Literature Review

Cognitive State Estimation in VR

Emily Doherty, NSF IRES 2023

Week 1

Began with a literature review of Simon’s recent CHI work and some related papers exploring real-time cognitive state estimation using physiological signals in virtual environments.

Kimmel, S., Jung, F., Matviienko, A., Heuten, W., & Boll, S. (2023, April). Let’s Face It: Influence of Facial Expressions on Social Presence in Collaborative Virtual Reality. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1-16).

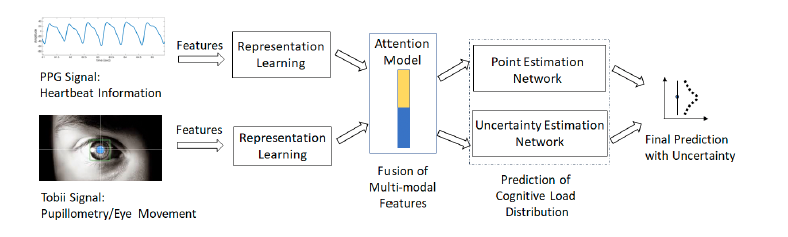
* Real-time tracked facial expressions contribute positively to social interactions in VR.
* Is facial expression mediated by type of collaboration?
* Investigated four types of expressions: mouth movements, eye movements, their combination, and none for both verbal and graphical explanations among two collaborative VR tasks.
  + Verbal explanation + eye movements induce highest feeling of co-presence.
* Social presence: “sense of being with each other”
  + Importance of relaying non-verbal indicators in Social VR environments
  + describes the unique psychological phenomenon of perceiving a technologically mediated counterpart as “real.”
  + predictor of positive communication outcomes such as trust, enjoyment, attractiveness
* Facial expressions positively influence SP in VR – through elevated co-presence levels and gaze duration.
  + Verbal explanations have higher impact on SP than graphical.
* SP is impacted by user characteristics, task type, user representation.
  + Behavioral realism is more reliable at increasing SP than visual realism.
* Gaps in SP literature: impact of self-embodiment and non-verbal cues
* Facial expressions have been shown to be more important to SP than bodily movements.
* Novelty: purely VR setting (both users in VR, not an asymmetrical design)
* Dyads were strangers.

Measures

* Tobii VR4 Platform eye tracking (60hz), VIVE facial trackers (60hz)
  + Movements were mapped to avatars using ready Player Me SDK
  + Gaze Duration
  + Gaze Frequency
  + Mouth Weight Changes
  + Head Position/Rotation Changes
* Networked minds Social Presence Inventory (NMSPI) + behavioral measurements
  + Co-Presence
  + Perceived Affective Understanding
  + Perceived Affective Interdependence
* Discarded NMPSI measures: Attentional Allocation. Perceived Message Understanding, Perceived Behavioral Interdependence
* Additional Post-experiment measures: manipulation check (did they notice a difference?), ranking question (which did they prefer?), social interaction feedback (likes/dislikes open questions)

Siegel, E.H., Wei, J., Gomes, A., Oliviera, M., Sundaramoorthy, P., Smathers, K., Vankipuram, M., Ghosh, S., Horii, H., Bailenson, J., & Ballagas, R. “HP Omnicept Cognitive Load Database (HPO-CLD) – Developing a Multimodal Inference Engine for Detecting Real-time Mental Workload in VR” *Technical Report*, HP Labs, Palo Alto, CA.

* Assesses cognitive workload (CL) using behavioral (NASA-TLX) and physiological measures.
  + ML models trained to predict task difficulty and momentary self-reported cognitive workload.
  + Classification accuracy of 79.08% using n= 738 (ages 19-61) (test dataset n =100 is available)
* CL is predictor of learning, memory, performance, stress, burnout.
  + A combination of long-term memory, sensory + attentional processes
  + Impact of cognitive workload on social interaction + collaboration?
* This method of CL measurement is novel and doesn’t require expensive and biased neuroimaging technology.
* Facial expressions alone are not a reliable measurement of CL.
* Speech (acoustic features) alone has also not been validated as a reliable measurement.
* However, eye tracking (pupillometry), HR, BP, EDA are better indicators.
  + Complimentary and overlapping information – stronger algorithms that demonstrates the behavior of the entire autonomous nervous system.
  + Having multi-modal measurement is also good for noise reduction.
* Several ML algorithms used to measure CL is real time.
  + KNN, NB, log regression, LDA, SVM, ensemble methods, neural networks
  + NN typically outperform other ML method.
* HP’s algorithm is novel given that they have a greater sample size than other papers (n=738) and did not restrict the demographics of their subjects to fully encompass all variability among different genders, races, ages, etc.
  + Also, a calibration-free solution
* This paper goes in depth on how the features for the algorithm were created.
  + Eye-tracking, PPG, HR, RR
  + Filtering methods of each
  + Used task difficulty + NASA-TLX scores to label training data.
  + Limitation: only one NASATLX score per condition, must assume was constant throughout condition
* Feature importance: 4 eye tracking features (mean saccade speed, std of saccade duration, mean saccade duration) and 1 HRV feature (psd from 0.2-0.4)
* Additionally, more measures are included in final model for robustness (20 total 11 eye tracking, 9 PPG)
* Using both Tobii + PPG features resulting in 79.08% accuracy, whereas just Tobii was 73.45% and just PPG was 54.56%



Wei, J., Zhang, S., Ji X., Sundaramoorthy P., Kelley N., Rawlings B., Yraguen M., Huang Y., Siegel,

E.H., Ballagas, R., Yang J., Lin Q., Zhu M., Allebach J., “HP Omnicept Face Tracking in VR”, Technical

Report, HP Labs, Palo Alto, CA.

* Omnicept has single infrared mouth camera to track face movement in real time.
* Quantifiable measures according to FACS definition used to animate avatars in VR.
* FACS breaks down facial expressions into individual components of muscle movements called Actional Units (AUs)
* HP team developed face tracking deep regression model to predict AU intensities from single facial images captured by Omnicept’s camera.
* This face tracking allowed for expression reenactment of the avatars.

Reddy, G. R., Spencer, C. A., Durkee, K., Cox, B., Fox Cotton, O., Galbreath, S., ... & Hirshfield, L. (2022, May). Estimating cognitive load and cybersickness of pilots in VR simulations via unobtrusive physiological sensors. In *Virtual, Augmented and Mixed Reality: Applications in Education, Aviation and Industry: 14th International Conference, VAMR 2022, Held as Part of the 24th HCI International Conference, HCII 2022, Virtual Event, June 26–July 1, 2022, Proceedings, Part II* (pp. 251-269). Cham: Springer International Publishing.

* Omnicept’s CL measurement is real-time and ranges from 0 to 1.
* CL of a pilot can be defined in three categories: Objective, Subjective, Physiological
  + Obj: PIW using flight stick.
  + Subj: self-reported measures (NASA-TLX, VR sickness VRSQ, MSAQ, MSSQ)
  + Phys: HR, HRV, eye-tracking, and Omnicept’s CL measure
* Used 30s window based on task characteristics.
* Task difficulty significantly affected NASA-TLX ratings and Omnicept CL measure (substantially), number of saccades.
* Unexpected result: number of saccades was negatively correlated to Omnicept CL measure.
* Refer back to this paper for Omnicept specs + limitations regarding its built-in eye tracking device (low sampling rate, etc.)

Ideas

* Quantifying cognitive load in real-time using eye gaze, facial expression?, HR (PPG)
* To inform social interactions + cooperative tasks
* HP provides datasets used to create their cognitive workload measurement and face tracking algorithm.
* Multimodal presence scale = standard presence questionnaire.

Week 2

Began brainstorming some research projects using insights from literature. Most of the week was taken up by the CHIWORK conference.

6/12/23

* Cognitive workload estimation in real-time for application in VR environments
* Could be used to inform interventions (prompting a teammate to take over if other teammate is overwhelmed)
  + Also has implications towards automated systems that respond to increased workload accordingly.
* To estimate workload in VR, EEG is most commonly used due to its superior temporal resolution.

Ideas

* Translating cognitive workload into facial expressions? (Exasperation, stress, relaxed, etc.)
  + We could possibly show one’s cognitive workload measurement on a scale and compare it to just facial expressions that represent their load.
* Could we use reinforcement learning to quantify load in real time? (action/reward system)
  + User is overloaded, other user is prompted (action), reward = cog load is lessened in first user
* Is there a relationship between social presence and cognitive workload?
* LSTM to classify states?

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| --- | --- | --- |
| **VR System** | **Measures** | **Workload Estimation** |
| [HP Reverb G2 Omnicept Edition](https://www.hp.com/us-en/vr/reverb-g2-vr-headset-omnicept-edition.html) | Muscle movement, gaze direction, pupil size, HR  Integrated Tobii eye tracking + pupillometry sensor, HR sensor, + Face camera  Motion tracking of arms  \*Planned for the future: facial expression + emotion. | Cognitive workload estimation using 11 eye-tracking features and 9 PPG features |
| [Pico Neo 3 Pro Eye](https://www.picoxr.com/global/products/neo3-pro-eye) | 2x eye tracking cameras (400x400 @120Hz)  Additional measures (Kimmel, et al. 2023)   * Tobii VR4 platform eye tracking (60hz) * 2 VIVE facial trackers for mouth tracking * Facial trackers with infrared illumination (60hz) | Mouth and eye movements mapped to avatars using Ready Me SDK and Oculus Lip Sync SDK. |

Algorithms

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| --- | --- | --- |
| [HP Reverb G2 Omnicept Edition](https://www.hp.com/us-en/vr/reverb-g2-vr-headset-omnicept-edition.html) algorithm | * HTC Vive Pro-eye with Tobii eyetracking (120hz), pupillometry * Heart rate: BITalino (r)evolution wired PPG * NASA-TLX * N=738 * 12.5s sliding window and 1s skip to segment signals + label | Omnicept SDK – Windows only |
| Luong, et al., 2020 | * Random Forest trained with data from n=75 * VR simulator * NASA-TLX * 4 levels of workload (accuracy up to 65%) |  |

Luong, T., Martin, N., Raison, A., Argelaguet, F., Diverrez, J. M., & Lécuyer, A. (2020, November). Towards real-time recognition of users mental workload using integrated physiological sensors into a VR HMD. In *2020 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (pp. 425-437). IEEE.

* While NASA-TLX is a validated measure of workload, questionnaires can disrupt a user’s immersion.
* Use of physiological signals allow for unobtrusive, real-time quantification of workload.
* MW estimation can be difficult in VR due to imposed workload caused by VR set (different constraints from the real world, cumbersomeness of set, lack of visual feedback, cybersickness)
* They compared a VR HMD equipped with physiological signals to Commercial Grade Systems (CGS) such as bracelets, torso belts, and electrode patches.
* Similar classification performances between the two with up to 65% accuracy (n=75)
* Ocular features (as in most papers) were especially important, followed by EDA, cardiac, and task performance measures.
* Random forest to classify 4 levels of MW
* Real time prediction using wrappers were to communicate the estimated levels from Python to C# for Unity3D
  + Use scikit learn
* Eyetracking, GSR, subjective measures

**Sharing of Physiological signals in collaborative VR environments**

Rinnert, T., Walsh, J., Fleury, C., Coppin, G., Duval, T., & Thomas, B. H. (2023). How Can One Share a User’s Activity during VR Synchronous Augmentative Cooperation?. *Multimodal Technologies and Interaction*, *7*(2), 20.

* Evaluation of placement of activity monitor in VR
* Detect when a partner needs assistance.
* (1) instantaneous indicators of users’ activity are preferred to indicators that continuously display the progress of a task, and (2) that participants are more confident in their ability to detect users needing help when using activity indicators.
* Sharing spontaneous indicators rather than also including past data is preferred.
* This is all about activity tracking, not physiological states.

Moullec, Y., Saint-Aubert, J., Manson, J., Cogne, M., & Lécuyer, A. (2022). Multi-sensory display of self-avatar's physiological state: virtual breathing and heart beating can increase sensation of effort in VR. *IEEE Transactions on Visualization and Computer Graphics*, *28*(11), 3596-3606.

* Represent a user’s breathing and heartrate through a VR avatar to increase effort sensation.

\*Sasikumar, P., Pai, Y. S., Bai, H., & Billinghurst, M. (2022, October). PSCVR: Physiological Sensing in Collaborative Virtual Reality. In *2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct)* (pp. 663-666). IEEE.

<https://github.com/prasanthsasikumar/PSCVR>

* Short paper on displaying real-time estimation of cognitive workload, attention, and heart rate
* GSR, EEG, HR, and Eyetracking
* No real details on how they are calculating cog load + attention
* Github available but no documentation, not sure if this is the latest version but I can explore further if this has value.

A screenshot of a computer

Description automatically generated with low confidence

Dey, A., Piumsomboon, T., Lee, Y., & Billinghurst, M. (2017, May). Effects of sharing physiological states of players in a collaborative virtual reality gameplay. In *Proceedings of the 2017 CHI conference on human factors in computing systems*(pp. 4045-4056).

* Displaying heart rate in VR gameplay to understand emotion.
* Real time heart rate displayed from one player to another.
* 2 games eliciting happy and scared emotions.
* Game type had significant effect on dependent variables.
* HR visualization showed non-significant yet more positive effect than in the control condition. Likely due to small n = 13.

**Commercial VR State Estimation Programs**

Cognitive3D

* Spatial analytics system platform for 3D applications
* Measurement of spatial data, can be used in most VR systems
* Dashboard of optics
  + Eye tracking, 3D insights, biometric sensors
* Advanced analytics
  + Objectives systems
  + After action review
  + Active session view

In this blog [post](https://cognitive3d.com/blog/hp-cognitive3d/), they propose that they will be able to display cognitive workload in the simulations, however I do not yet see this feature advertised on their website.

A computer screen shot of a room

Description automatically generated with low confidence

emteqPro

* Flexible sensor platform to collect physio data using multi-sensor array built into VR headset
* facial muscle activations, heart rate features, skin impedance, and movement data
* VR wired sensor mask insert.
* Real-time measurement for EMG, PPG, linear/rotational accelerable.
* Heart rate feature extraction.
* Datastreams are displayed in SuperVision application.

<https://www.frontiersin.org/articles/10.3389/frvir.2022.781218/full>

OvationVR

* Training program in VR
* Uses physio measures to create immersive experience.

<https://www.ovationvr.com/omnicept/>

Week 3

6/19/23

* Downloaded HP Cognitive Workload Open Dataset
  + 100 files containing Bitalino PPG, Tobii eye tracking and pupillometry data, demographic data
  + Randomly selected out of 738 participants in data collection protocol
  + Readme files contains more details

I’m not sure it would be efficient or possible to collect enough data to train a model that classifies states within the short timeframe, so I propose to work with HP’s provided datasets. I am thinking the following workflow (I am very flexible):

1. Look into the Cognitive Workload dataset, do some initial stats, perhaps look into training a model
2. Look into the Face tracking data, follow the same steps.
   1. Perhaps compare with CHI paper data?
   2. If enough data lines up with the HPs dataset, I could incorporate the CHI data into a model with this existing data.
3. Write up results and how future datasets at OFFIS collected by your existing technology (i.e. Omnicept, Pico + with additional measures, etc.) could be added to my models. Set up some research questions to test in the future, for example:
   1. Does displayed cognitive workload in virtual teams increase performance / team cohesion?
   2. Does displayed cognitive workload affect ratings of social presence among virtual teams?
   3. Compare the effects of displayed level of cognitive workload vs. facial expressions alone on teamwork/performance/other measures.

If time allows, I could play around with the CHI dataset to see if social presence could be estimated in real time, could set up the architecture to train a model with new data.

Meeting 6/19/23 Notes

* Simon’s CHI data is summary stats, not time series data, which is not ideal for ML.
* The lab only has one Omnicept which is tethered.
  + They haven’t used this yet, so I offered to get it up and running.
* They have several Pico’s that are not tethered, but only have eye tracking capabilities.
* Idea from Simon: Using real-time cognitive load estimation to adapt the VR environment (i.e., reducing background, focusing on the task, etc.).
* States to estimate in real time: cognitive workload, attention, emotion, social presence.
* How do we do real-time estimation without any data to train a model?
* Is there a public repository of VR physiological data that could be used to train a model? Consider reaching out / exploring the CHI community?
* Can I access HP’s or anyone’s model for real-time state estimation and improve it?

Gupta, K., Zhang, Y., Gunasekaran, T. S., Sasikumar, P., Krishna, N., Pai, Y. S., & Billinghurst, M. (2023, March). VRdoGraphy: An Empathic VR Photography Experience. In *2023 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)* (pp. 1013-1014). IEEE.

* Galea VR HMD with EEG, EOG, EDA, HRV, EMG, and Eye gaze biosignals
* Live emotion recognition system + adapts colors of the scene + audio to respond to measured emotional state
* Virtual characters (empathetic companion) also changes tone based on measured emotion
* BioSignal Processor – all datastreams are processed through python based LSL, features are extracted from raw signals through data cleaning, preprocessing, and feature extraction steps
* Features are tested through the Emotion Predictor’s pre-trained emotion classification model
* Predicted emotional state is shared with Empathetic adaptor embedded in VR via LSL

G. Bernal, T. Yang, A. Jain, and P. Maes. Physiohmd: a conformable,

modular toolkit for collecting physiological data from head-mounted

displays. In Proceedings of the 2018 ACM International Symposium

on Wearable Computers, pp. 160–167, 2018.

* Uses LeNet-5 five layer CNN to classify data
  + 2 convolutional layers, 2 pooling layers, 1 full-connection layer
* Trained the network use data from 6 users for 12 different expressions
* Need for channel selecting algorithm
* Github: <https://github.com/mitmedialab/physioHMD>

K. Gupta, J. Lazarevic, Y. S. Pai, and M. Billinghurst. Affectivelyvr:

Towards vr personalized emotion recognition. In 26th ACM Symposium

on Virtual Reality Software and Technology, pp. 1–3, 2020.

* AffectivelyVR, a system that is based on a personalized real-time emotion recognition model that was trained using low-cost physiological sensors.
* Custom ML model with max personal accuracy of 96.5%
* Used EEG + GSR
* KNN outperformed SV, RF, and NB

K. Gupta, Y. Zhang, Y. S. Pai, and M. Billingshurst. Wizardofvr: An

emotion-adaptive virtual wizard experience. In SIGGRAPH Asia 2021

XR, pp. 1–2. 2021.

* Adaptable VR environment using EEG, EDA, HRV to measure emotion
* User trains the system in calibration phase
* Personalized ML model for each individual using sensors + self assessment to label the data \
* During task, VR adaptive engine stores model from calibration stage, collects data + preprocesses, extracts features in 10s increments
* Used HP Onnicept with EEG from OpenBCI and EDA/HRV from Shimmer3 (so all sensors were external to the Omnicept\*)

Lee, S., El Ali, A., Wijntjes, M., & Cesar, P. (2022, April). Understanding and Designing Avatar Biosignal Visualizations for Social Virtual Reality Entertainment. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-15).

* Exploring different ways of visualizing biosignals in Social VR environments
* Specifically looking at HR and breathing rate
* Arousal interference caused by skeuomorphic visualizations for both HR + BR
* Survey responses + follow-up context mapping interviews to see how users prefer biosignals to be displayed in VR
* Led to an online codesign session + followed by prototype of 4 different visualizations for HR and BR signals
* So no-real time classification of emotion/state
* GitHub for biosignals visualizations: <https://github.com/cwi-dis/CHI2022-AvatarBiosignalVisualizations>
  + [BiosignalVisualizationPackage.unitypackage](https://github.com/cwi-dis/CHI2022-AvatarBiosignalVisualizations/blob/master/source/BiosignalVisualizationPackage.unitypackage) is a Unity package file that includes biosignal visualizations with an example simulated biosignal.

Notes

* After more research, people have successfully classified emotion in real-time in VR.
  + And some have even adapted the VR environment based on emotion
* Emotion detection is possible – so what do we want to do with that?
  + To build upon social presence work, I could aim to get a real-time emotion classification model working, so that it could perhaps be translated to facial expression or some way to display emotion to test effect on social presence?
* Look into Omnicept/VIVE differences in terms of sensors.
* I did also find some data for emotion classification.
  + I’m going to practice constructing neural networks with these dat.
  + Going to try to find some future application for VIVE / Omnicept systems using trained model
* I reached out Kunal Gupta (an author on many of these emotion papers) as the papers mention disseminating the data to the public but I can’t find it, asked him to advise
* Lots of papers use external (to the VR headset) to train their models

Ideas:

1. Can emotion be classified in real-time using biosensors built into Omnicept?
2. How will we train the model?
   1. Find emotion data set with same measures from Omnicept?
   2. Omnicept/Unity data streaming repo <https://github.com/dylanlavon/OmniceptDataStream>
   3. <https://developers.hp.com/omnicept/docs/unity/sensors>
3. Can see if existing VIVE sensors (eye-tracking, face/mouth tracking) can be used to train a model to estimate emotion?

Steps:

1. Need to do a bit of learning on constructing CNNs from scratch
2. Leverage existing datasets + github repos
   1. Especially interested in this dataset: <https://www.kaggle.com/datasets/lumaatabbaa/vr-eyes-emotions-dataset-vreed>
      1. Used GSR +ECG (Biopac), ECH (Lead II0)
      2. FOVE-0 headset – eyetracking, head orientation tracking

Week 4 6/26/23

* Novelty of detecting emotion in real-time comes from the multi-user environment
* I will create a model using all open access data
* In my final deliverable, I will brainstorm future work in how this algorithm could be used to relate to Simon’s research topic of social presence
* Something to consider – pupillometry can be affected by VR light brightness, discuss this with Sebastian
* Can also consult the AI group as I work on my model

Dataset resources:

* Google datasets
* Kaggle
* zenodo

Public Datasets:

1. Analyzing VR user experiences improves design, comfort, and customization <https://www.kaggle.com/datasets/aakashjoshi123/virtual-reality-experiences>
2. COLET: A dataset for COgnitive workLoad estimation based on eye-tracking <https://www.sciencedirect.com/science/article/pii/S0169260722003716>
3. <https://github.com/ShikhaIIMA/Cognitive-Load-Detection-Ubittention>
4. <https://github.com/Tech4People-BMSLab/mwl-detection>, <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7829255/>
5. <https://www.kaggle.com/datasets/emteqlabs/emgdatavr>

Real time Detection of Emotion in VR

1. <https://www.mdpi.com/1424-8220/20/18/5163>
2. <https://github.com/rageappliedgame/EmotionDetectionAsset_CPP>
3. Virtual Reality Emotion Recognition Dataset using Eye Tracking, ECG and GSR <https://www.kaggle.com/datasets/lumaatabbaa/vr-eyes-emotions-dataset-vreed>

See Data Dictionary Document for data details

Datasets I came across but will not include:

* **DER-VREEG (**EEG only)
* [**Valence and Arousal Videos in VR**](https://stanfordvr.com/360-video-database/)(videos only)
* Emteq EMG (EMG only)

This week I also completed Kaggle’s intro to Machine learning course.

Week 5 7/3/23

* This week I’m working on creating the data dictionary and completing the Kaggle’s intro to deep learning course.
* Need to organize features of interest + pre-processing steps

**CEAP** - has labeled time series data for classification

* + run py scripts for data extraction \*in baseline folder for DL
  + or feature extraction for ML, need to figure out what the input is for this script
* **AV Reality** - unfiltered time series data
  + need to extract features
* It's worth noting that the decision to use time series data or extracted features is not always binary. In some cases, you may choose to combine both approaches, where you use extracted features as additional input alongside the raw time series data to enhance the model's predictive capabilities.

Data Dictionary

Classifying Emotion in VR

Emily Doherty

IRES 2023

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| Dataset | Features |
| **CEAP-360VR**  <https://ieeexplore.ieee.org/document/9599346>  <https://github.com/cwi-dis/CEAP-360VR-Dataset/tree/master>  Eye tracking, head movements, ACC, EDA, SKT, BVP, HR, IBI | N=32  8 Videos  Questionnaires   * SSQ, IPQ, NASA-TLX * V-A within VR SAM ratings   Raw data was rescaled to 1-9 to be consistent with SAM rating range. HM/EM converted to longitude + latitude of viewing direction. Physiological data was normalized after filtering. All data was resampled.  Head position   * X-axis (u) and y-axis (v) of joystick head position in [1,9] * Transformed: Timestamp, Valence, Arousal   \* need to extract features  BVP @64Hz  EDA 4 Hz microSec  SKT 4Hz (celcius)  BVP, EDA, SKT – third-order low pass filter with 2Hz cutoff applied, then normalized to [0,1]  HR 1 Hz  IBI time interval between beats  Citation: T. Xue, A. El Ali, T. Zhang, G. Ding, and P. Cesar, "CEAP-360VR: A Continuous Physiological and Behavioral Emotion Annotation Dataset for 360° Videos," in IEEE Transactions on Multimedia, doi: 10.1109/TMM.2021.3124080. |
| **Audiovirtual Reality to induce anger and happiness emotions: A physiological response (EEG, GSR, BVP and TMP) database** | N=28  E4 wristband was used for the recording of the Autonomous Nervous System responses: - Galvanic skin response was recorded at 4Hz. - Blood volume pulse was recorded at 64 Hz. - Temperature was recorded at 4Hz.  Data is provided in raw form.  Citation: Ramirez-Lechuga, Sharon; Alonso-Valerdi, Luz Maria; Ibarra-Zarate, David I (2023), “Audiovirtual Reality to induce anger and happiness emotions: A physiological response (EEG, GSR, BVP and TMP) database”, Mendeley Data, V3, doi: 10.17632/y76vbw92y9.3 |
| Virtual Reality and Flat Screen Database  <https://github.com/VREmotions/VRFS/tree/main> | N=6  we can effectively calculate Heart Rate  variability (HRV) using BVP [70]. We then extract the Low frequency (LF) and High-frequency (HF) features from the  HRV. The LF band (0.04–0.15 Hz) is affected by breathing  from 3 to 9 bpm. [71] while the HF or respiratory band (0.15 – 0.40 Hz) is influenced by breathing from 9 to 24 bpm [72]. (LF/HF ratio)  *We use the FLIRT module [87] in Python to extract various*  *statistical and signal features for the EDA and HRV data.*  *FLIRT module preprocessed the data for artifact removal and*  *noise filtering using the extended Kalman filter (EKF) for EDA*  *data and the Malik [88], Kamarth [89] and Acar [90] rule for*  *the heart rate. Accelerometer data is ignored in our analysis*  *because it does not carry significant impressions useful for*  *the final analysis. The trial was conducted on 36 participants;*  *however, three of the data points had to be dropped due to*  *participants’ inability to complete the gameplay for various*  *reasons. This led to a total of 33 participants, split between*  *4 games(see Table III). We provide anonymized ACC, BVP,*  *EDA, HR, IBI, and TEMP data in the form of CSV files for*  *both VR and FS. Each CSV file starts with a timestamp,*  *followed by the frequency of the recording and the data*  *collected over the recording. We have also added the script*  *we used to get the results of this study.*  Citation: Vatsal, Ritik, et al. "An Analysis of Physiological and Psychological Responses in Virtual Reality and Flat Screen Gaming." *arXiv preprint arXiv:2306.09690* (2023). |

Summary of Features

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Dataset | Heart Rate | IBI | BVP | HM | GSR/EDA | TMP/SKT | Eye Tracking | ECG | Behavioral |
| CEAP  Empatica E4 (GSR, SKT, BVP)  VIVE Pro Eye (HM/EM) w/ Tobii Pro | Yes  MMM | Yes  MMM | Yes  MMM | Yes  MMM  Yaw/Pitch | Yes  MMM | Yes | EM (MMM)  Fixation  Saccades  Yaw/Pitch |  | SAM  A/V 3- and 5- class  SSQ  IPQ  NASA-TLX |
| AVR  Empatica E4 (GSR, SKT, BVP) | Can get from BVP | Can get from BVP | YES  Raw |  | YES  Raw | Yes  Raw |  |  |  |
| VRFS  Empatica E4 | Can get from BVP | Can get from BVP | YES  Raw |  | YES  Raw | Yes  Raw |  |  |  |