^n : \exists \mathbf{x}_{t|t} \in \mathcal{X}, \exists \mathbf{u} \in \mathcal{U}, \mid \mathbf{x} = f(\mathbf{x}_{t|t}, \mathbf{u})\}. \quad (4.4)$$

An illustration of the reachable set for the initial states $\mathbf{x}_{t|t} \in \mathcal{X}$ under the dynamical system (4.2b) subject to (4.2c)-(4.2d) is shown in Figure 4.2. Further details concerning reachability analysis for constrained systems are provided in [107].

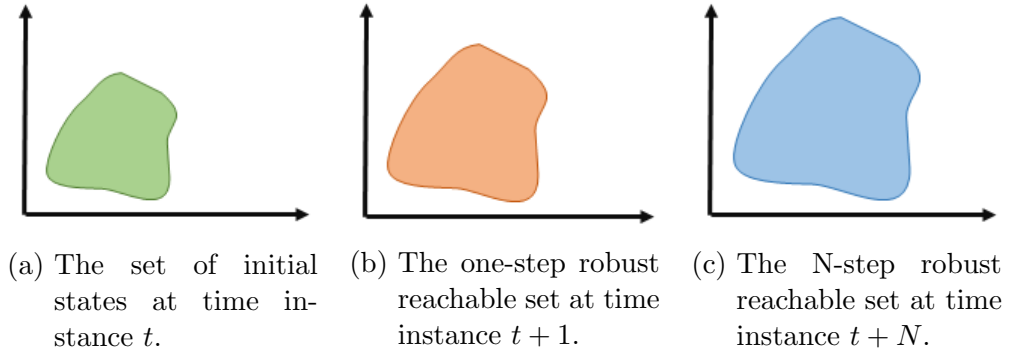


Figure 4.2: Reachable set.

Summary and contribution of Paper A-D

In addition to the common benefits which the trajectory planning algorithms presented in Paper A-D in Part II of this thesis share as described in Section 1.3, the scientific contribution of each individual paper is summarized in sections 5.1-5.4 respectively.

5.1 Paper A

J. Nilsson, P. Falcone, M. Ali, and J. Sjöberg, “Receding Horizon Maneuver Generation for Automated Highway Driving,” *Control Engineering Practice*, vol. 41, pp. 124-133, August, 2015.

Paper A focuses on the problem of decision-making and control in an automated driving application for highways. By considering the decision-making and control problem of highway driving as an obstacle avoidance trajectory planning problem, the paper proposes a novel approach to lane change trajectory planning which exploits the structured environment of one-way roads. As such, the trajectory planning problem is formulated as a convex QP optimization problem within a receding horizon control framework, as the minimization of the deviation from a desired velocity and lane, subject to a set of constraints introduced to avoid collision with surrounding vehicles, stay within the road boundaries, and abide the physical limitations of the vehicle dynamics. The ability of the proposed approach to generate appropriate traffic dependent maneuvers which can be tracked by a low-level controller is demonstrated in simulations concerning traffic scenarios on a two-lane, one-way road with one and two surrounding vehicles.

The main scientific contribution in Paper A is the linear formulation of the collision avoidance constraints which enables the decision-making and control problem of highway driving to be formulated as a low complexity convex QP. Furthermore, the proposed problem formulation allows for simultaneous optimization of the longitudinal and lateral control signals in order to determine an appropriate collision-free maneuver without the assumption of an explicit reference trajectory. As such, the proposed trajectory planning algorithm is able to determine whether a lane change maneuver should be executed, as well as plan the corresponding trajectory to either perform the lane change or remain in the current lane.

Author's contribution: the author of this thesis is responsible for developing the main idea in collaboration with M. Ali, developing the problem formulation under the supervision of P. Falcone, planning and implementing the simulations with the assistance of A. Carvalho and Y. Gao in activities related to the low-level controller [10], and authoring the paper.

5.2 Paper B

J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Longitudinal and Lateral Control for Automated Yielding Maneuvers,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1404-1414, May, 2016.

Paper B presents a trajectory planning algorithm for automated yielding maneuvers i.e., maneuvers where the ego vehicle does not have right-of-way e.g., lane change, roundabout entry, and intersection crossing. By considering yielding maneuvers as primarily a longitudinal motion planning problem, the proposed algorithm determines whether there exists a longitudinal trajectory which allows the ego vehicle to safely position itself in a gap between surrounding traffic participants and objects e.g., vehicles, pedestrians, and road barriers. Furthermore, if such a trajectory exists, the algorithm plans the corresponding lateral trajectory for the maneuver. The proposed trajectory planning algorithm can thereby be formulated as two loosely coupled low-complexity convex QPs which can be efficiently solved to obtain longitudinal and lateral motion trajectories for various maneuvers. Simulation results show the ability of the proposed trajectory planning algorithm to generate smooth and safe trajectories which are appropriate in various traffic situations i.e., lane change, roundabout entry, and intersection crossing.

The main scientific contribution in Paper B is the formulation of the low-complexity trajectory planning algorithm for longitudinal and lateral control

in various maneuvers for which the ego vehicle does not have right-of-way i.e., yielding maneuvers e.g., lane change, roundabout entry, and intersection crossing.

Author's contribution: the author of this thesis is responsible for developing the main idea and problem formulation in collaboration with M. Brännström, planning and implementing the simulations, and authoring the paper.

5.3 Paper C

J. Nilsson, M. Brännström, J. Fredriksson, and E. Coelingh, “Lane Change Maneuvers for Automated Vehicles,” Accepted for publication in *IEEE Transactions on Intelligent Transportation Systems*, 2016.

Paper C extends on the results presented in Paper B by integrating the trajectory planning algorithm for lane change maneuvers with a novel approach inspired by reachability analysis for selecting an appropriate inter-vehicle traffic gap in the target lane and the time instance to initialize the lateral movement into the selected gap. Furthermore, Paper C includes experimental results of a Volvo V60 performing lane change maneuvers on a test track, which demonstrates the real-time ability of the proposed lane change maneuver algorithm to generate smooth and safe lane change trajectories which are appropriate in various traffic situations.

The main scientific contribution in Paper C is the formulation of the approach for selecting an appropriate inter-vehicle traffic gap in the target lane and the time instance to initialize the lateral movement into the selected gap, which significantly reduces the required computational time of the lane change trajectory planning algorithm. In addition, the capability of the proposed trajectory planning algorithm to generate appropriate lane change maneuvers in real-time on a standard passenger vehicle platform is demonstrated by experimental tests.

Author's contribution: the author of this thesis is responsible for developing the main idea of the approach for selecting an appropriate inter-vehicle traffic gap in the target lane and the time instance to initialize the lateral movement into the selected gap, planning and implementing the simulations, involvement in the vehicle implementation in collaboration with colleagues at Volvo Car Group, planning and conducting the experiments with the assistance of colleagues at Volvo Car Group and Hällered test track, and authoring the paper.

5.4 Paper D

J. Nilsson, J. Fredriksson, and E. Coelingh, “Trajectory Planning with Miscellaneous Safety Critical Zones,” Submitted for possible conference publication, 2017.

Paper D extends on the results presented in Paper B and Paper C by allowing the algorithm to plan trajectories which account for motion dependent safety critical zones of miscellaneous shape. As such, in Paper D the proposed algorithm does not only account for rectangular safety critical zones which are defined by e.g., a time gap which the ego vehicle must maintain to surrounding traffic participants, but rather allows for safety critical zones defined by both the planned longitudinal and lateral motion of the ego vehicle. The ego vehicle is thereby able to efficiently utilize the free road space and traverse dense traffic situation in a self-assertive manner rather than exhibit an excessively conservative behavior.

The main scientific contribution in Paper D is the extension of the trajectory planning algorithm proposed in Paper B and Paper C which allows the algorithm to account for safety critical zones of miscellaneous shape defined by both the planned longitudinal and lateral motion of the ego vehicle.

Author’s contribution: the author of this thesis is responsible for developing the main idea and problem formulation, planning and implementing the simulations, and authoring the paper.

Concluding remarks and future research directions

During the last decades, the capability of automated vehicles has increased from lane centering and vehicle following to driving on public roads where a few research platforms have shown remarkable performance. However, the ability of automated vehicle technology with respect to e.g., sensing with corresponding motion prediction and intention recognition of surrounding traffic participants, decision-making, and trajectory planning, has not yet reached the same level as that of skilled human drivers. Nonetheless, numerous ADAS e.g., ACC, LKA, and collision warning and mitigation systems are currently successfully offered in standard passenger vehicles. If the automated functionality in passenger vehicles continues to increase, the long term consequence is that intelligent vehicle systems will have the capability to perform more and more of the traditional driving tasks and eventually become highly automated. It is expected that automated passenger vehicles will initially be introduced in highways since the structured environment of highways renders a high level of vehicle autonomy realizable [108]. Furthermore, due to congestion, accidents, and high variation in vehicles' velocity, highway driving can be both tedious and stressful and as such it is desirable to improve the driving experience by allowing drivers to safely engage in secondary tasks.

For automated vehicles to be successfully commercialized, the safety and reliability of the technology must be guaranteed. As such, a reliable and robust trajectory planning algorithm is among others a key enabling technology to realize a safe and dependable intelligent vehicle system for automated driving that can cope with both normal and high risk driving situations. This thesis thus focuses on the problem of real-time trajectory planning for safe

and smooth automated lane change maneuvers. In addition, the thesis addresses the trajectory planning problem of other maneuvers where the ego vehicle does not have right-of-way i.e., yielding maneuvers e.g., roundabout entry and intersection crossing. The considered problem of generating an appropriate, safe, and smooth trajectory consisting of a sequence of longitudinal and lateral control signals is formulated as convex optimal control problems in the form of QPs within the MPC framework in a manner that allows for reliable, predictable, and robust, real-time implementation on a standard passenger vehicle platform. The proposed algorithms in Paper A-D in Part II of this thesis is thereby able to deal with the conflicting demands of limited computational resources, planning in a dynamic and uncertain environment, and generating provable safe trajectories, while abiding traffic rules and regulation, as well as satisfying the ego vehicle's physical and design limitations. The contribution of the thesis i.e., the trajectory planning algorithms presented in Paper A-D in Part II, is thus considered to be a building block for ADAS regarding yielding maneuvers e.g., lane change, and eventually highly automated vehicles.

In terms of further developing any of the algorithms presented in Part II of this thesis into industrial applications, the trajectory planning algorithm presented in Paper B, Paper C, and Paper D is considered to have the best potential due to its simplicity and flexibility which renders it applicable to trajectory planning for various yielding maneuvers e.g., lane change, roundabout entry, and intersection crossing. Hence, in order to fully understand the range of possible industrial applications which could arise from the proposed trajectory planning algorithm, its performance should undergo extensive testing in real world traffic situations for various traffic scenarios.

Since the proposed trajectory planning algorithm presented in Paper B, Paper C, and Paper D is developed under the assumption that the intelligent vehicle system knows which maneuver to perform e.g., a lane change, a decision-making algorithm that determines which maneuver to perform, ought to be developed and incorporated with the proposed trajectory planning algorithm e.g., as described in [109]. Furthermore, in order to make an appropriate decision regarding which maneuver to perform and plan a safe trajectory which accounts for the surrounding traffic participants and objects, it is crucial that the intelligent vehicle system has a good understanding of the surrounding traffic environment. As such, reliable sensor systems which acquire information regarding the surrounding traffic environment and prediction systems e.g., [14] which estimates the motion trajectories of surrounding traffic participants over a time horizon are essential for the performance of the proposed trajectory planning algorithm.

As previously mentioned in Section 1.2, the trajectory planning algorithm

has the ability to account for uncertainties resulting from the sensor technology or motion prediction by e.g., increasing the safety distance which the ego vehicle must maintain to surrounding traffic participants and objects over the prediction horizon in relation to the confidence level of the sensor and motion prediction systems. In addition, the re-planning nature of MPC allows changes in the perceived environment to be accounted for at each time instance. Nonetheless, how to cope with limited sensor information and prediction uncertainty is an important topic which should be further evaluated in order to ensure the performance of the proposed trajectory planning algorithm. A related topic is the issue of determining when and how to generate backup trajectories to e.g., abort a maneuver in case it becomes unfeasible e.g., due to unexpected events in the surrounding traffic environment.

In order to introduced new and improved ADAS to the market e.g., an automated lane change assistance system, and eventually highly automated vehicles, each functional component must be technically implemented to comply with the ASIL requirements of ISO-26262, as aforementioned in Section 2.2.2. As such, a functional safety concept to ensure the overall safety of the system in terms of e.g., the safe management of likely operator errors, hardware failures, and environmental changes, should be developed. Hence, the development of a method that guarantees that the ego vehicle will always be able to execute a safe maneuver without excessively conservative constraints under which the trajectory planning algorithm should operate, is perhaps the final key to realize automated vehicles which are safe, smooth, and self-assertive.

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