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Situation Awareness at Autonomous Vehicle Handover: Preliminary Results of a Quantitative Analysis

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***Abstract*— Enforcing system level safety is a key research domain within self-driving technology. Current general development efforts aim for Level 3+ autonomy, where the vehicle controls both lateral and longitudinal motion of the dynamic driving task, while the driver is permitted to divert their attention, as long as she/he is able to react properly to a handover request initiated by the vehicle. Consequently, situation awareness of the human driver has become one of the most important metrics of handover safety. In this paper, the preliminary results of a user study are presented to quantitatively evaluate emergency handover performance, using custom-designed experimental setup, built upon the Master Console of the da Vinci Surgical System and the CARLA driving simulator. The measured control signals and the questionnaire filled out by participants were analyzed to gain further knowledge on the situation awareness of drivers during handover at Level 3 autonomy. The supporting, custom open-source platform developed is available at `https://github.com/ABC-iRobotics/dvrk_carla`.**

***Index terms*—Autonomous Vehicle Safety, Self-driving, Situation Awareness, Driving Simulator, Hand-over.**

I. Introduction

Autonomous driving technologies are on the rise worldwide, aiming to increase road safety in general. However, significant system and human failures have happened in the near past, indicating that the underlying technology and regulations are still just evolving [1]. The Society of Automotive Engineers (SAE) provided the most recognized scale for the levels of automation in the case of self-driving [2], a classification that is often used in different research domains as well [3], [4]. These Levels of Autonomy are:

- L0: no autonomy
- L1: user assistance
- L2: partial automation
- L3: conditional automation
- L4: high automation
- L5: full automation.

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At L3 (conditional automation), most of the essential driving functions are automated, however, the driver should be ready to take control whenever it is necessary. Hazardous situations are typical sources of this transfer of control, when the automated system cannot handle the situation, and thus it notifies the user to resolve it. In the case of L3, safety considerations are crucial: due to the fact that most of the functions are automated, the driver can easily be distracted, unfocused and bored, while a smooth transfer of control requires constant attention from the user. Furthermore, drivers usually over-trust the system, causing lower level of Situation Awareness (SA) [1], [5]. One solution for this problem chosen by manufacturers is to implement higher level of automation directly (L4+), without these restricting conditions. Another, technically more feasible approach is to maintan high SA; the driver has a constant task to perform, such as handling the pedals solely, while it means retrogression in technology.

In driving automation, the term “handover” refers to taking back the control from the vehicle, and “takeover” (time) indicates the necessary timeframe in witch it actually happens [6]. Takeover is typically between 1.9 and 25.7 seconds in non-critical cases, however, it may get prolonged under critical conditions [7]. Takeover can be estimated from a control system model introduced in [8].

Situation Awareness is a key factor of driving safety (especially at L2 and L3). SA is defined on 3 levels based on the cognitive understanding of the (past–present–future) environment [9], [10]:

- **Level 1 SA**: Perception of the environment;
- **Level 2 SA**: Comprehension of the current situation;
- **Level 3 SA**: Projection of future status.

SA can be categorized into the following classes: spatial (locations), identity (salient objects), temporal, goal and system awareness (Fig. 1).

In this paper, we introduce an SA experiment, which examines the handover in emergency situations. In order to simulate these emergencies, we used a widely available driving simulator, CARLA[1] and the Master Console of the da Vinci Surgical System (Intuitive Surgical Inc., Sunnyvale, CA). We studied seven subjects’ handover performance under critical conditions.

II. Experimental Setup

The da Vinci Surgical System was originally developed for the purpose of robot-assisted minimally inva-

[1]http://carla.org/

sive surgery [11]. Its human–machine interface is versatile enough to be used for the purpose of self-driving handover experiments. The head-in type stereo display is an excellent tool to control and monitor the driver's attention—just like the surgeon's attention in the conventional, clinical use. When the driver's head is not inserted, they are not able to see the simulation, and likewise, when their head is inserted, no external visual disturbances may pass into their field of view. Furthermore, thanks to the built-in photogates, the insertion of the head into the display area can be easily detected. The Master Tool Manipulators (MTMs) of the da Vinci Master Console, as well as the foot pedals were tailored to offer similar functionality to the steering wheel and foot pedals of a car [12].

The implemented system (Fig. 2) was built upon two mayor open-source software components: the Da Vinci Research Kit (DVRK) [13] and the CARLA Simulator [14]. The MTMs of the Master Console mimic the behavior of a steering wheel, relying on the impedance control built into the DVRK; the built-in head sensor is also interfaced to the control PC through the DVRK platform; the foot pedals extended with Hall effect sensors are connected using an Arduino board (Arduino Co., Somerville, MA) [15], sending the measured values to a Robot Operating System[2] (ROS) environment; the stereo display is connected to the PC using DVI interface. The control PC runs the *cisst-component* [16] to interface DVRK—and so do the MTMs and the head sensor—to ROS and the CARLA server, responsible for the simulation. Moreover, a ROS node sets the gains of the impedance control dynamically, and a CARLA client forwards the control values to the CARLA server and sends the stereo video stream to the displays.

The MTMs of the da Vinci are programmable using the open-source DVRK platform [16], which is based on the highly modular ROS, used widely in robotics research [17]. At the tips of the MTMs, 3D printed wheel segments were fixed (Fig. 3). The motion of this DVRK steering wheel is restricted to a circular trajectory around a virtual center point using the built-in impedance control of the DVRK [12], and

[2]https://www.ros.org/

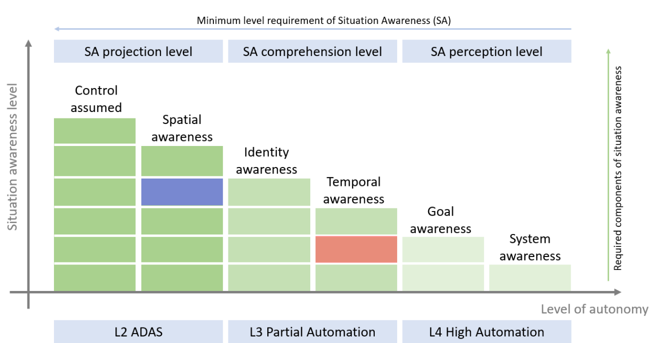

Fig. 1. Hierarchical representation of Situation Awareness (SA) in self-driving vehicles. For every level of autonomy(L2 Advanced Driver-Assistance System (ADAS), L3 Partial Automation and L4 High Automation), the quantitative metrics must fulfill the requirements for each category.

the steering angle value is interfaced to the CARLA client over ROS (Fig. 2).

The usage of the foot pedals of the da Vinci Master Console for the driving experiments was an obvious choice. However, those pedals offer simple binary output by default. To get continuous reading, the pedals were completed with Hall effect sensors and small-sized magnets, connected to the PC using an Arduino board, serving as accelerator and break pedals. The sensor values were read using the `rosserial_arduino` package, and were forwarded through ROS topics towards the CARLA client (Fig. 2).

The two displays of the da Vinci—serving as stereo display pair—have been replaced with LCD screens to enhance image quality—, which is a commonly used enhancement of the DVRK platform. These screens were connected to the PC over DVI to provide the stereo video stream to the driver. The head-in type display allowed attention control for the drivers, as they were not aware of the environment and the simulator at the same time. Moreover, using the built-in photogates of the console, the insertion of the driver's head was also monitored. The signal of the photogates was forwarded to a ROS topic through one of the DVRK controllers (Fig. 2).

The CARLA Simulator was chosen to be used in the experiment; this open-source driving simulator is used widely in the research of autonomous driving, furthermore, it offers built-in scenarios, autopilot and ROS communication [14]. The CARLA Server offers the core of the simulation, while a CARLA client forwards the steering angle and pedals values form ROS using Remote Procedure Calls (RPC). Moreover, it defines the two cameras to ensure stereo vision (Fig. 2.), forwarding the video stream to the display of the da Vinci Master Console.

III. Experimental Protocol

In the experiments, it was our aim to model hand-over processes at L3 autonomy during emergencies. Each individual experiment was divided into 8 successive scenarios, none of the subjects participated in more than one experiment. Before each experiment, the subjects had one minute to practice driving in the simulator.

Every scenario started by the car driving autonomously, while the subject was instructed to type a text message on a smartphone, and not to insert her/his head into the simulator display nor pay attention to it. After 40–60 seconds of autonomous driving the system raised an emergency audio alarm and yielded the control to the human subject. This time delay was randomly chosen for the 8 scenarios at the beginning of the experiment, and was the same for each subject. This way, despite subjects would not expect the alarm at the same time instant, the results remained comparable between subjects. Then, the subjects had to take control of the vehicle and tried to solve the traffic situation. The subjects were also instructed that unnecessary braking (e.g., in the case of false alarm, see below) was unwanted and inflicted penalty. Each of the the 8 emergency scenarios happened at the same location on the simulation's map, with

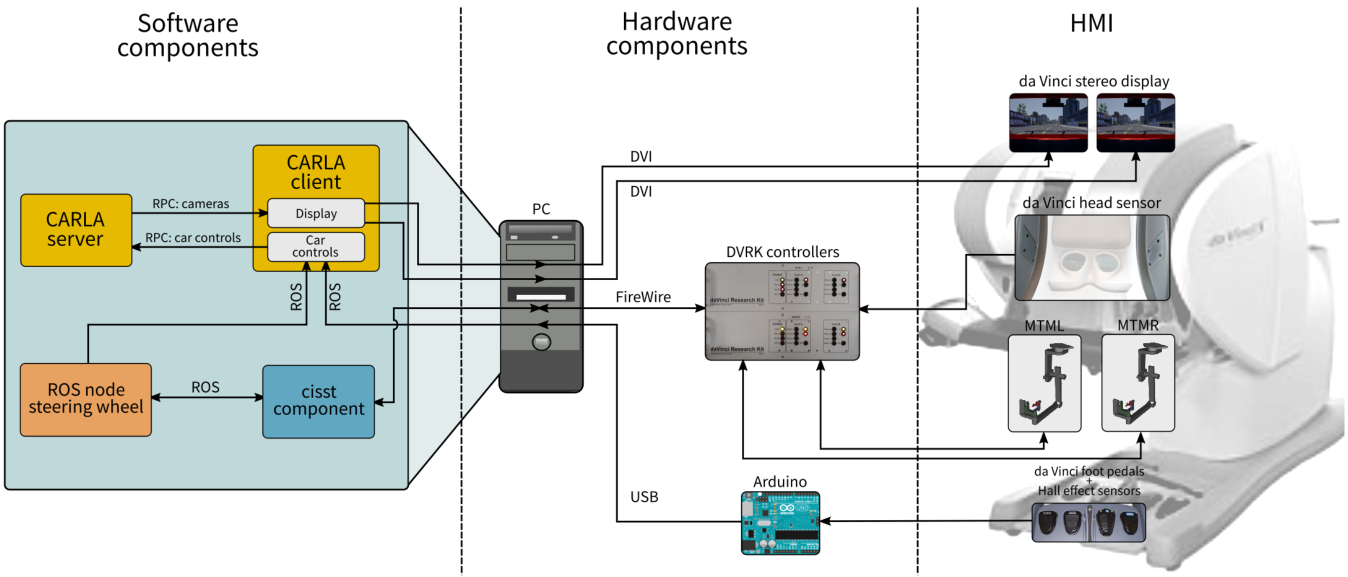

Fig. 2. Block diagram of the experimental setup. The display, the head sensor, the input manipulators and the pedals of the da Vinci Master Console are used to create a handover simulation user interface. The Da Vinci Research Kit is used for control, while the setup is interfaced to the CARLA Simulator via ROS components.

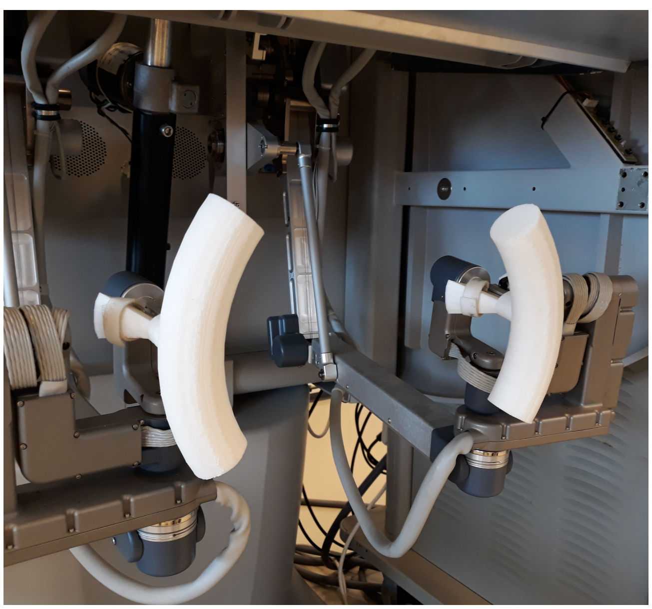

Fig. 3. The da Vinci MTMs with the 3D printed steering wheel segments, push-fitted and fixed by the built-in hook-and-loop fasteners. Using impedance control, the arms are mimicking the behavior of steering wheels, and rotate around a virtual axis.

the combination of the two states of the following three conditions:

1) **True/False alarm:** A pedestrian was involved in the emergency in all of the designed scenarios. In the case of the true alarm, the pedestrian stepped in front of the vehicle from behind a vending machine (Fig. 4), and the car was about to hit him. In the case of the false alarm, the pedestrian was moving on the sidewalk, parallel to the road. This case could have also been done without a pedestrian, however, we decided to leave the pedestrian in the scenario because his motion could also trigger braking at some of the subjects. The audio alarm was always raised three seconds before reaching the pedestrian's location;
2) **Car coming from front/No car coming from front:** To make the scenarios more challenging, opposing traffic was added to the scenario at the location of the emergency at some of the scenarios. In the case of no car coming from the opposite lane, there were no other vehicles on the road;
3) **Clear weather/Heavy rain:** To change visual conditions, the weather was also changed between scenarios.

Using the three varying conditions above, the following order of scenarios was compiled (the same for each subject):

1) True alarm, No car, Clear weather;
2) False alarm, Car coming from opposite lane, Clear weather;
3) True alarm, Car coming from opposite lane, Heavy rain;
4) True alarm, Car coming from opposite lane, Clear weather;
5) False alarm, Car coming from opposite lane, Heavy rain;
6) False alarm, No car, Heavy rain;
7) True alarm, No car, Heavy rain;
8) False alarm, No car, Clear weather.

In parallel to the scenarios on the simulator, the subjects were also asked to fill in a questionnaire. Before the introductory driving practice and the scenarios, they were asked to read and agree to a consent form; the data gathered was completely anonymous. Afterwards, some general questions were asked regarding their age and driving experience. Following

Fig. 4. Screenshot of the simulation in one of the emergency scenarios. The pedestrian is stepping down to the road ahead the vehicle from behind a vending machine; the weather is clear with good visual conditions and there is no traffic on the road.

each scenario, questions regarding the simulated event and the details of the environment were asked to gain further information on their SA. Furthermore, after each scenario, they were asked to evaluate their own reaction on a scale 1–5. See the details of the questionnaire in Section IV.

IV. Results

We measured the SA of the participants by asking questions about their surroundings. They got 1 point for the good answer, 0 point for neutral answer (I do not know) and 1 point for a wrong answer. There was a specific case when they were asked about the direction of travel after the accident scene, where straight and left was also a good answer, although the road turned to left in a short distance; in this case straight was also accepted as a good answer with 0.5 point. The evolution of the SA along the scenarios are shown in Fig. 5 for all the participants.

We measured the takeover time as the difference between the time of the *handover request* (alarm sound) and the time of the first physical reaction (large change in steering wheel angle or break pedal operation) after the handover request. The car switched to manual drive as the handover was initiated, thus by the time the participants looked into the display, the car already started drift off the lane. As a result, an immediate intervention was always necessary in all the scenarios. The values of takeover times for each participant and each scenario are shown in Fig. 6.

The takeover time for each scenario is shown in Fig. 7, using a compact box plot. The circles are outlier data, dotted circles indicate the median. The thick lines show the range, where the second and third quadrant of the data are, and the thin lines show the range of other non-outlier data. One can observe a slight decrease in the takeover time medians as the scenario index increases, which may imply that as the subjects gained SA, thus their handover performance increased.

The increase of SA can be observed in the slight increase of general satisfaction in Fig. 8. The figure shows how the mean satisfaction increased (based on the survey) during different scenarios. The satisfaction for each scenario was

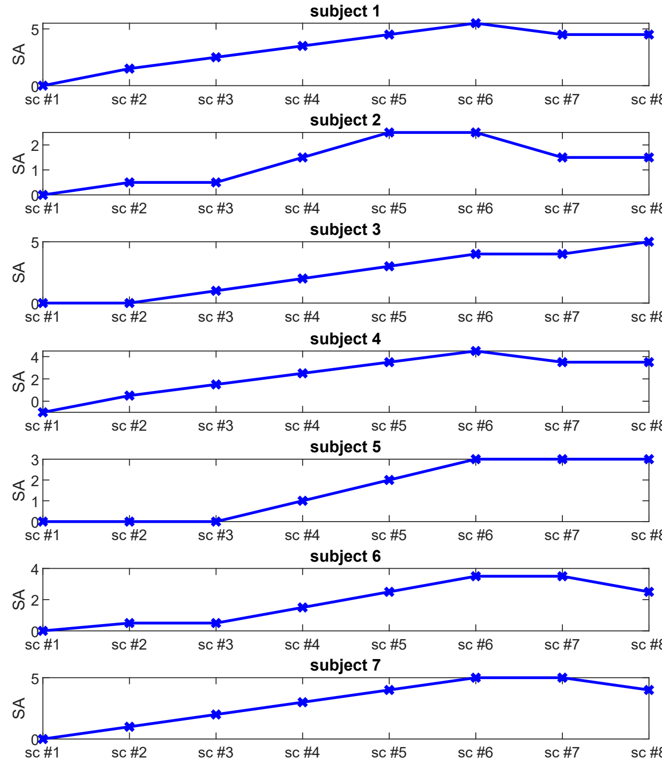

Fig. 5. The evolution of Situation Awareness (SA) of the participants along the scenarios.

acquired from the questionnaire, where the participants were asked to rate their own reaction on a scale from 1–5 (1–bad, 5–excellent). The SA was also checked by asking questions about the surroundings, which become more accurate as the participants moved forward in the experiments. Fig. 8 shows that polling the self-satisfaction might be indicative of the SA of the subject.

The mean satisfaction of the subjects is shown versus their mean takeover time in Fig. 9. The subjects could be divided into three groups intuitively. The first group consisted of subject 7, who had the smallest mean takeover time, and the largest satisfaction. The second group was composed of subjects 1 and 3, who had the larges takeover time, but still high satisfaction. The third group was composed of subjects 2,4,5,6, who had relatively small takeover time, but also small satisfaction. This shows that general satisfaction does not correlate with the mean takeover time.

Although Fig. 9 shows that the mean satisfaction does not correlate with mean takeover time, Fig. 8 and the answers from the questionnaire show that mean satisfaction correlates with SA. This may imply that SA has does not correlate with mean takeover time, but this implication is wrong. Subject 1 had large mean takeover time, however, this is because of the large takeover time in scenario #1, and as the SA of subject 1 increases, the takeover times decreases (Fig. 6). For subject 3, the takeover time was large for the first and the last scenarios, but there is a weak decreasing tendency in the takeover times, which may be connected to increasing SA. The large takeover times can be associated with the unique

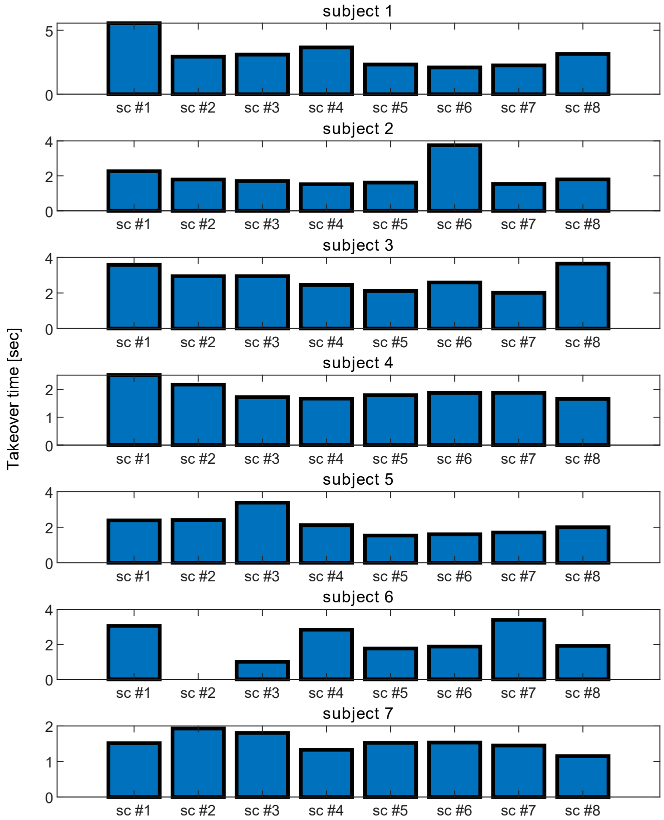

Fig. 6. The takeover times of the participants in the 8 scenarios.

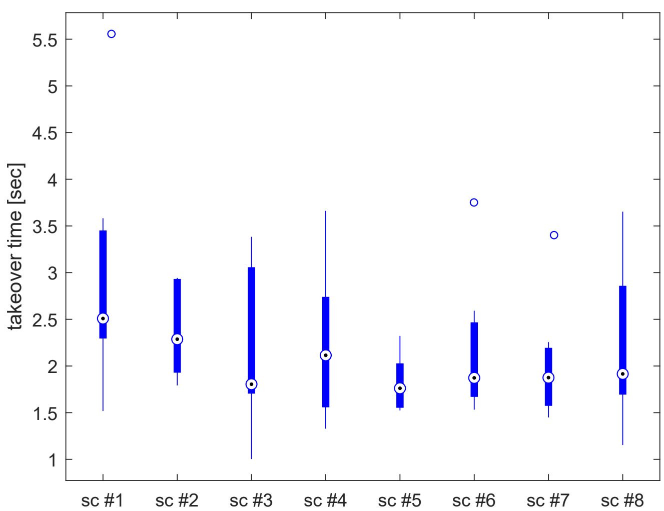

Fig. 7. The takeover times in the 8 scenarios depicted in a compact box plot: circles show outliers, dotted circles are the medians, the thick lines show the ranges where the second and third quadrant of the takeover times are (25–75%), and thin lines show the range of all the other takeover times in the current scenario.

personal capabilities of subject 3. This alludes that using plots like Fig. 9 for evaluation of a handover system may be misleading due to the different abilities of the subjects.

V. Conclusion and Future Work

In this paper, a preliminary user study was presented based on our objective human performance assessment platform,

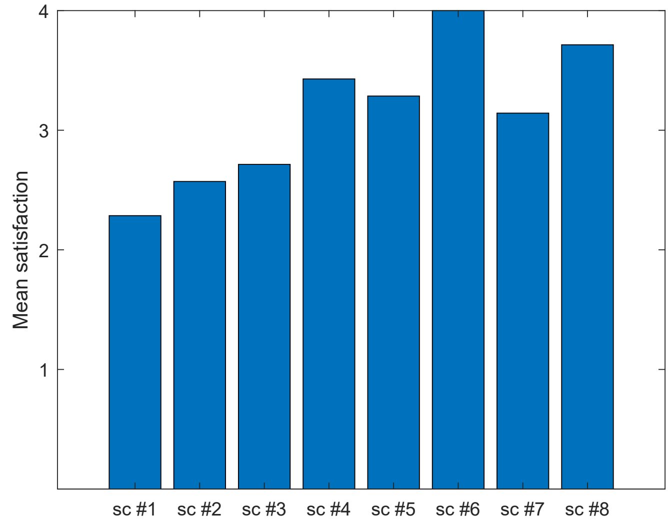

Fig. 8. The mean satisfaction (averaged for all the participants) for each scenario. Satisfaction was asked from the participants after each scenario, they rated their performance on a scale of 1–5 (1–bad, 5–excellent).

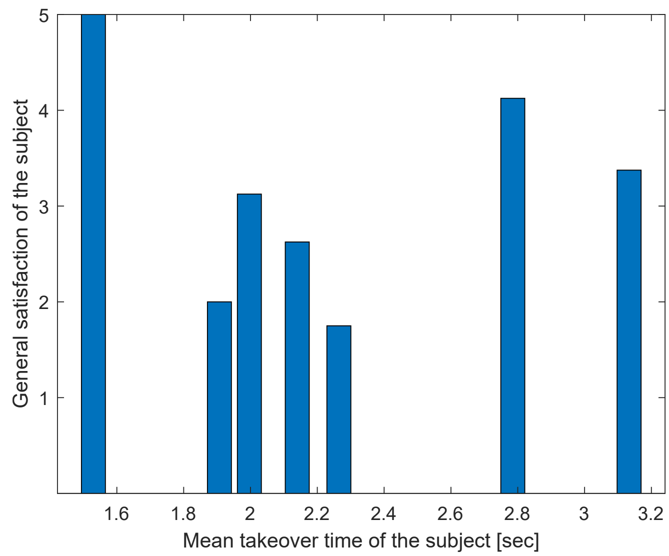

Fig. 9. The mean satisfaction of the subjects and their mean takeover times. Repeated scenarios' outcome was averaged for the same subject. Two subjects presented a certain self-biased behavior during the experiment. One subject was arguably best.

built on DVRK and CARLA Simulator. The system was used to evaluate the handover process during emergency situations of autonomous driving at L3. The user trial, including a questionnaire, was conducted on 7 test subjects, in 8 successive scenarios. We found the resulting takeover times on the simulator to be concordant with the values described in the literature, which projects that our results in the simulated environment can be translated into real life situations. It was observed the slight decrease of takeover time over the successive scenarios, which may imply the increasing Situation Awareness of the test subjects. The SA scoring, based on the questionnaire, shows an increasing tendency during the scenarios, that, similarly to the takeover time, implies the gaining of SA of the subjects. However, the results of the rating of the subjects' own performance from the questionnaire, which should also be closely related to SA, do not seem to correlate with the takeover time. This contradiction is possibly originating from the subjective nature of this question of the questionnaire. In the upcoming user studies, with a greater number of subjects and improved scenarios, these questions might be answered with higher certainty.

The open-source implementation of the platform is available on GitHub at `https://github.com/ABC-iRobotics/dvrk_carla`.

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