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A Survey of Personalization for Advanced Driver Assistance Systems

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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 user base due to wider market penetration. To deal with such a large variety of usage conditions and patterns, personalization methods have been developed to ensure optimal user experience. In this paper we review current approaches in the literature that demonstrate 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 with their practical realization and point out open issues in the design and implementation of a personalized driving experience. Based on this analysis we propose a general conceptual framework to personalization in ADAS. It suggests a modular decomposition for the next generation of personalized ADAS and HMI which can be expected to continuously adapt in interaction with the driver.**

I. Introduction

PERSONALIZATION in the sense of "to make something suitable for the needs and preferences of a particular person" has gained considerable interest from various disciplines over the last 20 years [1], [2]. In the automotive area personalization is still a relatively recent trend that is gaining momentum. This is not only reflected by the increasing number of academic publications in this area but also car makers have realized the potential of personalization and announced concepts for personalized vehicles, e.g., [3]–[5].

While the general concept of personalization is intuitive, the understanding and goals of personalization differ between various disciplines and researchers [6], [7]. 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.

In the automotive area, advanced driver assistance systems (ADAS) are a very important application area for personalization. ADAS have matured over the last years and have become available to a larger group of customers. Their aims are to prevent accidents caused by human error, to inform and warn the driver on possible dangerous situations and to generally improve the driving experience and make driving safer, more relaxed and joyful. While these are laudable aims, drivers will only use ADAS if they experience them as useful. This, in turn, will be the case if the ADAS are intuitive in usage and understanding, if they do not annoy the driver with irrelevant or untimely recommendations and precautions, and, in cases where the ADAS takes over part of the vehicle control, if its driving style matches the driver's expectations. However, drivers differ in their preferences, skills, and needs and, even worse, their preferences may change depending on their state and the driving situation. Hence the rationale for personalization in ADAS is to improve the driving experience and the performance of the assisted drivers by adapting the assistance system to their preferences and needs.

Table I
Pros and cons of explicit and implicit personalization.

Mode	Advantage	Disadvantage
explicit	feeling of control	requires attention & effort
		complexity & scope limits
implicit	no cognitive load	mismatch with user expectation
	complex adaptations possible	opaqueness

Personalization can be achieved in two ways (see Table I), either *explicitly* [6] by offering drivers to choose their favored selection from among a number of predefined system settings or *implicitly* [6] by estimating the drivers' preferences based on observing their behavior. The explicit possibility leaves the drivers in direct control but limits the possible options to a small number of standard system settings and to system parameters they can understand intuitively. The drivers also need to allocate attention and effort to this task which may be prohibitively distracting during normal driving. The implicit mode offers the chance of a more fine tuned individual and complex adaptation of the system at the risk that the driver may not always have a clear understanding of the behavior and configuration of the assistance system. This review will mainly focus on approaches to personalization in ADAS that fall into the second category of implicit personalization and learn a driver model from the observation of driver behavior.

Driver modeling has been the subject of intense research in the past years, cf. [8] and [9] 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 integrate these models with vehicle control to achieve personalized driver assistance systems.

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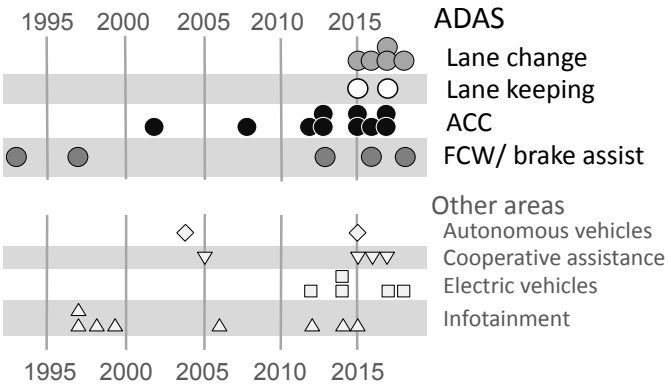

Figure 1. Time line of personalization in the automobile sector. The papers of this review are grouped by application area as discussed below. Our focus is on personalized ADAS, i.e. forward collision warning (FCW) and brake assistance, adaptive cruise control (ACC), lane keeping, and lane change. Other areas related to personalization in the automotive sector are infotainment, electric vehicles, cooperative assistance, and autonomous vehicles.

We will see that basically all ADAS lend themselves to personalization and that all parameters that determine the system behavior may be personalized: from preferred warning thresholds, frequency and timing in warning systems to features describing driving characteristics in systems that take over or support longitudinal and lateral control. Currently most existing prototypes focus on the personalization of a single ADAS, but with a growing number of ADAS becoming available in consumer vehicles, it will become necessary to develop a more comprehensive concept of personalization that takes into account how information on personalization can be shared between various ADAS components. In the closing sections we extend our previous review of this field [10] and propose a modular approach to the design of interactive, personalizable systems that clearly distinguishes between ADAS, personalization module, and human machine interface (HMI).

The paper is organized as follows: In the next, 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. Since the field is relatively young, there are a number of questions that have not been considered yet. Sec. VI briefly discusses these open issues. In Sec. VII we propose a general, unifying concept for a modular approach towards personalized ADAS that allows for a more general use of personal information for different ADAS functions. Sec. VIII concludes the paper.

II. Personalization in the Automobile Sector

Personalization in the automobile sector that goes beyond the customization of color and accessories, a memory function for the driver's seat, side mirror, and steering column positions, is still a relatively recent trend with an increasing number of publications in the recent years. Fig. 1 illustrates the development in this area. Apart from some early work on the adaptation of warning thresholds, the first target of personalization was in-vehicle infotainment, with the main focus on navigation systems. Next, work on the personalization of advanced driver assistance systems started, where personalization is following the development in this field: the first approaches dealt with the adaptation of assistance systems for longitudinal control, i.e., adaptive cruise control. More recently lateral control, i.e., lane departure warning and lane keeping assistance, has been included and first steps towards personalized lane change assistance have been made. Due to the experience with partially automated control in these systems, there is a growing awareness of the importance of driving style for user acceptance in the emerging field of autonomous driving. This is reflected in approaches that aim to learn their driving style directly from the observations of, and in interaction with, the driver. A third application area of personalization in the automobile sector are electric vehicles (EV). Here the main target is the mitigation of range anxiety by an accurate prediction of the driving range that strongly depends on the driving style. In the following, we will review these application areas of personalization with a focus on advanced driver assistance systems.

A. Infotainment

The main target of personalization in vehicles has been the infotainment area. Based on the work by Langley [11], [12] on adaptive user interfaces, an early example is a driving route recommendation system [13], [14] 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. [15] 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 [16] 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. [17]. 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 [18] a personalized prediction system is introduced that makes adaptive suggestions to limit the necessary selection 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 Sec. IV.

C. Electric Vehicles

A different, and increasingly important, application area of personalization in the automotive context are electric vehicles (EVs). EV 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. [19] present a personalized driving behavior monitoring and analysis system for hybrid electric vehicles (HEV). Ondrúška and Posner [20] predict the attainable range of HEVs based on the drivers 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. Tseng et al. [21] present approaches for personalized vehicle energy consumption prediction using participatory sensing data that are empirically shown to improve prediction accuracy. In the area of mobile devices applications, Ferreira et al. [22] propose an an EV assistant application that is based on tracking the driver's behavior, and thus creating a driver profile, from trip information, EV characteristics and driving style. This driver profile is then used for range prediction. Jiménez [23] use smart-phone sensor data to build real-time energy consumption models for EVs. Model accuracy can be improved significantly by including a classification of the driving style.

III. Approaches to Personalization

In this section we will first outline the steps of the most common current personalization approaches in the automotive field. After that we will briefly highlight the role of driver models.

A. Personalization Process

Current personalization approaches in the automotive field mainly target 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 then used as a surrogate for the driver, cf. Fig. 2 for a conceptual view on personalized ADAS.

The main steps in the personalization process are:

1) Observe the driving behavior.
   The basic, albeit tacit, assumption in personalization is that drivers are 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 evaluated by drivers 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.

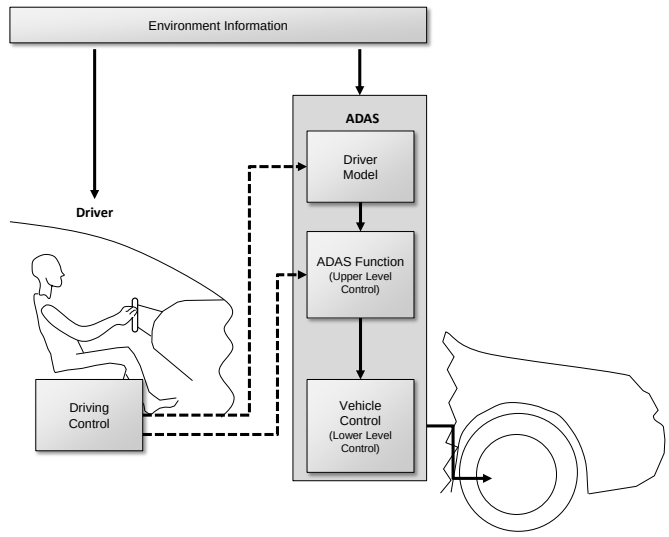

Figure 2. Personalized ADAS with pre-trained driver model. The driver model is trained on previously recorded data and then seen as a surrogate for the driver. In this context personalization of an ADAS function is implemented via an adaptation of the parameters of the driver model to the individual driving behavior observed from the driver.

We denote approaches that follow this sequence of steps as *personalization with a pre-trained driver model* (compare Fig. 2).

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 of the vehicle's actuators. In ADAS they are used to mimic or to predict the drivers' 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 non-deterministic 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. [8]. Lin et al. [9] review and discuss methods for modeling driver behavior characteristics.

IV. Personalized ADAS

The potential of personalization or adaptation to the driver in driver assistance systems has been realized early [24] 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 to 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 [25]–[27]. It is known since the introduction of ACC that drivers appreciate the freedom to choose different time gaps [24] 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. [28], [29] 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. [30]. 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. [31], [32], ACC is adapted in real-time to individual drivers 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) [33] 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 has been 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. [34], [35] 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 [36] 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.

A similar approach, also basing the control on model predictive control, is used by Ramyar et al. [37]. In their approach the driver is modeled by random forest regression [38], and the system uses rule-based switching between path following mode, car following mode, and lane change mode.

Chen et al. [39] note the importance of continuous on-line learning from the driver. They propose a personalized adaptive cruise control system that can adapt to driver strategies in dynamic traffic environments by using a reinforcement learning approach, Neural Q-Learning [40], to realize the high level driving strategy in combination with a PID controller for the low level control of the brake and throttle commands. The system is tested in simulation and found to be able to keep different expected distances in different cases in a smooth and comfortable way when learning from an experienced human driver.

Wang et al. [41] 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 [33] 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 has 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. [42] 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 [43], [44]. Wang et al. [45] present a real time identification algorithm for warning thresholds by recursive least squares along the lines of their approach [41] 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. Govindarajan et al. [46] demonstrate a method for personalized brake reaction time estimation for improved timing of forward collision warning systems. They use supervised machine learning to predict the reaction time from thermal facial analysis and EEG sensor readings.

C. Lane Keeping

Lefèvre et at. [34] 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 turn signals are 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 (TLC) approach. The work by Wang et al. [47] also aims to reduce the false alarm rate of lane departure prediction systems. They develop a personalized Gaussian mixture model based hidden Markov model to predict whether or not a lane departure behavior will be corrected by the driver without warning. Based on this driver model, a warning strategy is developed. The proposed method is validated in off-line playback and outperforms the standard TLC and a TLC-directional sequence of piece-wise lateral slopes method.

Wang et al. [48] present a personalized dynamic control strategy for the steering ratio of vehicle steering systems that aim to assist drivers in tracking a given path with smaller steering wheel angles and change rate of the angle by adaptively adjusting the steering ratio to the drivers path-following characteristics. The system is validated in a simulator study and found to improve the drivers' task performance as well as their mental and physical workload in path following. Schnelle et al. [49], [50] also develop personalized driver steering and desired path models that can replicate each drivers steering wheel angle signal for a variety of highway and in-city maneuvers.

D. Cooperative Assistance

The concept of cooperative automation [51] 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 [52] that answers spoken information requests about relevant cars on neighboring and own lanes during a highway overtaking maneuver. Pacaux-Lemoine et al. [53] have discussed the importance of an adaptation of a cooperative ADAS to the personal competences and capacities of its human user. Schömig et al. [54] 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. [55] 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 an active and an adaptive approach to personalization by allowing the driver to control the situation-dependent activation of the assistant system and automatically tuning the parameters according to the observed driving patterns.

E. Lane Change

Butakov et al. [56] 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. Vallon et al. [57] develop a data-driven model of the lane change decision behavior of human drivers that does not depend on the driver's explicit initiation of the maneuver by using the turn signal lever. The lane change decision is made by a support vector machine (SVM) based classifier. Based on this decision, model predictive control is used to follow the reference trajectory while satisfying comfort and safety constraints. The model is validated in off-line playback and is shown to be able to learn individual driving behaviors for different drivers.

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 employ methods developed in that area, notably learning by demonstration [58]. 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 [59] 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 [59] 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. [60] 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 usage 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 the human driver and the vehicle and is supposed to better adapt assistance systems or automated driving to the drivers' needs and expectations, the interaction between the human and the 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 drivers feel 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. [61] and Hartwich et al. [62] 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. [63] focus on differences between assertive drivers, who like to drive at or above the speed limit and enjoy high accelerations, compared to defensive drivers, who prefer a less risky driving style in manual driving. They simulated automated driving in a Wizard of Oz 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. [64] 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. In fact, they preferred a style which they believe is their own, even though their actual driving style tends to be more aggressive.

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 something that is finished once a personalized system is achieved. Yet Adomavicius [65] formalizes personalization as an iterative cyclic process that, if we transfer it to the automotive context, consists of a cycle of (i) understanding the driver, i.e., observing the driving

behavior, (ii) making available the personalized functionality to the driver, and (iii) measuring the impact and adjusting the personalization strategy if necessary. Wang [41] was one of the first to replace the commonly found linear approach with such a continuously updating and improving approach. More recently Chen et al. [39] were the first to address the necessity of continuous on-line learning in personalized ACC and, by using a reinforcement learning approach, to apply a learning model that is explicitly designed to learn in interaction with its environment. Other authors [32], [34] are aware of variations in driver preferences and propose to consider on-demand re-calibration of the personalization parameters [32] to accommodate changes in driver preferences.

C. Driver Assessment of Personalized ADAS

A key element of the understand-deliver-measure cycle of Adomavicius is the assessment of the impact of the personalization. This requires a personalization which can be assessed by the driver in relevant situations. When looking at the currently found 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 [32], [34], [45], [60] and only one study reports a prototype of a personalized controller [41] that may even be continuously updated by driver interaction. The authors state that they collected their participants' 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 usability problems may outweigh any benefit of personalization. Jameson [66] 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. A General Future Concept Proposal for Personalization in ADAS

Future approaches to more advanced personalized ADAS need to take into account both explicit and implicit personalization methods and should be capable of real-time and interactive adaptation of their parameters.

We propose that such an operation mode will require a clear decomposition of the main function blocks, as we visualize in Fig. 3. The three main system component columns in Fig. 3 refer to

i. HMI functions that provide the interface between driver and vehicle,
ii. a personalization system that models individual characteristics of the driver and their individual driving history, and
iii. the ADAS function(s) with parameters that can be adapted based on personalization.

By this decomposition we suggest to separate the driver modeling from the HMI and the actual ADAS function to allow for a more general use of personal information for different ADAS functions. This separation is particularly important if the system performs a continuous adaptation in interaction with the driver. In addition to the internal interactions, all contributing system component columns in the graph as well as the driver need continuous access to the dynamic environment information. Information passed within the system should always be interpreted in relation to this environment context. In the following we explain the functional columns in more detail:

Explicit and implicit HMI. The interaction of driver and vehicle is carried out via the human-machine-interface (HMI). Some HMI input devices are directly associated to the primary driving task, like steering wheel, brake, gas pedal, and indicator. They serve as the main control input for the vehicle, but they may also be used to infer individual driver characteristics, like driving style or skill. With respect to their use for personalization, we define these channels as *implicit* HMI, because they can convey information for implicit personalization. Here two cases can be distinguished: (i) Normal driving patterns of an unaware driver are observed and used for estimating a driver model that is later used for personalization. (ii) The driver deliberately chooses or modifies the current primary driving control in order to influence the immediate or later actions of a personalized ADAS system. A simple case may be where the driver uses a primary control to overwrite or correct a partially automated ADAS function (e.g. manual acceleration to overwrite a conservative gap setting for an ACC system). The situation gets considerably more challenging in ADAS shared control responsibility modes where driver actions directed towards the implicit personalization have to be distinguished from undirected regular driving control.

We define *explicit* input channels as those HMI input devices which are not required for the primary driving task. Typical examples are touch screens for infotainment and navigation, speech recognition, or recently also gesture input. Explicit HMI channels are used for deliberate driver-initiated explicit personalization with its pros and cons (cf. Table I).

Analogously to the HMI input channels, we differentiate between *implicit* and *explicit* HMI feedback channels. An implicit feedback channel is determined by the primary driving task and the physical reaction of the car to the combination of human and machine control through an ADAS. In the example of an emergency braking system, the driver directly notices when the vehicle activates the brakes which also informs

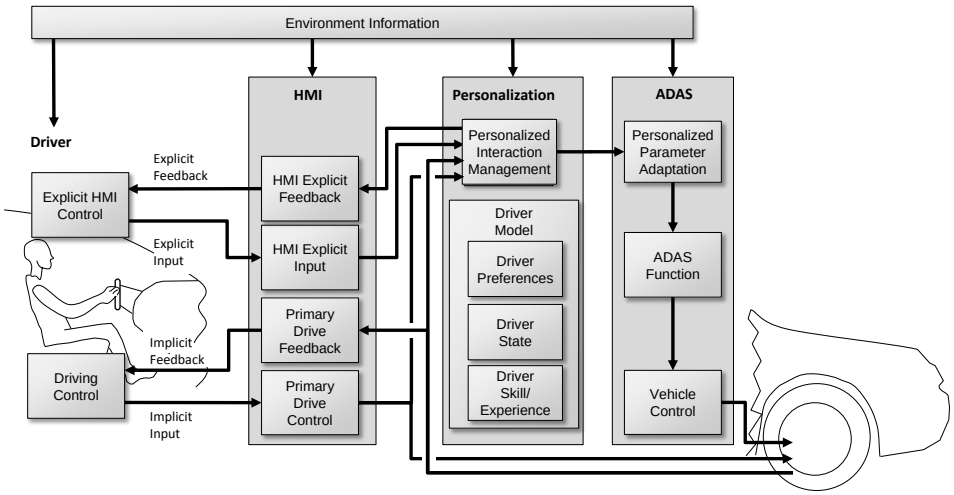

Figure 3. Our future concept proposal for a modular approach towards a continuously adapting personalized ADAS and HMI. The HMI components interact via explicit channels (switches, touchscreen, speech input, etc.) and implicit channels (steering, brake, gas pedal) with the driver. Personalization components model driver characteristics and preferences independent of single ADAS functions. ADAS functions need to interpret the driver parameters to adapt their internal function model to the driver.

them on a critical situation. Similarly, in the "car gesture" concept [67], the physical reaction of the car is used for implicit communication of warnings. Weak evasive steering movements are induced to inform the driver about approaching dangers on or next to their lane. Explicit HMI feedback channels, on the contrary, are not directly determined through the primary driving task and use channels like lights, displays, sound, or haptic feedback.

The HMI must capture all relevant explicit and implicit driver input and provide adequate explicit and implicit feedback to the driver in a way that can be understood well and merged intuitively with own action plans and patterns.

We believe that also the basic operation of the HMI should be personalized to better adapt the interface to the driver's needs and capabilities. We attribute the personalization of the HMI, however, rather to the personalization system component, while the HMI supplies the basic channels and interface devices to the driver.

Personalization Component. The personalization component models the driver with respect to preferences, state, skill, experience, and other individual traits or states. It then supplies personal parameters to the adaptable ADAS system. Additionally it should monitor both explicit and implicit driver input and vehicle feedback to supply suitable personalized feedback via the HMI. A typical example case may be the adaptation of the HMI depending on the current skill level of the driver and their experience with the personalized ADAS system. The latter will be of particular importance for continuously adapting systems. These adaptations have to be made transparent and understandable to the drivers such that they can establish a mental model of the system workings and build trust in the system [68], [69].

ADAS Component. The ADAS is responsible for contributing to the vehicle control or supplying the driver with information and warnings. Based on the driver characteristics delivered from the personalization system, internal parameters are adapted using an appropriate mapping to the driver model. The modular separation of personalization and ADAS components ensures that multiple different ADAS may use the personal information differently to adapt their optimal settings.

Considering the current state of the art there are no personalized ADAS prototypes yet that include the full functional set of components as sketched in Fig. 3. We expect that this clear decomposition into a strongly modular approach towards personalized ADAS will be particularly beneficial for more complex future scenarios with multiple assistance functions. In this case the different assistance functions will contribute different aspects to the driver model. It is then the role of the personalization component to build a coherent representation and adapt the different assistance functions in a consistent way.

VIII. Conclusion

We have provided a survey of the current state of the art for personalization in advanced driver assistance systems and autonomous driving. In our overview we concentrated on methods that combine individual driver models and controllers for the design of personalized ADAS. The main target in personalizing ADAS is to improve driver acceptance and system usability. This is relevant in safety critical applications where warnings and their timing should be adapted to the driver's skills and needs for preventing disuse of the system. Personalization also contributes to safety in adapting warning times to the individual driving skills and patterns. Similar adaptation can be applied to comfort functions like adaptive cruise control.

Personalized ADAS are implemented by training driver models from driver behavior observation and then designing vehicle controllers that can be parameterized to adapt to specific driving styles using these models. Consequently, a first main focus in the field were adaptable and parameterized models for ADAS functions like adaptive cruise control, forward collision warning, lane keeping, lane change, and

autonomous driving. While most demonstrations are carried out in simulation based on real field data, some work towards real prototypes is in progress.

Since the field is rather young there are still several open questions with respect to the technical realization of personalization as well as the interaction of driver and personalized vehicle. Personalization is currently mainly investigated as a procedure carried out once at the beginning of a drive or requested repeatedly by the driver. Most approaches lack concepts for a continuous interaction with the driver for an incremental improvement of the personalized ADAS. The increased availability and capability of personalized systems will, however, require more intuitive sophisticated HMI models to make the full function range easily accessible to the driver. We expect that this can be best achieved by also personalizing the HMI to individual driver capabilities, needs and preferences. Another important concept for the HMI design is the differentiation into explicit channels where HMI operation is not directly coupled to driving and implicit channels which employ the primary driving controls for implicit information transmission to the personalized ADAS. We believe that special care will have to be taken to make the role and effect of the two channels understandable to the driver.

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