A Methodology for Safety Assessment of Highly Automated Vehicles

From Scenario Classification to Corner Case Identification

Dissertation
to obtain the academic degree of
Doktor der Technischen Wissenschaften
in the Doctoral Program
Technische Wissenschaften
Sworn Declaration

I hereby declare under oath that the submitted thesis has been written solely by me without any third-party assistance, information other than provided sources or aids have not been used and those used have been fully documented. Sources for literal, paraphrased and cited quotes have been accurately credited.

The submitted document here present is identical to the electronically submitted text document.

Linz, 18 June 2019

DI. Jinwei Zhou
Acknowledgement

Five years have passed since I joined the Institute of Design and Control Mechatronical Systems to pursue a Ph.D. degree. Since then, it has been a journey full of passion, learning, and intellectual growth. As I stand at the end of this road, I would like to appreciate those who are an indispensable part of this wonderful journey.

First I would like to take a moment to thank my supervisor, Prof. Luigi del Re, who assisted me along this road. Without his help, I could not have reached the point where I stand now. His inspiration and influence on me are beyond what this dissertation reflects, and I will benefit from it for all my life.

Second, I would like to thank my office colleague Dr. Pavlo Tkachenko, who helped me to think about the problem deeply and was always ready to help. I would like to thank my colleagues at the Johannes Kepler University Linz (JKU), Institute of Design and Control Mechatronical Systems. Thanks for all their unreserved help. They provided a wonderful research environment. Their professional attitudes and great supports always encourage me to improve my work and become a better engineer. Specifically, I would like to give my thanks to Ass.-Prof. Harald Waschl, who brought me into the world of researchers and gave me immeasurable help.

I want to thank all my family for their unconditional support. My father and my mother have always been my best friends and models for how to live life.

I further express my thanks to KendoLinz SportUnion, which is like a family to me in Linz.

Lastly, I would like to close this acknowledgment with poetry lines from a chinese poet, Mr. Guozhen Wang, which helped me to survive the hardest period of my life:

我不去想, 是否能够成功, 既然选择了远方, 便只顾风雨兼程。
我不去想身后会不会袭来寒风冷雨, 既然目标是地平线, 留给世界的只能是背影。
Abstract

Autonomous driving represents a technological leap forward that will likely solve key aspects of the transport problem and so have beneficial effects for some critical social and ecological issues as well.

Indeed, thanks to increasing levels of automation, the Highly Automated Vehicle (HAV) is expected to be able to handle more and more complex traffic situations so that it can take over driving tasks and free human beings from driving for long periods of time. It is also expected to reduce accidents and improve traffic fluidity, reducing the overall carbon footprint, among other advantages.

However, the higher the automation level, the more complex the HAV. As addressed by many, testing and validation of the HAV, so as to guarantee safety, is one of the most challenging tasks that still prevent the HAV from commercial release. Complexity excludes the use of well established methods for testing of classical vehicles, by on-road testing. This has led to a wide consensus that simulation - “virtual testing” - must be included as early as in the design phase. However, even simulation cannot test all possible situations. As HAVs will include many functions which can be updated frequently and require re-evaluation in short time, fast re-evaluations will be needed to prevent new dangers arising from the updates.

This leads to the dilemma of HAV testing: on one side, we need to test enough situations to be confident about the behavior of HAV in the general, unknown case, but on the other side these tests need to be as limited as possible.

Against this background, this research work is focused on developing such a methodology. The key idea is to replace on-road testing by accident statistics – so to say “involuntary” fleet testing – and to use model based methods as well as Design of Experiments to determine a limited set of cases to be tested.

As an example to explain our approach, we concentrate on highways and starts by establishing a catalogue of countable scenarios, which cover over 90% of the (near-) crashes reported in U.S. highway databases between 2010 and 2013. Utilizing the catalogue, an approach has been developed leading to a realistic but parsimonious model based parametrization of the scenarios using experimental measurements. This allows covering the majority of the measured real traffic situation with a rather simple parameter set. The parametrization can then be used to determine a boundary that separates safe conditions from unsafe ones by a suitable Design of Experiment strategy.
The region near the boundary is what the further validation should focus on: the so-called corner cases. Based on this collision free boundary, we also developed an approach quickly estimating the collision probability of the HAV with respect to the real traffic situation. The collision probability is often taken as the criteria for the safety assessment of the HAV in term of collision detection and avoidance.

Usually, the collision probability is computed only in view of the behavior of the HAV, even though in a real setting it is also altered by the reaction of other traffic participants. As an example, the HAV can change correctly lane to the left, but if another vehicle on the new lane is approaching from behind with higher velocity, a collision can still result. Or cutting in in front of a slower vehicle can be completely safe for the HAV, but it may cause a panic reaction by a human driver in the other vehicle and lead to an accident between other vehicles. Therefore, we propose to extend the safety assessment by an additional criteria, which we call cautiousness, which in the mentioned cases would be related to the gaps left in front of the other vehicles.
Kurzfassung


Je höher jedoch der Automatisierungsgrad, desto komplexer ist das HAV. Wie in verschiedenen Literaturen angesprochen, ist die Prüfung und Validierung des HAVs, um die Gewährleistung der Sicherheit zu gewährleisten, eine der schwierigsten Aufgaben, die das HAV an der kommerziellen Freigabe hindern. Um das Testen und Validieren des HAV bereits in der Designphase zu ermöglichen, muss die Simulation (Virtual Testing) einbezogen werden.

Daher liegt der Schwerpunkt dieser Forschungsarbeit auf der virtuellen Erprobung des HAV. Die These betrifft die Entwicklung einer Methodik zur Begrenzung der Anzahl der Fälle, die bei der virtuellen Prüfung der HAV sowie verschiedene Ansätze zur Beurteilung der Sicherheit des HAVs.


Basierend auf der kollisionsfreien Grenze haben wir auch einen Ansatz entwickelt, der die Kollisionswahrscheinlichkeit des HAV in Bezug auf die reale Verkehrssituation schnell schätzt. Die Kollisionswahrscheinlichkeit wird oft als Kriterium für das Sicherheitskeller des HAV im Hinblick auf die Kollisionserkennung und -vermeidung herangezogen.
Für einige Situatio nen wird die Kollisionswahrscheinlichkeit nicht nur durch das Verhalten des HAVs bestimmt, sondern auch durch die Reaktion anderer Verkehrsteilnehmer verändert. Z.B. in der Einfahrsituation wechselt das HAV die Spur nach links, wobei sich ein anderes Fahrzeug mit höherer Geschwindigkeit von hinten dem HAV nähert. In diesem Fall ist der auf Kollisionswahrscheinlichkeit basierende Ansatz für die Sicherheitsbewertung nicht einfach anwendbar, da das Bremsmanöver dieses Hinterfahrzeugs hauptsächlich bestimmt, ob es mit dem HAV kollidiert.

Ergänzend zur Kollisionswahrscheinlichkeit haben wir auch alternative Kriterien für das Sicherheitskeller des HAVs mit Spurwechselfunktion, meist bekannt als autonome Überholfunktion, vorgeschlagen. Dieser Ansatz konzentriert sich auf die Bewertung der Vorsicht des HAVs in einer Spurwechselsituation durch Beobachtung der Wahl der verschiedenen Lücken, die unabhängig von der Reaktion anderer Verkehrsteilnehmer sind, vor Beginn eines Spurwechselmanövers. Es ermöglicht eine schnelle Abschätzung der potenziellen Auswirkungen des Spurwechselmanövers des HAVs auf die anderen Verkehrsteilnehmer auf der angrenzenden Fahrspur und bewertet so seine Sicherheit in Bezug auf die reale Verkehrssituation.
## Contents

Acknowledgement iii

List of Figures xiii

List of Tables xvii

1 Introduction 1

1.1 Motivation ........................................ 1

1.2 Overview of Highly Automated Vehicles .............. 4
1.2.1 Levels of Automation .............................. 4
1.2.2 Current Industrial Status of HAVs ............... 5

1.3 Methods for Safety Testing ........................... 7
1.3.1 What is safety for HAVs? .......................... 7
1.3.2 Current Safety Testing Concepts in Automobile Industry ... 7
1.3.3 Safety Testing for HAVs ............................ 8
1.3.4 State-of-the-Art Virtual Testing of HAVs .......... 9

1.4 Contributions of this thesis .......................... 10

1.5 Outline ............................................ 14

2 Test Scenario Catalogue 17

2.1 Preliminaries ....................................... 17

2.2 From Human Driver Accidents To Scenario Catalogue for Safety Assessment of HAVs ................................. 19
2.2.1 Crash Causation and Testing Scenarios of HAVs ......... 19
2.2.2 Crash Database .................................. 20
2.2.3 Overview on Scenario Catalogue ..................... 21

2.3 Basic Scenarios ..................................... 23
2.3.1 Formation of Scenarios ............................ 23
2.3.2 Inference of Basic Scenarios ....................... 25
2.3.3 Summary ....................................... 27

2.4 Complex scenarios ................................... 28
2.4.1 The Transition between Basic scenarios ............. 29
2.4.2 Generation of Complex scenarios ................... 29

2.5 Summary ............................................. 32
## List of Figures

1.1 The relationships between each phase of the development life cycle and its associated phase of safety evaluation, source: [94] .......................... 3

1.2 Definitions for levels of automated driving, level 1 (hands on), level 2 (hands off), level 3 (eyes off), level 4 (mind off), level 5 (steering wheel optional), source: [86] ................................................................. 4

2.1 Empirical segmentation of the space around the EGO ........................ 18

2.2 Relevance of the crashes in terms of testing of HAVs ........................ 20

2.3 Composition of SHRP 2 NDS database, 36822 records in Total ........ 20

2.4 Threat actions from (near-)crashes that are not covered by the catalogue 23

2.5 Screening and states of the maneuvering vehicles .............................. 23

2.6 Exemplary classification used in this work ........................................ 24

2.7 Exemplary inference of the complex scenario: braking as transition ...... 30

2.8 Complex scenarios: lane change evasive action as transition ............ 30

3.1 Concept: safety testing of HAVs based on a parametrization of scenario and separation of abnormal cases using FOT measurements ................. 34

3.2 Scenario No.10: Cut-in ................................................................. 35

3.3 Equipment for data acquisition ......................................................... 36

3.4 Exemplary post-processed data of the surrounding vehicles ............... 37

3.5 Extracted lane change maneuvers (from the left lane to the right) ...... 37

3.6 The coordinate used in this thesis .................................................. 38

3.7 Characterizing human drivers’ lane change maneuver by linear piecewise function .......................................................... 39

3.8 The equivalent lane change features for the hyperbolic tangent function based lane change model ..................................................... 40

3.9 Distribution of MAE for 2–dimensional time course using hyperbolic tangent function and resulting lane change characteristics ................. 43

3.10 Exemplary approximation of 2–dimensional time course using hyperbolic tangent function and the distribution of the mean absolute errors MAE .... 45

3.11 MAD of longitudinal and lateral part versus ξ .................................. 46

3.12 Fitting performance comparison of all 167 recorded lane change maneuvers: parametrization Eq. (3.8) \( v(t) = v_0 \) and Eq. (3.12) \( v(t) = v_0 + a_0 \cdot t \) ........ 47

3.13 Fitting performance with respect to the parametrization complexity .... 51

3.14 lane change characteristics and fitting errors ................................. 52
3.15 Exemplary trajectory generation for lane change maneuver via Eq. (3.15) 53
3.16 Parametrization of Scenario No.10 53
3.17 Simulation Environment 55
3.18 Exemplary three dimensional parametrization and simulation results 56

4.1 The criteria of safety assessment based on an exemplary test scenario 60
4.2 Exemplary three dimensional parametrization and simulation results 61
4.3 Output of the GPC Pr contour and the variance \( V_q \) vs \( \{ \Delta v_0, \Delta y_0 \} \) for the simplified two dimensional parametrization of scenario No.10 65
4.4 Pr contour vs \( \{ \Delta v_0, \Delta y_0 \} \) and predictive collision boundary over various iterations 66
4.5 Variance \( V_q \) and predictive collision-free boundary over various iterations 67
4.6 Equipment for data acquisition 68
4.7 The distribution of predictive probabilities over iterations 69
4.8 Analyzing the correlation between \( e_\% \) and \( \Theta_{th,\%} \) 70
4.9 Comparison of simulation results after different iteration steps 72
4.10 Relative Approximation error \( e_\% \) and distribution of predictive probability \( \Theta_{th,\%} \) 73
4.11 Estimated joint distribution of 3 Parameters for the exemplary parametrization of scenario No.10 75
4.12 Estimate the occurrence of the crash related subspace 76
4.13 Parametrization of scenario No.11 77
4.14 Measurements of the lane change maneuver: from right lane to the left lane 78
4.15 Characteristics of lane changing maneuvers: from right lane to the left lane 79
4.16 Exemplary 3-dimensional parametrization of scenario No.11 80
4.17 Comparison of simulation results after different iteration steps 81
4.18 Estimated joint distribution of 3 Parameters for the exemplary formalization of scenario No.11 and the exposure of those specified testing scenarios (crash) 82

5.1 Exemplary scenarios: 1) front-vehicle cuts in front of the EGO (HAV), 2) the EGO (HAV) pulls out and encounters a rear-vehicle in the adjacent lane [117] 87
5.2 Parameters, defining the gaps in Eq. (5.1) 90
5.3 Measurements of human driver in cut-in situation 92
5.4 Maximum deceleration \( a_{min} \) of rear vehicles in response to \( \text{TTC}_0, \Delta v_0, \) and \( \Delta y_0 \). \( g \approx 9.8 \text{ m/s}^2 \) 93
5.5 Deceleration measured the rear-vehicle’s continuous reaction to the cut-in with respect to \( \text{TTC}, \text{THW}, \) and \( \Delta y, \ g \approx 9.8 \text{m/s}^2 \). 94
5.6 Illustration of the pass-by scenario 95
5.7 Parametrization of scenario Pull-Out 96
5.8 Distribution of accepted gaps \( \text{TTC}_0 \) and \( \Delta y_0 \) of 2 autonomous overtaking systems [51] compared with human drivers 97
5.9 Distribution of continuous changing of gaps, over the cut-in duration, of 2 autonomous overtaking systems [51], compared with human drivers 98
5.10 The exemplary lateral trajectories of normal cut-in and cut-in with evasive steering
# List of Tables

1.1 Classification of the driver-related critical causes, source: [58] .................. 2
1.2 Predicted road maps on development and release of the HAVs of selected companies (Source:[82]) ................................. 7

2.1 Assignment of Critical Causes of NMVCCS Crashes (Source:[82]) ............... 19
2.2 Details on Critical Events ................................................................. 21
2.3 Assignment of 631 Critical Events .................................................... 22
2.4 Basic scenarios: The EGO is in the free-driving state ............................ 26
2.5 Basic scenarios: EGO in the course of lane change maneuver ................. 27
2.6 Basic scenarios: EGO in the car-following situation ............................ 28
2.7 Complex test scenarios: via braking evasive action ............................. 31

3.1 Fitting performance indices with respect to parametrization complexity .... 50

4.1 GPC based iterative algorithm for boundary searching ......................... 68

5.1 \( \text{TTC}_0 \) acceptance of human driver and 2 autonomous overtaking functions in \([s]\) ................................................................. 97
5.2 minimum gaps, appeared during the cut-in, of 2 autonomous overtaking functions, comparing with human driver ................. 98

A.1 Complex test scenarios: via lane-changing evasive action .................. 104
A.2 Complex test scenarios: via lane-changing evasive action .................. 105
To my parents:

金文菲 (JIN Wenfei) & 周玉龙 (ZHOU Yulong)
Chapter 1

Introduction

1.1  Motivation

Highly Automated Vehicle (HAV) technologies have advanced dramatically in recent years and offer an impressive potential to transform ground mobility in the future. Over the past few decades, considerable efforts have been made to develop automated transportation technology and have manifested tremendous technological advances in numerous areas.

The first concern with automated transportation’s safety. Automobile safety is a crucial issue that has existed since the beginning of mechanized road vehicles. The earliest recorded car death was in a small town in central Ireland in 1869 [21], and the deceased was named Mary Ward. According to the World Health Organization’s (WHO) World Report on Road Traffic Injury Prevention [65], approximately 1.2 million people worldwide die from traffic crashes each year, and 25 million people suffer permanent disabilities due to traffic accidents. Although the fatality rates per vehicle registered and per vehicle distance traveled have steadily decreased, the raw number of fatalities generally increases as a function of rising population and more vehicles on the road. By 2020, road traffic accidents may become the sixth most common cause of death worldwide [54] and third in rank order of DALYs\(^1\) for the 10 leading causes of the global burden disease [65]. Since the launch and promotion of safety glasses and seat belts in 1930 [100], efforts have been made to develop technologies and introduce various safety systems such as crumple zones, safety belts, airbags, and active safety systems, (for example, Anti-lock Braking System (ABS), Electronic Stability Program (ESP), collision warning/avoidance, and intelligent speed adaptation [98]). As a consequence of these efforts, road mortality in the United States is halved every two decades: 51 per billion Vehicle-Mile-Traveled(VMT) in 1960 to 11 per billion VMT in 2011 [5]. In National Highway Traffic Safety Administration (NHTSA)’s report on Tesla, it has pointed out that crash rates involving Tesla cars have dropped by almost 40 percent since the wide introduction of Autopilot system

\(^1\)DALY: Disability-adjusted life year. A health-gap measure that combines information on the number of years lost from premature death with the loss of health from disability [65].
which can be classified as somewhere between levels 2 and 3 under Society of Automotive Engineers (SAE)’s automation level definitions.

As illustrated in [58], the critical causes of the on-road accidents can be assigned to the human driver at approximately 94% of all accidents, which can be broadly classified into several error types listed in Table 1.1. Therefore, it is likely that all these errors can be avoided by a broad adoption of the HAVs of automation level 4 and above, see Fig. 1.2.

Table 1.1: Classification of the driver-related critical causes, source: [58]

<table>
<thead>
<tr>
<th>Error types</th>
<th>Actions of drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recognition errors</td>
<td>• driver’s inattention</td>
</tr>
<tr>
<td></td>
<td>• internal and external distractions</td>
</tr>
<tr>
<td></td>
<td>• inadequate surveillance</td>
</tr>
<tr>
<td>Decision errors</td>
<td>• false assumption of other traffic participants’ actions</td>
</tr>
<tr>
<td></td>
<td>• driving too fast for conditions or for the curve,</td>
</tr>
<tr>
<td></td>
<td>• illegal maneuver and misjudgment of gap or others’ speed</td>
</tr>
<tr>
<td></td>
<td>• aggressive driving behavior</td>
</tr>
<tr>
<td>Performance errors</td>
<td>• overcompensation</td>
</tr>
<tr>
<td></td>
<td>• poor directional control</td>
</tr>
<tr>
<td>Non-performance errors</td>
<td>• sleep</td>
</tr>
<tr>
<td></td>
<td>• heart attack</td>
</tr>
<tr>
<td>Others</td>
<td></td>
</tr>
</tbody>
</table>

Besides improved safety, another possible benefit is time saving. According to the Federal Highway Administration (FHWA)’s report on Traffic Volume Trends (August 2014) [63, 90], it is estimated that Americans are driving about 3.2 trillion miles per year. That’s approximately 5.15 trillion kilometers, almost 16,000 kilometers per person in the U.S. per year. If we assume that the average travel speed is 50 kilometers per hour, and that each vehicle holds one person, then it would translate to around 103 billion hours spent in the car. By introduction of the HAV, you will have more time to do things other than drive.

Apart from safety and time saving, the advancement of HAVs can bring massive social and economic benefits [17, 5, 31], especially for elderly and disabled people. They can ease the traffic congestion, decrease the fuel consumption, and limit the release of harmful emissions and greenhouse gas. Research has found that the broad implementation of autonomous vehicles can potentially drop the total greenhouse gas by approximately 40 – 60% [34]. The impact of HAVs on traffic capacity has been addressed in [25]. It has been found that the capacity of a lane in proportion to the share of autonomous vehicles for pure passenger car traffic increases with the wide adoption of HAVs in the traffic due to less traffic oscillation and the reduced
average headway. In their example, at 0% (pure human driver), the capacity is below 2500 cars per hour, at 50% HAVs, capacity reaches a value of about 3100 cars per hour, thus obtaining 33% of the increase that would be possible if all vehicles were autonomous (about 4300 cars per hour) [25].

Summarizing, HAV are a technological leap and effectively solve many current transportation problems. However, before HAV commercialization, it needs intensive testing to guarantee high security and reliability, which is a daunting task. Fig. 1.1 illustrates the standard procedure of the development and verification, widely used in the automotive industry, based on the V-Model. This procedure is also applicable for the advancement of the HAV with a low level of automation, also known as Advanced Driver Assistance Systems (ADAS), due to their limited functionality and operation situations. Nevertheless, the higher the automation level, the broader and more complex the operation field is. This means that the standard approach used with testing of conventional vehicles, on-road fleet testing, would be much more complicated as many more cases need to occur with a sufficient frequency to allow an estimate of the accident probabilities. To cope with this problem, the National Highway Traffic Safety Administration’s (NHTSA) [108] released a policy on testing and evaluating the performance of the HAV based only on the real world scenarios (i.e. a sequence of driving events like accelerating, lane changing etc.) that are relevant to the corresponding functions of the automation systems. Unfortunately, it is hard to predict all possible relevant scenarios. To the best of author’s knowledge, there is still no suitable approach for it.

![Figure 1.1](image)

**Figure 1.1:** The relationships between each phase of the development life cycle and its associated phase of safety evaluation, source: [94]

In this work we propose a methodology for safety testing of the highly automated vehicles of Level 3 (*eyes off*) and above. The first step consists in determining the critical scenarios using available accident data bases for conventional vehicles. The underlying idea is that the scenarios will be the same for automated functions, as these are performing the same tasks as human drivers, and have to work in a mixed environment in which most drivers will be human for a significant time. However, as
the performance of the automated functions should be better than the average human drivers, it is necessary to actively search the parametrization of the scenarios, i.e. the combination of speeds and distances, which may prove challenging for the automated function. This leads to determine the cases which are likely to produce accidents even for automated functions, and must be specifically tested.

1.2 Overview of Highly Automated Vehicles

1.2.1 Levels of Automation

The Society of Automotive Engineers (SAE) defined six levels of automated driving in the SAE J3016 Standard [86] as shown in Fig. 1.2.

Between manually driven vehicles (SAE Level 0) and fully autonomous vehicles (SAE Level 5), there are a variety of vehicle types with a varying degree of automation. These are collectively known as semi-automated vehicles. A key distinction is between level 2 ("hands off"), where the human driver performs only part of the Dynamic Driving Task (DDT), and level 3, where the Automated Driving Function (ADF) performs the entire DDT task when engaged. Since it will take a while before the technology and infrastructure are developed for full automation, it is likely that vehicles will first have a higher level of automation and full automation will become widespread only at
1.2 Overview of Highly Automated Vehicles

a future time. These semi-automated vehicles could potentially harness many of the advantages of fully automated vehicles, while still keeping the driver in charge of the vehicle. As the ESP has been mandatory in new cars in the U.S and the European Union since 2012 and 2014, respectively, all new passenger vehicles can readily be called at least level 1 automated vehicles [101].

Currently most automakers are developing vehicles at level 2, where the vehicle can assist with steering or/and acceleration functions and allow the driver to disengage from some of their tasks. The driver must always be ready to take control of the vehicle and is still responsible for most safety-critical functions and all monitoring of the environment.

1.2.2 Current Industrial Status of HAVs

We initially give a brief rough overview of ADFs industrial status. As the development is continuous and names are different, this is not meant to be exhaustive. In some cases, some functions are introduced, and then removed, so progress is not necessarily continuous.

1.2.2.1 Level 1 ADFs

Most ADFs for one degree of freedom is at automation level 1 ("hands on"). The automation system takes over one or two of the 3 control inputs of the vehicle, namely steering, accelerating, or braking. The driver is usually responsible for monitoring the traffic situation and handling the remaining control inputs to accomplish the driving tasks. Some existing ADFs for one degree of freedom are listed in the following [99].

- **Cruise Control (CC)** (sometimes known as speed control or autocrui se, or tempomat in some countries) is a system that automatically controls the speed of a motor vehicle as set by the driver.
- **Adaptive cruise control (ACC)** is an extended cruise control system for road vehicles that automatically adjusts the vehicle speed to maintain a safe distance from vehicles ahead.
- **Autonomous Emergency Braking (AEB)** is a one dimensional Collision Avoidance System (CAS) designed to prevent or reduce the severity of a collision. It uses various sensors to detect an imminent crash and take the brake action autonomously without any driver input.
- **Lane Centering (LKA)**, also known as auto steer, is a mechanism designed to keep a car centered in the lane, relieving the driver of the task of steering.

1.2.2.2 Level 2 ADFs

Most ADFs for two-degrees of freedom can be classified at automation level 2 ("hands off"). The dynamic driving tasks are achieved by means of coordinated control of the steering angle and speed which takes into account the actual situation in the
environment to ensure collision-free motion within the available space. The driver is usually responsible for monitoring the traffic situation and must be ready for taking back the control of the driving tasks when ADF is not engaged. Some existing ADFs for two degrees of freedom are listed in following [99, 102].

- **Automatic parking (APA)** is an autonomous car-manuvering system that moves a vehicle from a traffic lane into a parking spot to perform parallel, perpendicular, or angle parking.

- **The Traffic Jam Assist (TJA)** supports the driver in traffic jam situations. By activating the Traffic Jam Assist, the vehicle takes control of steering-, acceleration- and brake processes. Starting-up, braking and the maintenance of a safe distance happens automatically. Thus, in the meantime, the driver can take his hands off the steering wheel.

- **Cruising Chauffeur** assumes the complete steering of the vehicle after its activation. The assistant adjusts automatically to traffic conditions, it controls speed and keeps the vehicle in lane. When the vehicle exits the motorway, the system announces it in a timely manner. Hence, the driver resumes control.

**1.2.2.3 Semi-automated**

This category included functions at the automation level 2 or 3. The ADF can execute more complex maneuvers (e.g. a lane-changing maneuver) and achieve the control of most DDTs without any help of the human driver but still need human driver’s monitoring for emergency situations.

- **Collision Mitigating System** is an enhanced 2-dimensional version of the collision avoidance system. The system detects slower or stopped vehicles ahead, and provides steering assistance if the collision cannot be avoided by braking alone (evasive steering).

- **Tesla Autopilot** also known as Enhanced Autopilot after a second hardware version started to be shipped, is an advanced driver-assistance system feature offered by Tesla that has lane centering, adaptive cruise control, self-parking, ability to automatically **Change Lanes** with driver confirmation, and enables the car to be summoned to and from a garage or parking spot.

**1.2.2.4 ADFs of Automation Level 3 and above**

At the current stage, there is still no level 3+ HAVs in the market, mainly owning to the legal responsibility of safety. Some noteworthy road maps of development and release of HAVs are summarized in the Table 1.2.
Table 1.2: Predicted road maps on development and release of the HAVs of selected companies (Source: [82])

<table>
<thead>
<tr>
<th>Company</th>
<th>Announced Product Introduction</th>
<th>Predicted Level 5 HAVs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Audi/VW</td>
<td>2016 – Piloted Driving</td>
<td>Full AV by 2021</td>
</tr>
<tr>
<td>BMW</td>
<td>2014 – Traffic jam assist &amp; automated parking</td>
<td>Available by 2021</td>
</tr>
<tr>
<td>Daimler-Benz</td>
<td>2014 – Intelligent Drive</td>
<td>Available by 2020</td>
</tr>
<tr>
<td>Ford</td>
<td>2015 – Fully assisted parking</td>
<td>To mass produce HAV in 2021</td>
</tr>
<tr>
<td>Waymo</td>
<td>2015 – Driverless Pod prototype</td>
<td>Available by 2018</td>
</tr>
<tr>
<td>Tesla</td>
<td>2016 – Highly autonomous</td>
<td>Self-driving 2020–2025</td>
</tr>
</tbody>
</table>

1.3 Methods for Safety Testing

1.3.1 What is safety for HAVs?

In general terms, safety can be easily defined, and there is a wide choice of metrics, e.g. in terms of collisions or casualties for a given number of driven kilometers. As already mentioned, the final numbers will be a combination of driver specific contributions, vehicle contribution and possibly others, like weather conditions or state of the roads. Of these three, the driver is by far the dominant one. In the case of HAVs, however, driver and vehicle so to say merge, so that the vehicle becomes the key culprit or at least suspect. Correspondingly, a naive public expectation would assume accidents going down to zero, up to extreme cases beyond control, like a bridge failure. Of course, this is impossible, because no system is absolutely fail safe, and the number of different situations in which HAVs can be used is enormous.

For this reason, the work in this thesis is guided by the idea that HAVs must be significantly safer than human drivers, not perfectly safe. This is part of the rationale why we suggest using accident databases of human drivers, without waiting for specific fleet tests with HAVs. Implicitly, we also assume that the accident pattern as produced by human drivers is also valid for HAVs. This seems very sensible from at least two points of view, on one side traffic will consist for long time mainly of human-driven vehicles, on the other side we would expect HAVs to lead less frequently to dangerous situations, so any estimate of the risk based on human-driven vehicles will be on the safe side.

1.3.2 Current Safety Testing Concepts in Automobile Industry

Safety is critical to the public acceptance of HAV. The challenges faced by most automakers and technology companies are focused on the lack of security, as society is less likely to tolerate any machine-induced death from traffic accidents (HAV) than those due to human errors. Each crash related to automated vehicles, such as Tesla [13]
and Uber [67] accidents, are always in the media spotlight – even though crash rates involving Tesla cars have dropped by almost 40 percent since the wide introduction of Autopilot system [57].

Even if the main purpose of developing the HAVs is to prevent traffic accidents, system failures will inevitably occur. Indeed not even airbags are failure free [85]. So the practical approach in the system design and development - especially for safety critical aspects - is to bring the failure ratio at system level below a certain threshold, so that the failure probability is negligible, not to aim for zero failures. In this context, the purpose of testing is to estimate the probability of a failure within a given confidence interval, independently from the causes.

In the automotive industry, there are established ways to estimate the impact of a faulty component on overall functionality, for instance the standard ISO 26262 [3] for safety. Tests are typically conducted at the component level to test and improve their reliability. Based on component-level failure rates, engineers can estimate failure rates over the entire design life at a system-level, which is the only important level for customers. There are different ways to express this quantity, for instance as a failure probability defined as the ratio between the number of kilometers driven by all the sold vehicles, and the total number of failures. This ratio, however, is not available a priori for the certification, so estimations are needed.

In this context it is important to stress that the situation for classical vehicles was very different in terms of complexity. For them, a failure means that the vehicle does not follow a command of the driver up to a given tolerance. Fleet testing was an expensive, but possible option. In fact, currently there exists no safety-relevant function in a production vehicle that has not also had on-road testing. As an example, before the production release of the Mercedes Benz E-Class (W212), a total of 36 million test kilometers were completed [94].

1.3.3 Safety Testing for HAVs

As for HAVs, a failure is more difficult to define, because HAVs (with automation Level 3 and above) take over the tasks of decision making and actuation. It is also important to keep in mind that most attention in the regulations until now has been devoted to fixing performance requirements and test methods for single ADAS. For example, EURO-NACP for Autonomous Emergency Braking (AEB) [87] and ISO 15622 [2] for Adaptive Cruise Control (ACC) fix requirements and test methods for the functional performance of the these ADAS, and so define nominal cases for testing. In contrast to this, safety is mainly an issue in unexpected cases. so this kind of specifications cannot be used to determine the safety of HAVs. In fact, to the best knowledge of the author there is no safety standard for the decision making capabilities of HAVs. As a result, attempts to guarantee safety just relying on the performance specifications, collecting miles and using some statistical approach to estimate the failure rate, are naive at best.
As addressed by [103, 25, 94], HAVs would need to drive over 200 million kilometers to prove that they are at least as safe as human drivers for the highway scenarios. [80] shows that the amount of data required to guarantee a probability of $10^{-9}$ fatality per hour is roughly in the order of 45 billion kilometers. This is infeasible for real driving tests.

So estimating the crash probability in the early design phase to reduce the amount of driving test is necessary. In order to achieve a reliable estimation, choosing relevant test scenarios is crucial, because exactly reproducing the real world traffic is impossible and usually meaningless, e.g. reproducing long distance driving on the highway without other traffic participants.

To remove some limitations of on-road driving test, there is a wide consensus that virtual testing must be included. Unfortunately, virtual testing is not infinitely fast, i.e. it is simply impossible to test all possible situations. This is where the search for scenarios comes into the play.

### 1.3.4 State-of-the-Art Virtual Testing of HAVs

Virtual testing is a powerful tool addressing some limitations of on-road driving test. It reduces total kilometers of on-road driving tests enormously. It allows testing and evaluation of ADAS/ADF in a safe and reliable condition, and ensures the exact repeatability of test scenarios as well. In order to achieve a reasonable result, properly defining the scenario and choosing suitable assessment criteria are crucial tasks. However, with the appearance of other traffic participants and increasing level of automation, the total number of scenarios to be tested, explodes. As a result, it is impossible to test, even by simulation, an ADAS/ADF in all possible situations, so some scenarios must be singled out, and they need to be representative for the conditions of the intended use.

Stochastic modeling and similar methods are usually applied for massive generation of test scenarios. In [109, 26, 27], the authors build up stochastic models using real measurements and produce various test scenarios through randomized sampling, searching for the situations with fault behavior, such as a crash. Nevertheless, they are usually applied to some simple traffic situations, e.g. emergency braking in a car-following situation. In the case of complex situations, e.g. modeling the large scale traffic [42], it is normally time-consuming, due to the low occurrence of critical events, e.g. cases in which the specified test scenarios result in a crash.

To overcome these limitations, [76, 78, 16] have proposed a methodology for scenario generation in a deterministic way, through the combination of various components, e.g. the weather, road type, driving maneuver, etc. In [32, 33, 6] the surrounding area of the ego-vehicle (EGO) is divided into various observation cell according to the possible relative position of other vehicles to the EGO. Depending on the cell occupancy and vehicle location, the static combination of possible behavior of the

---

<sup>2</sup>Noting that the safety validation of a current driver assistance system (automation level 1) alone requires up to 2 million test kilometers.
EGO and/or surrounding vehicles form the concrete scenarios. However, this method greatly relies on engineers’ expertise knowledge to single out the realistic scenario and to test the critical situations.

Alternatively, [24] proposes a list of objective scenarios for testing of safety related ADAS, based on analysis of the most frequently occurring crash types addressed in [56], nonetheless, they require the predefined behaviors or reactions of the system under test (SUT), that is not available for HAVs.

In spite of these and other attempts up to now there is still no clear way to find the relevant scenarios for systematically testing of HAVs, evaluate the coverage of the obtained scenarios with respect to real traffic situations, and assess the safety of HAVs in terms of real traffic by simulation.

1.4 Contributions of this thesis

As already mentioned, the dilemma of safety testing for HAVs consists in the impossibility of performing sufficient large scale on-road tests but also in the need of the information usually derived from such tests, namely which situations may lead to a dangerous situation. This thesis proposes an approach which combines information from accident databases for conventional vehicles, so to say involuntary large scale on-road tests, with a stochastic parametrization based on real measurements and a deterministic search for limit cases.

The first contribution of this thesis concerns a methodology to extract the necessary information from the accident databases in a way suitable to the search of critical conditions for HAVs. Indeed, accident databases are simply records of dangerous situations with some information on the events leading to the accident (or in our cases, to a near-crashes as well).

As we show at the example of a highway data base, it is possible to classify the available data with a limited number of scenarios - i.e. sequences of driving events - so that it is possible to derive a parsimonious catalogue of scenarios that cover the majority of crashes or near crashes reported in traffic accident databases, i.e. with a very good ratio of complexity to coverage. Measurements in the database are related to human drivers.

Once the scenarios have been fixed, we need to determine more in general under which conditions the HAV under test could fail as well. To this end, we need to derive a general description of the scenarios to be used for parameter studies. This means transforming the accident description to a parametrized model. As the information in the database is very limited, we achieve this target using experimental measurements of the single elements of the scenarios, e.g. of the cut-ins, to derive a stochastic parametrization of the chosen scenarios. The yields relatively simple models which include the majority of the measured cases as specific realizations.
A second contribution concerns the way we compute the test cases. As usual, we are interested in the reaction of HAVs to a critical situation caused by other traffic participants, e.g. braking to avoid front-end collision with a preceding vehicle. Using the stochastic models mentioned above, which include parameter ranges and distributions, we use a design of experiments (DoE) approach to determine in a fast way the parameter sets which are expected to lead to a collision. Notice that we suggest considering only the corner cases, i.e. those in which a collision is possible, but not unavoidable. The rationale for this is that an ADAS/ADF should offer at least the same safety as an experienced, attentive human driver, but there will always be conditions under which no reaction can prevent an accident, and testing an ADAS/ADF under these circumstances is not very sensible.

As this thesis has been developed inside a large project (ENABLE-S3\textsuperscript{3}), a wide search was done to determine available alternative approaches for the same purpose. Only two real alternatives were found, one by AVL and one by TNO. For information we joined a table of the differences taken from a project report, where $\theta$ and $\Theta$ denote input parameter and input space, respectively. $|\Delta x|_{min}$ is the safety criteria, defined as the minimal space gap between two vehicles. $|\Delta x|_{min} = 0$ means a crash, namely $y = 1$. $y$ is the simulation outcome indicative of whether a crash is avoided ($y = 0$) or not ($y = 1$).

\textsuperscript{3}European Initiative to Enable Validation for Highly Automated Safe and Secure Systems [20]
The approaches of AVL, TNO and JKU were compared as far as known. Summarizing the similarities/differences:

<table>
<thead>
<tr>
<th></th>
<th>AVL</th>
<th>TNO</th>
<th>JKU</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Target</strong></td>
<td>${\theta;</td>
<td>\Delta x</td>
<td>_{\text{min}} = 0}$</td>
</tr>
<tr>
<td><strong>General idea</strong></td>
<td>- Replacing $</td>
<td>\Delta x</td>
<td>_{\text{min}} = f(\theta)$ by a universal approximator: $</td>
</tr>
<tr>
<td><strong>Data basis</strong></td>
<td>- Pre-defined manoeuvers Pre-defined range of parameters, no measured data</td>
<td>- Pre-defined manoeuver Real parameter PDF $\Pr(\theta)$ from measurements</td>
<td>- Pre-defined or learnt manoeuvers range of parameters from measurements</td>
</tr>
<tr>
<td><strong>Modeling</strong></td>
<td>- Compute $</td>
<td>\Delta x</td>
<td>_{\text{min}} = f(\theta)$ for chosen ${\theta_i \in \Theta}$ by CARMAKER or VTD (detailed ego vehicle dynamic) Using CAMEO to steer the choice of ${\theta_i}$ to obtain a good direct approximation of $</td>
</tr>
<tr>
<td><strong>Evaluation</strong></td>
<td>${\theta;</td>
<td>\Delta x</td>
<td>_{\text{min}} = 0}$ is obtained using $g(\theta)$ by CAMEO.</td>
</tr>
<tr>
<td><strong>Result</strong></td>
<td>- Border ${\theta; g(\theta) = 0}$ is an good estimation of ${\theta;</td>
<td>\Delta x</td>
<td>_{\text{min}} = 0}$</td>
</tr>
<tr>
<td><strong>Catalogue</strong></td>
<td>From ACC use cases 1 case reported</td>
<td>From accident data plus online extension</td>
<td></td>
</tr>
<tr>
<td>Advantages</td>
<td>Flexible,</td>
<td>Less complicated, higher exposure to critical situations for the given exemplary case</td>
<td>Faster, detecting the true boundary,</td>
</tr>
<tr>
<td>------------</td>
<td>-----------</td>
<td>--------------------------------------------------------------------------------</td>
<td>------------------------------------</td>
</tr>
<tr>
<td>Extras</td>
<td></td>
<td></td>
<td>• Estimation of parameterization accuracy with respect of real traffic is available, namely 90% of data can be represented by ( \theta ) with error &lt; ( \delta )</td>
</tr>
<tr>
<td>State flow</td>
<td>Parameter: ( \theta \in \Theta )</td>
<td>Parameter: ( \theta \in \Theta )</td>
<td>Parameter: ( \theta \in \Theta )</td>
</tr>
<tr>
<td>• CAMEO</td>
<td>Modeling ( \Delta x_{\text{min}} = f(\theta) ) through DoE with limited number of simulation runs: ( { [\Delta x_{\text{min}}, \theta_i], i = 1, \ldots, N } )</td>
<td>Randomize the choice of ( \theta ) inside ( \text{Pr}(\theta) ), Compute ( \Delta x_{\text{min}} = f(m(\theta)) )</td>
<td>Compute ( \Delta x_{\text{min}} = f(\theta) ) for new parameter ( \theta' \in \Theta ), Classify through boolean indicator: ( y = 1_{\Delta(x_{\text{min}})} )</td>
</tr>
<tr>
<td>• CarMaker</td>
<td>Behavior model: ( \Delta x_{\text{min}} = g(\theta) ) s.t. (</td>
<td>g(\theta) - f(\theta)</td>
<td>\leq \delta )</td>
</tr>
<tr>
<td>• CAMEO</td>
<td>Boundary estimation using DoE and identified model ( \Delta x_{\text{min}} = g(\theta) )</td>
<td>• Monte Carlo</td>
<td>Build up boundary model ( \hat{\theta} = h(y = 1), \hat{\theta} \in \Theta )</td>
</tr>
<tr>
<td>( \theta': \Delta x_{\text{min}} = 0, \hat{\theta} \in \Theta )</td>
<td>• Monte Carlo</td>
<td>Pr(( \Delta x_{\text{min}} = 0 )) \geq \text{Pr}(\Delta x_{\text{min}} = 0) ).</td>
<td>next testing point ( \theta' \in \Theta )</td>
</tr>
</tbody>
</table>
|          | Matlab    |                                                                               | no \[ \hat{\theta} - \theta | x_{\text{min}} = 0 | \leq \delta ? \]
|          |           |                                                                               | yes \[ \hat{\theta} = h(y = 1), \hat{\theta} \in \Theta \]
We do not discuss it in more detail, but the key differences are the use of a catalogue derived from accident data and not by the intuition of the test designer or extracted from some time series, and the accelerated determination of corner cases (a collision-free boundary) in a deterministic way by applying DoE instead of the randomized method or the model-based estimation [7, 26, 19].

A third contribution is the use of the method mentioned above to estimate the total crash probability. The occurrence of the all parameter sets can be estimated from the measurements by applying kernel density estimation (KDE). Together with the critical parameter sets (those which are expected to lead to a collision) determined using DoE, the total crash probability of the HAV can be computed in a simple way.

A fourth contribution is the consideration of a slightly unusual but very important effect of maneuvers by the HAV, which we may call the cautiousness. Indeed, the action of the HAV may be safe, as it does not lead to an accident, but may bring other traffic participant into dangerous situations, especially if they are driven by human drivers. This means for instance to choose a proper gap to cut in front of another traffic participant, so that it does not have to brake hard to avoid the crash with the HAV. We suggest to use the same methods as for safety for cautiousness, e.g. to derive a stochastic model of speed changes of an overtaken vehicle during the cut in phase at the end of the overtaking that does not lead to a change of its speed, the so called critical gap. This allows a cautiousness assessment of autonomous overtaking functions of HAVs without needing a model of the complex reaction of the human driver of the overtaken vehicle.

1.5 Outline

The structure of the rest of the thesis is as follows: in Chapter 2 we establish incrementally a catalogue of safety relevant test scenarios based on an analysis of traffic accident data of human drivers. We first build up the basis of a catalogue, consisting of various single critical events, which we then gradually extend to complex scenarios by increasing the number of critical events and evasive actions of the HAVs.

Chapter 3 elaborates the model-based and data-driven parametrization of the scenario. The approach is presented via the example of the lane-changing maneuver, one of the most relevant safety critical maneuvers and the cut-in scenario (scenario No.10 in Table 2.6). The method indicates that the proposed model can cover the major part of the measurements with rather simple parameter set.

Chapter 4 sheds light on the HAV safety assessment based on boundary search. A Design-of-Experiment (DoE) approach is proposed to find the limit boundary in a fast way. This boundary represents the performance limit of the HAV in terms of safety. The kernel density estimation method is approached to estimate the occurrence of a collision-related parameter combination, thereby allowing a fast estimation of the collision probability of the HAV in actual traffic based on the obtained collision
boundary. The proposed method is proposed by testing an exemplary ACC system in a simulation.

Chapter 5 focuses on cautiousness assessment of HAVs with autonomous overtaking functions. The approach is presented on the example of scenario No. 17 in Table A.1, in which the HAV changes lane and encounters another vehicle in the adjacent lane from behind. First, we investigate the human driver’s reaction to a cut-in maneuver in terms of various inter-vehicle gaps for cut-in maneuver. We derive safety criteria via driving requirements on human driver in terms of defensive driving behavior. The proposed approach is supported via testing of an exemplary autonomous overtaking function in simulation.

Chapter 6 presents some summaries and outlooks of this work.
Chapter 2

Test Scenario Catalogue

2.1 Preliminaries

Scenario generation is one of the crucial aspects for HAV testing and verification. Not surprisingly, much work has been done and partly published to find an appropriate catalogue of scenarios that offers a good coverage of the intended use but remains parsimonious.

Traditionally, good coverage has been the key focus. Approaches can be roughly divided in deterministic and data driven. For example, [76, 78, 16] have focused on a deterministic scenario generation by combining various basic traffic elements such as the weather, the daylight, the action of other traffic participants and the road shape. Another deterministic approach has been pursued for instance by [32, 33, 6, 33], who have concentrated on the interactions between dynamic objects, namely the EGO and the surrounding vehicles. The authors group the surrounding vehicles based on their relative position to the EGO. As shown in the panel (1) of Fig. 2.1, taking the case of a three-lane as an example, units U1-U8 represent the areas of possible locations of the surrounding vehicles. Depending on the occupancy of the unit and the position of the vehicle, the scene can be formed systematically by a static combination of the possible directions of movement of the surrounding vehicle and the EGO, see panels (2)-(3). Adopting a combinatorial approach can produce a large number of possible scenarios, allowing to cover the traffic situations as much as possible. However, as the number of other traffic participants increases, it can lead to an enormous increase of the size of the catalogue.

Mainly at the industrial level, scenario catalogues are also been built from the analysis of travel data, e.g. the test scenarios developed in the project PEGASUS [79] and MOOVE [49], and the catalogue proposed in [107, 18].

However, all these approaches tend to produce very large catalogues which could not be easily used for testing in simulation - therefore, limiting the size of the catalogues is still an important and open issue.
Against this background, we propose to simplify the setup of the catalogue by using available database which include accidents or near crashes for conventional vehicles, in order to determine the traffic situations relevant to testing of the HAV. We analyze these traffic situations and classify them in a systemic manner, e.g. creating a catalogue, so that on one hand the total amount of relevant cases to be considered for testing of the HAV. The rationale behind that is that the critical situation is produced by the other traffic participants, and for a long time HAV will work in a mixed environment.

In this chapter, we show how to derive such a scenario catalogue from a database. In this thesis, we use the SHRP2 NDS\(^1\) database, and show that a relatively simple catalogue (22 scenarios) covers more than 95\% of highway (near-)crashes. To this end, we need first to analyze the link between critical causes of the (near)collisions and the operation field of the HAV.

In this research we define as scenario as a sequence of events both by surrounding vehicles and the HAV. The basic elements of a scenario are the participants, the influence factors, and the avoiding actions of the EGO. The participants include both the EGO and one or more other traffic participants (human driven vehicles surrounding the EGO). The influence factors are the threat actions due to other traffic participants which may potentially result in a collision with the EGO. The avoiding actions are the reactions by the EGO vehicle to prevent the accident in response to the threat action.

The definition and classification of the surrounding vehicles and threat actions are explained in the section 2.3. The avoiding actions of the EGO are introduced in the section 2.4.

---

\(^1\)The Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study(NDS), known to be the largest study of naturalistic driving behaviors available to date [29].
It is worth mentioning that this research focuses on the (near-)crash due to interactions between vehicles, i.e. the accidents, like the loss of control of the vehicle and the collision with animals or a fixed obstacle, like a barrier, are excluded form this work.

In the following sections the EGO, the surrounding vehicle, the threat action, and the evasive maneuver are meant to represent the HAV, the human driven vehicles, the influence factor, and the avoiding action of the HAV, respectively.

### 2.2 From Human Driver Accidents To Scenario Catalogue for Safety Assessment of HAVs

#### 2.2.1 Crash Causation and Testing Scenarios of HAVs

Manual driving is the main cause of road traffic accidents. As mentioned in a study conducted by NMVCCS\(^2\) from 2005 to 2007 \cite{82}, it is estimated that 94% of the direct causes of NMVCCS collision events can be attributed to driver action, and the vehicle and driving environment are estimated as only 4% of direct causes. Relevant statistics on key causes are detailed in Table 2.1. It is worth noting that the focus of our research is not on the key causes themselves, such as various human driver errors \cite{82}, but on pre-crash actions caused by these errors. Therefore, concentrating on the driver-related collisions, we can find the pre-crash actions responsible for 94% of the collisions on the road.

#### Table 2.1: Assignment of Critical Causes of NMVCCS Crashes (Source:\cite{82})

<table>
<thead>
<tr>
<th>Critical Cause Attributed to</th>
<th>Estimated Percentage ± standard deviation(^1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drivers</td>
<td>94% ± 2.2%</td>
</tr>
<tr>
<td>Vehicles</td>
<td>2% ± 0.7%</td>
</tr>
<tr>
<td>Environment</td>
<td>2% ± 1.3%</td>
</tr>
<tr>
<td>Unknown Critical Causes</td>
<td>2% ± 1.4%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
</tr>
</tbody>
</table>

\(^1\) ±95% confident limits

Two make the distinction more clear between accident cause and pre-crash action, let us consider as an example the non-performance error "sleep" in Table 1.1. Fig. 2.2 panel (1) shows the actions resulting from a sleeping driver that leads to collision with another vehicle, whereas in panel (2) it leads to crash with road barrier. In the case of panel (1), the HAV is required to react appropriately to avoid the crash. If we switch both vehicles, as in panel (2), the HAV does not need to react. Technically, as we consider only accidents of the HAV, only the pre-crash action of the red vehicle in panel (1) represents a relevant scenario for safety testing of HAV. These two cases will be discussed further in chapter 4 and 5, respectively.

\(^2\)National Motor Vehicle Crash Causation Survey (NMVCCS)
2.2.2 Crash Database

Just as a comment, of course also the situation shown in panel (2) is important, and could be a test scenario for active safety systems such as Sleepiness Warning System (SWS) [60] and Lane Departure Warning System (LDW) [91], however this is out of the focus of the work.

Analyzing the accident data in a similar way, we can find out the challenging situations that HAVs can encounter in real traffic. In addition, if we can systematically describe these situations through a limited number of cases, we can limit the overall scenario and make the test feasible.

The following sections focus on extending this idea to the whole database. Notice that the same work could be done for other data basis, but in this work we have limited the study to highway traffic.

As already mentioned, the proposed scenario catalogue is derived from highway (near)crashes reported in SHRP2 NDS [29]. Approximately 3,400 participant drivers
were monitored and produced over 4,300 years of naturalistic driving data between 2010 and 2013. Over 3,300 participant vehicles were instrumented with a Data Acquisition System (DAS) that collected four video views (e.g. forward roadway, rear roadway), vehicle network information (e.g., speed, brake, accelerator position), and information from additional sensors included with the DAS (e.g., forward radar, accelerometers) [81]. Fig. 2.3 clarifies the composition of SHRP2 NDS database. There are 36822 records in total in this database, of which 10364 records - consisting of 775 (near-)crashes and 9589 baseline events³. "Highway traffic" means a limited-access road⁴. It has many or most characteristics of a controlled-access highway (freeway or motorway), including limited or no access to adjacent property, separation of opposing traffic flow, use of grade separated interchanges to some extent, prohibition of some modes of transport such as bicycles or horses, and very few or no intersecting cross-streets [43, 1].

775 highway (near-)crashes reported in SHRP2 NDS database are analyzed. Among them 637 (near-)crashes are considered relevant. The remaining 138 non-relevant events, categorized as non-relevant due to animals or objects in the road (invalid traffic participants), EGO losing control (irrelevant events) and intersections (irrelevant traffic environment), are excluded from the catalogue at the current stage. Further details are given in Table 2.2.

<table>
<thead>
<tr>
<th>Highway traffic relevant:</th>
<th>637</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covered by catalogue</td>
<td>631</td>
</tr>
<tr>
<td>Not covered</td>
<td>6</td>
</tr>
<tr>
<td>Non-relevant:</td>
<td>138</td>
</tr>
<tr>
<td>Animal &amp; object in road</td>
<td>41</td>
</tr>
<tr>
<td>EGO lost control</td>
<td>56</td>
</tr>
<tr>
<td>Intersections</td>
<td>31</td>
</tr>
<tr>
<td>Others</td>
<td>10</td>
</tr>
<tr>
<td>Total (near-)crash events:</td>
<td>775</td>
</tr>
</tbody>
</table>

### 2.2.3 Overview on Scenario Catalogue

In this study, we classify the scenarios by basic cases with only one threat action (basic scenario). Later we gradually increase the number of threat actions and evasive maneuvers to form the complex scenarios. In other words, the complex scenario is a combination of basic scenarios via evasive action.

The catalogue consists of 12 basic and 10 complex scenarios. It covers 99.06% of the highway traffic relevant (near-)crashes reported in SHRP2 NDS, see Table 2.2. 631 (near-)crashes can be attributed to one of the 22 scenarios in the catalogue. The 3

³For further details on composition of SHRP2 NDS database, refer to [29].
⁴It refers to the locality type of 'Bypass/Divided Highway with Traffic Signals' or 'Interstate/Bypass/Divided Highway with no Traffic Signals' in SHRP2 NDS
most common (near-)crash types are front-end collision due to the threat action of the leading vehicle (scenario No.1), front-end collision or sideswipe due to the threat action of the front vehicle in adjacent lane when EGO is in a free driving state (scenario No.2), and a car-following state (scenario No.10). Detailed information about each scenario is detailed in the next section. Table 2.3 details the distribution of events.

Table 2.3: Assignment of 631 Critical Events

<table>
<thead>
<tr>
<th>Scenario:</th>
<th>No.1</th>
<th>No.2</th>
<th>No.3</th>
<th>No.4</th>
<th>No.5</th>
<th>No.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occurrence:</td>
<td>309</td>
<td>108</td>
<td>10</td>
<td>0</td>
<td>32</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>1</td>
<td>18</td>
<td>63</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>11</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total:</td>
<td>631</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As for 6 non-covered cases, three threat actions are identified:

(i) Brake to a full stop during the process of lane change
(ii) Double lane change maneuver (in the same two lanes)
(iii) lane change over two lanes from 1st lane to 3rd lane

as shown in Fig. 2.4 panel (1)-(3), respectively.

Given the low incidence of such incidents, we excluded them from the scenario catalog until further investigations into such driving events or data in similar traffic situations are possible. Despite the occurrence of 0, the scenario No.4 is included in the catalog because it is the basic maneuvering complex scenario No.13, see Table 2.7 and lane change maneuvers appeared in scenario No.4 often occur in real traffic.

We analyze actions that are threatening during driving, rather than analyzing the pre-crash action of human-driven vehicles. If it does not respond in time and is functioning properly, it may cause a collision with the EGO.

In the following sections, we analyze the crash database and derive the scenarios in the view of the EGO. We call it threatening action(s) rather than the pre-crash action(s) to represent a generic description of safety relevant traffic situations. If the HAV does not respond in time and is functioning properly, it may cause a collision.

Furthermore, we do not distinguish between the left or right adjacent lane of the EGO. All scenarios listed in the catalogue can be mirrored, see section 2.3.1.

Finally, it is assumed that we have perfect sensors so that the automation system has sufficient knowledge of all surrounding vehicles and the static environment. Consequently, detection errors will not be discussed within this work.
2.3 Basic Scenarios

In order to form the scenario in a systematic manner, we first define the way to interpret the scenario.

2.3.1 Formation of Scenarios

Real world driving conditions are complicated. Interaction among the traffic participants, actions and the corresponding responses, are usually continuous and dynamical. In order to create a representative catalogue with evaluable scenarios for the HAV assessment, screening and segmentation are typically applied to select the relevant operations to describe the scenarios in a systematic manner.

Screening

Figure 2.4: Threat actions from (near-)crashes that are not covered by the catalogue

Figure 2.5: Screening and states of the maneuvering vehicles
We consider the traffic situation as frozen (a snapshot) when surrounding vehicle \( \text{1} \) initiates a maneuver (action) that has any direct impact on the driving statue of the EGO \( \text{2} \) or vice versa. In panel (1) of Fig. 2.5, the traffic situation is frozen at the time point when the surrounding (red) vehicle \( \text{1} \) initiates a lane change maneuver to overtake in front of the (green) EGO \( \text{2} \). The state of vehicle \( \text{1} \), such as velocity, acceleration/deceleration, and relative distance to the EGO \( \text{2} \), are the initial state of the corresponding lane change maneuver. They are used to generate specified scenarios for safety testing of the HAV in simulation in chapter 3 and 4. Panel (2) explains the situation, in which the EGO \( \text{2} \) initiates the lane change maneuver to cut in front of the vehicle \( \text{1} \). The states of the vehicle \( \text{1} \), who is affected by the action of the EGO \( \text{2} \), can be the criterion of safety assessment for HAVs. This case is explained in detail in chapter 5.

**Classification of the surrounding vehicles**

The frozen traffic is centralized on the EGO and all surrounding vehicles are grouped according to their relative positions to the EGO, the maneuver complexity, and the occurrence of the corresponding actions, as shown in Fig. 2.6 from a five-lane demonstrator.

First are U4 and U5. all of the traveling vehicles in the middle lane, including the EGO and the surrounding vehicles, are divided into three groups according to their relative positions with the EGO, the preceding vehicle (the front vehicle at the same lane as the EGO), the EGO, and the following vehicle (the rear vehicle at the same lane as the EGO). In this case, the grouping is clear and unique because the preceding and following vehicles are physically separated by the EGO. The interaction between the preceding/following vehicle and the EGO (collision threat) is quite simple, only
longitudinal movement. However, they have the highest probability of colliding with each other, such as scenario No.1 and No.3 in Table 2.3.

Second are U2, U3, U6, and U7. The vehicles in adjacent lanes (next to the EGO) are divided into two groups, namely front- and rear-vehicles in the adjacent lane. The interactions between EGO and the vehicles in the adjacent lane are more complex than the previous one. It requires either EGO or the vehicle in the adjacent lane to execute a lane change maneuver - both longitudinal and lateral movements - so as to cause the threat of a crash. However, this type of interaction is less frequent but occupies the second highest occurrence in the crash database, e.g. scenario No.2 and No.4 in Table 2.3.

Third are U1 and U8. For vehicles in the outermost lane, all vehicles are grouped together due to complex movements and low collision rates. Both EGO and the surrounding vehicle in the most outer lane must do lane change maneuver to switch to the same destination lane so that they can potentially affect the driving states of each other (possibly lead to a collision), e.g. scenario No.9 in Table 2.3.

2.3.2 Inference of Basic Scenarios

In order to develop the basic scenario, we divided all the traffic participants (the EGO and the surrounding vehicles) into two categories according to the direction of the movement. A vehicle that is normally traveling in a lane can perform various longitudinal driving operations such as acceleration, deceleration, movement at a constant speed or stop before a collision occurs. This will not appear in the scene description but in the parameterization of the scenario, which will be covered in the chapter 3.

The basic scenarios are grouped mainly according to the functionality of the EGO (with or without lane change function) and the amount of the surrounding vehicles associated with the threat action, as described below.

Basic Scenarios without lane change function

Based on the relative motion between surrounding vehicles and the EGO, we define the basic scenario in the case of free driving based on the longitudinal motion of the EGO, as shown in Table 2.4.

It is worth noting that we use the preceding vehicle to describe all threat actions due to the preceding vehicle. According to the actual situation, the preceding vehicle can be designated as a leading vehicle or a EGO approaching vehicle. For example, the following is a standard test scenarios for evaluating the Autonomous Emergency Brake (AEB) and Forward Collision Warning (FCW) systems defined by the European NCAP in its test protocol for the AEB system [87], when the EGO is in a free driving or car following state.

- The EGO approaching a preceding vehicle moving at lower constant speed
The EGO approaching a stopped preceding vehicle

The EGO in a car-following situation, the leading vehicle executes an emergency brake.

Similar scenarios are designed to assess the safety of various Adaptive Cruise Control (ACC) systems in several research works.

Table 2.4: Basic scenarios: The EGO is in the free-driving state

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario Description</th>
<th>Occ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>front-end collision threat between the EGO ( \text{H} ) and a preceding vehicle ( \text{H} )</td>
<td>309</td>
</tr>
<tr>
<td>2</td>
<td>front-end collision or sideswipe threat due to the lane change maneuver of a front vehicle ( \text{H} ) in the adjacent lane</td>
<td>108</td>
</tr>
<tr>
<td>3</td>
<td>rear-end collision threat between the EGO ( \text{H} ) and the following vehicle ( \text{H} )</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>rear-end collision threat from the lane change maneuver of a rear vehicle ( \text{H} ) on the adjacent lane</td>
<td>0</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3

Similarly, various scenarios are established by studying lane change vehicles that are not listed in the catalogue. This will be handled in the step parameterization. For example, a vehicle that is slower or decelerating is while performing a lane change maneuver or cutting into a lane, or it cuts into a lane at the same speed as the EGO and then brakes.

**Basic Scenarios with lane change function**

In the case of a HAV with autonomous overtaking function, the presence of front/rear vehicles in adjacent lanes as well as preceding/following vehicles entering the same adjacent lane as the EGO may cause collisions with EGO [56]. In this case, the HAV should be able to perform safe lane change maneuvers and handle emergency situations during the lane change maneuver. Therefore, we define the basic scenario and consider
the EGO encounter collision threats in the process of lane change maneuver. Table 2.5 gives a description and illustration of the set of scenarios.

Table 2.5: Basic scenarios: EGO in the course of lane change maneuver

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario Description</th>
<th>Occ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>front-end collision threat due to the action of the front vehicle on the adjacent lane when the EGO ( H ) is in the course of lane change maneuver</td>
<td>32</td>
</tr>
<tr>
<td>6</td>
<td>rear-end collision or sideswipe with a rear vehicle ( 1 ) on the adjacent lane when the EGO ( H ) is in the course of lane change maneuver</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>front-end collision or sideswipe threat due to the lane change maneuver of a preceding vehicle ( 1 ) when the EGO ( H ) is in the course of lane change maneuver</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>rear-end collision or sideswipe threat due to the lane change maneuver of a following vehicle ( 1 ) when the EGO ( H ) is in the course of lane change maneuver</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>front/rear-end collision or sideswipe threat from lane change maneuver of the vehicle ( 1 ) on the most outer lane when the EGO ( H ) is in the course of lane change maneuver</td>
<td>18</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3

Basic Scenarios with Multiple Surrounding Vehicles

In addition to the scenarios in which the EGO is in a free-driving state or lane change maneuver, we also identified two basic scenarios when the EGO is in the car following state. These scenarios include multiple surrounding vehicles, but only one collision threat. See Table 2.6 for details.

2.3.3 Summary

The basic scenarios contributed to the basis of scenario catalogue. The occurrence of each scenario reflects the importance and relevance in terms of safety assessment of HAVs.
Table 2.6: Basic scenarios: EGO in the car-following situation

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario Description</th>
<th>Occ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Rear-end collision or sideswipe threat due to the lane change maneuver (cut-in) of a front vehicle 2 on the adjacent lane when the EGO 1 is following a preceding vehicle 1</td>
<td>63</td>
</tr>
<tr>
<td>11</td>
<td>Front-end collision threat due to the action of the preceding vehicle 2, resulted from the lane change maneuver (pull-out) of the preceding vehicle 1 that reveals the preceding vehicle 2 when the EGO 1 is following the preceding vehicle 1</td>
<td>5</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3

It is worth mentioning that, with proper parameterization, the scenarios listed in Table 2.4 and 2.6 can be directly applied to HAV testing, while the scenarios given in Table 2.5 can be applied to HAV testing only after defining the lane change behavior of the EGO.

2.4 Complex scenarios

Complex scenarios are basically combinations of basic scenarios. A complex scenario is normally due to the fact that the EGO encounters a first threat action and goes over into a normal car-following state before encountering the next threats action [76]. Nevertheless, by analyzing the SHRP2 NDS database, we find that some (near-)crashes are resulted from a prior evasive action of the EGO to prevent an impending crash. In order to describe such complex (near-)crash situations systematically, we need to define some transitions combining various sequential threat actions as one complex scenario.

In the following, we first clarify the definition of the transition, which is used to combine the basic scenarios, and then introduce a derivation of complex scenarios in details.
2.4 Complex scenarios

2.4.1 The Transition between Basic scenarios

In SHRP2 NDS, the transitions are categorized in 8 explicit evasive actions as follows:

- brake
- accelerate
- steer to left
- steer to right
- brake and steer to left
- brake and steer to right
- accelerate and steer to left
- accelerate and steer to right

However, they are unsuitable for building up a combination of two threat actions i.e. the basic scenarios. They either require an explicitly predefined behavior of the EGO or can lead to a combinatorial explosion. But the detailed reactions of HAVs to a threat action can be acknowledged due to the complexity of the algorithms (e.g. optimal control, stochastic MPC, machine learning, etc). Furthermore, the combinatorial explosion can make the testing infeasible (the curse of dimensionality).

Since we do not strictly distinguish the lateral motion direction (steer to left or right) of the EGO, we select three abstract evasive actions according to the control input of vehicles, namely

(i) braking (brake pedal)
(ii) accelerating (gas pedal)
(iii) lane change (steering wheel)

as transition between basic scenarios. The realistic combination of basic scenarios using these transitions results in complex scenarios, consisting of sequential, nearly simultaneous threat actions. Fig. 2.7 panels (1)-(3) manifest an example of the complex scenario, in which the EGO applies an emergency braking to avoid a threat action (collision) from the preceding vehicle, then has to confront another threat action (collision) from a following vehicle, respectively.

2.4.2 Generation of Complex scenarios

Once we define the basic scenarios and transitions, some complex scenarios consisting of two or more basic scenarios can be built up systematically via transitions. A complex scenario elaborates on the situation, in which the EGO encounters multiple sequential threat actions from the surrounding vehicles’ maneuvers almost simultaneously. As a result, either the EGO ends up in a crash or the automation system brings the EGO back into a normal driving state.
Fig. 2.7 illustrates how a complex scenario is formed by the combination of basic scenarios via transition. The preceding vehicle is considered as a primary threat action whereas the following vehicle as a secondary threat action. The braking maneuver of the EGO is considered as the transition between two basic scenarios. It is defined by:

- (Secondary) rear-end collision threat due to the action of the following vehicle 2, resulting from the braking evasive action of EGO 1 to avoid the (Primary) rear-end collision threat due to the action of the preceding vehicle 1, see Fig. 2.7.

Table 2.7 summarizes the complex scenarios using braking as a transition.

The exemplary complex scenarios, derived from a combination of basic scenarios employing the lane change evasive action as transition, can be:

- (Secondary) front-end collision or sideswipe threat due to the preceding vehicle 1 in its course of lane change maneuver, resulted from the lane change evasive
action of EGO (H) to avoid the (primary) front-end collision threat from the same preceding vehicle (1), see Fig. 2.8.

With an increasing number of evasive actions from the EGO, the total number of complex scenarios explodes. That is undesirable. Moreover, some combinations might be unrealistic. In fact, by analyzing the SHRP2 NDS crash database, only one crash situation was identified, in which the EGO’s driver executed lane change evasive action twice to avoid collision with a preceding vehicle which switches the lane when EGO is in the course of the lane change maneuver and resulted in a front-end collision with a preceding vehicle in the third lane, see scenario No. 21 in Table A.2.

Table 2.7: Complex test scenarios: via braking evasive action

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario Description</th>
<th>Occ.†</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>(Secondary) rear-end collision threat from a following vehicle (2), resulted from the braking evasive action of the EGO (H) to avoid the (Primary) front-end collision threat from a preceding vehicle (1)</td>
<td>20</td>
</tr>
<tr>
<td>13</td>
<td>(Secondary) rear-end collision threat from the lane change maneuver of the rear vehicle (2) on the adjacent lane, resulted from the braking evasive action of the EGO (H) to avoid the (Primary) front-end collision threat from a preceding vehicle (1)</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>(Secondary) rear-end collision threat from a following vehicle (2), resulting from the braking evasive action of the EGO (H) to avoid the (Primary) front-end collision or sideswipe threat due to the lane change maneuver of a front vehicle (1) on the adjacent lane.</td>
<td>1</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3

Since we only take the realistic complex scenarios into account, which appear in SHRP2 NDS crash database, we limit the surrounding vehicles in collision threat below three vehicles and the transitions below two evasive actions. The rest of the
complex scenarios, summarized in the catalogue, are given in Table A.1 and A.2 in Appendix A, respectively.

2.5 Summary

In this chapter, we proposed to establish a scenario catalogue for the testing and validation of the HAVs concerning highway driving situations. By studying on SHRP2 NDS crash database, the presented scenario catalogue is proven to have a good coverage on critical cases of highway driving with countable scenarios. Moreover, the list of complex scenarios can be further explored via the realistic combination of basic scenarios and transitions, if new cases are identified in other crash data.
Chapter 3

Model-based and Data-driven Parametrization of Scenarios

3.1 Preliminary

In this chapter, we discuss how to use the scenarios introduced in the previous chapter for safety testing of HAVs. We propose a model-based and data-driven method to achieve the parametrization of the scenario. Specifically, we use an extended set of Field-Operational-Test (FOT) measurements to determine a basic behavior, so to say a common driving behavior, and search for a suitable mathematical description (model) with corresponding parameter set so that it allows parametrization to effectively reduce the complexity of parameters and to cover traffic situations in the real world with a rather narrow interval between parameter values. The parameter set and its corresponding value ranges form a parameter space. Thus, through variation of parameter values within the parameter space, we can obtain various specified testing scenarios. All these specified testing scenarios together describe the possible operation of HAVs in actual traffic.

For the sake of clarity and conciseness, the approach in this study is explained at the example of the lane change maneuver in highway traffic, because it is one of the most relevant safety-critical maneuvers. It shows that the majority of measured cases can be covered by a rather simple parametrization. Accordingly, a reasonable estimate of the collision risk can be obtained.

Without doubt, not all measurements can be represented in this way with the desired approximate precision. Some cases might be identified as abnormal cases. Hence, manual process might be required. Fig. 3.1 clarifies the concept of safety testing of HAVs based on a model-based and data-driven parametrization and abnormal behavior separation.

In the following sections, we will explain the proposed approach through modeling of the lane change maneuver and exemplary parametrization of scenario No.10 (see Fig. 3.1). For the sake of simplicity, it is referred to as the ‘cut-in’ scenario hereafter.
Note: the results can be improved by using methods from artificial intelligence, in particular Dynamic-Time-Warping (DTW) or similar methods [88].

3.2 Modeling of lane change Maneuver

3.2.1 Backgrounds

Lane change is one of the most safety-critical maneuvers in highway traffic. It can be found in the catalogue that 14 scenarios are related to lane change maneuvers of other
traffic participants, in which No.2, No.5, No.9, No.10, and No.11 have high occurrence in actual traffic conditions, see Table 2.3 in Chapter 2.

Over the past two decades, research has been undertaken to investigate the characteristics of lane change maneuvers and modeling of lane change-related scenarios such as the cut-in scenario shown in Fig. 3.2. In [109] [75], the lateral movement of the lane change maneuver is neglected and the lane change maneuver related cut-in scenario is simplified to a specified longitudinal critical situation, which is characterized by the longitudinal distance gap $\Delta y$ and velocity gap $\Delta v$ (see Fig. 3.2). In [42], lane changes occur at constant lateral velocity and longitudinal velocity, while in [117] the lateral movement of the cut-in vehicle is characterized through its constant heading angle. However, they are still based on rather simplified situations that do not meet the needs of HAVs testing. For example, ADFs introduced in [45, 59] detect or predict the dangerous cut-in maneuvers of other traffic participants and act in advance to reduce the risk of collision or sudden hard braking. In this case, finding a suitable curve model for the lane change maneuver is necessary. In previous studies various curve models are investigated for modeling and trajectory planning of lane change maneuvers, including polynomial curves [95, 64], spline curves [66, 8], linear piecewise 'S'-like curves [41], and dynamic models [105]. [83] By comparing these curve models, it can be concluded that the lane change trajectories generated by the 5th order Polynomial Curve, Bezier Curve, and Rampssinord curve fit the requests of safety, comfort, and efficiency at best in terms of vehicle dynamics. However, it does not show how well it fits the modeling of actual lane change maneuvers of different drivers. [96] By investigating polynomial curves, it is found that the 5th order polynomial curve can fit measured lane change trajectories well. However, it only focuses on modeling the time profile of the lateral displacement. Some important features such as longitudinal velocity variation during the lane change maneuver are still missing. In addition, all the curve models introduced above are based on high dimensional parameter sets. For example, 6 parameters are used for the 5th order polynomial curve merely in order to model the lateral movement. That can lead to combinatorial explosion, if their parameters are used to generate specified scenarios through parameter variation.

Therefore, in the following sections, we focus on the analysis and modeling of 2-dimensional time course of the lane change maneuver based on road measurements. It
3 Model-based and Data-driven Parametrization of Scenarios

aims to determine suitable curves, which can describe time profiles of both longitudinal and lateral movements of lane change maneuvers in highway scenario with limited parameter complexity.

3.2.2 Data Acquisition

(1) Test Vehicle

![Test Vehicle Image]

(2) Sensors set-up

![Sensors set-up Image]

Figure 3.3: Equipment for data acquisition

For traffic data acquisition, the production standard BMW 320d was equipped with 2 standard radar sensors (front, back), which were primarily developed for automotive application such as Adaptive Cruise Control (ACC), 2 stereo cameras and GPS system. Fig. 3.3 illustrates the sensor setting of the test vehicle.

The measurements used in this study were collected through experimental driving on the highway between Linz (AT) and Maranello (IT). The raw data recorded are post-processed to extract the various driving maneuvers (shown in Fig. 3.4). A total of 167 lane change maneuvers (from the left lane to the right) are extracted from more than 1,700 km of test driving (see Fig. 3.5). For more details, see [50].

The following results and discussion are based on the analysis of these 167 lane change maneuvers.
3.2 Modeling of lane change Maneuver

Figure 3.4: Exemplary post-processed data of the surrounding vehicles

Figure 3.5: Extracted lane change maneuvers (from the left lane to the right)
Note that in this study, we follow a slightly different definition of coordinate, namely the road fixed orientation, in which \( y \) and \( x \) axis stand for the longitudinal and lateral direction respectively (see Fig. 3.6).

\[
\text{Coordinate: longitudinal} \sim y, \text{ lateral} \sim x
\]

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure.png}
\caption{The coordinate used in this thesis}
\end{figure}

### 3.2.3 Investigating the Lane Change Characteristics

#### Understanding the Lane Change maneuvers

Human drivers’ lane change maneuvers are complex. According to [74, 89, 96], there are 3 phases of lane change maneuvers, namely; the initiation of lane change, the lateral movement of lane change, and the completion of lane change.

The lateral movement is the core of the lane change maneuver. The time period between the start and end time points of the lateral movement is usually defined as the lane change duration, ranging from 1 s to 16 s and following the log-normal distribution [89, 96].

The initiation phase is the time period shortly before the lateral movement and the completion phase is the time period right after the vehicle reaches the desired lateral position in the destination lane and stabilizes its dynamic. A lane change maneuver can begin from various lateral positions in the initial lane and end up in various lateral positions in the destination lane. The recorded lane change trajectories (in Fig. 3.5) illustrate the variation in lateral positions of the initiation and completion phase.

In actual lane change trajectories, the lateral position during the initiation and completion phase are not constant. A slight difference in the definition of the start and end time point can lead to a significant difference in the initial and end lateral position. Furthermore, the start and end time points are difficult to determine in practice, because the slopes of the initiation and completion phase of the lane change trajectories are normally quite gentle [96].
3.2 Modeling of lane change Maneuver

(2) characterization of real lane−changing trajectory using piecewise function

\[
\Delta x = \begin{cases} 
\Delta x_1 + \Delta x_{lane}, & t < t_1 \\
\Delta x_1 + \Delta x_{lane} + \frac{(\Delta x_2 - (\Delta x_1 + \Delta x_{lane}))}{(t_2 - t_1)} (t - t_1), & t_1 \leq t \leq t_2 \\
\Delta x_2, & t > t_2
\end{cases}
\] (3.1)

where \(\Delta x_1, \Delta x_2, t_1,\) and \(t_2\) are the lateral positions in the initial lane and destination lane, the start and end time points of the lateral movement, respectively. \(\Delta x_{lane}\) is a constant that defines the lane width, and \(T = t_2 - t_1\) is the lane change duration.

Fig. 3.7 panel (1) explains the characteristics of lane change maneuver defined by a linear piecewise function. In panel (2), the lateral time course of an exemplary lane change measurement is approximated by Eq. (3.1). The parameters \{\(\Delta x_1, \Delta x_2, T\}\) are obtained by minimizing the modeling error (the Mean Absolute Error (MAE)) given by

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |\Delta x_i - \Delta x_{meas,i}|
\] (3.2)

where \(\Delta x_i\) and \(\Delta x_{meas,i}\) are approximation and measurement, respectively. \(n\) is the number of samples of each measurement, with sampling time \(\Delta t = 0.5s\). The resulting lane change characteristics are \(\Delta x_1 \approx 1.8\ m, \Delta x_2 \approx 2.3\ m,\) and \(T \approx 3.2\ s.\) The lane width constant is chosen as \(\Delta x_{lane} = 3.8\ m,\) according to European standard of highway construction [52].
Modeling 1-Dimensional Lane Change Time Course $\Delta x(t) = f(t)$

Although the linear piecewise function can achieve a nice characterization of various features of the lane change maneuver, the step changing in its trajectory is essentially unrealistic. It cannot describe the continuous transition between the lane-keeping behavior (occurring in the initiation and completion phase) and the lateral movement. Furthermore, the mean trajectory of 167 recorded lane change maneuvers shows a "S"-shaped curve (see Fig. 3.8 panel (1)).

Figure 3.8: The equivalent lane change features for the hyperbolic tangent function based lane change model

In this case, we propose to employ a sigmoid function, namely the hyperbolic tangent function, to model the lateral time course of the lane change maneuvers (see Fig. 3.8 panel (3)). It aims to achieve a high modeling precision and smooth transition between
3.2 Modeling of lane change Maneuver

each phase with rather simple parameters. The lane change model based on hyperbolic
tangent function is given as below:

\[
\Delta x_i = -z_1 \cdot \tanh \left( \frac{t_i - z_2}{z_3} \right) + z_4
\]

\[
t_i = (i - 1) \cdot \Delta t, \quad i = 1..n
\]

Variables: \( \bar{X}^T = [z_1, z_2, z_3, z_4] \)

where \( \Delta x_i, z_1, z_2, z_3, z_4, t_i \), and \( n \) are the lateral position, longitudinal position, the
amplitude, time shift, time scale, offset of lateral position, mean lane change velocity,
time and number of samples, respectively. The parameters are obtained by minimizing
the MAE given by Eq. (3.2), i.e.

\[
\begin{align*}
\text{minimize} & \quad \bar{X} \\
\text{subject to} & \quad \text{Eq. (3.3)} \\
\bar{X} & \succeq 0.
\end{align*}
\]

For the lane change model based on the hyperbolic tangent function, it is difficult to
determine an initiation time point of the lane change maneuver as with the linear
piecewise function. Therefore we define the equivalent time period as the lane change
duration \( (T) \), which is approximately equal to the lane change duration identified
via the linear piecewise function. Fig. 3.8 panels (2) – (3) explain the definition
of the equivalent lane change duration for the hyperbolic tangent function. It is
approximately equal to the time period in which the vehicle moves from 2\% to 98\%
of the total lateral movement \( 2 \cdot z_1 \) given by Eq. (3.5a) and (3.5b). Since Eq. (3.3)
is point symmetry about \( (z_2, z_4) \) (shown in Fig. 3.8 panel (3)), the equivalent lane
change duration \( (T) \) is defined as follows:
\[ 98\% = \frac{\Delta x_1 - (z_4 - z_1)}{2z_1} \]
\[ = -z_1 \tanh \left( \frac{t_1 - z_2}{z_3} \right) + z_4 - (z_4 - z_1) \]
\[ = -\frac{z_1}{2z_1} \tanh \left( \frac{t_1 - z_2}{z_3} \right) + \frac{z_1}{2} \]  
\[ = -\frac{1}{2} \tanh \left( \frac{t_1 - z_2}{z_3} \right) + \frac{1}{2} \]
\[ \frac{t_1 - z_2}{z_3} = \text{arctanh} \left( -98\% \cdot 2 + 1 \right) \approx -1.9459 \]  

\[ 2\% = \frac{\Delta x_2 - (z_4 - z_1)}{2z_1} \]
\[ = -z_1 \tanh \left( \frac{t_2 - z_2}{z_3} \right) + z_4 - (z_4 - z_1) \]
\[ = -\frac{z_1}{2z_1} \tanh \left( \frac{t_2 - z_2}{z_3} \right) + \frac{z_1}{2} \]
\[ = -\frac{1}{2} \tanh \left( \frac{t_2 - z_2}{z_3} \right) + \frac{1}{2} \]
\[ \frac{t_2 - z_2}{z_3} = \text{arctanh} \left( -2\% \cdot 2 + 1 \right) \approx 1.9459 \]  

\[ T = t_2 - t_1 \]
\[ = 1.9459 \cdot z_3 + z_2 - (-1.9459 \cdot z_3 + z_2) \]  
\[ \approx 3.9 \cdot z_3 \]  

where \( z_3 \) is the time scale constant. The equivalent initial and end lateral positions \( \Delta x_1, \Delta x_2 \) are obtained when \( t_i \) in Eq. (3.2) goes infinitive, namely

\[ \Delta x_1 = \lim_{t \to -\infty} -z_1 \cdot \tanh \left( \frac{t - z_2}{z_3} \right) + z_4 - \Delta x_{\text{lane}} = z_1 + z_4 \]
\[ \Delta x_2 = \lim_{t \to +\infty} -z_1 \cdot \tanh \left( \frac{t - z_2}{z_3} \right) + z_4 = -z_1 + z_4 \]  

Fig. 3.9 panel (1) illustrates the exemplary lateral time course of a recorded lane change maneuver and the corresponding approximation using hyperbolic tangent function. The modeling error is \( \text{MAE} \approx 0.1 \, m \). Panel (2) shows the distribution of \( \text{MAE} \) of 167 total recorded lane change maneuvers, whereas the lane change model based on hyperbolic tangent function covers the 77.57% of lane change maneuvers in highway scenarios with the mean absolute error \( \text{MAE} \leq 0.3 \, m \) and 95.65% with the mean absolute error \( \text{MAE} \leq 0.7 \, m \). The statistics of equivalent lane change features, namely the initial lateral position, the end lateral position, and the lane change duration, are
3.2 Modeling of lane change Maneuver

![Graph 1: Approximation of an exemplary measurement](image1)

![Graph 2: Distribution of Approximation Errors for 167 measurements](image2)

![Graph 3: Lateral position in initial lane](image3)

![Graph 4: Lateral position in destination lane](image4)

![Graph 5: Lane change duration](image5)

**Figure 3.9:** Distribution of MAE for 2-dimensional time course using hyperbolic tangent function and resulting lane change characteristics

given in Fig. 3.9 panels (3) – (5), respectively. Those are used to estimate the value interval of the parameters and the occurrence of corresponding scenarios, which are necessary for the safety assessment of HAVs. That will be discussed in Section 3.3.3 in detail.

### 3.2.4 The Lane Change Model

**Modeling 2-Dimensional Lane Change Time Course:** \( [\Delta x, y](t) = F(t) \)

We have analyzed the modeling of lateral time course of the lane change maneuver, namely \( \Delta x(t) = f(t) \). For testing of HAVs in cut-in situations, the longitudinal behavior of the cut-in vehicle is crucial for safety assessment. In previous research, the lane change maneuver for the cut-in vehicle is often simplified to a single-lane...
traffic model and is characterized by key parameters, such as longitudinal inter-vehicle
distance gap ($\Delta y$) and velocity gap ($\Delta v$), for the safety assessment of some simple
ACC systems [7, 36, 76, 109, 110, 93].

In this section, we extend the model to the 2-dimensional case, i.e.

$$
\Delta x(t) = f(t) \\
y(t) = g(\Delta x(t), \cdot )
$$

(3.7)

The model aims to model the time course of both longitudinal and lateral movement
of the lane change maneuver in highway traffic with good approximation quality under
the condition of low parameter complexity. In other words, we accept modeling errors
so as to limit the modeling complexity.

To include the longitudinal movement in the lane change model Eq. (3.3), we employ
the vehicle velocity $v(t)$ as an additional parameter. First, we assume constant vehicle
velocity during the lane change, namely $v(t) = v_0$. That leads to the lane change
model, which is given in Eq. (3.8).

$$
\Delta x_i = -z_1 \cdot \tanh \left( \frac{t_i - z_2}{z_3} \right) + z_4 \\
y_i = \sum_{j=1}^i \sqrt{v_j^2 - (\Delta x_j)^2} \cdot \Delta t \\
\quad = \sum_{j=1}^i \sqrt{v_j^2 - \left( -\frac{z_1}{z_3} \cdot \left( 1 - \tanh^2 \left( \frac{t_j - z_2}{z_3} \right) \right) \right)^2} \cdot \Delta t \\
v_i = v_0 \geq 0, \quad i = 1 \ldots n \\
t_i = (i - 1) \cdot \Delta t
$$

Variables: $\bar{X}^T = [z_1, z_2, z_3, z_4, v_0]

where $\Delta x_i$, $y_i$, $z_1$, $z_2$, $z_3$, $z_4$, $v_0$, $\Delta t$, and $n$ stand for the lateral position, longitudinal
position, the amplitude, time shift, time scale, offset of the lateral position, mean lane
change velocity, sampling time and the length of each measurement, respectively. It
aims to achieve a higher precision on modeling and smooth transition between each
phase, namely the continuous velocity in both lateral and longitudinal direction. The
parameters are obtained by minimizing the modeling error (MAE), which is given by:

$$
\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\Delta x_i - \Delta x_{\text{meas},i}| + \xi \cdot |y_i - y_{\text{meas},i}|
$$

(3.9)
where $\xi$, $\Delta x_{\text{meas},i}$, and $y_{\text{meas},i}$ are the weight of longitudinal error, the measurement of lateral position and longitudinal position, respectively. That is

$$\minimize_{\bar{X}} \quad \text{Eq. (3.9)}$$

subject to $\quad \text{Eq. (3.8)}$

$$\bar{X} \succeq 0. \quad (3.10)$$

Figure 3.10: Exemplary approximation of 2-dimensional time course using hyperbolic tangent function and the distribution of the mean absolute errors MAE

Fig. 3.10 panel (1) shows the approximation of some exemplary measurements of lane change maneuvers with $\xi = 0.1$. Their trajectories fit well to hyperbolic tangent function. Three of the velocity profiles are almost constant (dash lines with circle markers), whereas other velocity profiles change significantly (dash lines with triangle markers), whose MAEs are greater than 5m. The distribution of MAE of total 167 lane change maneuvers is shown in Fig. 3.10 panel (2), whereas the lane change model
based on hyperbolic tangent function covers 74.25% of recorded lane change maneuvers in highway situation with MAE < 1 m and 95.42% with MAE < 5 m.

\[
MAD = \frac{1}{n \cdot k} \sum_{i=1}^{n} \sum_{t=1}^{k} \| x_i(t) - x_{\text{meas},i}(t) \| \tag{3.11}
\]

where \( X_i(t) = \{ x_i(0), ..., x_i(k) \} \) denotes the fitted hyperbolic tangent function for the \( i \)th measurement, \( n \) is the number of lane change measurements. \( x_{\text{meas},i}(t) \) is the measurement, \( t = (k - 1) \Delta t \), and \( k \) denotes the number of data points of each measured lane change maneuver. Fig. 3.11 clarifies the MAD of longitudinal part \( y \) and lateral part \( \Delta x \) with respect to the weight \( \xi \).

Note that in real cases, there are several other variations, depending on vehicles and road conditions so that modeling errors in some specific measurements can be further reduced. However, the model complexity does not substantially change the overall
modeling precision. We do not aim to produce a perfect model, but to produce a testable case.

In conclusion, although a lane change maneuver has various driving trajectories in nature, it can be modeled with limited variables and high modeling precision.

**The Bias-variance Trade-off**

![Figure 3.12: Fitting performance comparison of all 167 recorded lane change maneuvers: parametrization Eq. (3.8) $v(t) = v_0$ and Eq. (3.12) $v(t) = v_0 + a_0 \cdot t$](image)

Fig. 3.10 panel (2) shows the fitting of velocity profiles of the lane change maneuvers. As we can see, $v(t) = v_0$ in Eq. (3.8) cannot describe all the measurements well. That leads to a large modeling error, especially in longitudinal part (underfitted). In order to reduce the modeling error, the lane change model needs to be extended. Owing to the fixed curve model of lateral movement defined by Eq. (3.3), we extend the longitudinal part by introducing additional parameters into the vehicle velocity. For example, the velocity $v(t)$ in Eq. (3.8) is extended with a constant acceleration $a_0$, namely $v(t) = v_0 + a_0 t$. That leads to a extended lane change model, which is as follows:
\[
\Delta x_i = -z_1 \cdot \tanh \left( \frac{t_i - z_2}{z_3} \right) + z_4
\]

\[
y_i = \sum_{j=1}^{i} \sqrt{v_j^2 - (\Delta x_j)^2} \cdot \Delta t
\]

\[
= \sum_{j=1}^{i} \sqrt{v_j^2 - \left( -\frac{z_1}{z_3} \cdot \left( 1 - \tanh^2 \left( \frac{t_j - z_2}{z_3} \right) \right) \right)^2} \cdot \Delta t
\]

\[
v_i = v_0 + a_0 \cdot t_i
\]

\[
t_i = (i - 1) \cdot \Delta t
\]

variable: \( \bar{X}^T = [z_1, z_2, z_3, z_4, v_0, a_0] \)

Fig. 3.12 compares the MAE of all 167 measured lane change maneuvers, obtained by the approximation of Eq. (3.8) and Eq. (3.12) respectively. The additional parameter in the velocity greatly improves the modeling precision by reducing the modeling error of the longitudinal part.

With the increasing dimension of the model (parameter complexity), the modeling errors can be further reduced. We extend the vehicle velocity with various additional variables shown as follows:
3.2 Modeling of lane change Maneuver

\[ v_i = v_0 \]  
\[ v_i = v_0 + a_0 \cdot t_i \]  
\[ v_i = v_0 + a_0 \cdot t_i + \frac{1}{2} c_0 \cdot t_i^2 \]  
\[ v_i = v_0 + a(t) \cdot t_i, \quad a(t) = \begin{cases} 
  a_0, & t_i \leq t_1 \\
  a_1, & t_i > t_1 
\end{cases} \]  
\[ v_i = v_0 + a_0 \cdot t_i + \frac{1}{2} c(t) \cdot t_i^2, \quad c(t) = \begin{cases} 
  c_0, & t_i \leq t_1 \\
  c_1, & t_i > t_1 
\end{cases} \]  
\[ v_i = v_0 + a(t) \cdot t_i, \quad a(t) = \begin{cases} 
  a_0, & t_i \leq t_1 \\
  a_1, & t_1 < t_i \leq t_2 \\
  a_2, & t_2 < t_i 
\end{cases} \]  
\[ v_i = v_0 + a_0 \cdot t_i + \frac{1}{2} c(t) \cdot t_i^2, \quad c(t) = \begin{cases} 
  c_0, & t_i \leq t_1 \\
  c_1, & t_2 < t_i \leq t_1 \\
  c_2, & t_i \geq t_2 
\end{cases} \]  
\[ v_i = v_0 + a(t) \cdot t_i, \quad a(t) = \begin{cases} 
  a_0, & t_i \leq t_1 \\
  a_1, & t_1 < t_i \leq t_2 \\
  a_2, & t_2 < t_i \leq t_3 \\
  a_3, & t_3 < t_i \leq t_4 \\
  a_4, & t_i > t_4 
\end{cases} \]  

where: \( t_i = (i - 1) \cdot \Delta t \)

parameters: \( X^T = [z_1, z_2, z_3, z_4, v_0, a_0, ..., a_4, c_0, c_2, c_1, c_3] \)

However, the improvement of modeling precision might be limited, that is the further increase of variables might lead to smaller, or even no reduction of the modeling error. Moreover, high dimensionality can lead to the combinatorial explosion. In order to limit the validation workload, it is crucial to find a balance between modeling precision (the fitting performance) and the parameter complexity. To evaluate the fitting performance in terms of modeling complexity, we calculate two performance indices: MAD (see Eq. (3.11)) and the Root of the Mean Squared Deviation (RMSD).
The root of the mean squared deviation (RMSD) index is an unequally weighted difference based on squared differences, which is given by

$$\text{RMSD} = \sqrt{\frac{1}{n\cdot k} \sum_{i=1}^{n} \sum_{t=1}^{k} [x_i(t) - \text{xmeas}_i(t)]^2}$$

(3.14)

where \(X_i(t) = \{x_i(0), ..., x_i(k)\}\) denotes the fitted hyperbolic tangent function for the \(i\)th measurement, \(n\) is the number of lane change measurements. \(x_{\text{meas},i}(t)\) is the measurement, \(t = (k - 1) \Delta t\), and \(k\) denotes the number of data points of each measured lane change maneuver.

Fig. 3.13 shows the variation of fitting performance indices with respect to the modeling complexity, where all the parameters are calculated via minimizing the MAE given in Eq. (3.9). Although the fitting errors tend to continuously decrease with the increasing number of parameters, the fitting performance indices of both longitudinal and lateral part reach saturated values when the number of parameters is greater than 6. Including jerk \(c\) in the lane change model brings more benefits in reducing the fitting errors than increasing the number of the acceleration segmentation (see Eq. (3.13d), (3.13f) and (3.13h)). It also indicates characteristics of the lane change maneuver in highway scenarios, that is, most drivers tend to keep constant jerk during the lane change maneuver.

**Table 3.1:** Fitting performance indices with respect to parametrization complexity

<table>
<thead>
<tr>
<th>Modeling: extension of Eq. (3.8)</th>
<th>Total parameters</th>
<th>Long</th>
<th>Lat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. (3.13a) n= 4</td>
<td></td>
<td>0.430</td>
<td>1.575</td>
</tr>
<tr>
<td>Eq. (3.13b) n= 5</td>
<td></td>
<td>0.103</td>
<td>0.476</td>
</tr>
<tr>
<td>Eq. (3.13c) n= 6</td>
<td></td>
<td>0.151</td>
<td>0.218</td>
</tr>
<tr>
<td>Eq. (3.13d) n= 7</td>
<td></td>
<td>0.0065</td>
<td>0.382</td>
</tr>
<tr>
<td>Eq. (3.13e) n= 8</td>
<td></td>
<td>0.077</td>
<td>0.202</td>
</tr>
<tr>
<td>Eq. (3.13f) n= 9</td>
<td></td>
<td>0.177</td>
<td>0.494</td>
</tr>
<tr>
<td>Eq. (3.13g) n= 10</td>
<td></td>
<td>0.050</td>
<td>0.142</td>
</tr>
<tr>
<td>Eq. (3.13h) n= 13</td>
<td></td>
<td>0.032</td>
<td>0.092</td>
</tr>
</tbody>
</table>

Details of fitting performance indices in terms of parameterization complexity are given in Table 3.1. As a result, we choose the Eq. (3.13c) as the best extension of the lane change model Eq. (3.8), according to Occam’s razor [61].

Noting that \(v_0\) in Eq. (3.13) stands for the initial velocity of the preparation phase of the lane change maneuver, whose duration differs from measurement to measurement (owing to the fixed time length of all measurements and the different lane change duration in each measurement). That is unwanted for scenario generation, because specifying an additional parameter for the duration of the preparation phase means to increase the model complexity. Furthermore, there is no specified definition on the duration of the preparation phase. Thus, we choose a constant time length...
3.2 Modeling of lane change Maneuver

(1 s) for the preparation phase and compute the parameter $v_0$ and $a_0$ at the time point $t^* = z_2 - \frac{T}{2} - 1$ s according to Eq. (3.13c) as the corresponding lane change characteristics.

That leads to a time continuous lane change model given by:

\[
\Delta x(t) = -z_1 \cdot \tanh \left( \frac{t - z_2}{z_3} \right) + z_4
\]
\[
y(t) = \int \sqrt{v(t)^2 - \Delta x(t)^2} \cdot dt
\]
\[
= \int \sqrt{v(t)^2 - \left( -\frac{z_1}{z_3} \cdot \left( 1 - \tanh^2 \left( \frac{t - z_2}{z_3} \right) \right) \right)^2} \cdot dt
\]  
\[
v(t) = v_0 + a_0 \cdot t + \frac{1}{2} c_0 \cdot t^2
\]
\[
t \in [0 , +\infty]
\]

Parameter: $\bar{X}^T = [z_1, z_2, z_3, v_0, a_0, c_0]$

The corresponding lane change characteristics are shown in Fig. 4.15

---

**Figure 3.13:** Fitting performance with respect to the parametrization complexity
(1) Distribution of the MAE: 167 measurements

(2) The statistics of lane change characteristics obtained from 100 best fitted measurements featured by MAE < 0.3 m

Fig. 3.14: lane change characteristics and fitting errors

Fig. 3.15 illustrates the trajectory generation using lane change model Eq. (3.15) with various parameter values in a given time horizon $t = 12$ s. Panel (1) shows the resulting trajectory of lane change maneuvers, in which we can observe the effect of lane change duration on the curve form. Panel (2) - (3) show the lateral and longitudinal time course, respectively. The velocity profiles are shown in Panel (4), in which we can see the effect of the acceleration and jerk on the speed profile over the time.
3.3 Exemplary Parametrization & Simulation

Now the parametrization of the scenario can be derived from the model with rather low parameter complexity. In the following section, we will take scenario No.10 as an example to explain the parametrization of scenarios using the lane change model.

3.3.1 Parametrization of Scenario No.10

Based on the lane change model, we can obtain the realistic parametrization of the scenario and assess the safety of HAVs according to the actual traffic.

Scenario No.10 is defined in Table 2.6. To be more specific, the ego-vehicle is following a preceding vehicle, driving at a constant speed $v_{\text{preceding}}$, in a suitable distance with $t_{\text{THW}}$, when suddenly the front vehicle in the adjacent lane changes the lane and cuts in between the ego-vehicle and the preceding vehicle. The interaction between
front vehicle and ego-vehicle is characterized by the longitudinal distance and velocity gaps \( \{\Delta y_0, \Delta v_0\} \) at the start time point of the lane change maneuver. The lane change trajectory \([\Delta x(t), y(t)]\) of the front vehicle is generated by lane change model Eq. (3.15), namely:

\[
\text{parameter: } \bar{\theta}^T = [\Delta y_0, \Delta v_0, z_1, z_3, a_0, c_0] \\
\text{so that: } \Delta x(t) = -z_1 \cdot \tanh \left( \frac{t - z_2}{z_3} \right) + z_4 \\
y(t) = \int_0^{T_{\text{sim}}} \sqrt{v(t)^2 - \Delta x(t)^2} \cdot dt \\
= \int_0^{T_{\text{sim}}} \sqrt{v(t)^2 - \left( -z_1 \cdot \left( 1 - \tanh^2 \left( \frac{t - z_2}{z_3} \right) \right) \right)^2} \cdot dt \quad (3.16) \\
v(t) = v_0 + a_0 \cdot t + \frac{1}{2} c_0 \cdot t^2 \\
\text{where: } v_0 = v_{\text{ego,0}} + \Delta v_0 \\
t \in [0, T_{\text{sim}}]
\]

where \( v_{\text{ego,0}} \) denotes the velocity of ego-vehicle at the start point of the lateral movement of the cut-in vehicle, and \( T_{\text{sim}} \) is the simulation duration. Fig. 4.13 illustrates the parametrization graphically. It is noteworthy that \( z_2 \), the time shifting parameter, does not appear in the parameter set, due to the fact that it has no influence on the variation of lane change characteristics shown in Fig. 4.15. \( z_2 \) is defined by simulation specification, which is as follows:

\[
z_2 = \frac{T}{2} + 1 + t_0 = \frac{3.9 \cdot z_3}{2} + 1 + t_0, \quad t_0 \geq 0 \quad (3.17)
\]

where \( t_0 \) is a given time offset, defining when the start point of the lane change maneuver of the cut-in vehicle in each simulation run. The resulting scenario class (set of all specified scenarios) covers 90\% operation situations of scenario No.10 in the highway traffic situation with mean absolute error: \( \text{MAE} < 0.5 \text{ m} \) according to the current available measurements.

### 3.3.2 Virtual Testing Environment

The simulation runs on \textit{IPG CarMaker} and \textit{Matlab Simulink}. The test vehicle of our institute is parametrized within the virtual environment by various parameters from test driving in the real world, data sheets, and through identification, see [119]. Specified testing scenarios are generated by \textit{Matlab} and are synchronized with \textit{IPG}
3.3 Exemplary Parametrization & Simulation

CarMaker through CM4SL\(^1\). An ACC system (ACC Controller and ACC Radar) is chosen as the SUT, where the following ACC strategy is implemented,

\[
\begin{align*}
    a_{des} &= k_1(\Delta y - \Delta y_{des}) + k_2(v_{ego} - v_{preceding}) \\
    \Delta y_{des} &= \Delta y_{min} + t_{THW} \cdot v_{ego}
\end{align*}
\]

where \(\Delta y_{min}, \Delta y, \Delta y_{des}, v_{ego}, v_{preceding}, \) and \(t_{THW}\) are the stillstand longitudinal distance, longitudinal distance gap, desired longitudinal distance gap, velocity of the ego-vehicle, velocity of the preceding vehicle, and set desired time headway of ACC controller, respectively. \(k_1\) and \(k_2\) are tuning parameters of the controller and \(a_{des}\) is the desired acceleration, see Fig. 3.17. The safety criteria is whether a collision is avoided or not.

For visualization purpose \(z_1\) and \(z_4\) are fixed, such that the cut-in vehicle’s lane change maneuver starts from the middle of the initial lane and ends up in the middle of the destination lane as well. The constant acceleration \(a_0\) and jerk \(c_0\) are set to 0. The lane change maneuver is characterized through 2 parameters, namely the lane change velocity \((v = v_0 = v_{ego,0} - \Delta v_0)\) and the lane change duration \((T)\), where \(v_{ego,0} \approx v_{preceding}\). That results in the parameterized scenario with a 3-dimensional parameter space \(\{\Delta y_0, \Delta v_0, T\}\), given as follows:

\[
\begin{align*}
    t_{THW} &= 1.5s, \quad v_{preceding} = 30\, m/s \\
    z_3 &= \frac{T}{3.9}, \quad z_1 = 1.9, \quad z_4 = 3.8 \\
    v_0 &= v_{preceding} + \Delta v_0, \quad a_0 = 0, \quad c_0 = 0 \\
    \Delta v_0 &\in [-6.5, -1.5]\, m/s, \quad \Delta y_0 \in [2, 45]\, m, \quad T \in [1, 15]\, s
\end{align*}
\]

Fig. 3.18 panel (1) clarifies the three dimensional exemplary parametrization.
(1) Exemplary 3 dimensional parametrization

(2) The simulation results via the full scale grid searching

(3) Two different variants of the resulted safe Cut-in

Figure 3.18: Exemplary three dimensional parametrization and simulation results
3.3.3 Simulation Results

Fig. 3.18 shows the simulation results, obtained through a full scale grid searching with grid width \{0.5 [m/s], 1 [m], 0.5 [s]\}. As a result, one has \(11 \times 44 \times 29 = 14036\) grid points.

Three different simulation results, that is, collision and two safe situations, are identified and shown in Fig. 3.18 panel (2). The red crosses represent the parameter combinations that leads to front-end collision or sideswipe between the ego-vehicle and the cut-in vehicle. The green circles represent the parameter combinations that the ACC controller reacts to the cut-in vehicle properly and avoids the crash successfully (see panel (3) variant (1)). The blue dots represent the situation that the cut-in vehicle successfully changes the lane without cutting in between the ego-vehicle and the preceding vehicle but behind the ego-vehicle, see panel (3) variant (2). We find that variant (2) is related to low time-to-collision \(TTC = -\frac{\Delta y}{\Delta v}\), namely low velocity gap or distance gap or both, and long lane change duration. It can appear in the actual traffic but the frequency is known, whereas the variant (1) is the most common and frequent cut-in situation in real traffic situation. The light blue hull that envelops the safe situations in panel (3) is the collision-free boundary. That indicates the safety performance limit of the HAV in terms of the cut-in situation.

3.4 Summary

In this chapter, we have introduced a scenario parametrization approach to generate specified test scenarios for virtual testing of HAVs. It is based on the model-based and data-driven method, presented at the example of the lane change maneuver and using real measurements. It allows us to search for free variables, such as the cases in which a collision would occur.

The approach presented is mainly according to Occam’s razor (the law of parsimony) to avoid overparametrization of the normal behavior so that the majority of measured situations can be covered with a rather simple parametrization. As for cases which are not of normal operation but are ones with exceptional situation, (although safety testing cannot be based on them) it is still important to detect and separate them as materials for further study or indicator for data collection.

\(^1\)CarMaker for use with Simulink
Chapter 4

Safety Assessment of HAVs via Collision-free Boundary Searching

4.1 Preliminaries

Until now, we have proposed a catalogue to limit the total scenarios being considered and a method to obtain the realistic parametrization of the scenario using experimental data. This allows the determination of a collision-free boundary in the parameter space separating the safe conditions (parameter combinations) from unsafe. This collision-free boundary represents the SUT’s performance limit in terms of crash avoidance, which measures the safety of HAVs. These parameter combinations close to the boundary are the so-called corner cases, on which the focus of the further testing, such as SiL, MiL and VehiL, should be laid.

In this chapter, we propose a combined criteria for safety assessment of the HAVs. It evaluates the performance safety of the HAVs through estimation of the collision probability in real traffic situations by simulation. We first propose a Design-of-Experiment (DoE) strategy for the fast determination of the collision-free boundary. And then, based on the resulted collision-free boundary, we propose an approach estimating the collision probability $P_c$ of the HAVs under test. The resulted probability $P = 1 − P_c$ can be seen as the safety performance criteria, as it tells the probability that no collision will occur for a whole range of the traffic situations. And the collision-free boundary describes the corner cases for the further validation. It is worth mentioning that $P_c$ itself can work as the feedback to optimize the tuning parameter of the HAV’s system as well [27].

Fig. 4.1 explains the proposed criteria on measure of safety. Panel (1) clarifies the simplified exemplary parametrization of a scenario with 2 parameters $\{\Delta y_0, \Delta v_0\}$, which build up a 2-dimensional parameter space as shown in panel (2). If crashes only occur within a subspace of it, which means no collisions in the complementary subspace, we can find a boundary that separates the crash situations from the collision-free ones, see green area in panel (2). Panel (3) shows a joint distribution $Pr (\Delta y_0, \Delta v_0)$ of the parameter space derived from measurements. In panel (4), we plot the 2-dimensional
probability contour of the safe region. If for instance, it tells us that the parameter combinations inside the collision-free region have high occurrence in terms of real traffic situation with \( P \approx 0.99 \), then, 99% of the cut-ins a HAV will encounter will belong to the collision-free parameter region, i.e. they do not present any risk. Only the region near to the collision-free boundary - the corner cases – should be considered for further validation.

**Figure 4.1:** The criteria of safety assessment based on an exemplary test scenario

The rest of this chapter is organized as follows: section 2 introduces the Gaussian Process Classifier based DoE strategy for boundary searching and the corresponding iterative algorithm. Section 3 clarifies the estimation of collision probability based on the obtained collision-free boundary, using the Kernel Density Estimation (KDE) approach. A simulation example, demonstrating the process from parametrization of scenario to the safety assessment of the HAV, is presented in Section 4 on an exemplary scenario No.11. A short summary is present in section 5.

### 4.2 Accelerated Iterative Boundary Searching

#### 4.2.1 Preliminaries

In chapter 3, the collision-free boundary is obtained through a full scale grid searching, which usually requires a large amount of simulation runs to achieve a certain accuracy (grid precision). That is highly time consuming and inefficient, because we are interested in finding the boundary, the so-called corner cases, which represents the performance limit of the HAVs.
To overcome this limitation, various DoE methods are developed in the previous works to speed up the process of boundary searching. The most common approaches are the methods based on convex hull or minimizing the parameters’ variance \[71, 68\]. However, for the parametrization of a scenario, the collision free boundary can be non-convex. A Gaussian Process Classifier (GPC) and a Support Vector Machine (SVM) based DoE strategy, proposed in \[62\] and \[38\], respectively, can find and describe the non-convex boundaries iteratively. However, there is no criteria to evaluate the approximation quality of the resulted boundary and thus, no stopping criteria for exiting the iteration. As the safety criteria in our work is a binary signal, namely crash or not, we employ the Gaussian Process Classifier based Design-of-Experiment strategy to accelerate the boundary searching task \[62\]. We extend the approach with an approximation quality estimator and thus, the stop criteria for the iterative algorithm. We apply GPC to model the static mapping from parameter space (inputs) \(\Theta\) of a parametrized scenario to the simulation output \(y(\theta)\) \(\in\{+1, -1\}\). The GPC learns and updates the model iteratively, and delivers the probability that the output of a new input \(\theta^*\) \(\in\Theta\) belongs to a class, namely \(\Pr(y(\theta^*) = +1)\), based on the previous knowledge (prior simulation runs). Fig. 4.2 panel (1) describes the work-flow of the

![Diagram](image)

**Figure 4.2:** Exemplary three dimensional parametrization and simulation results
accelerated boundary searching using GPC based DoE strategy, taking an exemplary parametrization of the scenario No.10 with 3 dimensional inputs $\theta = [\Delta v_0, \Delta y_0, T]^T$ and binary outputs $y \in \{+1, -1\}$ as the example, as shown in panel (2).

In following, we clarify the approach based on this exemplary 3-dimensional parametrization of scenario No.10.

### 4.2.2 Boundary model

Firstly, we define the boundary and collision-free region by probability. Assuming that the parametrization of a scenario is represented by the following nonlinear model

$$
\dot{x} = f(x, \theta), \\
y = g(x, \theta),
$$

(4.1)

where $x \in \mathbb{R}^{N_x}$, $\theta \in \mathbb{R}^{N_\theta}$ and $y \in \{-1, +1\}$ denote the state vector, input vector and binary output, respectively. The dimension $N_x$ depends on modeling details of vehicle dynamics and the system design of the Autonomous Driving Function (ADF) in HAVs. The parameters $\theta$ of the parametrized scenario is the input of the system Eq. (4.1). Thus, the input space (all possible parameter combinations) is divided into two regions described by a static function $h(\theta)$, according to the corresponding output classes, namely

$$
h(\theta) \begin{cases} 
\leq 0 & \text{inadmissible region (} y = +1) \\
> 0 & \text{admissible region (} y = -1) 
\end{cases}
$$

(4.2)

where the input vector $\theta$ is the decision vector of the regions [62]. In this case, the class label of the inadmissible region $y = +1$ means that the simulation ends up with a collision. Thus, the border of admissible region (boundary), which separates the admissible inputs from inadmissible, is given by

$$
\Theta_0 = \{\theta | h(\theta) = 0\}.
$$

(4.3)

In order to apply the GPC based DoE strategy on boundary searching problem, we squash $h(\theta)$ through a logistic function into the interval $[0, 1]$, 

$$
h_p(\theta) = \frac{\eta}{\eta + e^{\exp(-h(\theta))}}, \quad \eta > 0
$$

(4.4)

where $\eta$ is mandatory positive. As a result, the boundary of admissible region is given by

$$
\Theta_0 = \{\theta | h_p(\theta) = \Pr_{th}\}
$$

where:

$$
\Pr_{th} = h_p(\theta) \big|_{h(\theta) = 0} = \frac{\eta}{\eta + 1}, \quad \eta > 0
$$

(4.5)
Accordingly, the input space is divided into admissible and inadmissible region by Eq. (4.5) as follows:

\[ h_p(\theta) \in \begin{cases} [0, Pr_{th}] & \text{inadmissible region} \\ (Pr_{th}, 1) & \text{admissible region} \end{cases} \]

where:

\[ 0 = h_p(\theta) \big|_{h(\theta) \to -\infty} \]

\[ 1 = h_p(\theta) \big|_{h(\theta) \to +\infty} \ordspace{4.6} \]

Pr_{th} in Eq. (4.5) and Eq. (4.6) is a probability threshold for the boundary, which also determines the aggressiveness of algorithm during input space exploration. The details will be illustrated in the following sections.

### 4.2.3 Binary Gaussian Process Classifier

The classification problem is to output the correct class label for a new input data through the knowledge obtained from the existing data (training data set). The training data set can be any classified measurements, simulation results or knowledge. In following, we introduce the Gaussian Process Classifier from [70, 9]. GPC is a nonparametric classification method based on a bayesian methodology. In GPC, it is assumed that the probability of belonging to a class is monotonically related to the value of some latent real value function \( f_l(\theta) \in \mathbb{R} \) at that location \( \theta \). That is, for binary classification problem,

\[ \Pr(y = +1 | \theta, D, f_l(\theta)) = \Pr(y = +1 | f_l(\theta)) \ordspace{4.7} \]

where \( D = \{ \bar{\theta}, \bar{y} \} \) is the training data set. \( \bar{\theta} \in \mathbb{R}^{N_\theta \times N_D} \), \( \bar{y} \in \{-1, 1\}^{N_D} \), and \( N_D \) denote the input data, output class, and the number of samples of the training set, respectively. The monotonic relationship is obtained by squashing the latent function, which can lie in the domain \([-\infty, +\infty]\), into the range \([0, 1]\). We assume a Gaussian Process (GP) prior over \( f_l \) and squash it through a logistic function to obtain the prior for binary output,

\[ \Pr(y = +1 | f_l(\theta)) = \frac{1}{1 + \exp(-f_l(\theta))} \in [0, 1] \ordspace{4.8} \]

The inference is divided into 2 steps. For the sake of clarity, we simplify the expression by using the notation \( f_l = f_l(\theta), \bar{f}_l = f_l(\bar{\theta}) \) and \( f_{l*} = f_l(\theta_*) \), where \( \theta_* \in \Theta/\bar{\theta} \) refers to new input data.

First, we calculate the distribution of the latent variable corresponding to the new input data \( \theta_* \).

\[ \Pr(f_{l*} | D, \theta_*) = \int \Pr(f_{l*} | \theta, \bar{f}_l, \theta_*) \Pr(\bar{f}_l | D) d\bar{f}_l \ordspace{4.9} \]
where $\Pr(f_1|D) = \Pr(\bar{y}|\bar{f}_1) \Pr(\bar{f}_1|\Theta)/\Pr(\bar{y}|\Theta)$ is the posterior over the latent variables. $\Pr(\bar{y}|\bar{f}_1)$, $\Pr(\bar{f}_1|\Theta)$, and $\Pr(\bar{y}|\Theta)$ denote the likelihood function, the marginal likelihood and GP prior over $f_1$, respectively.

Second, we use the distribution of $f_1^*$ to predict the probability of output class label for the corresponding new input data $\Theta^*$ as follows:

$$
\Pr(y^* = +1|D, \Theta^*) = \int \Pr(y^*|f_1^*) \Pr(f_1^*|D, \Theta^*) df_1^* , \tag{4.10}
$$

Due to the non-conjugate Gaussian process prior to non-Gaussian likelihood $\Pr(\bar{y}|\bar{f}_1)$ in Eq. (4.9) and Eq. (4.10), the integrals are not analytically tractable. Therefore, the analytical approximation methods are applied. Two common analytical approximation methods are the Laplace and the expectation propagation approximations [70]. In this work, we apply Laplace method, using a Gaussian Approximation $q(\bar{f}_1|\Theta, \bar{y})$ to the posterior $\Pr(\bar{f}_1|\Theta, \bar{y})$ in Eq. (4.9). Accordingly, the prediction of the new input data $\Theta^*$ is evaluated through Gaussian Approximation:

$$
\Pr(y^* = +1|D, \Theta^*) \approx \int \Pr(y^*|f_1^*) q(f_1^*|D, \Theta^*) df_1^* , \tag{4.11}
$$

where $q(f_1^*|D, \Theta^*)$ is gaussian with $N(E_q, V_q)$ given by:

$$
E_q[f_1^*|D, \Theta^*] = \bar{k}_s^T K^{-1} \hat{f}_1,
$$

$$
V_q[f_1^*|D, \Theta^*] = k(\Theta^*, \Theta^*) - \bar{k}_s^T (K + W^{-1}) \bar{k}_s , \tag{4.12}
$$

in which $\hat{f}_1 = \arg \max_{\hat{f}_1} \Pr(\bar{f}_1|D)$ and $W \triangleq \nabla^2 \log \Pr(\bar{y}|\bar{f}_1)$. $\bar{k}_s = k(\Theta^*)$ and $K = K(\hat{\Theta}, \hat{\Theta})$ denote the vector of covariances between the new input point and the $N_D$ training points, and the covariance matrix of $N_D$ training points, respectively.

Thus, the predictive probability $\Pr$ of an output belonging to a class, Eq. (4.10) is approximated through the averaged predictive probability given by Eq. (4.11) and Eq. (4.12).

### 4.2.4 Design-of-Experiment Strategy for Iterative Boundary Searching

In this section, we introduce the DoE strategy based on variance $V_q$ from [62]. The approach is extended with an approximation quality estimator and a stopping criteria for the iteration algorithm.

#### 4.2.4.1 The variance $V_q$ and DoE strategy

In addition to the predictive probability model, which predicts the probability of an output belonging to a class for the corresponding input data, GPC generates an approximate variance model as well, due to the Gaussian Approximation of the posterior, see Eq. (4.12). Fig. 4.3 shows the output of GPC with 50 samples of training data for the simplified two dimensional parametrization of scenario No.10 introduced
4.2 Accelerated Iterative Boundary Searching

in Chapter 3. The lane-changing duration is fixed at $T = 5 [s]$, namely $\theta = [\Delta v_0, \Delta y_0]^T$. The predictive probability $Pr$ vs $\Delta v_0$ and $\Delta y_0$ is shown in panel (1). The black dash line is the true boundary, whereas the probability contours are plotted in various colors. The green solid curve in both panel (1) and (2) denotes the collision-free boundary $\Theta_0 = \{ \theta | h_p (\theta) = Pr_{th} \}$, predicted by GPC based on the current training data. We observe that the variance $V_q$ near the predictive boundary have larger values than in the rest, see panel (2).

![Figure 4.3: Output of the GPC Pr contour and the variance $V_q$ vs $\{\Delta v_0, \Delta y_0\}$ for the simplified two dimensional parametrization of scenario No.10](image)

Therefore, the DoE strategy is based on the idea that inside the admissible region

$$\Theta_a = \left\{ \theta | Pr(\theta) = 0, \theta \in \hat{\theta} \right\} \cap \left\{ \theta_s | Pr(\theta_s) \leq Pr_{th}, \theta_s \in \Theta / \hat{\theta} \right\}$$ (4.13)

the variance $V_q [f_{s*} | D, \Theta_s]$ will have larger values near the true class boundary that tells the next location to be tested [62]. As a result, we choose the next input of the parametrized scenario (parameter combination) inside predictive admissible region, where the variance has the maximal value, namely $\max_{\theta_s \in \Theta_s} V_q$.

Using variance, we determine the new input parameter values in the admissible region $\Theta_a$. A greater $Pr_{th}$ speeds up the space exploration, however, it is more likely to locate the new inputs with $y(\theta_s) = -1$, which is unwanted in some Hardware-in-the-Loop simulation due to the risk of hardware damage, e.g. engine test bed introduced in [62] [38].

Fig. 4.4 and Fig. 4.5 illustrate the GPC’s outputs over the iterations for the same exemplary parametrization of scenario No.10. Fig. 4.4 clarifies the expansion of the predictive collision-free boundary and how the DoE strategy steers the choice of new input such that the most tested inputs (parameter combinations) lie in the region close to the true boundary (black dash line). The predictive collision-free boundary
Figure 4.4: $Pr$ contour vs $\{\Delta v_0, \Delta y_0\}$ and predictive collision boundary over various iterations (green solid curve) separates approximately the safe conditions (red crosses) from collisions (blue circles). After 100 iterations, the true boundary is well approximated by predictive collision-free boundary. The 2-D views of the corresponding variance over the input space $V_q$ vs $\{\Delta y_0, \Delta v_0\}$ are given in Fig. 4.5.
The GPC based iterative algorithm for boundary searching can be summarized as follows:

### 4.2.4.2 Approximation Quality And The Stopping Criterion

The DoE strategy in [62] is designed to find the best approximation of the boundary for a fixed number of iterations, so there is no stopping criteria for the iterative algorithm. In our application, the proposed DoE strategy searches for an approximation of the true
Table 4.1: GPC based iterative algorithm for boundary searching

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>set some classified initial data set ( { \theta, \bar{y} } ) and some (artificial) forbidden points with adverse class label outside the inputs space, see Fig. 4.9 panel (1)</td>
</tr>
<tr>
<td>(2)</td>
<td>generate the class boundary using GPC based on ( { \theta, \bar{y} } ) and find the admissible region ( \Theta_a )</td>
</tr>
<tr>
<td>(3)</td>
<td>choose the new input data according to ( \theta^*<em>c = \arg \max</em>{\theta_c \in \Theta_a} V_q ) and find the class label of ( y ) through simulation or experiment,</td>
</tr>
<tr>
<td>(4)</td>
<td>stop the iteration if the exit condition Eq. (4.16) is satisfied, otherwise go back to <strong>Step (2)</strong></td>
</tr>
<tr>
<td>(5)</td>
<td>generate class boundary numerically</td>
</tr>
</tbody>
</table>

Figure 4.6: Equipment for data acquisition
boundary iteratively. Therefore, it is crucial to be able to evaluate the approximation quality after each iteration and thus, determine when to stop. In this section, we aim at finding the stopping criteria of the iteration algorithm. To achieve this task, we first take the relative approximation error of the boundary model as a reference. The relative approximation error $e\%$ is defined as follows:

$$e\% = (1 - \frac{ACC}{TP + TN}) \times 100$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

(4.14)

where TP, TN, FP, FN are numbers of true positive (correctly predicted collision), true negative (correctly predicted safe), false positive (falsely predicted collision), and false negative (falsely predicted safe), respectively. The ground truth are obtained through a full scale grid searching of a total 1500 grid points, see Fig. 4.6 panel (1). The discretization precision for $\Delta v_0$ and $\Delta y_0$ are $1 \, [m/s]$ and $1 \, [m]$, respectively.

Fig. 4.6 panel (2) shows the relative approximation error $e\%$ over iterations. We find that after 50 iterations, the relative approximation error $e\%$ is very close to zero and after 80 iterations $e\%$ becomes and stays zero. That means the boundary model can perfectly predict the output class label of every input scenario instance. However, because of the unknown output class label of the untested inputs, we can not measure the approximation error directly during the iteration. It is necessary to find some measurable variables which are closely correlated with approximation error, as approximation quality indicator.

Fig. 4.7 panel (1) − (5) shows how the distribution of predictive probabilities $Pr(y = +1|\Theta)$ changes over iterations. We find that the distribution of predictive probability tends to migrate out of the region near $Pr = 0.5$ over iterations, namely the number of $\theta_*$ with
\[ \Pr(y_s = +1|D, \theta_s) - \Pr_{th} \leq \Delta \Pr \quad \forall \theta_s \in \Theta_s = \Theta/\bar{\theta} \]  

(4.15)

decreases over iterations. It is worthy to mention that the output classes of the training data set \( \bar{\theta} \in D \) are known and the predictive probability of them are either 0 or 1. After a certain number of iterations, the distribution of predictive probability are separated by this probability margin \( |\Pr - \Pr_{th}| \leq \Delta \Pr \), namely the number of all elements in \( \Theta_{th} = \{ \theta \mid |\Pr(\theta) - \Pr_{th}| \leq \Delta \Pr \} \) approaches and stays zero, as shown in Fig. 4.7 panel (4) - (5). For further investigation on its correlation with \( e\% \), we define the relative distribution of the predictive probability \( \Theta_{th\%} \), expressed as follows:

\[ \Theta_{th\%} = \frac{|\Theta_{th}|}{|\Theta|} \times 100 \leq n_{th\%}, \]

(4.16)

where \( |\Theta| \) and \( |\Theta_{th}| \) are the cardinality (number of all elements) of \( \Theta \) and \( \Theta_{th} \), respectively.

![Figure 4.8: Analyzing the correlation between \( e\% \) and \( \Theta_{th\%} \)](image-url)
Fig. 4.8 panel (1) illustrates how $\Theta_{\text{th} \%}$ changes over iterations in comparison with the relative approximation error $e_{\%}$. At the beginning 20 iterations, the trend of $\Theta_{\text{th} \%}$ is not correlated with $e_{\%}$. That is due to lacking information, namely few samples of training data. In this period, the output of GPC is not reliable yet. After about 20 iterations, both $e_{\%}$ and $\Theta_{\text{th} \%}$ tend to decrease over the iterations. After 50 iterations, they approach to the value less than 1%, and from 80th iteration both of them stay at zero. Moreover, we observe that from 50th iteration on, the oscillations, appearing in the course of $e_{\%}$, are always accompanied with the oscillations in $\Theta_{\text{th} \%}$. A local zoom-in near $e_{\%} = 0$ is shown in panel (2). Panel (3) expresses $e_{\%}$ vs $\Theta_{\text{th} \%}$ over iterations. The red dots represent the first 50 iterations, that the resulted $\Theta_{\text{th} \%}$ are randomly dispersed over $e_{\%}$, whereas after 50 iterations (black dots), $\Theta_{\text{th} \%}$ starts to converge to zero and approximately linearly proportional to $e_{\%}$ near the origin, as shown in panel (4).

Thus, we employ $\Theta_{\text{th} \%}$ as the approximation quality indicator and propose the stopping condition of the iteration, given in the form of:

$$\Theta_{\text{th} \%} [k] = 0 \ & \ n_{\text{Iter}} > n_{\text{Iter,min}}$$

where:

$$\Theta_{\text{th} \%} [k] = \frac{1}{k} \sum_{i=0}^{k-1} \Theta_{\text{th} \%} (n - i)$$

(4.17)

is the mean value of the previous $k$ iterations’ $\Theta_{\text{th} \%}$ value at the n-th iteration. The minimum number of iterations can be chosen as, e.g. $n_{\text{Iter,min}} = 5\% \cdot |\Theta| \ [116]$.

### 4.2.5 Exemplary Simulation

To clarify the efficiency of the proposed method, we apply it to the 3-dimensional parametrized scenario No.10 introduced in Chapter 3. The iterative algorithm in Table 4.1 and the stopping criteria Eq. (4.17) is implemented in Matlab using GPML Matlab package available at [11]. The ground truth is obtained through the full scale grid searching of 14036 grid points over the whole input space $\Theta$, namely $|\Theta| = 14036$. 6 prior classified initial inputs, acquired through simulation in advance, are placed in the admissible region (safe condition, class label $-1$) and 22 artificially classified points (class labels $y = +1$) are placed outside input space $\Theta$, see Fig. 4.9 panel (1). These are the initial inputs of the GPC. The minimum number of iterations is chosen as $n_{\text{Iter,min}} = 5\% \cdot |\Theta| \approx 702$. The predictive probability threshold is $Pr_{\text{th}} = 0.5$ with margin $\Delta Pr = 0.05$, namely $\Theta_{\text{th}} = \{\theta \mid Pr - Pr_{\text{th}} \leq 0.05\}$. Fig. 4.9 illustrates how the algorithm steers the choice of new inputs optimally to accelerate the input space exploration and the corresponding prediction of the collision region. In panel (1) the initiation of the iteration algorithm is shown graphically. Panel (2)-(4) shows that the selection of inputs (parameter combinations) converge to the true safety boundary over iterations. The iteration stops after 1314 simulation runs, whereas most of the selected inputs are either next to the true boundary or close to the border of the input space (artificial boundary), see panel (4). For the sake of clarity and visualization purpose, we plot the prediction of collision region instead of the collision-free region.
Figure 4.9: Comparison of simulation results after different iteration steps

Panel (5) shows the ground truth obtained in the previous chapter. And panel (6)-(8) illustrate how the prediction changes over the iterations, respectively.
As the validation of the proposed stopping criteria, we run the simulation for another 186 iterations so that there are in total 1500 iterations. The relative approximation error $e_\%$ is evaluated by Eq. (4.14) based on the ground truth, shown in Fig. 4.9 panel (5). The correlation between $e_\%$ and $\Theta_{th\%}$ over full 1500 iteration length and last 1200 iterations are shown in Fig. 4.10 panel (1) and (2), respectively. As we find in panel (2) that after about 300 iterations $e_\%$ becomes approximately linear proportional to $\Theta_{th\%}$ near the origin. In panel (3), some abnormal rebounds in $\Theta_{th\%}$, spotted in the region near 1000 iterations (green circle), is closely related with the oscillations in $e_\%$. These rebounds can be found in the corresponding $e_\%$ vs $\Theta_{th\%}$ plot in panel (2) in the region close to $\Theta_{th\%} = 99, e_\% = 17$ (green circle).

A local zoom-in near the region $e_\% = 0$ as well as $\Theta_{th\%} = 0$ is shown in panel (4). For the last 216 iterations (1285th. to 1500th.), the values of the approximation quality indicator are $\Theta_{th\%} = 0$ except for 2 rebounds. The corresponding relative approximation errors in this interval are $e_\% \approx 0.0071\%$. That is: only one false positive (FP) in the prediction. Moreover, the initial inputs are placed in one of the two collision-free regions and the results show that both separated collision-free regions are identified by the algorithm. That is: the proposed approach works for non-connected space as well.
In conclusion, the GPC based DoE strategy can explore the input space searching for the boundary efficiently. Moreover, we propose to use the distribution of predictive probability over the iterations as an indicator of approximation quality and thus, the stopping condition for the iteration algorithm.

4.3 Collision Probability Estimation

4.3.1 Occurrence over the Parameter Space

The collision-free boundary represents the performance limit of the HAV in avoiding the crashes. However, for the assessment of HAVs’ safety with respect to real traffic situations, the occurrence of the crash related subspace (the collision region) in real traffic plays the role as well. If the situations, described by crash related subspace, appear less frequently in real traffic, the HAV is less likely to result a crash in real traffic. To achieve this task, we can estimate the collision probability of the HAVs. Different to the randomized methods applied in previous works [109, 110, 27, 42, 26], we estimate the collision probability of the HAVs in a deterministic way based on the obtained collision-free boundary. As we have already obtained the distributions of the corresponding parameters from FOT measurements in Chapter 3, we are able to evaluate the crash probability of the HAVs for the parametrization of the scenario No.10 via estimating the occurrence probability of the crash relevant subspace of the parameter space. That is to estimate how frequently the crash relevant parameter combination can appear in the real traffic.

For the estimation of the collision probability, we first need to derive the joint distribution of the parameters from the measurements. For the exemplary 3-dimensional parametrized scenario, it refers to the parameter set \( \{\Delta y_0, \Delta v_0, T\} \). Our target is to derive the multivariate distribution \( \Pr (\Delta y_0, \Delta v_0, T) \) from the measurements. That can be achieved by applying the KDE approach, which is a non-parametric way to estimate the probability density function of a random variable. It does not require the assumption that the underlying density function is from a parametric family, because KDE will learn the shape of the density from the data automatically. In this work, we apply the adaptive kernel density estimator for high dimensions in [10] using the kernel density estimation toolbox, which is available at [35].

The results are shown in Fig. 4.11. The blue triangles in panel (1) illustrates the measurements obtained in Chapter 3 in the 3-dimensional parameter space, whereas panel (2) and (3) show the corresponding 2-dimensional views of \( \{v_0, T\} \) and \( \{y_0, T\} \) with marginal distributions, respectively. The resulted multivariate distribution is shown as probability contours in panel (4). The probability contours are presented as surfaces in the 3-dimensional parameter space.

4.3.2 Collision Probability

Using the obtained distribution \( \Pr (\Delta y_0, \Delta v_0, T) \), we can now estimate the collision probability of the HAVs for the scenario No.10. In Fig. 4.12, those specified scenarios
4.3 Collision Probability Estimation

Figure 4.11: Estimated joint distribution of 3 Parameters for the exemplary parametrization of scenario No.10 (crashes) are highlighted and shown in various colors corresponding to their probability of occurrence. The crash probability can be approximated by

\[
P_c = \sum_{i=1}^{N_c} \Pr(\theta^i_c) \cdot \Delta \theta
\]

\[
\theta^i_c = [\Delta y_{0,c}, \Delta v_{0,c}, T_c]^T, \quad i = 1...N_c
\]

\[
\Delta \theta = d\Delta y_0 \cdot d\Delta v_0 \cdot dT
\]

(4.18)

where \([\Delta y_{0,c}, \Delta v_{0,c}, T_c]\) and \(N_c\) denote the parameter combinations that leads to crashes and the total number of the crash related parameter combinations, respectively. \(d\Delta y_0 = 1[m]\), \(d\Delta v_0 = 0.5[m/s]\), and \(dT = 0.5[s]\) denote the grid width (discretization precision) of \(\Delta y_0, \Delta v_0,\) and \(T_0\), respectively.

The collision probability of the tested ACC system is approximately \(P_c \approx 0.106\), namely the probability that no collision will occur for the whole range of the target traffic situations is approximately \(P \approx 0.894\). Depending on the resulting value for \(P\), the tuning parameters of controller can be optimized. In our example, it refers to the feedback gains \(k_1\) and \(k_2\). It is worthy to mention that it is not desirable for ACC system to achieve \(P = 1\), since it is designed as an ADAS for driving comfort and
efficiency\(^1\). E.g. the ACC system can be tuned to achieve \(P \approx 0.95\) so that the rest \(P_c \approx 0.05\) situations can be covered by employing additional systems like AEB and FCA as supplementary of the ACC system.

![Occurrence estimation of crash related subspace](image)

Figure 4.12: Estimate the occurrence of the crash related subspace

4.4 Example

4.4.1 Parametrization of Scenario No.11 & Specified Scenario Generation

In this section, we apply the proposed approaches on another example, scenario No.11.

Scenario No.11 is defined Table 2.6. In details: the EGO (1) is following a preceding vehicle (1) at a suitable distance with \(t_{THW}\), when suddenly the preceding vehicle (1) pulls out to the adjacent lane and reveals the preceding vehicle (2), which is driving at a slower but constant velocity \(v_{preceding}\). Fig. 4.13 describes the parametrization of scenario No.11 graphically. The interaction between preceding vehicle (1) and preceding vehicle (2) is characterized by the distance and velocity gaps \(\{\Delta y_0, \Delta v_0\}\) at the beginning of the preceding vehicle (1)'s pull-out (lane-changing) maneuver.

\(^1\)ACC field test results suggest that \(P \approx 0.95\) can be appropriate for highway cruising [22, 27]
4.4 Example

The corresponding lane-changing trajectory \([\Delta x(t), y(t)]\), is generated using the lane-changing model Eq. (3.15), namely:

\[
\begin{align*}
\text{variable: } \bar{\theta}^T &= [\Delta y_0, \Delta v_0, z_1, z_3, a_0, c_0] \\
\text{so that: } \Delta x(t) &= -z_1 \cdot \tanh\left(\frac{t - t_2}{z_3}\right) + z_4 \\
y(t) &= \int_0^{T_{sim}} \left(\sqrt{v_L(t)^2 - \Delta x_L(t)^2}\right) \cdot dt \\
v(t) &= v_0 + a_0 \cdot t + \frac{1}{2} c_0 \cdot t^2 \\
v_0 &= v_{\text{preceding}} - \Delta v_0 \\
z_2 &= \frac{T}{2} + 1 + t_0 = \frac{3.9 \cdot z_3}{2} + 1 + t_0, \quad t_0 \geq 0 \\
t &\in [0, T_{sim}]
\end{align*}
\]

(4.19)

where \(v(0) = v_0\), \(t_{\text{THW}}\), and \(T_{sim}\) is the cruising velocity of preceding vehicle (1) before the initiation of pull-out maneuver, the desired time headway of ACC controller, and the simulation duration, respectively. \(t_0\) is a given time offset, defining when the preceding vehicle (1) begins to pull out in each simulation run.

Fig. 4.14 shows the measurements of lane-changing maneuver used for parametrization. The corresponding lane-changing characteristics, shown in Fig. 4.15, are derived from FOT measurements using the approach introduced in Chapter 3. The resulting scenario class covers 95% operational situations of scenario No.11 in highway traffic with mean approximation errors: \(\text{MAE} < 0.6 \, m\), according to the current available measurements.

The specified scenarios (of scenario No.11) are obtained though variation of the variables within their value ranges. For visualization purpose \(z_1\) and \(z_4\) are fixed, such that the preceding vehicle (1)’s pull-out maneuver starts from the middle of the initial lane and ends up in the middle of the destination lane as well. The acceleration \(a_0\)
4 Safety Assessment of HAVs via Collision-free Boundary Searching

Figure 4.14: Measurements of the lane change maneuver: from right lane to the left lane and the constant jerk $c_0$ are set to 0. The lane-changing maneuver is characterized through 2 parameters, namely the lane-changing velocity ($v(t) = v_{\text{preceding}} - \Delta v_0$) and the lane-changing duration ($T$). That results in the parametrized scenario with a 3-dimensional parameter space $\{\Delta y_0, \Delta v_0, T\}$, shown in Fig. 4.16, given as follows:

\begin{equation}
\begin{align*}
&t_{\text{THW}} = 1s, \quad v_{\text{preceding}} = 20m/s \\
&z_3 = \frac{T}{3.9}, \quad \Delta v_0 = v_{\text{preceding}} - v_0 \\
&z_1 = 1.9, \quad z_4 = 3.9, \quad a_0 = 0, \quad c_0 = 0 \\
&T \in [2, 14] s, \quad \Delta v_0 \in [-15, -1] m/s, \quad \Delta y_0 \in [2, 130] m
\end{align*}
\end{equation}

4.4.2 Collision-free Boundary Identification

The simulation runs on IPG CarMaker and Matlab Simulink. The same vehicle model and ACC system used in Chapter 3 are employed as the HAV under test. The GPC based DoE strategy is applied to accelerate the identification of collision-free boundary. The indicator of safety is whether a collision occurs.

The input space is sampled by grid width $\{1[m/s], 1[m], 1[s]\}$. As a result, one has $20 \times 116 \times 13 = 30160$ grid points, in which there are 10617 cases (inputs) leading to collision between preceding vehicle 1 and preceding vehicle 2 (assuming
4.4 Example

Figure 4.15: Characteristics of lane changing maneuvers: from right lane to the left lane

blind drivers). These are marked as invalid inputs and excluded from the input space. As a result, one has the input space consisting of 19543 grid points over the whole valid input space $\Theta$, namely $|\Theta| = 19543$, see Fig. 4.16. 6 classified initial inputs, acquired through simulation in advance, are placed in the admissible region (safe condition, class label $-1$) and 22 artificially classified points (class labels $y = +1$) are placed outside input space $\Theta$, see Fig. 4.17 panel (1). These are the initial inputs of the
GPC. We chose the length for calculating $\Theta_{th\%}$ as $k = 20$. The minimum number of iterations is chosen as $n_{Iter, min} = 5\% \cdot |\Theta| \approx 977$ for the predictive probability threshold $Pr_{th} = 0.5$ with margin $0.05$, namely $\Theta_{th} = \{\theta | Pr - Pr_{th} \leq 0.05\}$.

Fig. 4.17 panel (2)-(9) illustrates how the algorithm steers the choice of new inputs optimally to accelerate the input space exploration. The green surface in panels (2)-(8) is the collision-free boundary found by GPC after the iteration stops (978 iterations). Panel (2)-(4) show that the selection of inputs converges to the final result of the predicted collision-free boundary over iterations. After 300 iterations, the new inputs are placed in the region close to this boundary. The iteration stops after 978 simulation runs, whereas most of the selected inputs are either next to the predicted collision-free boundary or close to the border of the input space (artificial boundary), see panel (4). The change of predicted forbidden inputs (collision relevant subspace) over iterations is shown in panels (5)-(8), in which panel (2) illustrate the initial prediction of the GPC based on the initial inputs. We notice that after 300 iterations, only few predicted forbidden inputs are still outside the final collision-free boundary (false positive). After iteration stops, all the predicted forbidden inputs are either inside or on the true boundary. Panel (9) shows the change of $\Theta_{th\%}$ over whole 978 iterations. As we can find that after 860 iterations, $\Theta_{th\%}$ approaches to zero and then stays until minimum iteration number is reached.

4.4.3 Collision Probability Estimation

Now we can estimate the collision probability of the HAVs for the scenario No.11 using the obtained collision-free boundary.

We first need to derive the joint distribution of the parameters from the measurements using KDE approach. Fig. 4.18 shows the results. The red triangles in panel (1) illustrate the measurements shown in Fig. 4.15 in the 3-dimensional parameter space, whereas panel (2) and (3) show the corresponding 2-dimensional views of $\{v_0, T\}$ and $\{y_0, T\}$ with marginal distributions, respectively. The resulted multivariate distribution is shown as probability contours in panel (4). The probability contours are presented as surfaces in the 3-dimensional parameter space. Using the obtained distribution $Pr (\Delta y_0, \Delta v_0, T)$, we estimate the collision probability of the HAVs for the scenario No.11 using Eq. (4.18). In Fig. 4.18, those specified scenarios (crashes) are highlighted and shown in various colors corresponding to their probability of

---

**Figure 4.16:** exemplary 3-dimensional parametrization of scenario No.11
4.4 Example

Figure 4.17: Comparison of simulation results after different iteration steps
Figure 4.18: Estimated joint distribution of 3 Parameters for the exemplary formalization of scenario No.11 and the exposure of those specified testing scenarios (crash) occurrence. The grid width (discretization precision) are $d\Delta y_0 = 1[m]$, $d\Delta v_0 = 1[m/s]$, and $dT = 1[s]$, respectively, namely $\Delta \theta = 1$. The resulting collision probability is
P_c \approx 0.0053, namely P_c \approx 0.995. That means the operation of the HAV under test is less probably to lead to a collision in a pull-out situation (scenario No.11) in real highway traffic.

4.5 Summary

In this chapter, we applied the iterative GPC based DoE strategy on the collision-free boundary searching problem in high dimensional space. We proposed a criteria for the evaluation of the approximation quality of the class boundary based on the distribution of the predictive probability generated by GPC. The resulted boundary refers to the corner cases, on which further advanced validation should focus. Furthermore, it also allows the estimation of the collision probability P_c of the HAV under test for given scenario. The resulting P = 1 – P_c is the measure of safety in terms of crash avoidance of the HAV with respect to real traffic situations.

The safety performance criteria can be summarized as follows:

(i) **Collision-free Boundary**: For a selected scenario, a safety boundary must be found. The safety boundary is the border separating all crash relevant specified testing scenarios (determined by some scenario parameters) from the safe testing scenarios.

(ii) **Low occurrence**: The crash related subspace should have a low occurrence in real traffic situations.
Chapter 5

Introducing human reaction: Gap Acceptance and Safe Overtaking

5.1 Preliminary

In the work presented until now, it was assumed that the other vehicles did not change their behavior as a consequence of the actions of the vehicle under test. As already stated, there are very good reasons for that, but in practice the reactions of other drivers usually contribute to reducing the probability of an accident. In this chapter, we analyze such a case as example of other driver’s reactions in such an extended view.

Cut-in maneuvers, when a vehicle enters a lane closely in front of another vehicle in the same lane, are very common but adversely affect roadway capacity and traffic safety [97]. Various research projects have been done to assess their impact on the traffic. For instance, [114] has addressed the negative effects on bottleneck discharge rate. It finds that the lane-change-vehicles create gaps in traffic streams due to the bounded vehicle acceleration, causing traffic abnormalities, including breakdown. It has also been linked to stop-and-go driving (also known as traffic oscillations).

[113, 97] have addressed the impact of vehicle lane change on traffic in adjacent lane. [97] finds that a majority of the vehicle decelerates in a range from $-3 m/s^2$ to $0 m/s^2$, whereas a number of driver brakes more urgently in order to yield quickly to the entering vehicle to avoid a collision. The highest observed decelerations goes up to $-6 m/s^2$ and can have a very negative influence on traffic flow. The citation [113] reveals that the standard deviation of the speed (thus, oscillations) is a significant variable of the crash occurrence. The likelihood of a crash increases by about 8% with an additional unit (1%) increase in the standard deviation of the speed. It also finds that lane change maneuvers induce changes in driver behaviours, which suggest that drivers tend to become more aggressive (characterized by smaller response time and minimum spacing).

Since the HAVs are required to be much safer than the human drivers, the introduction of the HAV with the autonomous overtaking function can be expected to reduce the
negative effects of the lane change actions on the traffic. Note that an overtaking maneuver normally consists of two lane change maneuvers, namely the lane change maneuver to the adjacent lane for the overtaking action and the lane change maneuver back to the original lane after finishing the overtaking action, i.e. a cut-in.

In several projects, various algorithms for the autonomous overtaking function have been proposed, for instance in [51, 48, 106, 92, 53, 77]. They focus on the decision making and the path planning for the collision-free overtaking. The interactions between other traffic participants and EGO or among other traffic participants are usually not considered. Against this background, in this chapter, we focus on assessing the safety the autonomous overtaking function by means of cautiousness. We propose a method to evaluate in a fast way the potential impact of vehicle lane change on the (human driven) rear-vehicle in the adjacent lane without modeling the reaction of the driver in detail.

The rest of this chapter is organized as follows: section 2 introduces human drivers’ response to a cut-in maneuver and the choice of both instantaneous and long-term variables as safety indicators for the assessment of autonomous overtaking function. Section 3 clarifies the proposed method through parametrization of the scenario No.17 and simulation test of 2 autonomous overtaking functions proposed in [51]. Some conclusions and outlooks are given in section 4.

For the sake of clarity, in the rest of this chapter, we employ cut-in maneuver to characterize the behavior that a vehicle enters the adjacent lane and confront a rear-vehicle approaching from behind.

5.2 Safety indicators for Cut-In action

5.2.1 Motivation

In the previous Chapters, an approach has been proposed to quickly estimate the collision probability of the HAV using the collision-free boundary and thus, evaluate the safety of HAVs. In this approach, a model-based and data-driven parametrization method is employed to model the human drivers’ behavior, which allows the estimation of collision probability of SUT in terms of real world traffic situations, e.g. how ACC systems perform in response to the cut-in maneuver of the human driver, see Fig. 5.1 panel (1).

The collision probability is frequently employed as safety criteria in various approaches [26, 28, 110, 111, 7, 116]. Nevertheless, the focus of these approaches is laid on safety assessment of the HAV in terms of avoiding a collision caused by other traffic participants, e.g. ACC system’s response to a sudden cut-in vehicle as described by scenario No.10 shown in Fig. 5.1 panel (1). However, the collision probability based approaches are not easily applicable in some situations, in which the reaction of other traffic participants can significantly alter the collision probability. Scenario No.17 in Fig. 5.1 panel (2) illustrates an exemplary critical situation derived from real accident
5.2 Safety indicators for Cut-In action

Figure 5.1: Examplary scenarios: 1) front-vehicle cuts in front of the EGO (HAV), 2) the EGO (HAV) pulls out and encounters a rear-vehicle in the adjacent lane [117]

data, where not only the pull-out maneuver of the EGO (green) but also the response of the rear-vehicle (red) in the adjacent lane determine whether a collision happens. The scenario pull-out shown in Fig. 5.1 panel (2) represents a very common operation situation of the autonomous overtaking function, where the EGO (HAV) makes a lane change maneuver and encounters a rear-vehicle in the adjacent lane. In this case, there are several reasons against using the collision probability metrics for safety evaluation.

First, modeling the human driver’s response to a cut-in maneuver of the HAV is crucial for the parametrization of the scenario. However, it involves a lot of effort. There are numerous factors, such as inattention, distractions, misjudgment of gap, overcompensation or even sleep [82], that affect the driver’s behavior and thus, the probability avoiding the collision. A driver reaction model in cut-in situations must include the information on decision making of the driver when encountering the cut-in vehicle (braking, accelerating, or steering), reaction time of human beings and the behavior afterwards (relying on the decision). This will result in a model of high dimensionality, which is not suitable for virtual testing [115].

Second, human beings can panic and have behaviors completely different when facing the safety critical situations. Modeling the drivers’ reactions to the cut-in actions must include both safety critical and none safety critical situations. That requires a large amount of measurements, including normal situations, near-crashes, and crashes.

Third, it is unknown whether the HAV changes lane in a manner consistent with the human driver. Thus, a driver reaction model based on the analysis of the human driver’s response to the human drivers’ cut-in maneuver may be invalid in the case of the HAV.
Introducing human reaction: Gap Acceptance and Safe Overtaking

Last but not least, the collision rate characterizes the probability that HAV can avoid colliding with the rear-vehicle. It says nothing of if the lane change maneuver of the HAV will indirectly cause a collision between the rear-vehicle and other surrounding vehicles, which is critical to the safety of road traffic as well [112].

As a result, an alternative way for safety assessment of the autonomous overtaking function without modeling the complex driver reaction is desirable [118].

5.2.2 Defensive driving and Safe cut-in Maneuver

Rather than assessing the safety of the autonomous overtaking system in a direct way based on the consequence of its cut-in maneuver, i.e. collision probability, we propose an alternative way by evaluating the cautiousness of the HAV, namely whether the HAV starts and executes the cut-in maneuver in a safe condition/way so that it has less impact on other traffic participants in the adjacent lane(s).

To achieve this target, we first define the safe cut-in maneuver.

Requirements on the safe cut-in maneuver

The Straßenverkehrsordnung (StVO)—or German traffic rules—is the main traffic code for regulating the behaviours of motorised vehicles in Germany. It covers both the scenarios for urban and highway driving: here we focus on the paragraph about overtaking (StVO) on highway scenarios. The English version of StVO is:

*When changing lane to the left lane during overtaking, no following road user shall be endangered* [StVO, §33].

That means whenever a vehicle changes to the left lane to overtake another road user, the driver has to ensure that those on the left lane will not be endangered. In particular, a vehicle that approaching on the left lane could be endangered in any way, overtaking is prohibited [72].

This can be interpreted in a more generic way by the so-called defensive driving.

Defensive driving

The standard sets forth practices for Safe Practices for Motor Vehicle Operations, [4] defines the so-called defensive driving as *driving to save lives, time, and money, in spite of the conditions around you and the actions of others*. Its aim is to reduce the risk of collision by anticipating dangerous situations, despite adverse conditions or the mistakes of others.

For the traffic situation like scenario No.10 illustrated in Fig. 5.1 panel (1), the EGO drives in a car-following situation and the front vehicle cuts in. The cut-in maneuver of the front-vehicle has the impact on the EGO that can potentially lead to a collision with the EGO. The ability of the EGO to resolve the situation and avoid the collision represents how defensive the EGO is, e.g. keeping a large headway gap, reacting in time and applying enough braking force.
5.2 Safety indicators for Cut-In action

Defensive driving in terms of the cut-in maneuver

In the situation like scenario No.17 described in Fig. 5.1 panel (2), the EGO approaches a slower preceding vehicle and attempts to apply a cut-in maneuver to keep the velocity. At the same time, another vehicle is approaching from behind on the adjacent lane with higher velocity to overtake both vehicles (preceding and the EGO). In this case, the EGO may have impact on the rear-vehicle due to its cut-in maneuver, which can result in hard braking of rear vehicle, serious or even fatal injury.

Accordingly, the defensive driving in terms of cut-in can be characterized by choosing a proper time/space gap, planing ahead for the unexpected so that no other vehicle is forced to slow down, speed up, or change lanes to avoid collision.

Thus, the HAV is responsible for choosing the safe gaps to start the cut-in maneuver and keeping the suitable gaps till the end of the cut-in maneuver, so that it is less likely to have any impact on the rear vehicle on the adjacent lane and thus, on the traffic.

5.2.3 Driver behavior and safety indicators

Driver response to the cut-in maneuver

Human driver’s response to a cut-in maneuver is complex. There are numerous factors that affect driver’s reaction. To achieve the proposed approach, we first find the gaps that are closely related to the braking reaction of the human driver.

TTC and THW are important safety indicator for detecting rear-end conflict in traffic safety evaluation. The higher a TTC or a THW value, the safer a situation. TTC value at an instant time \( t \) is defined as the time for two vehicles to collide if they continue at their present speed and on the same path[73]. THW is the time between two vehicles passing a specific point. It creates a buffer to prevent a rear-end collision, should the driver need to stop in an emergency [30]. TTC and THW at instant time \( t \) are given in the form of

\[
\text{TTC}(t) = \frac{y_{ego}(t) - y_{r}(t)}{v_{ego}(t) - v_{r}(t)} = \frac{\Delta y(t)}{\Delta v(t)} \\
\text{THW}(t) = \frac{y_{ego}(t) - y_{r}(t)}{v_{r}(t)} = \frac{\Delta y(t)}{v_{r}(t)}
\]

(5.1)

where \( \Delta v(t), v_{ego}(t), \) and \( v_{r}(t) \) denote longitudinal velocity gap, velocity of the EGO, and velocity of rear-vehicle, respectively. \( \Delta y(t), y_{ego}(t), \) and \( y_{r}(t) \) denote longitudinal distance gap, longitudinal position of the EGO and rear-vehicle, respectively, see Fig. 5.2. For the sake of clarity, we simplify the expression by using the notation \( \text{TTC} = \text{TTC}(t), \text{THW} = \text{THW}(t), \Delta y = \Delta y(t), \Delta v = \Delta v(t), v_{ego}(t) = v_{ego}(t) \) and \( v_{r}(t) = v_{r}(t) \).

As addressed in [84], at least over the initial 5 to 10s the braking behavior of a human driver in response to a cut-in maneuver is related to instantaneous variables such
Introducing human reaction: Gap Acceptance and Safe Overtaking

Figure 5.2: Parameters, defining the gaps in Eq. (5.1)

as relative velocity $\Delta v$, Time-To-Collision (TTC), and longer-term variables such as desired time-headway $\text{THW}_{\text{des}}$.

In a research project "PEGASUS" [14], the driver's reaction time and braking force in terms of TTC was studied. Relationships between human performance and the criticality of sudden cut-in maneuvers that drivers have to react to the TTC of up to 8 s of sudden cut-in maneuvers. The relationship between the strongest deceleration and the criticality of the cut-in maneuver reveals that the more critical the scenario (low TTC between EGO and cut-in vehicle), the earlier and the heavier do drivers decelerate and the longer do drivers apply the braking pedal. The most critical cut-in maneuver observed with a TTC of 1.7 s.

Therefore, we choose $\text{TTC}_0 = \text{TTC}(t_0)$, and $\Delta y_0 = \Delta y(t_0)$ at the initial time point of a cut-in maneuver as instantaneous variables, which represent the acceptable gaps of the HAV to start a cut-in maneuver, namely gap acceptance of the HAV. They also reflect the criticality of the conditions experienced by the rear-vehicle at the moment of cut-in. Due to a sudden perception of a threat (low $\text{TTC}_0$, and $\Delta y_0$), the driver may apply unnecessarily higher deceleration. In other words gap acceptance of the HAV reveals the aggressiveness of the cut-in maneuver started by the HAV and how probable this cut-in maneuver will avoid forcing the rear vehicle to apply sudden hard braking or even evasive cut-in maneuver.

The instantaneous variables $\text{TTC}_0$ and $\Delta y_0$ reflect the ability to cover the requirement on the safe cut-in maneuver in terms of choosing proper time/space gaps.

Besides instantaneous variables, it has been found that in some situations the driver may apply unnecessarily higher deceleration due to a delayed response [39] or under-estimation of the gaps during the process of the cut-in. Since the HAV is required to perform the cut-in maneuver in the way not forcing the rear vehicle to brake, we propose to monitor the TTC, and THW over the whole period of the cut-in maneuver and employ minimum value of TTC and THW appeared during cut-in as long-term
variables, namely \( \text{TTC}_{\text{min}} \) and \( \text{THW}_{\text{min}} \). The long-term variables reflect the ability of the HAV to maintain the safe gap during the cut-in process, namely gap maintenance.

Long-term variables \( \text{TTC}_{\text{min}} \) and \( \text{THW}_{\text{min}} \) cover the requirement on the safe cut-in maneuver in terms of planing ahead for the unexpected.

**Safety Criterion**

To enable the safety assessment through gap acceptance and maintenance analysis, we first need to analyze the braking behavior of the human drivers in terms of these variables. We need to identify the critical value, the thresholds \([\text{TTC}_{\text{th}}, \text{THW}_{\text{th}}, \Delta y_{\text{th}}]\), of these variables such that the human drivers are less likely to do any sudden hard braking if \( \text{TTC} > \text{TTC}_{\text{th}}, \text{THW} > \text{THW}_{\text{th}}, \) and \( \Delta y > \Delta y_{\text{th}} \) are fulfilled, namely

\[
\Pr (a < a_{\text{th}} | \text{TTC}_0 > \text{TTC}_{\text{th}}, \Delta y_0 > \Delta y_{\text{th}}) < \Pr_{\text{th}}
\]

\[
\Pr (a < a_{\text{th}} | \text{TTC}_{\text{min}} > \text{TTC}_{\text{th}}, \text{THW}_{\text{min}} > \text{THW}_{\text{th}}) < \Pr_{\text{th}}
\]

(5.2)

Thus, we can judge the cautiousness of the autonomous overtaking system in terms of not causing abrupt evasive maneuvers of other traffic participants through the observation of its gap acceptance and maintenance. It allows safety assessment of autonomous overtaking system without modeling the human drivers’ reaction to a cut-in maneuver.

Instantaneous variables \( \text{TTC}_0 \) and \( \Delta y_0 \) can be directly extracted and calculated from the trajectories. The corresponding peak deceleration of the rear-vehicle is considered as the reaction of the human driver to the sudden cut-in threat. According to [37, 12, 69], few drivers have a brake reaction longer than 2 seconds. It is defined as the time interval from the moment when a collision threat appears to the moment that the driver actually initiates brake to avoid the collision [23, 44]. Therefore, we choose the peak deceleration of the rear-vehicle within two seconds after the initiation of cut-in maneuver as the driver’s reactions to the instantaneous variables.

Long-terms variables \( \text{TTC}_{\text{min}} \) and \( \text{THW}_{\text{min}} \) are the minimum gaps identified before the appearance of the peak deceleration of the rear-vehicle during the cut-in maneuver. The long-term variables are considered similar to a situation where the human driver has detected the cut-in maneuver and has considered it as none safety critical. This can be considered similar to a car following situation but the cut-in vehicle is responsible to adapt the space till it finishes the cut-in maneuver.

Defining a threshold \( a_{\text{th}} \) to determine the overreacting deceleration of the human driver is critical for the method. Various values have been used in the literature. [55, 47] have set a threshold of \(-0.3g \approx -2.94m/s^2\) for categorizing the emergency braking behavior, \( g \) is the standard acceleration due to gravity. In [39], the authors have found that the driver generates a moderate deceleration of less than \(-0.3g\), with/without applying brakes, whereas [46] has a set threshold between \(-0.2g \approx -1.96m/s^2\) and \(-0.4g \approx -3.92m/s^2\) for detecting the deceleration of driver with
applying brakes. As for comfortable deceleration, the AASHTO\(^1\) set the threshold at \(-0.35g \approx -3.4m/s^2\) [15], whereas [104] has set the value at \(-0.2g\).

In this work, we choose the most conservative value as safety threshold of the critical deceleration according to [46], namely \(a_{th} = -0.2g\).

**Preliminary data analysis**

![Figure 5.3: Measurements of human driver in cut-in situation](image)

In order to build up a benchmark of safety indicators (gap acceptance and gap maintenance), we collected measurements in a highway driving environment with maximum speed \(130km/h\), using our experiment vehicle equipped with 2 radar systems. This experiment (with 11 test drivers) shows that 253 cut-in maneuvers were recognized in total, in which 168 cut-in maneuvers are characterized by \(TTC_0 > 0s\).

The identified cut-ins are shown in Fig. 5.3, where \(v_r\) and \(v_{cut-in}\) denote the velocity of the rear-vehicle in the adjacent lane and the cut-in vehicle, respectively.

The *instantaneous* variables \(TTC_0\) and \(\Delta y_0\), characterizing the gap acceptance of human drivers for the cut-in maneuver, are identified and calculated using the method introduced in [115, 88]. The corresponding human driver’s reactions, namely the deceleration \(a\) of the rear-vehicle, are identified as shown in Fig. 5.4. The figures in the first column illustrate the distribution of the overall peak braking force over the \(TTC_0\) due to instantaneous reaction, whereas the figures in the second column show the occurrence of the critical braking force \((a < -0.2g m/s^2)\) over the \(TTC_0\). In the last column, the probability distribution that the driver in the rear vehicle applies

---

\(^1\)American Association of State Highway and Transportation Officials
5.2 Safety indicators for Cut-In action

Figure 5.4: Maximum deceleration $a_{\text{min}}$ of rear vehicles in response to $\text{TTC}_0$, $\Delta v_0$, and $\Delta y_0$. $g \approx 9.8$ m/s$^2$

A hard braking $\Pr(a < -0.2g)$ in terms of $\text{TTC}_0$ and $\Delta y_0$ are shown in two figures respectively. This is given by

$$
\Pr_{th}(a < -0.2g|\text{TTC}_0) = \frac{n_{\text{critical}}(\text{TTC}_0)}{n(\text{TTC}_0)} \\
= \Pr_{th}(a < -0.2g|\text{TTC}_{0,i}) = \frac{n_{\text{critical}}(\text{TTC}_{0,i})}{n(\text{TTC}_{0,i})}
$$

(5.3)
where \( n_{\text{critical}}(\text{TTC}_{0,i}) \) and \( n(\text{TTC}_{0,i}) \) stand for the number of the critical braking reactions and a total number of the braking reactions, which are owing to the instantaneous response to the TTC gap ranging from \((i - 1) \cdot 10 \text{ s} \) to \(i \cdot 10 \text{ s} \). That is \( \text{TTC}_{0,i} \in [(i - 1) \cdot 10, i \cdot 10] \text{ s} \). Noting that \( \Pr_{th}(a < -0.2g | \Delta y_0) \), \( \Pr_{th}(a < -0.2g | \text{TTC}_{\text{min}}) \), and \( \Pr_{th}(a < -0.2g | \text{THW}_{\text{min}}) \) are obtained in the same way.

It is found that as mentioned above the lower the \( \text{TTC}_{0} \) or \( \Delta y_0 \), the heavier do drivers decelerate. For the desired probability threshold \( \Pr_{th} = 1\% \), the critical thresholds are identified as \( \text{TTC}_{th} \approx 39 \text{ s} \) and \( \Delta y_{th} \approx 145 \text{ m} \) for \( \text{TTC}_{0} \) and \( \Delta y_0 \), respectively. The outcome shows consistency with the work in [14].

![Figure 5.5: Deceleration measured the rear-vehicle’s continuous reaction to the cut-in with respect to TTC, THW, and \( \Delta y \), \( g \approx 9.8m/s^2 \).](image)

The long-term variables \( \text{TTC}_{\text{min}} \) and \( \text{THW}_{\text{min}} \) characterizing the long-term gap maintenance during the whole cut-in period, are identified according to the peak
5.3 Test example: Scenario No.17

5.3.1 Model-based and Data-driven Parametrization

Based on the safety requirements described in the previous section, we can model the scenario No.17 in the same way as traffic situation pass-by as shown in Fig. 5.6 panel (1). The rear-vehicle drives in an approximately constant velocity according to the recorded measurements shown in panel (2). Obviously, before the ego vehicle cuts into the adjacent lane, the rear-vehicle in the adjacent lane drives at a higher speed and plans to overtake both vehicles (ego and preceding vehicle). Since safe lane changing requires that the cut-in vehicle should not force the rear vehicle to slow down or change lanes to avoid collision, the rear vehicle drives at a constant speed. Thus, the scenario is defined based on the measurements shown in Fig. 5.3, as follows: the ego vehicle (HAV) equipped with ACC system, which has the autonomous overtaking function [51], drives at the right lane of a 2 lane motorway at desired velocity \( v_{des} = 30 \text{m/s} \). It approaches a preceding vehicle with velocity \( v_p = 25 \text{m/s} \), driving in the same lane.
as ego vehicle. At the same time, a rear-vehicle drives in the left lane with higher velocity $v_r$ than preceding vehicles, see Fig. 5.7.

Since the behavior of the HAV cannot be predefined, we vary the initial distance gap $\Delta x_{ini}$ and velocity gap $\Delta v_{ini}$ between preceding and rear vehicle, so that the ego vehicle will have diverse $TTC_0$ and $\Delta y_0$ gap during approaching. The parameters have been chosen as follows:

\[
\begin{align*}
\vbar &= 25 \text{ m/s} \\
\vbar &= 25 \text{ m/s} + \Delta v_{ini} \\
\vbar &= 30 \text{ m/s} \\
\Delta y_{ini} &\in [130, 230] \text{ m} \\
\Delta v_{ini} &\in [1, 20] \text{ m/s}
\end{align*}
\]  

(5.4)

where $v_p$ and $v_r$ are the velocity of preceding vehicle and rear vehicle, respectively. $v_{des}$ is the desired velocity of ACC system equipped in Ego vehicle.

\[
\begin{align*}
\vbar &= 25 \text{ m/s} \\
\vbar &= 25 \text{ m/s} + \Delta v_{ini} \\
\vbar &= 30 \text{ m/s} \\
\Delta y_{ini} &\in [130, 230] \text{ m} \\
\Delta v_{ini} &\in [1, 20] \text{ m/s}
\end{align*}
\]

The simulation has been performed in Matlab and IPG CarMaker, and the EGO is equipped with the Adaptive Cruise Control system (ACC) with 2 different autonomous overtaking functions proposed in [51]. The author made use of the mixed integer programming problem in the formulation of model predictive control (MPC) to take the switching nature of this problem into account, namely without fixing an explicit reference vehicle in complex traffic situations, such as scenarios shown in Fig. 5.1. Additionally, the proposed controller formulation uses a stochastic approach in stead of conventional optimistic assumptions, namely the exact knowledge of the surrounding vehicles along the prediction. Two different risk functions are included as a constraint in the MPC formulation as safety indicator, namely time to collision based risk function ($\text{ACC}_{TTC}$) and time headway based risk function ($\text{ACC}_{THW}$).

\[
\begin{align*}
\vbar &= 25 \text{ m/s} \\
\vbar &= 25 \text{ m/s} + \Delta v_{ini} \\
\vbar &= 30 \text{ m/s} \\
\Delta y_{ini} &\in [130, 230] \text{ m} \\
\Delta v_{ini} &\in [1, 20] \text{ m/s}
\end{align*}
\]
5.3.2 Simulation results

TTC\(_0\) & ∆\(y\) gap acceptance

The TTC\(_0\) gap acceptance of human driver and 2 autonomous overtaking functions are listed in Table 5.1. As one can see that both ACC systems are less aggressive than human driver, which attempts to start to cut in even in some situations with TTC\(_0\) = 1 s or ∆\(y\) = 4.45 m. It is found that the gaps accepted by (ACC\(_{TTC}\)) are close to human drivers, whereas (ACC\(_{THW}\)) is more conservative. In other words, it is more cautious. It performs overtaking only in cases when TTC\(_0\) > 7 s and ∆\(y\) > 70 m. The distributions of gap acceptance of human drivers and 2 autonomous overtaking functions are compared in Fig. 5.8. In this case, none of the three can ensure that the probability of rear vehicle applying a braking force with \(a > -0.2g\) m/s\(^2\) less than 0.01, namely Pr(\(a > -0.2g\)) ≤ 1%

Table 5.1: TTC\(_0\) acceptance of human driver and 2 autonomous overtaking functions in [s]

<table>
<thead>
<tr>
<th>Driver</th>
<th>(min(TTC_0)/[s])</th>
<th>(min(\Delta y_0)/[m])</th>
</tr>
</thead>
<tbody>
<tr>
<td>HUMAN</td>
<td>1.01</td>
<td>4.45</td>
</tr>
<tr>
<td>ACC(_{THW})</td>
<td>7.1</td>
<td>71</td>
</tr>
<tr>
<td>ACC(_{TTC})</td>
<td>2.5</td>
<td>20.7</td>
</tr>
</tbody>
</table>

![Histogram](image1)

![Histogram](image2)

Figure 5.8: Distribution of accepted gaps TTC\(_0\) and ∆\(y\) of 2 autonomous overtaking systems [51] compared with human drivers

THW\(_{min}\) & TTC\(_{min}\) gap maintenance

The minimum gaps THW and TTC, appeared during cut-in, of human driver and 2 autonomous overtaking functions are shown in Fig. 5.9. Their critical values (minimum gap) are compared in Table 5.2. As we expected, human driver is the most incautious one. That is obvious, since the human driver does not observe the rear
vehicle continuously during the whole cut-in maneuver, but only check the initial gap acceptance. Both $ACC_{TTC}$ and $ACC_{THW}$ are more conservative than human driver.

In this case, the overall THW gap of $ACC_{THW}$ is above the minimum threshold, which ensures that the driver of the rear vehicle is less likely to do any abrupt and heavy braking maneuver.

**Table 5.2:** minimum gaps, appeared during the cut-in, of 2 autonomous overtaking functions, comparing with human driver

<table>
<thead>
<tr>
<th>Driver</th>
<th>$min(THW)/[s]$</th>
<th>$min(TTC)/[s]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>HUMAN</td>
<td>0.32</td>
<td>1.2</td>
</tr>
<tr>
<td>$ACC_{THW}$</td>
<td>2.03</td>
<td>6.1</td>
</tr>
<tr>
<td>$ACC_{TTC}$</td>
<td>0.67</td>
<td>2.1</td>
</tr>
</tbody>
</table>

**Figure 5.9:** Distribution of continuous changing of gaps, over the cut-in duration, of 2 autonomous overtaking systems [51], compared with human drivers

**The evasive steering of the HAV**

In simulation we spot that in some cases, the EGO (HAV) applies an evasive steering maneuver to avoid the collision with rear vehicle, see Fig. 5.10. The autonomous overtaking function identifies the acceptable gaps for cut in maneuver. However, due to none optimally planned velocity profile, the gap becomes smaller and finally reaches the critical value (unacceptable gaps). To avoid the possible crash with rear vehicle, the EGO pulls back to the original lane to let the rear vehicle pass by and then changes to the left lane again. In real traffic situation, it can be attributed to the
ability of the HAV to respond to unexpected situations, e.g. rear-vehicle accelerates, which is rare but happens.

In our case, a couple of cut-in maneuvers, carried out by TTC risk function based ACC system have resulted in the evasive steering, e.g the red trajectory shown in Fig. 5.10. Due to the fact that the rear-vehicle is set to drive at constant speed (blind driver), the trajectory planning function of the autonomous overtaking system under test is still not perfect in terms of gap maintenance.

However, it is worth noting that in real traffic, it can be expected that the driver in the rear vehicle will brake to keep an desired gap, e.g. apply a soft braking maneuver. Fig. 5.10 blue trajectory shows the same simulation setup as red trajectory but rear vehicle brakes with $a \approx -0.1 g \ m/s^2$.

### 5.4 Summary

In this Chapter, we proposed an alternative approach on safety assessment of autonomous overtaking function. Instead of collision rate, which requires a very accurate model of human drivers’ response to cut in maneuvers, we proposed 2 types of variables as safety indicators. The instantaneous variables (gap acceptance) $TTC_0$ and $\Delta y_0$ for cut-in initiation; the long-term variables (gap maintenance) $THW_{min}$ and $TTC_{min}$ during the cut-in.

The simulation results show that the current setting of the both risk function based autonomous overtaking functions are more cautious than a human driver, whereas the TTC risk function based autonomous overtaking function is more aggressive than THW risk function based autonomous overtaking function. Considering the maximum deceleration of the rear-vehicle in terms of safety indicators $TTC_0$ and $\Delta y_0$, TTC risk function based autonomous overtaking function is more probable to cause the rear-vehicle in the adjacent lane to apply sudden hard braking than THW risk function based autonomous overtaking function.
In contrast, THW risk function based autonomous overtaking function is the most defensive one among the three (human drivers, $ACC_{TTC}$, $ACC_{THW}$) in terms of both gap acceptance and gap maintenance. It is less probable to cause the rear-vehicle to apply the sudden hard braking or emergency steering. However, it can not yet achieve the required probability threshold.
Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this dissertation, we have proposed a methodology that allows the determination of the limited cases to be considered in the safety assessment of highly automated vehicles, which covers the majority of the relevant situation appearing in real traffic. The proposed method consists of three layers.

In chapter 2, we built up a scenario catalogue that summarizes the critical situations (accidents) caused by human drivers’ errors. These critical situations are relevant for the safety assessment of HAVs as far as the operation field of the HAV is the mixed traffic situation. The amount of crash data ensures the catalogue’s coverage on critical situations in terms of real traffic. The catalogue can be further extended or validated by applying the proposed methodology on other traffic database, especially the accident databases in various counties or regions.

Second, in chapter 3, we applied a model-based and data-driven method allowing the realistic parametrization of the scenario using experiment measurements. The resulting specified scenarios can cover the majority of the measured case with a relatively simple parameter set. That helps to overcome the curse of dimensionality and make the simulation feasible (considering the huge amount of all the combinations of parameters).

In chapter 4, a GPC based DoE method has been developed to steer the choice of specified scenarios (parameter combinations) so that a collision-free boundary, separating the safety conditions from unsafe, can be found in an efficient way. This allows estimating the crash probability of the HAV in terms of the real traffic by simulation. This measures the safety of the HAV.

As a result, those cases (specified scenarios) in the region near the collision-free boundary can be the real cases of interest for the testing of the HAV, in particular for the further (SiL, HiL, or VehiL) validations.
Noting that the model-based and data-driven parametrization is applicable to various scenarios. It allows iterative update of the parametrization of scenarios along with the increase of measurements.

For some situations like cut-in, it is difficult to estimate the collision probability independent from the reaction of other traffic participants. Complementary to the collision probability based approach, a gap acceptance based concept has been clarified in chapter 5 for the safety assessment of HAV. The proposed approach allows simple parameterization of scenario (without modeling of complex human driver reactions) and thus, assesses the safety of the HAV in a cut-in situation independent from the reaction of other traffic participants. This method can not only be used to assess the safety of HAV by means of cautiousness, but also be applied to find a reference for HAV development in terms of minimizing its negative impact on the overall traffic flow.

6.2 Future Works

6.2.1 Catalogue Updating by Learning

Due to the fact that it is unknown how many (relevant) scenarios there are in real traffic and the crash data base may not cover all the type of crashes, learning and updating the catalogue with new measurements/crash data is important. Some research works have been started [88].

6.2.2 Catalogue Extension For Other Traffic Situations

In this thesis, we focus on the critical situation mainly resulted from traffic participants and restrict the investigation to accidents on highway traffic. Further research works may include other factors such as crash types at:

- junctions, traffic lights
- specified highway entrance and exit
- urban traffic
- etc

6.2.3 Safety Assessment by Means of Cautiousness

In this thesis, we extended the criterion an safety assessment of HAV by means of cautiousness. That is, not bring other traffic participants in to danger.

Further research focusing on the various driver reactions and perceptions can help to develop the experienced human-like HAVs. That can help to reduce the negative impact of maneuvering vehicles on the traffic flow, and thus, accelerate the commercialization of HAV.
Appendix A

Scenario Catalogue
<table>
<thead>
<tr>
<th>No.</th>
<th>Description</th>
<th>Occ.†</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>(Secondary) rear-end collision or sideswipe threat due to the lane-changing maneuver of the preceding vehicle when EGO (H) is in the course of lane-changing maneuver, resulted from the EGO (H)’s lane-changing evasive action to avoid the (primary) front-end collision threat due to the action of the preceding vehicle</td>
<td>4</td>
</tr>
<tr>
<td>16</td>
<td>(Secondary) rear-end collision or sideswipe threat due to the lane-changing maneuver of the preceding vehicle when EGO (H) is in the course of lane-changing maneuver, resulted from the EGO (H)’s lane-changing evasive action to avoid the (primary) front-end collision threat due to the action of the preceding vehicle</td>
<td>2</td>
</tr>
<tr>
<td>17</td>
<td>(Secondary) rear-end collision or sideswipe threat due to a rear vehicle on the adjacent lane, resulted from the EGO (H)’s lane-changing evasive action to avoid the (primary) front-end collision threat due to the action of the preceding vehicle</td>
<td>11</td>
</tr>
<tr>
<td>18</td>
<td>(Secondary) rear-end collision threat due to the action of the front vehicle on the adjacent lane, resulted from the EGO (H)’s lane-changing evasive action to avoid the (primary) front-end collision threat due to the action of the preceding vehicle</td>
<td>5</td>
</tr>
<tr>
<td>19</td>
<td>(Secondary) rear-end collision or sideswipe threat due to the lane-changing maneuver of the vehicle in the most outer lane, resulted from the EGO (H)’s lane-changing evasive action to avoid the (primary) front-end collision threat due to the action of the preceding vehicle.</td>
<td>7</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3

![Diagram](image-url)
### Table A.2: Complex test scenarios: via lane-changing evasive action

<table>
<thead>
<tr>
<th>No.</th>
<th>Scenario Description</th>
<th>Occ.†</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>(Secondary) rear-end collision threat due to the action of the front vehicle $\Box$ on the adjacent lane when the EGO $\Box$ is in the course of lane-changing maneuver, resulted from the EGO $\Box$’s lane-changing evasive action to avoid the (primary) front-end collision or sideswipe threat due to the lane-changing maneuver of another front vehicle $\Box$ on another adjacent lane</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>(Secondary) rear-end collision or sideswipe threat due to a rear vehicle $\Box$ on the adjacent lane, resulted from the EGO $\Box$’s lane-changing evasive action to avoid the (Primary) front-end collision or sideswipe threat due to the lane-changing maneuver of a front vehicle $\Box$ on another adjacent lane</td>
<td>3.</td>
</tr>
<tr>
<td>22</td>
<td>(Tertiary) rear-end collision threat due to the action of the vehicle $\Box$ on the most outer lane when the EGO $\Box$ is in the course of lane-changing maneuver, resulted from the EGO $\Box$’s second lane-changing evasive action to avoid (Secondary) front-end collision or sideswipe threat due to the lane-changing maneuver of the preceding vehicle $\Box$ when the EGO $\Box$ is in the course of lane-changing maneuver, resulted from the EGO $\Box$’s first lane-changing evasive action to avoid the (Primary) front-end collision threat due to the action of the preceding vehicle $\Box$</td>
<td>2</td>
</tr>
</tbody>
</table>

† Occurrence in Table 2.3
Glossary

**FOT** Field-Operational-Test. xiii, 33

**GPS** The Global Positioning System. 36

**KDE** Kernel Density Estimation. 60, 74, 80

**MPC** Model Predictive Control. 29

Abbreviations

**ACC** Adaptive Cruise Control. 5, 36, 86

**ADAS** Advanced Driver Assistant System. 3, 8–10

**ADF** Advanced Driving Function. 4–6, 9, 10

**DoE** Design of Experiment. 14, 59, 60, 62, 64, 65, 67, 73, 78, 83

**EGO** The ego-vehicle. xiii, xiv, xvii, 9, 17–19, 21–31, 76, 86, 88–90, 95, 97, 103

**GPC** Gaussian Process Classifier. xiv, xvii, 60, 62–66, 70, 71

**HAV** Highly Automated Vehicles. ix, xvii, 1–3, 5–10, 14, 15, 17, 19

**MAD** Mean Absolute Deviation. xiii, 45, 46, 49

**MAE** Mean Absolute Error. xiii, 39, 41, 42, 44, 48, 50, 51

**RMSD** Root Mean Square Deviation. 49

**THW** Time Headway. 89

**TTC** Time To Collision. 89
Bibliography


[31] Daniel Howard and Danielle Dai. “Public perceptions of self-driving cars: The case of Berkeley, California”. In:


[81] SHRP2 Naturalistic Driving Study. URL: https://insight.shrp2nds.us/.


[89] Tomer Toledo and David Zohar. “Modeling duration of lane changes”. In: Transportation Research Record: Journal of the Transportation Research Board (2007).


Curriculum Vitae

Personal
Name Jinwei Zhou
Born 30 December 1981 in Shanghai
Address Leonfeldner Strasse 150, Linz
E-Mail jinwei.zhou@jku.at
Citizenship China

Education
since 04/2014 PhD for Mechatronics
Johannes Kepler University Linz
03/2005–12/2013 Diplom-study for Mechatronics
Johannes Kepler University Linz
09/2000–06/2004 Bachelor for Mechanical Engineer and Automation
Donghua University, Shanghai
09/1997–06/2000 High School Education
Yangbo private school, Shanghai

Employment
since 04/2014 Researcher
Institute for Design and Control of Mechatronical Systems, Linz
01/2012–10/2012 Student Researcher
Institute for Polymer Injection Moulding and Process Automation, Linz
08/2011–09/2011 Internship
hofer Forschung&Entwicklung, Steyr

Others
Languages Chinese, English, German, Japanese
Hobbies Kendo, Outdoor sports
A Methodology for Safety Assessment of Highly Automated Vehicles

From Scenario Classification to Corner Case Identification

Autonomous driving represents a technological leap forward that will likely solve key aspects of the transport problem and so have beneficial effects for some critical social and ecological issues as well. However, testing and validation of the Highly Automated Vehicle (HAV), so as to guarantee safety, is one of the most challenging tasks that still prevent the HAV from commercial release. As HAVs will include many functions which can be updated frequently and require re-evaluation in short time, fast re-evaluations will be needed to prevent new dangers arising from the updates.

This research work is focused on developing such a methodology. The key idea is to replace on-road testing – well defined testing method for classical vehicles – by accident statistics and to use model based methods as well as Design of Experiments to determine a limited set of cases to be tested.