Detection of Motion Sickness in Participants Through Subjective and Objective Measurement

Lotte WAGNER-DOUGLAS[1], Paul SEIWERT[2], Nikolas SCHIERHORST[3], Srikanth NOUDURI[3], Alexander KIRMAS[1], Nikica HENNES[4], Gudrun VOß[1], Kai REWITZ[2], Alexander MERTENS[3], Dirk MÜLLER[2], Verena NITSCH[3], Lutz ECKSTEIN[1], Stefan LADWIG[1]

[1] *Institute for Automotive Engineering, RWTH Aachen University, Steinbachstraße 7, D-52074 Aachen, Germany*
[2] *E.ON Energy Research Center, RWTH Aachen University, Mathieustraße 10, D-52074 Aachen, Germany*
[3] *Institute of Industrial Engineering and Ergonomics, RWTH Aachen University, Eilfschornsteinstraße 18, D-52062 Aachen, Germany*
[4] *Research and Innovation Center, Ford-Werke GmbH, Henry-Ford-Straße 1, 50735 Köln*

Abstract: Automated vehicles offer many advantages, but also entail an increased risk of motion sickness. To avoid such an aversive experience, early and reliable detection of individual states of motion sickness is required to initiate appropriate countermeasures. To this end, a study was conducted to investigate different measures of motion sickness while traveling in a vehicle. A comprehensive data set of subjective measures of motion sickness and associated physiological parameters was collected which could be used to train learning algorithms for the early detection of motion sickness and thus pave the way for future countermeasures.

Keywords: Motion Sickness, Physiological Measures, Misery Score, Countermeasures

1. Introduction

The introduction of novel automated vehicles (AVs) offers numerous advantages. In 2020, about a quarter of professionals in Germany spent at least 30 minutes commuting to work (Statistisches Bundesamt 2022). Time that could be used efficiently for initial preparations for the day, such as checking emails or preparing for a client meeting, when traveling with an AV. A key factor here, however, is a comfortable travel environment, which also includes ensuring that passengers do not get motion sick during the journey. Previous research has shown that the risk of motion sickness (MS) increases, especially when passengers are engaged in non-driving related tasks while potentially sitting rearward facing (Diels & Bos 2016; Turner & Griffin 1999; Wada 2016). To reduce such aversive experiences and thus further increase the acceptance of AVs, the introduction of adequate countermeasures is needed. The aim should be to design countermeasures that respond to a passenger's state of MS at an early stage, i.e. before the passenger is subjectively aware of it. However, important prerequisites for the development and empirical investigation of such counter-measures are methods for early, objective and reliable detection of MS.

Previous research has shown consistent patterns between fluctuations in physiological parameters and subjectively perceived severity during MS provocation (Cowings et al. 1986; Cowings et al. 1990; Mazloumi Gavgani, Nesbitt et al. 2017; Sjörs et al. 2014; Stout et al. 1995). Studies have observed positive correlations between the heart rate (HR; Cowings et al. 1986; Cowings et al. 1990; Sjörs et al. 2014; Stout et al. 1995) and from electrocardiogram (ECG) derived respiratory rate (EDR; Cowings et al. 1990; Kim et al. 2005; Stout et al. 1995), while heart rate variability as a Root Mean Square of Successive Differences (RMSSD; Mazloumi Gavgani, Hodgson et al. 2017) showed a negative relationship. Similarly, the mean amplitude of raw signal data from Electrodermal Activity (EDA) measurements indicated positive correlations with subjectively perceived MS (Cowings et al. 1990; Mazloumi Gavgani, Nesbitt et al. 2017). Results on the correlation between skin/body temperature and MS are less clear, although a body of studies indicate a negative correlation (Kennedy & Frank 1985; Kim et al. 2005), there are also studies reporting contrary results (Mühlbacher et al. 2020; Sjörs et al. 2014).

As most previous studies on the relationship between physiological parameters and MS have so far been carried out under laboratory conditions, it is not clear to what extent the results can be transferred to the in-vehicle context. The aim of the present study is therefore to gain a more precise understanding of the relationship between subjectively perceived MS and the associated physiological parameters while in a vehicle to pave the way for in-vehicle MS detection and thus for the development of future countermeasures.

2. Method

Data were collected in a user study, separated into a pilot (N = 9 [n = 4 male, n = 5 female]; M = 23.67 years, SD = 2.16 years) and a main study (N = 48 [n = 25 male, n = 23 female]; M = 32.91 years, SD = 12.10 years). Based on the pilot study, the study design, boundary conditions and the measurement equipment were refined for the main study. To test the suitability of the various physiological parameters for the early and individual detection of MS, a within-subjects design with two test conditions was chosen: no MS (baseline, no maneuvers) and MS (parcours, 10 maneuvers). In this design, participants were seated in the back of a darkened vehicle with no visual contact to the exterior environment and driven over an elaborate parcours up to seven laps. A Misery Scale (MISC; Bos et al. 2005) score of 6 or higher was defined as the termination criterion. Participants were tested on two separate days, one for each condition, with the order of conditions randomized across participants. The experimenttal design consisted of an acclimatization phase, a testing phase, and a subsequent cool-down phase. Throughout the experiment, physiological parameters and questionnaire data on the subjective well-being and perceived MS of the participants were recorded (for a detailed representation of the experimental design see Figure 1).

During the pilot, two measurements (one for skin temperature and one for respiration rate) turned out to be unsuitable for the planned study and were therefore eliminated from the main study. Furthermore, the driving speed of the baseline condition was further decreased for the main study to reduce the effects of MS and keep the duration for both conditions at approx. 5 minutes per lap. The main study was conducted in two time periods (1: July-August 2022, 2: November 2022).

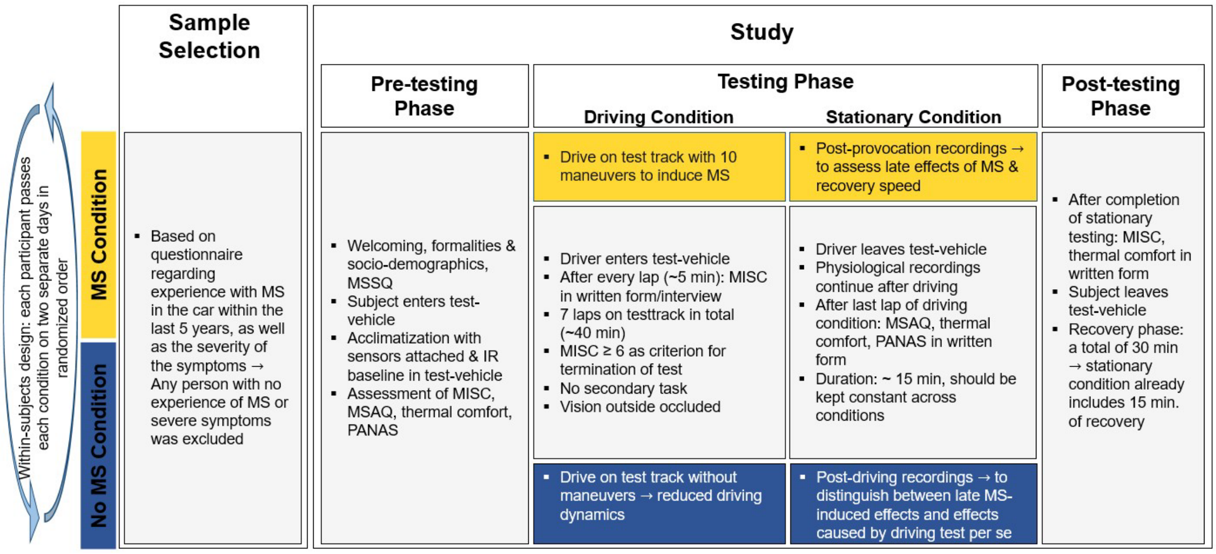

Figure 1: *Schematic representation of experimental design*

2.1 Subjective Measures

Subjective measures included a preliminary interview, obtaining information on socio-demographic information, such as gender and age. Furthermore, the Motion Sickness Susceptibility Questionnaire (MSSQ; Golding 1998) was used to assess the susceptibility to MS prior to the first testing phase. Items of this scale were rated on a Likert scale from 1 (never) to 4 (frequently). During the study, well-being was assessed using the MISC (Likert scale from 1 [no problems] to 10 [vomiting]) as well as the Motion Sickness Assessment Scale (MSAQ; Gianaros et al. 2001; items were rated on a Likert scale from 1 [not at all] to 10 [strong]). Participants' internal states were further recorded using a thermal comfort rating (based on ISO 28802:2012, ISO 7730:2005) along with the Positive and Negative Affect Schedule (PANAS; Watson et al. 1988). Items of the PANAS were rated on a Likert scale from 1 (very slightly or not at all) to 5 (extremely).

2.2 Objective Measures

To obtain objective physiological measures during the experiment, four ECG and two EDA electrodes were attached to the participants' body (ECG: above the chest [channel 1 and reference], below the left rib [channel 2], on the right shoulder [ground]; EDA: second and third finger of non-dominant hand). Both EDA and ECG data were recorded using a 2-channel g.GAMMAbox and a g.GSRsensor connected to a g.USBAMP amplifier (all from g.tec medical engineering GmbH). Both sensor systems were calibrated using the gtec measurement systems for individual session recordings at a frequency of 512 Hz.

Furthermore, skin temperature was measured with a specifically developed thermography-based sensor system. The sensor is a FLIR Lepton 3.5 infrared (IR) sensor positioned approx. 1 m in front of the participants facing towards the participant. The skin temperature was evaluated within a rectangular region of interest of 7 x 5 pixels on the participants' forehead. The sensor was continuously calibrated with a temperature-controlled reference surface (black coated copper plate at 35 °C) positioned within the sensors field-of-view, to improve accuracy. Additionally, cabin temperature was measured at the participants' right side at head level with a temperature sensor and controlled within a target range of 22–24 °C.

Post data acquisition, pre-processing of raw signals from multiple sensors was a critical step for extracting meaningful insights. Raw sensor data were prone to artifacts (environmental, body, motion), noise, outliers and missing values that could adversely affect the analysis later. Hence, data cleaning techniques such as filtering, smoothing, and outlier detection, were applied to mitigate these issues. Overall, eight indicators from individual sensor sets (ECG, EDA, IR) were extracted using software tools Kubios HRV, Ledalab, and MATLAB respectively (Tarvainen et al. 2014; Benedek et al. 2010). Pre-processing of cleaned sensor data also involved normalization of the data range, standardization, and dimensionality reduction techniques to reduce data complexities, enhance the quality, integrity and consistency of the extracted features.

3. Results

The data analysis running a repeated measures ANOVA of subjective measurements revealed a significant interaction of condition (baseline, parcours) and number of driven laps (Pre, 1, 2, 3, 4, 5, 6, 7, after 15 min) for MISC values, F (3.76, 157.92) = 12.48, p < .001, η_p^2 = .23, with higher scores for the parcours condition with increasing number of laps than the baseline condition. No further significant main or interaction effects were indicated by in the subjective data.

Overall, on a descriptive level, a weak relation between individual physiological measures and the MISC score could be observed. In Figure 2, exemplary measurement results for HR, z-scored Mean Amplitude of the raw EDA signal (RZMA) and forehead temperature (TEMP) are shown as a distribution of individual values. While HR and RZMA indicate a positive relation with MISC scores, this is negative for TEMP. The directions are in line with assumptions from previous studies. For the remainder the directions are either in line with assumptions as well (RMSSD), no clear directions may be identified (Frequency of Skin Conductance Responses [FSCR], z-scored Area Sum of the phasic component [CZAS], Ratio of Low & High Frequency Power [LF/HF]) or the observed direction counters the assumptions (EDR). Based on the results of the subjective measures and the descriptive findings, initial analyses of the obtained data sets were conducted using Linear Mixed Effects Models (LMEM), one for each physiological measurement. The following global parameters were used: MISC score as the dependent variable; the number of driven laps, the condition, the season and the appointment (first or second time the participant is tested) as the fixed effects, and the participant ID as the random effect to respect the inter-individual influences. Additionally, the interaction effect between the laps and condition was included. The predictors used in the model are based on the individual sensor sets. For the ECG measurements these included HR, RMSSD, LF/HF, and EDR. For the EDA measurements the FSCR, RZMA, and CZAS were used. For the measurements captured by the IR temperature sensor, TEMP served as a predictor.

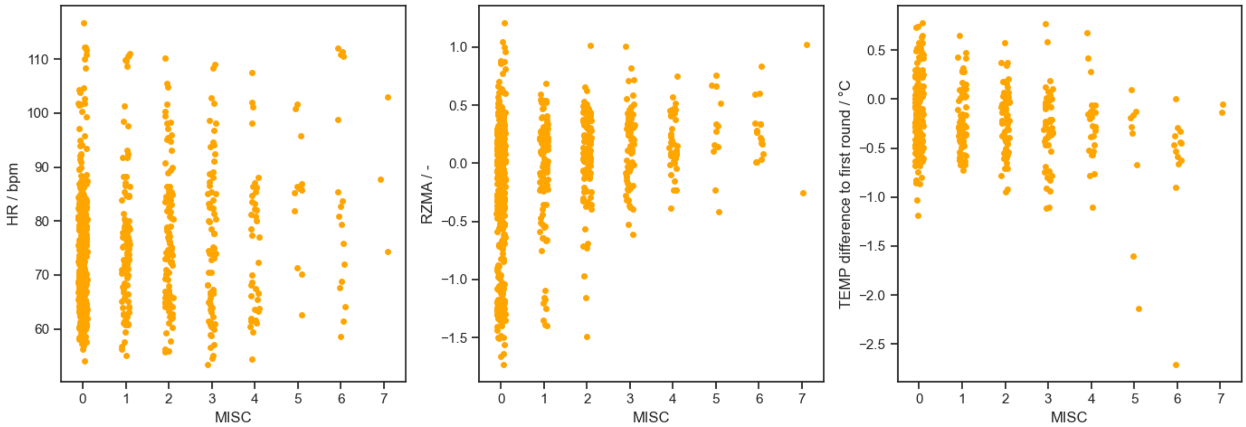

Figure 2: *Exemplary results of HR, RZMA and TEMP physiological measures for different MISC levels.*

Both the ECG and the IR model showed a significant interaction for number of driven laps and condition (ECG: β = 0.10, *SE* = 0.04, *p* = .020; IR: β = 0.11, *SE* = 0.05, *p* = .034), while in the EDA model only the respective main effects were significant (Lap: β = 0.19, *SE* = 0.03, *p* < .001; Condition: β = 0.75, *SE* = 0.20, *p* < .001). Analysis of the ECG model predictors showed significant effects for both HR (β = 0.03, *SE* = 0.01, *p* < .001) and EDR (β = -0.09, *SE* = 0.02, *p* <.001), although only HR follows the expected relationship. A significant effect for the EDA predictors was only observed for the RZMA (β = 0.02, *SE* = 0.19, *p* = .001), following the expected relationship to the MISC. FSCR and CZAS were both not significant and show the opposite relationship. The TEMP as measured by the IR sensor did not result in a significant effect as a predictor. Descriptively, TEMP shows a negative direction with increasing MISC values.

4. Discussion & Conclusion

The aim of this study was to gain a more precise understanding of the relationship between subjective MS and probably associated physiological parameters while in a vehicle. Analysis of the physiological measures indicates a link between measured signals and subjectively perceived MS, especially for ECG and EDA data. This further confirms the findings of relevant literature, showing that physiological measures could be used as indicators for MS. The combination of measures in multi-modal approaches (see e.g. Nouduri et al. 2024), could offer even more sensitive and reliable indicators.

The interpretability of the results, however, is limited due to both, measurement artefacts of physiological data as well as missing MISC data, due to the pre-defined termination criterion at a MISC value of ≥ 6. The data processing steps and further adjustments to the experimental setup aimed to reduce the effects of confounding variables to a feasible minimum, yet they are still visible (e.g. as differences in TEMP measurements between summer and winter conditions).

In summary, in this study an investigation of MS was conducted and initial insights into the relationship between physiological parameters and subjectively perceived MS while in a vehicle were gained. To form the basis for the successful and reliable detection of motion sickness using objective measures, the next step would be to train a classification learning algorithm with the data obtained here. By considering various physiological parameters in parallel, such an algorithm might enable a more precise prediction of a potential state of MS than the described LMEM.

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Geschäftsstelle der GfA
Simone John, Tel.: +49 (0)30 1300-13003, Alte Heerstraße 111, D-53757 Sankt Augustin
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