Personalization in Advanced Driver Assistance Systems and Autonomous Vehicles: A Review

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Abstract—The field of advanced driver assistance systems (ADAS) has matured towards more and more complex assistance functions, applied with wider scope and a strongly increasing number of possible users due to wider market penetration. To deal with such a large variety of use conditions and usage patterns, personalization methods have been developed to ensure optimal user experience and supplied system function. In this paper we review personalization approaches for ADAS systems that target an adaptation to the drivers' preferences, driving styles, skills and driving patterns. We discuss the general assumptions on which personalization in the automotive context is based, the general design of personalized ADAS, the current approaches, and their practical realization and point out open issues in the design and implementation of a personalized driving experience.

I. INTRODUCTION

Personalization of products and services in the sense of "to change or design (something) for a particular person" is not a new concept but has gained considerable interest from various disciplines over the last 20 years [1], [2] when advances in information and web technologies have made it possible for service and product providers to scale personalization from the basis of a one-to-one personal relationship to an individual customer or user to an automatized service based on the analysis of data collected on the individual preferences and behaviors of a huge number of users or customers.

While the general concept of personalization is intuitive, the understanding and goals of personalization differ between various disciplines and researchers [3], [4]. Here we will focus on personalization from the perspective of human-machine interaction and view it as a means to make technologies both more acceptable and useful for people. This is especially important in the area of advanced driver assistance systems whose goal it is not only to improve the driving experience but also to improve driving safety and to prevent accidents caused by human error. Since these systems can only take effect when they are actually used they must gain the drivers' trust, match their expectations with respect to driving behavior and avoid annoying the drivers with irrelevant recommendations and precautions. The drivers' expectations, however, differ from driver to driver as well as within individual drivers depending on their state and the driving situation. Hence driver assistance and related systems seem to be particularly suited to personalization.

Generally, personalization is categorized into explicit and implicit personalization. Explicit personalization requires users to state their preferences and to explicitly change the system by choosing a particular system setting that suits them best. Such an adaptable system restricts the user's choice to the system's offer but leaves them in direct control. The main drawback is the limitation to settings that the user can understand intuitively. For a more complex assistance function it is very difficult to design settings that e.g. go beyond a simple sporty/relaxed driving mode. Also the possible coupling effect of setting multiple parameters at the same time is very opaque to the user. Implicit personalization, in contrast, does not ask users directly for their preferences, but observes their behavior and derives a user model for the prediction of user preferences or behavior based on these user data. This review will mainly focus on approaches to personalization in ADAS that fall into the category of implicit personalization and learn a user model from the observation of driver behavior.

Driver modeling has been the subject of intense research in the past years, cf. [5] and [6] for recent surveys of the topic. Driver models have been used to predict driving maneuvers, driver intent, and driver state, among other things, usually with the goal to ultimately incorporate them into some driver assistance system. In this review we are not so much interested in driver models as such but rather aim at approaches that design personalized driver assistance systems by integrating the driver model with vehicle control.

The paper is organized as follows: In the next section, Sec. II, we outline the application areas of personalization in the automobile sector. In Sec. III, we discuss personalization in advanced driver assistance systems. We will start by lining out the general personalization process that is used in most approaches today. In the following we will review the state of the art in concrete approaches to the personalization of ADAS (Sec. IV) and of driving style in autonomous vehicles (Sec. V) against this background. Sec. VI briefly discusses open issues and Sec. VII concludes the paper.

II. PERSONALIZATION IN THE AUTOMOBILE SECTOR

Personalization in the automobile sector that goes beyond the customization of color and accessories and a memory function for the driver's seat, side mirror, and steering column positions, is still a relatively recent trend. In current vehicles

there are two main application areas of personalization: the personalization of the user interface of the in-vehicle infotainment systems and the personalization of driver assistance systems. A third application area in hybrid electric vehicles (HEV) is the prediction of the driving range.

A. Infotainment

The main target of personalization in vehicles has been the infotainment area. Based on the work by Langley [7], [8] on adaptive user interfaces, an early example is a driving route recommendation system [9], [10] that generates routes with the help of the driver, builds a model of the driver's preferences and refines this model through interaction with the driver. Along the same lines, but more recently, Letchner et al. [11] propose a route planner that incorporates traits of a recommender system to achieve personalization. They use a database of GPS traces to learn time-variant traffic speeds and include a driver's past GPS logs to propose routes that are suited to the driver's individual driving preferences. These ideas are taken a step further by Rodriguez Garzon [12] who proposes to include situation awareness into personalization: here the interactive user interface observes the user's situation-dependent interaction behavior and changes according to their situation-dependent preferences. The approach aims at real-time predictions of attainability of all destinations in a map and continuously adapts to user preferences using inverse reinforcement learning.

Another example of a personalized situation aware in-vehicle infotainment system is presented by Árnason et al. [13]. This system proactively recommends personalized audio content and uses car sensors to determine when to present this information in order to minimize distraction from the driving task. In [14] a personalized prediction system is introduced that makes adaptive suggestions to limit the necessary effort for standard infotainment operations.

B. Driver assistance systems

The personalization of advanced driver assistance systems (ADAS) is a more recent development than the personalization of infotainment systems. This may be due to the fact that the underlying technology only recently reached a sufficient level of maturity and availability to afford personalization. Additionally, safety and usability issues play a much more important role in ADAS if the system assumes control of the vehicle. We will give a more detailed discussion of personalization in ADAS with a focus on adaptive cruise control in the next section.

C. Hybrid Electric Vehicles

A different application area of personalization in the automotive context are hybrid electric vehicles (HEVs). HEV operation and driving range depend crucially on the actual driving behavior, i.e. speed and acceleration, and the road profile. Hence the prediction accuracy of the driving range can be expected to benefit from personalization. Li et al. [15]

present a personalized driving behavior monitoring and analysis system for HEVs. Ondrúška and Posner [16] predict the attainable range of HEVs based on the driver's generalized route preferences. Their approach significantly reduces the relative error in energy prediction as compared to driver-agnostic heuristics such as shortest-path or shortest-time routes.

III. PERSONALIZED ADAS AND PERSONALIZED DRIVING STYLE IN AUTONOMOUS VEHICLES

Advanced driver assistance systems (ADAS), such as adaptive cruise control, forward collision warning, lane departure warning, and lane change assistance, have become more and more common in the recent years and are no longer only available in upper-class vehicles. While the aim of these systems is to improve driving comfort and safety by relieving the driver of routine tasks and alerting them to potential problems, the driver's acceptance of ADAS interventions strongly depends on their skill, needs, and preferences. The goal in the personalization of ADAS is to make ADAS interventions more efficient and to improve the driving experience, and hence the usability of ADAS, by adapting the systems to the individual preferences of the driver. The same applies to the closely related field of autonomous driving: to be comfortable for different drivers, the driving style of an autonomous vehicle should be adapted to the individual driver's preferences.

In the following sections we will review the state of the art in the personalization of ADAS and of driving style in autonomous vehicles. We will start by lining out the general personalization process that is used in most approaches today and then discuss concrete approaches to personalized ADAS and personalized autonomous driving against this background.

A. Personalization Process

Current personalization approaches in the automotive field are mainly concerned with the technical implementation of a personalized functionality. Typically, they are data driven approaches, i.e. a model of the driver is learned from driving data. This model is either used to directly control the vehicle or to parameterize a controller. The main steps in the personalization process are:

1) Observe the driving behavior.
   The basic, albeit tacit, assumption in personalization is that the driver is most comfortable with a driving style that is similar to their own driving style. Consequently, driving data are collected in a field study from a group of drivers using an instrumented vehicle.
2) Build a model of human driving behavior.
   A driver model is learned from the data of an individual driver and directly used as part of the controller. Often the controller is divided into two parts: a high level controller, that models the driving behavior and whose parameters are adapted to the specific driver during personalization, and a low level controller, that is responsible for the actuation of the vehicle according to the input from the high level controller.

3) Validate the model.

Finally the resulting personalized system is validated and compared to a standard system to show that it actually adapts to different driving styles. Depending on the maturity of the approach this is done in 3 steps:

a) Off-line playback.

Here recorded driving data are fed into the personalized controller to verify that the controller correctly reproduces the observed driving behavior.

b) Simulation in a traffic simulator.

The personalized controller is tested in controlled traffic situations and often compared with a standard controller.

c) Field test.

Finally the personalized controller is implemented in a vehicle and tested in real traffic.

B. Driver Models

Driver models play a central role in personalized ADAS. They represent the driver and process information on the driving situation into actions on the vehicle's actuators. In ADAS they are used to mimic or to predict the driver intent and behavior to assist in a relevant manner. Currently most driver models represent the average driver, their parameters are fixed and they cannot adapt to different drivers. As human behavior is stochastic by nature and characterized by a high degree of inter- and intra-driver variability, the accurate modeling of driver behavior is a challenging task that has been studied in various disciplines. A recent review on driver models for ADAS from the control point of view is given by Wang et al. [5]. Lin et al. [6] review and discuss methods for modeling driver behavior characteristics.

IV. PERSONALIZED ADAS

The general approach in advanced driver assistance systems is to design the system for the average driver. While this is a reasonable design rationale, it ignores that drivers differ in their preferences. There are considerable interpersonal differences in driver preferences as well as there are intra-personal differences. Preferences of the same driver depend on their state and mood and may change over time and with experience. Especially with respect to safety and warning systems it is important to develop ADAS that do not annoy the driver with irrelevant recommendations and precautions so that they ignore or disable the system. The potential of personalization or adaptation to the driver in driver assistance systems has been realized early [17] but has become feasible only recently due to progress in sensory systems and increasing computational power on board of modern vehicles. Below we discuss approaches to the personalization of current driver assistance systems.

A. ACC

Adaptive cruise control (ACC) is a driving comfort system for the longitudinal control of the vehicle: it maintains a steady speed as set by the driver while keeping a desired time gap with the leading vehicle. The driver is free to choose a set speed but can only choose between a number of pre-defined time gaps which they adjust manually. ACC is generally perceived as a useful and comfortable system [18]–[20]. It is known since the introduction of ACC that drivers appreciate the freedom to choose different time gaps [17] according to their preferences.

In the personalization of ACC we can distinguish between group-based and individual-based approaches to personalization. In the former case drivers are assigned to one of a small number of representative driving styles for which an ACC control strategy is implemented. In the latter case, the ACC control strategy tries to best reproduce the driving style of an individual driver.

Rosenfeld et al. [21] present a group-based approach to the prediction of the driver's preferred ACC gap setting and when they tend to engage and disengage ACC. They cluster drivers who participated in a field test of driving behavior with ACC to create three general driver profiles and use these together with demographic information to predict the gap setting. The emphasis is on the analysis of the data using a regression model and decision trees and not on the practical application of the derived models. The models are not validated.

Another, more comprehensive, group-based approach to the personalization of adaptive cruise control with stop and go is proposed by Canale et al. [22]. The drivers are assigned to one of three pre-defined clusters based on the observation of their driving style. The cluster membership determines the parameters of a reference acceleration profile that serves as input to the low level controller of the ACC. The approach is based on data from field experiments and validated by off-line playback.

In the work by Bifulco et al. [23], [24], ACC is adapted in real-time to an individual driver based on the observation of their driving style. They propose an ACC controller framework based on a linear car following model that is solved by a recursive least squares filter (RLS) [25] to reproduce the time gaps observed in a short manual driving session. The vehicle trajectory is calculated from this personalized car following model using a linear, time-invariant dynamic system with acceleration and jerk as state variables. The vehicle actuation is then delegated to a low level controller. The personalized ACC is validated in off-line playback with satisfactory results. This approach distinguishes between two modes to achieve personalization: a "learning mode", that is activated on-demand by the driver, in which the current driving style is observed and the corresponding parameters of the car following model are learned, and a "running mode" in which the newly learned car following model is deployed to the controller.

Lefèvre et al. [26], [27] choose a different approach to controller design. They combine a learning based driver model that imitates the individual driving style observed from the driver with model predictive control [28] to create personalized driving assistance. The driver model consists of a hidden Markov model that represents human control strategies during car following, and Gaussian mixture regression to predict

the driver's most likely acceleration sequence. The model predictive controller then uses this acceleration sequence as a reference together with a confidence estimation and generates a safe acceleration sequence that complies with state and input constraints. The controller is evaluated by off-line playback and is able to reproduce different driving styles.

Wang et al. [29] develop a prototype of a longitudinal driving-assistance system, including ACC, that is personalized to an individual driver. They propose a linear driver model that, given the time gap to the lead vehicle and the inverse time to collision, simulates the driver's throttle and breaking pedal operations. Again the system operates in either a learning mode, in which the driver model parameters are identified by RLS [25] with a forgetting factor from the observation of manual driving behavior, or a running mode, in which the learned parameters are applied to the controller. Learning or identification of the driver model parameters takes place whenever the driver controls the vehicle manually and is following a lead vehicle. Once the parameters pass a sanity check and the process is converged, the new parameters are ready to be used by system control. This approach is the most advanced among the ACC personalization approaches: it has been implemented in a vehicle and validated by tests in real traffic.

B. Forward collision warning/ Brake assistance

Forward collision warning systems alert drivers of an impending collision with a slower moving or stationary car in front of them. The goal in personalized forward collision warning is to decrease the false alarm rate of the system and to increase the warning time to give the driver a longer reaction time. Muehlfeld et al. [30] present a statistical behavior modeling approach that estimates a driver specific probability distribution of the danger level of a situation to determine the activation threshold for a driver warning algorithm. The model is developed on driving simulator data and results in significantly earlier activation of the safety system than a similar, earlier model [31], [32]. Wang et al. [33] present a real time identification algorithm for warning thresholds by recursive least squares along the lines of their approach [29] to personalized ACC discussed in Sec. IV-A. Their approach is validated by off-line playback, reduces the false warning rate, adjusts its warning thresholds online and thus adapts not only to individual drivers but also to behavioral fluctuations in the same driver.

C. Lane Keeping

Lefèvre et at. [26] also apply their framework outlined in Sec. IV-A to lane keeping assistance (LKA) whose task it is to alert the driver when the system detects that the vehicle is about to deviate from a traffic lane. Here again the aim is to detect the lane departures early and to minimize the false alarm rate of the system. In this application of their personalization framework, the driver model is used to predict lane departures, i.e. it predicts steering as well as accelerations, and the model predictive controller keeps the vehicle in the lane. When it is likely that the vehicle is in lane change mode and the blinker is not set, the upcoming lane change is considered as unintentional and the controller takes charge of steering. The system is shown to be less intrusive and more effective at preventing lane departures than systems based on the standard Time to Line Crossing approach.

D. Cooperative Assistance

The concept of cooperative automation [34] in ADAS has been suggested as an approach to provide selective assistance functions based on direct requests, typically by speech commands. An example is an overtaking assistant [35] that answers naturally spoken information requests about relevant cars on neighboring and own lanes during a highway overtaking maneuver. Pacaux-Lemoine et al. [36] have discussed the importance of an adaptation of a cooperative ADAS to the personal competences and capacities of its human user. Schömig et al. [37] demonstrated in a simulator study that a speech-based assistance-on-demand, emulating an attentive co-driver, is preferred by the majority of drivers over visual head-up-display of information. They considered an intersection scenario where the driver has to observe multiple directions for performing a left turn into a major road. Recently Orth et al. [38] showed that the acceptance of the assistance on demand system can further be enhanced by estimating the acceptable gaps for each driver individually. The system combines both active and adaptive personalization by allowing the driver to control the situation-dependent activation of the assistant system and automatically tune the parameters according to the personally preferred driver behavior pattern.

E. Lane Change

Butakov et al. [39] develop a methodology for modeling individual driver behavior in lane changes. The method is envisioned as the basis of a possible lane change driver assistance system that may support the driver in assessing whether a lane change maneuver is feasible and safe considering their individual driving style. Lane changes are considerably more complex than the driving maneuvers discussed before. The driver needs to take into account three vehicles to judge whether a lane change is safe and comfortable: the leading vehicle in the own lane and the leading and following vehicle in the destination lane. The gap acceptance, the longitudinal adjustments to find an acceptable gap and the way the lane change maneuver itself is performed characterize the individual driving style and all three aspects are modeled by the authors. Avoidance of forward collisions is not considered. The approach uses a sinusoidal lane change kinematic model and a Gaussian mixture model to adjust the kinematic model parameters to the individual driving style. The models are intended to work in real time and to be updated continuously during driving to improve the accuracy. Data are collected from a field study and the models are validated against a test set from the same data to show the effectiveness of the approach.

V. Personalized Autonomous Vehicles

While the approaches discussed above are mainly motivated from the control point of view and directly aim at designing the control systems necessary to implement driver assistance systems, recently a second point of view emerged that aims at autonomous driving and that considers longitudinal and lateral control as building blocks for autonomous vehicle control. Those approaches often originate in robot control and the methods developed in that area, notably learning by demonstration [40]. Here the goal is to derive a suitable controller from the observation of human behavior. This approach is especially appropriate in tasks like vehicle control which can be easily demonstrated but for which it is difficult to state a cost or reward function explicitly. For learning often some variant of inverse reinforcement learning [41] is used which assumes that the human demonstrator follows an optimal policy with respect to an unknown reward function. Once the reward function is recovered, reinforcement learning can be used to find a policy that imitates the expert. Abbeel and Ng [41] show that their approach to apprenticeship learning can learn different driving styles in a stylized simulation of highway driving involving 3 lanes and 5 possible driving actions. Kuderer et al. [42] recently consider a more realistic scenario and stress the importance of driving style for user acceptance in the area of autonomous driving. They use a learning from demonstration approach to model individual driving styles. The driving styles are encoded by a cost function that consists of a linear combination of hand-crafted features, such as acceleration, jerk, following distance, desired speed, and that is derived by inverse reinforcement learning form observed data. The learning approach is embedded in a planning framework for an autonomous vehicle and results in optimized trajectories that are represented by 2D quintic splines in a continuous state space. For a viability test of their approach the authors focus on acceleration and lane change maneuvers. Data is collected from a field test and the ability of the approach to model different driving styles is demonstrated in simulation by off-line playback and the imputation of an off-line learned policy.

VI. Open Issues

So far we have discussed the emerging field of personalization in assisted driving. The field has gained interest in the recent years and a number of papers have been published that present approaches to the design of personalized assistance systems with tangible results, mostly in simulation but first steps towards prototypical implementations have been made. These approaches focus mainly on the technical side of personalization. However, since personalization is located at the interface between human driver and vehicle and is supposed to better adapt assistance systems or automated driving to the drivers' needs and expectations, the interaction between human and personalized system will require more attention. Below we outline some open issues that deserve further attention.

A. Driving style preferences in automated driving

The general assumption of personalization approaches is that the driver feels most comfortable with a system adopting a driving style that is similar to their own driving style. However, there is little empirical evidence to support this assumption. A discussion of the issue of driving style preferences in automated driving has only started recently. Scherer et al. [43] and Hartwich et al. [44] investigate the relation between manual driving style and automated driving preferences in a simulator study without motion feedback in both older (> 65 yrs) and younger drivers (< 45 yrs). They find that younger drivers tend to prefer their own driving style over other styles, while older drivers experienced their own driving style applied to highly automated driving as less comfortable and less enjoyable than other driving styles.

Yusof et al. [45] focus on differences between assertive drivers, who like to drive at or above the speed limit and enjoy high accelerations, and defensive drivers, who prefer a less risky driving style in manual driving. They simulated automated driving in a Wizard approach in real road conditions in which the participants were placed in the back seat. They found that both assertive and defensive driver groups preferred a defensive automated driving style. Basu et al. [46] conducted a similar study in a driving simulator without motion feedback and confirmed these results: Drivers typically prefer a more defensive driving style when they are passengers. Additionally, they found that while there was little correlation between the drivers' actual manual driving style and what they thought was their driving style in automated driving, there was a correlation between the automated driving style that drivers perceived as closest to their manual driving style and their preferred automated driving style.

These first empirical results indicate that finding an optimal driving style for individual drivers in automated driving is more complex than it may seem at first sight. Generally drivers will not be able to demonstrate their preferences to automated driving systems, but an additional interactive training phase will be necessary in which the driver will need to correct the system to find the driving style they perceive as most comfortable.

B. Personalization as a continuous process

Another aspect that is not yet fully covered is the treatment of personalization as a continuous process. Often personalization is viewed as a process that is finished once a personalized system is achieved. A personalized system that is continuously updated and improved using cues from driver interaction and thus implements personalization as a cyclic iterative process instead of a linear process is only realized by Wang [29]. Other authors [24], [26] are aware of variations in driver preferences and propose to consider on-demand re-calibration of the personalization parameters [24] to accommodate changes in driver preferences.

C. Driver assessment of personalized ADAS

Adomavicius [47] formalizes personalization as an iterative cyclic process that, transferred to the automotive context, consists of a cycle of (i) understanding the driver, i.e. observing their behavior, (ii) making available the personalized functionality to the driver, and (iii) measuring the impact and adjusting the personalization strategy if necessary. Comparing this understand-deliver-measure cycle with the current state of the art in the automotive personalization process as outlined in Sec. III-A, it becomes clear that this field is still quite young: while there are a number of approaches that envision the use of driver models for personalization in ADAS, only few studies actually implement a personalized controller for ADAS in simulation [24], [26], [33], [42] and only one study reports a prototype of a personalized controller [29] that may even be continuously updated by driver interaction. The authors state that they collected their subjects' opinion on the personalized system, thus almost closing the personalization circle, but do not report the results of the questionnaire study. Summarizing, personalized ADAS is generally not available yet to drivers and consequently a driver assessment of personalized ADAS is still missing.

D. The human machine interface in automotive personalization

Another important aspect in personalization, that has not been investigated yet, is the effect of the interface design between personalized vehicle and driver. Apart from the technical quality of the personalized system per se, the realization of the interaction between driver and vehicle will play a decisive role in the success of personalized systems since unintended usability problems may outweigh any benefit of personalization. Jameson [48] gives an overview over such problems, as e.g. the need to teach the system, unsatisfactory timing, the need for learning by the user, and inadequate predictability and comprehensibility, and outlines possible countermeasures. He stresses that these usability side effects need to be taken into account from the very start of the system design.

VII. Conclusion

In this paper, we review the current state of the art of personalization in advanced driver assistance systems and in autonomous driving. Our focus is on approaches that combine individualized driver models and controllers to design personalized systems. The primary goal in the personalization of ADAS is to improve the usability and hence the driver acceptance of the systems. This is especially important in safety relevant applications where alerts and their timing should be adapted to the driver's skills and needs in order to prevent disuse of the system. Furthermore personalization may contribute to improving the safety of assistance systems, e. g. by offering the possibility to increase warning times based on the observation of the individual driver. Finally, it is a means to improve comfort systems like ACC that can be adapted to preferred driving styles. Personalized systems are realized by learning driver models from the observation of driver behavior

and designing vehicle controllers that can be parameterized to adapt to specific driving styles using these models. Providing this technical basis for personalization has been the main focus in the field so far. Approaches to the personalization of ACC, forward collision warning, lane keeping, lane change, and autonomous driving have been published. They are mostly demonstrated in simulation based on field data. Work towards prototypes is in progress. The field is still relatively young and there are a number of open questions both with respect to the technical realization of personalization as well as with respect to the interaction between driver and personalized vehicle. Currently personalization is rather viewed as something that is done once at the beginning of a drive, or that can be requested repeatedly by the driver. Only few approaches take cues from the interaction with the driver for continuous improvement of the personalized system. With increasing availability of personalized driving assistance systems and autonomous vehicles the driver and their interaction with the vehicle will come more into focus. Studies of the drivers' assessment of personalized systems can be expected and the design of the human machine interface to personalized systems and the adaptation of this interface to individual driver preferences will become more important.

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