A Machine Vision Approach for Estimating Motion Discomfort in Simulators and in Self-Driving

SAFETY RESEARCH USING SIMULATION

UNIVERSITY TRANSPORTATION CENTER

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Table of Contents

List of Figures

List of Tables

Abstract

Motion discomfort in highly automated vehicles and in simulators represents a persistent problem that might be mitigated if it can be monitored. In driving simulators, motion discomfort can compromise data collection. In highly automated vehicles, motion discomfort can discourage people from riding in such vehicles, undermining the potential safety benefits. Monitoring motion sickness in real-time can help mitigate its negative consequences. This report investigates the potential of machine vision techniques in estimating motion discomfort in real-time for both, simulators and highly automated vehicles. Drivers' video data and simulator sickness scores collected in the NADS driving simulator were analyzed. The video data were reduced to the facial action units (basic units of facial expressions) and head pose estimations. While results did not show significant correlations between motion score and facial expressions, we found a significant correlation between the drivers' head position and motion sickness severity. One important outcome of this project was a computer-aiding tool for manual coding of videos. The tool can be used to advance research on the topic of motion sickness and also in other fields and areas that rely on video analytics like affective computing.

1 Introduction

Motion discomfort in highly automated vehicles and in simulators represents a persistent problem that might be mitigated if it can be monitored. In driving simulators, motion discomfort can compromise data collection. In highly automated vehicles, motion discomfort can discourage people from riding in such vehicles, undermining the potential safety benefits.

Driving simulators sometimes induce discomfort that ranges from a sense of visual strain and fullness of head to severe nausea and projectile vomiting. Obviously, the more extreme levels of simulator discomfort can compromise the research and training goals of driving simulators. Even mild forms of discomfort can shift the driver's behavior in a way that can undermine the validity of the research. For example, participants who begin to feel discomfort may compromise their attention to the driving task.

Because riders in highly automated vehicles are likely to look away from the road to perform other tasks (e.g., respond to email or watch videos) or to socialize with other passengers, highly automated vehicles are likely to induce motion discomfort similar to that seen in simulators [1]. This might discourage people from riding in such vehicles.

Motion discomfort in both simulators and highly automated vehicles can undermine their potential, so real-time monitoring and mitigating discomfort is an important concern. In driving simulators, real-time monitoring for motion discomfort would allow researchers to intervene and stop the experiment before a participant becomes seriously ill. The output of the real-time monitoring could also be combined with other simulator variables to identify data that might be compromised by participants trying to mitigate their feelings of discomfort (e.g., unusual steering behavior because they are driving through curves with their eyes shut).The output of the real-time monitoring of riders in highly automated vehicles could be used to adjust braking and steering algorithms or guide other motion-sickness mitigation (e.g., increase the field of view, stabilize the in-vehicle task [1], or adjust the air conditioning [2].

Real-time estimates of motion discomfort are clearly valuable, but no system has been developed to produce them. Experimenters currently rely on careful observations, queries to drivers concerning how they are feeling, and post-drive ratings. Therefore, this report investigates the potential of machine vision to generate a real-time estimate of motion discomfort.

1.1 Objectives

The objective of this project is to investigate the possibility of machine vision techniques to estimate motion discomfort in real-time for both, simulators and highly automated vehicles. The objective was achieved by the following steps:

1. Developing a tool that helps in exploring the videos. This tool is very valuable for video analytics in general; it provides a collaborative platform between machine learning algorithms and scientists.
2. Analyzing drivers' facial expressions to determine their potential for real-time estimation of motion discomfort in simulators and highly automated vehicles to replace other, more intrusive measures of discomfort.
3. Examining head posture data, obtained from an in-vehicle camera, and its effect on motion sickness.

1.2 Summary of results

In this project, we were able to develop a web application using R software and the shiny package [3], [4]. The application represents a powerful and promising tool for video analytics. It allows the scientist to label selected frames from videos by leveraging unsupervised machine learning algorithms that clusters frames based on the similarities in the facial expressions. Then, the scientists can manually provide a label for similar frames.

In addition, the results suggested a significant positive relationship between the driver's proximity (z-distance) to the camera and motion sickness score. A significant negative relationship between the driver's horizontal distance from the camera (x-axis) and motion sickness score. Figure 1 illustrates these dimensions.

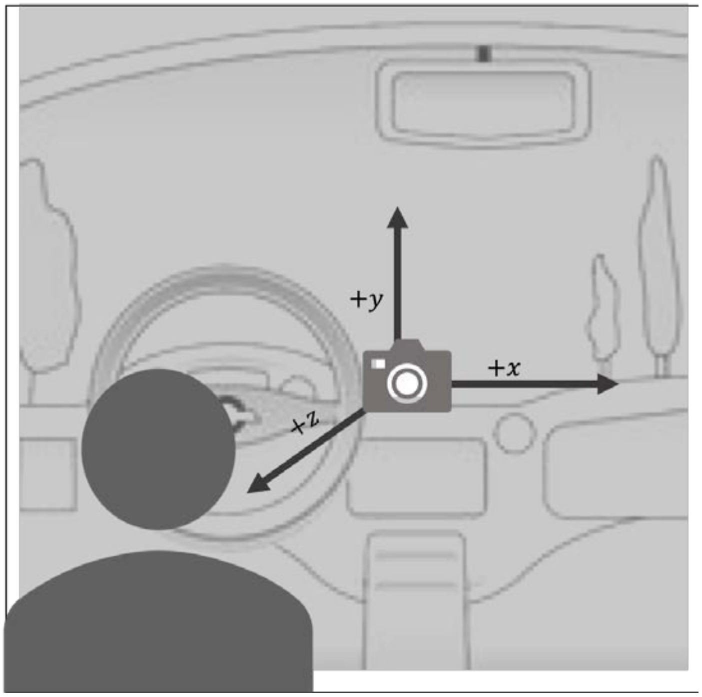

Figure 1. The three axes as measured from the mounted camera

Finally, there were some challenges in predicting motion sickness from facial expressions. Firstly, the lack of a continuous validating measure of motion sickness made it difficult to evaluate changes in facial expressions on a second-to-second basis. Instead, we relied on overall changes of the driver's facial action units throughout the start and the end of the drive. Secondly, most of the drivers who expressed feeling uncomfortable did so after a sickness-inducing maneuver and consequently, withdrew from the experiment. In other words, there was not much data from drivers while sick. Nevertheless, based on the results of this project, we made recommendations that will hopefully guide future research efforts.

1.3 Report structure

In addition to Section 1, which provided an overview of the project, this report consists of other sections as follows. Section 2 reviews the relevant literature on motion sickness in simulators and vehicles and highlights why we think machine vision monitoring will be valuable. Section 3 describes the data used in the analysis. Section 4 provides the analysis and results of the research and section 5 concludes with suggestions for future work and research.

2 Literature Review

2.1 Motion sickness

Motion sickness is defined as “a syndrome characterized in humans by signs such as vomiting, pallor, cold sweating, yawning, belching, flatulence, decreased gastric tonus and by symptoms such as discomfort, nausea, headache, feeling of warmth and drowsiness” [5]. There are two main theories that explain motion sickness: the sensory conflict theory [6] and the postural instability theory [7]. The first explains motion sickness as a result of a mismatch between the three movement sensing systems (nerves, eyes, and inner ear) [8]. The other theory explains motion sickness as a result of loss of the coordination and stability of body segments. A study by Warwick-Evans et al. [9] evaluated both theories, and their results validated the sensory conflict theory but did not validate the postural instability theory. Hence, the sensory conflict theory was adopted by scientists in explaining motion sickness. This theory explains why drivers are less likely to get sick in comparison to passengers and why reading in a moving vehicle can induce motion sickness; the eyes do not sense the movement that the inner ear senses.

Motion sickness is not limited to cars. It can be seen in the sea (seasickness), in the air (airsickness), in space (space sickness), or even in virtual spaces (simulator sickness). In this report, the collected sickness data was from a driving simulator study, and therefore, we will be referring to simulator sickness rather than the other categories of sickness. Nevertheless, what can be learned from simulators has the potential to be transferred to other domains such as automated vehicles.

Simulator sickness (which will be investigated further in this report) is very similar to motion sickness in symptoms but occurs in simulators and virtual reality even when the person is not moving. Symptoms can include vomiting, headaches, sweating, increased salivation, drowsiness, dizziness, and/or warmth. Sickness symptoms can undermine the effectiveness of simulator experiments and might even have safety consequences for the participants (e.g., if participants had to drive right after a simulator experiment while having one or more of the above symptoms). Therefore, investigating factors affecting motion sickness can help control it.

2.2 Current measures of motion sickness

Previous research on motion sickness reported different measures to quantify the severity of sickness. Such measures mainly rely on physiological changes in the human body and on subjective reports from participants.

2.2.1 Physiological changes

Motion sickness has been found to be associated with many physiological changes in the body. Table 1, taken from [10] summarizes these physiological changes. Physiological measures have been used widely to validate other driver state measures, such as mind wandering, through electroencephalogram (EEG) [11]. Similarly, physiological changes have been used to measure motion sickness. However, Shupak and Gordon [12] reported that there is no single measure that has sufficient sensitivity and specificity to accurately estimate or predict motion sickness in real-time. Another study by [13] confirmed the previous results of Shupak and Gordon; they tried to detect motion sickness through a wearable device that monitors EEG, heart rate, and blood pressure and were not able to confirm a definitive correlation between those physiological measures and motion sickness that would allow continuous monitoring of sickness in real-time.

Table 1. Physiological changes associated with motion sickness

Physiological System	Manifestations
Cardiovascular	Changes in pulse rate and/or blood pressure ↑ tone of arterial portion of capillaries in the fingernail bed ↓ diameter of retinal vessels ↓ peripheral circulation, especially in the skin of the head ↑ muscle blood flow
Respiratory	Alterations in respiration rate Sighing or yawning Air swallowing
Gastrointestinal	Inhibition of gastric intestinal tone and secretions. Salvation Gas or belching Epigastric discomfort or awareness Sudden relief from symptoms after vomiting
Body Fluids	Changes in Lactic Dehydrogenase concentrations
Blood	↑ hemoglobin concentration ↑ pH and ↓ $paCO_2$ levels in arterial blood, presumably from hyperventilation ↓ concentration of eosinophils ↑ 17-hydroxycorticosteroids ↑ plasma proteins ↑ ADH ↓ Glucose utilization
Urine	↑ 17-hydroxycorticosteroids ↑ catecholamines
Temperature	↓ body temperature Coldness of extremities
Visual System	Ocular imbalance Dilated pupils during emesis Small pupils Nystagmus

Adapted from Kennedy and Frank [10]

Hence, physiological changes are correlated to motion sickness and can be used as an additional layer of validation. However, on their own, they cannot estimate and monitor motion sickness. See Koohestani et al. [14], for a comprehensive review of physiological measures and motion sickness.

2.2.2 Subjective measures

Subjective measures are the most common measure of motion sickness. They are the person’s own assessment of their symptoms. Usually, surveys are administered to assess the severity of motion sickness symptoms and consequently quantify the level of sickness. A typical motion sickness questionnaire consists of many questions, making it impractical to get a measure of sickness in a continuous fashion.

One of the most common motion sickness questionnaires is the Pensacola Motion Sickness Questionnaire (MSQ) [15]. Their questionnaire assigned varying weights to different symptoms of motion sickness and the total severity score as a summation of the weights of all present symptoms. There are many variations of this scale with different numbers of items, and the most comprehensive one has 33 items [1].

Another widely used questionnaire is the Simulator Sickness Questionnaire (SSQ), and as the name suggests, this is used in simulators and virtual reality settings. SSQ was developed by Kennedy et al. [16] and it consists of 16 items. Factor analysis showed that these symptoms can be split into three categories: symptoms related to Oculomotor, symptoms related to Disorientation, and symptoms related to Nausea. Weights are assigned to the three different categories, and their summation provides a single sickness severity score. Participants are usually asked to rate the symptoms on a 4-point scale (0-3) [17]. Table 2 below shows the symptoms in the SSQ scale and their corresponding weights in each category. Those with a factor loading greater than 0.30 are bold. In this project, we use the SSQ score as the ground truth for sickness severity.

Table 2. SSQ symptom list and the corresponding factor loading for each category

Symptom	Category		
	Nausea	**Oculomotor**	**Disorientation**
Nausea	**0.75**	0.08	**0.30**
General discomfort	**0.65**	**0.40**	0.18
Stomach awareness	**0.64**	0.03	0.21
Sweating	**0.31**	0.24	0.08
Increased salivation	**0.53**	0.21	0.13
Vertigo	0.18	0.08	**0.37**
Burping	**0.41**	0.04	0.22
Difficulty concentrating	**0.32**	**0.39**	0.27
Difficulty focusing	-0.01	**0.61**	**0.43**
Eyestrain	0.00	**0.74**	0.17
Fatigue	0.15	**0.54**	-0.04
Headache	0.22	**0.53**	0.15
Blurred vision	0.01	**0.36**	**0.40**
Dizzy (eyes closed)	0.17	0.07	**0.76**
Dizzy (eyes open)	0.17	0.09	**0.65**
Fulness of head	0.12	0.17	**0.37**

Adapted from Balk et al. [17]

There have been efforts to measure motion sickness in a continuous manner. Young et al. [18] developed an efficient method that was used in the domain of centrifuge experiments. Their method involves participants verbally rating their motion sickness severity on a 20-point scale (i.e., 0 (no sickness at all) to 20 (frank sickness)) every minute. Eight years later, they validated their method in a driving simulator to demonstrate that it can be used in more domains [19].

2.3 Other potential measures of motion sickness

Both physiological and subjective measures have drawbacks, and neither can measure sickness continuously in real-time. Subjective reports are usually obtained over long periods of time and can be intrusive if measured more often. Furthermore, physiological measures are challenging because (i) they require high technical expertise to set up and obtain accurate data [20] and (ii) research on physiological measures was not able to validate their predictivity of sickness [12]. Hence, there is still a need for measures that allow for real-time monitoring to mitigate the consequences of motion sickness early on. By exploring other domains, we found that machine vision techniques can provide such a measure.

In affective computing, researchers rely on machine vision to track the user's facial expressions and gain insight to their emotions and have the system/computer react accordingly. This is typically done automatically and in real-time by relying on facial action units. Facial action units system is a taxonomy for the facial muscle movement. Ekman et al. [21], reported that combinations of the action units represent emotions. For example, activation of action unit 6 (cheek raise) and action unit 12 (lip corner puller) represent smiling, and hence, the person is said to be happy. Figure 2 illustrates the different action units and the corresponding emotions [22]. In addition, researchers have employed other cues such as body language and head pose [23]. Similar systems for motion sickness monitoring in simulators and highly automated vehicles would be extremely valuable. First, in simulators, the output of the monitoring system can be used by researchers to mitigate further consequences of sickness and to consider the participant' conditions in the data analysis process. Second, in highly automated vehicles, the car can adjust braking and steering algorithms, stabilize the in-vehicle task, or adjust the air conditioning [1], [2], [24]. Also, in the biological sciences domain, researchers have investigated sickness detection through image recognition. One study on rats found that there are facial expression changes (specifically eye-opening decrease) after injecting rats with nausea-inducing medication associated with nausea-like symptoms [25].

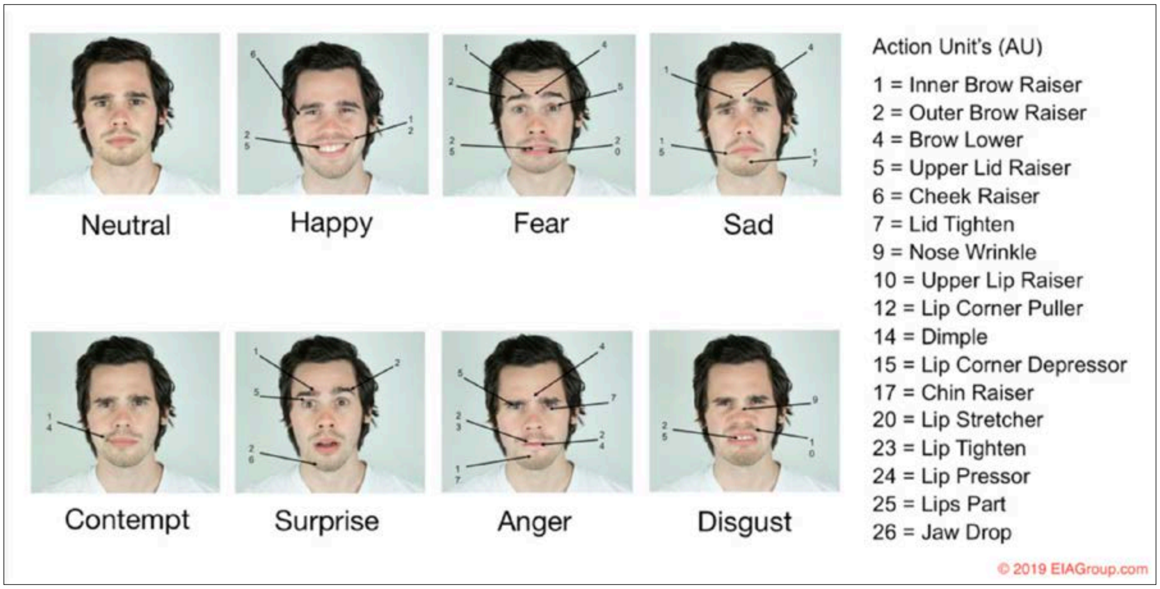

Figure 2. An illustration of the Facial Action Coding System. Taken from [22]**.**

2.4 Countermeasures of motion sickness

If we can detect motion sickness, we can mitigate its further progress. Research has found many useful techniques to reduce the symptoms of motions sickness. Examples of such techniques include increasing the field of view, stabilizing the in-vehicle task [1], adjusting the air conditioning [2], alternative virtual realities that mirror the real world, or displaying the intentions of the vehicle [26] as it is assumed that unpredicted motion contributes to sickness [27]. Another technique is the motion sickness goggles developed by Citroën. Their glasses have a blue fluid surrounding the eye that is meant to stabilize the view of the driver, as shown in Figure 3. Yet, the question remains of how to employ such techniques in simulators and automated vehicles.

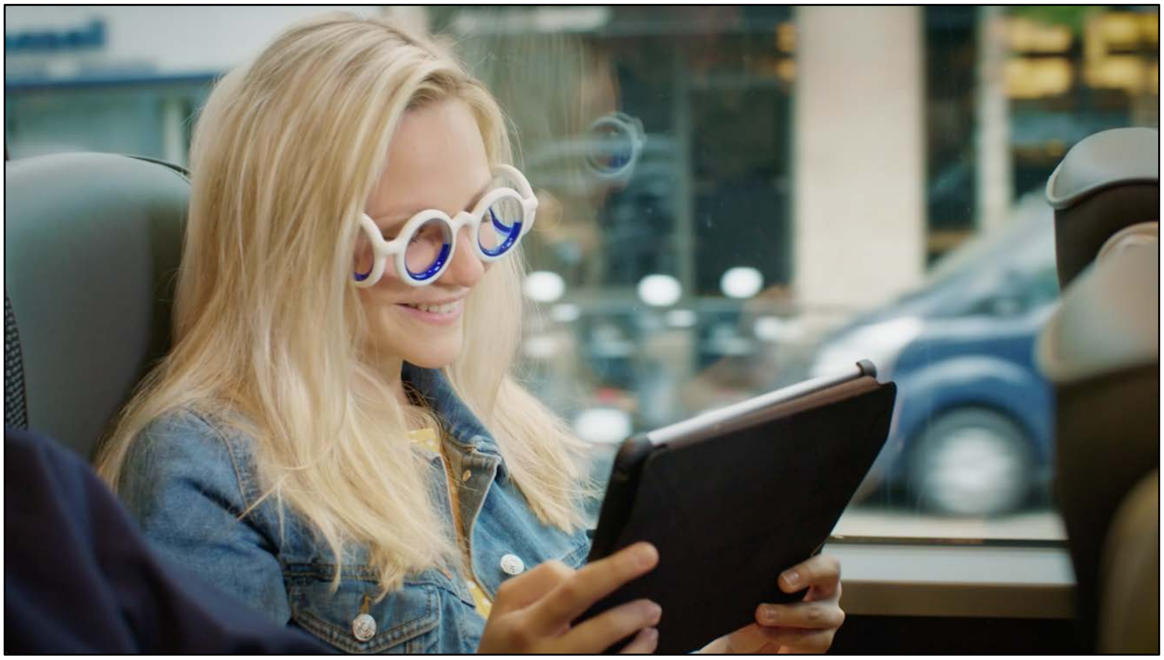

Figure 3. Citroën motion sickness glasses

2.5 Literature review summary

Motion sickness is a very common phenomenon that occurs in simulators and conventional vehicles and is likely to occur in automated vehicles. Motion sickness undermines research validity and will potentially undermine the benefits of vehicle automation. Monitoring motion sickness in real-time will allow for mitigating its negative consequences, yet, no such technologies have been developed. Previous measures of motion sickness relied on subjective reports and physiological changes. Physiological changes vary significantly across individuals, and there is no one single measure that can be used. Whereas subjective reports are usually collected over long periods of time. Hence, there is a need for a continuous real-time measure. This project investigated the potential of facial expressions and head positioning as a continuous estimation of motion sickness in simulators.

3 Method

3.1 Participants and data

Data was collected from 64 participants. Of the 64 participants, only 48 completed the three drives (one practice and two experiment drives) as required by the original experiment design [28]. The other 18 withdrew from the experiment at some point because of motion sickness. In this analysis, we included all 64 participants' data. At the end of each drive, participants completed the Simulator Sickness Questionnaire (SSQ) [16]. The collected data included 179 monochrome videos; one video for each drive. The videos were sampled at 30 Hz. The video data and the SSQ data were synched by the participant number. For the video data, we used an open-source software tool, OpenFace [29] to reduce the data. From the output of OpenFace, we included the following variables:

1. Confidence in face detection
2. Facial action units estimation (AU01, AU02, AU04, AU05, AU06, AU07, AU09, AU10, AU12, AU14, AU15, AU17, AU20, AU23, AU25, AU26, AU45)
3. Head position relative to the camera on 3D axes (x, y, and z) [30]
4. Head rotation from the camera (yaw, pitch, and roll)

3.2 Scenario and simulator

The data was collected in 2011 at the National Advanced Driving Simulator at the University of Iowa, shown in Figure 4. Some participants drove with motion in the simulator, while others drove without motion. The scenario included straight and curved road segments. More importantly, the drive included traffic circles as well. The combination of traffic circles and curved road segments are well-known to induce motion sickness in simulators [8].

Figure 4. The National Advanced Driving Simulator (NADS) at the University of Iowa

4 Data Analysis and Results

The sections below discuss the analysis and results of the video data and the SSQ data collected from the driving simulator experiment. The video data was reduced using the open-source software tool OpenFace [29]. All the data manipulation and statistical analysis were done in R [31].

4.1 Video reduction

We had a total of 179 videos, that included practice and experiment drives. They yielded a total of 4,028,267 frames sampled at 30 Hz. First, we processed the drivers' video in OpenFace [29]. OpenFace is an open-source toolkit for facial landmark and action unit detection as well as head pose and eye-gaze estimation. We used OpenFace to extract the drivers' facial action units, head position, and head rotation estimations from the videos. Table 3 shows the facial action units that OpenFace estimates and their definitions [21]. In addition, as part of the output from OpenFace, the confidence of the face detection is provided. For this analysis, and after careful exploration of the videos, we filtered out the frames with face detection confidence less than 75%. Frames with confidence less than 75% were very blurry, only part of the face detected, or no face detected at all. This resulted in a reduction of the total number of videos to 173 (i.e., there were six videos that had no frames above 75% confidence) and the total number of frames to 3,162,788. Figure 5 shows a histogram of the confidence across frames.

Table 3. A list of the facial action units estimated by OpenFace and their definitions

Action Unit	Definition	Muscle
AU 01	Inner Brow Raiser	Frontalis, Pars Medialis
AU 02	Outer Brow Raiser	Frontalis, Pars Lateralis
AU 04	Brow Lowerer	Depressor Glabellae, Depressor Supercilli, Currugator
AU 05	Upper Lid Raiser	Levator Palpebrae Superioris
AU 06	Cheek Raiser	Orbicularis Oculi, Pars Orbitalis
AU 07	Lid Tightener	Orbicularis Oculi, Pars Palpebralis
AU 09	Nose Wrinkler	Levator Labii Superioris Alaeque Nasi
AU 10	Upper Lip Raiser	Levator Labii Superioris, Caput Infraorbitalis
AU 12	Lip Corner Puller	Zygomatic Major
AU 14	Dimpler	Buccinator
AU 15	Lip Corner Depressor	Depressor Anguli Oris
AU 17	Chin Raiser	Mentalis
AU 20	Lip Stretcher	Risorius
Au 23	Lip Tightener	Orbicularis Oris
AU 25	Lips Part	Depressor Labii, Relaxation of Mentalis
AU 26	Jaw Drop	Masetter; Temporal and Internal Pterygoid relaxed
AU 45	Blink	Relaxation of Levator Palpebrae and Contraction of Orbicularis Oculi, Pars Palpebralis

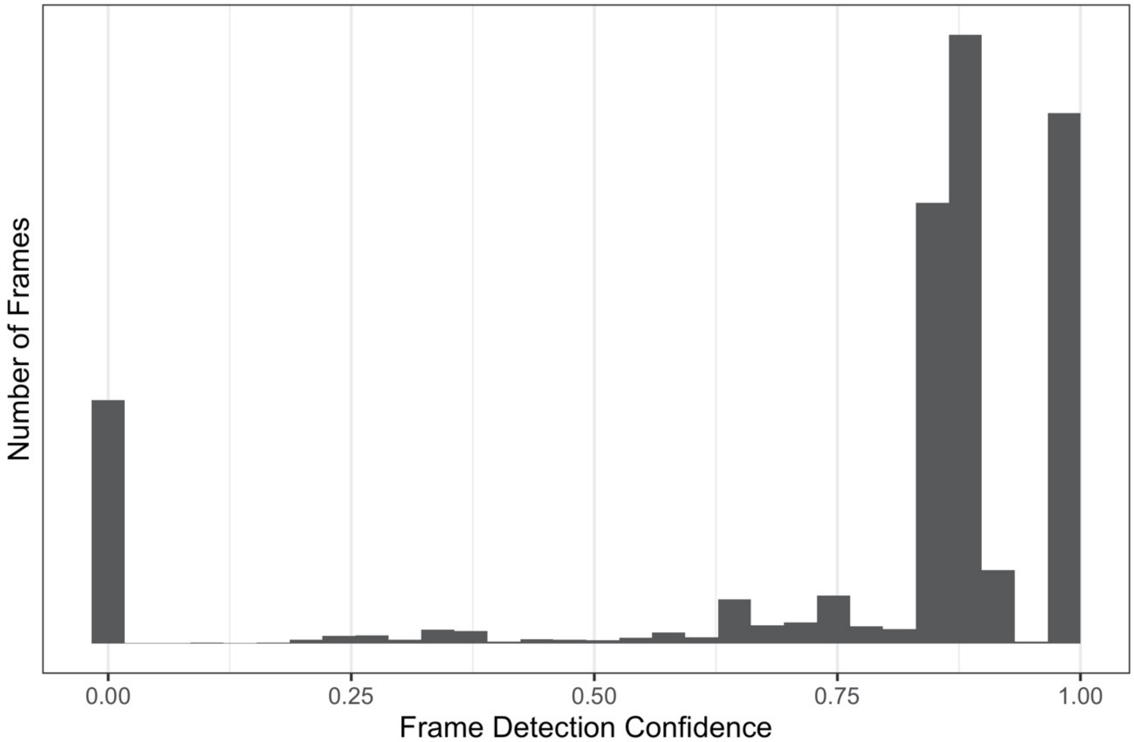

Figure 5. Histogram of frame detection confidence

4.2 SSQ severity categorization

We used two different representations of SSQ scores: continuous and discrete. The discrete representation was mainly used for visualization. For the discrete, we categorized motion sickness severity into four levels: none, low, moderate, and high, based on the distribution of motion sickness scores shown in Figure 6 and Table 4.

Table 4. SSQ scores and categories

SSQ Score	Corresponding Category	% of Participants
0	None	21%
> 0 & < 10	Low	29%
> 10 & < 50	Moderate	46%
> 50	Severe	4%

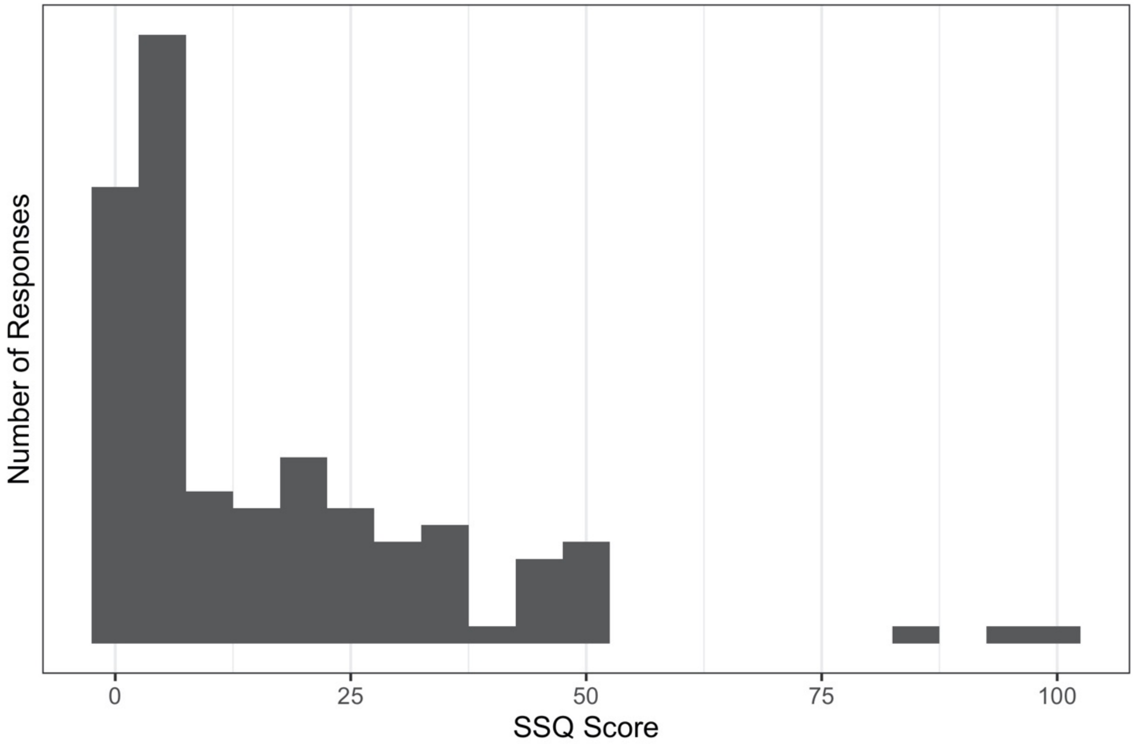

Figure 6. A histogram of the SSQ scores

4.3 <u>Facial action units analysis</u>

We expected that if facial action units change as a result of motion sickness, they change over time, and hence there should be significant correlation between action units' intensity and time. However, looking at the correlation matrix in Figure 7, there was no strong correlation between time and action units.

Although there were no significant correlations between time and action units, we developed multiple models to examine the predictability of SSQ score through changes in facial action units.

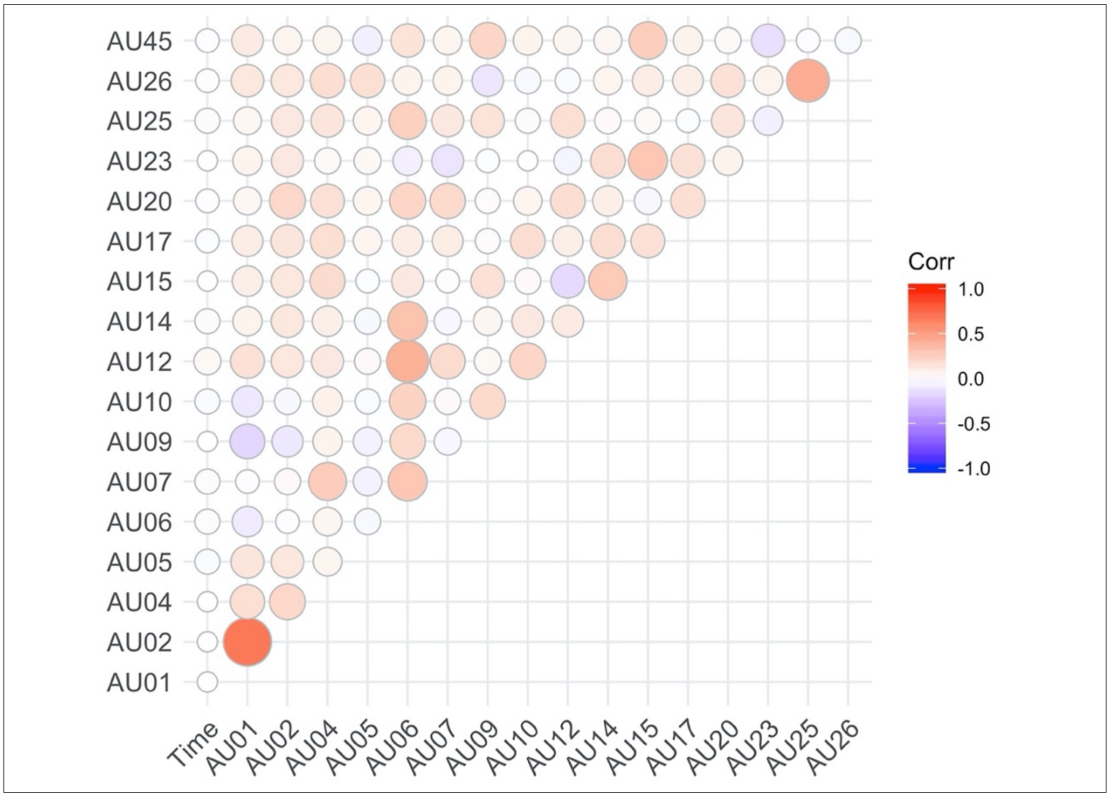

Figure 7. Correlation matrix of facial action units and time

First, we standardized the facial action units:

$$AU_{ij} = \frac{AU_{ij} - \mu(AU_i)}{\sigma(AU_i)}$$

Then we calculated the change in action unit values between the first 900 frames (30 seconds) and the last 900 frames (30 seconds). We used the difference of the 17 action units as predictor variables and the SSQ score as the dependent variable.

Then we developed models with varying levels of complexity, including linear regression models and support vector machines to account for the non-linearity in the data. There was no significance of the models predicting the SSQ score, and none of the models explained the variation in the data.

To visualize the underlying structure of the facial action units data and examine how they map to the scores of SSQ, given the high dimensionality of the data, we used a dimensionality reduction technique. Dimensionality reduction techniques reduce the dimensionality of the data into a few components that capture the most variance within the variables. Some of the techniques rely on linear correlations in the data such as Principal Component Analysis (PCA) [32] others find non-linear correlations, such as t-distributed Stochastic Neighbor Embedding (t-SNE) [33] and Uniform Manifold Approximation and Projection (UMAP) [34]. Here, we used UMAP because of its reproducibility and efficiency advantages while accounting for the non-linear structure of the data. Figure 8 shows a UMAP representation of the changes in each facial action unit for each person. We see there are no clear patterns between the action units and the motion sickness scores, which validates our previous findings of no correlations between action units and time.

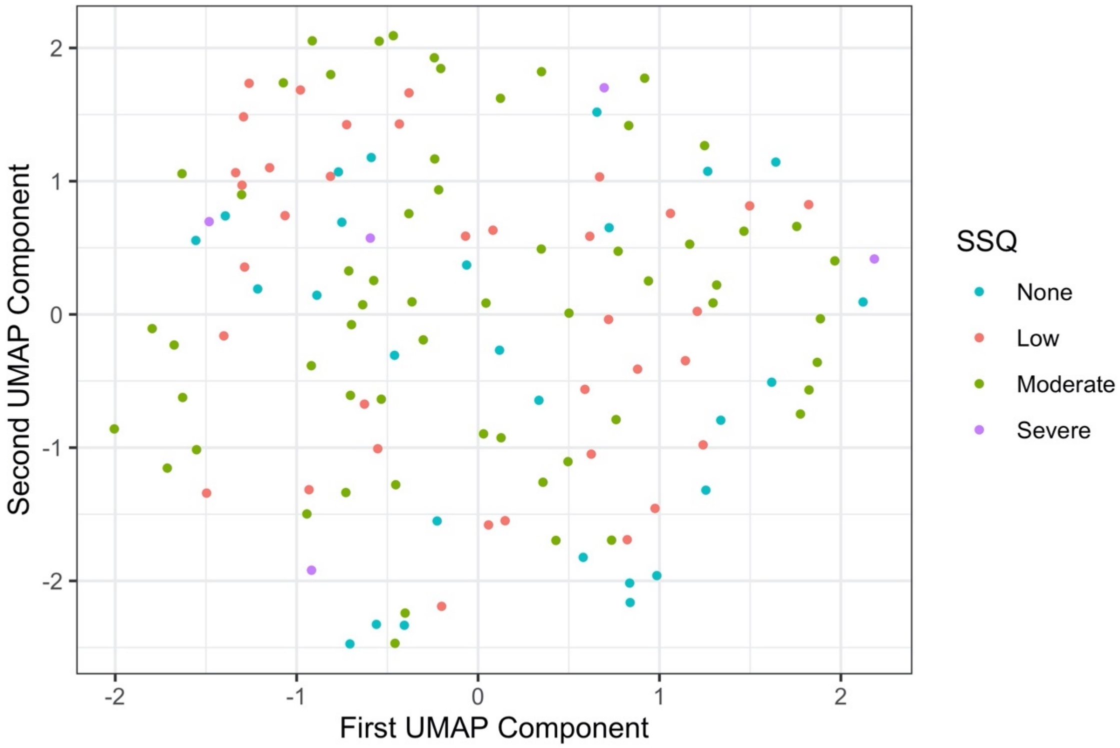

Figure 8. A UMAP dimensionality reduction presentation of the facial action units

We believe that our results did not show any correlations between facial action units and motion sickness scores due to two main reasons. First, by careful exploration of the videos, we found that participants tended to get severely sick after an evasive maneuver, and they stopped the experiment and withdrew right after. Hence, we do not think the video data were representative of motion sickness. Second, the present data provided one SSQ rating for each drive. Hence, we were not able to model facial action units in a continuous way to develop a potential continuous predictor of motion sickness.

4.4 <u>Head pose analysis</u>

Similar to the action units analysis, we examined the head position and rotation to investigate whether or not head pose is correlated to sickness. OpenFace defines the position of the head on a 3D coordinate system relative to the camera as shown in

Figure 1, and it defines the head rotation in terms of Euler angles (i.e., pitch, yaw and roll). For more details see Baltrusaitis [30].

Based on the postural instability theory [7], and previous research results [35], that suggest increased head movement as a contributor to motion sickness, we expected to see a positive correlation between the standard deviation of the head position and the SSQ score. Interestingly, this was not the case. However, a linear regression model revealed that drivers' z-distance from the camera was positively correlated with SSQ scores, while their x-displacement was negatively correlated with motion sickness scores. No other variables were found significant, including the existence (and lack of existence) of motion in the simulator. Table 5 shows the summary statistics of the linear model. This might be a result of visually induced motion sickness; the driver's eye point is not calibrated to the design eye point. Hence, careful calibration of the participant's seating position might reduce instances of motion sickness.

Table 5. Summary statistics for the linear regression model of head position, R^2 = 0.19

Variable	Estimate	SE	t-statistics	p-value
(Intercept)	4.43	21.63	0.21	0.84
Mean x-position	-0.21	0.08	-2.82	**0.005 ***
Mean y-position	-0.09	0.07	-1.35	0.18
Mean z-position	0.11	0.04	2.69	**0.008 ***
SD x-position	-0.21	0.28	-0.6	0.45
SD y-position	-0.26	0.29	-0.90	0.37
SD z-position	-0.05	0.10	-0.55	0.59
Mean x-rotation	1.01	15.65	0.07	0.95
Mean y-rotation	-14.24	28.97	-0.49	0.62
Mean z-rotation	-5.94	23.29	-0.26	0.80
SD x-rotation	-33.92	33.42	-1.01	0.31
SD y-rotation	-15.34	43.95	-0.35	0.72
SD z-rotation	39.68	46.78	0.85	0.40

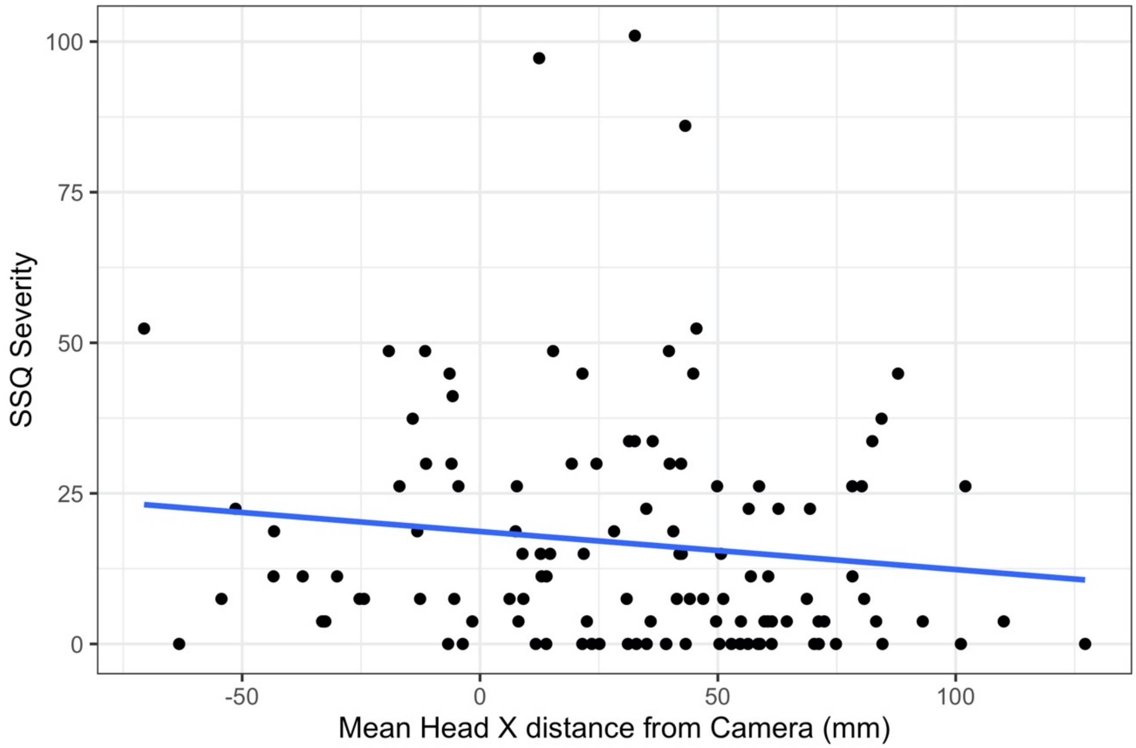

Figure 9. Scatter plot and regression line of X-axis head position and SSQ score

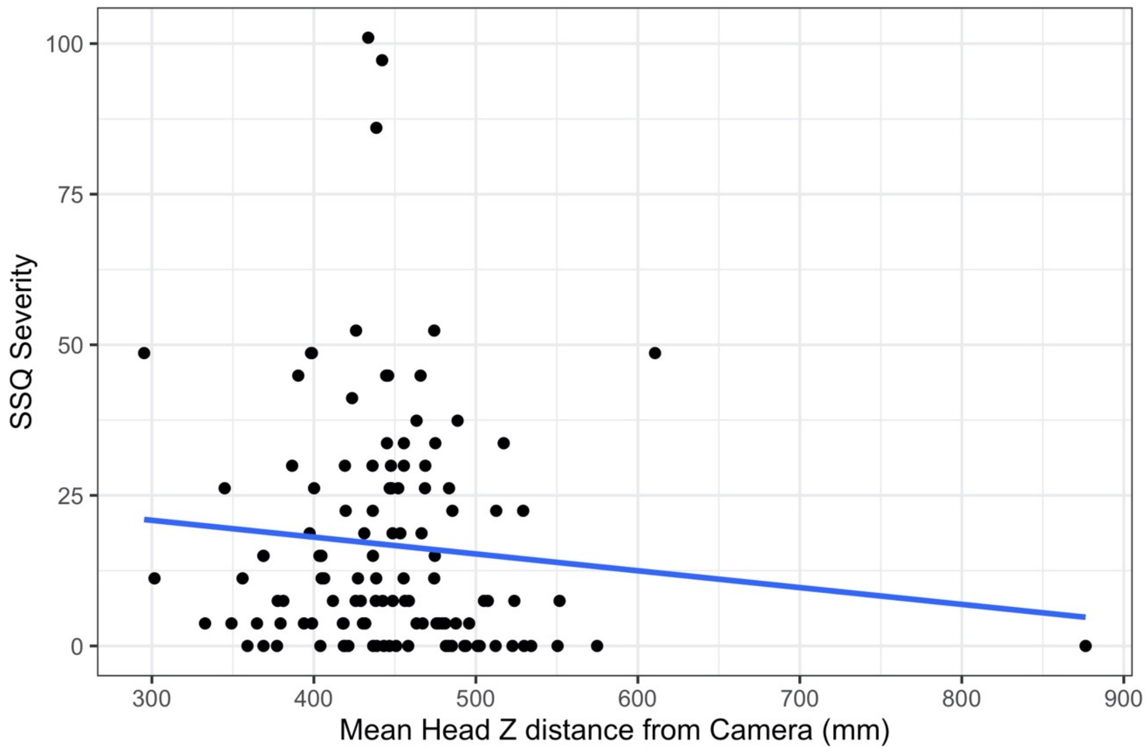

Figure 10. Scatter plot and regression line of Z- axis head position and SSQ

Even after removing the outlier in Figure 10, the results were consistent.

5 Tool Development

Through the exploration of the videos, we developed a tool for video analytics that is very promising and can enhance the human-machine vision partnership in coding video data collected from driving simulators and on-road situations. The tool provides insight to the analyst into which frames to label based on unsupervised machine learning clustering. The analyst can provide labels to the computer to be used in the training of a supervised machine learning algorithm. An overview of the app is shown in Figure 11.

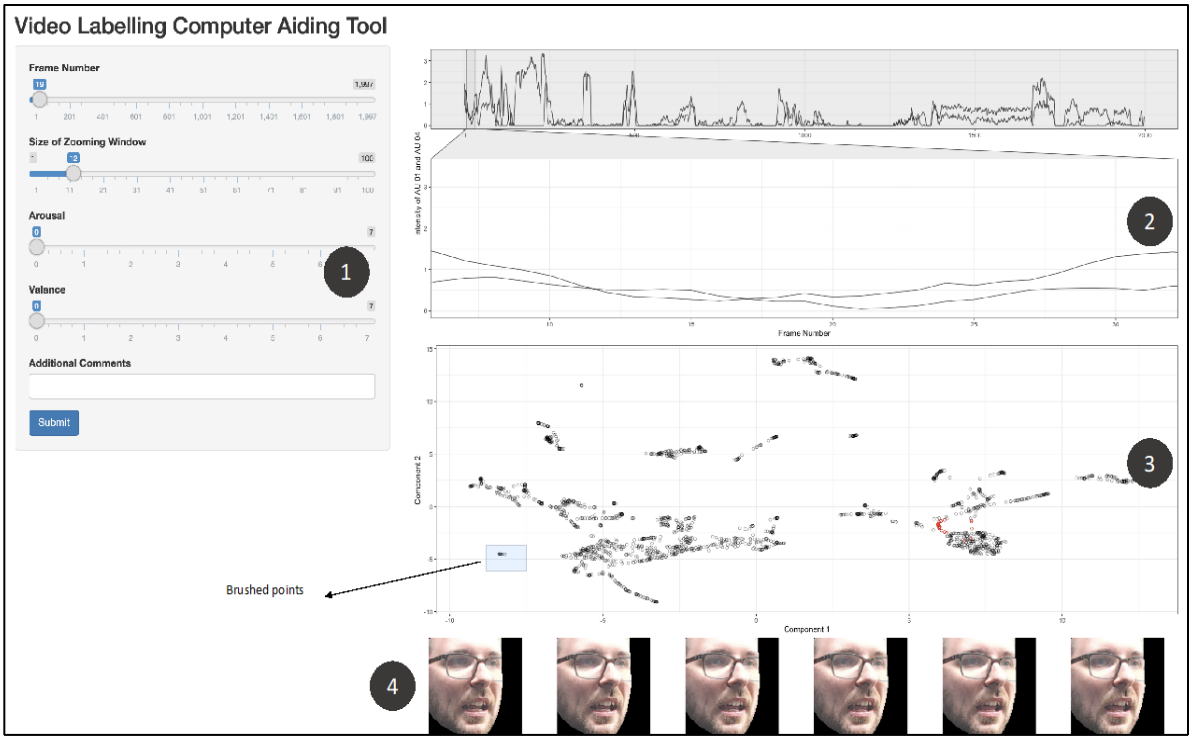

Figure 11. An overview of the labelling app

We used UMAP to reduce the dimensionality of the action units and head pose data obtained from OpenFace. The analyst can brush clusters in the UMAP visualization and see the corresponding frames, as shown in Figure 12.

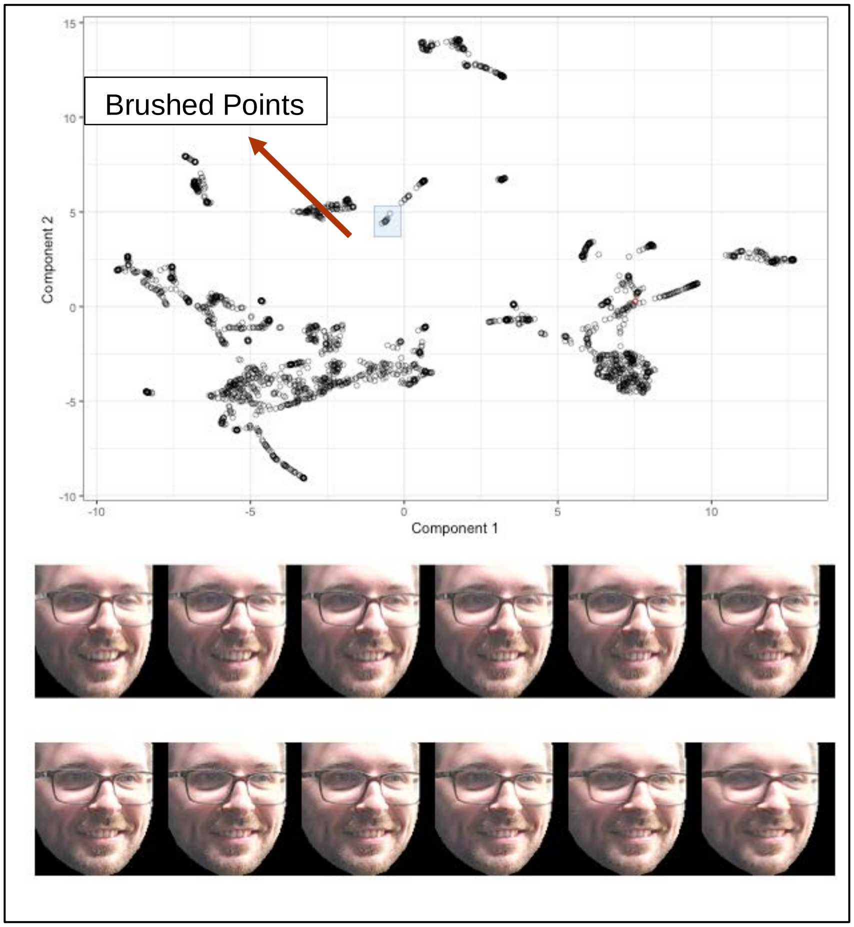

Figure 12. UMAP space and corresponding frames

The analyst can also explore a specific frame or frames in a specific window of time. By controlling the sliding bars shown in Figure 13-a, a close up of the action units timeline is projected as shown in Figure 13-b. The selected frames are then highlighted in the UMAP space as shown in Figure 14. In other words, the user will be able to look at spikes in the action units, see the corresponding frames, and investigate different clusters in the UMAP space before labeling similar frames.

Finally, the analyst can add labels to the brushed frames in the UMAP space by two sliding bars: one for arousal and one for valance, and also by adding detailed labels in the comments box as illustrated in Figure 15.

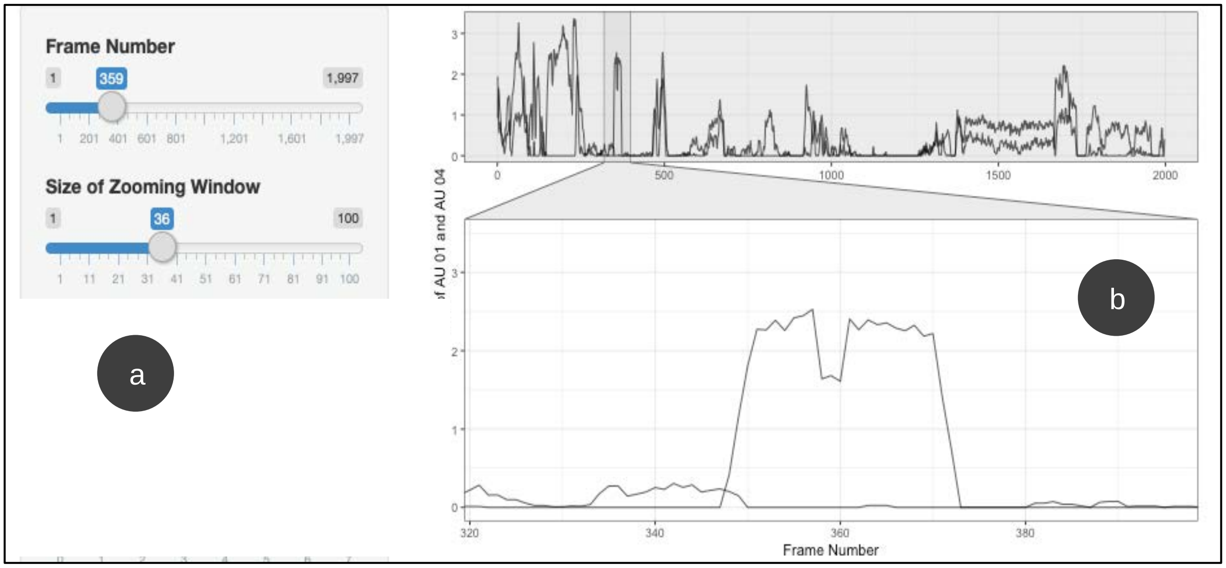

Figure 13. Action units timeline zooming window

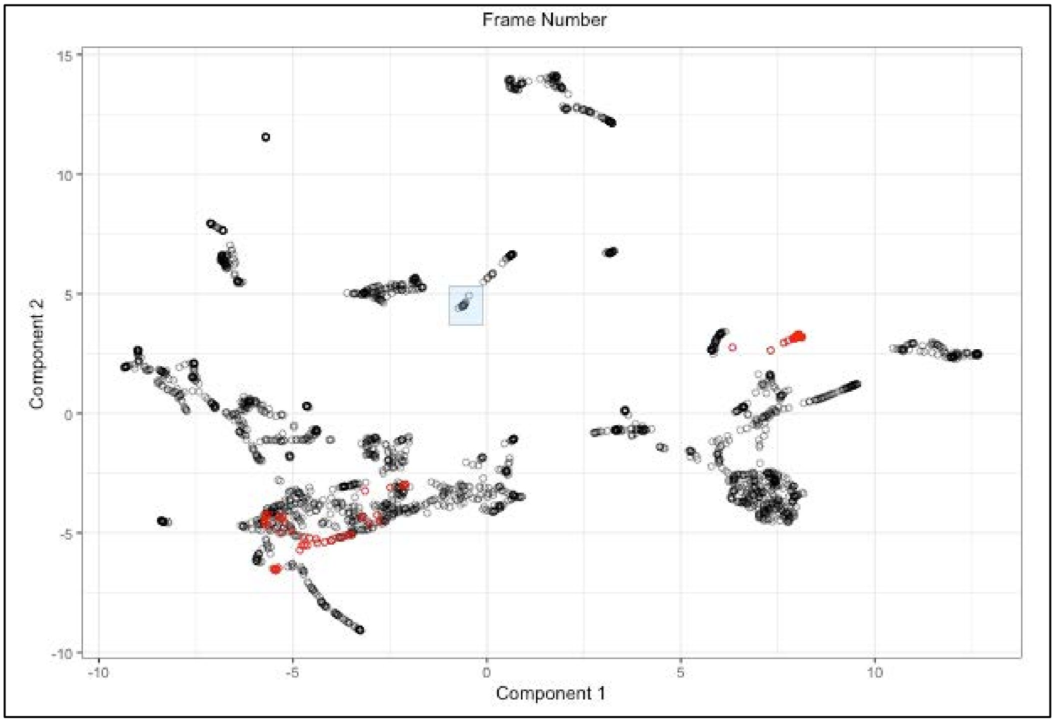

Figure 14. Highlighted selected frames

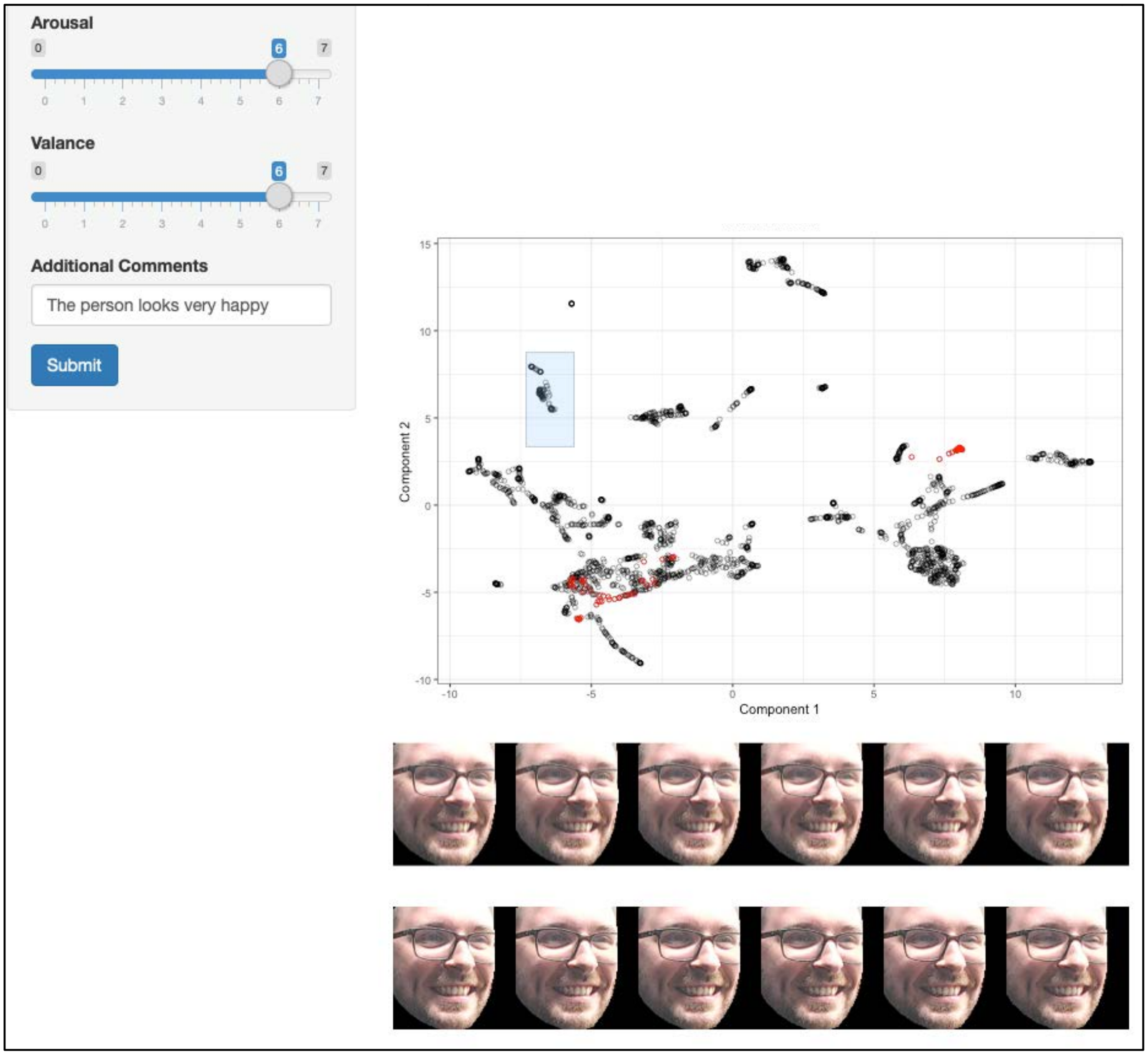

Figure 15. Labeling of frames

This tool can be used for further research on the topic of motion sickness and also in other fields and areas that rely on video analytics like affective computing. Humans can pick up cues that computers do not and vice versa. Hence, it is clearly valuable to use such a tool that leverages human judgment skills, particularly in innovative fields of research.

6 Conclusions

6.1 Summary of results and future work recommendations

In this project, we examined facial action units and head position as potential predictors and estimators of motion sickness. Developing a system to monitor motion sickness in real time can be valuable in multiple ways. First, it can be used in simulators. Simulators are a fundamental tool of human factors research with many advantages [36]. however, they induce motion sickness and that can undermine the validity of the collected data. Second, it can be used in automated vehicles where motion sickness is an actual risk that threatens their success [24].

In these analyses, we found the driver's proximity to the monitor to be strongly correlated to the severity of motion sickness. We believe that this is a result of visually induced motion sickness due to the difference between the design eyepoint and the actual eye point of the participant. Hence, we recommend careful calibration of participants' seating position in order to combat motion sickness.

Contradictory to our expectations, there were no significant correlations between facial action units and motion sickness. We believe that a combination of the present method of data collection and the experimental design presented a challenge in developing motion sickness predictive models from the facial action units. Hence, we recommend the following for future research:

First, we suggest designing an experiment that is specifically aimed at looking at motion sickness. Hence, a scenario that gradually builds up discomfort rather than sudden maneuvers that make drivers withdrew immediately afterwards. And second, we suggest the use of another more continuous measure of motion sickness rather than a one-time, severity score at the end of the drive [19].

Finally, for the purpose of video exploration, we developed a software tool that can be very beneficial to video analytics research. The tool allows the scientist and the computer to label frames of a given video collaboratively. This tool can be used in the future in a wide range of applications but is particularly valuable for underexplored areas that require human judgment skills to train the computer.

6.2 Summary of student involvement

The student led all steps of the project, from brainstorming ideas for the proposal to the final report writing. The project allowed the involved student to enhance her research, problem-solving, and project management skills. The project also allowed the student to demonstrate the results at a conference and network with experts from the transportation field at the Transportation Research Board Annual Meeting in January 2020.

6.3 Technology transfer

Data produced in this project from the video reduction will be made available through the SAFER-SIM website. In addition, a link to the software tool will be uploaded and made publicly available. As a final step of the project, a webinar will be scheduled to present the results of this work.

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