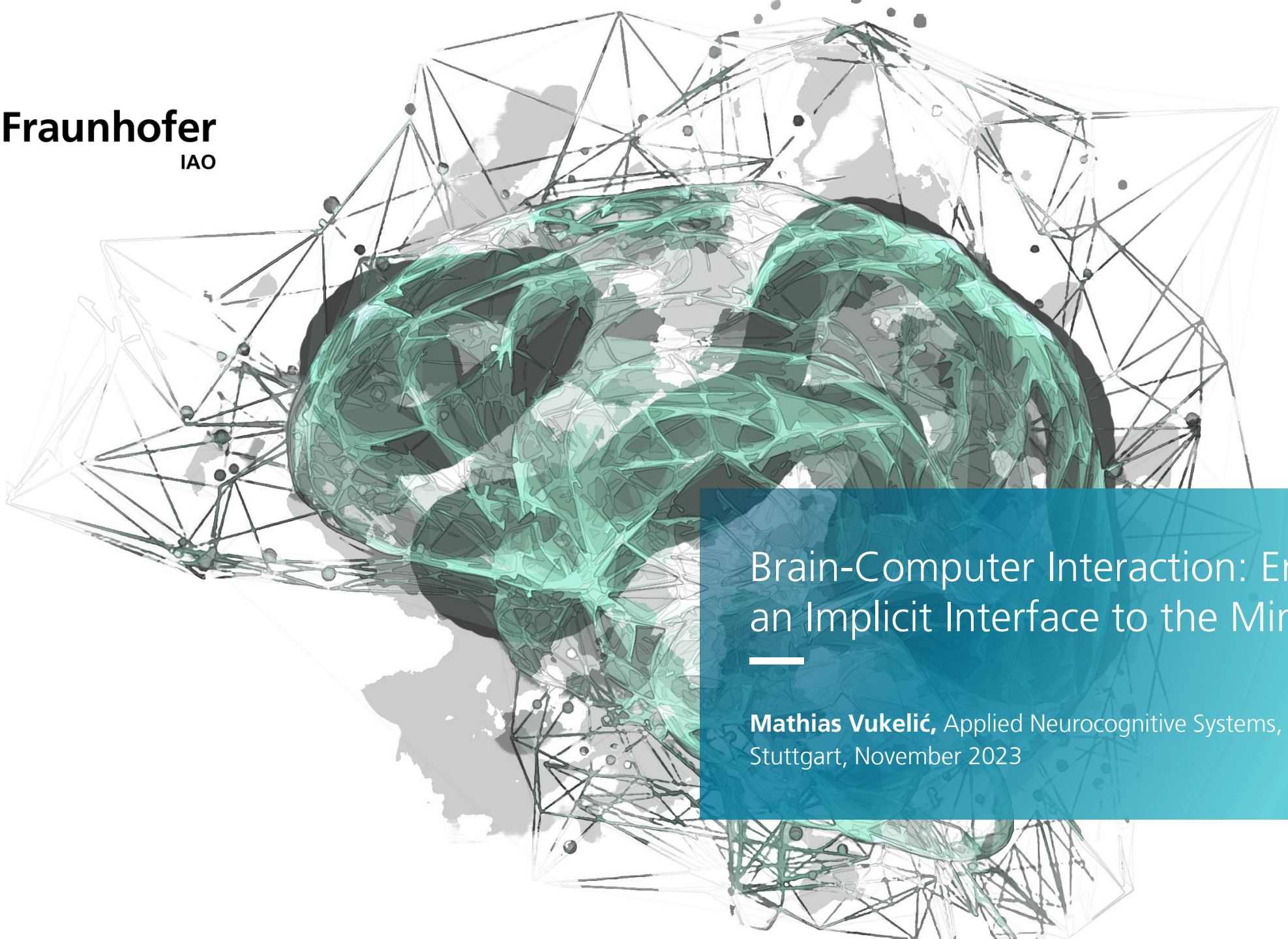
Fraunhofer IAO

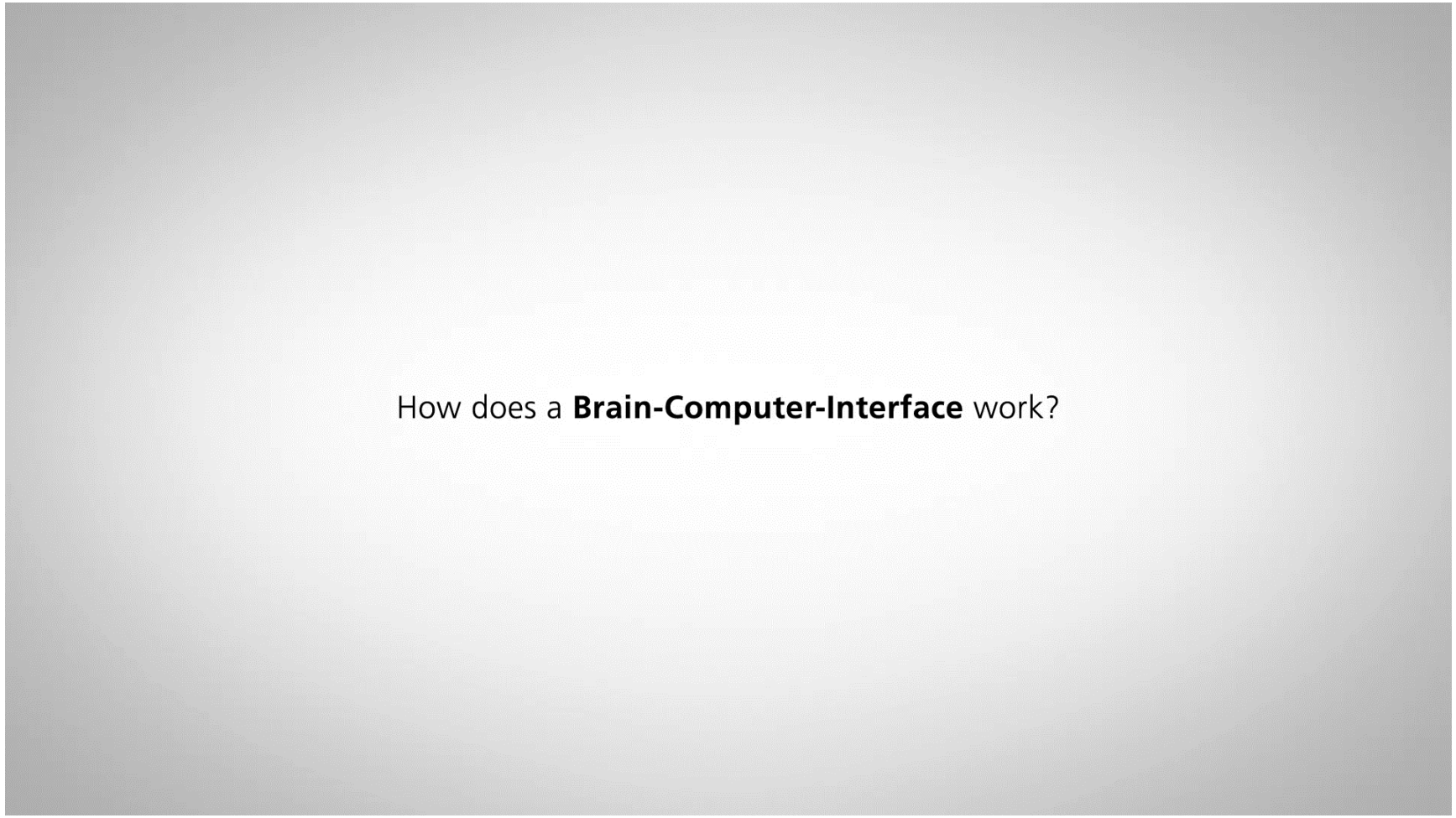


Brain-Computer Interaction: Enabling an Implicit Interface to the Mind

Mathias Vukelić, Applied Neurocognitive Systems,
Stuttgart, November 2023

Brain-Computer Interface (BCI)

interface to the mind

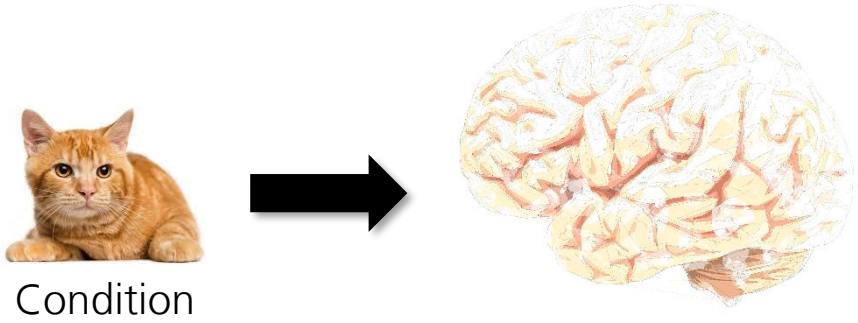


Vukelić, M. (2021). Connecting Brain and Machine – The Mind is the Next Frontier. Clinical Neuroethics Meets Artificial Intelligence - Philosophical, Ethical, Legal and Social Implications. Springer Verlang. Eds. O. Friedrich, A. Wolkenstein, C. Bublitz, R. Jox, E. Racine

Beyond Brain-Computer Interface (BCI)

encoding and decoding brain activity as a tool to…

Understand

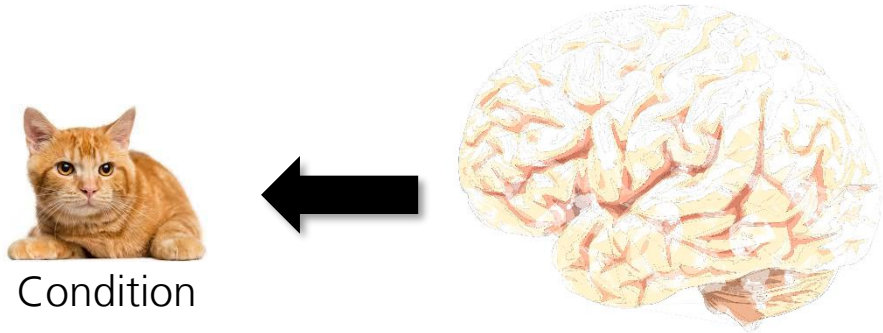


Condition

$Y = f(X)$

- *Forward Inference*: encoding describes prediction of data from experimental conditions

Interact



Condition

$X = f(Y)$

- *Inverse Inference*: decoding describes the prediction of experimental conditions from data

Holograf et al. Encoding and decoding models in cognitive electrophysiology. 2017 Front. Syst. Neurosc. 11:61

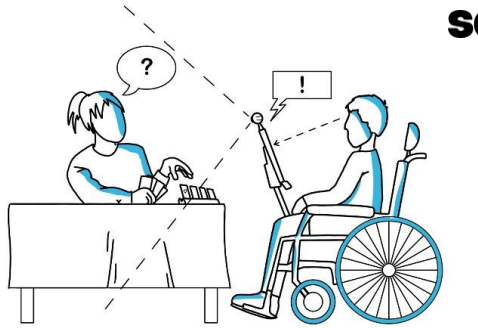
Applied Neurocognitive Systems (ANS)

application areas

Human-in-the-loop Learning

Multimodal Mental State Monitoring

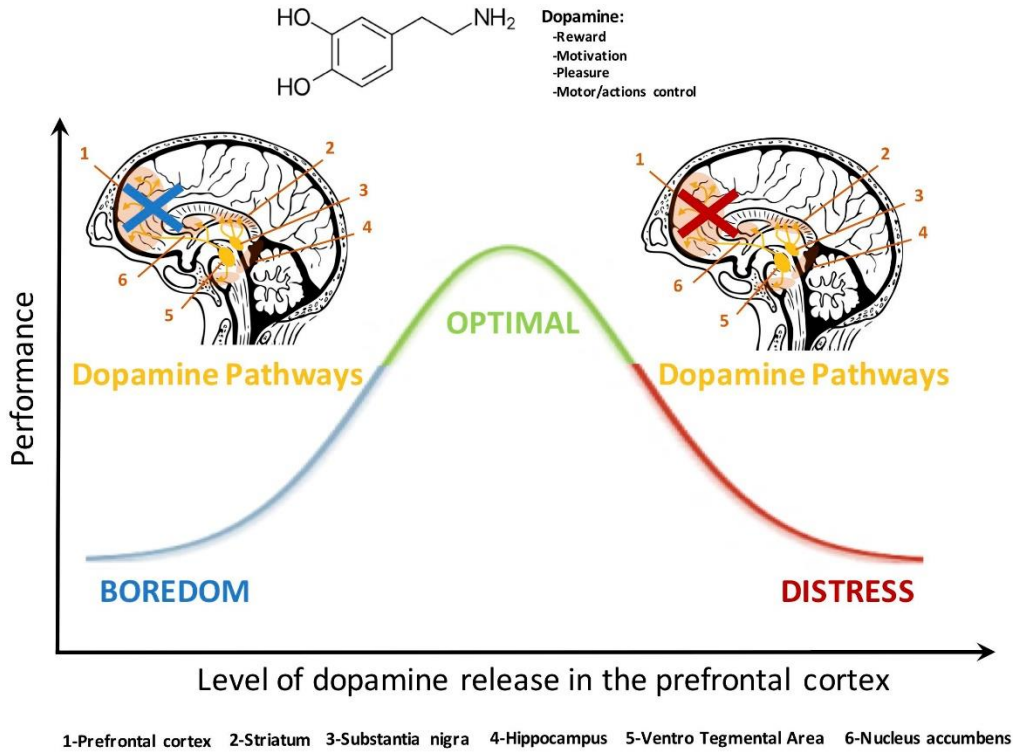
Assistive Communication Technologies



Neuroadaptive Learning

Towards User-aware VR Environments

neuroadaptive learning and mental state monitoring



fNIRS

VR

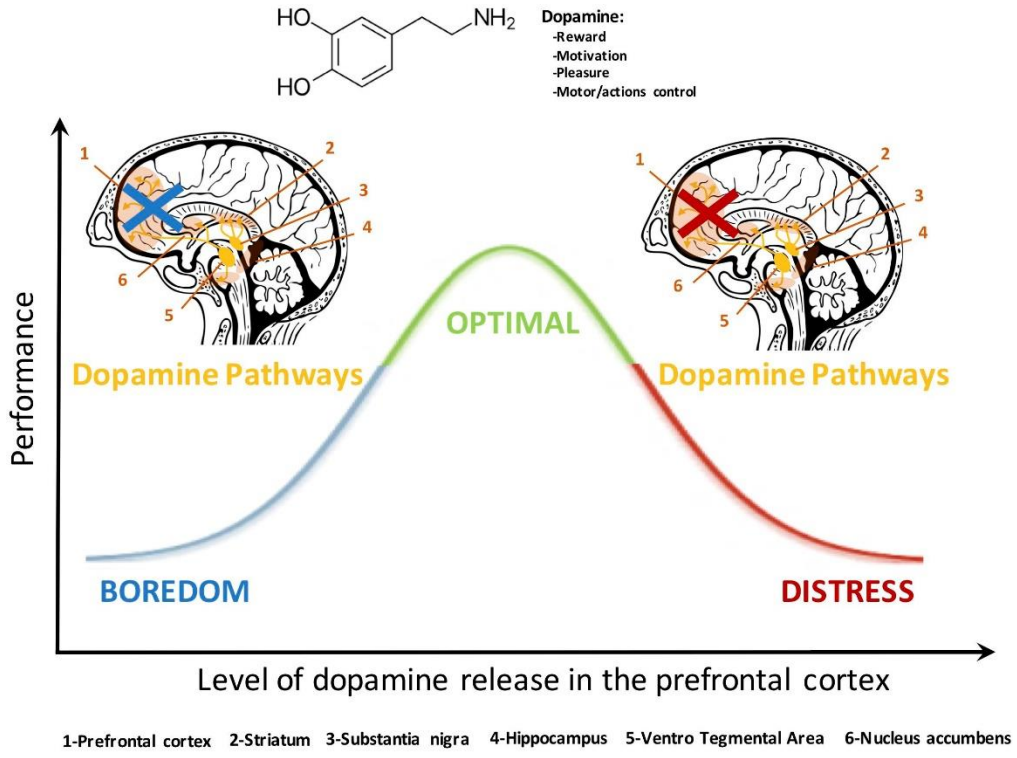
- **Machine learning to decode WM load**
  - *Extract statistical features from HbO and HbR concentration changes (Herff et al. 2014; Putze et al. 2019)*
  - *Extract coefficients of a general linear model (GLM) from HbO and HbR concentration changes (von Lühmann et al. 2020)*

fNIRS: funcitonal near-infrared spectroscopy
VR: virtual reality

F. Dehais et al.: A neuroergonomics approach to mental workload, engagement and human performance. Front. Neurosci. 14:268. (2020).

Towards User-aware VR Environments

neuroadaptive learning and mental state monitoring



Encoding

Condition

Do we understand the machine learning models and its underlying brain patterns?

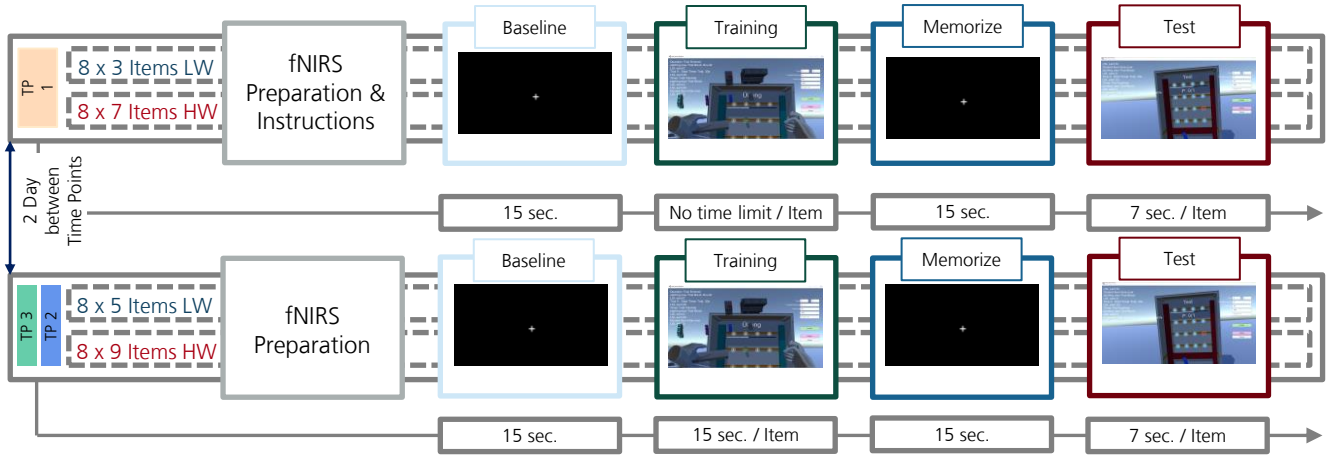
How can we use machine learning to identify the learning progress of individuals?

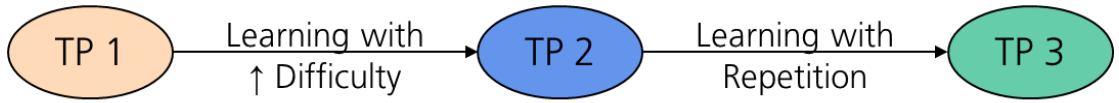
F. Dehais et al.: A neuroergonomics approach to mental workload, engagement and human performance. Front. Neurosci. 14:268. (2020).

Towards User-Aware VR Environments

memory load task in a VR learning scenario

Learning task: install electrical components (order and positioning) in a switch cabinet in a low (LW) and high working memory (HW) condition





Lingelbach, K., Diers, D. and Vukelić M (2023). Towards User-Aware VR Learning Environments: Combining Brain-Computer Interfaces with Virtual Reality for Mental State Decoding. In 2023 CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2023). Article No. 292, pages 1-8

Towards User-Aware VR Environments

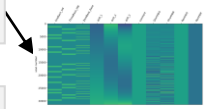
signal processing and machine learning

Encoding
Forward Models of Memory Load

TP 1 | TP 2 | TP 3

Individual-Level Analysis
Generalized Linear Model

Create Design Matrix and Run GLM



Compute Contrast
High - Low

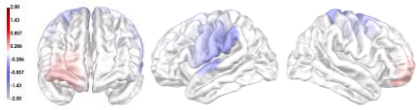
Group-Level Analysis
Linear Mixed-Effects Model

Compute Statistic

Plot Significant Effects

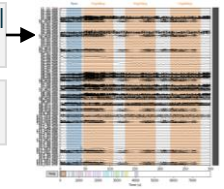
HbO LMM Coefficients

High - Low Working Memory Load

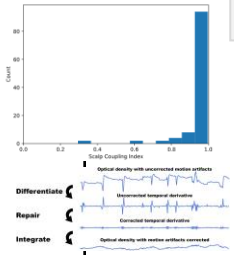


Pre-processing

Convert Raw Intensity to Optical Density



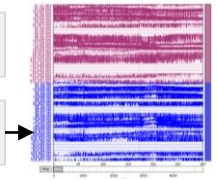
Evaluate Data Quality & Artifacts



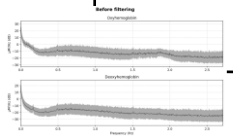
Scalp-Coupling-Index (< 0.5)

Temporal Derivative Distribution Repair

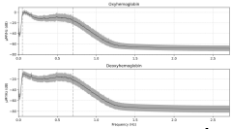
Short Channel Regression



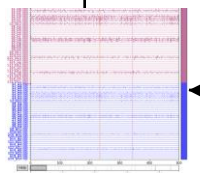
Convert Optical Density to Hemoglobin (PPF = 6)



Bandpass IIR Filter with Cutoff 0.05 and 0.7



Short Channels as GLM regressors



Epochs of 0 - 4 sec

Baseline Correction with Rest

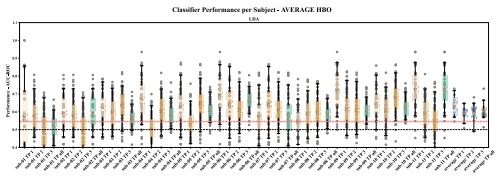
Decoding
Inverse Models of Memory Load

TP 1 | TP 2 | TP 3

Feature Extraction
Ø HbO Amplitude per Epoch and Channel

Multivariate Linear Classification with Linear Discriminant Analysis (LDA)

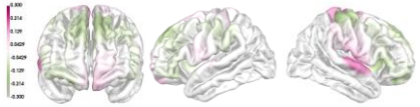
Nested (Repeated) Cross-Validation
Standard Scaler
Hyperparameter Optimization



Feature Coefficients Extraction

Ø HbO Concentration LDA Coefficients

High (1) - Low (0) Working Memory Load



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KI Fortschrittszentrum
LERNENDE SYSTEME UND KOGNITIVE ROBOTIK

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Towards User-Aware VR Environments

encoding model of brain activity indicates learning progress

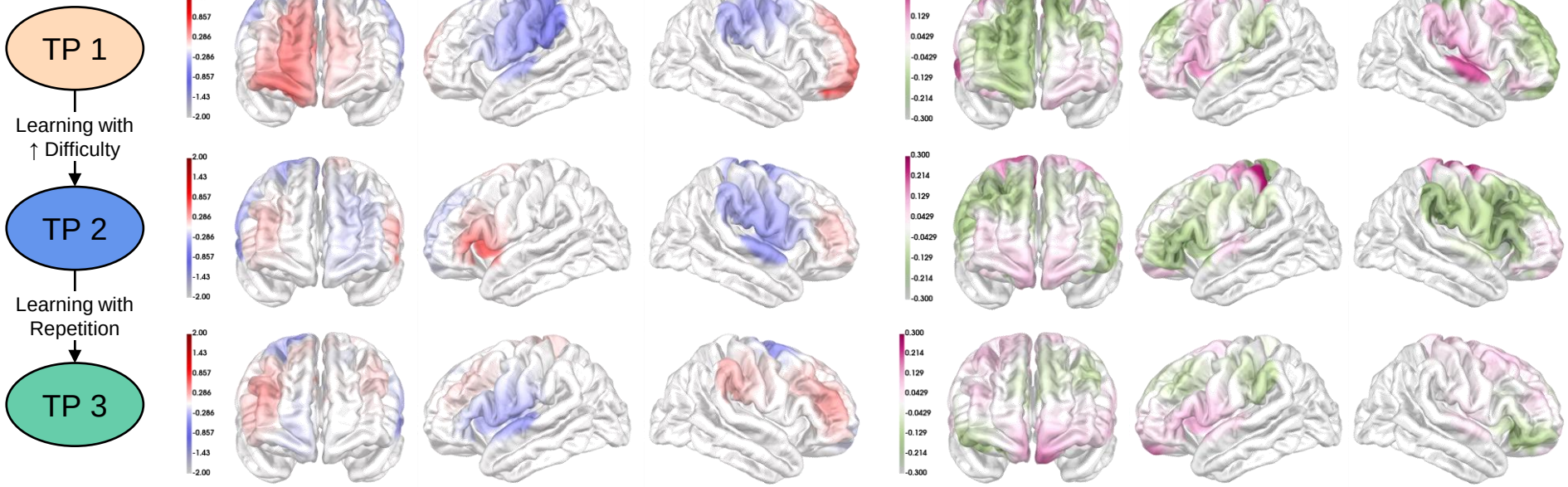
Bundesministerium für Wirtschaft und Energie
ZIM Zentrales Innovationsprogramm Mittelstand

Encoding
HbO GLM and LMM Coefficients

High - Low Working Memory Load

Decoding
ML Coefficients from Ø HbO Concentration

High (1) - Low (0) Working Memory Load



↑ right PFC for ↑ load

↑ PFC pattern for ↑ load disappears due to excessive/over-load

↑ right PFC re-established due to learning progress

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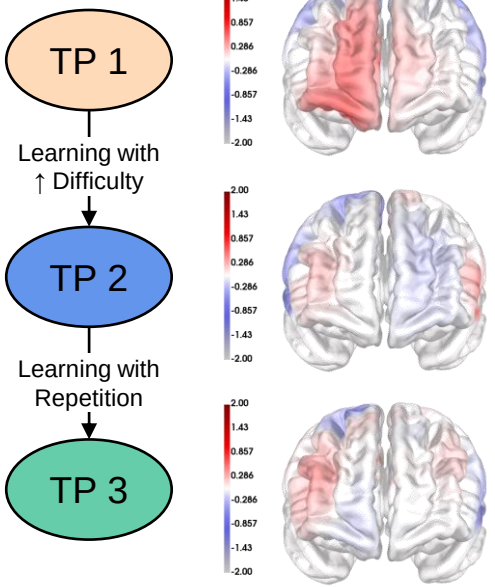
Towards User-Aware VR Environments

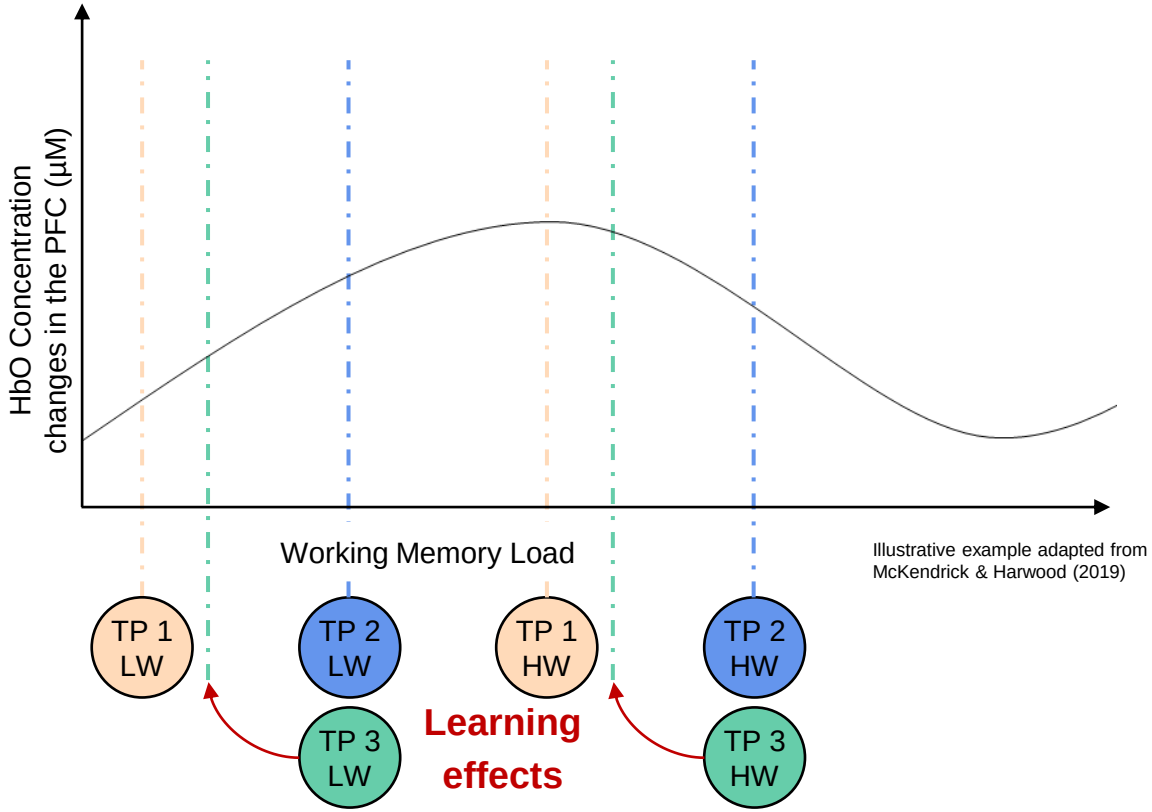
non-linear relationship between brain activity and memory load



↑ right PFC for ↑ load

↑ PFC pattern for ↑ load disappears due to excessive/over-load

↑ right PFC re-established due to learning progress



McKendrick, R. & Harwood, A. (2019). Cognitive Workload and Workload Transitions Elicit Curvilinear Hemodynamics During Spatial Working Memory. *Front. Hum. Neurosci., 13,* 405. doi:10.3389/fnhum.2019.00405

Towards User-Aware VR Environments

summary

- We showed complex non-linear relationship between working memory load, task difficulty level and the hemodynamic response in the prefrontal cortex.
- Learning effects are visible in this relationship and in the machine learning based classification performance.
- Encoding and decoding of brain patterns in VR learning scenarios can be applied to several use case scenarios:
  - safety trainings in critical infrastructures,
  - robot-assisted language learning or medical interventions, or
  - human-robot collaborations,

Full Paper

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Human-Robot Collaboration (HRC)

motivation

A. Bihlmaier, M. Wagner, et al. Cognitive Endoscopic Camera Guidance, Surgical Robot Challenge 2015.

Human-Robot Collaboration (HRC)

reinforcement learning and learning from human feedback

AffektoBotik

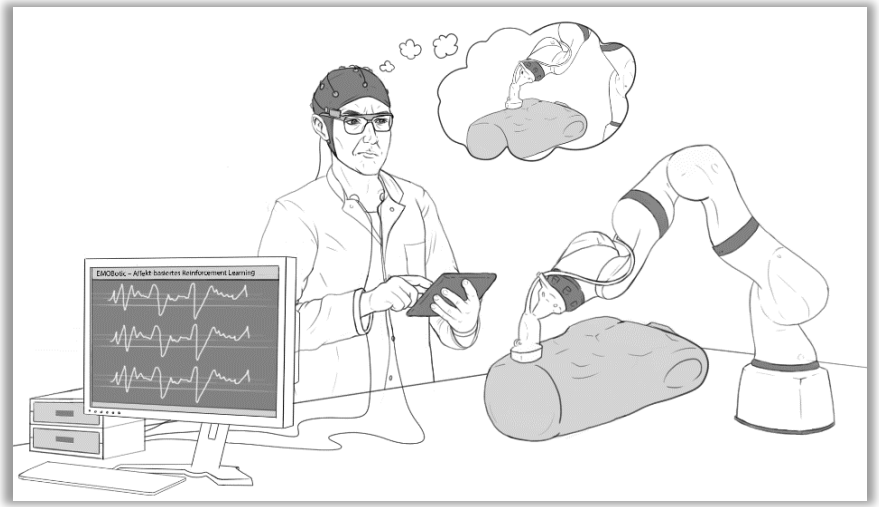
Fraunhofer

What do we need?

- good feedback function (criticism and reward) that captures the task to be learned

What are the real-world characteristics and problems?

- challenge of sparse extrinsic rewards – *sparse environments*
- sparsity is a natural way to define a reward - *agent only receives a positive reward if the task is completed, or a goal is achieved!*
- provide poor learning signals for the agent, especially if the task horizon is long - *very time-intensive training!*



Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

Learning from Human Feedback

BCI-based deep reinforcement learning

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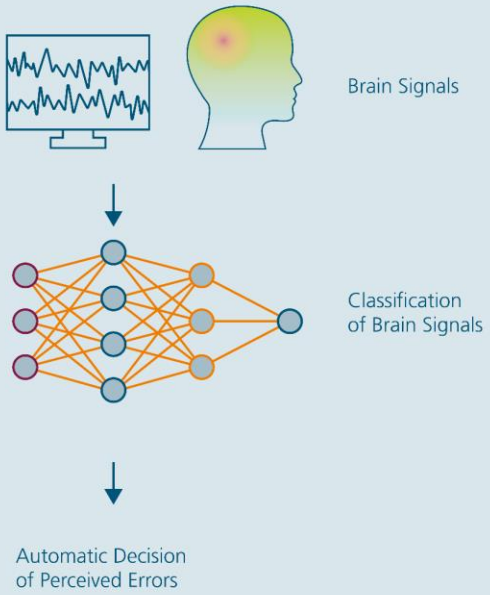
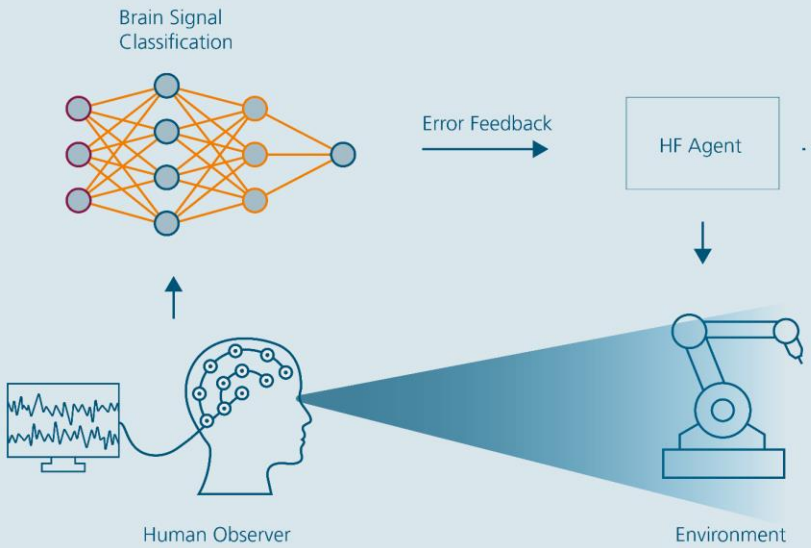
Fraunhofer

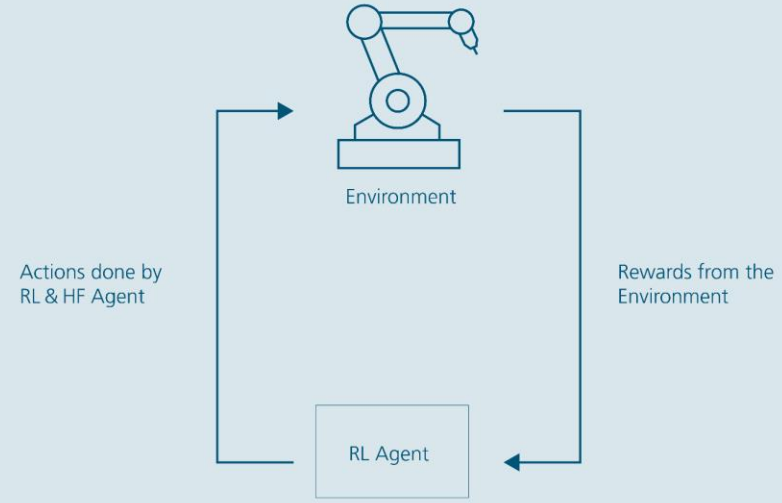
1. Brain-Computer-Interface (BCI) Calibration



2. Learning from Human Feedback (HF)



3. Reinforcement Learning (RL) with Human Feedback



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BCI-based Deep Reinforcement Learning

Study 1: decoding performance

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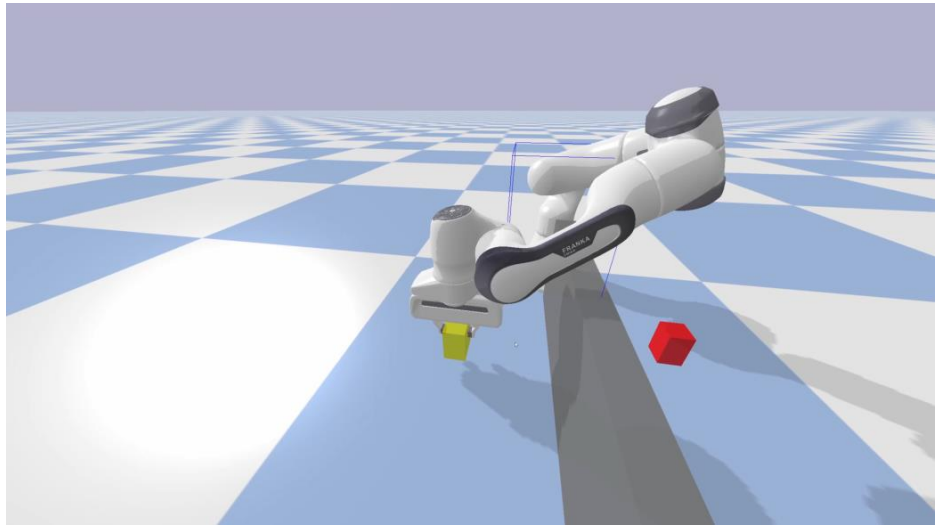
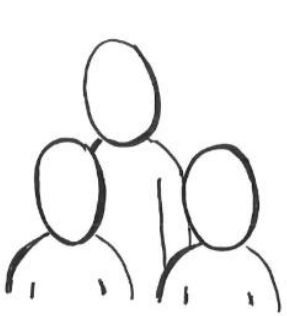
pybullet environment: https://github.com/bulletphysics/bullet3



Goal(s)

- practical feasibility of EEG (wet- vs dry-systems) for decoding Error-related Potentials (ErrP)
- comparison of decoding performance with different machine learning models



N = 16
(age = 18-35)

Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

BCI-based Deep Reinforcement Learning

Study 1: results

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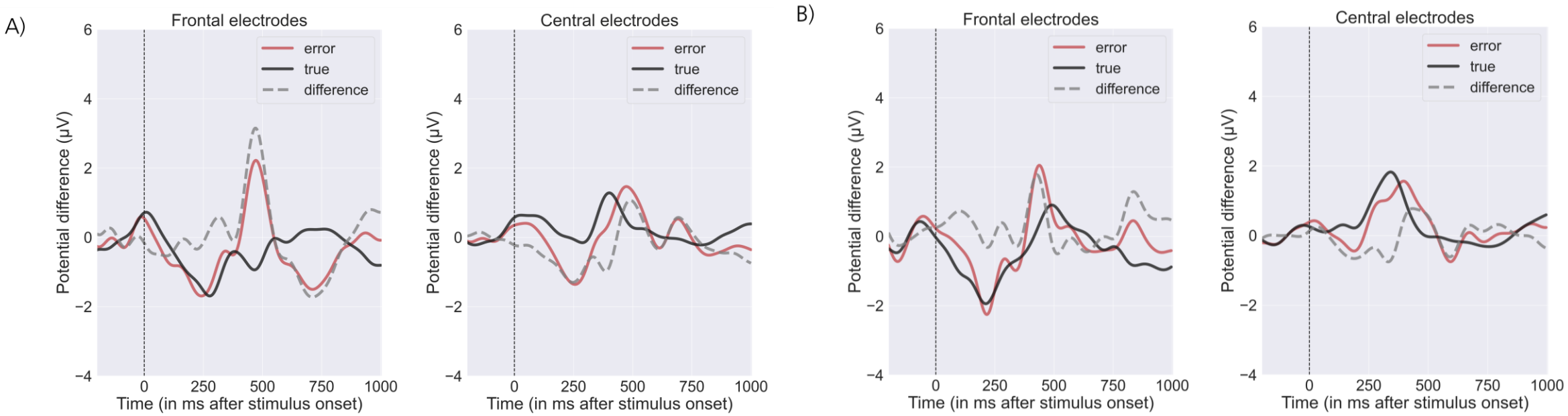

Grand averaged waveform of the Event-Related Potentials.

t=0: Onset of robot end-effector movement

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BCI-based Deep Reinforcement Learning

Study 1: results

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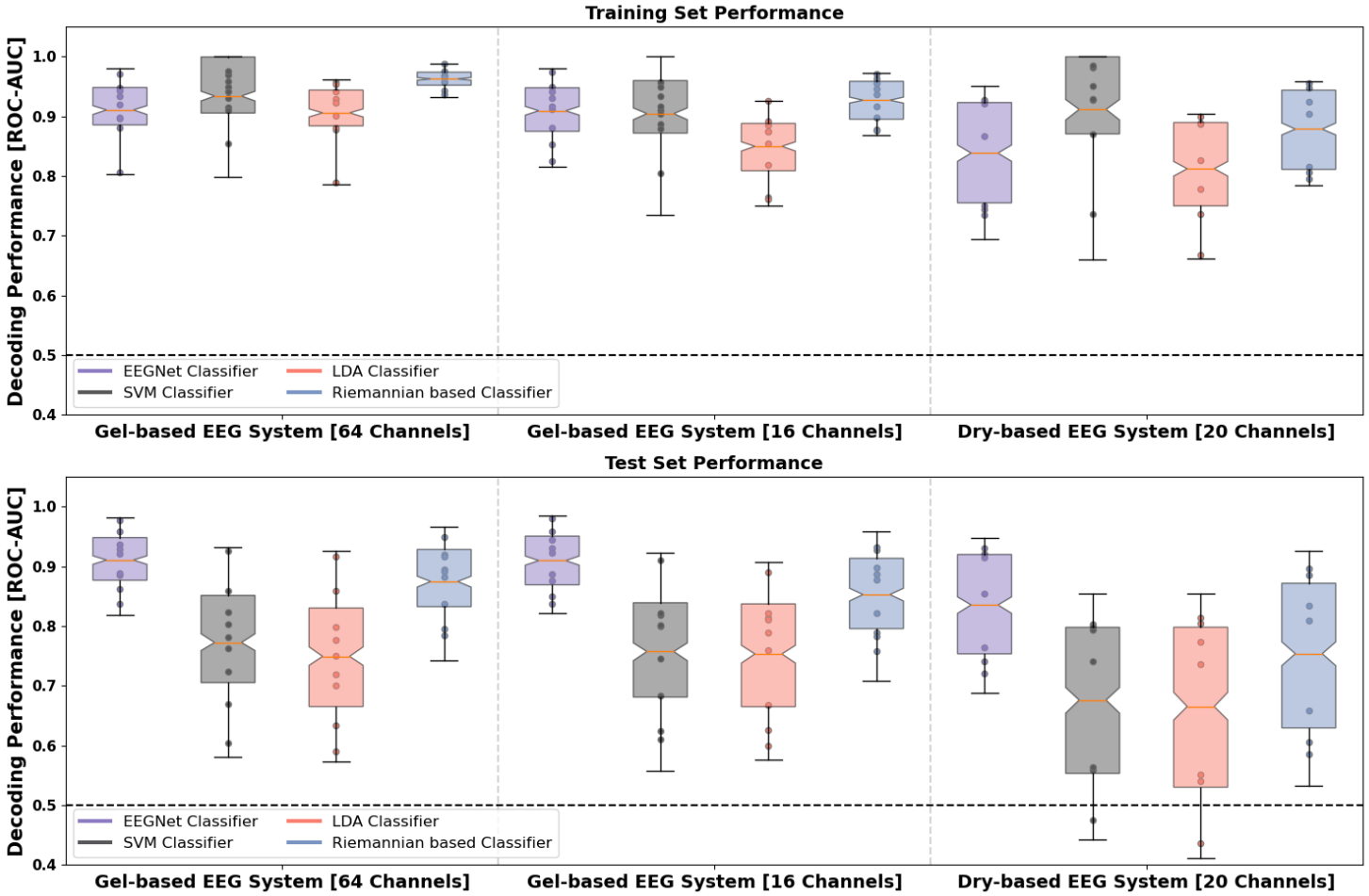


Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

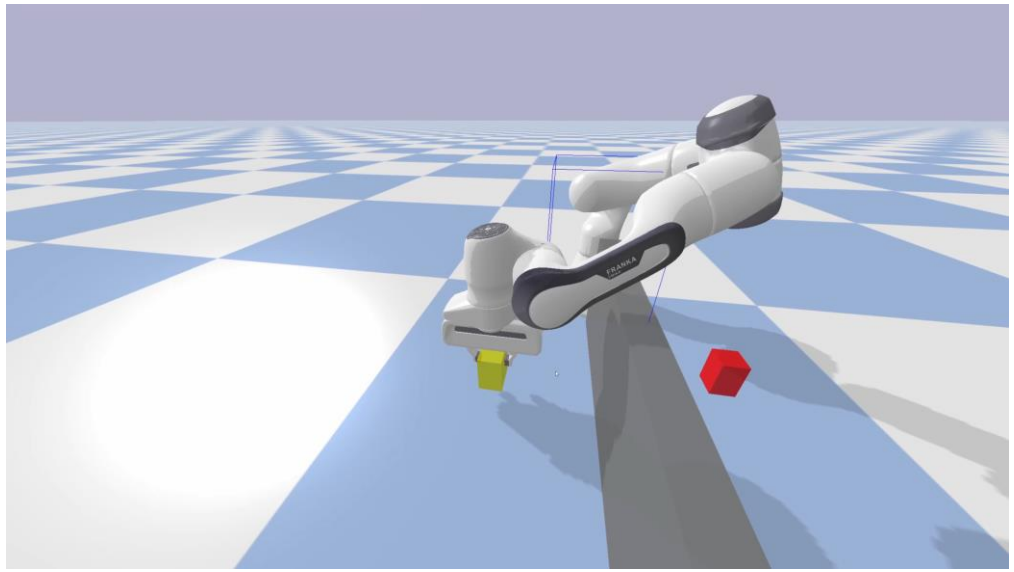
BCI-based Deep Reinforcement Learning

Study 2: feasibility study in simulation environments

AffektoBotik

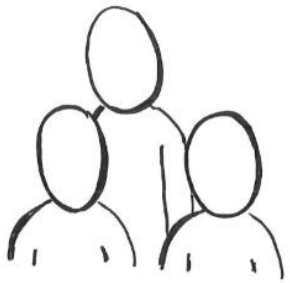
Fraunhofer

pybullet environment: https://github.com/bulletphysics/bullet3



Goal(s)

- comparison of two versions of the of the DeepRL + HF algorithm:
  - implicit BCI-based given feedback version
  - explicitly given feedback (keyboard input) version



N = 6
(age = 18-35)

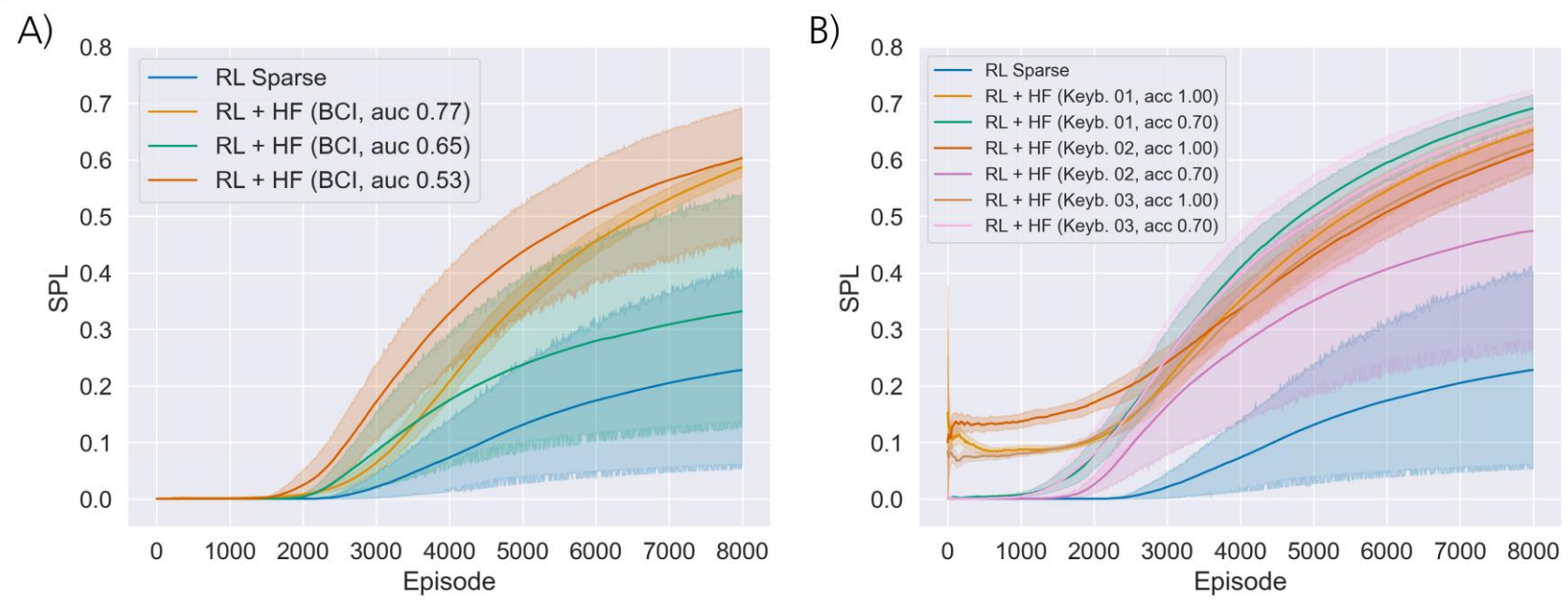
Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

BCI-based Deep Reinforcement Learning

Study 2: results

AffektoBotik

Fraunhofer



In all the experiments, 10 models of 8000 episodes were trained, where solid lines show the mean value estimated with bootstrapping (1000 times) and the shaded area the confidence interval

SPL, success weighted by the normalized path length; BCI = brain-computer interface

HF = human feedback policy (fully connected lightweight neural network)

RL = Deep Deterministic Policy Gradient (DDPG) Algorithm

Keyb. = Keyboard input

Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

BCI-based Deep Reinforcement Learning

summary

Study 1

- Dry-based EEG-system provides a robust and fast method for automatically assessing robot behaviour using deep learning model.
- The comparative analysis advance the applicability and accessibility in future BCI applications – dry-EEG is a valid and efficient alternative.

Study 2

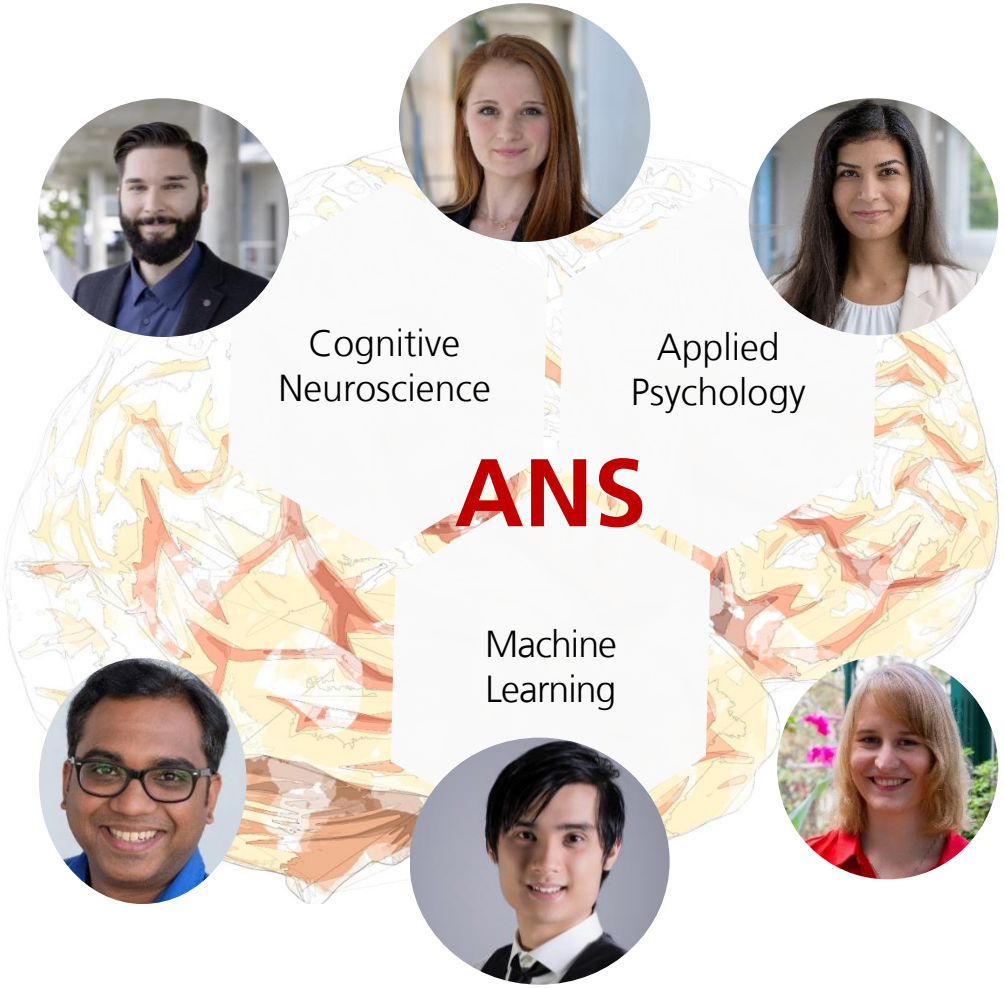
- BCI-based version (dry EEG-system) significantly accelerates the learning process with even comparable performance to that achieved by the approach with explicit human feedback.
- We provide a valid alternative in those human-robot applications where no access to cognitive demanding explicit human feedback is available.

Full Paper

Vukelić M, Bui M, Vorreuther A, Lingelbach, K. (2023). Combining brain-computer interfaces with deep reinforcement learning for robot training: a feasibility study in a simulation environment. Front. Neuroergonomics, Sec. Neurotechnology and Systems Neuroergonomics, Volume 4 - 2023

Applied Neurocognitive Systems (ANS)

better technology comes from better science



Our vision is to create a better future of work and everyday life; where people are at the forefront while technology is assistive in the background!

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