Handover Process of Autonomous Vehicles – Technology and Application Challenges

Dániel A. Drexler[1], Árpád Takács[1], Tamás D. Nagy[1], and Tamás Haidegger[1]

[1]Óbuda University, Antal Bejczy Center for Intelligent Robotics, University Research, Innovation and Service Center, Bécsi út 96/b, Budapest, H-1034 Hungary, e-mail: {daniel.drexler, arpad.takacs, tamas.daniel.nagy, tamas.haidegger}@irob.uni-obuda.hu

Abstract: Self-driving technologies introduced new challenges to the control engineering community. Autonomous vehicles with limited automation capabilities require constant human supervision, and human drivers have to be able to take back control at any time, which is called handover. This is a critical process in terms of safety, thus appropriate handover modeling is fundamental in design, simulation and education related to self-driving cars. This article reviews the literature of handover processes, situation awareness and control-oriented human driver models. It unifies the psychological and physiological control theory models to create a parameterized engineering tool to quantify the handover processes.

Keywords: autonomous vehicle safety; situation awareness; control-oriented model; takeover; hands-off control

1 Introduction

The versatile autonomous functions of vehicles require different knowledge and control approach from the users (i.e., the human driver). This can be characterized in various ways, broken down to categories from the technical point of view, e.g., Parasuraman et al. provide a well decomposed automation classification with 10 levels of automation [1]. However, the most commonly used automation level classification was created by the Society of Automotive Engineers (SAE), defining five levels of autonomy [2], which has been widely adopted, even by different domains [3, 4]:

- L0 no autonomous capability;
- L1 driver assistance: specific functions may be under computer control;
- L2 partial automation: combined function automation (e.g., Adaptive Cruise Control (ACC));

L3 conditional automation: automation of all critical functions with limitations (limited self-driving), the driver shall be ready to take control all times;

L4 high automation: vehicle can perform all driving tasks under certain conditions; driver may take control;

L5 full automation: vehicle performs all driving tasks under all conditions; driver may not be able to take control.

The safety considerations of cars with partial and conditional automation (L2–L3) are critical, because constant attention of the driver is required due to the limited capabilities of the car; albeit, due to the relatively large portion of fundamental (and comfortable) functions being automated, the driver can easily become distracted and bored, and start to look for other, non-driving related activities. As shown by Stanton et al., this is mainly due to the fact that humans are not efficient in long inactive monitoring tasks, and drivers usually over-trust the system [5]. The problem becomes critical and potentially fatal when the automated system faces a situation that is beyond its functional capabilities, and the human driver has to take back the control from the system, when the driver is not prepared to do so [6].

The situation when the human driver takes back control from the automated system is called both *handover* and *takeover*. In Morgan at al., the term handover is used to define the process when the automated system transfers the control to the human driver, while the term takeover refers to the time instant when the driver had taken full control of the vehicle [7], which has been adopted in many papers. This terminology will be used as well. The time between the handover signal and when the human driver has full control of the vehicle is called *takeover time*. The terminology of handover is reviewed in Section 2.

The safety of autonomous vehicles below L4 is critical in real-life applications. according to Stanton et al, car manufacturers should proceed to L4, or L2 and L3 should be modified such that the driver shall always be responsible for one control input modality, e.g., for handling the steering wheel or the pedals, thus the human would be forced to pay attention during the whole driving process [5], which is a well-established protocol in aviation industry. The first suggestion (i.e., jumping to L4) is not available yet due to technical limitations, while the second suggestion means that the vehicle practically becomes an L1 system. Banks at al. analyzed the fatal Tesla crash happened May 7, 2016, using the Perceptual Cycle Model [6]. Although the investigations showed that the accident was caused by driver error, the authors suggested that ”design error” was also part of the cause, which resulted in the over-boosted trust of the driver in the autonomous system. The human trust and situation awareness are critical components in the safety of L2–L3 systems, which are reviewed in Section 3. The connection of handover situations and situation awareness is analyzed in Section 4.

Human driver models and models of the closed-loop system based on a control theory (e.g., [8–10]) approach have been considered in [11]. A human model based on fractional order calculus has also been presented [12]. A recent review of pilot models based on control theory, physiology and soft computing techniques can be found in [13]. Control and system theoretic models are useful for simulation and analysis purposes, however, they do not provide sufficient insight into the underlying phenomena. The crucial elements in the models are the time delay parts that determine the stability and performance of the closed-loop system. The control oriented models are briefly reviewed in Section 5.

Takeover times in non-critical handover situations are reviewed in [14]. Under noncritical conditions, drivers needed 1.9 to 25.7 seconds to take back control. These data were derived from measurements in non-critical scenarios, however, these takeover times are dangerously high for critical situations (i.e., when the driver has to take back control to possibly avoid an accident). The large takeover time is the main weakness of L2–L3 systems from the safety point of view. The value of the time delay can be approximated by the model of Gold et al., who created an algebraic equation based on regression to calculate the time delay based on selected data (traffic density, time before the accident, age of the driver, the current lane, the number of times the driver has faced similar situations before, and the non-driving related activity of the driver during the handover) [15]. Models for time delays in handover situations are discussed in Section 6. Based on the findings of the literature review, a human driver model is suggested in Section 7, that combines control oriented models with models of situation awareness.

2 Handover Situations

The process of handover, i.e., the process when control is shifted from autonomous to manual, can be a result of various situations; based on the conditions, there are various classifications in the literature. Here, they are considered, the first one is based on the way of handover [16], the other one is categorized by the cause of handover [17].

Based on the way of the handover, four types of handover situations are given in [16]:

- *Immediate handover*, when the control is shifted immediately, e.g., the driver grasps the steering wheel;
- *Step-wise handover*, when the control is shifted step-by-step, e.g., first longitudinal control, then lateral control;
- *Driver monitored handover*, when the driver monitors the system behavior (e.g., force feedback in steering wheel). The control is handed over after a certain period of time (e.g., there is a countdown);
- *System monitored handover*, when the system monitors the inputs of the driver for a certain period of time after the handover, and the system can adjust the inputs if it considers the driver input unsafe.

Based on the cause of the handover, five types of handover situations can be given [17]:

- *Scheduled handover*, when the driver is notified in advance of the handover situation, and has time to prepare;
- *Non-scheduled system initiated handover*, when the driver is not notified in advance, the system realizes that the driver must take control immediately because in the current situation the system would need to operate beyond its functional limits; the driver may not expect this situation;
- *Non-scheduled user initiated handover*: the driver decides to take control while there is no specific need to do so;
- *Non-scheduled user initiated emergency handover*: the user spots a potential risk that was not recognized by the system, and the user takes immediate control;
- *Non-scheduled system initiated emergency*: the system can no longer operate (the cause of this emergency is internal system failure), and notifies the driver.

The handover situations that are non-scheduled and system initiated are also called *self-deactivation* processes. An important difference between L2 and L3 systems is that an L3 system must always be able to realize if a situation is beyond the limits and initiate handover. In this paper, we are interested in immediate handover situations, i.e., the whole control is turned to manual control immediately, caused by self-deactivation, when the handover situations are non-scheduled and initiated by the system. We will also call these handover situations *immediate self-deactivation*. Important to note that handovers could possibly be initiated by cyber-security attacks as well [18].

3 Situation Awareness

Situation Awareness (SA) is used to describe the perception and the understanding of the human driver about the situation. The critical point of L2–L3 systems is when the driver loses SA. Regaining SA during handover is crucial in terms of safety, since SA is indispensable for the driver to find a solution to the problem arose during the handover situation. Thus, designing systems that help drivers regain SA is fundamental in handover management.

3.1 Defining Situation Awareness

Human perception capabilities are modeled by SA, which is a key component in handover processes. SA of the driver is the dynamic understanding of "what is going on" [19]. SA was divided to three levels by Endsley [20]:

- Level 1: perception of the elements in the environment that are relevant to the task;

- Level 2: comprehension of the meaning of these elements relative to the task;
- Level 3: projection of their future states after particular actions.

SA was formally defined as "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*" [21].

Automation of SA was investigated in [22], SA with semi-autonomous agricultural vehicles was analyzed in [23], where they showed that at higher level of automation, the driver has lower SA. The authors used the Situational Awareness Rating Technique (SART) developed by Taylor, which is a self-rating post trial technique [24].

3.2 Measuring Situation Awareness

There are numerous metrics to quantify SA. Stanton at al. compared more than 30 measures of SA [25], which can be categorized into six groups [19, 26]:

1. Freeze probe techniques;
2. Real-time probe techniques;
3. Self-rating techniques;
4. Observer rating techniques;
5. Performance measures;
6. Process indices.

Freeze probe techniques are based on freezing the simulation, and asking questions from the participant right afterwards. Having answered the questions, the simulation continues. The simulation is stopped (frozen) typically randomly, and questions are asked about the tasks performed. The answers are evaluated after the simulation. A popular freeze probe technique measuring the SA along the three levels was proposed by Endsley, and is called Situation Awareness Global Assessment Technique (SAGAT) [27].

3.2.1 Real-time probe techniques

Real-time probe techniques are similar to the above with the difference that during real-time probing, the simulation is not frozen, thus they ask questions from the participants online during the simulation without stopping it. A typical real-time probe technique is the Situation Present Assessment Method (SPAM), developed for air traffic controllers' SA measurement [28].

3.2.2 Self-rating techniques

Self-rating techniques are carried out by the participants, who rate themselves typically after the trial. One such technique is the SART by Taylor [24], which uses ten dimensions to measure the participant's SA. The participant gives a score to each dimension between 1 and 7, and the result is a subjective measure of the SA.

3.2.3 Observer rating techniques

Observer rating techniques involve experts who observe the participants during task execution, and evaluate their SA. The advantage of this method is that it does not disturb the task execution of the participants, and observer bias is reduced. A typical observer rating technique is the Situation Awareness Behavioral Rating Scale (SABARS), which has been used to asses infantry's SA during field training [29].

3.2.4 Performance measures

Performance measures provide indirect measures of SA by recording some quantities during task performance. For example, Gugerty measured crash avoidance, blocking car detection and hazard detection for driver SA [30]. Process indices involve the recording of certain functions and behaviors that are related to the SA of the participant, e.g., eye-movement is tracked in the study of Smolensky [31].

According to a thorough review that compared these measurement techniques [26], the most typically used are the SAGAT and SART to assess individual or team SA. It was found that the SAGAT technique had the most significant correlation with the task performance [19].

3.3 Losing and Regaining Situation Awareness

During automated cruising, the driver can become inattentive, and start to participate in non-driving related activities, not paying attention to the traffic. This is called Driving Without Attention Mode (DWAM), and was formalized in [32] (also known as Driving Without Awareness (DWA) [17]). In this mode, the driver behaves as a conventional passenger, which is only in line with the SA mode of L4+ cars. For cars under L4, if the driver is in DWAM, wneh a handover request occurs, then the takeover time increases dramatically.

During handover, the driver has to regain SA from DWAM. Assistant systems that help the driver to regain SA may help reducing reaction times and increase safety. In order to understand this process, it is desirable to decompose SA. Matthews et al. describe the following components of SA [33]:

- Spatial awareness: knowledge of the location of all relevant objects in the environment;
- Identity awareness: knowledge of salient items;
- Temporal awareness: knowledge of the change of location of the surroundings;
- Goal awareness: knowledge of the navigational plan, trajectory tracking, maneuvering the vehicle in traffic;

- System awareness: knowing the relevant information about the driving environment.

Regaining full SA means regaining all three SA levels. Driver assistant systems may be characterized and specialized based on the component of SA they help to regain and the level of awareness that can be reached by the assistant system. For example, the car's dashboard can help to regain system awareness, more advanced Human–Machine Interface (HMI) can increase other components of awareness.

Augmented Reality (AR) was used by Lorenz et al. to improve takeover performance of the driver, as described in Section 7 [34]. This experiment showed that an assistance system that helps regaining SA improves takeover performance.

3.4 Critical Performance Assessment

The quantitative assessment of SA, based on the level of autonomy, is crucial for the development of safe and efficient automated driving systems. Until today, there is no widely accepted metrics to quantitatively describe SA indicators, both on global and component levels. Henceforth, new autonomous features are predominantly deployed into driver assistance systems without taking into account the quantitative requirements that the human driver needs to adhere to. In order to address this issue, a systematic assessment method is proposed. Employing this method could enhance the establishment of baseline metrics, and the definition of essential performance for deployment standards.

We call for an assessment method for critical handover performance, to quantitatively define the required level and components of SA with respect to the autonomous functionalities present. To improve system safety, driver assistance systems and automated driving functionalities shall be collected and organized in a hierarchical way, along with the two criteria of SA presented, as a standardized risk assessment protocol:

- Level of SA, based on state of the environment;
- Components of SA, based on knowledge.

Fig. 1 defines SA blocks in autonomous driving, and outlines their hierarchy in accordance to the level of autonomy and SA. As the level increases, i.e., new autonomous features are added incrementally, the required number of SA components decreases for the human driver, as critical driving tasks are temporally or permanently taken over by the system. This representation is in line with the SAE definition of level of autonomy, and can be interpreted as follows:

- L2 ADAS systems require the human driver to remain in control and stay fully aware of the driving situation, possessing all levels and components of SA.
- As a transition from L2 to L3 automated systems, the driver is allowed not to fulfill all the quantitative awareness criteria to the highest level of SA, and an increasing number of components for SA are overseen by the

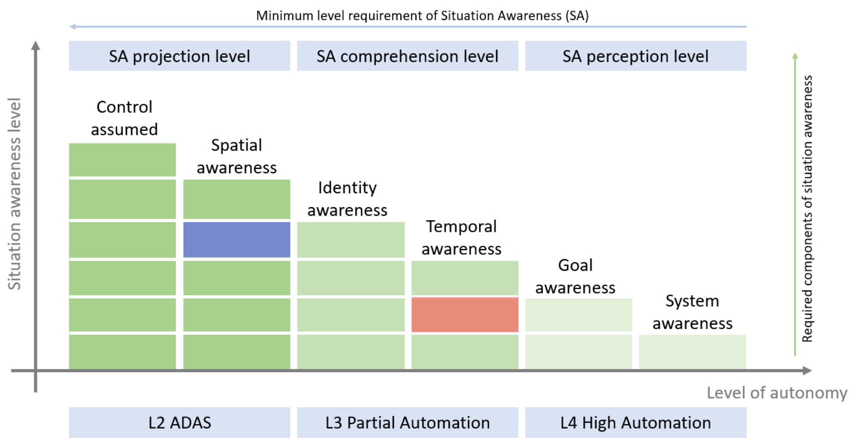

Figure 1
Hierarchical representation of SA blocks in autonomous driving. For each level of autonomy, quantitative requirements shall be defined. E.g., the block highlighted in red corresponds to the SA metrics for L3 autonomy for the comprehension of dynamic states, while the blue block represents the ability of the human driver understanding the spatial structure of the environment, while engaging an L2 driver assistance feature.

system (e.g., state of the traffic participants, expected behavior). However, some components need to stay active on the driver's side, such as handling unexpected behaviour or understanding the driving goals/trajectories.

- Transitioning from L3 to L4 automated driving, the driver is required to perceive the current state of the environment only related to his driving task. However, on the component level, *system knowledge* is interpreted as the knowledge of whether the system can solve critical driving tasks in the current driving environment, i.e., whether the user is educated about the capabilities of the used features.

Each block in Fig. 1 represents a quantitative criteria, which corresponds to the acceptance threshold for the integration of the new functionality into the system. The blocks incorporate metrics in terms of perception (object recognition distance, static and dynamic object state, road topology, actor movement probability and trajectories etc.), time factors (time to collision, takeover time, length of takeover action) and takeover ability (access to driving controls, pose of driver, environmental conditions). The measurement of these quantitative criteria is crucial, however, due to the complexity of the driving task and the human factors of the HMI, it can only be set empirically. The development of the testing framework related to this objective is part of our research, aiming to create a baseline for the definition of upcoming automotive standards.

3.5 Human Trust in Autonomous Systems

A potential safety problem of L2–L3 cars is that human drivers tend to overtrust the system, and as a consequence, they do not pay attention to critical situations [5]. On the other hand, some drivers do not trust autonomous systems at all, and thus do not want to rely on automated functions, even when those would boost their performance [35]. Human automation interaction systems and trust in automation was reviewed recently [36], where the authors pointed out the importance of trust when a human interacts with the autonomous systems. The effect of augmented SA on semi-autonomous car driving is analyzed in [37].

The way the driver treats the autonomous system and reacts to a handover situation can be considered as a problem of Human–Automation Interaction (HAI), which has a rich literature [1, 36, 38, 39]. Trust in Automation (TiA) is found to be a critical component of HAI systems, since TiA effects the decision of the human which leads to the interaction [36]. TiA is usually divided into two domains: compliance and reliance [40]. The advantage of using reliance and compliance is that they can be measured through observable behavior. The disadvantage of using only reliance and compliance is that they can not characterize TiA uniquely.

The tendency of accepting the lack of alarm or a warning is called *reliance*. If the reliance of the driver is large, then he or she believes that there is no problem as long as there is no alarm signal generated by the system, thus the autonomous system needs no supervision. If the driver has low reliance, then he or she believes that there may be errors or critical situation that are neglected by the autonomous system, thus they constantly supervise the functions. In general, the reliance of the driver should be high, however, too high reliance leads to overtrust, while too low reliance renders the autonomous functions idle. The reliance of the driver can change over time, e.g., if the system fails to generate alarms, the reliance of the driver decreases [41]. Since L2–L3 systems need constant supervision of the driver, these systems are unique in the sense that lower reliance is desirable.

The tendency of accepting and carrying out the recommendation from the autonomous system is called *compliance*. Ideally, the compliance of the driver is high, however, too high compliance means overtrust, and accepting all suggestions of the system without checking their validity. False alarms generated by the system decrease compliance, however, if the systems fails to generate an alarm, it has no effect on compliance [40].

Reliance and compliance can not completely characterize trust, since there are other factors that may affect decisions. One such factor is the workload of the driver, i.e., if the driver is kept busy, then they tend to accept the recommendations of the autonomous system, even if their compliance is low. Drnec et al. suggested to model trust as a decision process, since decision making can be objectively measured [36]. However, since decision measurement in their research is done by fMRI (functional magnetic resonance imaging), this measurement can hardly be carried out in a simulated driving environment.

Table 1
The critical SA components of non-scheduled handover situations and their effect on trust

Handover situation	**Critical SA component**	**Effect on trust**
non-scheduled system initiated	spatial awareness	reliance and compliance is increased (true positive alarms) or decreased (false positive alarms)
non-scheduled user initiated	spatial awareness	reliance is reduced
non-scheduled user initiated emergency	system awareness	reliance is reduced
non-scheduled system initiated emergency	system awareness	reliance and compliance is increased (true positive alarms) or decreased (false positive alarms)

4 Handover Situations and Situation Awareness

Handover situations are called *automation to human hands-off* in [42], where scheduled handovers are called *structured hands-off*, and non-scheduled handovers are referred to as *unstructured hands-off*. The term *takeover event* is also used to refer to a handover situation. Non-scheduled, system initiated handovers are also called *self-deactivation processes*.

Following the terminology from McCall et al. [17], we collected the non-scheduled handover types, and identified the critical SA components during handover, and the effect of the handover situation on the trust of the driver (Table 1).

4.1 Safety Critical Issues During Handover Process Management

In HAI systems, reliance is considered to be an important component, which should be kept high. However, overtrust can be fatal, since the driver fails to monitor the traffic situation, and may not be able to react in time. Moreover, if the system fails to detect the critical situation or detects the situation too late (e.g., right before the accident), then the driver has no chance to avoid that [43]. As a consequence, for L2–L3 systems, lower reliance is more desirable. Although low reliance implies that the driver has to monitor the system frequently, which is considered to be infeasible for HAI systems, this frequent monitoring is desirable for L2–L3 systems. Based on Table 1, reliance is decreased by non-scheduled user initiated handovers or false positive system initiated alarms. The latter also decreases compliance.

A critical component of handover management systems is the detection system that initiates handover. This system must be able to predict the critical situation as soon as possible, in order to alert the driver in time. If the system fails to alarm the driver in time, and the driver does not pay attention (due to high reliance), the consequences can be fatal. However, detection systems are not perfect, and can make mistakes [44]. Typical question in design is whether false positive or false negative alarms are less desirable. In handover situations, false negative alarms can be fatal if the driver has large reliance, while false positive alarms decrease reliance as shown in Table 1. Overall, the detection system must be created such that false negative alarms are minimized, while the amount of false positive alarms can be larger.

Too much false positive alarms can lead to significant drop of reliance and compliance, which is good for safety, since it forces the driver to pay attention constantly, however, it is bad for the technology, since drivers will be wary of these systems. In Autonomous Emergency Braking (AEB) systems, false positive detection is avoided by removing stationary objects from radar sensor data, and by treating an object as an obstacle only if it is in the way of the vehicle, which is calculated based on the steering angle [44]. The performance of detection systems will likely improve in the future due to the improvement in artificial intelligence algorithms, like deep neural networks [45] and their training algorithms [46].

Using augmented/virtual reality and advanced HMI can help to improve the performance of the drivers during handover by increasing the SA of the driver, and helping to regain the SA. However, this will only work if the driver trusts the system, and believes that the information given by the HMI is valid, i.e., the driver has high compliance. False positive alarms decrease compliance, and as a result, the trust of the drivers will decrease, and the performance increase due to the advanced HMI may deteriorate as well. To the authors best knowledge, other factors, such as the behavior of drivers when the information of the HMI is not valid has not been researched yet.

5 Control-oriented Driver Models

Control-oriented driver models date back to the ’70s. In the work of Kleinman et al., the control-oriented model of the human driver system described human behaviour as a time delay, an equalizer block and a neuro-motor dynamics block, shown in Fig. 2 [47]. The equalizer block contains an observer to estimate the states of the vehicle, and an inverse dynamics block for state estimation. Kleinman and Curry also used a control-oriented approach to predict human operator’s performance [48].

Human decision making is modeled as a process based on probabilities in [49, 50]. Gai and Curry modeled human decision making using switches and time delays [51]. Limits of human path tracking capabilities were explored in [52].

Eskandari et al. used a control-oriented framework to model the system under shared control, i.e., the control system with an automated system and the human operator are both presented in the loop [53], shown in Fig. 3. SA is present in the human operator model, along with decision making and acting. The authors modeled SA and regaining SA using dynamical systems in [54]. This model unified the control-oriented approach with the psychological approach characterized by SA [33].

Control-oriented driver modeling was used by Wang et al. to create a control law for a steering system [55]. Human models were used to evaluate system reliability using simulations in [56].

Driving state recognition is an important component of future autonomous cars. Machine learning was used to learn personalized driving state employing on-board sensor measurements in [57]. Clustering-aided regression is used to predict the driver workload in [58]. Mental workload dynamics was modeled in [59], where linear identification techniques are used to identify the nonlinear model online and show robust performance. Workload adaptive cruise control was created in [60], where the adaptive cruise control system is adapted to the current workload of the human driver in order to tailor the level of assistance to the needs of the driver. Tests in driving simulators showed that this workload adaptive cruise control enables safer driving experience.

6 Critical Components of a Handover Process

Human attention diversion is a critical issue in driving, many studies showed that mental workload has critical effect on the safety of driving [59, 60]. Nevertheless, the study of Gold et al. showed that traffic density has a major effect on takeover performance, while answering questionnaires during the driving process was found to have no significant effect [61]. Identifying large traffic density as a potential danger source in takeover performance leads to the conclusion that for systems under L4 automation, the driver should always pay attention when the traffic is heavy, e.g., by turning automated cruising off. This should not mean that the automated cruising shall be turned off in traffic situations with large density but low velocity, (i.e., traffic jams), which could be safely managed by autonomous vehicles under L4. A possible solution for this situation takes velocity information into account, which can be easily incorporated via on-board sensors. This way, automated cruising can be allowed in large traffic density with low velocity, and remain inaccessible with large traffic density and high velocity.

The U.S. National Highway Traffic Safety Administration (NHTSA) released an

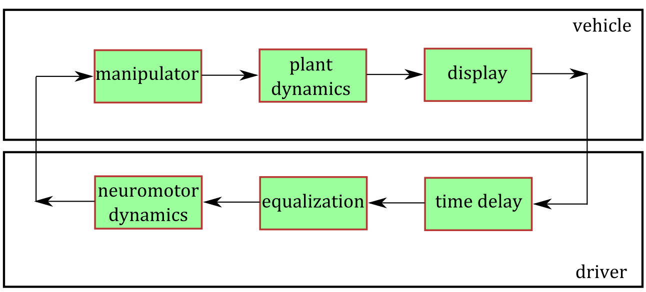

Figure 2
The human driver block, modelled fot the control theory aspect by Kleinman et al., neglecting the noises and disturbances [47].

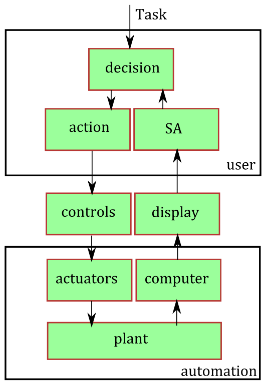

Figure 3
The block of the closed-loop system under shared control by Eskandari et al. [53].

updated policy *A Vision for Safety* in 2017 [62]: it encourages regularization entities on the definition and documentation of Operational Design Domains (ODD) for each automated driving system of the vehicle. An ODD should describe specific conditions under which the given features are intended to function for automated vehicles. The minimal information required for the definition of ODD for a given functionality includes roadway type, geographic area, speed range and environmental conditions. Pre-defined ODDs could aid the assessment of the required level of SA in the case of automated systems under L4.

6.1 Time Delay

Time delays are critical components of takeover performance. The takeover time during highway cruising is modeled by a polynomial in [15] which depends on the *time budget*, defined as the time between the takeover time and the system limit (the latest time instant when the driver must take control), the traffic density measured in cars/kilometer, the lane (right, middle or left), non-driving related task, repetition (the number of times the driver has faced similar situations before) and the age of the driver. The t takeover time is given as:

$$\begin{aligned} t \quad = \quad & 2.068 + 0.329 TimeBudget - 0.147(Lane - 1.936)^2 \\ & -0.0056(TrafficDensity - 15.667) \\ & -0.571 ln(Repetition) \\ & +2.121 \cdot 10^{-4}(Age - 46.245)^2. \end{aligned} \tag{1}$$

This model implies that traffic density decreases takeover time, and has the least decreasing effect for medium traffic density, and largest effect for small and large traffic density. The non-driving related task had no effect, similarly to the study carried out by Gold et al. [61]. However, it should be emphasized that the same 20-question-long form was used in both experiments. The age and lane did not affect the results significantly, but the repetition (which is related to the expe-

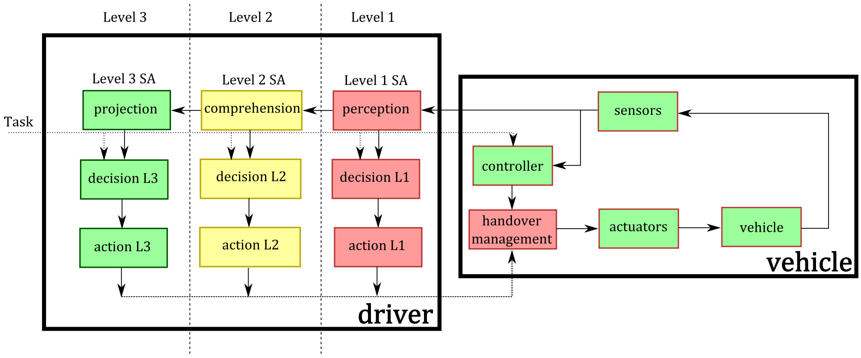

Figure 4
The model of the human driver included closed-loop control system. The driver block is divided into 3 levels based on SA, representing different decision and action blocks accordingly.

rience of the driver), the time budget (which is related to how early the system warns the driver) and the traffic density did.

6.2 Transient Quality

Improvement of takeover performance can be achieved through improving transient quality. Workload-adaptive cruise control does not necessarily reduce reaction time, but it contributes to the improvement of transient quality, e.g., participants started to break at the same time but the deceleration was lower, as reported by Hajek et al. [60].

Hence, SA also has an effect on the dynamics of the human model, along with the time delay. This effect can be incorporated into the human model through the neuromuscular level, i.e., different transfer functions describing the neuromuscular system for different stress levels. As the stress level increases, the settling time of the transfer function decreases, but other quality factors, such as damping are most likely to decrease as well.

Creating appropriate warning systems and prediction algorithms do not necessarily improve takeover performance by improving the takeover time, but by improving the reaction quality. This can be modeled through the dynamics of the human driver, and not the time delay. The importance of this observation lies in that most of the literature focuses on the time delay effect, and neglects the effect of dynamics. To incorporate these effects in the model, a combined approach is presented in the next Section, which is the main contribution of this paper.

7 Human Driver Model with SA

A new model is proposed by combining the model of the classical control theory block diagram of Kleinman et al. [47] with the SA-based block diagram of Eskandari et al. [53], as shown in Fig. 4. The vehicle block contains the controller block, being responsible for the automation, intelligence of the vehicle, actuators, vehicle model, sensors and finally the handover management block, which, in the trivial case, can be a system that overwrites the decision of the automation with the input signals generated by the human driver.

The human driver block is composed of three levels:

- The first level (Level 1 SA) is comprised of perception, decision and action;
- The second level (Level 2 SA) is responsible for the comprehension of the perceived signal and the corresponding decision and action;
- The third and largest level (Level 3 SA) projects the perceived information on the future, and carries out the corresponding decision and action.

The level of the driver's behavior is specified by the time available for the driver (the time budget by the terminology of Gold et al. [15]). If the time for decision and acting is low, only Level 1 SA is attained, and the driver will use the decision and action corresponding to Level 1 SA. If there is plenty of time, the driver can attain Level 3 SA, and act according to this level, i.e., use the Level 3 decision and action.

The action block contains the neuro-muscular dynamics and the inverse dynamics of the vehicle. The inverse dynamics is the same for all levels, since this block depends on the driver's knowledge of the car dynamics. Note that this statement does not hold if the car is in an extreme situation with unknown dynamics to the driver (e.g., the car slips on ice). The inverse dynamics here is not related to repetition in the model of Gold et al. [15] in (1), since the repetition refers to how many times the driver has faced the critical situation before, and not the knowledge of the car dynamics. While, the possibility of correlation is not excluded, it is not discussed in this work.

The neuro-muscular dynamics can be modeled with the transfer function [13]:

$$W_{\mathrm{NM}} = \frac{e^{-s\tau_{\mathrm{NM}}}}{s^2T^2 + 2\xi Ts + 1}, \tag{2}$$

with time constant T, damping coefficient ξ and time delay τ_{NM}. As the level of SA increases, the damping ξ increases, and the time constant T decreases. This way, the quality of the transient improves, as it has been observed [60]. From control theory point of view, decreased time constant would mean decrease in the performance, however, in the current application, decreased time constant results in decreased absolute value of the acceleration. This gives larger comfort to the passenger. This decrease in the acceleration is considered beneficial as long as the value of acceleration is large enough to avoid a possible accident, while it may present some discomfort to the driver and the passengers.

The various levels of SA (perception, comprehension and projection) can be modeled with different time delays with transfer functions:

$$W_{SA} = e^{-s\tau_{\mathrm{SA}}}. \tag{3}$$

As the level of SA increases, so does the time delay τ_{SA}. The modeling of the time delay in the decision block is straightforward.

The model in Fig. 4 gives insight into the process of driver assistance system from a different perspective. For example, Lorenz et al. showed in their study that using augmented reality improves takeover performance [34]. If a green corridor was projected on the path that could be used to avoid the accident, drivers tended to steer the vehicle into that direction, while in the case red corridor was projected onto the path that should have been avoided, the drivers started to brake intensively. This phenomenon could be explained by the decrease in time delays, as shown in [63]. The model presented in Fig. 4 can be used as an explanation, as the augmented reality helps the drivers to attain higher level of SA in a shorter time. Drivers can achieve comprehension through the presented solution (but this comprehension is highly affected by the information shown by the augmented reality), and thus they can achieve Level 2 behavior sooner. This observation can aid the development advanced systems that would improve the safety of autonomous cars.

Conclusions

A complete literature review was provided about the handover processes of autonomous cars. Various terminology can be found in the literature related to handover process, we built on the most common and clarified terms. SA was identified as a fundamental human driver related component in handover situations. We provided a short review about the quantification methods of SA, and established the relationship between SA and handover processes.

Control-oriented human driver modes were reviewed, and the models were extended to incorporate the model of SA. Control-oriented driver models are important to carry out simulations and to specify quantitative measures for human driver performance. Incorporating SA into control-oriented models enforces the fusion of physiological and psychological human models, which have greater modeling power and could enhance the developments aimed at improving handover performance. Out future plan is to build a complete simulator with this knowledge in order to asses SA more efficiently.

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