Improving driver performance and safety with automated driving decision assistance system integrating intention and varied takeover time budget

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To my creator
and inspiration

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Kurzfassung

Verkehrsunfälle führen zu schmerzhaften Verlusten von Leben und Eigentum. Fahrer sind für 94 % der Fahrzeugkollisionen verantwortlich, weil sie eine Situation nicht richtig einschätzen und keine richtigen Entscheidungen treffen. Um die Leistung des Fahrers zu verbessern, wurden Fahrentscheidungs-assistenzsysteme (DDAS) entwickelt, die dem Fahrer Warnungen und Fahrmanövervorschläge geben. Die Vorschläge werden in Bezug auf die Verkehrsszenarien einschließlich der Umgebungsbedingungen und der umgebenden Fahrzeugkonstellationen variiert. In dieser Arbeit wird zunächst ein Überblick über Beiträge im Zusammenhang mit assistierten und bedingt automatisierten Fahrentscheidungsassistenzsystemen und verschiedenen Kontexten für die Bereitstellung von Unterstützung einschließlich des Fahrerverhaltens integriert. Dazu gehören die Überwachung der Aufmerksamkeit des Fahrers, die Erkennung von Fahrmanöverabsichten und die automatische Analyse des Verkehrskontextes. Studien auf der Straße und im Simulator, die Online-Entscheidungsassistenz implementieren, werden analysiert und ihre Grenzen angegeben. Die rezensierten Beiträge zeigen, dass sich die Fahrentscheidungsassistenzforschung in den letzten Jahren weiterentwickelt hat, insbesondere in Bezug auf die Schnittstellen. Jedoch haben nicht viele Studien die Entscheidungsassistenz an das Fahrerverhalten angepasst, obwohl es eine große Anzahl von Studien zum Fahrerverhalten gibt. Zu den in dieser Arbeit untersuchten Forschungslücken gehören die Bereitstellung von Entscheidungsassistenz, die auf der Spurwechselabsicht des Fahrers basiert sowie die Budgetierung der Zeit, die der Fahrer benötigt, um erfolgreich vom vollautomatisierten Fahren zurück zum manuellen Fahren zu wechseln, wie anschließend diskutiert wird.

Übernahmeaufforderungen werden von einem automatisierten Fahrsystem an einen rückfallbereiten menschlichen Fahrer gegeben, wenn die Grenzen eines vollautomatisierten Fahrsystems erreicht sind. Frühere Studien kamen zu dem Schluss, dass mehrere Abhängigkeiten in Bezug auf die Zeit bestehen, die der Fahrer für eine erfolgreiche Übernahme benötigt, wenn eine Übernahmeaufforderung erteilt wurde. Wenn Fahrer erfolgreiche Übernahmen erleben, neigen sie dazu, unaufmerksam zu werden, was zu Schwankungen in der Übernahmedauer und -leistung führt. Außerdem erfordert die Unfallvermeidung eine frühzeitige Übernahmeaufforderung an den Fahrer. Um diese Interdependenzen zwischen den beteiligten Variablen zu evaluieren, werden verschiedene Szenarien und nicht fahrbezogene Aufgaben untersucht. Die Ergebnisse weisen deutlich darauf hin, dass verschiedene Szenarienarten abhängig von der bisherigen Übernahmeerfahrung unterschiedliche Zeitbudgets erfordern. Fahrer benötigen weniger Zeit für die Übernahme und erbringen bessere Leistungen, wenn die wahrgenommenen Situationen komplexer sind, vorausgesetzt, das Zeitbudget ist ausreichend, um einen Unfall zu vermeiden. Darüber hinaus reduziert sich in Autobahnszenarien mit Umgebungsverkehr die Übernahmezeit auf Kosten der Leistung im Vergleich zu Autobahnen mit einer Kreuzung und Landstraßen mit mehreren Kreuzungen. Außerdem ist das Situationsbewusstsein in Autobahnszenarien mit einer Kreuzung zur Berücksichtigung verschiedener Geschwindigkeiten höher als in Autobahnszenarien mit Umgebungsverkehr und Landstraßenszenarien mit mehreren

Kreuzungen. Daher sollte das Zeitbudget variiert werden, um ausreichend Zeit für die Übernahme zu gewährleisten und gleichzeitig die Aufmerksamkeit der Fahrer auf eine bevorstehende Übernahmeaufforderung zu lenken.

Darüber hinaus wird in dieser Arbeit die Implementierung eines online-absichtsbasierten Spurwechsel-Fahrmanöver- und Übernahme-Entscheidungsassistenzsystems integriert. Insbesondere werden die Absichten zum Spurwechsel nach links und rechts sowie zum Halten der Fahrspur genutzt, um den Fahrer vor einer möglichen Kollision im assistierten Fahrmodus zu warnen. Die Ergebnisse der absichtsbasierten Assistenz zeigen eine verbesserte Leistung für die Spurwechselmanöver nach links und rechts. Nachdem zuvor das Muster der Variation der benötigten Übernahmezeit in verschiedenen Szenarien ermittelt wurde, ist es andererseits wichtig, die Zeit, die der Fahrer für eine erfolgreiche Übernahme benötigt, quantitativ abzuschätzen. Daher wurden verschiedene Zeitbudgets auf ihre Eignung in unterschiedlichen Übernahmeszenarien untersucht. Es wurde ein Muster identischen Zeitbedarfs für Autobahnen mit hoher Geschwindigkeit und umgebenden Fahrzeugen im Vergleich zu Landstraßen mit mittlerer Geschwindigkeit und mehreren Kreuzungen gefunden. Basierend auf den erhaltenen Ergebnissen und den bereits bekannten Beziehungen zwischen den Übernahmevariablen wird ein erster formaler Ausdruck für die Berechnung des Zeitbudgets vorgeschlagen. Der vorgeschlagene Ansatz ist generalisierbar, integriert individuelle Stimulus-Reaktionszeit, Fahrerfahrung und szenariospezifische Anforderungen und ermöglicht eine erhöhte Sicherheit für Übernahmemanöver im Kontext des bedingt automatisierten Fahrens.

Abstract

Road traffic accidents result in painful loss of life and property. Drivers account for 94 % of vehicle crashes due to inaccurate understanding of a situation and decision making. In order to improve driver performance, driving decision assistance systems (DDAS) which are advanced driver assistance systems that provide warnings and maneuver suggestions to drivers have been in development. The suggestions are varied with respect to traffic scenarios including environmental constraints and surrounding vehicle constellations. This thesis first integrates reviews of contributions related to assisted and conditionally automated driving decision assistance systems and different contexts for providing assistance including driver behavior. These include, driver attention monitoring, driver maneuver intention recognition, automatic traffic context analysis. On-road and simulator studies implementing online decision assistance are analyzed and their limitations are specified. The reviewed contributions indicate that driving decision assistance research has evolved in the last few years especially in relation to interfaces. However, not many studies have adapted decision assistance to driver behavior despite the significant availability of driver behavior studies. The research gaps explored in this thesis include provision of decision assistance based on driver intention to change lanes and budgeting the time required for drivers to successfully transition from fully automated driving back to driving manually as discussed subsequently.

Takeover requests are given by an automated driving system to a fallback-ready human driver when the limits of a fully automated driving system has been reached. Previous studies concluded that several interdependencies exists in relation to the time required for drivers to successfully takeover when a takeover request has been issued. When drivers experience successful takeovers, they tend to become inattentive leading to variations in takeover time and performance. Moreover, an early takeover request to driver is important for the avoidance of accidents. To evaluate these interdependencies between variables involved, different scenarios and non-driving related tasks are studied. The results significantly indicate that different types of scenarios require different time budgets depending on previous takeover experience. Drivers spend less time to takeover and perform better if perceived situations are more complex provided the time budget is sufficient to avoid accident. In addition, in highway scenarios with surrounding traffic, takeover time reduces at the expense of performance compared to highway with one junction and country road with more junctions. Furthermore situation awareness in highway scenarios involving one junction for consideration at various speeds is higher than highway scenarios with surrounding traffic and country road with more junctions. Therefore, time budget should be varied to ensure sufficient time for takeover while also stimulating drivers to be attentive to an eminent takeover request.

Furthermore, this thesis integrates online intention-based lane change driving maneuver and takeover decision assistance system. Specifically, lane change to left and right and lane keep intentions are utilized to warn drivers of possible collision in assisted driving mode. The results of the intention-based assistance indicates improved performance for

lane change to left and right maneuvers. On the other hand, after previously establishing the pattern of variation in takeover time required in different scenarios, it is important to quantitatively estimate the time sufficient for drivers to successfully perform takeovers. Therefore, various time budgets were investigated for suitability in different takeover scenarios. A pattern of identical time demand for highway with high speed and surrounding vehicles compared to country road with medium speed and more junctions is found. Based on the obtained results and previously known relations between takeover variables, a first formal expression for computing time budget is proposed. The proposed approach is generalizable, integrates individual stimulus response time, driving experience, and scenario specific requirements and allows increased safety for takeover maneuvers in the context of conditionally automated driving.

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Nomenclature

Abbreviations

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
ANOVA	Analysis of Variance
AR	Augmented Reality
Avg. L. Displ.	Average lateral displacement
C	characteristics
DAS	Driver Assistance System
DDT	Dynamic driving task
Df	Degrees of freedom
DV	Dependent variable
FCW	Forward Collision Warning
HEV	Hybrid electric vehicle
HMI	Human-Machine Interface
HUD	Head-Up Display
IS	intelligent systems
IV	Independent variable
IVIS	In-vehicle information system
LCW	Lane Change Warning
LDW	Lane Departure Warning
LKW	Lane Keeping Warning
MANOVA	Multivariate analysis of variance
Max. Acc.	Maximum acceleration
NDRT	Non-driving-related task
RTI	Request to intervene
R	relations
RW	Real world
RCW	Rear Collision Warning
SA	Situation Awareness
STD	Standard deviation
SOC	State of Charge
TOR	Take-over request
TOT	Takeover time
TTC	Time to collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
S	situation
Sig.	Significance
Stat.	Statistic
Std.	standard

Symbols

v_{ego}	Velocity of ego vehicle
v_f	Velocity of vehicle in front
v_{fl}	Velocity of vehicle in front left
v_{fr}	Velocity of vehicle in front right
v_{bl}	Velocity of vehicle in back left
v_{br}	Velocity of vehicle in back right
v_b	Velocity of vehicle in behind
d_f	Distance to vehicle in front
d_{fl}	Distance to vehicle in front left
d_{fr}	Distance to vehicle in front right
d_{bl}	Distance to vehicle in back left
d_{br}	Distance to vehicle in back right
d_b	Distance to vehicle behind
TTC_f	TTC to vehicle in front
TTC_{fl}	TTC to vehicle in front left
TTC_{fr}	TTC to vehicle in front right
TTC_{bl}	TTC to vehicle in back left
TTC_{br}	TTC to vehicle in back right
TTC_b	TTC to vehicle behind
Ln	Current lane number
I	Indicator
G	Gearbox
S	Steering wheel angle
α	Heading angle of ego-vehicle

1 Introduction

1.1 Motivation

Many road accidents are due to human driver errors, distraction and fatigue [Nat18] [Nat19]. In other cases, these errors are due to flawed driver perception, information processing and decision making [RGE+17]. Road crashes also account for approximately 1.35 million deaths annually and presently the leading cause of death for children and young adults between 5 and 29 years [Wor18]. In addition, an international analysis estimates the costs of road traffic accidents are on average 2.7% of GDP in high income countries and 2.2% in low and medium income countries [WS13]. Therefore, considering the cause and cost of road accidents, it is assumed that development of methods of mitigation are required.

In view of the role of human drivers in the aforementioned problems, advanced driver assistance systems (ADAS) have been in development for more than three decades to help mitigate traffic tragedies by assisting drivers in various forms [BDF+14]. In addition, an analysis reveals that vehicles equiped with ADAS are 23 % less likely to crash compared to those without ADAS [SVB+18]. These systems monitor sensor signal input (e.g blind spot camera) continuously to provide assistance online. The input data are used to identify different situations in which driver assistance is required.

Situations and corresponding type of driving assistance vary widely. The SAE defined automation level 0 to level 5 which is used as bases for discussing assistance in this thesis [Soc18]. Level 0 driving includes automatic dynamic control systems (e.g. anti-lock braking system) that complement driver actions [BDF+14]. This group of systems have been proven to be the most efficient safety systems for drivers and are now legal requirements in Europe [BDF+14].

In level 1 - level 3 various forms of maneuver assistance are provided to the driver. Whereas, level 4 and level 5 integrates limited and unlimited autonomous driving functions respectively where human driver interventions are not required. In this thesis, focus is

given to recent developments in level 1 and level 3. Level 1 assistance is also called assisted driving while level 3 is also called conditionally automated driving. In the former, the driver receives warnings and suggestions to improve driving performance and in the later, the driver requires assistance to resume manual driving after autonomous driving system can no longer function reliably.

Various functions are integrated in automated driving systems to assist drivers in different situations as may be required. In level 1, this includes lane change assistance which is investigated in this thesis. Lane change assistance systems have previously integrated blind spot, frontal and rear collision warnings, and steering assistance. These functions have also become available in commercial vehicles since the last decade. More recently the focus has being on defining warning thresholds especially at different speed levels, and identifying warning thresholds at which drivers trust the automated system in addition to prediction of intention to change lanes [YELB17] [WSG+20] [FZW+20] [ZYZD18] [LCS+18] [YYW+20].

Furthermore, in level 3, different factors that influence driver performance, acceptance, and behavior are being studied [ZYF+19] [KY17], [WS19] [BRK17]. These include traffic scenario complexity, non-driving related tasks, interfaces etc.

1.2 Problem statement and objectives

Different variables such as traffic scenario complexity, driver attention [SA19] [RKA+19], and driving maneuvers [XLW+19] [DS21] are utilized in assisted and conditionally automated driving decision assistance systems. In addition, in conditional driving automation, the time duration between the takeover over request and eminent system failure has to be sufficient for driver to takeover in order to avoid accidents. The conclusions from studies regarding the time required for drivers to successfully takeover in conditionally automated driving mode ranges from 2 s to 10 s which are not sufficiently precise [WS19] [KY17] [DKZ+20] [YLJ21]. In addition, lane change which accounts

for 9 % of fatal accidents has not been studied in relation to assistance based on driver intention. Therefore, the objectives and achievements of this thesis include

- Identification of pattern of driver behavior in different driving scenarios and establishment of the first generalizable formula for estimating in advance the time required by drivers to successfully takeover in conditionally automated driving mode.
- Reduction of accidents and near accidents associated with lane changes by warning drivers of potential collision based on intention to change lanes.

1.3 Thesis outline

This thesis comprises 5 chapters. Some parts of the thesis have been submitted to journals [TS21a] [TS21b] [TS21c],and published in proceedings of conferences [DSTS20] [TS19b] [TS19a] [TNWS19].

Chapter 2 integrates review of contributions related to assisted and conditionally automated driving maneuver decision assistance systems and different variables influencing the type of assistance provided. These variables include, driver attention, driving maneuvers, and traffic scenario. On-road and simulator studies implementing online decision assistance are analyzed and their limitations specified. Among the research gaps are the need to (1) study the interdependence between takeover variables in order to determine a suitable approach to budgeting required takeover time in advance in conditionally automated driving, and (2) apply lane change intention recognition to lane change assistance.

Chapter 3 integrates an approach to investigate these interdependence between takeover variables with respect to scenarios and non-driving-related tasks having different complexity levels. In addition, a description of the driving simulator and measuring technique used for experiments in this thesis are also introduced in chapter 3. Furthermore, analysis and comparison of experimental results are presented with respect to combinations of scenarios

and NDRTs. Specifically, this includes various aspects of results of comparisons between takeover behavior of drivers with respect to complexity levels of scenarios and secondary tasks within a time budget of 7 s. Discussion of results and summary are also given.

Chapter 4 integrates relations which are considered in this thesis for a bi-modal assistance system. These relations include scenarios, timing, and intended driver lane changes. The integrated lane change assistance system is based on a statistical validation of online lane change intention recognition developed in collaboration with Deng [DSTS20]. The integrated conditional driving automation assistance system investigates the sufficiency of various takeover time budgets based on average values obtained for three scenarios introduced in chapter 3. Discussion of results and summary are also given.

Finally, summary of the thesis, conclusions, and outlook based on obtained results are outlined in chapter 5.

2 State-of-the-art literature review

This chapter comprises five sections. Section 2.1 includes an introduction to automated driving systems and summarizes the concept of driver vehicle interaction. Section 2.2 summarizes state-of-the-art regarding variables utilized in driving decision assistance systems. In section 2.3 and section 2.4, existing assisted and conditionally automated driving approaches are reviewed. Finally, section 2.5 includes a summary of the reviewed studies and the research gaps as well as the specific research scope of this thesis. The content of this chapter has been published in a conference proceeding [TS19b] and submitted in [TS21a] as a journal manuscript.

2.1 Introduction

Automated driving systems (ADS) are categorized as human-machine systems. In these kind of systems, the functions of the human (both individuals and groups) and machines are integrated in the use, control or supervision of tools, machines or technological systems [WS99]. The characteristics of these systems can be described by the list generated by [Fit51] in which the advantages of humans and machines are contrasted as outlined in Table 2.1.

Machines are able to perform assignment of defined events (information and connections), reliably process large amounts of data at very high speed, perform precise and smooth execution of stimulus responses, reliably execute algorithmic sequences with speed, are fatigue-free, capable of recognizing patterns in known contexts, execute deductive operations, execute formal logic operations, and have unlimited storage capacity. Humans have higher sensitivity for weak sensory stimuli, adaptive sensory learning, recognition of signal patterns in noisy contexts, ability to learn alongside pattern formation, recognize differences and deviations from known correlations, flexible in deciding and drawing conclusions, planning and handling capability especially in unfamiliar situations, are able to focus

Table 2.1: Comparison of human and machine abilities [Fit51]

Human surpass machines in	Machines surpass humans in
Detection	Speed
Perception	Power
Judgment	Computation
Induction	Replication
Improvisation	Simultaneous operations
Long term memory	Short term memory

on issues relevant to situations, ability of self-control and perception, have unrestricted learning ability. Cognitive abilities distinguish humans from machines and the optimal division of labor between human and machines is based on the intrinsic competences in which strengths are distributed or weaknesses are compensated for.

However, the ironies of automation described by [Bai83] indicates that as systems become more reliable, the less responsibilities human operators have, which results in the operator paying less attention to the system while in operation. The increased system reliability and resulting operator inattentiveness tends to make it difficult for operators to notice when system is malfunctioning. These are unintended consequences as a result of automation, that could detrimentally affect human performance on critical tasks. In order words, automation might some times increase human performance problems, rather than eliminate them.

A-three-layer performance model proposed by [Ras83] is used to describe the behavior regulation and competence level of humans as illustrated in Figure 2.1. The first level is skill-based behavior which refers to sensory learning (e.g. haptic) and motor coordination (manual, reflective, subconscious) with high repetition accuracy and low error rate e.g. driving a car, opening a door, and writing. Rule-based behavior refers to learning through practice leading to partly conscious and partly subconscious actions. This is characterized by algorithmic, complex, partly knowledge-based, easily repeatable actions with moderate error rate e.g. performing driving maneuvers and professional work. Knowledge-based behavior is very conscious, problem-oriented, highly complex, learned abstractly, hardly

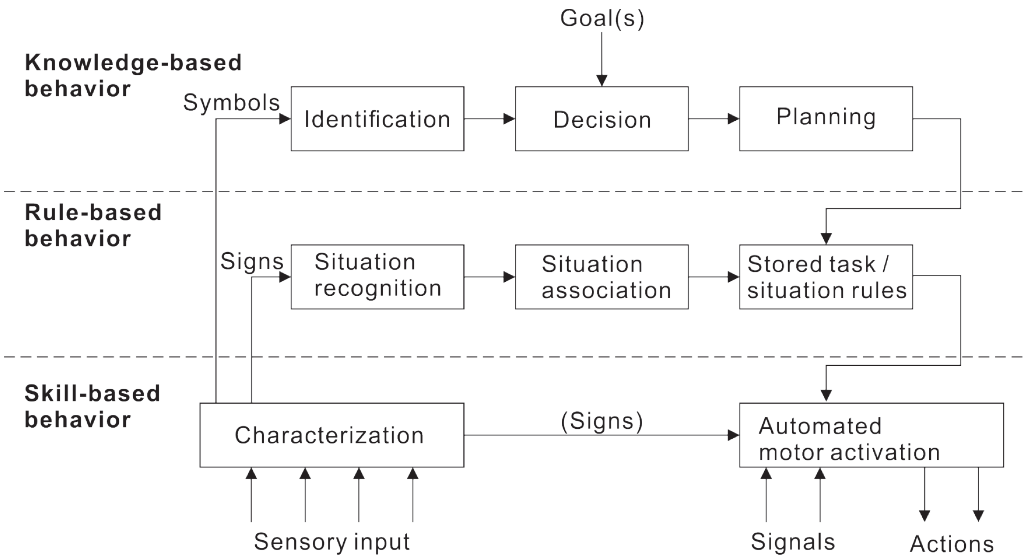


Figure 2.1: Three layer model of driver performance adapted from [Ras83]

repeatable, has high error rate as a result of solving new types of problems e.g. disaster management.

Learning always starts at the highest level (knowledge-based), practice and routine results in conscious, algorithmic (rule based) and later subconscious automatic behavior (skill-based). In the context of driving more experienced drivers (especially those who drive regularly) perform better and are able to respond safely to more complex situations compared to less experienced and novice drivers.

Automated driving systems

Automated driving systems (ADS) integrate various functions to enable drivers to perform safer and more efficient maneuvers. These functions either optimize hardware systems or warn drivers of eminent traffic danger and suggest safer maneuvers. These systems are grouped into six levels of driving automation as defined by the Society of Automotive Engineers (SAE) as described in Table 2.2 [Soc18]. In level 0, active safety systems enhance driver maneuvers e.g. automatic steering return to center position. The ADS

begins to perform some driving functions from level 1 onward where the operational design domain is limited until level 5 where this is unlimited. Specifically, Level 4 and level 5 involves limited and unlimited autonomous driving functions respectively where human driver interventions are not required.

Furthermore, in level 0 to level 3, the human driver serves as the fallback performer of all driving tasks when the functional and operational limits of the automated driving system has been reached. Level 1 assistance provides in-vehicle warnings (e.g. forward collision warning (FCW) and blind spot warning (BSW)) to alert drivers of eminent dangers and guide driving maneuvers (e.g. parking assistant) [LZW+17] [WS19].

Level 2 integrates partially automated driving systems (e.g. adaptive cruise control (ACC), lane change assistant (LCA) and lane keeping assistant (LKA), lane departure warning (LDW), emergency braking etc.) that relieve the driver of some driving functions when engaged. A combination of these systems are sometimes provided as options which the driver can choose from [HW17]. Furthermore, some studies give drivers the option of adjusting the parameter of the engaged system based on their preferences. For example ACC controls a vehicle longitudinally at a defined speed set by driver while maintaining a safe time gap (selected by driver) to other vehicles. The time gaps that can be selected by drivers are pre-defined.

Level 3 assistance integrates conditional automation (also known as takeovers) where the ADAS performs all driving tasks under suitable conditions. Under unsuitable conditions, which may be due to driving tasks performance-relevant system failures in vehicle systems, the on-board human driver is required to resume dynamic driving tasks (DDT) [WS19]. The on-board human driver requires assistance to gain sufficient awareness of the situation and takeover driving successfully [EPZ+19]. Level 1 and level 3 are the focus of this literature review.

Table 2.2: Levels of driving automation according to [Soc18]

Automation level		Description	Steering & Acceleration / Deceleration	Monitoring driving environment	Fallback performance of driving	Operational design domain
		Human driver monitors driving environment				
0	No Automation	Driver performs all DDT, including when enhanced by active safety systems.	Human driver	Human driver	Human driver	N/A
1	Assisted driving	ADS performs either the lateral or the longitudinal vehicle motion control subtask of the DDT (but not both simultaneously) with the expectation that the human driver performs the remainder of the DDT.	Human driver and system	Human driver	Human driver	Limited
2	Partial automation	ADS performs both the lateral and longitudinal vehicle motion control subtasks of the DDT with the expectation that the human driver monitors the driving environment and supervises the driving automation system.	System	Human driver	Human driver	Limited
		Automated driving system monitors driving environment				
3	Conditional automation	ADS performs the entire DDT with the expectation that the fallback-ready human driver is receptive to ADS-issued requests to intervene, as well as to DDT performance-relevant system failures in other vehicle systems, and will respond appropriately.	System	System	Human driver	Limited
4	High automation	The ADS performs the entire DDT and DDT fallback within the operational design domain without any expectation that a human driver will respond to a request to intervene.	System	System	System	Limited
5	Full automation	The ADS unconditionally performs the entire DDT and DDT fallback without any expectation that a human driver will respond to a request to intervene.	System	System	System	Unlimited

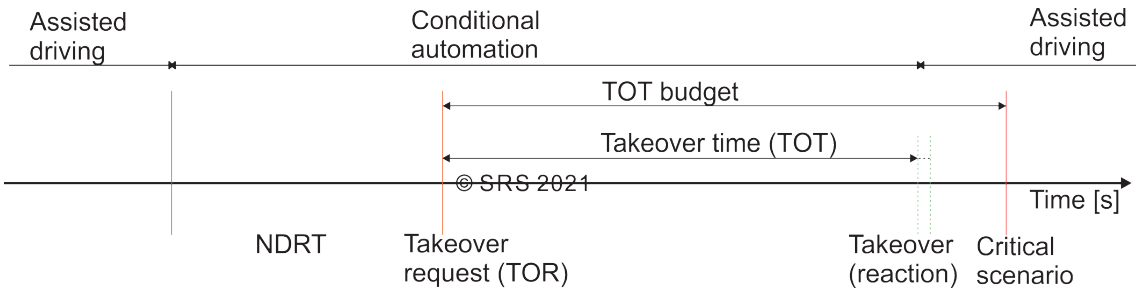


Figure 2.2: Assistance timeline definitions according to [ZYF+19] [KY17], [WS19] [BRK17] and adapted from [TS19b]

Driver-vehicle interaction

Inputs for generating and adapting suggestions or warnings in dynamic situations include traffic scenarios, driving maneuver, and driver attention as outlined in Table 2.3 [KL19]. As illustrated in Figure 2.3, driver and traffic scenario data are analyzed and matched to the assistance situation using appropriate rules to generate and present a suitable information to the driver via an interface. These include congestion notification, eco-safe driving suggestions, pedestrian warning, TORs etc.

Table 2.3: Data utilized in driving decision assistance systems submitted in [TS21a]

Categories	Data sources and variables
Traffic scenario	Ego-vehicle current position (using GPS and digital map), Relative distance, velocity and acceleration (using camera, laser, radar and/or Lidar). Cameras (vehicle front, back and side views),
Driver attention	Cameras (Head rotation, head pose, gaze direction, foot dynamics), Kinect (line of motion, gesture recognition, motion capture), Electroencephalography (EEG), Electromyography (EMG), Heart rate etc.
Driving maneuver intention	CAN bus signal (time stamp, yaw rate, engine speed in RPM, steering wheel angle, steering wheel velocity, throttle/brake/accelerator pedal position, velocity, heading angle, odometer torque converter, odometer, gear, wiper, turn signals, lateral acceleration, head/brake lights, time to collision (TTC) wrt surrounding vehicles etc.)

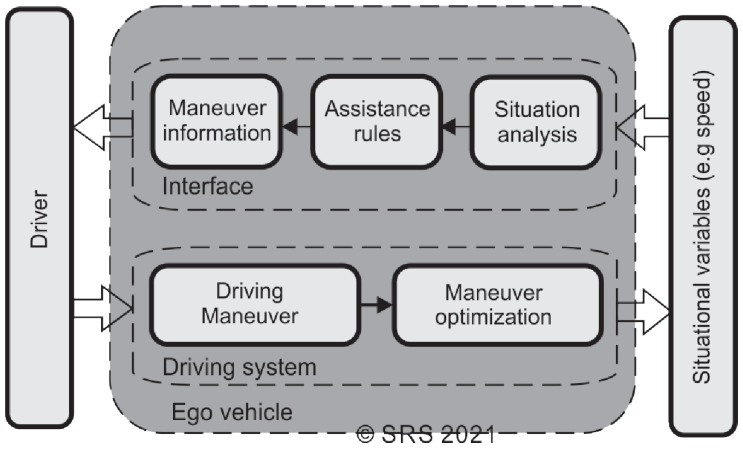


Figure 2.3: Interaction in driving decision assistance systems submitted in [TS21a]

The situation operator modeling (SOM) approach proposed in [Söf08] can be used to further describe the driver vehicle interaction. The core of the SOM approach is the assumption that changes of the considered parts of the real world (RW) are understood as a sequence of effects described by items scenes and actions (of the RW) as illustrated in Figure 2.4. In the proposed approach the definition of the items scenes and actions are coordinated in a double win. They are related to each other and they relate the assumed structure of the RW to the structure of the database - called mental model of intelligent systems.

Intelligent systems (IS) and human operators (HO) are included in the real world (RW). Depending on their principal sensor inputs, their natural (HO) or technical (IS) perceptions, and on the related knowledge base, the ISs and HOs adapt and learn only parts or aspects of the RW. These parts are modeled using the developed situation and operator calculus. The describable part of the RW is called a situation, which is a time-fixed-system and problem equivalent one used to describe the internal system structure (as a part of the RW). Here only the logical structure of the 3D-space, time and functional-oriented connections are of interest. The item operator is used to model effects / actions that change the real world scenes (modeled as situations) in time. The situation S consists of characteristics C and a set of relations R.

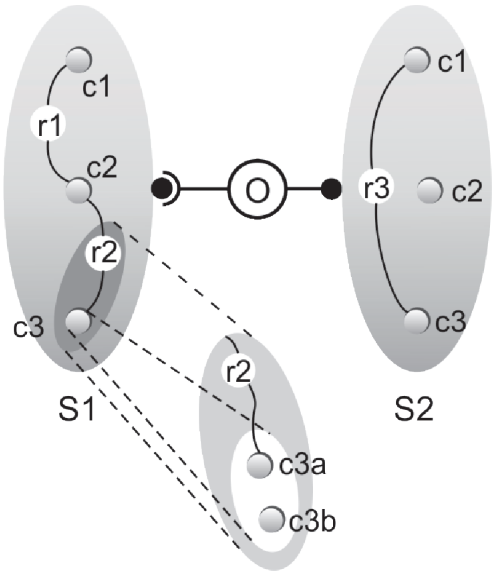


Figure 2.4: SOM modeling approach [Söf04]

In the context of driving, the human operator is the driver, the modeled real world is the driving environment or situation and the intelligent system is the vehicle. The modeled operators (e.g. brake, accelerate) of the situation are actions that the driver takes in the course of driving and the characteristics (e.g. current lane position) and relations describe the status of the situation. The SOM approach enables the description of sequence of planning, actions, and processes.

2.2 Variables influencing driving decision assistance

2.2.1 Variables influencing assisted driving

Driving maneuvers

Assistance can be provided in relation to different maneuvers drivers perform. These often involve at least one or a combination of steering, braking and accelerating. In a broader sense of time scale, maneuvers are grouped into functional or operational, tactical, and

strategic maneuvers as illustrated in Figure 2.6 [DT11] [XLW+19]. Functional maneuvers result from the need to follow the rules of a road segment (e.g speed limits, allowed U-turns etc.) and operate a vehicle within its limits (e.g. changing gears to accommodate higher or lowers speeds) [DT11]. Tactical maneuvers describe an ordered set of operations intended to fulfill a short-term goal (e.g turns, lane changes, and stops)" [DT11]. Strategic maneuvers are influenced by driver's long term destination goals, personal preferences and comfort (e.g. fastest route, fast flowing traffic etc.).

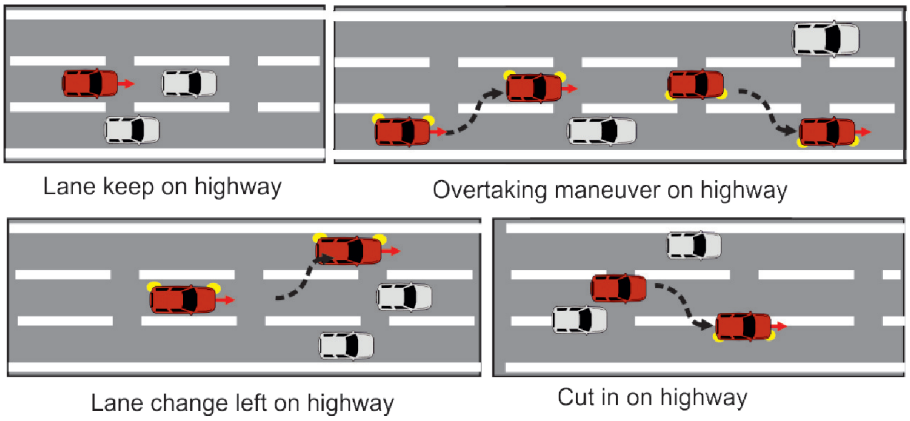


Figure 2.5: Traffic constellations and tactical driving maneuvers on highways submitted in [TS21a]

A behavioral classification of driver maneuvers include; aggressive, neutral, conservative, defensive, and reckless as illustrated in Figure 2.7 [LWR19] [SDJ14] [ZYF+19]. These behavioral maneuvers are characterized by different time duration and headway utilized by drivers when performing tactical maneuvers. For example aggressive drivers tend to overspeed and perform sharp turns, cut-ins, and hard braking [LWR19] [SDJ14]. While defensive drivers anticipate the maneuvers of other drivers and respond ahead of time to avoid collision [ZYF+19]. On the other hand, reckless drivers may violate right of way, or and speed, or and drive under the influence (DUI) of drugs, or and alcohol etc. [LWR19] [SDJ14].

Different aspects of driver maneuvers are being studied to encourage good driving behavior and to determine appropriate situations for giving warnings when otherwise. These aspects

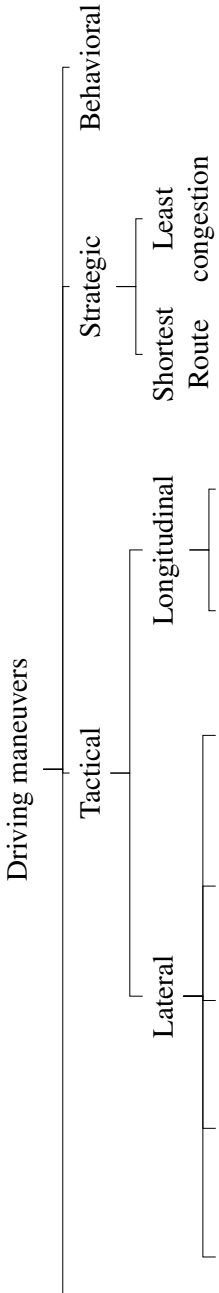


Figure 2.6: Classification of driving maneuvers submitted in [TS21a]

Figure 2.7: Classification of behavioral driving maneuvers submitted in [TS21a]

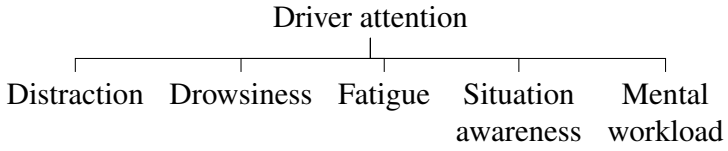


Figure 2.8: Aspects of driver attention submitted in [TS21a]

include tactical maneuver (e.g. speed change, lane change, turn) intention recognition of the subject vehicle [XLW+19] [TSLL15] [JF17] and or surrounding vehicles [GKÖ14].

A variety of classification and machine learning algorithms are commonly applied to driver maneuver prediction or intention recognition as reviewed in [XLW+19] [DS21]. These algorithms utilize data effecting vehicle control and dynamics (e.g steering angle), driver physiological features (e.g eye gaze direction, head pose, and hand position), traffic constellation related information (e.g time to collision to front vehicle), and the time horizon (usually a few seconds) of driver actions [XLW+19].

Driver attention

Driver attention cannot be directly measured but, can be discussed in terms of variables that affect it. This is characterized by different states such as drowsiness, fatigue, distraction, situation awareness, and mental workload as illustrated in Figure 2.8 [SA19] [RKA+19]. Measurement devices used for estimating these states include; electroencephalogram (EEG), electrocardiogram (ECG), electrooculography (EOG), electromyography (EMG), eye tracker, electrodermal activity (EDA) sensor, skin temperature sensor, and hybrid techniques as detailed in Table 2.4.

Methods utilized in detection of different driver attention states (e.g. distraction, drowsiness, fatigue, workload etc.) include rule-based, machine and deep learning, subjective reporting, fuzzy logic, hybrid techniques etc. [SA19] [RKA+19]. Other variables for estimating situation awareness include vehicle brake force, steering wheel angle etc. [PFT+15].

Table 2.4: Devices for driver attention monitoring submitted in [TS21a]

Device	Meaning	Variable
EEG	Record electrical activity of the brain	Fatigue, Workload
ECG	Records a graph of the electrical activity of the heart (voltage versus time)	Workload
EOG	measures corneo-retinal standing potential that exists between the front and the back of the human eye	Workload
EMG	Evaluates and records electrical activity produced by skeletal muscles	Workload
EDA	Measures variation in the electrical characteristics of the skin (e.g conductance)	Workload
Eye tracker	Measures head and eye motions relative to head (e.g Saccades)	Distraction, drowsiness, fatigue, workload, situation awareness
Microsoft kinect	Integrates RGB cameras, a monochome CMOS camera, a multi-array microphone, infrared laser projectors that map depth and perform real-time gesture recognition, speech recognition and body skeletal detection	Drowsiness, fatigue, workload, situation awareness

In [KL19], the authors recommended that, driver's attention should be monitored to determine the most effective option to alert driver to gain high awareness of a situation and to avoid accidents. Online assessment of driver mental workload using eye tracking variables have been extensively studied [MCd15] [WCS+20]. Variables associated with workload are pupil diameter, blink frequency, blink latency, gaze entropy/distribution, fixation distribution, and perclos. The magnitude of these variables increase with increased visual and mental workload [MCd15].

Traffic scenario

Generally, a traffic scenario comprises physical location, road terrain (e.g. undulating, curvy etc.), road class (highway, rural, country), road features (e.g. intersection, roundabout), traffic agents (e.g cars and pedestrians) and their constellations as illustrated in Figure 2.9.

Drivers typically need to consider all these aspects if present before making a maneuver decision. The complexity of the decision increases if multiple aspects are present at the same time.

Traffic scenario representation and classification describes an instantaneous constellation of traffic agents relative to subject vehicle [UNMH14] [HTSR17]. This could be graph-based [UNMH14] [TSES13], rule-based [XDW16], decision tree-based [HTSR17] etc. Meanwhile, simultaneous localization and mapping (SLAM) techniques extend traffic context representation by estimating position and orientation (or pose) in space while continually generating a dynamic map of the traffic environment [BAYG17] [SL19]. They utilize data from on-board vehicle sensors such as; Radar, Lidars, cameras etc.

Furthermore, object detection, classification and tracking may include traffic agents (e.g vehicles, bikes, pedestrians etc.) and stationary ones (e.g. trees) [MGM+14] [MXT15]. The traffic constellation is constantly changing due to driving behavior of driver and other traffic agents as illustrated in Figure 2.5.

2.2.2 Variables influencing conditionally automated driving

In addition to previously discussed traffic scenario complexity (e.g. speed of ego vehicle, traffic density, number of lanes etc.), other variables affect conditionally automated driving. Drivers ability to have sufficient awareness of these variables in each context strongly influence the performance of takeovers and is denoted as situation awareness (SA) as discussed below [KY17].

1. **Takeover request (TOR)** This is also called a request to intervene (RTI) and is a notification from the autonomous driving system to the on-board human driver to resumes performance of DDT e.g steering and braking.

2. **Takeover time (TOT)** This is the time between TOR and when the on-board human driver resumes DDT [HLK17]. This is detected by measuring output values of steering and pedals or computer vision-based methods [ZYF+19].

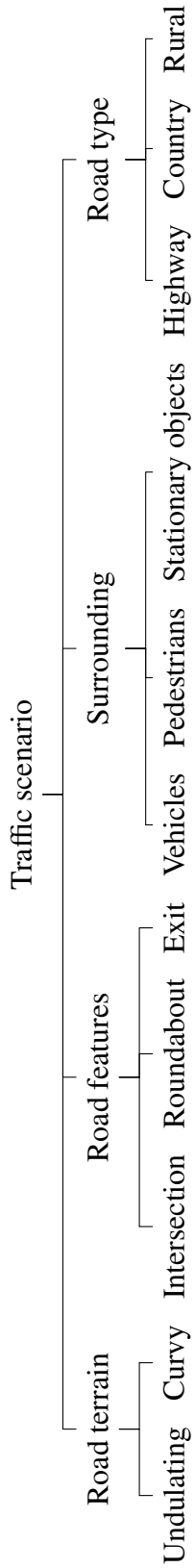


Figure 2.9: Aspects of traffic scenarios submitted in [TS21a]

3. **TOT budget** This is the time between TOR and when ego vehicle will encounter critical system failure if present conditions (e.g. speed) persist as illustrated in (Figure 2.2) [KY17], [WS19].

4. **Non-driving related tasks (NDRT)** (also known as secondary tasks) are tasks the driver may perform while the ADS is performing DDT, e.g. reading an email [BRK17].

5. **Mental workload** modulates the tuning between the demands of an environment and the capacity of the human [Kan00]. As a result, unsatisfactory performance occurs whenever there is a discrepancy between environmental demands and the capabilities of the human whenever workload is too high or too low.

6. **Automation trust** involves factors that relate specifically to limitations of a technology such as reliability, validity, utility, robustness, and false-alarm rate [HJBU13]. Trust in automation can rapidly decrease when the human is under time pressure or when obvious system faults occur.

7. **Situation awareness (SA)** is the "perception of elements of current situation using senses, comprehension of their meaning, and projection of their status in the near future" [End88]. The level of situation awareness a driver has enables safe maneuver planning and is related to takeover time which also strongly varies with the aforementioned variables [KY17], [WS19], [BRK17].

2.3 Existing assisted driving approaches

Different assistance systems have previously integrated blind spot, frontal and rear collision warnings, parking assistance, navigation and steering assistance. These functions have also become available in commercial vehicles since the last decade. More recently the focus has being on defining warning thresholds especially at different speeds or distances, and identifying warning thresholds at which drivers trust the driving system.

Recent studies providing decision assistance are discussed below and summarized in Table 2.5 and Table 2.6. Different approaches are compared in different traffic scenarios with respect to different types of assistance, online adaptivity (to traffic scenario and driver behavior), warning levels, and information directionality.

2.3.1 Functional assistance

Giving drivers maneuver assistance (e.g. gear and accelerator recommendations) to improve fuel efficiency in hybrid electric vehicles have been studied in [RR14] [WS16]. Drivers often rated recommendations as useful and desirable and better performances are obtained compared to without suggestions. In [RR14], less experienced drivers motivation to drive in eco-safe way increases with ranking and recommendations of more experienced drivers from a social driving assistance system. Additionally, in [WS16] the authors concluded that eco-driving text suggestion are preferred, faster understood and demand less workload compared to visual interfaces. Similarly, [LVR+20] in another study on eco-safe driving the authors concluded that the use of visual interfaces increases mental workload within a reasonable level. Similarly in [HJJ15], the authors concluded that haptic pedal feedback yields better performance compared to visual interface suggestions. In [QWH+17] [SMS20], the authors presented an algorithm for predicting and representing state of charge of electric vehicles that considers driving routes but without statistical number of participants.

In [SR16], shared braking assistance was studied using 15 elderly drivers that enables safe trajectory for pedestrian avoidance without statistically relevant number of participants. Similarly, in [TSW16] [YSW20] [CYO+20], the authors developed a system for haptic steering guidance for backward parking and lane change trajectory realization also without statistically relevant number of participants.

2.3.2 Strategic assistance

In [SHBS18], the authors investigated landmark vs distance navigational information presentation and concluded that landmark decreases visual distraction and mental workload for both males and females.

In [RGE+17], warnings were provided to drivers when approaching accident hotspots defined as locations (e.g. intersection) with historically high accident record. The result indicate that warning drivers about causes of accidents (e.g. disregarding right of way, potential collision with pedestrians etc.) 15 s before arrival at the associated accident hotspot significantly improves performance over time after repeated warnings.

In [NT14], the authors concluded that drivers adapt their behaviors to reduce performance when previously warned about potential traffic congestion points along their route. In [KCP+18] the authors developed and tested an assistance system that identifies with 74 % accuracy opportune moments along a route to provide 29 drivers with suggestions without causing confusion. Similarly, on-road study by [SBV18] using three drivers yielded 88 % accuracy when predicting opportune moments for giving rounding information. In [LBAS18], the authors used a conversational assistant to engage drivers in conversations during fatigued driving sessions and concluded that it increases alertness and performance compared to without it.

2.3.3 Tactical assistance

In [LBHB15], the authors concluded that utilizing directional vibrotactile suggestions for lane change maneuvers reduces driver reaction times. However, this did not include statistically valid number of participants and the studied warning thresholds were commented as too early by drivers. Similarly, in [LHB15], the authors concluded that using adaptive lighting intensity to warn against lane change maneuvers results in improved responses compared to constant light intensity . In [TJC18], the authors concluded that delaying non-critical information during adjacent vehicle cut-in and lane changes in highway

Table 2.5: Comparison of assisted functional and strategic driving approaches submitted in [TS21a]

Traffic scenario							Adaptivity			N	Data gen.	Information	Warning level		Directionality		References
Country	Highway	Rural	Intersection	Entry	Exit	LC	M	A	C				Sngl.	Mult.	Sngl.	Mult.	
Functional assistance																	
-	✓	-	-	-	-	-	-	-	-	20	Simulator	Fatigue assistant	-	✓	-	-	[LBAS18]
✓	✓	-	✓	✓	✓	-	✓	-	-	32-36	Simulator	Fuel & battery mgt.	-	✓	✓	-	[WS16] [LVR+20] [MCG18]
✓	✓	✓	✓	✓	✓	-	-	✓	✓	1, 9	On-road	Fuel & battery mgt.	-	✓	✓	-	[SMS20] [RR14]
✓	✓	✓	✓	✓	✓	✓	-	-	-	15-28	Simulator	shared control	-	✓	-	✓	[TSW16] [SR16] [YSW20] [LCS+18] [YYW+20]
Strategic assistance																	
✓	✓	-	✓	-	-	-	-	-	-	22	Simulator	Navigation	✓	-	-	✓	[KTFO18]
✓	✓	-	-	-	-	-	-	-	✓	29, 3	On-road	Navigation	-	✓	-	✓	[KCP+18] [SBV18]
-	✓	-	-	-	-	-	-	-	-	16	Simulator	Congestion notification	✓	-	✓	-	[NT14]
✓	✓	✓	✓	✓	✓	-	-	-	✓	57	On-road	Accident hotspots	✓	-	✓	-	[RGE+17]

✓: included, -: not included, LC: lane change, M: maneuver, A: attention, C: automatic complexity analysis of traffic scenario, N: no. of participants

scenarios decreases workload for both elderly and younger drivers. In addition, elderly drivers are are described as slow to perform cognitive tasks tasks such as engaging in a conversation about current vehicle system conditions during lane changes compared to younger drivers. In [SWS19], the authors proposed a system than enables merging decision making based on a general model of merging behaviors that reduces workload in a study of 30 participants.

In [DLZH19], the authors estimate potential angle of collision, and [WWQ20] [CSWY20] [ZYF+19] anticipate surrounding vehicle lane changes and recklessness to identify risky lane changes on highways and generates a warning which when tested on simulation platforms without participants. In [OCP17], the authors concluded that lane change decisions with stop and go traffic are influenced by movement of vehicles ahead irrespective of their positions (e.g current or target lanes). While lane change decision without stop and go traffic are influenced by vehicles on the target lane. Though useful for warnings, how these are applied to assist drivers has not been realized.

Overtaking behavior with respect to age and gender studied by [LGMP13] reveal that overtaking assistance should be varied between drivers. For example young male drivers tend to be impatient and overtake faster when longer wait times are needed. whereas, older drivers showed opposite behavior in the same situation.

In [WKV18], the authors concluded that head-up display (HUD) imagery warning strategy should adapt to situation, driver reaction, attention as a multi-stage warning. In addition, stop sign on an HUD is a generic warning that stimulates fast and strong brake reactions. In addition, caution sign is an attention generic warning for moderate reactions before a stop sign. In [KMC+20a], the authors concluded that dynamic AR HUD improves driver perception compared to static or instrument cluster display. In [TFY+18] and [FHN+19], the authors concluded that feedback improves performance in subsequent drives and increases perceived ease of use of automated system for both young and elderly drivers. In [KTFO18] the authors investigated a multi-party (three virtual agents) conversation system and concluded that it reduces workload and distraction compared to a one-on-one

conversation with the driver. In [WS19] driver view visual interface increases situation awareness compared to birds eye view.

In [RS19], the authors concluded that high reliability is required for ADAS that is adaptive to driver attention to improve safety and to prevent delayed responses or ignored warnings. Similarly, in [NKN16] contrasted false and unnecessary alarms and concluded that drivers delay response to false alarms with audio-visual interface but tend to ignore it when presented only visually. On the other hand, with actual dangerous situations, drivers respond faster and safer with audio-visual interface (even when warning were unnecessary) compared to with only visual. Furthermore, in [YAAW+21], the authors concluded that directional forward collision warning is effective in different scenarios depending on driver (e.g inexperienced, female, and past collision experience).

Furthermore, [SHW+18], the authors concluded that a speech-based on-demand assistance system is preferred to a visual interface, continually active system and enables easier monitoring of vehicles while waiting at intersections. Similarly, in [CDFB20], the authors concluded that AR warnings decrease delays at intersections. Furthermore, in [NG+15] the authors concluded that warnings are not necessary in situations already anticipated by drivers (e.g. giving right of way to another vehicle at a country road intersection with less traffic). Driver ratings also indicate that warnings are preferred if given between 2 s and 3 s before arriving at an intersection. In [XW18], the authors proposed an assistance system for guiding driver decisions at intersections and conclude that it improves mobility by significantly reducing unnecessary stops in a simulation without participants.

2.4 Existing conditionally automated driving approaches

The major goals of assistance in conditionally automated driving include avoiding accidents, and ensuring driver comfort and successful takeover when required. Therefore, different contributions focus on different associated variables such as warning timing, traffic scenario, and secondary tasks intended to reach the aforementioned goals as discussed

Table 2.6: Comparison of assisted tactical driving approaches submitted in [TS21a]

Traffic scenario							Adaptivity			N	Data gen.	Information	Warning level		Directionality		Ref.
Country	Highway	Rural	Intersection	Entry	Exit	LC	M	A	C				Sngl.	Mult.	Sngl.	Mult.	
✓	-	-	✓	-	-	-	-	-	-	15	Simulator	Approach alert	✓	-	✓	-	[YELB17] [TFY+18]
✓	✓	-	-	-	-	✓	-	-	✓	38	Simulator	FCW, BSW, LDW	✓	-	✓	-	[WS19]
✓	-	-	-	-	-	✓	-	-	-	14 - 22	Simulator	Collision warning	-	✓	-	✓	[LBHB15] [WSG+20] [FZW+20]
✓	-	-	-	-	-	✓	-	-	-	30	Simulator	Collision warning	-	✓	✓	-	[LHB15]
✓	✓	✓	✓	-	-	-	-	-	-	20	Simulator	Approach & FCW	✓	-	-	✓	[NG+15]
✓	-	-	✓	-	-	-	-	-	-	80	Simulator	Warning reliability	-	✓	-	✓	[NKN16]
✓	✓	-	✓	-	-	-	-	-	-	24-41	Simulator	FCW	✓	-	✓	-	[YAAW+21] [CDFB20] [SHW+18]
-	-	-	✓	-	-	✓	-	-	✓	-	Simulated	LC, intersection risk	✓	-	✓	-	[ZYF+19] [DLZH19] [WWQ20] [CSWY20]
-	-	-	-	-	-	✓	✓	✓	-	2-17	Simulator, on-road	-	-	-	-	-	[XLW+19]
✓	✓	✓	-	-	-	✓	✓	-	-	3	Simulator	Collision warning	✓	-	✓	-	[ZYZD18]

✓: included, -: not included, LC: lane change, M: maneuver, A: attention, C: automatic complexity analysis of traffic scenario, N: no. of participants

below. Furthermore, interaction is discussed in relation to the adaptivity of conditionally automated driving approaches to driver attention and driving maneuver, warning urgency and directional information about potential collision hazard as summarised in Table 2.7.

In [ZYW21] the authors predicted SA using eye tracker data obtaining root mean square values of 0.216 and less. In [DZP+20] the authors predicted takeover performance using a random forest classifier and physiological data obtaining an accuracy of 84.3 % 3 s before the takeover request. In [HOKS21], the authors concluded that a significant relationship exist between glance duration and situation awareness during transition from autonomous to manual driving. The takeover assistance system requires drivers to spend sufficient time glancing in a particular direction with oncoming traffic to increase situation awareness. While the authors of [BRK17], concluded that traffic scenario complexity has stronger influence in the classification of driver situation awareness compared to eye variables. In addition, secondary task and eye measures when combined with traffic scenario had similar influence on classifiers. The authors applied the designed system in a simulation with previously collected driving data which showed that the system would have given alerts 63 % of the times low situation awareness was detected.

Various authors have investigated takeover time and have different conclusions ranging from 2 s to 10 s about the time that drivers require to successfully takeover [WS19] [KY17] [DKZ+20] [YLJ21]. In addition, some concluded that interface support results in decreased takeover time in some situations [YGL+17], while others conclude that interface support increases SA without significant difference in takeover time in different conditions. In addition, in [WS19] the authors concluded that using an average time budget for different drivers in different situations is not appropriate. In [YLJ21], the authors concluded that drivers require a minimum of 2 s to takeover and hand-held NDRTs require more time. A study using animated takeover video clips observed by 32 participants (instead of performing takeovers) [LHd20] the authors concluded that drivers require sufficient time to observe situations and takeover. In [LBG+19], the authors concluded that older drivers require an average of 0.37 s more reaction time (RT) and takeover time increases with

visual interface support. In [WKT+19], eye data (e.g. saccades) compared with different NDRTs to estimate visual and cognitive workload and drowsiness indicate the more visually demanding tasks result in the worst performances. In [BPN+18] the authors concluded that reduced road glances result in increased takeover time and individual reaction times affect takeover time. Similarly, in [ES17], the authors concluded that takeover time varies with different drivers who have different reaction times and levels of driving experience.

In [ASUI19] the authors concluded that multi-level takeover (L3, L2, L1, and L0) confuses and reduces driver performance compared to simple takeover from L3 to L0. In [WS19] the authors also reported that NDRT engagement and performance increases from assisted to conditionally automated driving indicating mode awareness and reduces workload. In [YJ19] [NT17], [RFB19], the authors concluded that takeover time and workload increases and performance decreases with NDRTs on hand held devices.

In [EPZ+19] the authors concluded that highlighting the reason for takeover request (e.g. truck) and potential safe and unsafe maneuver trajectory options using augmented reality is useful and satisfactory to drivers and results in better performance. In [LMR19] [OKD18], the results indicate improved SA, reduced takeover time and improved overall performance using visual, audio, haptic and augmented reality interfaces during takeover compared to without support. Specifically, the order of decreasing preference is haptic, audio and visual. In [LBG+19] [HKD21] [SWN+18], the authors concluded that indicating the reason for TOR and verbal status of system, surrounding traffic information, and automation capability information to drivers increases anticipation of TOR. In addition, AR display of TOR information is preferred compared to instrument cluster.

In [RB20] the authors concluded that matching the level of urgency of takeover using visual-tactile interface warning results in better performance in less urgent cases compared to more urgent ones but did not reduce takeover time. Similarly, in [SZJ20], the authors concluded that indicating urgency results in faster responses, angry drivers perform more risky takeovers, and increased auditory warning frequency and repetition results in faster takeover reaction times. In addition, in [TBC+16], the authors concluded that reduced

system confidence notifications prior to a takeover request reduces takeover time and increases performance. In [SWS18], the authors concluded that integrated shared steering control during takeover results in improved stability and better performance.

In [KMC+20b], the authors concluded that decreased trust in automated system occurs after a failure and explanations are considered helpful though without increasing automation trust. In [FNN16], in a study comprising 6 experts the authors concluded that indicating turns using HMI interface increases usability and acceptance. In [SR20] the authors studied scents as a means to mitigate motion sickness during automated driving and concluded that ginger scent are considered more hash compared to lavender scent.

2.5 Summary and research gaps

This thesis integrates reviews of different aspects of assisted and conditionally automated driving maneuver decision assistance. These include traffic scenarios, driver attention and driving maneuvers. Assisted driving is categorized into functional, tactical, and strategic maneuvers. While conditionally automated driving assistance is discussed in relation to the various associated goals such as safety and comfort. Interfaces most appropriate for different assistance purposes include text and tactile for functional assistance (especially eco-safe driving), audio, tactile and dynamic AR HUD for various tactical and strategic as well as conditionally automated assistance situations. In general, tactile is preferred more in most situations compared to other interfaces. The suggestions and warnings are required neither too early or too late to be considered helpful.

Furthermore, different studies are compared and contrasted in Table 2.5, Table 2.6 and Table 2.7 with respect to online adapativity of interaction to various inputs (driving maneuver, driver attention, and complexity analysis of traffic scenario), integration of warning levels and directional information about potential collision hazard.

A common challenge of these systems is different timing and adaptivity considerations that are appropriate for different situations. In addition, few studies presently integrate

Table 2.7: Comparison of conditionally automated driving decision assistance systems submitted in [TS21a]

Effect			Adaptivity		Traffic scenario					N	Traffic agents		Takeover request		Ref.
T	S	NDRT	A	M	Country	Highway	Intersection	Entry	Exit		Vehicle	VRU	Urgency	Directional	
-	✓	-	-	-	✓	✓	-	-	✓	20 - 38	✓	-	-	-	[WS19] [YLJ21] [YGL+17]
-	-	✓	-	-	-	✓	-	-	-	27-53	✓	-	-	-	[YJ19] - [RFB19]
-	✓	✓	-	-	✓	✓	-	-	-	52, 36	✓	-	✓	-	[RB20] [SZJ20]
-	-	-	✓	-	-	✓	-	-	-	12	✓	-	-	✓	[HOKS21]
-	✓	✓	-	-	✓	✓	-	-	-	33, 81	✓	-	-	-	[ZYW21] [BRK17]
✓	✓	-	-	-	✓	✓	-	-	-	26-80	✓	✓	-	-	[KY17] [DKZ+20] [ES17]
-	-	-	-	✓	-	✓	-	-	✓	24	-	-	-	-	[SWS18]
-	✓	✓	-	-	✓	-	✓	-	-	18	✓	-	-	✓	[LMR19]
-	✓	✓	-	-	✓	✓	-	-	-	24 - 76	✓	-	-	✓	[EPZ+19] [LBG+19] [OKD18] - [SWN+18]

✓ : included, -: not included, A: attention, M: maneuver, N: no. of participants, S: traffic scenario, T: TOT budget, VRU: vulnerable road users e.g pedestrians

adaptivity to driver behavior, statistically relevant number of participants, and on-road scenarios. Challenges in different aspects need to be addressed as discussed subsequently.

Research gaps in assisted driving

Majority of existing contributions related to eco-safe driving and fuel economy are focused on instantaneous suggestions to guide driving maneuvers to appropriate acceleration and deceleration. Recent studies such as [QWH+17] [SMS20] presently include driving route to estimate in advance required fuel consumption but without statistical relevant number of participants. Therefore, it is necessary to apply fuel estimation together with traffic predictions and route options to enable driver choose routes with more fuel efficient options together with statistically relevant number of participants.

In addition, tactical maneuver assistance for exits and entries have been less studied compared to intersections. Although exits and entry are a kind of intersection, specific studies are necessary to address associated road merging accidents. In addition, considerable number of studies that recognize driver attention [SA19] [RKA+19], driving maneuver intention [XLW+19] [DS21] and analyze traffic scenario complexities [DLZH19] [WWQ20] [CSWY20] [ZYF+19] [MGM+14] [MXT15] also exist. However, online adaptivity to driving maneuvers (e.g. lane change, turn, overtaking) intention, driver attention, and complexity analysis of traffic scenarios that integrates anticipation of surrounding vehicle behavior has not been considerably applied. Various combinations of driver attention states (e.g. fatigue, drowsiness, situation awareness, and workload), varying traffic scenario (e.g. intersection with bicyclists and pedestrians) and varying driving experiences need to be considered.

Furthermore, drivers tend to be confused or reject warnings when they are already aware of the situation or already anticipated it which may lead to mistrust and misuse of an assistance system. That is, habitually ignoring warnings may result in doing same in situations where they are necessary which may result in accidents. Therefore, an approach

is required for the ADAS to know when driver has already anticipated a situation. Existing methods do so by testing drivers in different situations and curating them. This is time consuming and an automatic methods e.g the pedestrian awareness method presented in [PFT+15] should be tested with drivers to evaluate suitability. In addition, driver ability to anticipate situations might be subject to driving experience and should therefore be considered.

In addition, pacing and prioritization of warnings about detected objects in traffic scenarios would be necessary to direct driver attention to most eminent danger to avoid confusion and ensure safety. Furthermore, it would be necessary to compare interface options most suitable for different assistance situations that integrate different aspects of driver attention, intention, and traffic scenario. In addition, more road trials are still required to obtain driver feedback from real world scenarios. In addition, age, gender, and cultural considerations necessary to make these systems suitable for different demographics need to be clearly defined.

Research gaps in conditionally automated driving

Majority of existing contributions related to conditionally automated driving assistance integrate highway and country road scenarios. Regarding scenarios, intersections, entry, exits, and vulnerable road users e.g. pedestrians have not been sufficiently studied. In addition, the effect of scenario and NDRT are more studied compared to the effect of TOT budget.

Furthermore, few studies integrate online adaptivity to driver attention (attention guiding) and maneuvers (specifically shared control). Shared control as a stability measure during takeover has been applied to a simple highway exit situation without surrounding vehicles and vulnerable road users. It is necessary to apply shared control to more complex scenarios and age groups.

Indicating warning urgency leads to faster responses in one case and better response without reduction in time in another context. Therefore, study of warning urgency in various complex driving scenarios is required to determine when it is suitable.

The time required by drivers to takeover in different situations have been concluded to be withing a range of 2 s to 10 s. This makes TOT budgeting for various scenarios ambiguous and arbitrary. For example a low TOT budget may cause elevated workload for older drivers and more experienced drivers require less time. Therefore, it is necessary to determine a generalized approach to TOT budgeting for various scenarios that sufficiently accommodates different drivers and age groups.

Directional audio warnings such as “slow car ahead, please takeover” have been studied in simple situations. However, directional audio for more complex scenarios should be studied to determine easily understood expressions to avoid confusing driver.

Scope of thesis

The research presented in this thesis is limited to

1. studying the interdependence between takeover variables in order to determine a suitable approach to budgeting required takeover time in advance in conditionally automated driving, and
2. application of lane change intention recognition to lane change assistance through warnings to driver.

3 New experimental analysis of conditionally automated driving takeover behavior in complexity levels of different traffic scenarios

This chapter comprises six sections. Section 3.1 includes a discussion of the research statement. Section 3.2 includes variables utilized in the experimental analysis of driver behavior in takeover scenarios with different levels of complexity. In section 3.3 the experimental design and setup are outlined. In section 3.4 and 3.5 the results and discussion of results are presented. Finally, section 3.6 includes a summary. The content of this chapter has been published in conference proceeding [TS19b] [TS19a] [TNWS19] and is under review as a journal submission in [TS21b].

3.1 Research Statement

In conditional driving automation, the ”automated driving system (ADS) performs the entire dynamic (lateral and longitudinal) driving task (DDT) within defined conditions until system limits are reached” [Soc18]. At that point, the ADS presents a request to intervene (RTI) also denoted as a takeover request (TOR) to the driver to resume performance of the DDT [BRK17], [HLK17]. Usually, the driver has a few seconds to respond and to ensure successful takeover.

Furthermore, the TOT budget strongly affects takeover time because drivers has to takeover within this time frame to avoid accidents. This chapter focuses on studying the interdependencies necessary to define an approach for budgeting TOT online based on prevailing variables. That is, though the ADS is unable to continue performing driving tasks, it should still be able to automatically analyze the scenario to budget sufficient time to warn the driver.

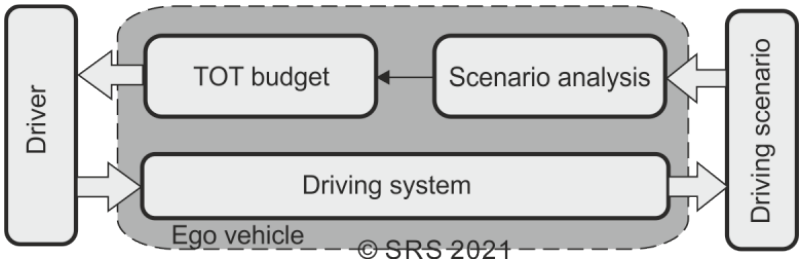


Figure 3.1: Online determination of TOT budget submitted in [TS21b]

In [HLK17] [WS19], the authors concluded that when drivers have previously experienced at least one takeover, they perform better in subsequent ones. In [KVV17], the authors concluded that 90 % of drivers require more than 8 s to complete most actions required to resume driving tasks (e.g. glance at road, mirror, and speedometer, feet on pedals, hands on steering, and switching off ADS). In [KY17], the authors concluded that a short TOT budget increases situation awareness but result in insufficient time to respond correctly. On the other hand, a long TOT budget allows sufficient time to respond correctly but could not always guarantee sufficient situation awareness.

In [NT17] [NPWM19] the authors concluded that drivers performing NDRTs with a hand-held device e.g. playing a game on a mobile phone require more time. In [WS19], the drivers were notified to takeover 8 s before critical situations. The authors reported that the average takeover time for first takeover experience was 9 s indicating that not all drivers are able to successfully respond within 8 s. In [BPN+18] the authors concluded that reduced road glances result in increased takeover time and individual reaction times affect takeover time. Similarly, in [ES17], the authors concluded that takeover time varies with different drivers who have different reaction times and levels of driving competence.

In [OKD18] [FNNH17], the authors concluded that guiding drivers using visual and audio interfaces during takeover results in improved SA, reduced takeover time and improved overall performance compared to without support. This is also concluded in [LWR19] using a haptic interface and in [LMR19] [SWN+18] [EPZ+19], using augmented reality interfaces though without reducing takeover time. In [RB20] the authors concluded that

matching the level of urgency of takeover using visual-tactile interface warning results in better performance in less urgent cases compared to more urgent ones but does not reduce takeover time.

The aforementioned studies reveal that if the TOT budget is too small the driver will not have sufficient time to react correctly and if too large, the driver may ignore the warning or delay response either of which could lead to unsuccessful takeovers and accidents. Accordingly, improving SA with interface support and TOT budgeting should be further explored. To address this problem, this thesis considers different complexity levels of takeover variables and discusses takeover time with respect to variations.

The long-term goal would be to determine a suitable approach for a takeover assistance system to automatically analyze the scenario and budget appropriate time for the driver as illustrated in Figure 3.1.

3.2 Systematic approach to study conditional takeovers

Having established how the presence and magnitude of different variables affect takeovers, driving scenarios and NDRTs having different complexity levels will be considered to better understand how to budget TOT time online. It is expected that by comparing different combinations of complexity levels of scenarios and NDRT, a pattern of variation could be established.

3.2.1 Takeover scenarios

Driving scenarios are strongly affected by human cognitive abilities - decision, planning, and interaction. Here they are regarded as a complex dynamical system because the human operator is acting both as a (simple-reflex or rule-based) controller and a knowledge- and experience-guided individual. Citing [Dör96], a complex dynamical system is characterized by several dimensions namely - complexity, connectivity, dynamics, intransparency,

Table 3.1: Dimensions of complex dynamical systems based on [Dör96] [Söf04] [Sch93] and published in [TS19a]

Characteristics of complex dynamical systems [Dör96] [Söf04] [Sch93]		Driving scenarios [TS19a]
Complexity	Increased number of interacting agents increases complexity	Vehicles, pedestrians, and bikes
Connectivity	Changes in agents' behavior causes changes in others	Different vehicle behaviors
Dynamics	Ability to change problem constellation with time	Various vehicle positions and speeds
Intransparency	Non-'visibility' of agents and features limits observability	Curved terrain and fog
Polytely	Prioritization between conflicting goals	Drive duration and safety prioritization
Openness of goal	Goals can only be approximately accomplished	Individual driving styles and pace

polytely, and openness of goal. These properties are defined in [Dör96], and interpreted in a formal sense in [Söf04].

Connectivity describes how changes in the behavior of one agent results in changes in the behavior of other agents within the system. Traffic scenarios are connective when drivers' interests are affected by others. A sudden breaking action of a lead vehicle due to an obstacle may cause the vehicles behind it to also break suddenly because of the shared safety interest to avoid collision. This can ripple through to several vehicles behind.

The **Dynamics** property describes the ability of a system to change the problem constellation and/or to evolve with time even without any external influences acting on it. This is because the interacting agents are free within the system. In a typical traffic scenario, the vehicles are in continuous motion while constantly changing the appearance of the system. Increasing the degree of freedom of interacting vehicles increases the dynamics of the system.

Intransparency describes the circumstance where the states of some agents are not immediately detectable. Any effect leading to restrictions for the drivers' behavior which

can not be directly seen (from the traffic scenario) will generate (partial) intransparency. This may happen due to non-visibility of vehicles, but also due to sudden changes in the traffic scenario. Increasing the number of invisible agents (vehicles, pedestrians etc.) increases the intransparency of the system.

Polytely is the property of a system which requires human intervention. During intervention, multiple goals or required states of the agents can be considered. The goals could contradict. The fulfillment of one goal automatically induces the non-fulfillment of others. In this case, a traffic scenario involving human drivers is polytelitic, when the driver runs into conflicts due to prioritization of goals. A conflict such as a situation in which a turning maneuver is required but may not be realized without collisions with other traffic participants. Here, the goals 'drive safely' and 'reach the destination' and 'reach the destination in time' are in conflict with one another.

Openness of the goal situation means that the goals to be achieved by an operator's intervention are not completely accomplishable but only approximately. That is, a human driver's task to reach a destination in time is open with respect to the goal situation if the destination is not defined in detail, such that the subtask where to drive at each time is not discrete. Furthermore, requirements for 'safe driving' is always open, because it is usually relative.

An outline of the characteristics of complex dynamical systems and some examples of environment variables that can produce the related effects in a driving scenario are displayed in Table 3.1. To design driving scenarios the different dimensions of complex dynamical systems are considered and suitably modified.

Four takeover scenarios (S1, S2, S3, and S4), each having two complexity levels (I. low and II. high) in which the ADS issues a TOR are designed. The named complexity levels are for purposes of observing effects between presence and magnitude of different dynamic traffic scene characteristics e.g. ego vehicle speed, number of surrounding vehicles etc. This is such that, by varying the magnitude of some dynamic traffic scene characteristics,

the difficulty of level II is higher than those of level I. The considered levels of the eight takeover scenarios are illustrated in Table 3.2 and Figure 3.2.

Specific traffic scene characteristics for each scenario during which the ADS issues a TOR, are outlined to reveal how the related difficulty increases from level I to level II. Scenarios 1, 2, and 3 occurred on a three-lane dual carriage highway. While scenario 4 occurred on a single-lane dual carriage country road. For reference purposes, the levels of the scenarios are abbreviated as outlined in Table 3.2.

S1: Stationary front vehicle on highway: In each level of this scenario, the ADS issues a takeover request because of a stationary vehicle ahead on the right lane. The speed of the ego vehicle is 80 km / h in S1|I and increased to 130 km / h in S1|II. In addition, there is an approaching vehicle on the middle lane to the left of ego vehicle in S1|II.

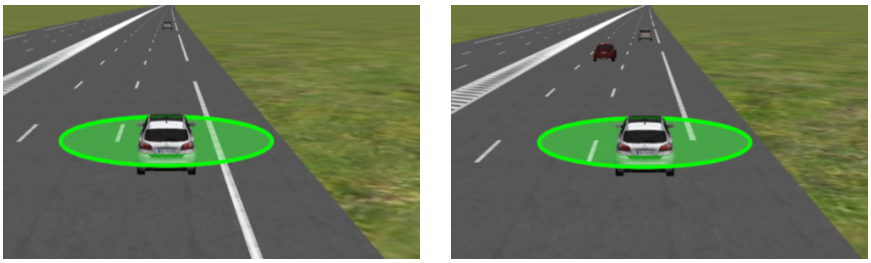
S2: Slow front vehicle on highway: In each level of this scenario, the ADS issues a TOR due to a slow vehicle ahead. The speed of the ego vehicle is set at 80 km / h in S2|I and increased to 130 km / h in S2|II. There is also an approaching vehicle in the middle lane to the left of the ego vehicle in S2|I.

S3: Exit highway: The ADS issues a TOR to driver to maneuver exiting a highway while on the right lane (exit lane). The speed of the ego vehicle is set at 50 km / h in S3|I and increased to 100 km / h in S3|II.

S4: Turn right at country road intersection: The ADS issues a TOR to driver to maneuver making a right turn. The speed of ego vehicle is set at 50 km / h in S4|I and increased to 80 km / h in S4|II. In addition, there is a bicyclist and a pedestrian at the intersection of the right adjourning road where the driver should make a right turn. The pedestrian is crossing, while the bicyclist is making a right turn.

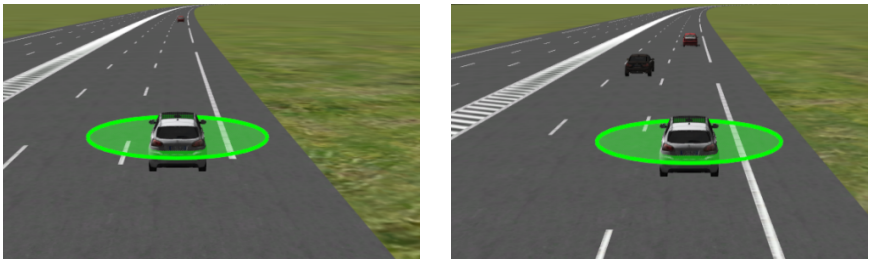
3.2.2 Non-driving related tasks

Non-driving related tasks (NDRTs) are activities that the driver can engage in while the ADS is controling the vehicle. [KVV17] suggests conditions that should be considered



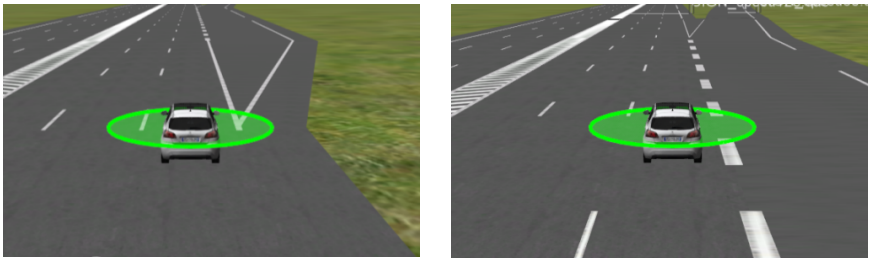
S1|I S1|II

Stationary front vehicle on highway



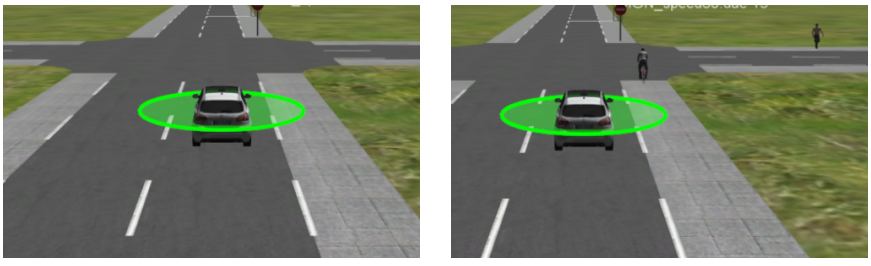
S2|I S2|II

Slow front vehicle on highway



S3|I S3|II

Exit highway



S4|I S4|II

Turn right at country road intersection

Figure 3.2: Graphical illustration of takeover scenarios published in [TS19b]

Table 3.2: Technical description of takeover scenarios published in [TS19b]

Scenarios		Complexity levels	
		I. Low	II. High
S1	Stationary front vehicle on highway	S1|I Speed: 80 km / h No additional traffic	S1|II Speed: 130 km / h Approaching vehicle on middle lane
S2	Slow front vehicle on highway	S2|I Speed: 80 km / h No additional traffic	S2|II Speed: 130 km / h Approaching vehicle on middle lane
S3	Exit highway	S3|I Speed: 50 km / h No additional traffic	S3|II Speed: 100 km / h No additional traffic
S4	Turn right at country road intersection	S4|I Speed: 50 km / h No additional traffic	S4|II Speed: 80 km / h Bicyclist on right bicycle path Pedestrian crossing at right turn

for the development of non-driving related task include: completely different task from driving, motivating and immersive, require motor skills, be difficult enough to interrupt and easy to learn.

Considering the aforementioned criteria, three levels of NDRTs namely reading, proofreading and proofreading aloud (by saying correct word) are designed. The increasing complexity (multitasking) of the NDRTs are explained with the theory of threaded cognition [ST08]. Threaded cognition represents cognitive processes as process threads coordinated by a serial "procedural" resource and utilizes other available resources (e.g. perceptual and motor resources). "The theory defines a parsimonious mechanism that describes concurrent thought execution and projections of possible interference during multitasking" [ST08]. In other words, it illustrates a clear increase in cognitive task complexity.

Three levels of Non-driving related tasks (NDRTs) namely, reading, proofreading, and proofreading aloud are considered for drivers to perform when ego vehicle is in autonomous mode as illustrated in Table 3.3. The increasing multitasking complexity of the NDRTs are explained with the theory of threaded cognition [ST08].

Considering threaded cognition, the NDRTs can be described by several cognitive resources

namely procedural, declarative, visual, motor, and vocal. Each of these resources is capable of independent processing interference [ST08]. Procedural resource represents procedural skill towards a goal. It always precedes the execution of another resource [ST08]. Declarative resource retrieves static knowledge stored in memory. Aural and visual resources are perceptive resources. They acquire sound and visual information from the environment. While motor (manual) resource actuates necessary action (such as moving arms) in the environment. In other words, procedural and declarative resource utilize and process existing knowledge. Aural and visual resource acquire new knowledge and inference from the environment. While motor resource actuates decided action in the environment which is based on the output of the other resources. Utilizing the aforementioned theory of threaded cognition [ST08], the designed NDRTs are explained in detail.

The complexity from NDRT 1 to NDRT 3 is increased due to increased number of cognitive resources utilized [ST08]. Procedural resource always executes first and then coordinates other resources [ST08]. Visual resource enables perception of text and declarative resource enables memory recall of words when the NDRT is reading. Motor resource enables highlighting text by hand when the NDRT is proofreading. Vocal resource enables pronunciation of the correct word aloud when the NDRT is proofreading aloud.

In line with the assumptions of threaded cognition [ST08], occurring resource conflicts (interference between processes) and a time delay (blue text in Table 3.3) is generated for one process while the other executes. Since the procedural resource always precedes the execution of other resources, it is often a source of conflict. The interconnecting blocks represent the sequence and presence of time delay (not duration) within each process. The parallel process sequences clearly show increase in the complexity and by extension, increase in difficulty from NDRT 1 to 3.

If there is no wrong word to highlight, the correction process of the proofreading task (second column of Table 3.3) returns to the beginning of the thread after the “declarative: retrieve instruction” step. While in the proofreading aloud task (third column of Table 3.3),

the vocal thread occurs only when there is a wrong word detected, hence why it begins alongside the “Procedural: initiate moment” step. The process sequence of each task is repeated for each word.

3.3 Experiments

The experiment was designed such that variations in takeover time and performance can be studied with respect to varying traffic scenario and NDRT complexity levels. This is required to determine sufficient time for takeover based on prevailing variables. Previous studies indicate that takeover time increases with scenario and task complexity [BRK17] [KY17] [WS19]. Therefore different scenarios are designed on different road types.

3.3.1 Participants

To perform TOR experiments, experienced drivers were invited to drive in the different levels of the designed scenarios previously displayed in Table 3.2. Each laboratory appointment lasted approximately three hours. First, participants filled a pre-questionnaire about their driving experience and received an introduction to the simulator and the procedure and goal of the study for approximately 15 minutes. If participants had questions, they were answered. The audio sound with which the TOR would be given was played for the participants.

Afterwards, the participants performed a test drive for approximately 10 minutes to adapt to the driving simulator. During the test drive, participants practiced how to operate the switch between conditionally automated and manual driving modes. Finally, they performed four experimental drive procedures including filling questionnaires as detailed in the next section. Each drive procedure lasted approximately 30 to 35 minutes with a few minutes break in between.

Table 3.3: Complexity levels of NDRT published in [TNWS19]

Proofreading aloud (NDRT 3)		
Proofreading (NDRT 2)		
Reading (NDRT 1)		
Procedural: attend word	(Waiting until procedural is free)	(idle)
Visual: encode word	Procedural: retrieve instruction	(idle)
Procedural: lexical access	Declarative: retrieve instruction	(idle)
Declarative: lexical access / Visual: encode word	(idle)	(idle)
Procedural: retrieve syntax	coloured	(idle)
Declarative: syntax element	(idle)	(idle)
Procedural: attach syntax	(Waiting until procedural is free)	(Waiting until procedural is free)
(idle)	Procedural: initiate movement	(Waiting until procedural is free)
(idle)	Manual: highlight text	Procedural: retrieve instruction
(idle)	(idle)	Declarative: retrieve instruction
(idle)	(idle)	Procedural: retrieve tone response
(idle)	(idle)	Declarative: retrieve word
(idle)	(idle)	Procedural: respond to instruction
(idle)	(idle)	Vocal: say word aloud

No specific age group, type of experience or gender was targeted. A total of 70 drivers (60 males and 10 females) were recruited. All drivers held valid driver's licenses, 29 of them have previously used vehicles equipped with one or more ADAS features, 28 of them have previously experienced driving simulators and additional descriptive statistics obtained from the pre-questionnaire are outlined in Table 3.4.

As reward, participants either received 15 EUR or attended a three-hour time management seminar. In accordance with the relevant ethics rules, participants signed a participation consent declaration. Participants were also informed that their participation was voluntary and were free to discontinue the experiment if desired. Approval was also obtained from the ethics committee of the Faculty of Engineering at the University of Duisburg-Essen, Germany.

Table 3.4: Participant quantitative descriptive statistics submitted in [TS21b]

Participant detail	Mean	STD	Min	Max
Age [Yrs.]	25.98	4.85	19.33	46.16
Driving experience [Yrs.]	6.75	5.35	0.08	28.16
Driving experience [Km/Wk]	191.9	296.17	0.5	2000

3.3.2 Experimental procedure

Different random combinations of independent variables (Scenarios and NDRT) were given to participants during experiments. Due to the large number of combinations, all participants did not experience all combinations but were distributed evenly. That is, 8 $\times$ 3 factor randomized statistical design approach was employed to study the variation of the between-subject factors (scenario and NDRT levels). Participants were also not allowed to experience the two levels of the same scenario e.g. a participant can not experience scenario 1 levels I and II. This was to avoid adaptation affecting the results.

Drivers were first required to drive manually for about 10 to 15 minutes before being asked to change to autonomous mode where they performed the NDRT. Afterwards, the TOR was issued to drivers 7 s before each critical scenario. To announce TOR, audio and

visual interfaces were utilized at the same time. Based on recommendation by [WLSM12] for emergency situations, audio message: ”full autonomous driving assistant has failed” alerts driver to danger. On the HUD and Control pad, the text message: ”failed” is displayed without obstructing the driver's views [WL96]. Participants could switch from autonomous to manual by touching the manual button on the control pad or steer and continue driving while applying the pedals. After takeover, participants filled situation awareness rating technique (SART) [Tay89] and NASA task load index (NASA-TLX) with pairwise comparison [HS88] questionnaires.

3.3.3 Experimental environment

The scenarios are implemented in SCANeR^{TM} studio (a professional driving simulator software by AVSimulation). The data acquiring frequency of SCANeR^{TM} studio is 20 Hz. The driving simulator setup includes five displays that provide 270 ^{0} field of view, a fixed-base driver seat, steering wheel, clutch, brake, and accelerator pedals as displayed in Figure 3.3. A rear view mirror and two side mirrors are displayed on the appropriate positions of the monitors. A control pad (touchscreen) displays the driving modes on one-fourth of the screen and three-quarter of the screen is used for performing the NDRTs in conditionally automated driving mode.

3.3.4 Data measures and analysis approach

Measured dependent variables include takeover time, SA, workload, lateral displacement and maximum acceleration for comparison with independent variables scenarios, NDRT, ordinal. The ordinal refers to the order of the drive e.g. first, second, third, or fourth. The definition and extraction of measured dependent variables include:

- Takeover time: Time from TOR to 5 % difference in brake or steering input depending on method of takeover used by participant.

Figure 3.3: Driving simulator laboratory, Chair SRS, U DuE, Germany

- Situation awareness: Subjective rating of participant using (SART) [Tay89]. High ratings indicate increased situation awareness.

- Workload: Subjective rating of participant using NASA-TLX with pairwise comparison [HS88] questionnaires. Increased workload ratings indicate increased task difficulty.

- Average lateral displacement: The average lateral displacement (DISPL) from the lane center before and after TOR is expressed as

$$Avg\ L\ Displ.[m] = \frac{\sum L\ Displ.\ (before - after)\ TOR}{\sum Time\ frame\ before\ and\ after\ TOR}. \tag{3.1}$$

  This is an indication of lateral (steering) control. Increased average lateral displacement indicates poor performance [KY17].

- Maximum resultant acceleration: maximum resultant acceleration value attained

between TOR and takeover is expressed as

$$Max.\ Acc. = \sqrt{Acc._{longitudinal}^{2} + Acc._{lateral}^{2}}. \tag{3.2}$$

This is an indication of forward collision risk. Increased acceleration indicates poor performance [HLK17].

The analysis approach is from the view that increased takeover time does not necessarily indicate more complexity. Performance, SA and workload should be considered in the overall conclusions. Significance level 0.5 is used for the analysis.

Data from the first drive of three participants who did not understand the instructions when they experienced the first takeover and three other participants who experienced accidents in the first drive are excluded. The three accidents occurred in S2|II, S1|I, and S2|I and are the only accidents recorded. The hypotheses investigated include:

- Hypothesis 1: Takeover time increases with perceived nonurgency and scenario complexity. In addition, takeover time for complexity level II is expected to be higher than level I of scenarios.

- Hypothesis 2: Takeover time increases for more complex NDRTs. In addition, takeover time for NDRT 3 is expected to be higher than NDRT 2 and NDRT 1.

- Hypothesis 3: Situation awareness decreases for more complex tasks. Therefore, SA for scenario complexity level II is expected to be lower than for level I of scenarios. In addition, SA for NDRT 1 is expected to be higher than NDRT 2 and NDRT 3.

- Hypothesis 4: Workload increases for more complex scenarios. In addition, workload for complexity level II is expected to be higher than for level I of scenarios.

- Hypothesis 5: Performance decreases for more complex scenarios. In addition, performance in terms of lateral displacement and maximum acceleration for complexity level II is expected to be higher than level I of scenarios.

3.4 Results

Quantitative descriptive statistics of the dependent variables with respect to scenario are provided in Table 3.5. Parametric analysis assumptions of normality, homogeneity of variances and co-variance of data are satisfied by dependent variables but lateral displacement and maximum acceleration. Specifically for takeover time, normality is satisfied after conversion. Non-parametric approach is applied to analyze lateral displacement and maximum acceleration.

Table 3.5: Quantitative descriptive statistics Of dependent variables with respect to scenario levels submitted in [TS21b]

DV | Mean (STD)	S1|I	S1|II	S2|I	S2|II	S3|I	S3|II	S4|I	S4|II
TOT [s]	3.33 (2.53)	3.15 (0.89)	2.89 (1.38)	3.44 (1.09)	3.11 (1.32)	3.99 (1.61)	4.60 (2.36)	3.28 (1.68)
Avg. L. Displ [m]	1.51E-1 (9.37E-3)	1.46E-2 (6.08E-3)	1.46E-2 (7.35E-3)	2.20E-2 (3.01E-3)	1.03E-4 (4.65E-4)	6.85E-4 (2.84E-3)	8.67E-6 (1.56E-6)	8.43E-5 (3.49E-4)
Max. acc. [m/s^2]	1.61 (0.34)	0.08 (0.05)	2.19 (0.61)	1.06 (0.16)	0.15 (0.30)	0.35 (0.58)	0.23 (0.57)	0.18 (0.36)
SA [Tay89]	20.45 (7.27)	16.91 (9.03)	20.26 (7.32)	16.00 (7.17)	25.55 (6.00)	24.70 (6.18)	23.14 (7.63)	20.35 (9.08)
Workload [HS88]	40.51 (21)	47.38 (16.85)	42.02 (19.64)	51.16 (17.66)	33.52 (14.24)	37.79 (16.84)	41.51 (19.07)	40.93 (22.66)

Two-way Manova between independent variables (Scenarios, NDRT, ordinal) and dependent variables (takeover time, SA, workload) indicate significant interaction between independent variables and dependent variables $F(282,246.9) = 5.2$, $p < 0.05$; Wilks' $\Lambda = 0.003$; partial $\eta^2 = 0.856$.

One-way Manova to check the effect of scenario on the combined DVs indicates significance ($F(21,482.96) = 2.4$, $p < .05$; Wilks' $\Lambda = 0.75$; partial $\eta^2 = 0.091$). One-way Manova

to check the effect of ordinal on the combined DVs indicates significance (F(9,418.75) = 2.71, p < .05; Wilks' Λ = 0.87; partial η^2 = 0.045). One-way Manova to check the effect of NDRT on the combined DVs indicates significance (F(6,346) = 2.54, p < .05; Wilks' Λ = 0.92; partial η^2 = 0.028).

3.4.1 Takeover time

Two-way Anova indicates no significant two factor and three factor interaction between the IVs on takeover time. Significance is found between the individual factors ordinal (F(7,174) = 7.13, p < 0.001, η^2 = 0.1169) and scenario (F(7,170) = 2.57, p < 0.01, η^2 = 0.1016) on takeover time. No significance is found between NDRT levels which disagrees with hypothesis 2 but also confirmed in a parallel study [RFB19].

Takeover time between scenarios (Figure 3.4)

Having verified the significance between scenarios and takeover time, post hoc tests are performed. Multi-comparison Bonferroni test with correction for independent samples indicates S2|I is significantly different from S4|I. Specifically, S4|I takeover time is higher compared to S2|I. Considering that S2|I is more complex because of a higher speed and requirement for better steering control, the increased takeover time in S4|I indicates delayed response due to perceived nonurgency as hypothesized in sections and 4.4.3.

Furthermore, S4 indicates significance between its levels and the mean difference in takeover time indicate that S4|I is larger than S4|II. Whereas, S1, S2, and S3 indicate no significance between levels I and II.

Takeover time between each ordinal level (Figure 3.5)

Multi-comparison Bonferroni test indicates significance between first and subsequent drives. In addition, no significance is seen between second and subsequent drives as well

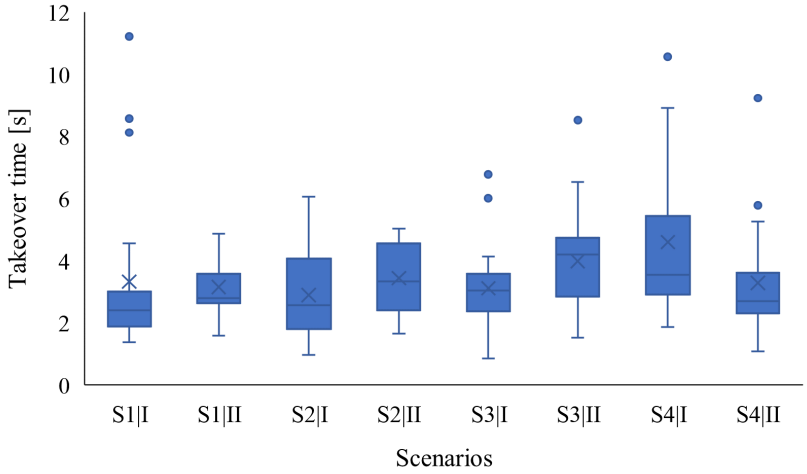


Figure 3.4: Takeover time for scenario levels submitted in [TS21b]

as between third and fourth drives. In all cases with respect to scenario as illustrated in Figure 3.6, the mean takeover time for first drive requires more time. Then the values decrease and increase with respect to scenario levels until the fourth drive as similarly reported in [WS19].

Furthermore, the mean takeover time with respect to ordinal reduces from level I to level II of each scenario but S3 as illustrated in Figure 3.6. The highest average is recorded in the first drive of S4|I. Therefore, increasing the complexity of the scenario given the same time budget requires drivers to pay more attention and act fast to avoid accident.

3.4.2 Situation awareness (SA)

Two-way Anova indicates no significant two factor or three factor interaction between IVs on SA. Significance is found between the individual factors scenario ($p < 0.001$, $F(7,170) = 4.0698$, $\eta^2 = 0.1363$) and NDRT ($F(2,175) = 3.1499$, $p < 0.05$, $\eta^2 = 0.0474$) on SA.

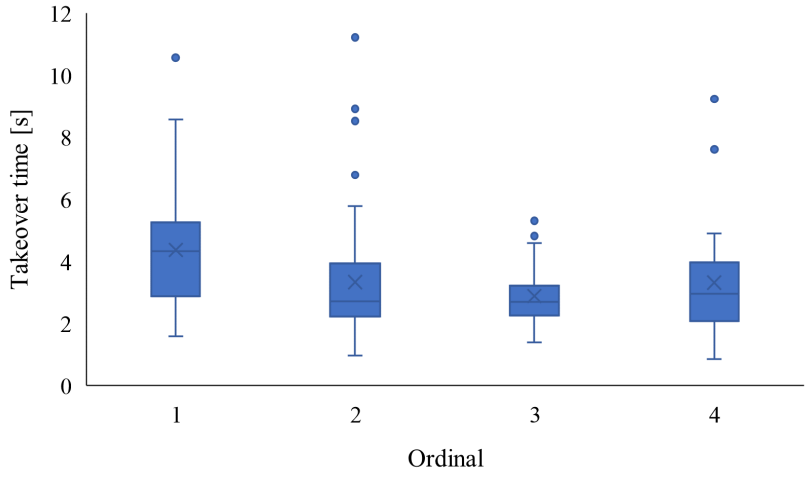


Figure 3.5: Takeover time for 1st to 4th drives submitted in [TS21b]

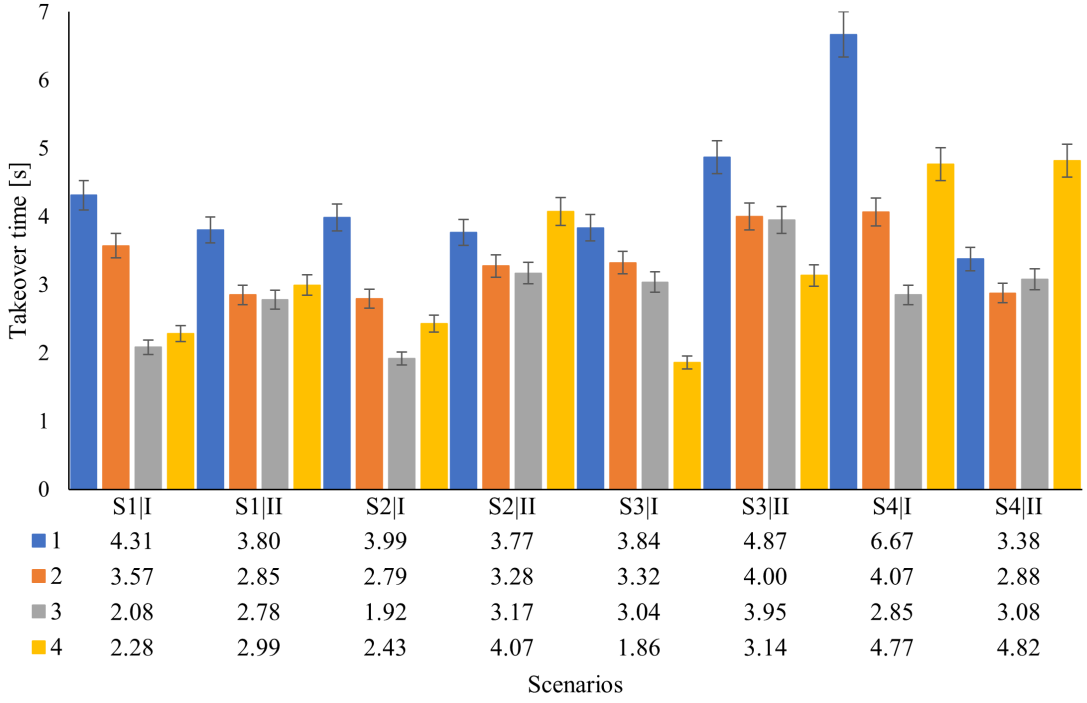


Figure 3.6: Average takeover time for scenario levels and ordinal of takeover submitted in [TS21b]

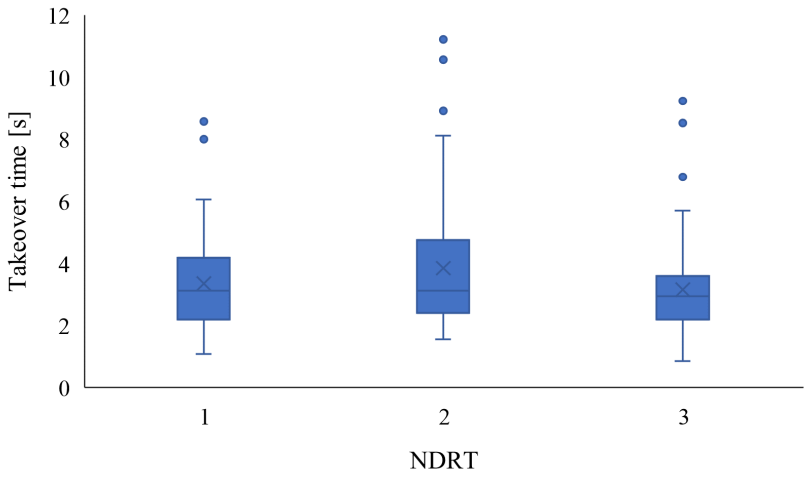


Figure 3.7: Takeover time for NDRTs submitted in [TS21b]

Situation awareness between scenarios (Figure 3.8)

Similar to observations for takeover time, one-way Anova of SA with respect to scenarios indicates significance between different types of scenarios. Using Bonferroni multi-comparison, S1|II and S2|II are significantly different from the two levels of S3 as illustrated in Table. 3.6. The mean SA of S1|II and S2|II are significantly lower than the two levels of S3, indicating higher SA in the levels of S3 and agrees with the first part of hypothesis 3. The increased SA in levels of S3 indicates simpler scenario with one exit and increased speed in S3|II compared to S3|I. However, no significance in SA is found between S3|I and S3|II. Therefore, the non-significant rated SA between S3|I and S3|II disagrees with the second part of hypothesis 3.

Though the mean differences indicate that level II is higher, no significant difference is found between the levels of S1, S2, and S4 as well as between the levels of S3 and S4. Therefore, similar SAs are recorded for levels of S1 and S2 in relation to levels of S4. In addition, similar SAs are recorded for levels of S3 in relation to levels of S4. Therefore, the increased SA in levels of S3 agree with the first part of hypothesis 3.

Table 3.6: Multi-comparison test of situation awareness for scenario levels submitted in [TS21b]

Scenario (i)	Scenario (j)	Mean diff. (i-j)	Std. error	Sig.	Lower bound	Upper bound
S1|II	S3|I	-8.64	2.257	0.007	-15.92	-1.35
S1|II	S3|II	-7.79	2.232	0.022	-14.99	-0.58
S2|II	S3|I	-9.55	2.257	0.002	-16.83	-2.26
S2|II	S3|II	-8.70	2.232	0.005	-15.9	-1.49

SA between NDRTs (Figure 3.9)

Using Bonferroni multi-comparison, significance is found between NDRT 1 and NDRT 2, where the mean SA for NDRT 1 is higher. In addition, no significance is found between SA for NDRT 2 and NDRT 3 nor between NDRT 1 and NDRT 3. In summary, NDRT 1 results in increased SA compared to NDRT 2 and NDRT 3 as hypothesized in hypothesis 3.

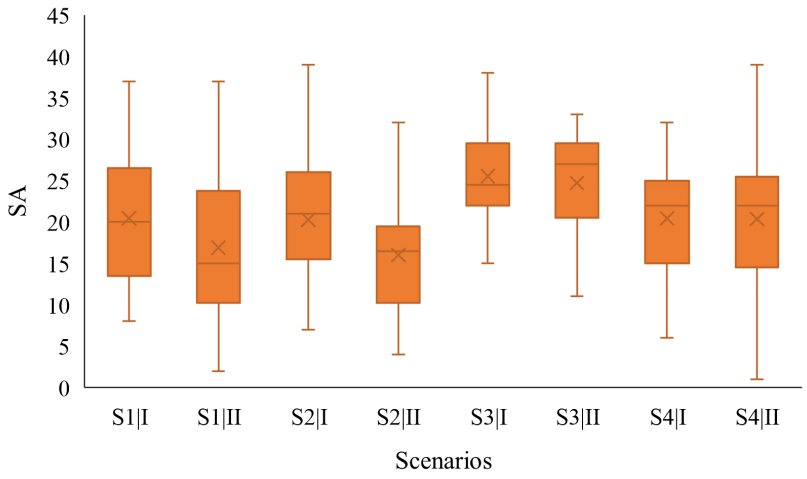


Figure 3.8: Situation awareness for scenario levels submitted in [TS21b]

3.4.3 Workload

Two-way Anova indicates no significant two-factor or three-factor interaction between the IVs on workload. One-way Anova also indicates no significance between individual IVs

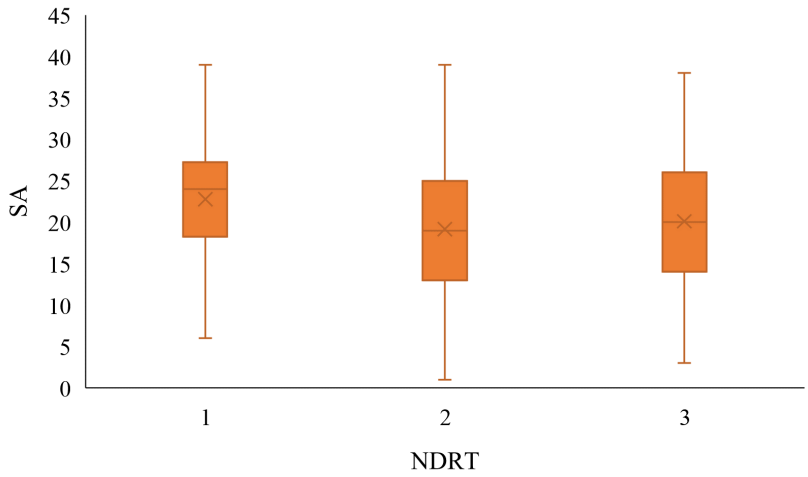


Figure 3.9: Situation awareness for NDRT levels submitted in [TS21b]

(scenario, NDRT, and ordinal) on workload.

Furthermore, the workload ratings are evaluated to determine the general effect of takeover scenarios on participants. According to [Gri15] NASA-TLX rating for driving tasks within 28.05 % is low, between 28.05 % and 41.5 % is average and above 41.5 % high. The recorded ratings in this thesis range from low to high, with mostly average ratings as illustrated in Figure 3.10. Therefore, the rated workload indicate the studied scenarios did not result in overwhelming workload for most drivers.

3.4.4 Evaluation of takeover driving performance

Lateral displacement and scenario (Figure 3.11)

One-way analysis of variance using Kruskal wallis test indicates significance between scenario levels and lateral displacement. Specifically using Bonferroni correction, significance is found between different scenarios with respect to lateral displacement as outlined and abridged in Table. 3.7.

- Only in S1 is significance between levels I and II is found. Specifically, the lateral displacement for S1|II is lower than S1|I indicating better performance in S1|II.

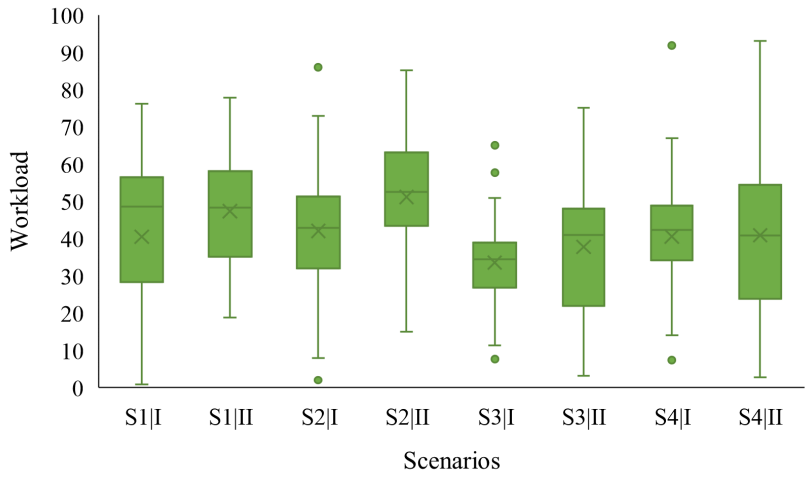


Figure 3.10: Workload for scenario levels submitted in [TS21b]

- Worst lateral displacement is found in S1|I.
- Mean lateral displacement in all levels of S3 are lower than all levels of S1 and S2.
- Mean lateral displacement in S4|I is lower than all levels of S1 and S2 but S1|II indicating better performance in S4|I.
- Lateral displacement in S4|II is lower than all levels of S1 and S2.

Therefore, better lateral displacement is found in S1|II and all levels of S2, S3, and S4. In rejection of hypothesis 5, increased complexity results in increased effort and better performance.

Maximum resultant acceleration and scenario (Figure 3.12)

One-way analysis of variance using Kruskal wallis test indicates significance between different scenarios with respect to maximum resultant acceleration. In addition, multi-comparison using Bonferroni test are outlined in Table 3.8.

- Statistically significant better performance is found in S1|II compared to S1|I indicating erratic rather than smooth reaction in level I.

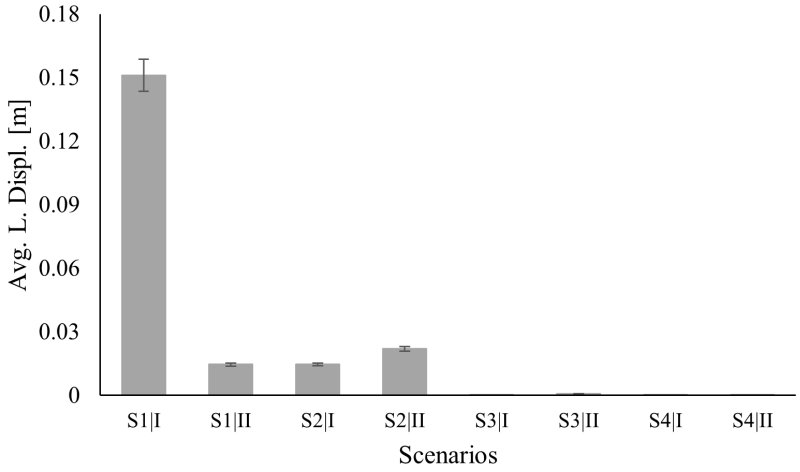


Figure 3.11: Average lateral displacement for scenario levels submitted in [TS21b]

Table 3.7: Multi-comparison test of average lateral displacement for scenario levels submitted in [TS21b]. a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Scenario (i)	Scenario (j)	Test stat.	Std. error	Std. test stat.	Sig.	Adj. sig.[a]
S3|II	S1|II	85.235	15.367	5.547	2.91E-08	8.15E-07
S3|II	S2|I	94.565	15.195	6.224	4.86E-10	1.36E-08
S3|II	S2|II	112.69	15.367	7.333	2.24E-13	6.28E-12
S3|I	S1|II	80.591	15.536	5.187	2.13E-07	5.98E-06
S3|I	S2|I	89.921	15.367	5.852	4.86E-09	1.36E-07
S3|I	S2|II	108.045	15.536	6.954	3.54E-12	9.92E-11
S4|II	S1|II	52.887	15.367	3.442	5.78E-04	1.62E-02
S4|II	S2|I	62.217	15.195	4.095	4.23E-05	1.18E-03
S4|II	S2|II	80.342	15.367	5.228	1.71E-07	4.79E-06
S4|II	S1|I	109.978	15.367	7.157	8.25E-13	2.31E-11
S4|I	S2|I	49.644	15.552	3.192	1.41E-03	3.96E-02
S4|I	S2|II	67.768	15.72	4.311	1.63E-05	4.55E-04
S4|I	S1|I	97.405	15.72	6.196	5.79E-10	1.62E-08
S1|II	S1|I	57.091	15.536	3.675	2.38E-04	6.67E-03

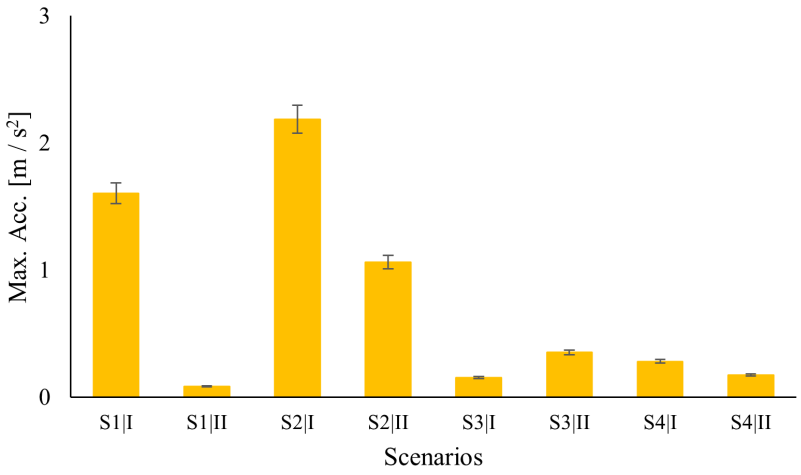


Figure 3.12: Maximum resultant acceleration for scenario levels submitted in [TS21b]

- Significance is found between S3|I and all levels of S2.
- The worst performance is recorded for S2|I.
- No significance is found between the levels of S3 and S4.
- Significance is found between the levels of S3 and S4 compared to the levels of S1 and S2 (exceptions, S1|II and S3 in relation to S1|I).
- No significance is found between S1|I, S2|I, and S2|II.

Therefore, similar to lateral displacement, better maximum acceleration is recorded for S3 and S4 and vice versa for S1 and S2. In disagreement with hypothesis 5, increased complexity results in increased effort and significantly better performance.

3.5 Discussion

3.5.1 Variation in takeover time, SA, and performance

- Takeover time: The experimental design avoided learning effects influencing results by ensuring no driver experienced the two levels of the same scenario. Different

Table 3.8: Multi-comparison test of maximum resultant acceleration for scenario levels submitted in [TS21b]. a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Scenario (i)	Scenario (j)	Test stat.	Std. error	Std. test stat.	Sig.	Adj. sig.[a]
S3|I	S2|II	69.295	15.536	4.46	8.19E-06	2.29E-04
S3|I	S1|I	94.932	15.536	6.11	9.94E-10	2.78E-08
S3|I	S2|I	113.758	15.367	7.403	1.33E-13	3.73E-12
S1|II	S2|II	-60.295	15.536	-3.881	1.04E-04	2.91E-03
S1|II	S1|I	85.932	15.536	5.531	3.18E-08	8.91E-07
S1|II	S2|I	-104.758	15.367	-6.817	9.28E-12	2.60E-10
S4|II	S2|II	59.951	15.367	3.901	9.56E-05	2.68E-03
S4|II	S1|I	85.587	15.367	5.57	2.55E-08	7.15E-07
S4|II	S2|I	104.413	15.195	6.872	6.35E-12	1.78E-10
S4|I	S2|II	54.53	15.72	3.469	5.23E-04	1.46E-02
S4|I	S1|I	80.167	15.72	5.1	3.40E-07	9.53E-06
S4|I	S2|I	98.993	15.552	6.365	1.95E-10	5.46E-09
S3|II	S2|II	50.929	15.367	3.314	9.19E-04	2.57E-02
S3|II	S1|I	76.565	15.367	4.983	6.27E-07	1.76E-05
S3|II	S2|I	95.391	15.195	6.278	3.43E-10	9.61E-09

scenarios types have different effects on takeover time. Specifically, significance is found between takeover time for country road. In this case, the takeover time for S4|I is higher than S4|II. Therefore, drivers felt more urgency to respond in S4|II. In addition, significance is found between takeover time for highway and country road. Specifically takeover time for highway is lower than that for country road in level I. Afterwards, in level II on country road, takeover time reduces and becomes similar in comparison to results from highway. In all cases, takeover time for first drive is higher than subsequent drives. From the results, it can be concluded that less complexity on country road leads to increased takeover time due to perceived nonurgency.

- Situation awareness: SA varies between scenarios that have one and more junctions and or surrounding traffic. Specifically, best SA is recorded for S3|I and S3|II involving one highway exit, reduced relative speed, and without surrounding traffic compared to S1|II and S2|II. The rated SA are however similar for highway and country road with higher relative speed and surrounding traffic. Furthermore, SA varied with NDRT and the highest SA as expected is found for NDRT 1. Furthermore, SA for NDRT 3 hypothesized to require more cognitive resources based on the theory of threaded cognition is not significantly different from NDRT 1 and NDRT 2. From the results, it can be concluded that SA is identical on country road with more junctions in comparison to highway with higher speed. In addition, utilization of more cognitive resources does not always lead to significantly reduced SA with handsfree devices.

- Performance: S1 and S2 indicate identical characteristics with the difference that the car causing the TOR in S2 is moving slowly. Furthermore, S2 involves less lateral displacement compared to S1 indicating that the slow car in S2 requires less steering urgency to avoid collision. Generally, moving from level I to II results in better performance indicating adaptation to situation and increased effort with increased complexity. From the results, it can be concluded that increased effort due

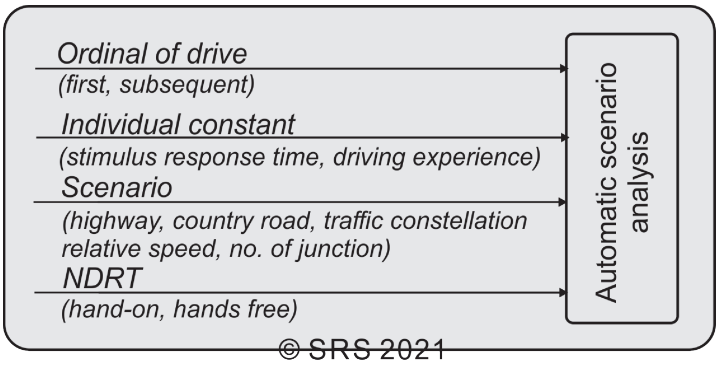


Figure 3.13: Considerations for automatic online scenario analysis submitted in [TS21b]

to increased complexity results in increased performance.

Takeover time is still higher for first drive given that participants practiced how to operate the switch between conditionally automated and manual driving modes during the test drive. This is similar to previous study [HLK17] when participants previously experienced a takeover in a training session on an open stretch of road before the experimental procedure. It can be therefore assumed that increased takeover time in the first drive and fluctuation in subsequent drives is an indication of overconfidence rather than unfamiliarity with experiment platform. In other words, time budget should be varied to stimulate participants to respond to each takeover with the same level of seriousness.

Based on the aforementioned, the considerations for budgeting TOT online are summarized in Figure 3.13 as an extension of Figure 3.1. The updated illustration integrates previously stated studies [RFB19] [NT17] that conclude that takeover time is significantly higher with NDRTs that involve use of hand-held devices compared to NDRTs involving handsfree devices as utilized in this thesis. Individual stimulus response time and driving experience are also integrated based on conclusion of [BPN$^+$18] and [ES17]. That is, individual variables should be factored into TOT budgeting.

3.5.2 Recommendations for automatic scenario analysis

Takeover time budget should be varied for different scenario types and more time should be budgeted for the first drive due to higher time requirement. Reduced performance in S1 and S2 levels indicates a response compromise between available time budget and reduced SA. Given more complexity and same time budget, takeover time is lower at the expense of performance. Therefore, it is recommended that more should be given for S1 compared to S2 levels. Whereas the time budget for S1|I should be reduced slightly given that the two measures of performance are poor in order to increase SA and stimulate more effort.

In S3, increased complexity (higher speed in S3|II compared to S3|I) results in reduced takeover time and acceptable performance. Therefore, given more complexity and the same time budget, takeover time is lower and performance is acceptable at a highway exit without surrounding traffic.

Acceptable performance in levels of S4, reduced takeover time in S4|II and similar SA indicates that given more complexity and the same time budget, takeover time is lower. Therefore, it is recommended that TOT budget should be reduced for S4|I.

In general, it is recommended that takeover time should be budgeted in decreasing order of S1|II, S4|II, S2|II, S1|I, S2|I, S4|I, S3|II, and S3|I.

Overall, the aforementioned recommendations are provided assuming that the workload is not significant enough to overwhelm the driver as observed in this thesis. If driver is overwhelmed, accident may occur instead of an increase in takeover time.

3.6 Summary

This chapter integrates an approach for studying the interdependencies of variables in conditionally automated driving takeovers. The aim is to define a suitable strategy for takeover assistance systems to budget TOT online to inform driver with respect to different

situations. The generated time budget should be sufficient for takeover with good performance. Four takeover scenarios each having two levels of complexity and three NDRTs are investigated with 70 participants. The takeover requests are given to drivers at 7 s TTC before each critical situation. The results indicate that that the recommendation for budgeted time can be useful.

4 New lane change and takeover decision assistance system with quantitative estimation of takeover time budget

This chapter comprises six sections. Section 4.1 includes a discussion of the research statement. Section 4.2 and section 4.3 includes variables utilized in the design of a lane change and takeover decision assistance system. In section 4.4 the experimental design and setup are outlined. In section 4.5 the results and discussion of results including a new generalizable formula for estimating takeover time in advance are presented. Finally, section 4.6 includes a chapter summary. The content of this chapter has been published in conference proceeding [DSTS20] and submitted as a journal manuscript in [TS21c].

4.1 Research statement

Drivers account for 94 % of vehicle crashes and lane change and merging account for approximately 9 % of fatal accidents [Nat15]. Lane change assistance systems have considerably improved driver awareness and safety but are still limited by implementations that consider driver behavior. It is assumed that providing more detailed warnings based on driver intended lane change actions will reduce lane change crashes. As a result, many studies have focused on predicting driver lane changes as basis for providing warnings as reviewed in [XLW+19] but have not been applied to assistance.

Lane change assistance using vibrotactile [LBHB15], adaptive lighting intensity compared to constant light intensity [LHB15], information displays on dynamic augmented reality HUD compared to instrument cluster [KMC+20a] improves driver perception and performance. In [YELB17] [WSG+20] [FZW+20], the authors concluded that drivers are receptive to and trust lane change warnings if given and repeated at certain defined thresholds. In [YELB17] directional warnings are not included and directional warnings

are included for only front right vehicles in [WSG+20] and left rear approaching vehicles in [WSG+20] [FZW+20] as to why the lane change is unsafe. But the participants did not perform maneuvers and indicated suitability by pressing a button. It is possible that depending of vehicle speed and driving experience, the ability to perform a safe lane change maneuver might be different from driver perception.

In [ZYZD18], aggressive, normal and cautious lane change behaviors were classified, simulated in Matlab, and tested with three drivers in a driving simulator. The authors concluded that drivers can be warned based on individual driving styles and assisted to achieve safe lane change trajectories. However, this did not include statistically valid number of participants which is necessary to conclude whether the method would reduce lane change accidents.

In [LCS+18], the authors applied lane change intention recognition to shared steering control and concluded that the system enables obstacle avoidance and safe trajectory realization during lane changes. In a similar study by [YYW+20], the authors applied lane change intention to provide haptic steering guidance for lane changing and lane keeping and concluded that the system supports fast and stable lane change maneuvers and decreases lane departure risk. The intention recognition was not applied to warn drivers of potential collisions.

According to SAE levels of driving automation, lane change assistance systems are in level 1 [Soc18]. This chapter focuses on lane change assistance in assisted driving mode (L1) and takeover assistance in conditionally automated driving mode (L3) as illustrated in Figure 4.1 and further discussed below.

When conditions become suitable, drivers can switch from level 1 to level 3. In level 3, the ADAS performs all dynamic driving tasks such as steering and lane changes such that the human driver is momentarily free or can engage in non-driving related tasks (NDRT) e.g. reading. If conditions become unfavorable or system limits are reached, the ADAS issues a takeover request (TOR) which is also denoted as a request to intervene (RTI) to the driver [Soc18]. Driver would need to takeover driving within a few seconds later

switching back to assisted driving as illustrated in Figure 4.1. Ideally, the human driver should takeover successfully within the time budget before the critical situation which may result in a fatal collision. Therefore, to enable a safe and successful transition, driver requires sufficient time budget and awareness of the traffic situation. Situation awareness is the "perception of the current situation, comprehension of its meaning, and projection of its status in the near future" [End88].

Furthermore, in this chapter, it is assumed that the ADAS can anticipate critical situations ahead of time and issue a takeover request to drivers early enough. Most studies focus on defining a general time budget (denoted as TOT budget in this chapter) that would be sufficient for all drivers to takeover in all situations [KY17] [DKZ+20] [KVV17]. However, other studies indicate that TOT varies between repeated drives and scenarios [HLK17] [WS19]. If the time is too much, situation awareness decreases and drivers delay response. On the other hand, if the time is insufficient, drivers may encounter collisions.

In addition, it is also assumed that the ADAS can automatically analyze the scenario and provide hazard information to the driver at the time of the takeover request. Therefore, some studies have provided information to drivers using various interfaces [OKD18] [RB20] [EPZ+19]. In some situations, this has increased situation awareness and performance and reduced takeover time. In other situations, the converse is the case. Therefore, it is necessary to estimate in detail the time required to takeover in different situations in order to ensure optimal driver performance.

4.2 Design of bi-modal maneuver decision assistance system

To study assistance in L1 integrating driver maneuver intention and L3 integrating varied takeover time budgets, a bi-modal design is employed as illustrated in Figure 4.1. Specifically, an individualized lane change intention recognition system was integrated in which drivers are warned about potential collision with surrounding vehicles. In addition, various TOT budgets are investigated in different scenarios for suitability.

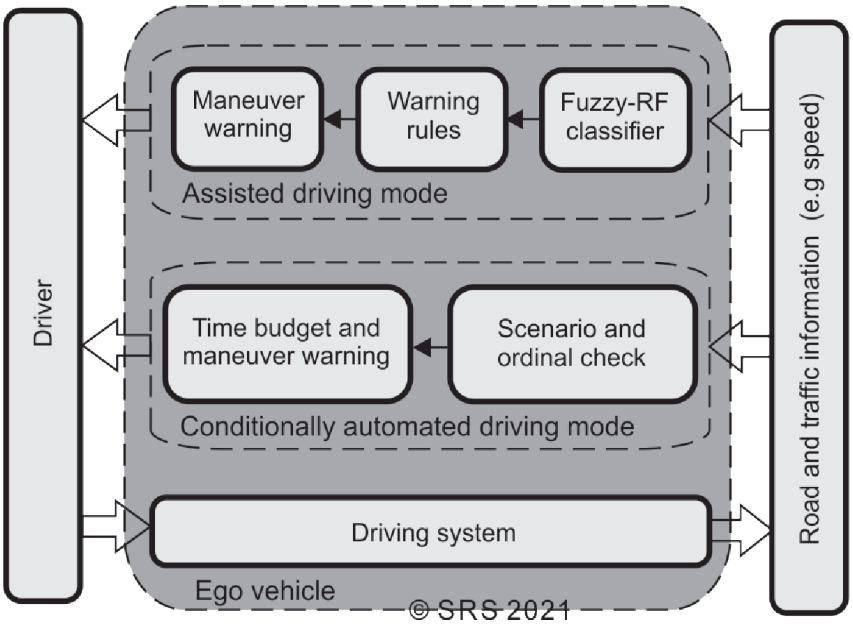


Figure 4.1: Lane change and takeover assistance system extended from [DSTS20] and submitted in [TS21c]

4.2.1 Intention-based lane change assistant using fuzzy-RF classifier

To establish an intention-based assistance system, lane changing which has been extensively studied will be considered in this chapter [XLW+19]. Three different driving maneuvers namely lane keeping (LK), lane change to Left (LCL), and lane change to right (LCR) are modeled as outputs in a previous contribution [DSTS20]. The model utilizes a fuzzy Random Forest (fuzzy-RF) approach applied to online driving intention recognition. Membership functions are applied to quantify input signal data into fuzzy sets for RF training.

- Input and labeling: As input, 24 variables that affect drivers' decisions such as the states of the ego vehicle (position, speed, acceleration, steering wheel angle, etc.) and information about surrounding vehicles were used as input as outline in Table 4.1. A set of membership functions were generated for the real value input variables (features). The integer inputs namely lane number, gear box mode and indicator

mode were not fuzzified. Altogether, the inputs were utilized in training a fuzzy random forest classifier. Lane Keeping (LK), lane change to Left (LCL), and Lane change to right (LCR) are the classes of intentions. The data has to be automatically labeled with the classes. The current lane i is determined through the position of the vehicle's center point. Therefore, the lane changing behavior at time t_{lane} is recognized when the value of lane i changes. The variable t_{lane} denotes the end time of the lane change as illustrated in Figure 4.2. In a previous contribution [DWH+19], the start time of lane change maneuver is determined by the moment driver turns on the indicator denoted as $t_{indicator}$. The interval between the beginning of lane change $t_{indicator}$ to the end of lane change t_{lane} is the total time required for the lane change intention defined as t_{change}. When drivers change lanes without turning on the indicator, the average value of all t_{change} is used to determine the lane change time. Previous results comparing 3 s, 2.5 s and 2 s indicate that 2.5 s as t_{change} results in accuracy of more than 99.6 % [DWH+19] [DSTS20]. Therefore, a label t_{change} = 2.5 s was applied to predict lane change intentions.

- Fuzzy-RF approach: As an extension of decision tree method RF is used to solve classification or regression problems. In this chapter, trapezoidal membership function was used to convert the signal data to membership degrees. The output of fuzzy logic (FL) is a vector that contains all membership degrees of signals. Core and support parameters of each membership function (MF) are unknown and defined automatically using "Fuzzy Neighborhood density-based spatial clustering of applications with noise (FN-DBSCAN)" [DHO08].

The driving intention recognition model based on fuzzy-RF is illustrated in Figure 4.3. The model consists of off-line training and online application for assistance, which are described subsequently.

To perform the offline training process, participants were invited to an initial appointment to drive manually for about 25 to 35 minutes to obtain data used to generate membership

Table 4.1: Description of selected input features published in [DSTS20]

Input	Definition	Range	Unit	Data type
v_{ego}	Velocity of ego vehicle	[0 220]	km / h	Real
v_f	Velocity of vehicle in front	[0 220]	km / h	Real
v_{fl}	Velocity of vehicle in front left	[0 220]	km / h	Real
v_{fr}	Velocity of vehicle in front right	[0 220]	km / h	Real
v_{bl}	Velocity of vehicle back left	[0 220]	km / h	Real
v_{br}	Velocity of vehicle back right	[0 220]	km / h	Real
v_b	Velocity of vehicle behind	[0 220]	km / h	Real
d_f	Distance to vehicle in front	[0 250]	m	Real
d_{fl}	Distance to vehicle in front left	[0 250]	m	Real
d_{fr}	Distance to vehicle in front right	[0 250]	m	Real
d_{bl}	Distance to vehicle back left	[0 250]	m	Real
d_{br}	Distance to vehicle back right	[0 250]	m	Real
d_b	Distance to vehicle behind	[0 250]	m	Real
TTC_f	TTC to vehicle in front	[0 12]	s	Real
TTC_{fl}	TTC to vehicle in front left	[0 12]	s	Real
TTC_{fr}	TTC to vehicle in front right	[0 12]	s	Real
TTC_{bl}	TTC to vehicle back left	[0 12]	s	Real
TTC_{br}	TTC to vehicle back right	[0 12]	s	Real
TTC_b	TTC to vehicle behind	[0 12]	s	Real
Ln	Current lane number	[1, 2]	-	Integer
I	Indicator	[0, 1, 2]	-	Integer
G	Gearbox	[1,...5]	-	Integer
S	Steering wheel angle	[-3.14 3.14]	rad	Real
α	Heading angle of ego-vehicle	[-3.14 3.14]	rad	Real

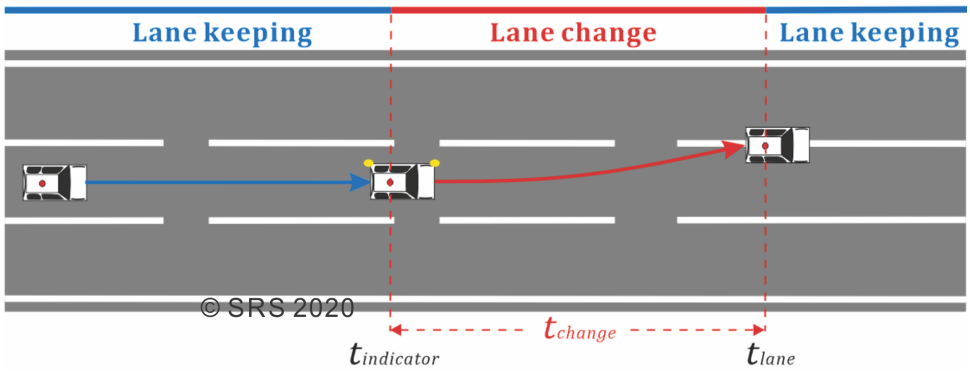


Figure 4.2: Lane change intention adapted from [DWH+19]

functions and for training an individualized fuzzy-RF classifier. Finally, the individualized fuzzy-RF models were saved for driving intention recognition online during the experiment.

4.2.2 Takeover assistant integrating varied time budgets

From Chapter 3, the following recommendations were made for budgeting TOT:

- Takeover time should be varied between scenarios.
- Takeover time should be varied between first and subsequent drives.

In chapter 3, three complexity levels of NDRT namely reading, proofreading, and proofreading aloud and two complexity levels (I and II) of four scenarios on highways and country roads were designed [TS19a] [TS19b]. Altogether, there were eight scenarios presented in the previous chapter. One secondary task, reading, and three scenarios were integrated in this chapter. In this chapter, two of the selected scenarios (S1|II and S4|II) represent the most complex and one (S3|I) represents the least complex of the previously designed eight scenarios. In addition, all three scenarios approximately integrate conditions in the previous eight scenarios.

Time budgets were derived from average results obtained in chapter 3 considering ordinal for the selected scenarios [TS19a]. The time budgets are sums of rounded up average

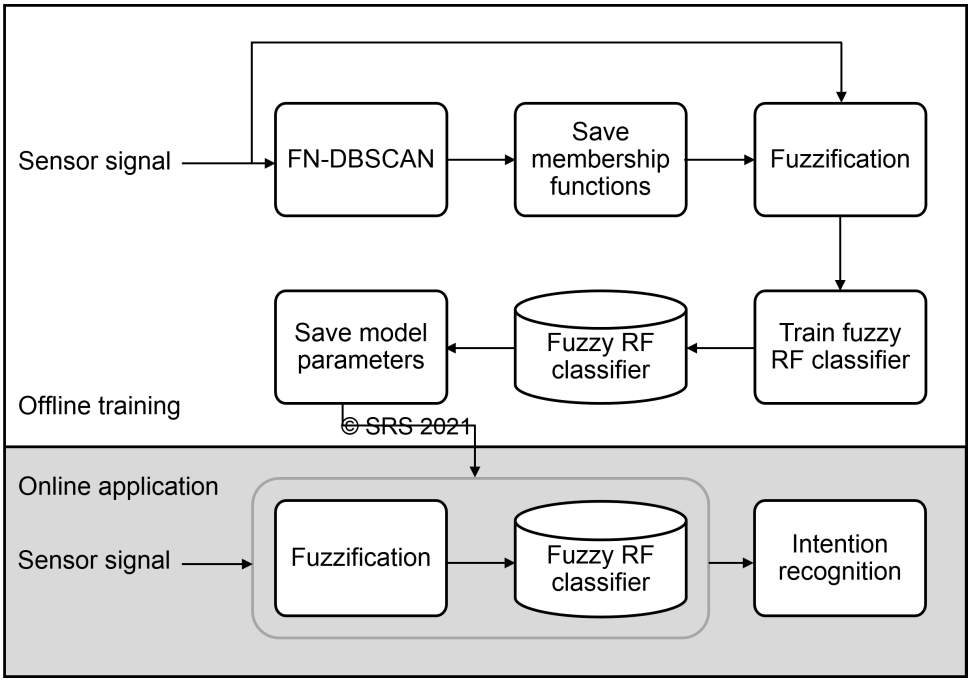


Figure 4.3: Flow chart of fuzzy-RF model adapted from [DSTS20]

values and additionally assumed 1 s decision time. The additional 1 s was necessary because the average takeover time in the higher complexity scenarios are significantly lower than the 7 s time budget provided. To investigate time budget suitability the selected scenarios are described in detail in the next section.

4.3 Scenarios, timing, and related imagery

4.3.1 Intention-based assisted driving

After predicting driver intention, the constellation of surrounding vehicles in the driving scenario should be analyzed before driver can be warned. That is, automatic scenario analysis is necessary to determine if driver's intended lane change or keep actions are unsafe. Therefore, recommendations from literature are discussed in subsequent paragraphs to determine safe time thresholds for successful action performance.

To determine warning threshold, time-to-collision was considered. Time-to-collision (TTC) is the time required by two objects to collide if current longitudinal speed is maintained. In [WYH19], the authors recommended that TTC should be at least 3 s between lead and following vehicles for safe lane changes. Therefore, 3 s to 4 s TTC were selected as the warning threshold for lane keeping intention. The additional 1 s is to ensure that drivers had sufficient time to respond after warnings.

To determine warning threshold if driver intends to make unsafe lane changes, lane change duration was considered in addition. Thus 2.5 s was added to TTC of adjacent lead and following vehicles to accommodate average lane change duration on highways as recorded in [WYH19].

As recommended in [Soc02], opinion of experienced drivers were solicited to determine the applicable surrounding vehicles to consider when giving warnings to drivers. Four experienced drivers with 10 years to 50 years driving experience were polled as listed in Table 4.2. Recommendations from the experienced drivers include warning drivers about vehicles on the intended lane and then anticipatory warning about vehicles on same lane to increase situation awareness.

All finally integrated considerations and TTC threshold values based on aforementioned references are outlined in Table 4.2. That is, if TTC values were less than values in Table 4.2 at the same time that predicted intention was either lane change left, lane change right or lane keep respectively, driver would be warned if attempting to accelerate or change lanes. Altogether, there were six different warnings displayed for 2 s whenever drivers violated the thresholds as illustrated in Figure 4.4. Several applicable warnings based on the defined thresholds were displayed at the same time.

Considering predicted intention and scenario analysis a corresponding warning was selected. All visual warnings were accompanied by the audio expression ”collision risk”.

Furthermore, location of the risk was specified (by augmented reality on scenario) which in accordance with literature enables warning to be comprehensible [NKN16]. This also avoids increased workload in reconciling view reference frame.

Table 4.2: Responses of experienced drivers regarding vehicles to consider and associated TTC [s] warning thresholds submitted in [TS21c]

Maneuver	Driver	Response	Conclusion (threshold [s])
LK	1	f, b, fl, fr	f, b, fl, bl
	2	f	4, 3, 3.5, 3.5
	3	f, b, fl, fr	
	4	f, b, bl, br	
LCL	1	f, b, fl, bl	f, b, fl, bl
	2	fl, bl	4.5, 4, 5.5, 5.5
	3	f, b, fl, bl	
	4	f, b, fl, bl	
LCR	1	f, b, fr, br	f, b, fr, br
	2	fr, br	4.5, 4, 5.5, 5.5
	3	f, b, fr, br	
	4	f, b, fr, br	

Figure 4.4: HUD imagery specifying direction of collision warning

The scenario implemented in this study integrating intention recognition is a two-way highway, each consisting of three lanes. Light foggy daytime weather (without rain, snow, storm etc.) condition is implemented in the scenario. Besides ego vehicle driver, other interacting vehicles were introduced intermittently such that ego vehicle driver could accelerate, decelerate, maintain relative speed, and change lanes to left or right as

determined by driving rules in Germany. This requires driving on the right lane unless overtaking or having approximately the same pace as other vehicles present in other lanes. In addition, while on the right lane, when ego-vehicle speed was higher than that of a front vehicle, driver could change lanes to left, overtake and return to the right lane.

Drivers could also overtake slowly on middle lane whenever there was high traffic congestion. The vehicles interacting with the driver were dynamically inserted into the traffic scenario and had different driving behaviors - cautious, normal and aggressive. Aggressive drivers performed short overtaking maneuvers and allowed shorter TTC of 2.2 s to 3 s to front vehicles. Normal and cautious drivers performed longer overtake maneuvers and allowed longer TTC to front vehicles.

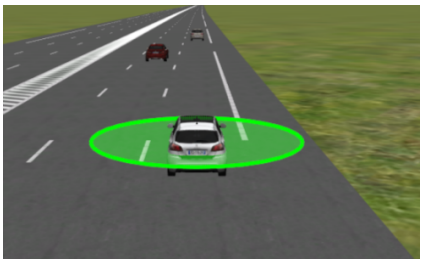
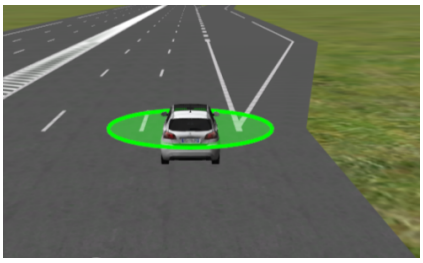
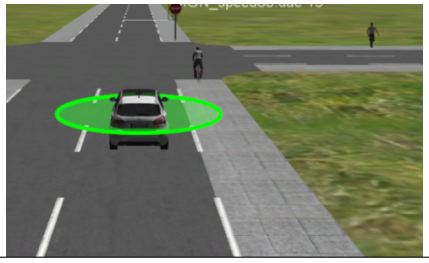
Data describing ego vehicle dynamics (e.g. speed, steering angles etc.) and surrounding interacting vehicles status (e.g. time to collision (TTC), speed) relative to ego vehicle were collected to predict driver lane change intentions continually online.

4.3.2 Variable time budget takeover assistant

As previously mentioned, the chosen scenarios were taken from chapter 3. The highway scenarios integrated three lanes in two directions and the country road scenario integrated one lane in two directions. Three scenarios were selected, two level II and one level I as illustrated in Table 4.3 and described below.

- **Stationary car on highway (S1|II):** The ADAS issues a TOR at a speed of 130 km / h because of a stationary vehicle ahead on the right lane and an approaching vehicle on the middle lane to the left of ego vehicle.
- **Exit highway (S3|I)**: The ADAS issues a TOR to driver to maneuver exiting a highway while on the right lane (exit lane) at a speed of 100 km / h.
- **Turn right at country road intersection (S4|II)**: The ADAS issues a TOR to driver to maneuver making a right turn at 80 km / h at a four junction country

Table 4.3: TOT budget for scenario and ordinals submitted in [TS21c]

Scenario		HUD imagery
S1|II	Stationary front car on highway (Speed: 130 Km / hr) TOT [s] budgets (6,4,4)	
S3|I	Exit highway (Speed: 50 Km / hr) TOT [s] budgets (5,4,4)	
S4|II	Turn right at country road intersection (Speed: 80 Km / hr) TOT [s] budgets (5, 4,4)	

road intersection. A bicyclist and a pedestrian are at the intersection of the right adjourning road where the driver should make the right turn. The pedestrian is crossing the road, while the bicyclist is making a right turn.

4.4 Experiments

4.4.1 Participants

Experienced drivers were invited to drive in the previously described scenarios for assisted and conditionally automated driving. Participants were divided into two groups - experimental and control group. The experimental group experienced the scenarios with the designed warnings and the control group experienced the same scenarios without warnings.

Each laboratory appointment lasted approximately two hours. First, participants filled a pre-questionnaire about their driving experience and received an introduction to the simulator and the procedure and goal of the study for approximately 10 minutes. The visual imagery for assisted driving was shown to the participants. The visual imagery for the TOR scenarios were not shown to the participants because takeover situations are meant to be surprising. However, participants were informed that the TOR imagery would similarly indicate the position of collision hazard. The audio sound with which the warnings were given in assisted and conditionally automated driving were played for the participants.

Afterwards, the participants performed a test drive for approximately 10 minutes to adapt to the driving simulator. During the test drive, participants practiced how to switch between conditionally automated and assisted driving modes. Finally, they performed three experimental drive procedures integrating dynamic traffic in assisted mode and the previously described three takeover scenarios including filling questionnaires as detailed in the next section. The order of experiencing the three takeover scenarios were randomized between participants to accommodate learning effects. Each drive procedure lasted approximately 25 to 30 minutes with a few minutes break in between.

No specific age group, type of experience or gender was targeted. A total of 44 drivers (39 males and 5 females) were recruited. All drivers held valid driver's licenses, 10 of them have previously used vehicles equipped with one or more ADAS features, 11 of them have previously experienced driving simulators and additional descriptive statistics obtained from the pre-questionnaire are outlined in Table 4.4.

As reward, participants either received 15 EUR or attended a three-hour time management seminar. In accordance with the relevant ethics rules, participants signed a participation consent declaration. Participants were also informed that their participation was voluntary and were free to discontinue the experiment if desired. Approval was also obtained from the ethics committee of the Faculty of Engineering at the University of Duisburg-Essen, Germany.

Table 4.4: Participant quantitative descriptive statistics submitted in [TS21c]

Participant detail	Mean	STD	Min	Max
Age [Yrs]	27.2	3.5	20.0	35.1
Driving experience [Yrs]	7.5	4.2	0.4	17.8
Driving experience [Km / wk]	256.7	1035.3	5.0	7000

4.4.2 Experimental procedure

The same experimental setup described in the Chapter 3 (Figure 3.3) was utilized. Drivers were first required to drive in assisted mode for about 10 to 15 minutes during which the experimental group received warnings based on the fuzzy-RF intention recognition system. Afterwards, participants were asked to change to conditionally automated mode, during which the experimental group filled a mid-questionnaire about the assisted driving mode and then both groups performed the NDRT reading. Afterwards, the TOR was issued to drivers in the previously stated variable time before each critical scenario. To announce the TOR, audio and previously illustrated imagery (Table 4.8) were utilized for the experimental group. While the participants from the control group only saw a simple image informing them to take control of the steering. Participants could switch from conditionally automated to assisted mode by touching the a button on the control pad or steer and continue driving while applying the pedals. After takeover, participants filled situation awareness rating technique (SART) [Tay89] and raw NASA task load index (NASA-TLX) [HS88] questionnaires. In addition, the experimental group filled a post questionnaire at the end of all three drives.

4.4.3 Data measures and analysis approach

Assisted driving mode

In assisted driving mode, the TTC relative to surrounding vehicles at which participants performed maneuvers were evaluated.

- Time to collision: The number of times a participant performed each of the three maneuvers (LK, LCL, LCR) at critical TTC thresholds based on [NKN16] is compared to the number of each maneuver performed during the drive. That is, the ratio of violations are computed for all surrounding vehicles that pose a risk of collision. Mathematically, the ratio of TTC violations is expressed as

$$TTC\ [s] = \sum \frac{TTC\ <\ threshold}{LK,\ LCL,\ or\ LCR\ manuever}. \tag{4.1}$$

  Expressing TTC this way ensures that the behavior of the participants throughout the assisted drive is adequately represented compared to instantaneous observation using minimum or maximum TTC.

Conditionally automated driving mode

In conditionally automated mode, measured dependent variables include takeover time, situation awareness (SA), workload, lateral displacement and maximum acceleration for comparison with independent variables scenarios, ordinal, and group. The ordinal refers to the order of the drive e.g. first, second, or third. The independent variable ”group” refers to previously mentioned experimental and control groups (Section 4.4.1) and data from Chapter 3 integrating 7 s time budget denoted as reference group. That is, a $3 \times 3 \times 3$ factor statistical analysis approach was employed to study the variation of the between-subject factors (scenario, ordinal, and group) levels. The definition and extraction of measured dependent variables include:

- Takeover time: Time from TOR to 5 % difference in brake or steering input depending on method of takeover used by participant.
- Situation awareness: Subjective rating of participant using (SART) [Tay89]. High ratings indicate increased situation awareness.

- Workload: Subjective rating of participant using NA- SA-TLX [HS88] questionnaires. Increased workload ratings indicate increased task difficulty.

- Average lateral displacement: The average lateral displacement (Avg. L. Displ.) from the lane center before and after TOR is expressed as

$$Avg.\ L.\ Displ.\ [m] = \frac{\sum L.\ Displ.\ (before{-}after)\ TOR}{\sum Time\ frame\ before\ and\ after\ TOR}. \tag{4.2}$$

  This is an indication of lateral (steering) control. Increased average lateral displacement indicates poor performance [KY17].

- Maximum acceleration: Maximum resultant acceleration value attained between TOR and takeover is expressed as

$$Max.\ Acc.\ [m/s^2] = \sqrt{Acc._{longitudinal}^2 + Acc._{lateral}^2}. \tag{4.3}$$

  This is an indication of forward collision risk. Increased acceleration indicates poor performance [HLK17].

The analysis approach is from the view that increased takeover time does not necessarily indicate more complexity but performance, SA and workload should be considered in the overall conclusions. In addition the obtained data are compared to those of previous study [TS19b] with fixed time budget of 7 s. Significance level 0.05 was used for the analysis.

Corrupted data and data from four participants who either disobeyed instruction to perform the reading task or did not understand the instructions when they experienced the first takeover are excluded. The hypotheses investigated include:

- Hypothesis 1: Warning drivers of eminent danger due to intended lane change will result in improved performance compared to control group in assisted driving mode.

- Hypothesis 2: In conditional driving automation mode, variable mean-based TOT budget is adequate for S1|II, S3|I, and S4|II compared to 7 s assuming TOT is optimal if SA, workload, and performance are acceptable.

- Hypothesis 3: In conditional driving automation mode, warning support will decrease takeover time and workload and increase SA and performance.

4.5 Evaluation of results and discussion

4.5.1 Experimental results of lane change assistance

The performance of participants in assisted driving mode was evaluated by computing the ratio of TTC threshold violations in relation to number of maneuvers as illustrated in Figure 4.5 and Figure 4.6. Using t-test, significantly ($p < 0.05$) improved performance is found for f vehicles during LCL and fr and br vehicles during LCR maneuvers in the experimental group due to reduced near collisions.

In addition, most near collisions occurred during LCR maneuvers and participants are more cautious during LCL maneuvers. The performance of the experimental group participants is significantly ($p < 0.05$) worse for b and bl vehicles during LCL and f vehicles during LCR maneuvers. This result indicates that the experimental group participants mostly ignored warnings for b and bl vehicles during LCL and f vehicles during LCR maneuvers.

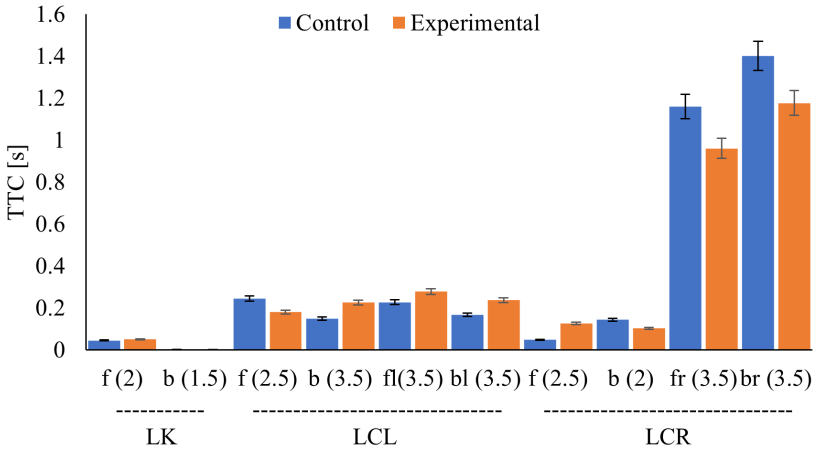


Figure 4.5: Comparison of performance between experimental and control group at various TTC thresholds redrawn from [TS21c]

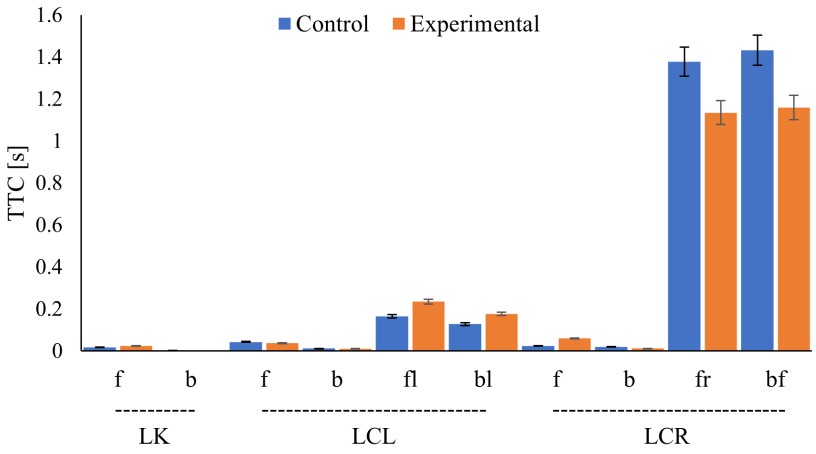


Figure 4.6: Comparison of accident rate between experimental and control group at TTC < 1 s redrawn from [TS21c]

Furthermore, the experimental group filled a 5-point Likert scale mid-questionnaire in the middle of each drive immediately after switching to conditionally automated mode. The questions are about helpfulness, SA increment, comprehensibility, timeliness, and increased performance.

At least 80 % of participants rated system as helpful, increased situation awareness and warnings were timely in the mid-questionnaire. Regarding improving performance, ratings were average which correlates with the ignored warnings indicated by the previously mentioned threshold violations of the experimental group. In addition, approximately 30 % of participants, commented that the system should integrate automatic anticipation of the lane change maneuvers of surrounding vehicles to be considered more acceptable.

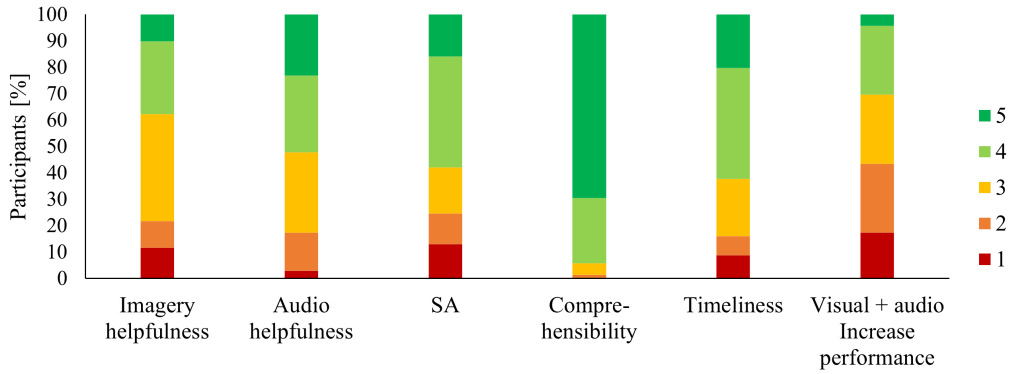


Figure 4.7: Mid-questionnaire submitted in [TS21c]

The experimental group also filled a 5-point Likert scale post-questionnaire about acceptability, ease of use, usefulness, noticing danger early, increased safety, intent to use, and endangering others adapted from [NKN16]. Most participants rated the system favorably, helped to increase their SA and is desirable for every day use.

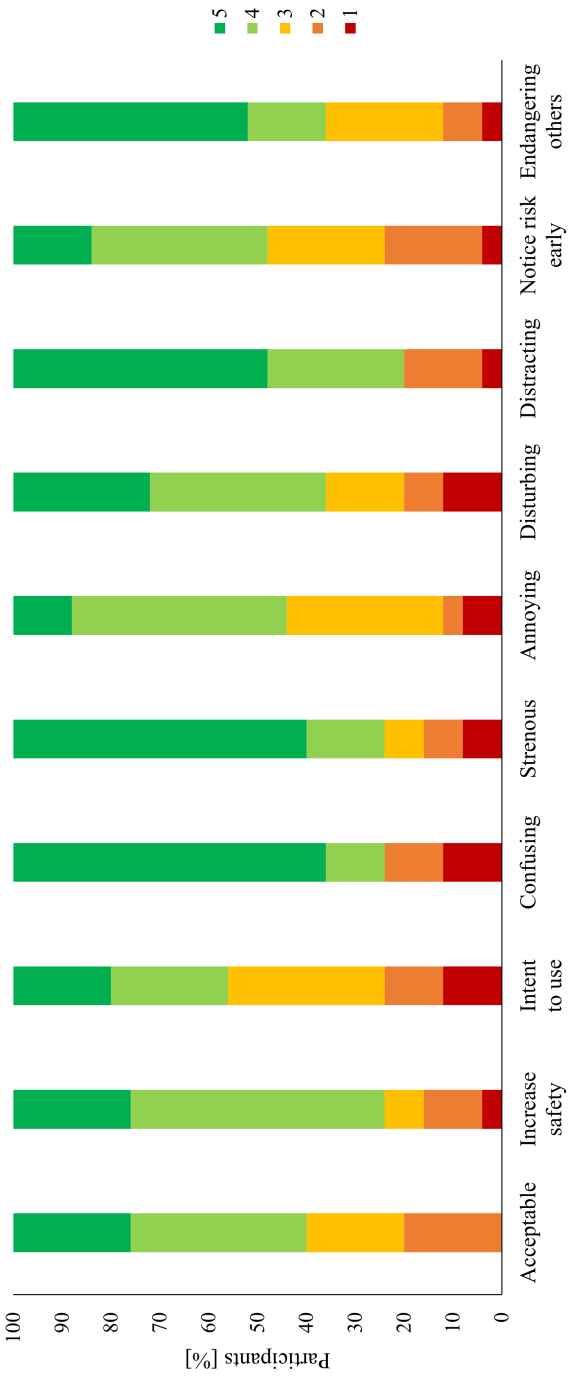


Figure 4.8: Post-questionnaire submitted in [TS21c]

4.5.2 Experimental results of takeover assistance

Descriptive statistics of the IVs and DVs are outlined in Table 4.5. Two-way Manova indicates significant main and interaction effects of IVs on all DVs combined as outlined in Table 4.6. The main and interaction effects (1-way and 2-way Anova) of the IVs on individual DVs are outlined in Table 4.7. In total nine accidents occurred as outlined in Table 4.8. Increased accident rate in S1|II for control group indicates insufficient time budget. The accident rate decreased in the experimental group for the same scenarios indicating improved performance.

Table 4.6: Manova between IVs and DVs submitted in [TS21c]

IV	Wilks' Λ	F	Df	Error Df	Sig.	Partial η^2
Group	0.277	27.405	10	304	4.68E-37	0.474
Ordinal	0.347	21.198	10	304	8.38E-30	0.411
Scenario	0.075	80.802	10	304	1.63E-79	0.727
Ordinal * Group	0.488	6.092	20	505.08	1.26E-14	0.164
Scenario * Group	0.164	18.308	20	505.08	9.43E-48	0.364
Ordinal * Scenario	0.202	15.642	20	505.08	3.44E-41	0.329
Ordinal * Scenario * Group	0.304	5.227	40	665.35	7.48E-21	0.212

Takeover time

No 2-way or 3-way interaction effect between IVs on takeover time is found. No significant main effect of scenario on takeover time is found indicating that participants always tend to utilize all available time. Significant main effect of group and ordinal on takeover time is found. Post hoc Bonferroni test indicates Control < Experimental and Reference < Experimental groups for takeover time. This indicates that the imagery support did not reduce takeover time as previously stated in hypothesis 3. In addition, ordinal 1 > ordinal 2 given that a higher time budget was assigned to the first drive.

Table 4.5: Descriptive statistics of IVs for scenario and group levels submitted in [TS21c]

DVs | Mean (STD)	S1|II			S3|I			S4|II		
	C	E	R	C	E	R	C	E	R
TOT [s]	2.89	3.64	3.17	2.61	3.99	3.31	3.56	4.22	3.05
	(1.31)	(1.83)	(0.96)	(1.84)	(1.97)	(1.29)	(2.51)	(3.07)	(1.2)
SA [Tay89]	12.11	10.95	16.58	24.48	23.55	24.89	15.29	15.95	20.45
	(7.87)	(8.57)	(9.42)	(4.78)	(6.15)	(6)	(7.79)	(8.43)	(9.24)
Workload	47.96	48.12	49.64	31.83	29.9	35.79	41.45	48.63	38.68
[HS88]	(14.35)	(20.79)	(16.81)	(15.85)	(14.69)	(13.32)	(19.94)	(22.78)	(21.06)
Max Acc.	1.16	1.68	0.08	0.45	0.61	0.17	0.15	0.16	0.12
$[m\ s^2]$	(1.52)	(1.75)	(0.04)	(0.44)	(0.38)	(0.32)	(0.22)	(0.41)	(0.18)
Avg. L	3.52E-2	7.10E-2	1.33E-2	1.05	1.16	1.39E-6	5.04E-8	1.04E-8	9.56E-5
Displ. [m]	(9.59E-2)	(1.51E-1)	(8.27E-4)	(7.63E-1)	(7.39E-1)	(1.14E-8)	(1.54E-7)	(9.40E-9)	(3.83E-4)
C: Control, E: Experimental, R: Reference									

Table 4.7: Anova between IVs and DVs submitted in [TS21c]

IV	DV	Type III SS	Df	Mean Sq	F	Sig.	Partial η^2
Group	Tot	34.486	2	17.243	4.92	8.47E-3	0.059
	Max. Acc.	15.471	2	7.735	16.355	3.56E-7	0.173
	Avg. L. Displ.	5.301	2	2.651	148.911	6.71E-37	0.656
	SA	441.934	2	220.967	3.659	2.80E-2	0.045
	Workload	183.255	2	91.627	0.289	7.50E-1	0.004
Ordinal	Tot	30.604	2	15.302	4.366	1.43E-2	0.053
	Max. Acc.	6.008	2	3.004	6.352	2.23E-3	0.075
	Avg. L. Displ.	4.361	2	2.18	122.495	1.05E-32	0.611
	SA	22.084	2	11.042	0.183	8.33E-1	0.002
	Workload	20.101	2	10.05	0.032	9.69E-1	4.06E-4
Scenario	Tot	8.316	2	4.158	1.186	3.08E-1	0.015
	Max. Acc.	22.646	2	11.323	23.941	8.55E-10	0.235
	Avg. L. Displ.	19.384	2	9.692	544.471	4.39E-71	0.875
	SA	3777.174	2	1888.587	31.277	3.79E-12	0.286
	Workload	8335.98	2	4167.99	13.136	5.34E-6	0.144
Ordinal *	Tot	6.178	4	1.545	0.441	7.79E-1	0.011
Scenario	Max. Acc.	18.878	4	4.72	9.979	3.24E-7	0.204
	Avg. L. Displ	7.334	4	1.833	102.997	9.67E-43	0.725
	SA	131.308	4	32.827	0.544	7.04E-1	0.014
	Workload	1113.696	4	278.424	0.878	4.79E-1	0.022
Ordinal *	Tot	10.573	4	2.643	0.754	5.57E-1	0.019
Group	Max. Acc.	3.566	4	0.891	1.885	1.16E-1	0.046
	Avg. L. Displ.	2.099	4	0.525	29.484	2.92E-18	0.431
	SA	441.928	4	110.482	1.83	1.26E-1	0.045
	Workload	1429.119	4	357.28	1.126	3.46E-1	0.028
Scenario *	Tot	9.097	4	2.274	0.649	6.29E-1	0.016
Group	Max. Acc.	14.05	4	3.512	7.427	1.68E-5	0.16
	Avg. L. Displ.	9.354	4	2.338	131.374	6.92E-49	0.771
	SA	128.808	4	32.202	0.533	7.11E-1	0.013
	Workload	897.745	4	224.436	0.707	5.88E-1	0.018
Ordinal *	Tot	37.697	8	4.712	1.344	2.25E-1	0.064
Scenario *	Max. Acc.	10.884	8	1.361	2.877	5.16E-3	0.129
Group	Avg. L. Displ.	3.472	8	0.434	24.385	5.02E-24	0.556
	SA	336.153	8	42.019	0.696	6.95E-1	0.034
	Workload	4608.075	8	576.009	1.815	7.79E-2	0.085

Table 4.8: Takeover accident rate submitted in [TS21c]

Scenario	Ordinal			Group
	1	2	3	
S1|II	5	1		Control
	1		1	Experimental
S4|II	1			Control

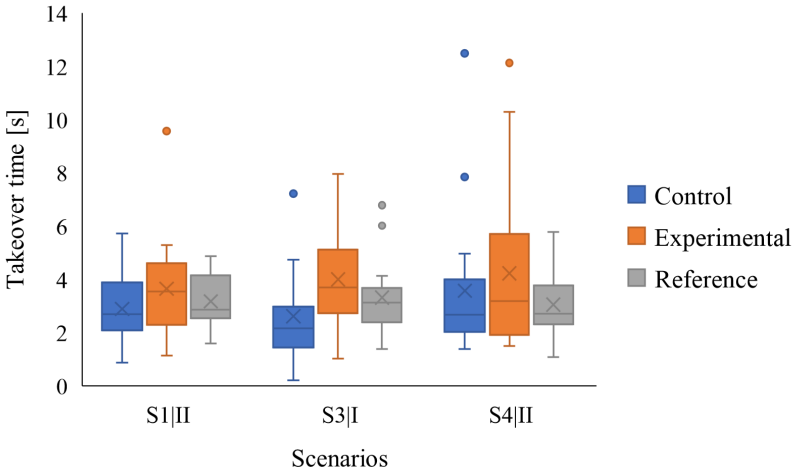


Figure 4.9: TOT for scenarios submitted in [TS21c]

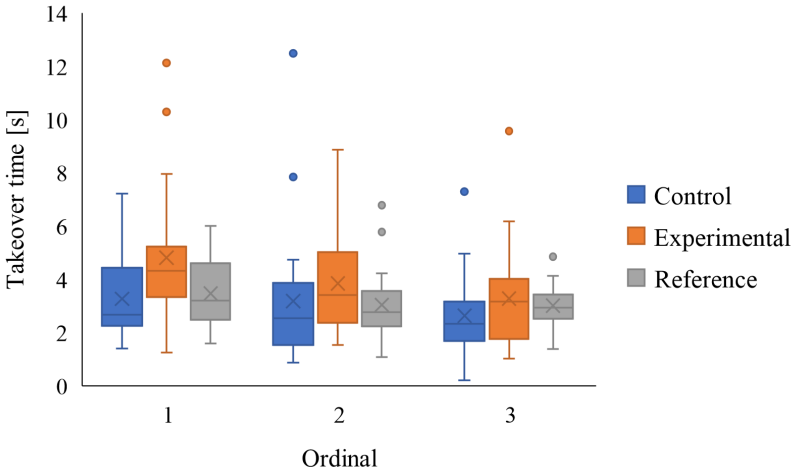


Figure 4.10: TOT for ordinal submitted in [TS21c]

Situation awareness

No 2-way or 3-way interaction effect between IVs on SA is found. Significant main effect of group and scenario on SA are found. Post hoc Bonferroni test indicates S1|II < S4|II < S3|I. This indicates, significantly reduced SA in S1|II and S4|II. In addition, SA for experimental < reference indicating reduced time budget compared to reference group is not suitable.

Workload

No 2-way or 3-way interaction effect between IVs on workload is found. No significant main effects of ordinal and group on workload. Significant main effect of scenario on workload is found. Post hoc Bonferroni test indicates S1|II > S3|I and S4|II > S3|I. This indicates, significantly increased and identical workload in S1|II and S4|II. In addition, most participants commented that the time was not sufficient to turn right in S4|II.

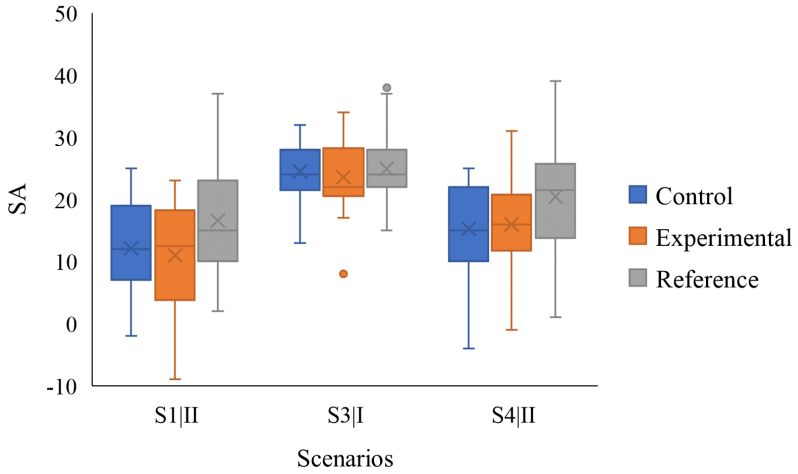


Figure 4.11: SA for scenarios submitted in [TS21c]

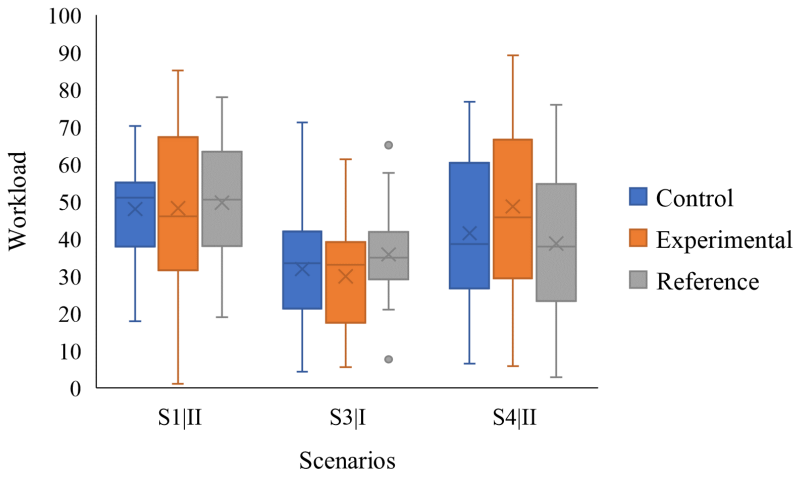


Figure 4.12: Workload for scenarios submitted in [TS21c]

Maximum acceleration

Significant 3-way and 2-way interaction effect between IVs on maximum acceleration is found. Significant main effect of ordinal, group, and scenario on maximum acceleration is also found. Post hoc Bonferroni test for scenarios in relation to maximum acceleration significantly indicates S1|II > S3|I and S1|II > S4|II. This indicates significantly reduced performance in S1|II compared to S3|I and S4|II due to reduced time budget. In addition, maximum acceleration in ordinal 1<2 and 1<3 indicating better performance in the first drive due to higher time budget in the first drive. Maximum acceleration for control > reference and experimental > reference indicating better performance in reference group which has a comparably higher time budget.

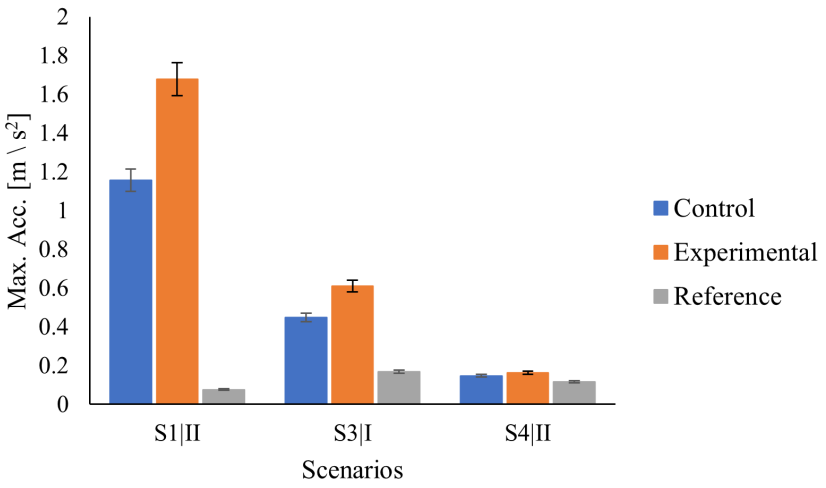


Figure 4.13: Maximum acceleration for scenarios submitted in [TS21c]

Lateral displacement

Similar to maximum acceleration, significant 2-way and 3-way interaction effect between IVs if found for lateral displacement. Significant main effect of ordinal, group, and scenario on lateral displacement is also found. Post hoc Bonferroni test indicates for Lateral displacement, S1|II < S3|I and S4|II < S3|I. Ordinal 1 < 3 < 2 indicating better performance in first drive with a higher time budget and improved performance in third drive compared to second due to learning effects and increased effort. In addition, control > reference and experimental > reference indicating poorer performance in the experimental and control groups due to reduced time budget.

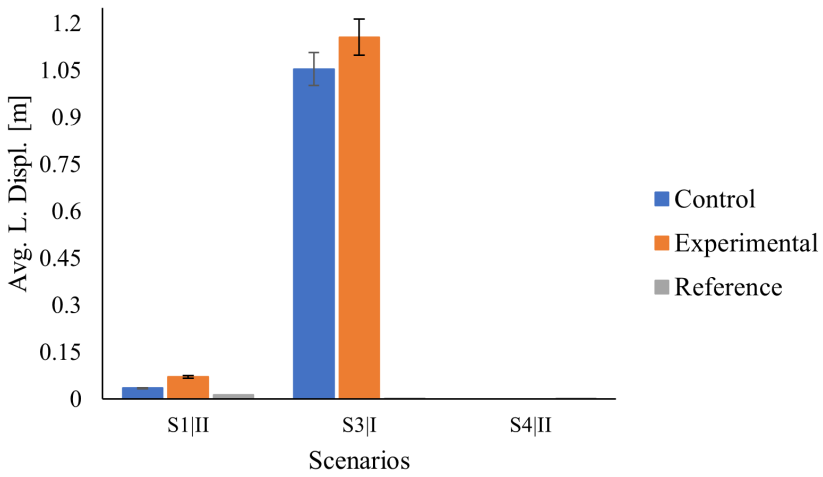


Figure 4.14: Lateral displacement for scenarios submitted in [TS21c]

In summary, even though average values measured from previous study [TS19a] were applied in the same scenarios, performance is worse in S1|II and S4|II indicating that takeover time depends on perception of time sufficiency for success. Improved performance is found in the first drive due to higher time budget for S1|II and S4|II indicating that the time budget should be readjusted to the reference value in which participants performed better. In relation to maximum acceleration, improved performance is found in the third drive compared to second though having the same time budget which indicates that varying time budget between repeated drives is still required. Visual interface support with lower time budget results in increased takeover time in experimental group due to visual demand. Decreased SA is found at lower time budget and more traffic agent on highway. Decreased SA is also found at lower time budget and visual interface support. Workload on highway with more traffic is identical to country road at lower time budget. In addition to most participants being unable to perform the right turn, this also indicates that S1|II and S4|II require identical time budgets. Lower time budget in subsequent drive results in decreased performance in S1|II and S4|II. Time budget for S3|I seems suitable in comparison to S1|II and S4|II.

Table 4.9: Time estimation of coefficients based on [TS21b] and [TCB+92] and submitted in [TS21c]

RSC		DEC		SRT	
Km / hr	s	Km /wk	s	Class	s
RSC ≤ 50	0.25	DEC ≤ 30	2	Fast	SRT ≤ 0.20
50 < RSC ≤ 80	0.5	30 < DEC ≤ 100	1.5	Mid	0.20 < SRT ≤ 0.30
80 < RSC ≤ 130	1	100 < DEC ≤ 200	1	Slow	0.30 < SRT ≤ 0.40

Estimation of TOT budget

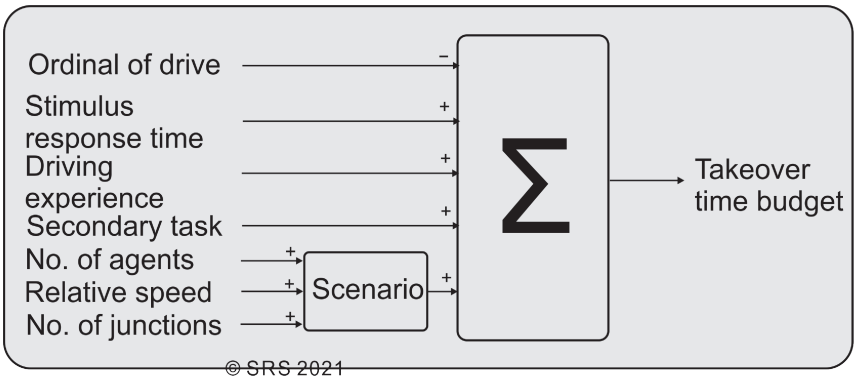


Figure 4.15: Variables for quantitative estimation of takeover time submitted in [TS21c]

Based on the aforementioned results, the additive and subtractive effects of variables for budgeting TOT online are summarized in Figure 4.15 as an extension of the conditionally automated mode section of Figure 4.1. The updated illustration also integrates previous studies [RFB19] [NT17] that conclude that takeover time is significantly higher with NDRTs that involve use of hand-held devices compared to NDRTs involving handsfree devices as utilized in this chapter. Individual stimulus response time and driving experience are also integrated based on conclusions of [BPN+18] and [ES17]. That is, individual variables should be factored into TOT budgeting. Accordingly, this can be expressed mathematically as

$$TOT\ budget\ [s] = SRT + DEC + SST + NDRTC - OC. \tag{4.4}$$

In which

$$SST\ [s] = NOA \times 1.8 + NOJ \times 0.2 + RSC. \tag{4.5}$$

In which

- Stimulus response time (SRT): An auditory stimulus requires 140-245 ms, while a visual stimulus requires 180-270 ms in patients with stimulus-induced jerking and first year medical students according to [TCB+92] [JBKS15] and conservatively extended to assigned levels in Table 4.9 because it is affected by intelligence and physical exercise.

- Scenario specific time (SST): Comprises time required for number of agents, number of junctions, relative speed coefficient.

- Driving experience coefficient (DEC): More experienced drivers specifically, those who drive frequently are more skilled and require less time based on assigned levels in Table 4.9 defined by 25 %, 50 %, and 75 % percentiles from previous study [TS19b]. This coefficient is known to be within a typical range of 0.5 s to 1.5 s during active driving and represent simultaneous identification, decision, and muscle activation time after observation of the scenario [Ste13]. In this chapter, a conservative assignment of levels of driving experience is defined within a range of 1 s to 2 s for takeovers.

- NDRT coefficient (NDRTC): Defined by the difference between hand-held and hands-free secondary tasks which according to [NT17] is 2.73 s.

- Number of agents (NOA) with coefficient of 1.8 per traffic participants derived from observed pattern of identical time demand for highway with high speed and surrounding vehicles (S1|II) compared to country road with medium speed and more junctions (S4| II) in this chapter. That is, assuming that 7 s the upper time bound

for the slowest stimulus response time, least driving experience, reading task, in the first drive, the coefficient of NOA C_{NOA} by substitution into equations 4.4 and 4.5 is expressed as

$$C_{NOA} = 0.4 + 2 + 2 \times C_{NOA} + 0 \times C_{NOJ} + 1 = 7. \tag{4.6}$$

- Number of junctions (NOJ) with coefficient of 0.2 per direction derived from observed pattern of identical time demand for highway with high speed and surrounding vehicles (S1|II) compared to country road with medium speed and more junctions (S4|II) in this chapter. That is, assuming that 7 s is the upper time bound for the slowest stimulus response time, least driving experience, reading task, in the first drive, the coefficient of NOJ C_{NOJ} by substitution into equations 4.4, 4.5, and previously computed value of C_{NOA} is expressed as

$$C_{NOJ} = 0.4 + 2 + 2 \times 1.8 + 3 \times C_{NOJ} + 0.5 = 7. \tag{4.7}$$

- Relative speed coefficient (RSC): Defined by effort required due to speed based on assigned levels in Table 4.9 derived from [TS19b].

- Ordinal coefficient (OC): Less time is required for second and subsequent drive taken as 0 s for first drive and approximately 0.4 s for subsequent drives obtained by multiplying the ordinal effect size (partial η^2) 0.053 by the assumed upper bound time budget of 7 s.

As an example, the time required by a driver with the fastest SRT = 0.2 s, first drive, driving experience = 80 km / wk, S1|II and performing reading secondary task using a hands-free device would be

$$TOT\ [s]\ budget = 0.2 + 1.5 + 2 \times 1.8 + 0 \times 0.2 + 1.0 = 6.3\ s. \tag{4.8}$$

4.6 Summary

This chapter integrates implementation of individualized driver lane change maneuver intention-based assistance and varied takeover time budgets based on average values obtained from chapter 3 for specific scenarios. Inputs features are matched to warnings that are given to drivers whenever an unsafe maneuver is intended in assisted driving mode. The results indicate improved performance for lane change to left and right maneuvers in the experimental group.

Furthermore, time budgets based on average values for different takeover scenarios are validated in conditionally automated driving mode. Together with scenario complexity, secondary task demand, and individual variables from known literature and obtained results in this chapter, a new quantitative approach for budgeting TOT is proposed. The quantitative approach enables more precise budgeting of TOT and enables an assistance system to determine in advance whether a driver will be able to successfully takeover in the available time. If available time will not be sufficient, additional measures can be applied to ensure driver safety.

5 Summary, conclusion, and outlook

Driving decision assistance systems utilize different variables such as traffic scenarios and driver behavior to provide warnings and improve driver performance in different situations. Current challenges of such systems include adapting assistance to driver behavior especially in relation to timing. The specific problems addressed in this thesis are summarized alongside conclusions below.

5.1 Summary and conclusion

In chapter 2, variables influencing assisted and conditionally automated driving are reviewed in relation to driver vehicle interaction. Furthermore existing studies are reviewed and research gaps are identified. Among the identified research gaps the following research questions are investigated in this thesis.

- How can the time required by drivers to successfully takeover in different situations be quantitatively estimated in advance?
- Does predicting lane change intention and warning drivers accordingly improve driving performance and reduce collisions?

In Chapter 3, several interdependencies that exists between takeover variables were investigated. Existing literature indicates that drivers require various time budgets to successfully takeover in different situations. It is necessary that the time is neither too much or too little otherwise drivers might delay responses or not have sufficient time to takeover which may result in accidents. Therefore, a suitable strategy for takeover assistance systems to budget TOT to inform drivers online with respect to different situations is important. The generated time budget should be sufficient for takeover with good performance. Four takeover scenarios each having two levels of complexity and three NDRTs were investigated with

70 participants. The takeover requests were given to drivers at 7 s TTC before each critical situation. As hypothesized, drivers delay responses in situations that the time budget is too much and increase effort in situations with reduced time budget as concluded below.

- More time should be budgeted for the first drive due to observed higher takeover time demand.
- The time budget were too much for the lower complexity scenarios leading to delayed and poor performances.
- Takeover time for highway decreases in lower complexity levels compared to country road.
- In highway scenarios with surrounding traffic, takeover time decrease at the expense of performance compared to highway and country road with one or more junctions.
- Takeover time is identical for highway and country road in higher complexity levels.
- The time budget for the levels of S1 (Fixed obstacle ahead on highway) should be higher than those of S2 (slow vehicle ahead on highway).
- Reading using a hands-free device as an NDRT results in less distraction compared to proofreading and proofreading aloud using same device setup.
- Situation awareness at a relatively high speed (e.g. 130 Km / hr) and surrounding traffic is identical to country road intersection at lower speed (e.g. 80 Km / hr).
- Increased scenario complexity increases performance provided workload is not overwhelming

Furthermore, in Chapter 4, given the high rate of lane change accidents, this thesis integrates an individualized driver lane change maneuver intention-based assistance system. For the first time, output predictions are matched to warnings that are given to drivers whenever

an unsafe lane change maneuver is intended during assisted driving (SAE level 1). In addition, varied takeover time budgets for specific scenarios are validated in conditionally automated driving mode. The time budgets are based on average values for three of the previously introduced eight scenarios in chapter 3. Together with scenario complexity, secondary task demand, and individual variables from known literature and results from this thesis, the following results are obtained in Chapter 4.

- Predicting driver lane change intention and given directional warnings if collisions are eminent increases safety and performance in relation to adjacent lane vehicles.
- Drivers ignore forward and back collision warnings during lane changes and lane keeping and may benefit from multiple warning levels.
- Intention-based assistance is acceptable and desirable by drivers.
- Imagery warnings are not helpful at comparably low TOT budget in S1|II and S4|II due to increased complexity. However, imagery is helpful with fewer considerations before takeover.
- Decreased TOT budget results in increased workload in S1|II and S4|II.
- Takeover time depends on driver perception of time sufficiency for success.
- TOT budget should be determined in order of relative speed, number of agents, and junctions.
- Highway with high speed (e.g. 130 km / hr) and country road intersection at lower speed (e.g. 80 km / hr) require identical time budgets.
- It is possible to explicitly estimate TOT budget. Therefore, for the first time, a generalizable quantitative approach for budgeting TOT is proposed. The quantitative approach enables more precise budgeting of TOT and enables an assistance system to determine in advance whether a driver will be able to successfully takeover in

the available time. If available time will not be sufficient, additional measures can be applied to ensure driver safety. The studied takeover scenarios are less complex compared to those that frequently occur in reality. For example country roads include buildings, trees, and packed cars that may additionally obscure driver view. In addition, the participants were mostly alert and not tired or fatigued. However, this thesis presents a systematic approach to estimate required takeover time and to extrapolate to more complex scenarios.

5.2 Outlook

The next step for the assisted driving mode, is to integrate various warning levels for the intention-based system to further improve performance for lane change left and lane keep maneuvers as well. Combination of automatic surrounding vehicle anticipation with the intention-based assistance system can be performed to improve warnings.

In addition, the proposed quantitative approach for computing TOT budget for drivers can be extended to integrate more variables (e.g., fatigue time demand) and validated online for more complex scenarios. Specifically, the stimulus response time of each driver will be measured and integrated to vary time budgets in the future. Furthermore, individual variations in age, driving experience, and stimulus response time can be investigated.

Considerable literature exists in driver attention monitoring, intention recognition, and automatic traffic scenario analysis that are yet to be applied in experimental contexts. Therefore, more work is required to integrate existing methods, close the loop and generate contextual suggestions for new unknown or a combination of known scenarios. The developed methods have be applied to drivers and comparison between different realized systems is required.

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This thesis integrates results and development steps presented in the following publications:

Journal articles

[TS21a] Tanshi, F.; Söffker, D.: Assisted and conditionally automated driving decision assistance systems: review of existing and future interaction perspectives. *IEEE Transactions on Intelligent Vehicles (T-IV)* (2021), submitted

[TS21b] Tanshi, F.; Söffker, D.: Design and analysis of conditionally automated takeovers in complexity levels of traffic scenarios. *IEEE Transactions on Intelligent Transportation Systems (T-ITS)* (2021), submitted.

[TS21c] Tanshi, F.; Söffker, D.: Driving decision assistance system integrating lane change intention and varied takeover time budget. *IEEE Transactions on Human-Machine Systems (THMS)* (2021), submitted.

Conference papers

[TNWS19] Tanshi, F.; Dargahi Nobari, K.; Wang, J.; Söffker, D.: Design of Conditional Driving Automation Variables to Improve Takeover Performance. In *10th IFAC Symposium on Intelligent Autonomous Vehicles*, Gdansk, Poland, 2019, pp. 170-175.

[TS19a] Tanshi, F.; Söffker, D.: Modeling drivers takeover behavior depending on the criticality of driving situations and the complexity of secondary tasks. *IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, Las Vegas, USA, April 8-11, 2019, pp. 67-73.

[TS19b] Tanshi, T.; Söffker, D.: Modeling of takeover variables with respect to driver situation awareness and workload for intelligent driver assistance. In: *IEEE Intelligent Vehicles Symposium (IV'19)*, Paris, France, 2019, pp. 1667-1672.

[DSTS20] Deng, Q.; Saleh, M.; Tanshi, F.; Söffker, D.: Online Intention Recognition Applied to Real Simulated Driving Maneuvers. In: *IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, Victoria, BC, Canada, May 4-7, 2020, pp. 1-6

Workshop presentations

[TSW19] Tanshi, F.; Söffker, D.: Understanding the Dependencies Of Human Takeover Behavior from Various Dimensions of Criticality. *8. Interdisziplinärer Workshop Kognitive Systeme: Verstehen, Beschreiben und Gestalten von komplexen Mensch-Maschine-Szenarien*, Duisburg, Germany, March 26-28, 2019

[TSW18] Tanshi, F.; Söffker, D.: Analysis of Driver Assistance and Supervision Approaches with Respect to Research Goals and Cognitive Efficiency. *7. Interdisziplinärer Workshop Kognitive Systeme: Mensch, Teams, Systeme und Automaten*, Braunschweig (DLR), June 21-22, 2018

Other publications, which are not included in this thesis:

Conference papers

[HTS20] He, C.; Tanshi; F; Söffker, D.: Human online reliability estimation applied to real driving maneuvers. In: *IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*, Victoria, BC, Canada, May 4-7, 2020, pp. 149-154

In the context of research work at the Chair of Dynamics and Control, the following student theses have been supervised by Foghor Tanshi and Univ.-Prof. Dr.-Ing. Dirk Söffker. Development steps and results of the research work and the student theses are integrated in this thesis.

Student Theses

[Sad20] Sadiq, R., Development of a driver assistance system for decision support, Master Thesis, July 2020

[Ali19] Ali Y., Optimization and utilization of a filtering tool for data capturing in automated and assisted driving, Bachelor Thesis, June 2019

[Dar18] Dargahi Nobari, K., Development of TOR to improve takeover behavior, Master Thesis, July 2018

The following student theses have been supervised by Foghor Tanshi and Univ.-Prof. Dr.-Ing. Dirk Söffker, which are not included in this thesis:

Student Theses

[Soo20] Soon S. M. S., Cognitive technical systems case study analysis of driver gaze behavior, Bachelor Thesis, October 2020

[Zha20] Zhang Y., Development of motion cueing interface software for 3 DOF motion simulator, Master Thesis, July 2020

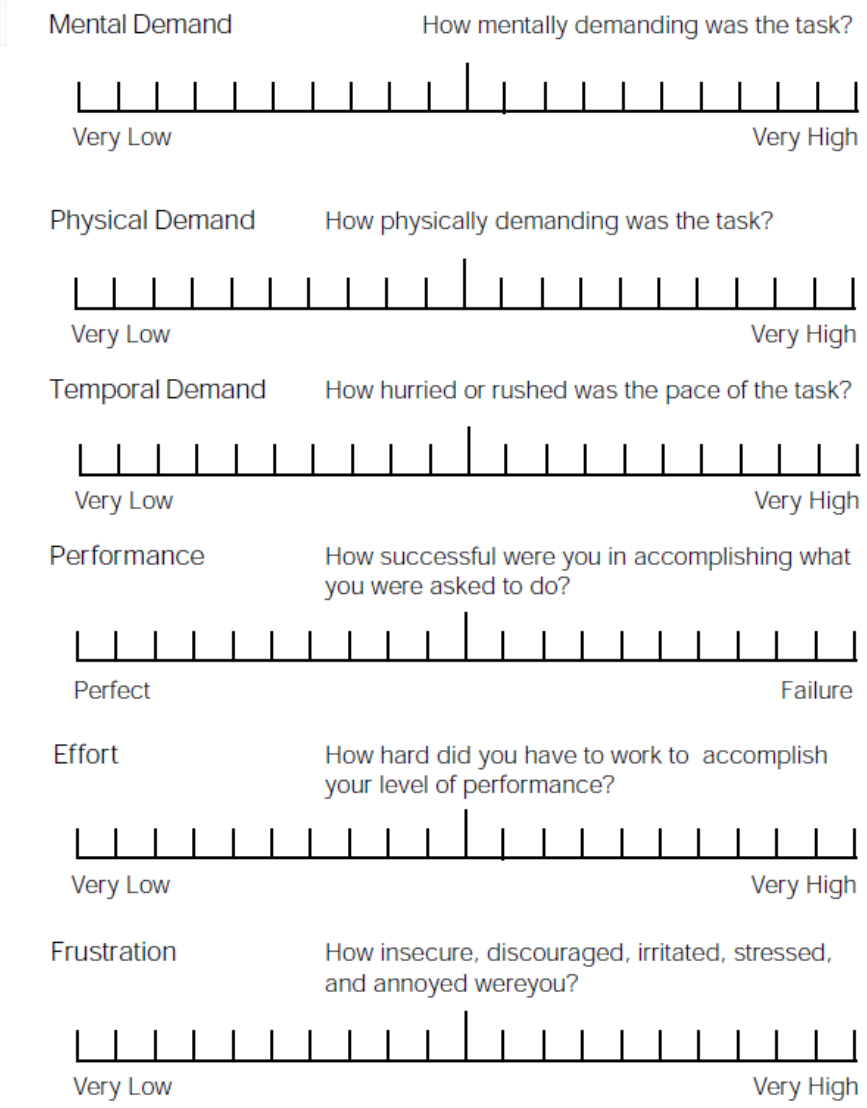
[Abd19] Abdallah M., Development, Construction and Commissioning of Rigid Lightweight Frame for Driving Simulator, Instrument Cluster and Controls, Bachelor Thesis, October 2019

Appendices

NASA-TLX questionnaire

English

NASA-TLX questionnaire about the transition or takeover from autonomous driving and secondary task or NDRT back to manual or assisted driving [HS88].

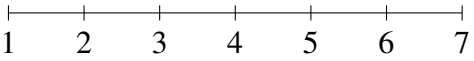


SART questionnaire

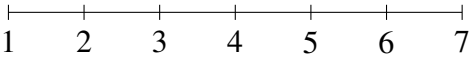
SART questionnaire about the situation and transition from conditionally automated back to manual or assisted driving adapted from [Tay89].

In the moment that you received the alert,

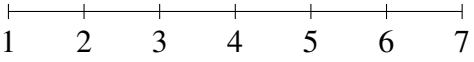
1. Was the situation highly dangerous (7) or it was safe (1)?



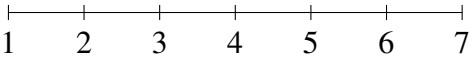
2. Was it difficult to manipulate the situation (7) or was it simple (1)?



3. Were there large number of factors (e.g. vehicles, pedestrians, high speed, etc.) to consider before making a decision (7) or were there very few factors to consider (1)?

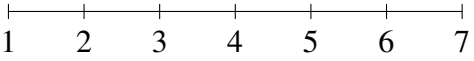


4. Were you ready and alert for activity (7) or did you have a low degree of alertness (1)?

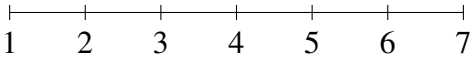


Immediately after receiving the alert,

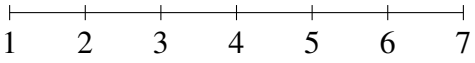
5. How deep did you concentrate on the situation?



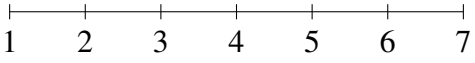
6. Were you concentrating on many aspects of the situation (e.g. obstacle, speed, other vehicles, etc.) (7) or focused on only one (e.g. obstacle)(1)?



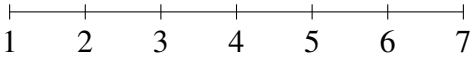
7. Were you capable of going through a more complex situation (7) or this situation took your maximum effort (1)?



8. How much information have you gained about the situation? Have you received and understood much knowledge (7) or very little (1)?



9. How familiar were you with the situation? Have you had several relevant experiences (7) or was it a new situation for you (1)?



Mid-questionnaire regarding situation awareness in Chapter 4

1.	What is your evaluation of the (red) visual warnings?	Not helpful	1	2	3	4	5	Very helpful
2.	What is your evaluation of the auditory (sound) warnings?	Not helpful	1	2	3	4	5	Very helpful
3.	Did the (red visual + auditory) warnings improve your awareness of surrounding vehicles?	Not at all	1	2	3	4	5	Very much
4.	Were the (red visual + auditory) warnings easy to understand?	Not easy	1	2	3	4	5	Very easy
5.	Were the (red visual + auditory) warnings timely?	Not timely	1	2	3	4	5	Very timely
6.	Were the (red visual + auditory) warnings necessary to achieve the level of performance you had?	Not at all	1	2	3	4	5	Yes very

Post-questionnaire about usability in Chapter 4

1.	Did the driving assistance system improve your way of driving in the situations where suggestions were given?	Very bad	1	2	3	4	5	Very good
2.	How did your awareness of surrounding vehicles improve when assisted by system compared to without system?	Not at all	1	2	3	4	5	Yes very
3.	Did you find the driving assistance system acceptable?	Not at all	1	2	3	4	5	Yes very
4.	Did you find the driving assistance system increasing your safety during driving?	Not at all	1	2	3	4	5	Yes very
5.	Would you like to use this driving assistance system for everyday driving?	Not at all	1	2	3	4	5	Yes very
6.	Are there any suggestions or warnings that you were not able to understand?	Not at all	1	2	3	4	5	Yes very

7.	Reading the warnings was strenuous.	Not at all	1	2	3	4	5	Yes very
8.	The warnings were annoying.	Not at all	1	2	3	4	5	Yes very
9.	The warnings were disturbing.	Not at all	1	2	3	4	5	Yes very
10.	The warnings distracted me from driving.	Not at all	1	2	3	4	5	Yes very
11.	Because of the warnings I could recognize traffic conflicts earlier.	Not at all	1	2	3	4	5	Yes very
12.	The warnings were helpful.	Not at all	1	2	3	4	5	Yes very
13.	Because of the warning I endangered other road users.	Not at all	1	2	3	4	5	Yes very
14.	Do you think the image for lane suggestion/warning could have been any better?							

15.	Do you have further suggestions?

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