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Design of a data-driven communication framework as personalized support for users of ADAS.

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Abstract

Recently the automotive industry has made a huge leap forward in Automated Driver Assistance Systems (ADAS) development, increasing the level of driving processes automation. However, ADAS design does not imply any individual support to the driver; this results in a poor understanding of how the ADAS works and its limitations. This type of driver uncertainty regarding ADAS performance can erode the user's trust in the system and result in decreasing situations when the system is in use. This paper presents the design of a data-driven communication framework that can utilize historical and real-time vehicle data to support ADAS users. The data-driven communication framework aims to illustrate the ADAS capabilities and limitations and suggests effective use of the system in real-time driving situations. This type of assistance can improve a driver's understanding of ADAS functionality and encourage its usage.

Keywords: driving context; event recognition; automated services; naturalistic driving data

1. Introduction

The automotive industry today, stimulated by the runaway enthusiasm of Industry 4.0, is globally competing in the development of smart programmable systems where the automatization of driving processes, development of smart sensors, and utilization of real-time data is of critical importance. Automated Driver Assistance Systems (ADAS), as an example of such systems, aim to help the driver to handle various driving situations by providing longitudinal control of a vehicle through accelerating or braking in different traffic conditions, and/or lateral control by implementing steering assistance. This research is focused on ADAS with levels 1-2 of driving automation [1]. The sustained basis of driver-system interactions when the driver's role is fully or partially eliminated during the driving task is essential for this framework. The control shift of the driving activity between the driver and the system requires a good driver understanding of how the interaction is built and who has control over the driving activity at a particular moment.

Although the ADAS functionalities offer advanced support to a driver, nowadays systems are still not able to handle all challenging driving conditions, for example: (i) slippery road conditions; (ii) a great deal of water or slush on the road; (iii) heavy rain or snow; (iv) poor visibility; (v) curving roads; (vi) highway ramps, and (vii) situations when clear markings on the road are missing [2]. Thus, the systems remain semi-autonomous - a fact that makes the driver fully responsible for the performed driving activities. The research on user behavior related to ADAS shows that a significant number of drivers do not fully understand the limitations of driving support systems [3,4]. In many cases drivers expect the system to be able to handle on-road situations when the system activation preconditions are not fulfilled. The study conducted by Jenness et al. [4] demonstrated that drivers' expectations were higher than the actual system capabilities. The study revealed that 81% of respondents were unaware that ADAS does not have the

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capability to detect stationary obstacles, pedestrians, or pets. Another misconception regarding the speed for ADAS activation was identified by Aziz et al. [5]. Participants in that study mistakenly believed that the ADAS function could work at any speed. The misinterpretation of the ADAS capabilities creates misunderstandings between the driver and the system. Consequently, this has an impact on the driver´s trust and reliance on the technology [6,7].

Moreover, the design of ADAS does not imply explicit communication support between driver and system. Even the transition phase from the system to the driver is not clearly communicated. According to the developers, there is a need to keep the driver's attention on the performed tasks and to avoid the situations when the driver can feel overconfident with the system performance. The lack of system support to the driver subsequently often results in a poor understanding of how the system is performing and what limitations it has [8]. This type of uncertainty regarding ADAS performance can erode the user's trust in the system and result in a decrease in the time that systems are in use. According to McDonald et al. [9], further research is needed to determine the way to transfer critical information regarding ADAS capabilities and limitations to the driver.

Modification of the ADAS functions on a physical level to fit individual driver needs is not feasible due to the diversity of driver needs and the high cost of such development. A possible solution could be the design of data-driven communication support solutions for ADAS users. Historical data on driver performance can help in the analysis of the driver's needs for additional support. The ability to identify the driving event and evaluate the driving conditions for ADAS performance in real-time can help to understand correct "situational" attributes for communication. Processing of the real-time data, together with historical usage data for the identified driver, can potentially enable the development of personalized support to the driver.

Thus, the question we address in this research is, "How can vehicle sensors data be used to convey system design features to ADAS users?" This paper presents the design of a data-driven communication framework that utilizes historical and real-time data. The developed framework aims to convey the ADAS capabilities and limitations to the driver, providing personalized support. Personalized support, in turn, can build drivers' confidence and increase ADAS usage.

2. Related work

Today the interest in data-based quantitative evaluation has increased due to the improved feasibility of in-vehicle sensor data. Naturalistic Driving (ND) studies have become helpful in understanding driving behavior in a driving context, investigating the complexity of driver and system interaction in ADAS. Data obtained from vehicle sensors, as the primary source of ND data, enable inobtrusive driver behavior evaluation in a time-efficient and reliable way. The great potential of analyzing vehicle data for diverse purposes is shown in various user-related studies [10-13]. Sensor-based data offers the possibility to determine individual user behavior, describe, categorize, and compare it to the average within a group. Furthermore, it is possible to identify specific use errors, change the use strategy regarding the ADAS, and assess the severity of identified problems. All of the above mentioned provide the possibility for the effective application of qualitative research methods focusing on an in-depth investigation of detected driver behavior.

However, to design data-driven personalized communication in real-time, it is not enough to only understand and categorize driver behavior regarding ADAS. There is also a need to assess the driving situation on the road and prioritize primary driving activities. Moreover, we need to estimate the driver's workload, including secondary task performance, not to hinder or interrupt driver activities with higher priorities. Thus, the driving event recognition and the driver workload estimation that consists of the evaluation of the primary and supplementary driving tasks are the main processes contributing to the framework.

A variety of methods for driving event recognition have been developed over the past ten years. In general, driver event recognition can be achieved through smartphone sensors [14-16], vehicle sensors [17-19], and social sensors [20]. The development of smartphone sensor technology is relatively fast and usually low cost compared to the vehicle sensors [19]. However, vehicle sensors provide more precise and reliable data. Additionally, vehicle sensors allow better data synchronization and support local data saving. Smartphone sensors are not designed to detect the vehicle environment. The position of the phone and its orientation are not always optimal for the reliability of data [21]. The data from smartphone sensors also depends on cloud computing, energy efficiency, and additional sensors that need to be added to achieve the desired results. Nowadays, when the number of vehicles with built-in telematics systems is increasing, the development of data acquisition methods utilizing on-board diagnostics looks likely to be the most natural approach for in-vehicle communication design. This will provide better integration of data regarding driving events, system and driver performance data.

To identify the right moment for driver-system communication, we need to improve the system awareness about the driver workload. We need to evaluate the driver distraction caused by primary driving activities and the driving situation on the road. We also need to consider the performance of secondary tasks that the driver can be involved in. Driver-system communication must only take place when a driver's workload is medium-low. The safety of a driver must always be prioritized.

According to Aghaei et al. [22], a number of studies with a focus on smart driver monitoring have been published. Several attempts were made to measure driver distraction and predict heavy driver workload due to the situation on the road. A considerable amount of research has focused on combining vehicle data with individual physiological measures [23-26]. However, the ability of driver workload estimation, based solely on vehicle sensors data, is also a prominent topic of research. For example, Li et al. [27], based on ND data, identified a correlation between driver distraction and steering entropy. They proposed a method for driver distraction prediction based on this correlation. Kircher et al. [28] illustrated how visual distraction could be predicted by calculating vehicle-based measures, such as throttle hold rate, steering wheel reversal rate, and speed variability. They found a relationship between vehicle-based measures and visual distraction, but the accuracy rate (76%) was not good enough to rely only on the results of this method. Kanaan et al. [29] investigated how ND data can be utilized to predict long off-path glances and secondary task engagement, which indicates the level of distraction. This research took into consideration the motor control activities with the aim of understanding if a critical driving context caused the driver distraction.

Although there has been significant progress in the development of methods for the detection of driver distraction and driver workload estimation, the quality of the results shows that further development is required. Moreover, many driver interactions that can cause a driver distraction (e.g., adjustments on the HMI panel or different activities on the phone) still cannot be further tracked. In general, the above research reveals that vehicle sensors cover the assessment of driver workload caused by primary driver activities in a better way. The evaluation of driver secondary task performance is covered less. Therefore, the means and methods for driver secondary task estimation need to be developed further.

3. Data-driven communication framework

The data-driven communication framework aims to facilitate ADAS usage by providing the driver with personalized support in various driving conditions. This support aims to improve the understanding of hidden system processes and explains the ADAS capabilities and limitations in real-time driving. Fig. 1 presents the framework design that will be described further in detail.

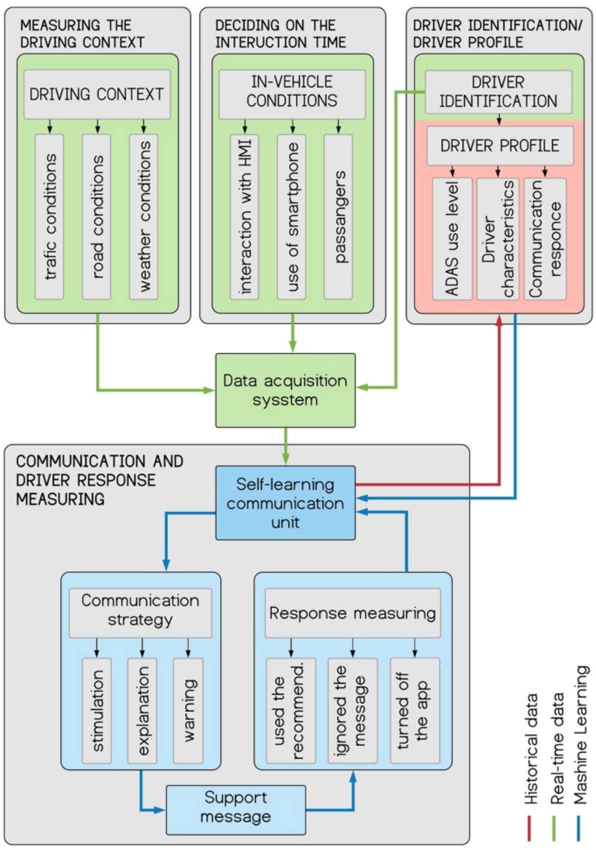

Fig. 1. Data-driven communication framework.

The data-driven communication framework consists of four predefined processes: (1) measuring the driving context, (2) deciding on the interaction time, (3) driver identification and driver profile loading, (4) communicating and response measuring. Three types of data are supposed to be used in the data-driven communication framework: the real-time data, historical data, and data generated through the Machine Learning (ML) process as the result of communication. Real-time data has to be used for the driving context measuring, driver identification, and measuring of the driver workload to ensure that the provided support will not distract the driver from more urgent tasks. Historical data needs to be used to load the respective driver profile to design a personalized communication strategy for the driver. The driver profile in this context is the sum of the parameters that allow understanding of how the particular driver usually uses the ADAS and vehicle itself. All driver profile parameters need to be recorded after every driving activity and saved as historical data for the driver. Both real-time data and historical data are based on Controller Area Network (CAN) bus data. It is necessary to use an in-vehicle data acquisition system, which reads CAN bus data and allows the real-time transfer of data to the self-learning communication unit.

The self-learning communication unit aims to integrate real-time and historical data processing analyzing the input and making decisions on the communication strategy, interaction time, communication process, and measuring the driver response. Data generated as an outcome of ML processes, needs to be saved as historical data and considered during the next driving activity.

3.1. Measuring the driving context

The driving context is the summary of external factors that affect driver behavior while using the evaluated system [30]. For the ADAS specifically, the driving context is defined as the aggregation of traffic, road, and weather conditions that, in association, encourage or discourage the ADAS usage. The driving context plays a central role in designing the communication between the system and the driver. ADAS, due to its limitations, does not perform in all driving conditions. Therefore, to be able to support the drivers in various driving situations, all contextual data affecting the ADAS performance needs to be collected. Driving context variables that are relevant for the ADAS driving context assessment are presented and described in Table 1.

Table 1. Summary of driving context variables for the ADAS assessment.

Driving context variables	Description
Wiping status	to detect heavy rain or snow
Fog illumination	to control visibility on the road
Ambient temperature	to exclude slippery road conditions
Lane markings reading	a precondition for ADAS performance
Speed limits	to identify the road type
Driving speed	to see the deviation from speed limits
Driving distance	to determine the distance between changes
Braking/Acceleration	to identify condense traffic

The driving context description, however, is not something predefined or stable. It highly depends on the evaluated objectives [30] and therefore needs to be set accordingly for every evaluated function. Thus, more variables can be included, depending on the selected ADAS.

Moreover, according to SAE International [1], there are three primary actors in driving with ADAS: the driver, the ADAS, and other vehicle systems and components that the ADAS performance depends on. The effect of the other vehicle systems and components also need to be considered as a part of the ADAS context while the prompt message is designing.

3.2. Deciding on the interaction time

A driver's primary driving activities (such as driving speed control, steering, braking, acceleration, and others) together with the driving context supervision (such as the road in front, road signs, traffic situation, etc.) demand a high concentration from the driver. To achieve a safe communication and avoid the driver's distraction from tasks with higher priority, the driver's involvement in different driving tasks needs to be considered before communication starts. The system must be designed in a non-distracting, supportive way.

To understand the driver workload, not only primary driving tasks but also secondary task performance needs to be evaluated. Secondary task performance (such as driver activities on the human-machine interface, usage of the mobile phone, distraction from the passengers, and similar) is focused on the evaluation of in-vehicle conditions in this framework. Estimation of in-vehicle conditions contributes to the overall driver workload assessment, which needs to be done prior to the communication moment.

Moreover, communication for primary driver activities and other more safety-related processes in the vehicle always needs to be prioritized. The support message from this framework can be sent only if the situation outside and inside the vehicle is stable, and the driver does not have a heavy workload or highly demanding tasks.

3.3. Driver identification and driver profile loading

To be able to decide if a particular driver needs additional stimulating communication, we need to identify the driver's identity. It will help to connect the correct driver profile to the specific driver. The driver profile in this framework implies:

- *Level of ADAS usage:* total driving time, total driving distance, driving start/end time, ADAS activation start/end time, ADAS statuses (active mode, standby mode, off mode), activation duration time, activation duration distance, longitude/latitude for all activations and other.
- *Level and types of driving activities:* number of driving events per day/month, number of kilometers driven per day/month, driving event types (long/short DCs, inside/outside the city), etc.
- *Driver characteristics:* active/passive driving style, the driving mode used, etc.
- *Driver response to the communication:* after the contact with the driver is established, the driver's reaction needs to be measured and saved together with the rest of the driver profile data. This will enable the real-time adjustment of the communication strategy, according to the driving response. The driver profile needs to be updated after every single driving event, adding the driver performance data during the last driving event to the driver profile.

3.4. Communication and driver response measuring

Several communication strategies can be used, depending on the common issues identified during the historical data evaluation. The examples of the communication strategies are the stimulation, explanation and/or warning strategies. The stimulation strategy can be used when needed to encourage drivers to use the system in specific conditions where the system works typically well.

The explanation strategy can be used to explain the deactivations of the system. If the driver understands why the system behaves as it does, the driver can learn the system's limitations more quickly. This will positively affect the driver's perception regarding ADAS as a reliable system that works perfectly according to the set limits. The warning strategy can be used to raise the driver's attention in situations where the system performance is not stable or is about to deactivate. The warning strategy aims to prevent cases leading to the mode confusion.

The flow chart describing the decision-making process in the data-based communication framework (Fig.1) is illustrated in Fig. 2. According to the framework design, historical data is used to identify the individual communication strategy. If the driver is new for the system, communication will not be provided until a significant amount of data on this driver is collected and analyzed. The feasibility of communication is decided based on real-time data by evaluating the driving context, in-vehicle conditions, and complete vehicle performance. If the overall conditions are considered as equal or less prioritized, the communication will take place. Otherwise, it will be postponed as any secondary task for a driver. When communication with the driver takes place, the driver's response to this communication is measured. The response measuring is based on ML algorithms; the data is analyzed in real-time. Depending on the driver's reaction, the number of scenarios is proposed. The primary purpose is not to guide the driver all the time, but allow him/her to decide and act independently. Therefore the "day off strategy" is implemented, aiming to exchange ADAS support with free driving activity. If the driver shows an improvement of ADAS usage during the system's day off, the communication strategy will be adjusted or even disengaged.

Furthermore, the communication strategies need to be optional for a driver. As soon as the driver understands the ADAS limitations, he/she should be able to disengage from the explanation about ADAS limitations. If the driver does not want prompting messages, he/she should be able to turn the stimulation strategy off. The communication strategies need to be adjusted in real-time, based on the data saved in the driver profile. For example, if the driver turned off or ignored the system message, this should be considered in the next event.

4. Discussion

The proposed data-driven personalized support is a novel approach based on vehicle data utilization. Analysis of

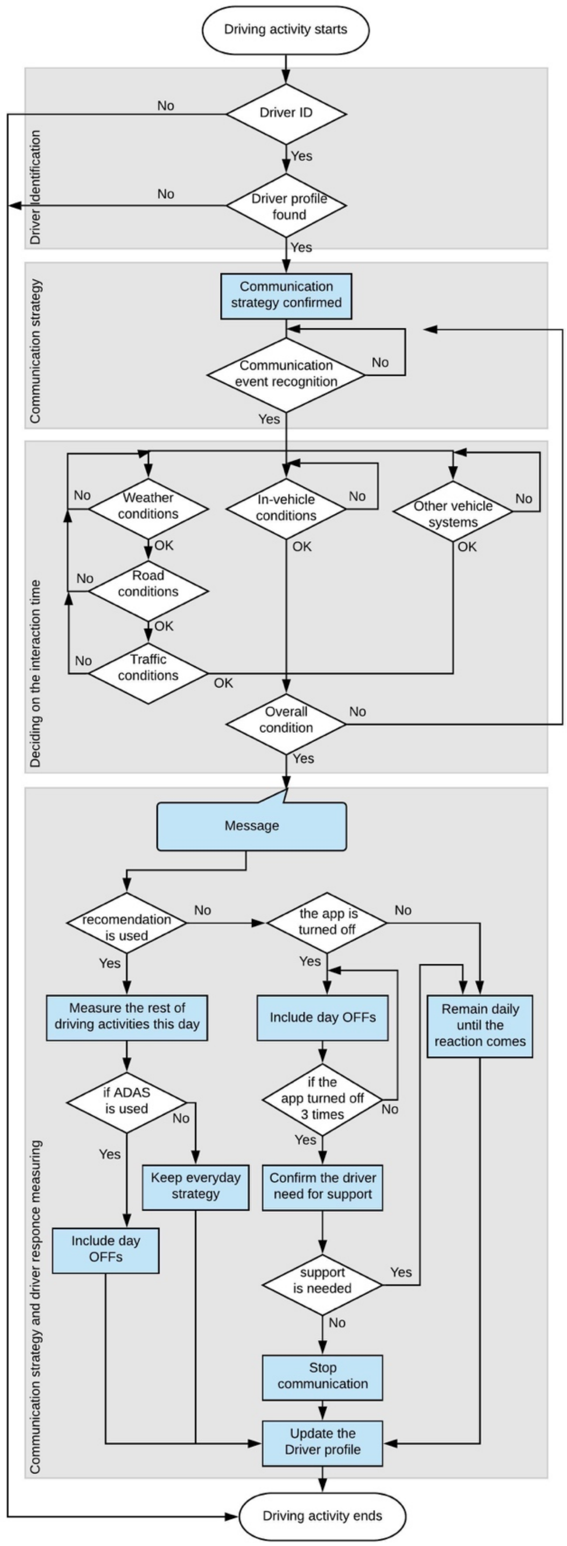

Fig. 2. The flow chart of the decision-making process for the data-driven communication framework.

historical and real-time data helps to understand the usage of in-vehicle functions, and subsequently provide personalized assistance to the drivers, explaining the implications, applicability, and limitations of the ADAS functions. The framework contributes to the development of methods for automated driving event recognition, methods for real-time driving context assessment, and ML algorithms, creating new opportunities to design data-driven support for smart in-vehicle systems, like ADAS.

Since data-driven support is a relatively new topic for the automotive area, the feasibility of all data types used in the framework needs to be assessed. The data feasibility mostly depends on the particular OEM's industrial practices on data utilization. In the course of this research, three main limitations leading to low availability of the vehicle data were detected.

Firstly, the data in the automotive industry is traditionally linked to the vehicle's ID, but not the driver's ID. The driver recognition unit is often absent in the current vehicle models. However, driver recognition is a critical factor for this framework and any driver-oriented research. We need to know who is operating the vehicle to use correct historical data in the driving profile to make the right choice regarding the communication strategy. Several methods for driver identification [31,32] and driving style recognition [33,19] have been proposed. This research is a step forward in the understanding of future perspectives regarding driver identification. Consequently, methods mentioned above can be tested as an indirect driver identification in this framework.

Secondly, the analysis of vehicle data for many years was focused mainly on the evaluation of system performance. As a result, we are now better informed about the status change of the system, rather than about understanding which driver interactions with the system led to this change. The capacity for capturing the user-related data is often limited. As previously mentioned, the assessment of driver activities regarding the secondary task performance (e.g., changing route at the navigation system or making a phone call) is not covered by the CAN bus data. This limitation becomes one of the main constraints, leading to an incomplete set of data information that is needed for the assessment of driver secondary task performance.

Finally, one of the limitations is connected to the quality of the driving context description received through sensors data. The detailed description of a dynamic driving context obtained through vehicle sensors data (e.g., oncoming-traffic, uphill/downhill driving, curving roads) is not fully determined and needs to be developed further. The detailed description of the driving context also contributes to a better driving event recognition process. Overall, better driving context-awareness improves the quality of the decision-making process prescribed by the proposed framework.

During the design validation stage, which planned as a next step, design improvements will be considered. The description of the driving context and the "smart" communication strategy have to be a focus of the validation process. Considering the current limitations, we are planning to use only drivers who are the sole users of their vehicles. To extend the framework applicability to the concept of shared vehicles, the problem of in-vehicle driver recognition needs to be solved.

Conclusion

In this paper the design of a vehicle data-driven communication framework that utilizes historical and real-time data to support ADAS users is proposed. The aim of the designed framework is to develop driver understanding regarding the ADAS performance, illustrating its capabilities and limitations in real-time driving situations. Communication of this type can improve driver confidence while using ADAS and consequently can increase its usage.

However, the limitations regarding the data feasibility identified in this research might restrict the framework applicability. Thus, the means and methods for better development of data support in the current framework need to be further investigated. Better data feasibility will contribute to a higher level of awareness regarding the driving context and driver state at the moment of the driver-system communication. Moreover, we suggest that subsequent research needs to be focused on developing methods for driver recognition and driving event recognition. These methods can allow the development of new personalized solutions for driver-system communication in the dynamic driving task.

The implementation of this communication can potentially improve the driver comprehension of the ADAS complexity, which will have a positive impact on developing the trust toward the automation in general and make the transition to a higher level of automation easier.

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