Evaluation of physiological responses due to car sickness with a zero-inflated regression approach

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Abstract

Motion sickness as a reaction to passive movement is a serious issue in various forms of transportation like cars. The goal of the study is to identify physiological changes that can be measured as a response to motion sickness in a real driving environment. The observed features were heart rate, pulse, respiration, skin temperature and electrodermal activity. Forty volunteers were passengers in a car while watching a movie. Meanwhile the car moved in a half-automated stop-&go-scenario, which represented the motion sickness stimulus. A remarkable part of the recorded data had to be neglected due to a high level of signal noise caused by the car environment. The minutely recorded subjective sickness feedback had a zero-inflated poisson distribution. Therefore a zero-inflated regression model was used to identify the relevance of each of the aforementioned features. The model shows that electrodermal activity and pulse were the most relevant features indicating an increase in motion sickness. The observation of physiological parameters in the car environment is a promising method to objectively determine motion sickness.

Introduction

The issue of motion sickness (also called kinetosis) has a long history and occurs in all cultures, ages, and genders. Being out of the loop regarding the driving task bears a higher risk of getting motion sickness (Diels, Bos, Hottelart, & Reilhac, 2016). With the ongoing development of fully automatic cars the risk of having more passengers experiencing motion sickness gets more attention. Passengers should be able to enjoy the given opportunities to fill the spare time i.e. with reading in automated cars. Currently, the process of evaluating countermeasures against motion sickness requires the subjective passenger's feedback. The development of countermeasures that ought to reduce motion sickness illustrates the deficiency of objective motion sickness detection. Approaches vary from enhancing situation awareness (Yusof, 2019) to display concepts (Diels & Bos, 2015). In order to evaluate those countermeasures and objectively estimate the passengers' state in terms of motion sickness, more work is needed. The aim is to have objective feedback through physiological measurement in the future. This study provides preparatory work regarding the opportunities coming from the relationship between physiology and self-rated motion sickness.

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A short overview on some relevant research and findings, done so far, is given here. The idea of measuring physiological parameter to obtain objective motion sickness levels is decades old. Thereby only those features will be considered, which can be collected without making the customer (passenger in the car) feel less naturalistic or be restricted in any way (for example due to head-worn tracking systems). Some research groups focused on single items while others looked at multiple physiological features. In the following, some results are described. A rise in heart rate for motion-sick participants was found by several studies; however, some of those changes were only weak and not significant (Yates & Miller, 1996; Yates et al. 1998; Graybiel & Lackner, 1980). A significant change in heart rate could be found in the beginning of the trial by Cowing (1985), whereas Holmes & Griffin (2001) found significant changes when strong nausea occurred. It has been observed that the respiration frequency, as a further physiological feature, rises shortly before and while vomiting due to motion sickness (Yates et al., 1998). Deep breathing can be used to combat motion sickness (Jokerst et al., 1999). Nobel (2010) found that motion sickness leads to a dysfunction in the autonomous thermoregulation. His result supports the findings that body temperature is not a good indicator for motion sickness (Scott, 1988; Graybiel & Lackner, 1980). On the other hand, it could be shown that skin conductance is a robust and reliable predictor for motion sickness. The electrical skin potential rises when motion sickness increases (Crampton, 1955; Bertin, 2005; Meusel, 2014).Yates & Miller (1996) indicate that skin colour could play an important role when detecting motion sickness using physiological data, since pallor changes with sickness and is seldom a response to other stressors. Since pallor seems to proceed the onset of nausea (Crampton, 1955), it has a high potential of being a good indicator of motion sickness (Scott, 1988; Holmes et al., 2002).

In short, some features show potential, but most features are not cause-specific: the change of a single feature cannot be traced back to motion sickness with certainty. Therefore, finding a pattern of multiple physiological changes is required. Such a pattern could detect or predict motion sickness more robustly and would not be as vulnerable to unexpected physiological behaviour of the individual. The aim of this investigation was to develop an objective rating method allowing the evaluation of countermeasures without using self-rated indicators by the help of multiple features. An approach in a real driving scenario is presented along with first results.

Method

Ethical Approval

Participants read and signed an informed consent prior to participation. Any participants with one of the following conditions were excluded from the trial: cardiovascular weakness, hypertension, hypotension, epilepsy, balance disorder, pregnancy, other health impairments or of age younger than 18 years. For a conducted trial the participants received a voucher (value €20) as compensation regardless of the trial duration. All participants reported normal or corrected-to-normal visual acuity. The experiment was approved by the Ethics Committee of the Brandenburg University of Technology Cottbus-Senftenberg. To prevent participants from harm, those with a high risk of getting severe motion sickness (high susceptibility) were

excluded from the trials. The derivation of the participants' susceptibility is explained in Table 1.

Participants

Forty volunteers (20 women, mean age = 37.9 years, SD = 11.4 ranging from 21-57 years) which were employees of the Volkswagen AG participated. They are not involved in motion sickness research and participated during their private time. The recruiting process contained an assessment of the participants' susceptibility. By using the Motion Sickness Susceptibility Questionnaire – Short (MSSQ) (Golding, 1998) susceptible (n = 23) and non-susceptible (n = 17) participants for the trial were chosen. Therefore categories were defined using the MSSQ-Score (final score) and the item regarding the experienced motion sickness over the last 10 years in cars (interim score). The categorization can be found in Table 1.

Table 1. Susceptibility Categories

Category	MSSQ-Score	Interim Score	Accounted as
A	Final score = 0	0 or 1	Non-Susceptible
B	Final score > 0	1	
C	Final score > 6 and < 11	2 or 3	Susceptible
D	Finale score >11	2 or 3	
E	Final score > 20	4	highly susceptible

Interim code: never felt sick '1', rarely felt sick '2', sometimes felt sick '3', frequently felt sick '4'

Materials and Set up

The motion sickness stimulation during the trial was a stop-&go-scenario.Two cars drove behind each other and the participant sat in the rear car in the front passenger seat. A vehicle acceleration profile was created before the trial and replayed for the vehicle in front, while the participants' car followed with adaptive cruise control. This should assure a constant motion sickness provocation in all trials for all participants. A trained security driver was in the driver seat and the experimenter in the rear passenger seat.

The lead car was a VW Passat, while the rear car was an Audi A8 D5. During the experiment the participant had a display (Nanovision MIMO UM-1010S, 10.1" USB Multi-Touchscreen Display) fixed to the leg. They were asked to give feedback every minute about their motion sickness status on a seven-point scale ranging from zero - "no symptoms" to six - "unbearable" in German language. The scale, illustrated in Figure 1, was located on the bottom of the touch screen and the participants gave feedback by tapping on the screen.

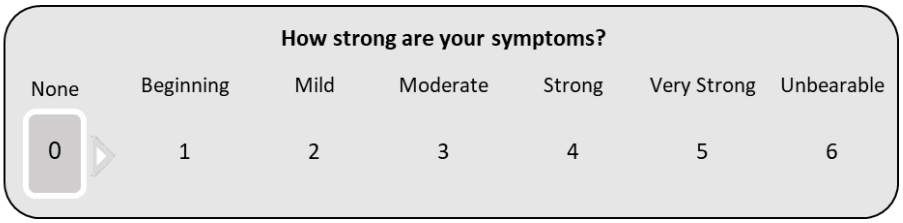

Figure 1. Illustration of the Questionnaire

Kinetosis appears more often if passengers are involved in tasks in which their eyes are off the street. Therefore participants were instructed to keep their eyes on the monitor during the whole drive. To ensure that participants would be watching the monitor, they had to count either jelly fish or clown fish (randomized over the trials) in a coral reefs film. The film was screened throughout the entire time on the upper part of the display above the questionnaire.

The study was conducted in November and December 2018. All participants were able to get acclimated for several minutes after getting into the car, coming from the cold temperatures outside (approximately 5°C). The car temperature was set to constant 23°C, which is supposed to be the optimal temperature for measuring electrodermal activity (Boucsein, 2012).

Procedure

Each participant completed two trials to increase reliability of the data which were organized on different days. After giving informed consent, participants were seated in the car. During the time given for acclimation, the sensors were attached to the participants. The first part of the experiment was a seven-minute session in the standing car, therein the recorded data was used to create a baseline. The baseline measures were followed by the actual trial, where participants would experience the stop-&go-driving scenario for a maximum of 20 minutes or until an abort criterion was reached. During both sections, the baseline and the drive, participants had the visual counting task. There was always only one participant at a time. After the trial, the vouchers were handed over,participants were provided refreshment and asked to stay at the location until the symptoms fully disappeared.

Physiological measurements

The physiological data acquisition was carried out by the use of a ProComp Infinity encoder with ProComp Infinity Sensors and recording from the BioGraph Infinity Software (Thought Technology Ltd, 2019). Electrocardiac activity (ECG) and blood volume pulse (BVP) were recorded at 2048 Hz. Electrodermal activity (EDA), temperature and respiration were measured at a sampling rate of 256 Hz. The respiration sensor was placed in a stretch belt and placed around the chest. Skin conductivity was measured by placing sensors on the pointer and ring finger of the non-dominant hand, while ECG was recorded using wrist straps. The BVP sensor as well as the temperature sensor were placed on the middle finger of the non-dominant hand. Furthermore, a second measurement of temperature and pulse was derived from

the inner ear by using the device Cosinuss° One (Cosinuss°, 2019). The accuracy from the temperature in the inner ear is a constant offset to the body core temperature but dynamic changes can be recorded precise enough for most medical applications. Pulse oximetry in the external auditory canal is comparable to pulse oximetry on the finger, while it is more robust towards motion artefacts. (Kreuzer, 2009) The approach in measuring the features twice was realized to improve overall data quality. The dynamic environment could cause a low signal-to-noise-ratio which therefore requires a backup system.

Data Analysis

On average the time series of the 70 trials per physiological parameter containing over 2100 observations in total were used for the data analysis. Each of the parameters was statistically and visually screened for outliers and noise. Initial analysis for the heart rate signal included cascading high- and lowpass filtering, afterwards QRS complexes were detected using wavelet analysis. Downsampling processes were done for the blood volume pulse on the finger (finger pulse) as well as the temperature data. The finger pulse and the respiration signal were waveform data, wherein a peak was considered a beat or a breath respectively. Electrodermal activity was divided into tonic and phasic movement with a 0.5 Hz highpass filter. From the phasic component skin conductivity reactions (SCR) were extracted. SCRs were identified as responses with an amplitude of SCRs/min ≥ 0.03 µS. Rejection rate was set to 10 %, meaning that amplitudes SCRs/min < 0.003 µS were rejected. Almost all of the features were normalized using the baseline measurements and were averaged per minute. Only the SCRs were not normalized, since its appearance itself is an indicator for motion sickness (Golding, 1992).
Since several physiological features were derived from the participants and a human body rarely shows any independent physiological changes, it has to be assured that no information is used in the analysis multiple times (multicollinearity). Multicollinearity describes the case when information is redundant in a set of variables and the redundancy gets apparent in a combination of several variables. Physiological reactions of humans are mostly dependent which increases the chance of multicollinearity in the data. To test that no harmful multicollineariy was present firstly pairwise correlation was calculated. Before calculating the correlations, the features need to be centred and scaled which led to lead to a mean of zero and standard deviation of one for all of the features. If the pairwise correlation shows high coefficents (Pearson's $r < 0.7$) this is considered as indicator for severe multicollinearity. In addition, the variance inflation factor (VIF) was calculated. The VIF is a predictor of whether variables have a strong relationship to one or more variables. The calculation of VIF was necessary since multicollinearity can also appear, if pairwise correlations are low. A conservative threshold indicating harmful multicollinearity is VIF = 4 (Slinker& Glantz, 1985).
In accordance to the rating distribution, a zeroinflated poisson regression model was computed. For the model all ratings of 4 were transformed to 3, because the amount of reported 4s was too little. Furthermore, only cases where recording of all features was successful, could be considered, resulting in 895 observations. The model consists of two separate processes: one considers the count part of the model. The count model examined how ratings evolve, if the participant experiences motion

sickness at some point (susceptible to the provocation). The second process contains a logistic regression considers those participants which are unsceptible to the stop&go scenario and reported only zeroes. The results of the zero-inflation model coefficients, shows the odds of reporting no motion sickness symptoms (Atkins, 2007). To verify the model, the combined probability of no symptoms (Rating = 0) were calculated and compared to the actual appearance of no symptoms.
A 5 % significance level was accepted in all tests, data analysis and statistical calculation were carried out using Matlab 2016b and R 3.5.3.

Results

Correlation between Blood Volume Pulse on the finger (finger pulse) and inner ear was high (r = 0.78), therefore the ear pulse was not further used. Furthermore, skin temperature was not used, since the measurement showed high fluctuation which has most likely been caused by the airconditioning fan of the car, instead, the temperature derived from the inner ear was used. The measurement of the heart rate showed a low signal-to-noise-ratio, possibly due to the unsteady environment of the movement and electrical components in the car led to many artefacts. Therefore the heart rate was excluded from further analysis. The remaining features were the finger pulse, inner ear temperature, respiration rate and skin conductivity components (tonic and SCRs). Table 2 lists the features wherein all but the SCR-Peak were normalized by the baseline (substraction of baseline mean from each data point).

Table 2. Normalized features used along variance inflation factor

Measurement	**Derived Feature**		**Mean**	**SD**	**VIF**
Blood Volume Pulse	Peak	[Counts per minute]	0.83	3.79	1.02
Temperature	Mean Temperature	[K]	0.58	0.88	1.06
Respiration	Peak	[Counts per minute]	0.35	2.97	1.06
Skin Conductivity	Mean Tonic Level	[µS]	0.26	0.48	1.27
	SCR-Peak	[Counts per minute]	2.22	1.79	1.37

The listed measurements in Table 2. were used for the further analysis and have pairwise correlations r < 0.7. Each of the features has a VIF < 4, therefore none of them indicated harmful multicollinearity. For those remaining components, the correlations to the ratings are plotted in Figure 2. The displayed boxplots bring out the partial relationships between the dependent variable and the indented regressors. The negative SCR-correlations appeared, when particpiants showed a relieve in symptoms but SCRs still occurred. In the tonic part of the EDA a positive tendency can be observed. The correlation of respiration to rating has a negative tendency, while the residual parameters BVP and temperature have mainly positive correlations.

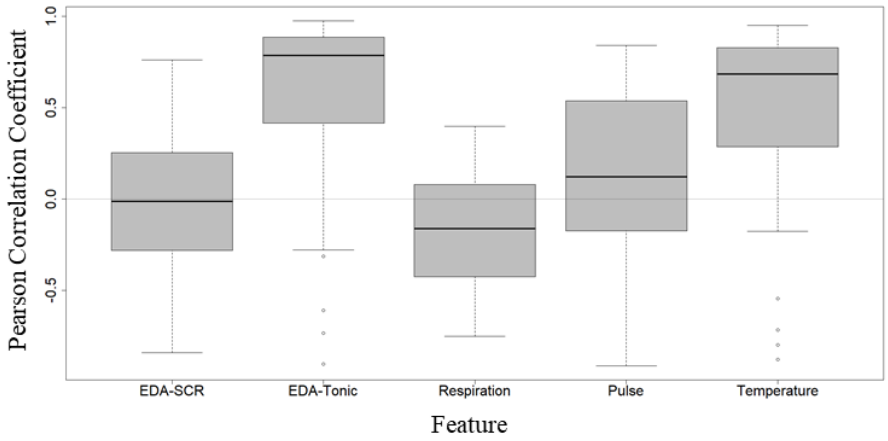

Figure 2. Boxplot of correlations of physiological features to sickness rating

The given ratings plotted in a histogram (Figure 3) indicate that the distribution is not Gaussian, but tends to a Poisson distribution which was also found by Reason (1967) for a motion sickness rating. In total 1293 ratings were given during the provocation wherein 718 were '0 – no symptoms' and 21 ratings were '4 – strong symptoms'. Testing a zeroinflation with the Score-Test from van den Broek (1995) reveals that the data have a zeroinflation (χ^2 = 195,99, df = 1, p < .001).

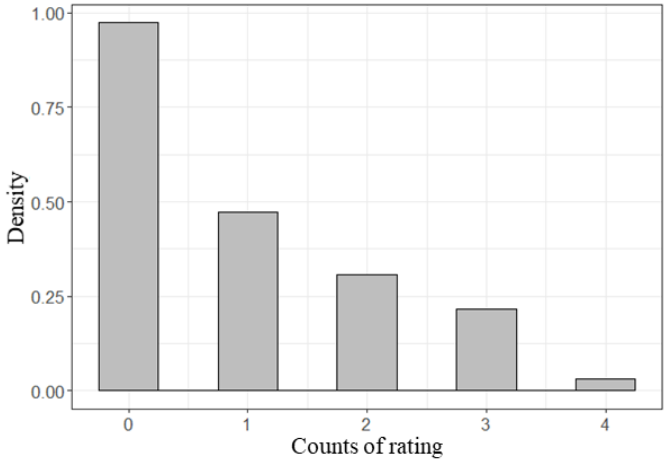

Figure 3. Histogram of the rating during the drivings

The reported mean sickness development over all subjects are plotted in Figure 4. The '+' at rating 4 represents the break-off criterion of which 19 occured in total due to subjects reporting the level of 4. Two times participants reported a motion sickness level of 4 very early which was assumed a mistake until the rating was repeated. When a rating of 4 occurred, the remaining minutes were filled with 4 to enable the plot.

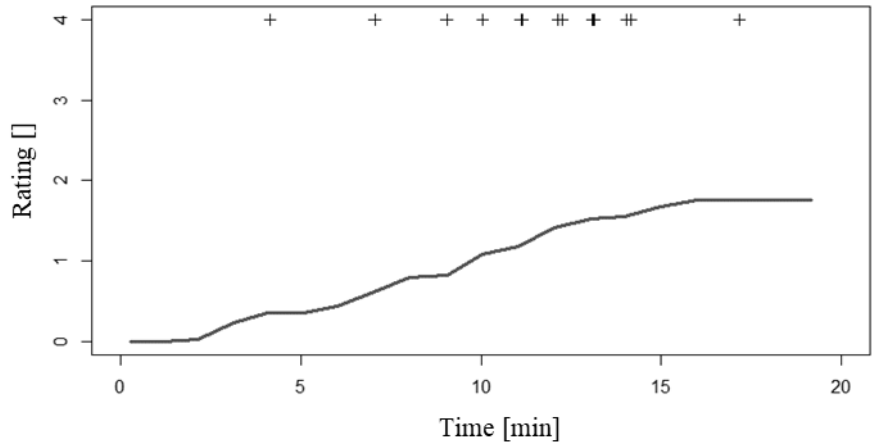

Figure 4. Mean reported motion sickness development

The resulting model is shown in Table 3. The unprocessed results of the modelling lead to numbers which are calculated using log link. Therefore the estimated slopes (Est) of the coefficients are on a log scale and shown along with their exponentiated values (Exp(Est)) to ease interpretation. The estimate of any coefficient in the count model describes how the rating changes if the respective coefficient changes one unit. Generally one outcome of the log link function is a non-linear relationship of the predictor variables with the result (Beaujean & Morgan,2016). The percentage of the rating change can be calculated using Equation (1).

$$\text{Percentage of Rate-Change} = 100\text{x}[\exp(b_0)\ \text{x}\ \exp(b_1\ \text{x}\ \Delta\text{EDA, SCR})\ \text{x}\ \exp(b_2\ \text{x}\ \Delta\text{EDA, tonic})\ \exp(b_3\ \text{x}\ \Delta\text{Respiration})\ \text{x}\ \exp(b_4\ \text{x}\ \Delta\text{Temperature})\ \text{x}\ \exp(b_5\ \text{x}\ \Delta\text{BVP})] \quad (1)$$

Therein b_0 represents the intercept while $b_{1\text{-}5}$ are the regression coefficients and Δ are the changes in the respective predictors. The distance of the result to 1 can be interpreted as the increase or decrease of the percentage (Atkins et al., 2013). For a better understanding the influence of Blood Volume Pulse change shall be described as an example. The residual parameters are kept at an average level (as measured during the baseline condition). The coefficient calculated by the model for the influence on rating due to the change of BVP is 1.37 (exp(Est)), the BVP changes in the range of its standard deviation (1 unit, since the data were centred and scaled). The influence on rating can be calculated using Equation (1):

$$\text{Percentage of Rate-Change} = 100\ \text{x}\ \exp(0.01)\ \text{x}\ \exp(0.31*1) = 137.94$$

Meaning that there is approximately 38% of increase in motion sickness rating, when the BVP changes one peak/minute.

Table 3. Zeroinflated poisson model

Coefficient	Est	SE	exp(Est)	z-Value	Exp(95% CI) Lower	Exp(95% CI) Upper	p	
Count model coefficients								
Intercept	0.01	0.06	1.01	0.19	0.91	1.12	0.85	
EDA, SCR	-0.12	0.05	0.89	-2.19	0.80	0.99	0.03	*
EDA, tonic	-0.00	0.06	1	-0.05	0.89	1.12	0.96	
Respiration	-0.04	0.03	0.96	-1.21	0.9	1.03	0.23	
Temperature	-0.30	0.07	0.74	-4.60	0.68	0.80	<0.001	***
BVP	0.31	0.04	1.37	8.41	1.28	1.45	<0.001	***
Zero-inflation model coefficients								
Intercept	-2.42	0.48	0.09	-5.07	0.02	0.24	<0.001	***
EDA, SCR	0.71	0.19	2.04	3.82	1.42	2.94	<0.001	***
EDA, tonic	-3.68	0.60	0.03	-6.17	0.01	0.08	<0.001	***
Respiration	-0.33	0.15	0.72	-2.17	0.51	0.95	0.03	*
Temperature	-2.66	0.62	0.07	-4.27	0.01	0.28	<0.001	***
BVP	0.33	0.17	1.39	1.93	0.97	2.06	0.05	

Note. Est: Unstandardized coefficient (log link), SE: Standard error, exp(Est): 95% CI confidence interval: Exponentiated regression coefficient. Log Likelihood: -978.5 (df = 12)

The number of correctly and incorrectly predicted observations can be found in the confusion matrix (Table 4) along with the derived sensitivity (proportion of positive cases correctly predicted).

Table 4. Confusion matrix

Observed / **Predicted**	**0**	**1**	**2**	**3/4**	**Total**
0	460	140	91	38	729 (81.45%)
1	57	30	28	38	153 (17.10%)
2	0	2	7	3	12 (1.34%)
3	0	0	0	1	1 (0.11%)
4	0	0	0	0	0
Total	517 (57.77%)	172 (19.22%)	126 (14.08%)	80 (8.94%)	895
Sensitivity	88.97%	17.44%	5.55%	1.25%	

Discussion

The conditions of the real driving experiment introduced confounding factors that cause notable noise as influence, which negatively affects the signals (i.e. temperature, influence of sun, driving conditions, car movements or technical artifacts). These factors as well as internal biological variations have an impact on the variance of the data (Scholz, 2006) and prevent a full use of all of the measurements.

The rating data are derived from susceptible and non-susceptible participants. The non-susceptible participants are a source contributing only zeros to the rating, therefore the distribution of the rating results in a zeroinflation. The use of an zero-inflated model is therefore appropriate. Each observed feature of the model is within the confidence interval. The models' overall validity is therefore considered to be given. Interpretation of the slopes in Poisson models (which become multiplicative models) has to be done very carefully, it is described in more detail by Atkins et al. (2013). Generally, it is shown that Skin Conductivity Responses, temperature and Blood Volume Pulse have a significant explanation range regarding the rating. The negative relationship between sweat (SCR) and motion sickness is surprising. A calculation according to Equation (1) results in a decrease of the rating when the SCR rises 1 unit. It was expected that sweat activity rises along with a development of motion sickness. The findings, as in several studies, of a higher amount of perspiration as one of the characteristics of a motion-sick group compared to a non-motion-sick group, could not be found here (Crampton, 1955; Scott, 1988; Golding, 1992; Bertin et al., 2005). Temperatures seems to reduce as motion sickness rises. An increasement of temperature in a thermoneutral environment was also described by Nobel (2010). Contrarily in preceding studies temperature was behaving variable (Jarvis & Uyede, 1985) or did not change significantly (Drylie, 1987). The significant effect found is therefore surprising. Further the model indicates that a rise of BVP leads to a rise of a motion sickness rating. This is in agreement with findings from literature (Crampton, 1955; Dahlman, 2009). The output of the model dealing with the zeros would be interesting regarding the onset of motion sickness symptoms. This would require, the threshold of 0 - "no symptoms" to 1 - "beginning" symptoms was similar understood by all of the participants. Correct categorization of the participants' motion sickness into the scale was assumed but due to subjective judgement it cannot be assured, especially when "beginning" symptoms were reported.

Conclusion

The presented study examined the relationship between physiological data and reported motion sickness. Participants were situated in a stop&go-scenario, while being involved in a non-driving related task, which caused them to have their eyes off the street. This scenario was sufficient to provoke motion sickness over time: Out of the 40 participants 7 participants had severe motion sickness, while 27 participants had at least mild or a higher degree of motion sickness symptoms. The recordings were done in a real-driving scenario, where the challenge of transfering and reproducing results from laboratory environments in real-driving experiments became apparent. Physiological features were used to perform regression analysis in order to analyse the associations between a reported motion sickness level and physiological reactions. The distribution of the rating led to a zero-inflated poisson model.

The generated model revealed that sweat (SCR), temperature and Blood Volume Pulse changes significantly with the rise of motion sickness. Reversely these results indicate that sweat and blood volume pulse are good indicators for motion sickness. The model had a good sensitivity considering the predicition of 'no symptoms' (~89%). Ratings indicating the appearance of motion sickness (Rating > 0) were in average predicted lower than the observation. The significant features along with narrow confidence intervals substantiate that motion sickness expresses itself in physiological changes, which can be recorded during a real-driving scenario. This is considered a promising basis when continuing the work towards objective detection of motion sickness.

Future Strategy

The model can be adjusted in two possible ways. One will be to change the general model. The zero-inflated poisson model considers the rating as an numeric value, while the numbers 0-4 represent the categories of having "no symptoms" to "strong symptoms". Therefore an zeroinflated ordered probit regression model will be calculated, which does not assume the numbers 0-4 to be equidistant but still represents an ordered scale. Alternatively, a binary model will be computed, wherein ratings of 0 and 1 are grouped as "no symptoms" and ratings greater than 1 as "symptoms present". This will allow to overcome the uncertainty of the onset of reported motion sickness. Comparison of the models will allow to choose the best fit.

After choosing the best model the independent variables could be varied. According to literature motion sickness is influenced by several factors, for example personality, sex, age, exposed time to stimulus (Brietzke et al., 2017; Dahlman, 2009) or theoretically derived susceptibility via a questionnaire (MSSQ by Golding, 1998). Therefore including such parameters into the model should influence the outcome and informative value of any model. It is expected, in example, that the results from a model including data of self-assessed susceptible passengers are more precise in the outcome. The adjustments should confirm if the grouping factors significantly influence of the participants' rating of motion sickness. This allows conclusions, whether the model can be built more accurately if certain groups are considered. Practically this includes assertions on how motion sickness is connected to physiology in people with a certain profile and which indicators are important. Adjusting the models towards the actual susceptibility (i.e. choosing people with a rating higher than 2 – "mild symptoms") would probably lead to the most reliable results. By taking the temporal development of the physiology with regard to the onset of motion sickness into account it could be feasible to recognize motion sickness even before the passenger is totally aware of it. In an additional step, it will be tested to what extent the accuracy of prediction can be enhanced using the aforementioned factors. In general the research question regarding the potential of objective motion sickness detection in cars is currently referred based on literature that mostly addresses the laboratory context. These results need to be proven relevant and feasible for implementation and application in the car. The presented work is one method towards transporting laboratory findings into the car. The approach of using multiple features in a mathematical model will leed to helpful results in the progress of evaluating the importance of physiology for objective detection of motion sickness in cars.

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