Towards a Rule-based Approach for Estimating the Situation Difficulty in Driving Scenarios

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Abstract: The task of safe driving poses a huge challenge for drivers in day to day driving situations. Many times, this task can be very difficult, e.g., due to dense traffic, bad weather conditions, or a risky driving maneuver, and thus demand high concentration of the driver. The difficulty level escalates by the ever-increasing infotainment offers inside vehicles or distractions caused by occupants thus making substantial contribution to the driver distraction. This often results in dangerous driving situations which could be avoided by Advanced Driver Assistance Systems or highly automated driving systems taking the situation difficulty into account. E.g., an incoming phone call is postponed during a difficult situation. However, current systems do not consider all factors that influence the difficulty of a given situation. In this paper, we present an approach for estimating the difficulty of a driving situation by combining a number of different factors, such as environmental, inside-vehicle, driver state and personal characteristics, respectively. Our approach follows a rule-based paradigm to make the difficulty estimation reproducible and adjustable to current traffic rules. It is based on a generic and modularized architecture to allow integration and abstraction from heterogeneous data sources. Further, a feedback is provided to the driver or system to explain the contribution of the various factors to the difficulty status. Finally, we demonstrate the capability of the proposed approach with concrete examples, where we estimate the difficulty in various driving scenarios and for different drivers.

1 INTRODUCTION

Vehicles with Advanced Driver Assistance Systems (ADAS) aim to take some work-load of the driver to improve comfort and efficiency and to enhance driving safety (Bengler et al., 2014). More advanced systems, so-called highly automated driving (HAD) systems, drive almost autonomously but may require the driver to take-over driving in situations where the system is not capable to handle the situation safely (Bazilinskyy et al., 2018). However, ensuring safety is one of the biggest challenges that remain in both applications. To drive safely can often be very difficult, e.g., due to dense traffic, bad weather conditions, or a risky driving maneuver, and thus demand high concentration of the driver. It requires an understanding of the current driving situation which includes perceiving the current traffic situation, comprehending their meaning and predicting what could happen in the near future. Furthermore, it includes the driver's capability and physical state, her moment-to-moment knowledge and understanding of the driving situation as well as possible distractions like conversation with occupants, using the infotainment system or smartphone. To ensure safety, a system should consider a number of different factors that influence safety. This includes the difficulty level of the driving situation, environmental condition, driver capability and current driver state like distraction or sleepiness. Therefore, these systems should be aware of particularities of driving situations and exploit the information from various levels, such as perception, decision making and action (Röckl et al., 2007).

In this paper, we present an approach for estimating the difficulty of a driving situation by combining the environmental factors (e.g., weather and road conditions, traffic or driving maneuver) and the inside-vehicle factors (e.g., occupant behavior or loudness). In addition, the driver state (e.g., drowsiness or attentiveness), as well as the personal characteristics of the driver (e.g. experience, preferences, abilities) are considered. Since reproducibility and explainabil-

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ity are crucial for a safety-relevant system, we based our approach on a rule-based paradigm that conforms to traffic rules, traffic standards and that can be easily verified by humans. The approach is based on a generic architecture comprising a number of components for allowing the integration and abstraction from heterogeneous data sources. Thus, a feedback can be provided to the driver or system to explain the impact of the various factors to the difficulty status. We demonstrate the capability of our approach with concrete examples estimating the difficulty in various driving scenarios and for different drivers. As a result, considering the human factors during difficulty estimation will have an impact on increasing the safety aspects of ADAS and HAD systems.

The remainder of this paper is structured as follows: A motivating scenario is described in Section 2. Related work is outlined in Section 3. Section 4 presents a detailed description of our approach. The architecture and its main components as well as the implementation details are shown in Section 5. Section 6 demonstrates the application of the approach with a concrete example. In Section 7, we conclude the paper and give an outlook of future directions and possible extensions of this work.

2 MOTIVATION EXAMPLE

Estimating the difficulty status of a driving situation can make an important contribution to increase safety and comfort for the driver. As for our motivation examples, we illustrate the following scenarios, where difficulty estimation including various personal characteristics is of paramount importance:

- Comfort: Anna, a novice driver, is on her way to a customer meeting. It is raining heavily and this makes her feel very uncomfortable. Her *adaptive cruise control* (ACC) system detects a difficult situation and increases the distance to the vehicle ahead. Sophie is an experienced driver, she is driving on the highway immediately behind Anna. She is not having any difficulties with the heavy rain. The system estimates the situation as less difficult, so her ACC system chooses the shortest safe distance to Anna giving her the possibility to eventually overtake.
- Managing Secondary Tasks: Anna is driving on the highway, it is drizzling, the traffic density is on an acceptable level, and she listens to her favorite music. Due to a small construction site, the lane is very narrow which makes her feeling very uncomfortable. In this moment, a call from her friend is coming in. The system detects a difficult situation and holds back the information about the call and displays it when the situation is relaxed again.
- Misuse Detection: Anna is using an HAD system that supports hands-free mode. Using driver monitoring camera signals, the systems recognizes that she is using her mobile phone for a longer time and not following the traffic situation. This can lead to a hazardous situation and the system informs Anna to focus on steering her car.

3 RELATED WORK

Over years, many approaches that deal with specific topics concerning difficult driving situations coming from outside the vehicle and driver state have been presented. Such approaches typically are focusing on measuring the difficulty level for a particular specific factor, i.e. environmental related factors.

Outside the Vehicle. (Kita, 2000) proposed an approach for personalizing the level-of-service (LOS) for roads by including the perception of the driver for the driving environment. The effects of weather conditions, light conditions, and road lighting on vehicle speed are analyzed by (Jägerbrand and Sjöbergh, 2016). (Heinzler et al., 2019) present an approach for detecting and classifying rain and fog using lidar sensors. They do not provide a method for calculating the difficulty but emphasize the contribution of these factors to the situation difficulty. (Park et al., 2018) analyzed the situation complexity resulting from mixing of autonomous and manually driven vehicles using simulation. They calculate the situation complexity using vehicular data communication via V2X (Vehicle-to-X). However, they only consider driving situations and maneuvers for a mix of autonomous and manually driven vehicles.

Driver State. In (Paxion et al., 2015) and (Paxion et al., 2014), the authors examine the influence of situation complexity and driving experience on a driver's subjective workload and driving performance. (Braunagel et al., 2017) present a method for detecting secondary tasks of a driver, e.g., reading, watching a movie, or being idle when driving. This method could be integrated in our approach for determining the driver state w.r.t. attentiveness. A model to represent driver behavior and situation awareness under hazardous conditions is described in (Kaber et al., 2012). (Bier et al., 2019) discuss the risks of monotony related fatigue while driving. (Martinez et al., 2018) present a survey of approaches dealing with the recognition and classification of driving styles. The authors discuss rule-based and data-driven algorithms, and propose to combine algorithms, depending on the application. Furthermore, they summarize input signals that can be used for driving style recognition.

Combining Multiple Factors. (Fazio et al., 2016) discuss a technique for driving style recognition using fuzzy logic, considering environmental context, such as road types (e.g., urban, highway, or city), and time of day (e.g., morning, evening, or noon). It can be used to provide classifications of dimensions, such as the presented driving style recognition. Another method targeting the estimation of the difficulty level in a given situation is developed in the aircraft domain (Wang et al., 2018). Its main objective is modeling the complexity of air traffic situations with a dynamic weighted network approach. Considering the aircraft, way-points, and airways as nodes, as well as the relationships among these nodes as edges, a dynamic weighted network is constructed. Air traffic situation complexity is defined as the sum of the weights of all edges in the network. Our work for situation difficulty estimation is inspired by this approach.

To the best of our knowledge, there is no approach in the automotive domain that estimates the difficulty status of a driving situation, where all important factors in- and outside the vehicle, as well as the current state and characteristics of the driver are considered.

4 APPROACH

For safety reasons it is mandatory to achieve required and reproducible results and to quickly adapt to country-specific or even changing traffic rules. Therefore, we conceive an approach following a rule-based paradigm to comply with the above mentioned aspects. As a result, it is possible to deliver the reason for the necessary adaptions to the driver by communicating the factors mainly contributing to the *driving situation difficulty status* (DSDS). In order to estimate the DSDS, our approach combines various factors from the vehicle environment (e.g., weather and road conditions, traffic or driving maneuver), the inside of the vehicle (e.g., occupant behavior or loudness), the driver state (e.g., drowsiness, posture, or eye gaze), and personal characteristics of the driver (e.g. driving experience, preferences, abilities). In the following, we call such factors *difficulty dimensions*, or dimensions for short.

4.1 Difficulty Dimensions

In this section, we describe each category of dimensions relevant for estimating the DSDS in more detail. The DSDS is influenced by a combination of various difficulty dimensions, each describing a specific part of the driver state and vehicle context:

Outside-vehicle Context:
Groups the dimensions related to the environment outside the vehicle, such as weather condition, road condition, traffic situation, other traffic participants, or driving maneuver.

Inside-vehicle Context:
Comprised of dimensions originating from the cabin and its passengers, such as the loudness in the car, unsuitable cabin temperature, or fighting children on the back seats.

Driver State:
Includes the dimensions describing the current state of the driver, such as attentiveness, fatigue, drowsiness, or seating position.

A dimension is characterized by three levels: 1) the observable difficulty level; 2) the personal ability level; and 3) the personal difficulty level. These levels are further classified into dimension-specific difficulty intervals.

Observable Difficulty Level:
The observable difficulty level of a given dimension describes the degree of difficulty that is measured, e.q., by sensors or video cameras, or calculated by services such as drowsiness detection.

Personal Ability Level:
The personal ability level is used to personalize the DSDS estimation. It depends on rather static driver characteristics, such as driving experience or driver type. E.g., a novice driver can handle only light rain, whereas a more experienced driver can easily handle even the heavy rain. The values of this level can be obtained e.g., by asking the driver for a self-assessment, using common-sense information, or analyzing the driving behavior.

Personal Difficulty Level:
Describes how difficult a dimension is perceived by a driver. It is estimated from the measured observable difficulty level, the personal ability of the driver to handle the situation caused by the specific dimension, and additional factors relevant to the overall situation.

4.2 Estimating the DSDS

Our DSDS estimation is based on the principles presented by (Wang et al., 2018). We consider the difficulty status of the situation as a vector of difficulty dimensions, where each value describes the personal difficulty level of a dimension. The process of the DSDS estimation comprises three consecutive steps:

1. Compute the personal difficulty levels of each dimension;
2. Normalize the personal difficulty levels of each dimension; and
3. Compute the DSDS based on the obtained values.

4.2.1 Estimating the Personal Difficulty Level

The personal difficulty level for a specific dimension is estimated based on the dimension's observable difficulty level and personal ability level. While the observable difficulty level is an objective measure, the personal ability is a subjective attribute and should be adapted to the overall situation, taking into account a maximum value for the personal ability level and the number of dimensions.

Including the Maximum Allowed Personal Ability Level in the Estimation. The maximum personal ability level should only be a fraction of the maximum observable difficulty level, depending on a given weight. This restriction is to prevent the user from being too self-confident in assessing her abilities, since it is unlikely that a driver can easily handle extremely difficult situations.

Let i be the index for dimension i, p_i^{basic} the basic personal ability level, e.g., specified by the driver. Let e_i^{max} be the maximum observable difficulty level, and $w_i^{maxAbility} \geq 1$ a weight for defining the maximum personal ability level. Then the maximum allowed personal ability level p_i^{max} is calculated using the equation:

$$p_i^{max} = min(p_i^{basic}, \frac{e_i^{max}}{w_i^{maxAbility}}) \tag{1}$$

Including the Number of Dimensions in the Estimation. Depending on the driver experience and her ability to handle a particular situation, the personal ability of a specific dimension decreases with the number of dimensions and thus increases the perceived difficulty. For instance, if it is dark and heavy rain, the situation is mostly perceived as more difficult than if it would be only dark without rain.

The higher the number n of difficulty dimensions, the lower the personal ability level for a single dimension should be considered. This is expressed by the weight factor $w_i^{experience} \geq 0$. For a very experienced driver, this must not necessarily be the case, which can be defined by setting the weight to $w_i^{experience} = 0$. The personal ability level p_i is finally adapted to the number of dimensions using the equation:

$$p_i = \frac{p_i^{max}}{n^{w_i^{experience}}} \tag{2}$$

Estimate Personal Difficulty Level of each Individual Dimension. The personal difficulty level of a dimension is the difference between the observable difficulty level and the adapted personal ability level.

Let $e_i(t)$ be the observable difficulty level of dimension i at time t, and p_i, the adapted personal ability level calculated from equation 2. Then the personal difficulty level $d_i(t)$ of dimension i at time t is estimated using equation:

$$d_i(t) = max(0, (e_i(t) - p_i)) \tag{3}$$

4.2.2 Normalizing the Personal Difficulty Level

The dimensions can have different maximum personal difficulty levels, see also section 4.1. In order to obtain comparable values for all dimensions, we normalize these levels in the interval $[0, 1]$.

Let min_i and max_i be the minimum and maximum values, respectively, of the personal difficulty level of dimension i. Then the personal difficulty levels for given dimensions are normalized to $[0, 1]$ using feature scaling provided in equation:

$$d_i(t) \rightarrow \frac{d_i(t) - min_i}{max_i - min_i} \tag{4}$$

4.2.3 Estimating DSDS

Let $\overrightarrow{D}(t)$ be the difficulty vector for time t:

$$\overrightarrow{D}(t) = (d_1(t), d_2(t), \ldots, d_n(t)) \tag{5}$$

The DSDS at time t is the L2-norm of the difficulty vector and estimated using equation:

$$DSDS(t) = ||\overrightarrow{D}(t)|| = \sqrt{(d_1(t))^2 + \ldots + (d_n(t))^2} \tag{6}$$

4.3 Algorithm

In Algorithm 1, we show the procedure and the intermediate steps for estimating the DSDS. This procedure is repeated each time, when the observable difficulty level of a dimension is changed.

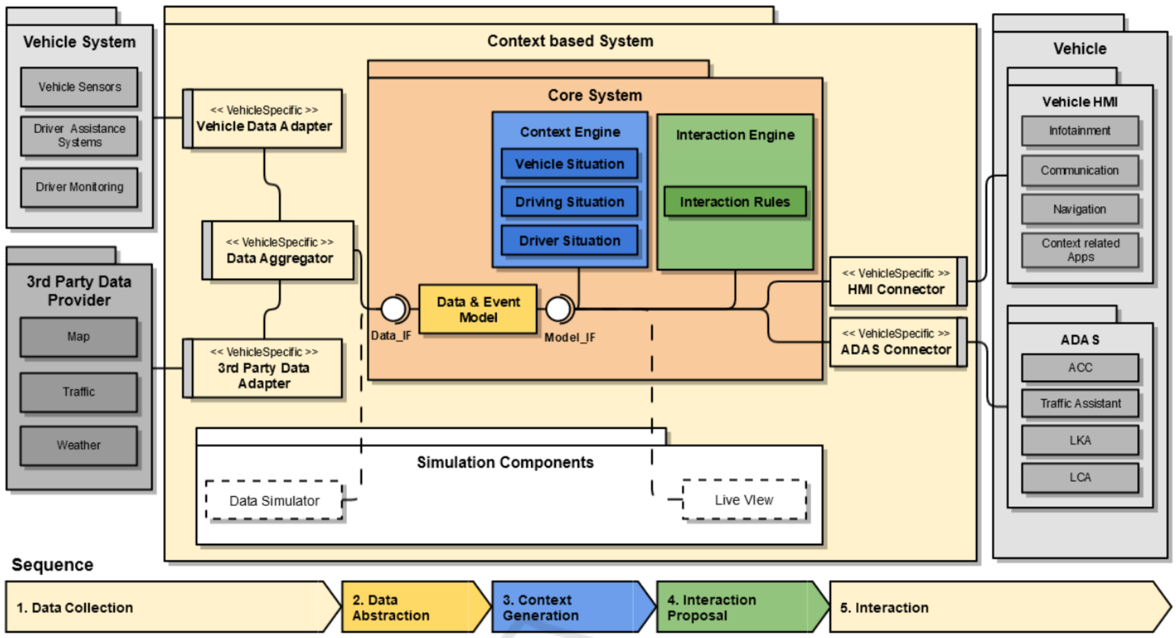


Figure 1: General Architecture. It is comprised of five main steps: 1) Data Collection; 2) Data Abstraction; 3) Context Generation; 4) Interaction Proposal; and 5) Interaction. In each step, a number of components connected to each other perform dedicated tasks.

Algorithm 1: Estimating the DSDS.

estimateDSDS *(dimensions[])*
  foreach *dimension* **do**
    if *dimension's abilityLevel conditions changed* **then**
      adapt ability Level according to eq. 1 and 2;
    end
    estimate dimension's personal difficulty level according to eq. 3;
    Normalize dimension's personal difficulty level according to eq. 4;
    Estimate *dsds* according to eq. 6;
  end
  return *dsds*

5 ARCHITECTURE AND IMPLEMENTATION

The architecture of our approach, illustrated in Figure 1, follows generic and modularized principles to allow integration from heterogeneous data sources and data abstraction. This results in a service based, decoupled and extendable structure that can be used for realizing multiple different use cases. It consists of five consecutive steps: 1) Data Collection; 2) Data Abstraction; 3) Context Generation; 4) Interaction Proposal; and 5) Interaction.

Data Collection. Different data providers such as vehicle systems (e.g. sensors, ADAS, driver monitoring) or other 3rd party data sources (e.g. maps, traffic, weather) can be connected to the *context based system* via adapters. This way, only the adapter modules have to be adjusted for each type of vehicle or for including a new type of data source. The data aggregator component converts the vehicle-specific or source-specific data into a well-defined, common data structure, defined by the data and event model. It can be used to combine different low level data to a required information item (e.g. speed, rain level), or simply adapt the values to fulfill the required unit definition (e.g. convert km/h to m/s). As a result, the context based system is decoupled from specific data sources.

Data Abstraction. The data and event model defines a common data structure for the core system and acts as a publish subscribe broker. It provides a unified data and model interface where a number of different components can be integrated. The data interface serves as an interface to retrieve new data from the data sources. The model interface is considered as the interface where different components can subscribe to or publish new content to the data and event model. An additional data access component can be included to regulate which component is allowed to subscribe to certain information or to publish certain information to the data and event model.

Context Generation. The context engine consists of one or multiple services that subscribe to the model interface and processes data in order to publish enriched context information back to the data model. This can for example be the estimation of the driving situation difficulty presented in this paper.

Interaction Proposal. The interaction engine may include one or multiple services that subscribe to the aggregated context information and define interaction proposals based on the context (e.g., a proposal to postpone an incoming call at a difficult situation).

Interaction. The HMI and ADAS connectors are vehicle-specific components that act as data abstraction layer and map the interaction proposal to a data format supported by the vehicle. This way our context based system can be used for different vehicles by only adapting the HMI and ADAS Connector.

Additional components can be integrated in order to perform specific tasks related to the type of vehicle or more generic investigations about information flow among components. For instance, a simulation component can be used to simulate data, gain insights, or demonstrate the context based system without the need to be connected to a vehicle.

5.1 Implementation

We developed a prototype to estimate the DSDS, focusing on exploring different configurations of the context and visualizing the impact of these configurations. For this reason, a simplified data and event model, the context engine, and the simulation components are used. Furthermore, a web socket server is established to enable the communication between these components. As a result, it is possible to deploy the different components on different devices. E.g., deploying the components on different devices allows us to estimate the DSDS on one device and use another device, such as a tablet, to simulate the input data and display the results. The communication via web sockets is also used to update the estimation of the DSDS and to forward the results in order to retrieve the displayed values in the respective chart.

The prototype is implemented as a NodeJS web-based solution using version 13.8.0, and the following libraries: Express v4.17.1, WebSocket v6.14.5, and HTML5. For visualization of the diagrams, we used Chart.js v2.9.0 and Chartjs-gauge v0.2.0. The estimation of the driving situation difficulty is implemented via Typescript. A number of web-based forms are developed to enable configuration of different scenarios. For example, the *SimulationConfig* is a form for simulating input data, as well as changing the personal ability of a driver. Other forms contain charts to display the results in an explainable way and gain insights into the driving situation difficulty estimation. Some examples of the gauge charts and the radar charts are displayed in Figure 2. The gauge chart displays the result of the DSDS estimation, where a value of 1 or higher (dark red area) indicate that the highest amount of concentration is required from the driver and no disturbance like secondary tasks should be performed. The radar chart visualizes the observable difficulty level, the personal ability level and the resulting personal difficulty level for each dimension.

6 APPLICATION

We applied our approach presented above to estimate driving situation difficulty status as a basic requirement to enhance vehicle systems, such as adaptive HMI systems, ADAS, or HAD systems.. An adaptive HMI system helps the driver in two ways:

- Visualization: by adapting the content to be displayed according the difficulty of the current driving situation. For instance, the new content is reduced to the absolute minimum during a difficult driving situation. Additional content, such as music playlists, will be displayed in a less difficult driving situation.
- Interaction: adapting the interaction between driver and vehicle w.r.t. the situation difficulty. For example, to reduce the distraction of the driver, the notification for an incoming call is postponed in a difficult driving situation. If the situation is less difficult again, the missed phone call and a proposal to call back is communicated.

An ADAS can increase the comfort and safety for the driver. We chose: 1) the adaptive cruise control (ACC); and 2) the misuse detection as example applications for our approach. First, an *ACC* automates the longitudinal control of the vehicle, while the driver is still in charge and has to supervise the situation. For example, in a driving situation with a high personal difficulty level, such as heavy rain, the minimal distance to the vehicle in front is enlarged. Second, if the driver is not focused on the traffic ahead, a *misuse detection system* warns the driver earlier in difficult situations. For instance, if the driver is turning his head to the rear or scrolling through a playlist, depending on the situation difficulty, the system alerts the driver to turn the attention back to the driving situation.

Table 1: Example dimensions and observable difficulty classification.

Dimension	Classification	Explanation
Rain level rl	0: $rl = 0$ 1: $0\% < rl < 33\%$ 2: $33\% \leq rl < 66\%$ 3: $66\% \leq rl \leq 100\%$	no rain light rain heavy rain cloud-burst
Lane width lw	0: $lw \geq nw$ 1: $lw < (nw - ot)$ OR $lw < (nw - mr)$ 2: $lw \leq vw$	norm narrow very narrow
Traffic density td	$td = 0$: $LOSA$ $td = 1$: $LOSB$ $td = 2$: $LOSC$ $td = 3$: $LOSD$	Low density Moderate High Very high
Loudness level ll	0: $ll \leq 60dB$ 1: $ll \leq 70dB$ 2: $ll \leq 80dB$ 3: $ll \leq 90dB$ 4: $ll \geq 90dB$	quiet below comfort above comfort just below max above max
Eyes off-road time eo	0: $eo < 0.6sec$ 1: $eo < 1sec$ 2: $eo < 1.3sec$ 3: $eo < 1.6sec$ 4: $eo < 2sec$ 5: $eo \geq 2sec$	not distracted slightly distr. moderately distracted considerably distracted highly distr. extremely distr.

In the following, we show the applicability of the two examples mentioned above and the obtained results which can be used in an adaptive HMI system.

6.1 Use Case Description

Anna and Sophie both own a vehicle having functionalities of adaptive HMI, ACC, and misuse detection.

Since they are driving at the same time on the federate autobahn from Frankfurt to Stuttgart, the outside-vehicle context is the same for both of them. However, the inside-vehicle context and the driver state and its characteristics is typically different.

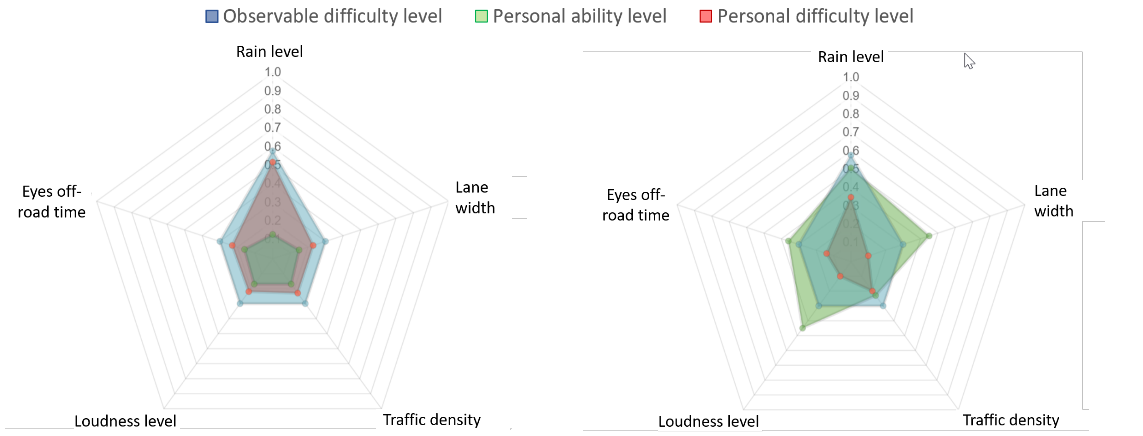
6.2 Difficulty Dimensions

Without loss of generality, we concentrated on the following dimensions.

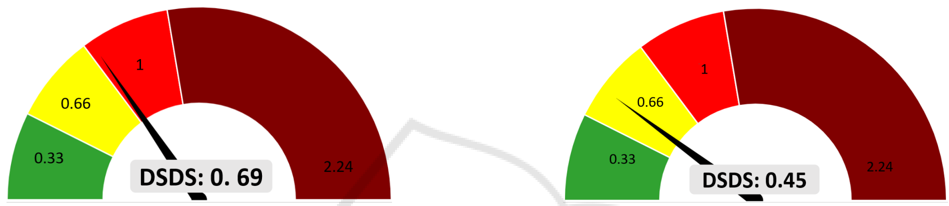
Outside-vehicle Context. This context comprises the largest part of dimensions. For simplicity reasons, we use only the traffic density, the rain level, and the lane width as measurement. For the *rain level*, classifications suggested by (Michenfelder et al., 2007) or (Beritelli et al., 2018) are used. The observable difficulty level can be measured by a rain sensor. For the *lane width* classification, we use country-specific norms that define a norm width nw for each road type. It includes the vehicle width vw, a movement range mr, and an oncoming traffic tolerance ot. We refer to a lane as narrow, if either mr or ot is missing. E.g., in Germany, the norm width is defined as $nw = 3,5m$ for rural roads, and $nw = 3,75m$ for motorways. The observable difficulty level could be measured by video camera and lidar using computer vision technologies (e.g., (Li et al., 2018)). For the *traffic density*, classifications are suggested by the spatial organization of transportation and mobility (Rodrigue, 2020). It defines six levels of service (LOS) from free flow (LOS A) to congestion (LOS F). Authors in (Papadimitriou et al., 2010) suggested to reduce the six density classes to three classes, based on further user studies. In our approach, we use the first four classes presented by (Rodrigue, 2020), since we do not classify congestion as extremely difficult. The observable difficulty level can be measured by video cameras as described in (Ma and Qian, 2019).

Inside-vehicle Context. Regarding the context occurring in vehicle, we use only the loudness level in the car (e.g., from music or talking passengers), although additional measures such as the source of distraction (e.g., music, news, conversations with passengers, telephone calls, screaming kids, and many more) could also be considered. This challenge level can be measured e.g., by a microphone. In our approach, we use classifications suggested by the American Speech-Language-Hearing Association (ASHA, 2021), and University of Michigan (Berger et al., 2015). The classification depends on two thresholds: 1) the maximum loudness handled by the driver with a little effort; and 2) the threshold of discomfort. For use case demonstration, respective manually defined values are used. However, since both thresholds are personalized values, we foresee they could be learned via Machine Learning algorithms.

Driver State. As a driver state, we only use the eye gaze direction although additional dimensions such as fatigue, seating position, driver drowsiness, and could be easily included as well. In order to measure the observable difficulty level, we use the so-called eyes-off-road time which can be detected by a video cam-



(a) Dimension levels of a novice driver with heavy rain. (b) Dimension levels of an experienced driver with heavy rain.



(c) DSDS for a novice driver with heavy rain. (d) DSDS for an experienced driver with heavy rain.

Figure 2: Situation 1: DSDS and dimension levels for a novice driver with low abilities and an experienced driver with mid abilities. The observed difficulty level for rain is in the mid range, all other observed difficulty levels are in the lower range.

era tracking the driver's eye-gaze. The classification used here are based on the National Highway Traffic Safety Administration (NHTSA) (NHTSA, 2013; NHTSA, 2014), and a 100-Car Naturalistic Driving Study (Simons-Morton et al., 2014). These classifications w.r.t. the observable difficulty levels are summarized in Table 1. In order to refine the classification, we divided each interval into ten sub-intervals. For example, an observed loudness difficulty level $ll = 2.7$ describes a loudness level much higher than the comfort level.

Driver Profiles: Personal Ability Levels. Table 2 shows the personal abilities of Anna and Sophie. Anna is a novice driver with low personal capabilities. Sophie is a more experienced driver with moderate personal abilities.

6.3 Discussion

The approaches listed in section 3 are tailored to specific situations such as driver attentiveness, driving style, or weather conditions; considering only a small number of dimensions. It would be a high effort to extend them by new dimensions, whenever new dimensions are emerging. Our approach can handle a huge number of dimensions. It is extensible and can easily be adapted to completely new situations by adding classifications for the necessary dimensions.

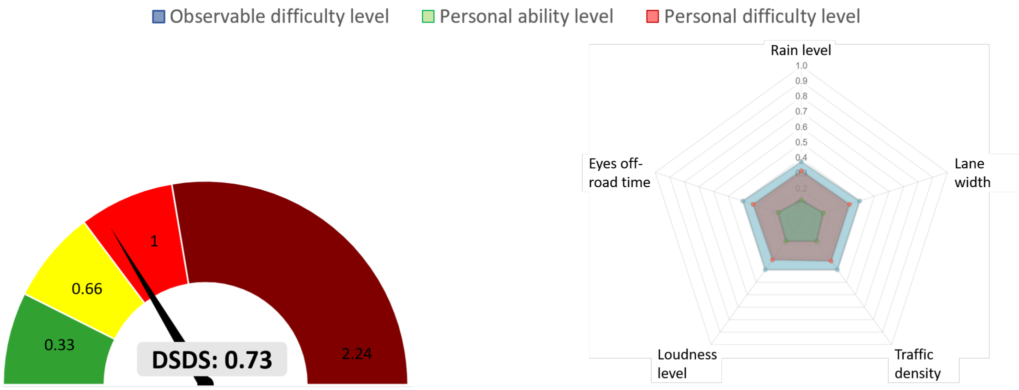
Table 2: Personal abilities for Anna and Sophie.

Personal ability level	Anna	Sophie
Rain level [0..100]	13.0	51
Lane width [0..2]	0.3	0.9
Traffic density [0..3]	0.5	0.7
Loudness level [0..4]	0.7	1.8
Eyes off-road time [0..5]	0.8	1.8

Table 3: Observable difficulty levels of the given situations.

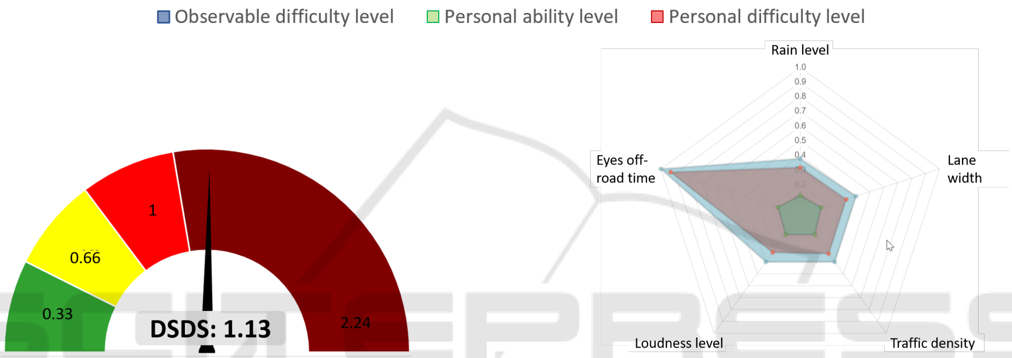
Observable diffic. level	Sit. 1	Sit. 2	Sit. 3
Rain level [0..100]	58	38	38
Lane width [0..2]	0.6	0.8	0.8
Traffic density [0..3]	0.9	1.2	1.2
Loudness level [0..4]	1.2	1.6	1.6
Eyes off-road time [0..5]	1.5	2	5

In the following, we discuss the results of the DSDS for three situations. In each situation, the effect of one of the aforementioned HMI or ADAS systems on the two drivers is described in detail. Table 3 shows the observable difficulty levels for the three situations described in the following.



(a) DSDS for the novice driver. (b) Difficulty levels the novice driver.

Figure 3: Situation 2: DSDS and difficulty levels for the novice driver. All observed difficulty levels are in the low to mid range, but the DSDS sums up to high difficulty.



(a) DSDS for the novice driver. (b) Difficulty levels for the novice driver.

Figure 4: Situation 3: DSDS and difficulty levels for the novice driver. The observed difficulty level of the eyes off-road time has reached the maximum value 1. All other observed difficulty levels are in the low to mid range, resulting in a DSDS > 1.

Situation 1. Same Observable Difficulty Level and Different Personal Ability Levels. In this situation, it is raining heavily, the rain sensor provides a value of 58% whereas all other difficulties are in the lower range. Figure 2 depicts the DSDS and the difficulty levels for Anna and Sophie. In the spider depicted in Figure 2a, we can see that for Anna as a novice driver: the green area showing her personal abilities is quite small. The personal difficulty level (red area) for the rain dimension is nearly the observed difficulty level (blue area). This results in a high DSDS for Anna, as shown in Figure 2c. Based on these values, the ACC of Anna's vehicle can increase the distance to the vehicle in front. On the other hand, Sophie is an experienced driver, as depicted in Figure 2b. Her personal abilities are higher compared to Anna, so the personal difficulty level of the rain dimension is less than the observed difficulty level which results in a much lower DSDS as shown in Figure 2d. The ACC of Sophie's vehicle can tolerate a small distance to the vehicle in front, considering that is still safe.

Situation 2. Many Moderate Difficulties Sum up to a Difficult Situation. Table 3 shows the observable difficulty levels for the second situation. Each of the observable difficulty levels alone would be between the green and the yellow area. But all together, they result in a difficult situation. The DSDS of 0.73 is in the red area, as illustrated in Figure 3. Anna's adaptive HMI postpones the information about the incoming call until the situation difficulty decreases.

Situation 3. Extremely Difficult Situations Need Time-critical Actions. The driving situation is the same as in situation two, except that Anna is using her mobile for more than two seconds. The system estimates a DSDS of 1.13 lying in the dark red area, as shown in Figure 4. The dark red area indicates a situation difficulty higher than the maximum difficulty level of one dimension. The misuse detection system prompts her to immediately concentrate back on steering the vehicle.

7 CONCLUSIONS AND OUTLOOK

In this paper, we describe an approach for estimating the situation difficulty in driving scenarios by combining important factors like traffic density, road conditions, environmental factors, inside-vehicle distractions, driver capabilities and driver state. It is based on a rule-based paradigm for difficulty estimation which has several advantages. The rules are reproducible and easily verifiable playing an important role in safety relevant systems. Further, a holistic architecture composed of various loosely-coupled components is designed with the objective of allowing the integration of heterogeneous data sources. Finally, we demonstrated our approach in three concrete situations where calculating DSDS including personal characteristics could have a high impact on the road safety. For simplicity, we have used discrete values for the individual factors for a number of difficulty dimensions that impact situation difficulty. These could be extended to continuous-valued functions, like a sigmoid function or could be learned if sufficient training data is available.

As future work, we will work on including Fuzzy Logic algorithms to provide classifications for a dimension's observable difficulty levels. Next, we will investigate adopting machine learning techniques regarding individual difficulty dimensions. Particularly for cases where rules cannot be defined with sufficient evidence and where enough data is available for training, learning based methods could be applied. Another direction of further analysis is related to the maturity of sensors to determine the necessary parameters and knowledge about their influence in the overall situation difficulty which can vary from domain to domain. For example, much research has been done for eye-gaze tracking and determining its influence in driving, whereas in other areas like the quantification and analysis of driver distraction by music, conversation and others is less well known. How much individual capabilities and experience manifest themselves in day-to-day driving situations is subject of current research (Kaber et al., 2012). But how these are influenced by other factors like conversations, infotainment or other distractions is unclear. Furthermore, we would like to learn individual capabilities, how they change over time, and how they are influenced by other factors.

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