Adaptation and Personalization in Driver Assistance Systems

Andrew Ponomarev[1,2], Anastasiia Chernysheva[2]
[1]SPIIRAS, St.Petersburg, Russia
[2]ITMO University, St.Petersburg, Russia
ponomarev@iias.spb.su, chernysheva.anastasiia@gmail.com

Abstract—**Driver-related factors (e.g., driver inattention) are a cause of majority of traffic accidents. To reduce the number of accidents and improve traffic safety a variety of driver assistance systems have been proposed. Today, many of these systems do not adapt recommendations and warning to the particular driver (having his-/her own driving style, reaction time etc.). However, in many cases utilization of personal characteristics and preferences may improve the quality of the driver assistance, besides if a driver's expectations about the functionality provided by the assistance system are not met, it may decrease the trust to the system and lead to turning it off, therefore ignoring its potential utility and influence on increasing the safety. In this paper we review scientific publications in the area of driver assistance systems and a) identify most widely used directions of personalization and adaptation in driver assistance systems, b) identify and describe the most widely used models and methods leveraged for personalization and adaptation, c) identify existing research gaps. The paper may serve as mapping study as well as a reference and a toolset of how to deal with driver variability in driver assistance systems.**

I. Introduction

According to the World Health Organization report [1], the number of annual road traffic deaths is about 1.35 million; a majority of these accidents can be attributed to human errors [2]. E.g., the US National Highway Traffic Safety Administration reports that 25% of the registered crashes were caused simply by driver-inattention [3].

To reduce the number of accidents and improve traffic safety by addressing human-related causes of traffic accidents the concept of (advanced) driver assistance system (or, ADAS) has been introduced. These systems aim to increase safety and support drivers by supplying relevant information about the environment, providing warnings in risky situations and automating some driving tasks to excuse the driver from manual control [4]. The functionality of driving assistance systems vary significantly (suggesting that it is a kind of an umbrella term); while some systems only provide warnings (visual, haptic or audible), other actively intervene in control when a potential risk is detected [5]. Currently, driver assistance systems perform a number of functions: antilock braking, adaptive cruise control, forward collision prevention, driver inattention and abnormal status monitoring to name a few.

Modern driver assistance systems vary not only by specific functionality but also by employed hardware and software as well as business model. While most of the driver assistance systems are embedded in the vehicle's hardware by manufacturer, there are also a number of independent third-party solutions, running on custom hardware (e.g., smartphone-based driver assistance systems [6], [7], [8].

There is a plenty of evidence (both common-sense and scientific [9]) that drivers vary significantly on goals (e.g., private and commercial) and driving habits. For some assistance functions this difference does not really matter (e.g., antilock braking system deals with mostly physics of friction), while for other functions (involving the processing of visual/audio signals/commands from the driver or recommending some actions to the driver) utilization of personal characteristics and preferences may improve the quality of the system. Another important aspect is that if a driver's expectations about the functionality provided by the assistance system are not met, it may decrease the trust to the system and lead to turning it off, therefore ignoring its potential utility and influence on increasing the safety [10], [11], [12].

The aim of this paper is to review scientific publications in the area of driver assistance systems a) to identify most widely used directions of personalization and adaptation in driver assistance systems, b) to identify and describe the most widely used models and methods leveraged for personalization and adaptation, c) to identify existing research gaps. Driver assistance is a complex area that includes not only systems that are aimed on the accident reduction, but also that provide trip related information to the driver. This paper focuses only on systems and approaches that are aimed on supporting driving tasks and reducing traffic accidents. In general, driving assistance system can be divided into three main modules: sensor's data preprocessing, dangerous event detection and recommendation processing.

First step is collecting data from different sensors and their preprocessing, so the driver assistance system could use it. If one system have to use data from different sensors models and even brands (this happens with systems, distributed as smartphone applications, because they are installed on different devices), the need to calibrate data to uniformed view may occur. This assumption was checked and rejected by [13]. The developers made conclusion, that further event detection does not depend on device.

Next step of driver assistance system is to process all given data to detect some events, such as aggressive lane change, reducing the distance to heading vehicle or driver drowsiness. This paper is mostly dedicated to personalization in such approaches.

After detecting the event the system has to inform the user about situation, warn him/her about dangerous state or produce some recommendation to prevent unwelcome situation. Here there is also a great field for development of personalized methods, because every driver will react differently on different signals and recommendation. So, that is where adaptive user interface methods are taking their place. Some adaptive user interface approaches are shortly described in [9] and [14] and won't be reviewed in this paper.

In parallel to user information, some built-in systems can perform actions to prevent dangerous situation (for example, adaptive cruise control systems). Some of such systems will be described further.

The paper may serve as mapping study as well as a reference and a toolset of how to deal with driver variability in driver assistance systems.

There is some thematic overlap with a recent review paper [9], but [9] focuses mostly on some active ADAS and autonomous driving systems, sidestepping, for example, personalization in driver monitoring. This paper reviews mostly driver assistance systems that perform driver monitoring and provide warnings and recommendations.

The rest of the paper is structured as follows. Section II describes research methodology. Each of the following sections discusses one of the research questions posed in Section II. Section III lists driver assistance functions where personalization is important. Section IV discusses driver characteristics that are taken into consideration by personalized driver assistance systems. Section V outlines main models and methods used for personalization. Sections VI and VII describe quality characteristics used to measure the effect of personalization and evaluation guidelines respectively.

II. Research Methodology

The general aim of the paper has been decomposed into a number of specific research questions:

1) What are the driver assistance subtasks where it is reasonable to personalize parameters of the system and adapt them to the particular driver (according to the authors of the published papers)?
2) What driver characteristics have to be accounted for in driver assistance personalization?
3) What are the concrete models and methods are most widely employed for personalization and adaptation in driver assistance systems?
4) What are qualitative and quantitative performance characteristics of driver assistance system are influenced by driver personalization and adaptation? How the efficiency of personalization and its effect are usually measured (in the current body of work)?
5) What is the accepted experimental methodology (existing benchmarks/datasets etc.) for personalization research in driver assistance systems?

These questions, first, set the specific targets during the analysis of the each publication, second, they structure the rest of the paper, as we dedicate one section to each of the questions.

Literature selection for the review was done in the following way. We searched the Scopus database (www.scopus.com) for papers title, abstract or keywords of which contained the following terms: *"driver AND (assistance OR assist OR recommend) AND (personalization)"* with no other restrictions.

We scanned the abstracts of the papers and selected only papers which abstracts contained a clear indication that one of the distinguishing features of the paper's contribution was some personalization and adaptation technique in the context of driver assistance or some reflection on the role of personalization in such systems.

During the analysis of the selected papers we also included some referenced papers that were not included into the initial set (probably, due to limiting keywords).

III. Personizable Driver Assistance Tasks

This section contains our findings about the driver assistance subtasks where it is reasonable to personalize parameters of the system and adapt them to the particular driver (according to the authors of the reviewed papers).

We found that currently elements of personalization are implemented in variety of driver assistance tasks. These "personalizable" tasks can be divided into the following categories.

A. Self-driving capabilities

Although the area of self-driving capabilities is studied mostly in the context of autonomous cars, some elements of vehicle "autonomy" are becoming typical for human-driven cars. The most prominent example is adaptive cruise control [9].

Adaptive cruise control system 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 predefined time gaps which they adjust manually [9].

The goal of personalization in adaptive cruise control systems is to mimic the acceleration profile of the driver to make the system behave as close to the driver as possible while maintaining the desired time gap.

For more detailed review of personalization in the context of self-driving capabilities the interested reader should refer to [9].

B. Monitoring capabilities

There are a number of driver assistance system's capabilities dealing with regular analysis of situation outside and/or inside of a vehicle and warning the driver in case some dangerous or urgent situation is detected.

We have found three types of monitoring where some research efforts has been undertaken to adjust the monitoring and classification of the events to the particular driver.

Forward collision warning. Forward collision warning systems alert drivers of an impending collision with a slower moving or stationary car in front of them. The goal of personalization in 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 (see [15]).

Lane keeping. The task of lane keeping assistant is to alert the driver when the system detects that the vehicle is about to leave a traffic lane. The aim of personalization is to detect the lane departures early and to minimize the false alarm rate of the system. The way to minimization of false alarm rate is modeling typical driving habits of a driver to better "understand" current intent by driver action monitoring (see [23]).

Drowsiness detection. Unlike the other capabilities mentioned under the category of driver monitoring, this one is targeted not on monitoring the situation around the car, but on monitoring the situation inside the car, specifically, the state of the driver. The goal of the system is to detect when the driver is sleepy and therefore his/her attention is reduced and provide some warnings to draw the driver's attention to the situation on the road, or some recommendations on how to effectively combat drowsiness. While there are two distinct features in drowsiness detection systems, i.e., determining the drowsiness state and recommending an effective countermeasure, in our research we have found only publications aimed on personalization of determining the drowsiness state. Personalization is especially important for drowsiness detection based on physiological parameters, as a) visual indicators of drowsiness are relatively similar (like yawning), while physiological indicators (photoplethysmogram, galvanic skin response etc.) are characterized by high variability, b) based on physiological parameters it is possible to implement early detection of drowsiness (before any visual indicators appear) (e.g. [16], [17], [18]).

C. Maneuver assistance

Maneuver assistance is a popular kind of the functionality of driver assistance systems. It provides visual, audial or haptic support while performing a maneuver by monitoring the situation (usually, outside the vehicle) and suggesting actions to the driver or warning about possible threats. Specifically, we have found evidence of importance of personalization for assistance in several typical maneuvers.

Lane change assistance. Lane change assistant monitors the situation in the lane vehicle is moving and adjacent lane and provides recommendations about acceptable opportunities of lane change (and also, possibly, required preparation – acceleration or deceleration). The rationale behind the personalization here is that different drivers have different acceptability criteria of the time gap in the adjacent lane and the relative speed. Providing recommendations without taking into consideration these individual preferences will decrease the driver's trust to the system and acceptance of the system in general [10].

Left turn assistance. Left turn (especially, from a minor road or on a non-regulated intersection) is complicated by a necessity to monitor the situation both from the left and from the right of the car. Left turn assistant helps the driver to monitor the approaching cars and estimate the expected time gap, as well as classify the time gap either as acceptable or not. The aim of the personalization here is to make the classification of the time gap as close as possible to the driver's natural classification, as different drivers perceive different gaps as acceptable/comfortable [12], [19], and [20]. It is worth noting that in the reviewed materials there were not found any references to right turn assistance. It may be due to the fact, that right turn is a relatively simple maneuver.

Route planning. The paper [11] proposes a personalized solution for intersection crossing, helping to select driving speed to optimize both fuel consumption and travel time (taking as many green lights as possible). The role of personalization here is twofold, first, on an upper level, it adjusts to driver's tradeoff between speed and energy consumption, second, on a lower level, it takes into account typical acceleration and deceleration styles of the driver, to make recommendations more natural for him/her.

IV. Driver Characteristics

This section discusses what particular characteristics and features are accounted in different kinds of driver assistance personalization and adaptation. A natural way to structure this section is by typical driver assistance tasks (derived in Section III).

A. Self-driving capabilities

The driver parameters taken into account for personalization of adaptive cruise control are: typical time gap to the car in the front, typical acceleration and deceleration (for more details refer to [9]). Typical here means that these parameters should be determined in the comparable context (i.e., following the other car).

B. Monitoring capabilities

Characteristics, that are used for monitoring driving state can be divided into three categories:

- driving vehicle characteristics;
- driver physiological characteristics;
- driver behavior characteristics.

Vehicle characteristics. Every car model has its own conditions, such as structure, weight, performance, depending on that vehicle behaves itself differently on the road. One of the application, that calibrate itself to detect events independently of different vehicle conditions, is SenseFleet [13]. Experimental evaluation of proposed approach shows that different car models may have different jerk deviation. Jerk is calculated as the time derivative of the acceleration magnitude. Another parameters, that are monitored for acceleration and steering event detection are average yaw rate, speed variation and bearing variation.

Vehicles vary in weight and tires width. It affects friction force and energy absorption (the wider the tires are the higher surface friction is the higher energy absorption will be and the

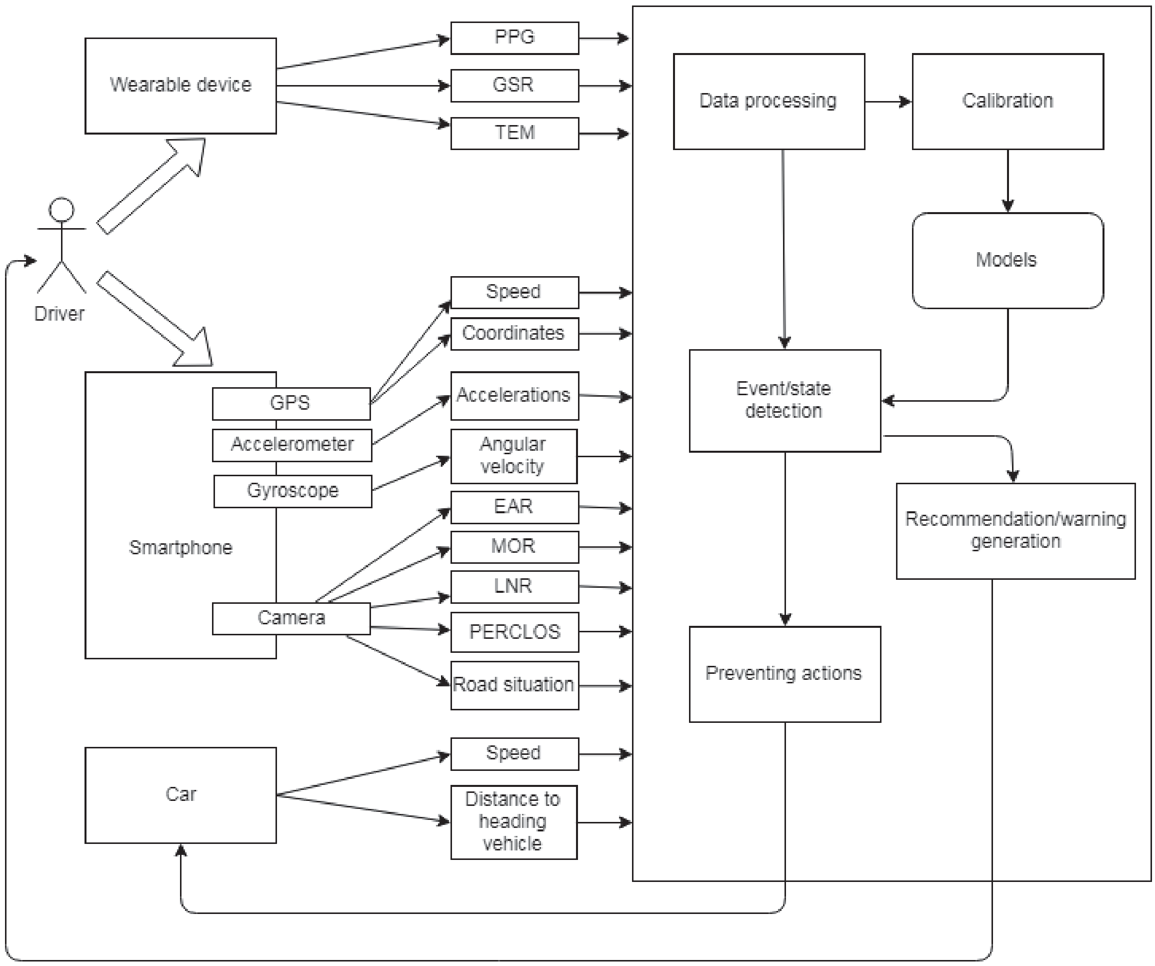

Fig. 1. Conceptual model of adaptive driver assistance system

heavier the vehicle is the higher energy absorption will be). Consequently, the real acceleration of vehicle and the one, experienced by the driver in the cabin, differ and every car model has its own difference value. To reduce the impact of this, developers of DriveSafe propose to calculate theoretical acceleration by multiplying angular and linear velocities and adjust accelerations events thresholds for every vehicle [21].

Driver physiological characteristics. Drowsy state can be recognized by eyes closeness, eye blinking rate, yawn or head bending. There is a research [18], that propose detect drowsiness by three feature: eyes aspect ratio (EAR – indicate eye blinking), mouth opening ratio (MOR – indicate yawning) and nose length ratio (LNR – indicate head bending, because the ratio of nose length to average nose length is measure of head bending). All these features are calculated by extraction facial landmarks from driver image using image recognizing methods. The size of eye (mouth and nose) can differ from person to person, so it is necessary to provide a calibration phase. During this phase average values of eye and mouth size and nose length for every person will be calculated. These values will be used as alert state values. Deviation from them will be the indicator of drowsy state.

In [16] a personalized classifier for detection of driver's drowsiness detection based on physiological data is proposed. It is based on the following driver characteristics, measured by a wearable device, described in [17]: photoplethysmogram (PPG), galvanic skin response (GSR), temperature (TEM), acceleration, and the rate of rotation. PPG is a signal that represents the change in blood volume in the blood vessels according to heartbeat. GSR is a signal that shows a change in skin conductance according to sweat gland activity.

Behavior characteristics. It is also possible to detect drowsiness by some driving characteristics such as lane deviation indicators. There are Time to Line Crossing, Mean Squared Error for lane position and heading error (angle between driving vehicle's direction and tangent line of driving lane). These lane deviation indicators proceed on the assumption that drowsy driver have problems in maintaining lane direction. There is an approach, that optimize indicator parameters to maximize detection accuracy [22].

In [15], proposing a forward collision detection, a driver is described by risk perception (unobservable variable) of a situation which is assumed to depend on two observable variables: time headway and inverse time-to-collision.

An important kind of behavioral characteristics is a temporal model of a driver, connecting driving situation (application-specific), state (lane keeping, lane change etc.) and control inputs applied in such situation and in this state (steering, acceleration). E.g., in [23] such model is used to detect possible lane departure.

C. Maneuver assistance

Considering maneuver assistance, it turns out that it is often impossible to name a single (and relatively simple) characteristic of a driver that is taken into account by a personalization routine. Instead, the whole process of personalization is aimed on learning some implicit decision rule inherent in the particular driver about safety and acceptance of a particular maneuver in a particular situation (described by a set of parameters). This inherent implicit rule is the most important driver-specific characteristic for this kind of driver assistance systems, however, it usually cannot be properly named unless by some rather vague phrase as "driving style". Having said that, in this section we mostly describe measurable parameters that are considered by the authors of different publications as significant for maneuver-dependent situation analysis (and therefore, the parameters used to learn driver-specific classifier of the maneuver acceptance).

The parameters taken into consideration while learning driver-specific decision rule for lane change are related to three vehicles: the leading vehicle in the origin lane, the leading vehicle in the destination lane and the following vehicle in the destination lane. Particular parameters taken into consideration are: relative speed between the subject and the vehicles of interest, distance between the subject and the vehicles of interest, the subject speed, direction of lane change and whether the lane change is mandatory or discretionary (mediated by blinker status) [10].

Also, if the gap is not acceptable, a driver has an option to align with the gap by increasing or decreasing the speed. In [10] the driver's preferences for longitudinal adjustment are captured by two parameters: the driver's willingness to perform adjustment and the preferred direction (both are encoded by empirical frequencies of the respective events).

In left turn assistance, one approach (implemented in [12], [19]) is to use detailed characteristics of driving: speed, longitude and latitude acceleration and steering wheel speed, collected in previous maneuvers. The other approach is just to model one personalized parameter – acceptable time gap [20].

In general route planning, two types of driver characteristics (preferences) are taken into account: low level (influencing acceleration and deceleration) and high-level (reflecting general priorities and values of the driver) [11]. Low level characteristics are: maximum speed (in certain context), typical deceleration while braking, acceleration profile – a model, describing dependency of the acceleration from the speed (after a full stop), and preferred speed of crossing an intersection (at green light) in each of the possible directions – straight, to the left and to the right. As for the high-level parameters, a driver is described by the compromise between time of the travel and fuel consumption (in a form of weights of the respective trip characteristics).

Fig.1 shows conceptual model of adaptive driver assistance system. There are represented some of possible options of measuring devices, sensor's data and collected characteristics. The system, which contains all of this data isn't considered in this paper. There are some devices with sensors, that provide data to system. One of the popular devices is smartphone, mounted on the windshield of the vehicle. It can collect data from accelerometer, gyroscope, GPS and cameras (back camera for road situation monitoring through lane or road objects detection, front camera for monitoring driver state such as drowsiness). Another device for monitoring driver state is some kind of wearable device, which can collect user's heart rate or temperature data. Furthermore, some system can include processing of data, provided by vehicle's sensors, such as speed or distance to heading object from radar. The system processes all collected data and pass it to event/state detection modules, which detect drowsy state or dangerous maneuvers. Some of data can be passed to calibration module to adjust personalized driver models. These models are used in event/state detection too. Depending on type of detected event, warning for user or recommendation to prevent dangerous situation is generated. The built-in systems with functions of lane keeping or adaptive cruise control can even intervene in vehicle's control (for example, to prevent unintentional lane changing).

V. METHODS OF ADAPTATION

This section describes specific approaches and methods that are used to adapt driver assistance to real (or expected) behavior of a driver. First of all, all these methods can be divided into two groups: explicit and implicit. In explicit methods of adaptation the driver sets the parameters of the assistance system him-/herself. Obviously, it can work only with the parameters that can be easily interpreted by human driver. Usually these parameters express a kind of preference or a goal, e.g., in [11] a driver can explicitly set the weights assigned to two objectives of the route optimization task – fuel efficiency and travel time. In implicit methods, the system tries to adapt based only on the analysis of driver's behavior. The methods of this group are much more numerous, and the rest of the section is dedicated to them.

A. Adaptive thresholds

A very popular technique in implementing driver assistance is using some threshold, separating acceptable values of some observable parameter from unacceptable. This technique is used in various driver monitoring (e.g., [13], [21], [18]) and maneuver assistance (e.g., [10]) systems. In the simplest case, thresholding is used for only one parameter (e.g., in [20] the left turn recommendation rule uses only time gap between vehicles – if time gap is more than the threshold, the assistant gives clearance for performing the maneuver), while in other cases there are several thresholds treated independently (e.g., in [8] there are independent thresholds on percentage of eyes closure and head nodding used to detect the drowsiness).

Usually threshold are set empirically. They are the same for different application's users, cars and road context. However, in practice thresholds can differ depending on user state and driving style, road situation, vehicle characteristics. Therefore, many driver assistance systems employ adaptive thresholds. This turns out to applicable when the accepted region is defined by a hypercube in the feature space and this hypercube is defined exactly by the (observable) parameters describing the driver. There are various different techniques to adapt the thresholds.

One of them is setting up a fuzzy system [24]. In this case, system performs two processes: calibration or fuzzification and normal functioning of application, based on fuzzy rules. Each fuzzy rule compares input variables with set of fuzzy values and outputs a type of event (e.g. aggressive steering).

Fuzzy system is implemented in SenseFleet application [13]. Calibration process includes collecting of a fixed number of input samples and the computation of their cumulative distribution function. After the collection of samples, the system adjusts the fuzzy variables and can start event detection process. In SenseFleet app each input sample consists of calculated from GPS and accelerometer speed variation, bearing variation, average yaw rate and jerk standard deviation. After calibration the system can determine each value as low, medium, high or very high (e.g. low speed variation). Fuzzy rule for detection of hard acceleration is:

if

(jerk standard deviation is HIGH or VERY HIGH) and

(yaw rate is LOW) and

(bearing variation is LOW) and

(speed variation is HIGH-ACC)

then event is acceleration.

So, the system checks for high speed variation and low yaw rate and bearing change.

Developers of SenseFleet application have noted, that fixed calibration phase can be non-representative because of abnormal conditions while calibration (if calibration is performed on low speed and accelerations, even normal acceleration will be marked as high). As a solution they suggest to use a continuous calibration, when input values are analyzed periodically. Another solution can be using dynamic calibration, when the system collect data for different speed and acceleration. Finally, system can use global parameters, that are computed from data, obtained from different users.

To overcome problem of prior calibration developers of DriveSafe application propose an adaptive fuzzy classifier, which implements online calibration process based on adjusting threshold using data, obtained in certain route section such as concentrated turns and uniformed accelerations [21]. Input samples of this app contain data from accelerometer (accelerations in longitudinal and transverse axis), GPS (linear velocity) and gyroscope (angular velocity).

For all features (a_z – longitudinal acceleration, a_y – transverse acceleration, linear velocity and angular velocity) are set fixed threshold. Velocities are precise and their thresholds don't need to be calibrated. At the same time a_z and a_y values depend on vehicle and need to be adjusted.

The a_y – acceleration in transverse axis – gives acceleration experienced by the driver. The vehicle itself has another acceleration because it is provided with energy absorbing system. The value of absorbed energy depends on tire width and vehicle's weight. To reduce the impact of this difference developers of DriveSafe propose to calculate theoretical acceleration by multiplying angular and linear velocities. The car, chosen as master vehicle, will perform some sharp turns to adjust one of thresholds. Theoretical acceleration for these events will be calculated, so there will be the theoretical range for thresholds. Now, if theoretical acceleration of another car falls in the range, the system get its acceleration as value to adapt threshold. In such way all thresholds are adjusted. The same process is performed for a_z value calibration. Theoretical longitudinal acceleration is calculated as second derivative of position of the vehicle obtained from GPS.

Thresholds can be adapted without using of fuzzy rules. There is research, that propose to use the size of eye (mouth and nose) to detect drowsiness state [18]. These size can differ from person to person, so during the calibration phase average values of eye and mouth size and nose length will be calculated. Then, if eye size smaller than average will be detected, drowsiness state will be registered. The same rule with mouth size and deviation of nose length from average nose length. If one of parameter exceed the threshold on 70 frames from 75 last frames, drowsiness is detected. Head bending and yawning are continuous processes, so if it is detected on consecutive frames, it will be registered as one event.

Similarly, in [11] the averaging is used for estimating driver-specific deceleration while breaking, turn speed, intersection passing speed.

In [20] an important parameter for left turn assistance in an acceptable time gap between cars. So, the system gives clearance when the gap is larger that some critical acceptable gap for the specific user. I.e., this critical acceptable gap is understood as an adaptive threshold, and the process of finding of the threshold is based on the assumption that this critical acceptable gap has a lognormal distribution and has a value between the shortest taken gap and the longest not taken. Therefore, the value of the driver-specific threshold is determined based on driver's history by maximum likelihood estimation.

In [22] authors use genetic algorithm to optimize indicator parameters for drowsiness detection. Indicators are Time to Line Crossing, Mean Squared Error for lane position and heading error. For detecting thresholding is used, rule for which contains parameters. These parameters can be set heuristically, but it does not ensure the best accuracy. To generate ground truth experts classify data samples into alert and drowsy state. Then, parameters for indicators were optimized with genetic algorithm. Because of lack of data this approach was not implemented to personalize system to particular driver, but to optimize parameters based on all available drivers data. Researchers noted, that it is hard to collect enough data for developing model for each individual driver. However, genetic algorithm could be used to optimize parameters to achieve personalization.

So, basically, we have found three techniques for determining adaptive thresholds: 1) estimation of a threshold based on average for particular driver/vehicle, 2) estimation of the threshold by maximum likelihood method, under assumption of some specific distribution of the respective characteristic (a more elaborated example of the previous one, as averaging can be seen as maximum likelihood estimation under assumption of normal distribution), 3) fuzzy logic.

B. Classifiers

As it was already noted, thresholds on observable parameters allow to build only rather limited variety of decision rules, besides, adaptive thresholds are applicable only when it is possible to describe a driver with some boundary value of an observable parameter (time gap, size of eyes and so on). In a more general case, a decision rule separating acceptable states from non-acceptable can be non-trivial and has to be modeled by a set of non-observable parameters of some driver-specific classification model. Personalization in this case is usually done by creating a specific classification model (based on the parameters listed in section IV) and learning the parameters by some machine learning algorithm (this approach is taken in papers [12], [15], [16]). After that, this classification model is used for personalized driver assistance.

In [16] online SVM is used to train a driver specific classifier for detecting drowsiness based on physiological data: PPG, GSR, temperature, acceleration, and the rate of rotation are used in the proposed system to monitor the driver's conditions. To learn the classifier the authors use ground truth provided by the driver (when warned about drowsiness state, a driver can agree or disagree with the system).

In [12] and [19] a personalized decision model is built with a help of an artificial neural network. The authors experiment with two types of driver-specific input for this model the first uses statistical characteristics of previous turns (min and max acceleration) the second uses the LSTM-models of the previous turns.

In [15] decision tree learning is used to adjust the decision rule to the actual decision-making of the driver.

One of the most interesting issues here is to implement a trade-off between a non-personalized solution (where there is a plenty of data but not very adapted to particular driving habits) and a personalized one (where there is much less data, but relevant to a particular driver). Surprisingly, we have found not so many papers that actively explore this tradeoff. A good example may be [16].

C. Personalized functional dependencies

Some authors propose to model personalized functional dependencies between some parameters. In some cases such dependencies play a role very similar to a classifier. E.g., in [10] a linear regression is used to predict acceptable gap for the lane change from the current road situation. In other cases these dependencies are used for personalized planning, for example, in [11] a driver-specific dependency of acceleration from speed (with a help of other parameters) allows to estimate energy consumption of an intersection crossing schedule.

D. Personalized temporal patterns

In some driver assistance systems driver-specific temporal sequences (e.g., steering sequences) are learned. These sequences are then exploited to predict future state of the car and recognize driver's intent. One of the most popular learning frameworks for this kind of driver models is Hidden Markov Model (HMM). E.g., HMM connecting driving situation, state and control inputs from the driver is used in [23] to detect possible lane departure.

VI. Quality of Personalization

In general, there are two (non mutually exclusive) types of declared goals for personalization in driving assistance systems: a) to mimic driving behavior of a particular driver (if it comes to elements of self-driving, e.g. cruise control) or to provide the most natural recommendations for a particular driver, b) to increase the overall acceptance of the system.

Quite symmetrically, effectiveness of personalization and adaptation is measured in the research papers under review in two different ways. In this paper we call them objective and subjective effectiveness respectively.

A. Objective effectiveness

The methods of this group are characterized by the fact that they use actual actions performed by the driver and actions recommended (or performed) by a driver assistance system. They are designed to formally measure the degree of accomplishment of some local (specific) goal of the system (or particular function of a system). For cruise control there are driver's actions and decisions while following vs. adaptive cruise control system. For external monitoring (forward collision warning system of lane keeping) there is subjective evaluation of a situation by the driver vs. evaluation made by a personalized model. For driver monitoring system there is real state of the driver vs. state of the driver evaluated by a personalized model. Anyway, there is some actual driver's decision, evaluation or state, and the respective entity predicted by a personalized model. The correspondence between actual and predicted driver's decision, evaluation or state is performed in some way typical for machine learning – by leveraging one of appropriate quality measures: accuracy, F1 etc. The particular effect of personalization corresponds to how the quality measure improves when a non-personalized model, trained with different drivers, is changed to a personalized one.

This approach is utilized in [12], [13], [16], [18] and [21]. E.g., [16] compares accuracy of drowsiness prediction with models build only with one driver, all drivers and some hybrid scheme (a contribution of the authors), [12] compares F1 score and accuracy of left turn acceptance prediction by model utilizing previous turns made by a particular driver and by driver-agnostic model.

B. Subjective effectiveness

The subjective effectiveness of the adaptation addresses the user's satisfaction and user acceptance of the system. Interesting fact is that although several reviewed papers noted that one of the goals of personalization is increasing user acceptance (e.g., [10], [11]), direct measurement of the change in user evaluation of the system and user acceptance was performed only in [20]. Specifically, it analyses how the acceptance and efficiency of the left turn assistance system can be increased by a personalization of the recommended gaps to the individual driver.

Typical instrument for performing a subjective evaluation is a carefully composed questionnaire and feedback collection protocol. For example, in [20] the participants were asked to drive under three conditions: a "manual drive" where the assistance system was not activated, a default assistance system drive and the personalized assistance system drive (the participants were not informed on differences between them). After each drive the participants were asked to fill in a questionnaire. Finally, another questionnaire with a direct comparison between the personalized and non-personalized assistance systems was answered by the participants. In addition, the participants were asked to give feedback about the

TABLE I. SUMMARY OF THE REVIEWED PAPERS

Task	Characteristics	Methods	Effectiveness measurement	Experiments	References
Forward Collision Warning	Driver specific probability distribution of the danger level of a situation, Time headway, Time to collision, Risk perception	Recursive least squares, Decision tree learning	Objective (accuracy, precision. true positive rate, true negative rate, false alarm rate)	Offline evaluation	[15]
Lane Keeping	Velocity, distance to the lane center, steering	HMM	Objective (rate of successful interventions, rate of false alarms)	Offline evaluation	[23]
Drowsiness Detection	EAR, MOR, LNR (camera)	Adaptive fixed thresholding (averaging)	Objective (sensitivity, specificity, accuracy)	Offline evaluation	[18]
	PPG, GSR, TEM (wearable device) Acceleration Rate of rotation	Online SVM	Objective (accuracy, total operation time)	Offline evaluation	[16], [17]
	Heading error, lane position, time to collision	Genetic algorithm	Objective (sensitivity, specificity, accuracy)	Offline evaluation	[22]
Lane Change Assistance	Relative speed Distance to leading and following vehicles, speed, lane change direction	Linear regression	Subjective	Offline evaluation	[10]
Left Turn Assistance	Speed, accelerations, steering wheel speed (from previous experience)	ANN (LSTM)	Objective (accuracy)	Offline evaluation	[12], [19]
	Acceptable time gap	Adaptive thresholding (maximum likelihood)	Subjective	Simulation	[20]
Route Planning	Maximum speed, typical deceleration, acceleration profile, compromise between time and fuel consumption	Adaptive fixed thresholding (averaging), Personalized functional dependency	Subjective	Offline evaluation	[11]
Acceleration/steering event detection	Jerk deviation Average yaw rate Speed and bearing variation	Adaptive thresholding, Fuzzy system	Objective (sensitivity, specificity, accuracy)	Offline/Field study	[13]
	Linear and angular velocities Accelerations	Adaptive thresholding, Fuzzy system	Objective (recall, precision)	Offline evaluation	[21]

appropriateness of the time gaps after every intersection during drives with assistance systems (both personalized and non-personalized). The questionnaires included following aspects: usefulness (useful, intuitive, easy to use, reliable, relied on system, time gaps comfortable), workload (relieved, facilitated monitoring, facilitated decision), affective evaluation (liked to use, not annoying) and safety (felt safe in usage, increased traffic safety).

VII. METHODS OF EVALUATION

Our review confirms typical approaches of evaluation personalization models and techniques enumerated in [9]:

- Offline evaluation. This approach relies on raw data collected from several drivers (in a real or modelled environment) probably including some additional markup (i.e. maneuver assistance models rarely need additional markup, as all the input and output parameters of the model are usually contained in the recorded actions and environment, while driver state monitoring models usually requires some ground truth markup). The data is processed by an assistance model and the results of the model are compared to the registered actions (or ground truth in the dataset). The effect of the personalization is measured by comparing output of the personalized model to the output of the non-personalized model. Examples of papers using this approach are: [10], [11], [12], [18], and [21].

- Simulation. The assistance model is deployed in a simulated environment. Each driver usually has several drives allowing to compare personalized and non-personalized assistants. Evaluation by simulation is done, e.g. in [20].

- Field study. Driving with an assistance model in real life conditions.

It should be noted that offline evaluation may include prior simulation (to collect the data). The key difference between offline evaluation and other approaches is that with offline evaluation the data is collected without the implemented driver assistance model. It should also be noted that particular evaluation technique is connected with the quality measures selected by the researchers. In offline evaluation it is possible to estimate only objective effectiveness (as the model being verified does not influence actions of the driver). On the other hand, experiments in simulated environments and field test allow to estimate both subjective and objective effectiveness of the model.

The number of drivers used to evaluate models in the reviewed papers ranges from three [10], [11] to 32 [12].

VIII. Conclusion

The aims of the research have been achieved. We have identified main approaches used for personalization in driver assistance systems, as well as directions of personalization and evaluation approaches (the approaches from the reviewed papers are summarized in Table I).

The review allowed us to identify several research gaps that have to be addressed in further research.

First, there is significant limitation of the driver's sample (e.g., see [22]), which is currently addressed either by structure of the model (that is why most models have rather few parameters) or by hybrid schemes allowing to account for both the specific driver and other drivers (we have found only one such paper – [16]). There is a need to systematically research the idea of such hybrid personalization methods.

Second, there is a gap in evaluation driver assistance quality. The fact is that one of the main reasons for applying personalization is usually called improving user acceptance, that is, increasing driver confidence in the system, greater willingness to listen to recommendations, etc. However, in practice these characteristics are not analyzed – instead typical measures of quality characteristic of machine learning tasks (accuracy, F1 etc.). Apparently, the measurement of the impact of personalization in various driver assistance tasks on user acceptance of the system is on the research agenda.

Third, the fundamental problem in the personalization of driver support systems is to find a balance between obviously safe parameters (recommended for most drivers) and personalized ones. The essence of the contradiction is that the safe parameters seem to be too conservative for drivers characterized by aggressive driving style, therefore, they are not credible and lead to the abandonment of the use of the assistance system. Probably, a more complicated process is possible here, including building trust and its exploitation, which can serve as a separate subject of study in organizing human-machine interaction in a given class of systems. It is also important to research how personalization affects traffic accident probability. Currently, personalization (especially, in maneuver acceptance prediction) techniques are evaluated mostly by measuring how a personalized model fits the style of a driver, while the whole idea of driver assistance is to reduce the possibility of an accident which in some sense is a conflicting goal (especially when it comes to aggressive driving style). It would be interesting to organize experiments in a simulated environment to explore this tradeoff.

Acknowledgment

The research was partially supported by the Russian State Research (# 0073-2019-0005) and the Government of Russian Federation (grant 08-08).

References

[1] World Health Organization, Global status report on road safety 2018, Web: https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/

[2] J.R. Treat, N.S. Tumbas, S.T. McDonald, D. Shinar, R.D. Hume, R.E. Mayer, R.L. Stansifer, N.J. Castellan, "Tri-level study of the causes of traffic accidents - final report", *UMTRI*, 82, 1979.

[3] T.A. Ranney, E. Mazzai, R. Garrott, M.J. Goodman, "NHTSA Driver Distraction Research: Past, Present, and Future", *Technical report, HTSA*, 2000.

[4] J. Piao, M. McDonald, "Advanced driver assistance systems from autonomous to cooperative approach", *Transp. Rev.* 28, 2008, pp. 659–684.

[5] A. Ziebinski, R. Cupek, H. Erdogan, S. Waechter, "A survey of ADAS technologies for the future perspective of sensor fusion", *in: Nguyen, N.-T., Manolopoulos, Y., Iliadis, L., Trawiński, B. (eds.) ICCCI 2016. LNCS (LNAI)*, vol. 9876, 2016, pp. 135–146.

[6] F. Yang, H. Wang, "A Driver Assistance System Based on Mobile Device", *Fourth Global Congress on Intelligent Systems*, 2013.

[7] A. Smirnov, A. Kashevnik, I. Lashkov., "Human-Smartphone Interaction for Dangerous Situation Detection & Recommendation Generation while Driving. Speech and Computer", *18th International Conference on Speech And Computer (SPECOM 2016), Lecture Notes in Computer Science, Springer, Heidelberg*, Vol. 9811., 2016, pp. 346–353.

[8] A. Smirnov, A. Kashevnik, N. Shilov, I. Lashkov, "Driver Assistant in Automotive Socio-cyberphysical System: Reference Model and Case Study", *2nd International Conference on Vehicle Technology and Intelligent Transport Systems*, Apr. 2016, pp. 104–111.

[9] M. Hasenjager, H. Wersing, "Personalization in advanced driver assistance systems and autonomous vehicles: A review", *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, Vol. 2018–March, Mar. 2018, pp. 1–7.

[10] V. Butakov, P. Ioannou, "Personalized Driver/Vehicle Lane Change Models for ADAS", *IEEE Trans. Veh. Technol.*, Vol. 64, № 10, Oct. 2015, pp. 4422–4431.

[11] V.A. Butakov, P. Ioannou, "Personalized Driver Assistance for Signalized Intersections Using V2I Communication", *IEEE Trans. Intell. Transp. Syst.*, Vol. 17, № 7., July 2016, pp. 1910–1919.

[12] H. Dang, F. Johannes, "Exploiting Maneuver Dependency for Personalization of a Driver Model Approach on Personalization", *Conference "Learning, Knowledge, Data, Analytics", LWDA 2018, CEUR Workshop Proceedings*, Volume 2191, 2018, pp. 93–97.

[13] G. Castignani, T. Derrmann, R. Frank, and T. Engel, "Driver Behavior Profiling Using Smartphones: A Low-Cost Platform for Driver Monitoring", *IEEE Intelligent Transportation Systems Magazine*, volume: 7 , issue: 1 , Jan. 2015, pp. 91-102.

[14] Y. Lilis et al., "Personalizing HMI Elements in ADAS Using Ontology Meta-Models and Rule Based Reasoning", *UAHCI*, 2017. *Lecture Notes in Computer Science*, vol 10277. ed. Antona M., Stephanidis C., *Springer International Publishing,* vol. 10277, 2017, pp. 383–401.

[15] J. Wang, C. Yu, S. E. Li, and L. Wang, "A forward collision warning algorithm with adaptation to driver behaviors", *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1157–1167, April 2016.

[16] M. Choi, S.W. Kim, "Online SVM-based personalizing method for the drowsiness detection of drivers", *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, 2017, pp. 4195–4198.

[17] M. Choi et al., “Wearable Device-Based System to Monitor a Driver’s Stress, Fatigue, and Drowsiness”, *IEEE Trans. Instrum. Meas.*, 2018, vol. 67, № 3. pp. 634–645.

[18] A. Kumar, R. Patra, “Driver Drowsiness Monitoring System using Visual Behaviour and Machine Learning”, *2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, 2018.

[19] H.Q. Dang, J. Furnkranz, “Using Past Maneuver Executions for Personalization of a Driver Model”, *in Proc. of the IEEE 21th International Conference on Intelligent Transportation Systems (ITSC-18)*, Nov 2018.

[20] D. Orth et al., “Benefits of Personalization in the Context of a Speech-Based Left-Turn Assistant”, *Proc. 9th Int. Conf. Automot. User Interfaces Interact. Veh. Appl. - AutomotiveUI ’17*, 2017, pp. 193–201.

[21] C. Arroyo, L.M. Bergasa, E. Romera, “Adaptive Fuzzy Classifier to detect Driving Events from the Inertial Sensors of a Smartphone”, *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, 2016.

[22] I.G. Daza, L.M. Bergasa, S. Bronte, J.J. Yebes, J. Almazan and R. Arroyo, “Fusion of Optimized Indicators from Advanced Driver Assistance Systems (ADAS) for Driver Drowsiness Detection”, *Sensors (Basel)*, 14(1), Jan,. 2014, pp. 1106–1131.

[23] S. Lefevre, A. Carvalho, Y. Gao, H. E. Tseng, and F. Borrelli, “Driver models for personalised driving assistance”, *Vehicle System Dynamics*, vol. 53, no. 12, pp. 1705–1720, 2015.

[24] J. Mendel, “Fuzzy logic systems for engineering: A tutorial”, *Proc. IEEE*, volume: 83 , issue: 3, Mar 1995.