Discomfort Detection in Automated Driving by Psychophysiological Parameters from Smartbands

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ABSTRACT

The research project KomfoPilot at Chemnitz University of Technology aims at assessing discomfort in automated driving using psychophysiological parameters from smartbands. In an empirical driving simulator study, 40 participants from 25 to 84 years experienced two highly automated drives including three potentially critical and discomfort-inducing approach situations in each drive. The own car drove in automated mode with 100 km/h and approached a truck driving ahead at a constant speed of 80 km/h. Automated braking started very late at a distance of 9 m reaching a minimum distance of 4.2 m and minimum time to contact (TTC) of 1.1 s. Participants reported perceived discomfort continuously by a handset control integrated into the driving simulator (Hartwich et al., 2015, 2018). Psychophysiological parameters were assessed using the Microsoft Band 2 and included heart rate (HR), heart rate variability (HRV) and skin conductance level (SCL). To analyse the potential of band data for discomfort detection, psychophysical metrics during discomfort periods were compared to the values at 10 s time intervals prior and after. HR decreased during discomfort periods, HRV showed the expected u-shaped pattern with a decrease during the discomfort intervals, and after correcting for linear growing trend, SCL decreased as well. Overall, psychophysiological metrics showed potential to detect discomfort and will therefore be included in the detection algorithm. One of the challenges for using smartbands will be the use of adequate signal analysis methods for gaining the maximum signal-to-noise ratio.

Keywords: discomfort, automated driving, smartbands, psychophysiological parameters.

1 BACKGROUND AND OBJECTIVES

Wearable devices such as smartbands / fitness trackers gain increasing popularity and offer cheap and easy-to-use assessment of psychophysiological parameters in daily live situations such as driving. With increasing vehicle automation, smartbands could provide valuable information about driver states such as discomfort to improve human-machine collaboration. Detected discomfort could subsequently be used to adapt driving parameters as well as information presentation. Comfort is understood as a subjective, pleasant state of relaxation given by confidence and an apparently safe vehicle operation (Constantin, Nagi, & Mazilescu, 2014), "which is achieved by the removal or absence of uneasiness and distress" (Bellem et al., 2016, p. 45). Next to safety and efficiency, the potential to increase driving comfort is considered one of the main motivations for forwarding driving automation (European Road Transport Research Advisory Council 2017). The research project KomfoPilot at Chemnitz University of Technology aims at the assessment of discomfort in automated driving using psychophysiological parameters from smartbands as one data source. Overall goal of the project is the development of an algorithm for real-time discomfort detection to subsequently adapt driving style and information presentation in real-time. The use of commercially available smartbands is an explicit project goal to estimate the potential and challenges of such devices. The present paper reports the results of the psychophysiological metrics Heart Rate (HR), Heart Rate Variability (HRV) and Electrodermal Activity (EDA) with regard to perceived discomfort during automated driving. All metrics were assessed in a driving simulator study using the smartband Microsoft Band 2 (Details on the MS Band 2 in Schmalfuß et al., 2018). The use of these metrics to infer mental states such as stress, workload, arousal, fear, panic… etc. has a long research tradition (overviews in Cowley et al., 2015; Backs & Boucsein, 2000; Andreassi, 2000; Schandry, 1998). Study results are not uniform, however, overall tendencies can be transferred into the topic of discomfort detection. HR and Skin Conductance Level (SCL) usually increases with physical, mental and emotional strain, whereas HRV decreases. Thus, we expected an increase in HR and SCL during discomfort periods with a return to the baseline levels after these situations (inverse U-shaped pattern) and the opposite for HRV (U-shaped pattern).

2 METHOD

Study design: The study was conducted in a fixed-base driving simulator (Software SILAB 5.1) with a fully equipped interior and a 180° horizontal field of view, including a rear-view mirror and two side mirrors. All 40 participants took part in two distinct driving sessions with approximately two months delay in between. In each of the two sessions, all participants experienced an identical 3 minutes highly automated drive including three potentially critical and discomfort-inducing approach situations. The own car drove in automated mode with 100 km/h and approached a truck driving ahead at a constant speed of 80 km/h. Automated braking started very late at a distance of 9 m reaching a minimum distance of 4.2 m and minimum time to contact (TTC) of 1.1 s (Fig. 1 left). Perceived discomfort was assessed continuously by a handset control integrated into the driving simulator (Hartwich et al., 2015, 2018; Fig. 1 right). Participants were instructed to press the lever in accordance with the extent of perceived discomfort and had no possibilities to intervene using pedals or steering wheel.

Figure 1 – Driving simulator study setup in the truck approach situation (left), smartband Microsoft Band 2 and handset control for continuous discomfort assessment during automated driving (right)

Participants: The sample consisted of 40 participants (25 male, 15 female) ranging from 25 to 84 years. The younger group (25 to 45 years) included 21 persons with a mean age of 30 years (SD = 4.3). A total of 19 persons formed the older group (65+ years) with a mean age of 72 years (SD = 6.0). None of the persons had previously experienced automated driving in the driving simulator. Participants signed an informed consent and were compensated with 20 Euro for each session.

Sensors and interval selection: Psychophysiological parameters were assessed continuously using the Microsoft Band 2 (Fig. 1 right) and included HR, HRV and SCL. In addition, accelerometer and gyroscope data was recorded from the band sensors to correct for movements. The MS Band 2 comes with a Software Development Kit, which allowed for programming a dedicated logging application via Bluetooth connection. The complete study also comprised additional sensors which are not part of these analyses such as Eye-Tracking (SMI Eye Tracking Glasses 2), marker-based Motion Tracking (OptiTrack), a seat pressure mat, two 3D-cameras and six 2D-cameras. To analyse the potential of band data for discomfort detection, psychophysiological metrics during discomfort periods were compared to the values at 10 s time intervals prior and after (Fig. 2).

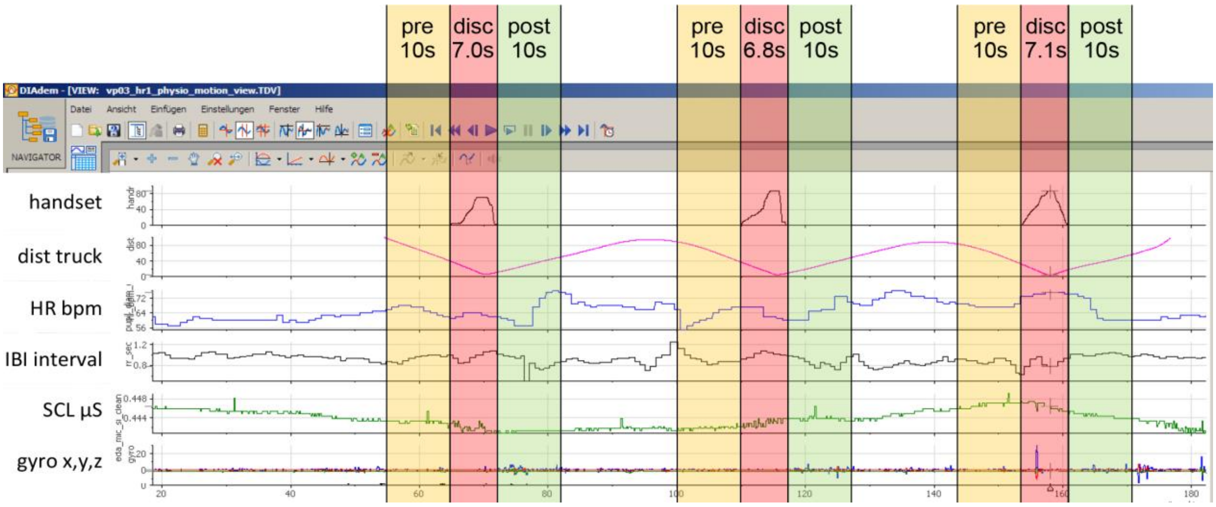

Figure 2 – Smartband data and three discomfort interval selections with 10 s interval before and after

Discomfort periods were extracted from the beginning of pressing the handset control lever until the lever was released – independent of the magnitude. The 40 participants experienced 6 approach situations in total, which would result in 240 situations. However, the handset control was only pressed in 208 situations. In addition, single data channels from the band were not recorded in some situations due to technical reasons. Finally, 206 discomfort periods entered the analysis for HR (M = 8.10 s, SD = 5.52 s), 202 sequences for HRV (M = 8.10 s, SD = 5.53 s) and 203 sequences for EDA (M = 8.16 s, SD = 5.51 s). Data preparation procedures are described in the results section for each sensor channel.

3 RESULTS

Heart rate: Raw HR-values in beats per minute were recorded with 1 Hz frequency from the MS Band 2. To correct for interindividual variability (Jennings & Allen, 2017), the raw values were transformed into z-scores for each of the 206 discomfort sequences including the 10 s before and after. Fig. 3 reports the means of these z-scores over the 206 sequences (repeated measures ANOVA with Greenhouse-Geisser correction and Bonferroni-adjusted post-hoc tests). HR decreased significantly in the discomfort interval compared to the 10 s before, however, HR did not return to the previous level in the 10 s after. A detailed timeline-plot of the mean z-scores showed that there was indeed a return to the baseline level, but the increase started only about 5 s after the end of the discomfort interval. Basically, a u-shape was present, but delayed for approximately 5 s with regard to the discomfort interval.

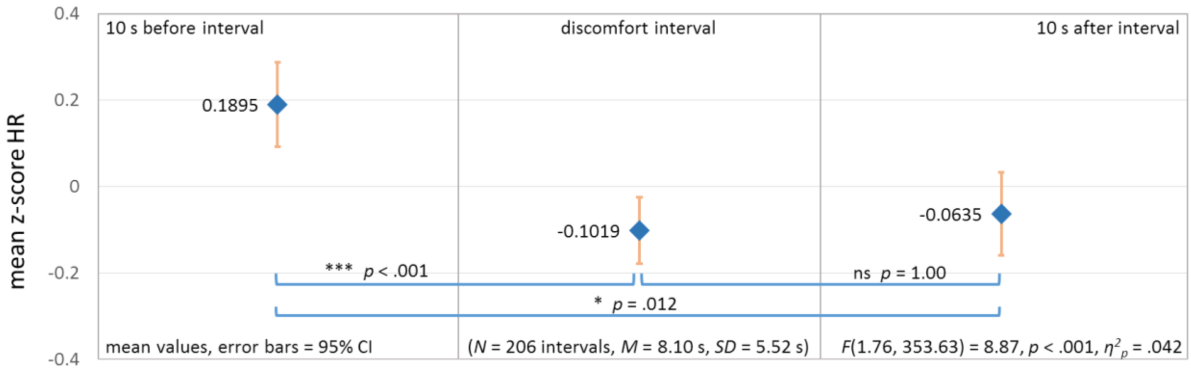

Figure 3 – Mean Heart Rate z-scores for discomfort intervals and 10 s before/after

Heart Rate Variability: To calculate HRV metrics, the inter-beat-intervals (IBI) values in seconds were recorded from the MS Band 2 with a new value for each detected IBI (no fixed frequency). In the specific case of the MS Band 2, HR and IBI are not reciprocal values, but IBI is recommended to be used for HRV-calculations (Cropley et al., 2017). The Root Mean Square of Successive Differences (RMSSD) was calculated for the discomfort interval and the 10 s prior and after. RMSSD is considered the best parameter for short periods and intervals with unequal length (Berntson et al., 2017). Mean RMSSD-scores over the 202 intervals showed the expected u-shaped pattern (Fig. 4) with a statistically significant decrease in HRV during the discomfort interval compared to the 10s prior and after ($\chi^2(2) = 40.05$, $p < .001$, Friedman's non parametric ANOVA).

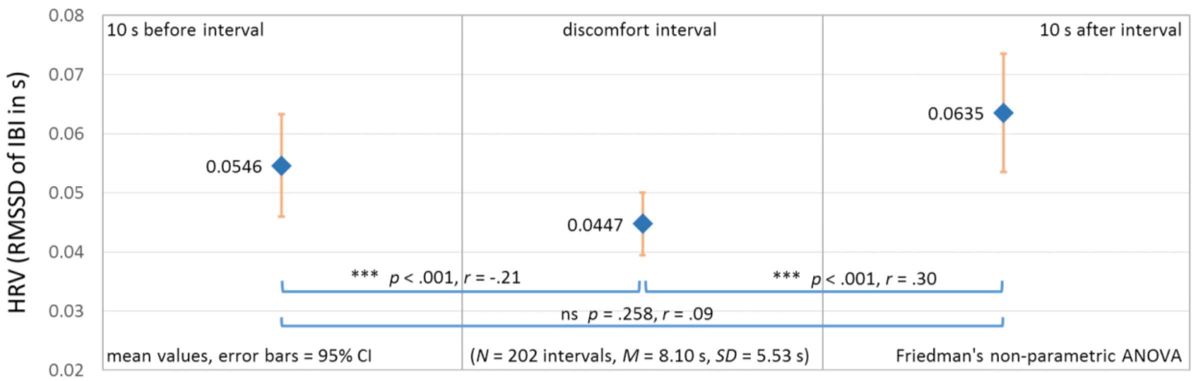

Figure 4 - Mean RMSSD (Heart Rate Variability) for discomfort intervals and 10 s before/after

Electrodermal Activity: The MS Band 2 measured skin resistance in kilo ohm with a frequency of 5 Hz using two electrodes on the opposite site of the display (see Fig. 1 right). Raw values were inverted to obtain the skin conductance level (SCL) in micro Siemens. As the EDA values were very sensitive to hand movements (e.g. placing the hand on the knees), SCL values during high movement episodes were excluded on the basis of the Band accelerometer and gyroscope data. Similar to HR, raw SCL values were transformed into z-scores for each of the 203 discomfort sequences including the 10 s before and after. A detailed timeline-plot of the mean z-scores showed a linear continuous increase in SCL over time, independent of the situation. In order to correct for this general linear trend, a linear regression was calculated for each sequence and subtracted from the z-scores to get the detrended z-scores. The mean detrended z-scores are reported in Fig. 5. Contrary to the expectations, results showed a u-shaped pattern for EDA with a decrease of SCL during discomfort intervals, however, with a small effect size of $\eta^2_p = .025$.

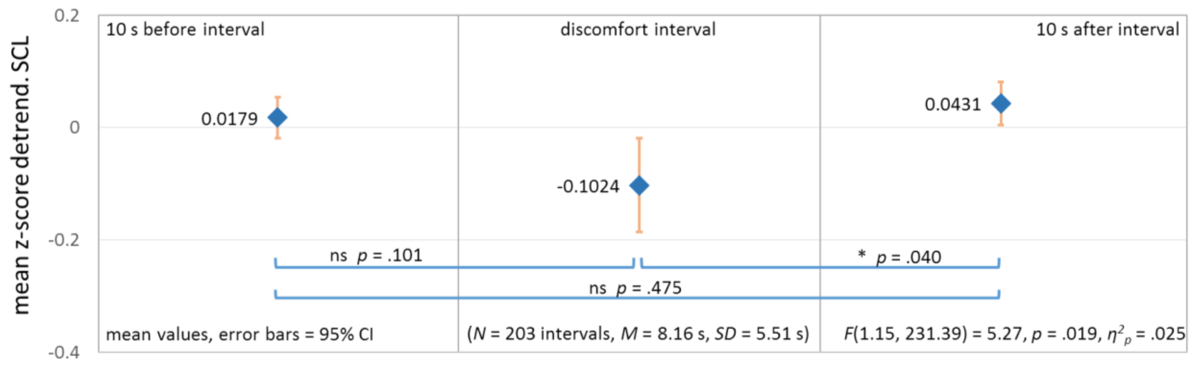

Figure 5 - Mean z-score of detrended Skin Conductance Level for discomfort intervals and 10 s before/after

4 DISCUSSION

The driving simulator study within the research project KomfoPilot at Chemnitz University of Technology aimed at assessing discomfort in automated driving using psychophysiological parameters from the smartband MS Band 2. Overall, the psychophysiological parameters HR, HRV and EDA showed changes associated with the perceived discomfort indicated by the handset control. In contrast to the hypothesis, HR decreased during discomfort periods. A possible explanation for this phenomenon could be the effect of "preparation for action", which means an anticipatory deceleration of HR prior to actions (Cooke et al. 2014; Schandry, 1998). This effect was reported for sport actions, but also for simpler reaction time paradigms: „It is well established that HR deceleration occurs during the fixed foreperiod of an RT task" (Andreassi, 2000, p. 270). HRV showed the expected u-shaped pattern with a decrease during the discomfort intervals. Raw EDA showed a linear increasing trend over time, which could be explained by the fact that participants got warm during driving. After correcting for this linear trend, EDA showed a slight decrease during reported discomfort, which is contrary to the expected evolvement. However, the effect size was small and the inverse effect could be related to measurement procedures associated with the smartband: Firstly, absolute EDA values were highly dependent on how tight the band was closed. These differences could be corrected using z-scores, however, some bias could remain e.g. when the band was worn very loosely. Secondly, EDA measures were taken from the outer side of the wrist, which is a much less sensitive place for SCL-changes compared to e.g. the fingers (Andreassi, 2000). Thirdly, hand movements caused partly strong effects/offsets in EDA values. The applied quite simple correction method of excluding these parts could potentially be improved by more sophisticated algorithms such as e.g. forward prediction and offset correction. The mentioned problems such as e.g. less control on how tight the band is closed are to some extend related to the use of smartbands instead of more sophisticated measurement devices. However, the aim of the project was and is to assess the potential of existing wearable devices with all the real-world usage challenges. Even with these problems, effects related to discomfort could still be identified in the data. One of the major challenges for using these devices to detect discomfort will be the use of adequate signal analysis methods for gaining the maximum signal-to-noise ratio. Additional improvements in detection could be achieved by the joint/multivariate analysis of these psychophysiological parameters including additional metrics such as eye-tracking, body movements, vehicle kinematic and situation information. These analyses and the development of a data fusion algorithm are the next steps in the project.

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