

I A H | Bath Institute for the Augmented Human

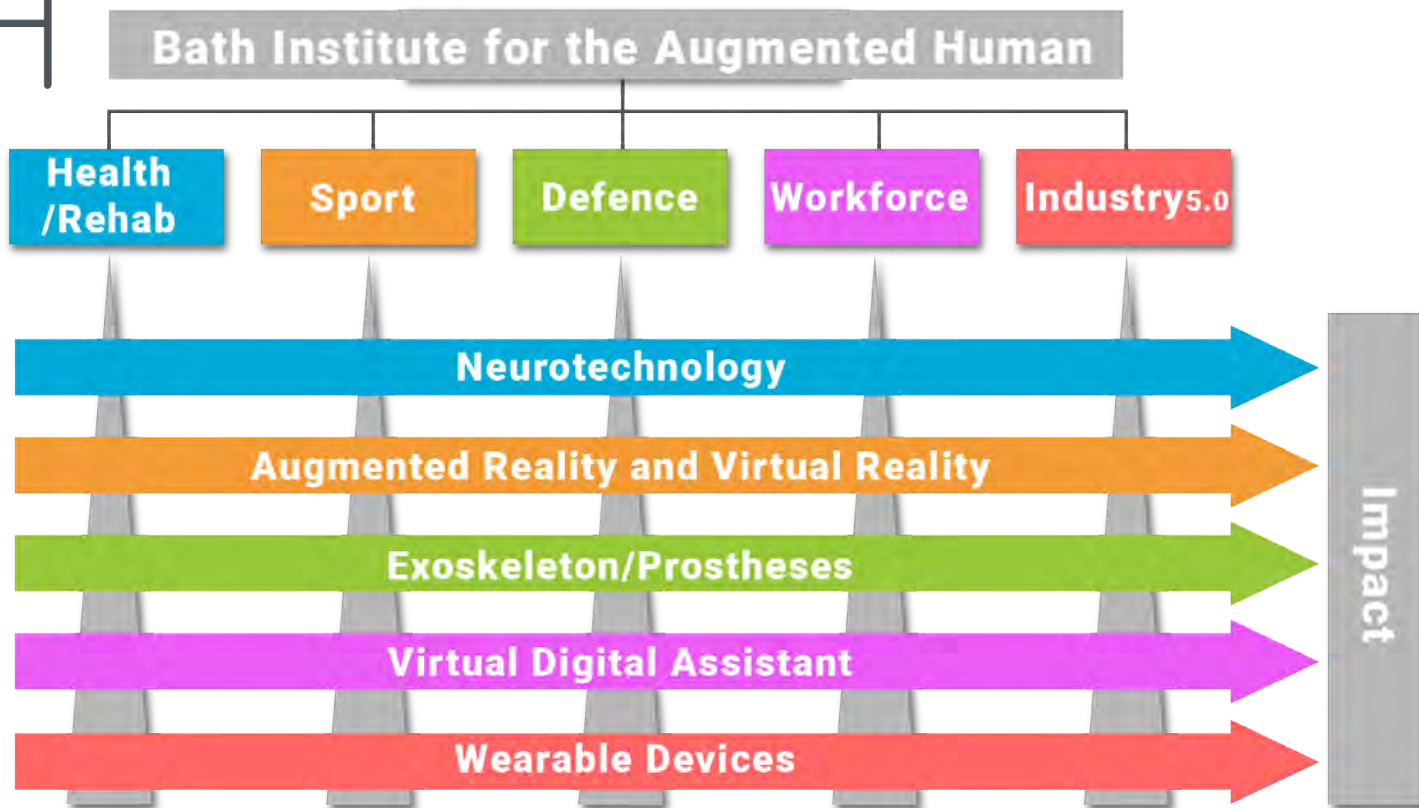
Director - Prof Damien Coyle,
Professor of Neurotechnology and Turing AI Fellow
AI & ML Research Group, Department of Computer Science
HCI Research Group, Department of Computer Science



UNIVERSITY OF
BATH

Human Augmentation

Human Augmentation may be defined as the application of science and technology to improve human physical and cognitive performance.



Innovation Ecosystem

Machine Learning for Neurotech

Brain-Computer Interfaces

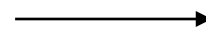
BCIs

Brain-Computer Interface

BCI



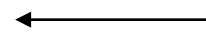
INTENT



ACTION

Command

PERCEPT

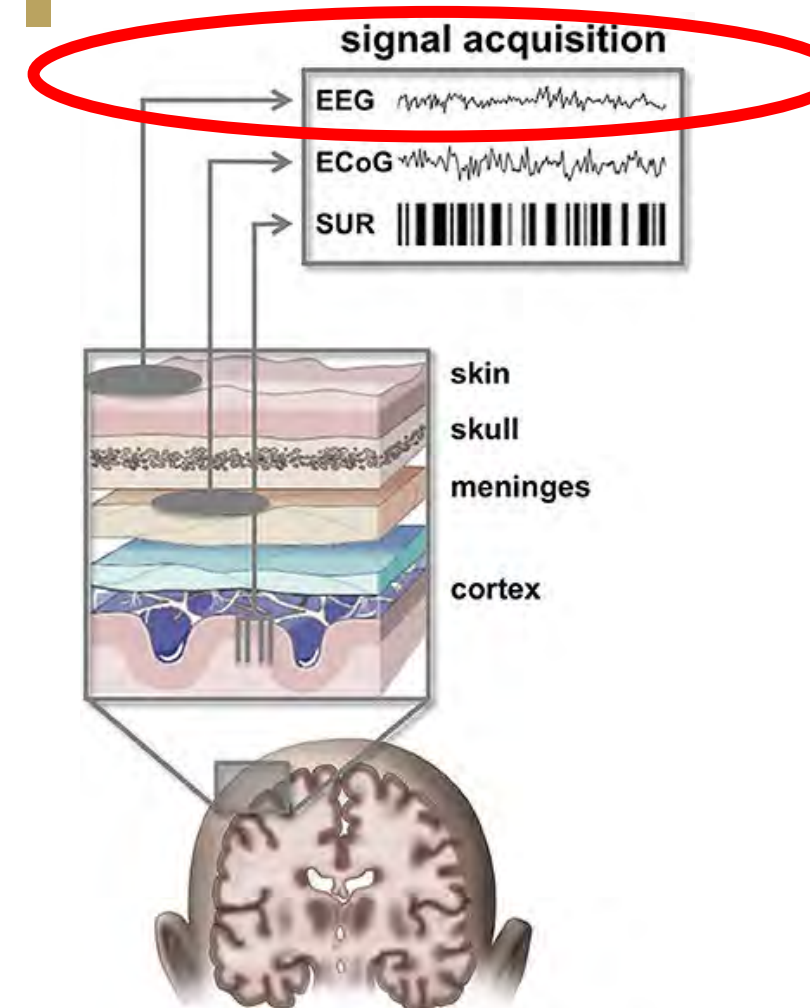


STIMULUS

Coding

Neural Interface

Physical Interface



Brain-Computer Interface

BCI is a learned skill and not simply a matter of “mind reading.”

Performance



Three pillars

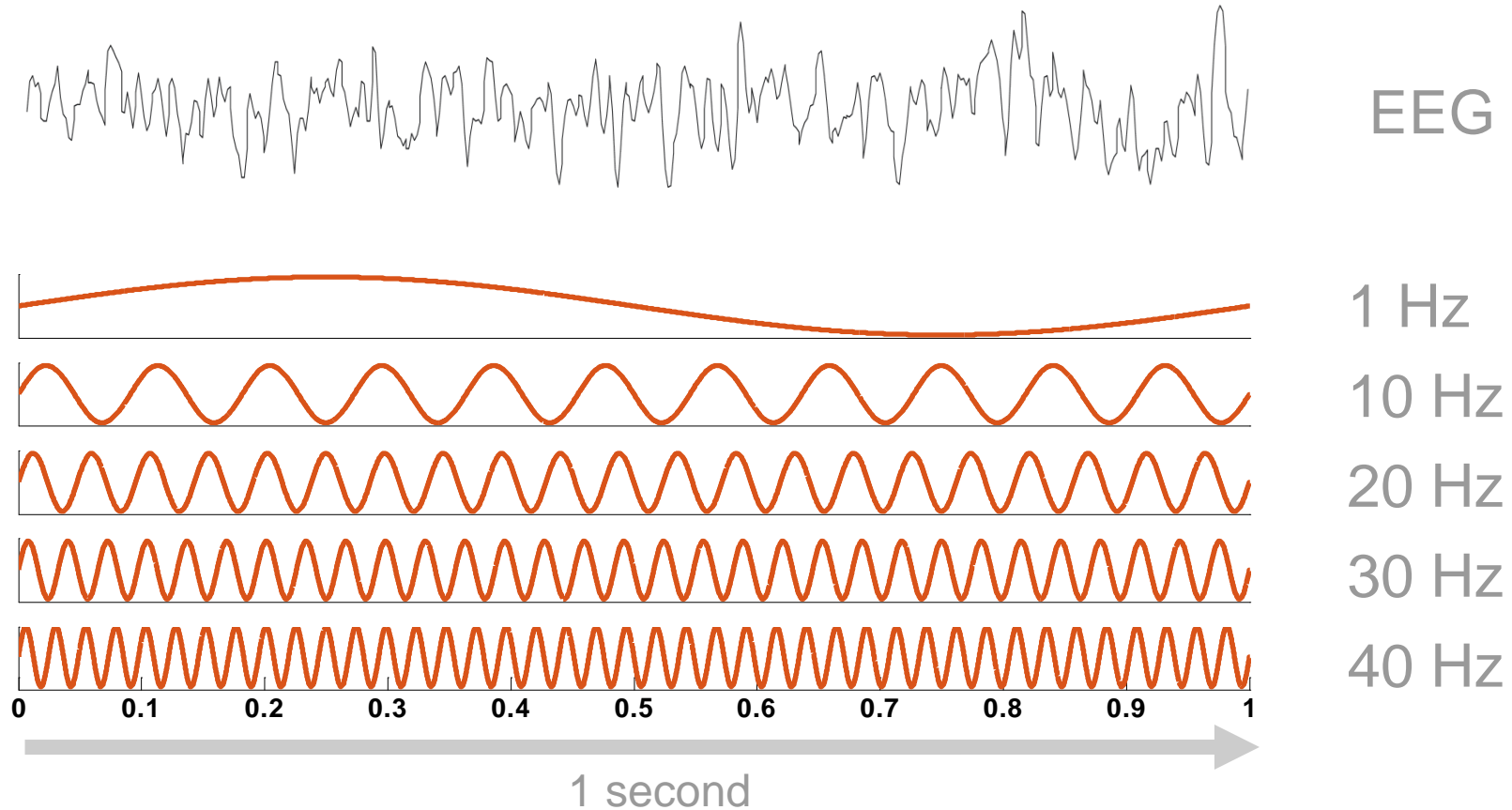
Machine Learning/AI

Training

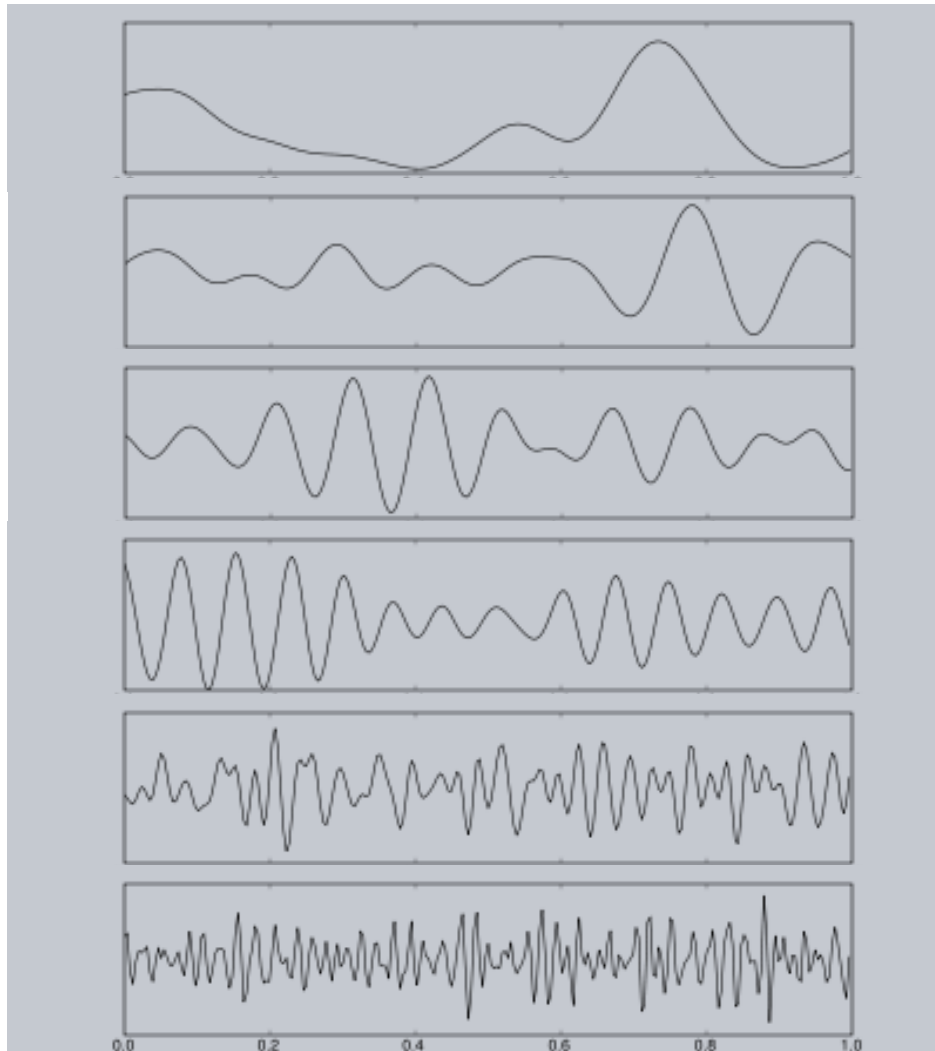
Application

Motor Imagery BCI Basics

EEG and Frequency (Hz)



Brain Rhythms/Oscillations



1 second

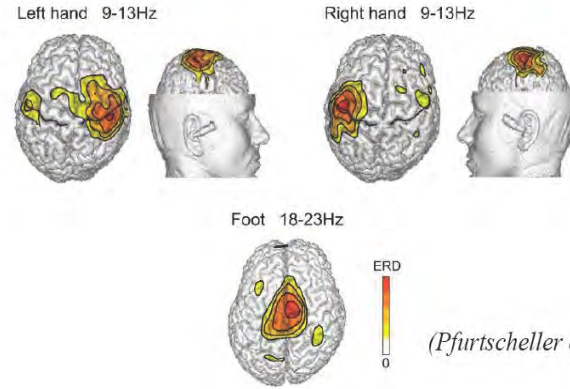
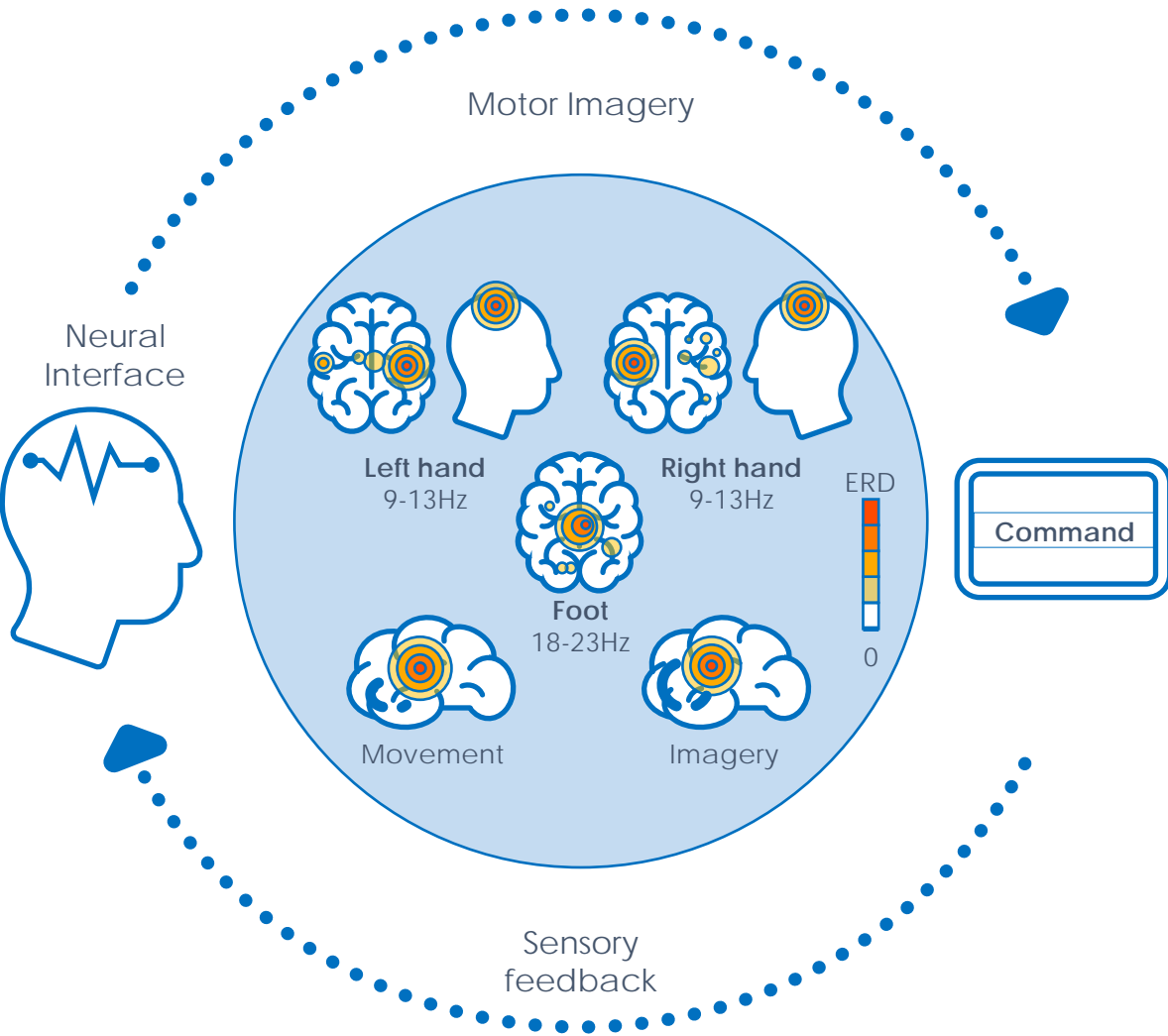
Name	Hz	Association
Delta(δ)	0.1-4	Deep sleep, comatose state movement
Theta(θ)	4-7.5	Sleeping, Abnormal in awake adults
Alpha(α)	8-12	Awake but relaxed
Mu (μ)	8-12	Sensorimotor cortex activity, movement inhibition
Beta (β)	12-30	Organisation of brain processes, arousal, anxiety, movement
Gamma(γ)	>30	High mental activity, anxiety, tension, burst of physical activity, local processing

HOMONCULUS: The little guy

- A geometrically-distorted image of the human body mapped onto the primary **motor cortex**
- Proportional to complexity of movement

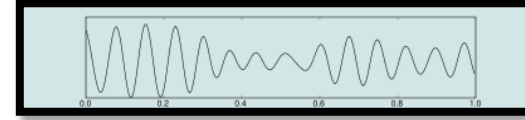


Why motor imagery?

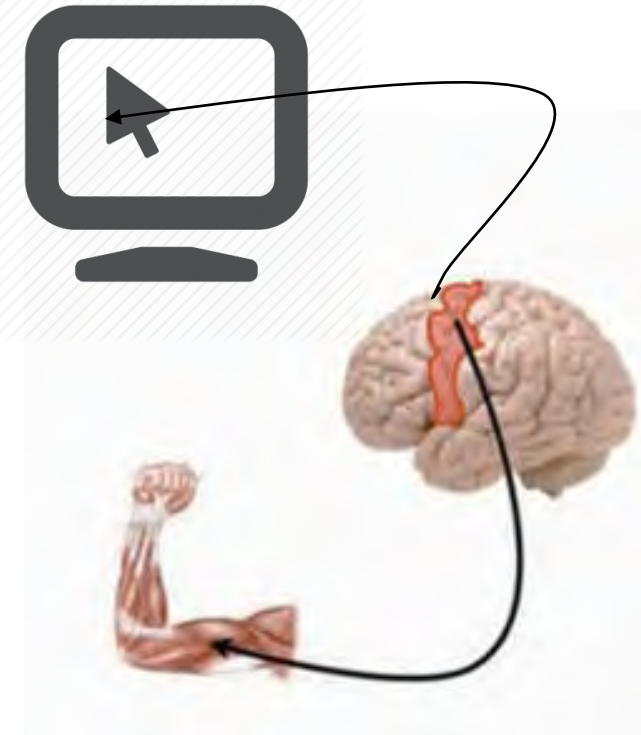
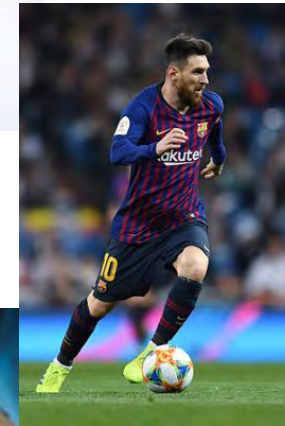
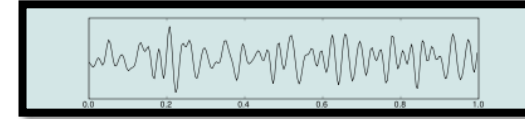


(Pfurtscheller et al, 2001)

- Mu

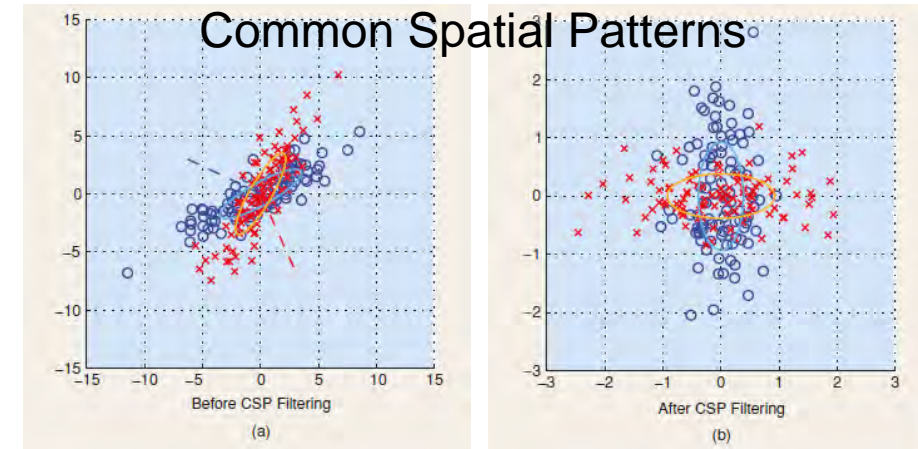
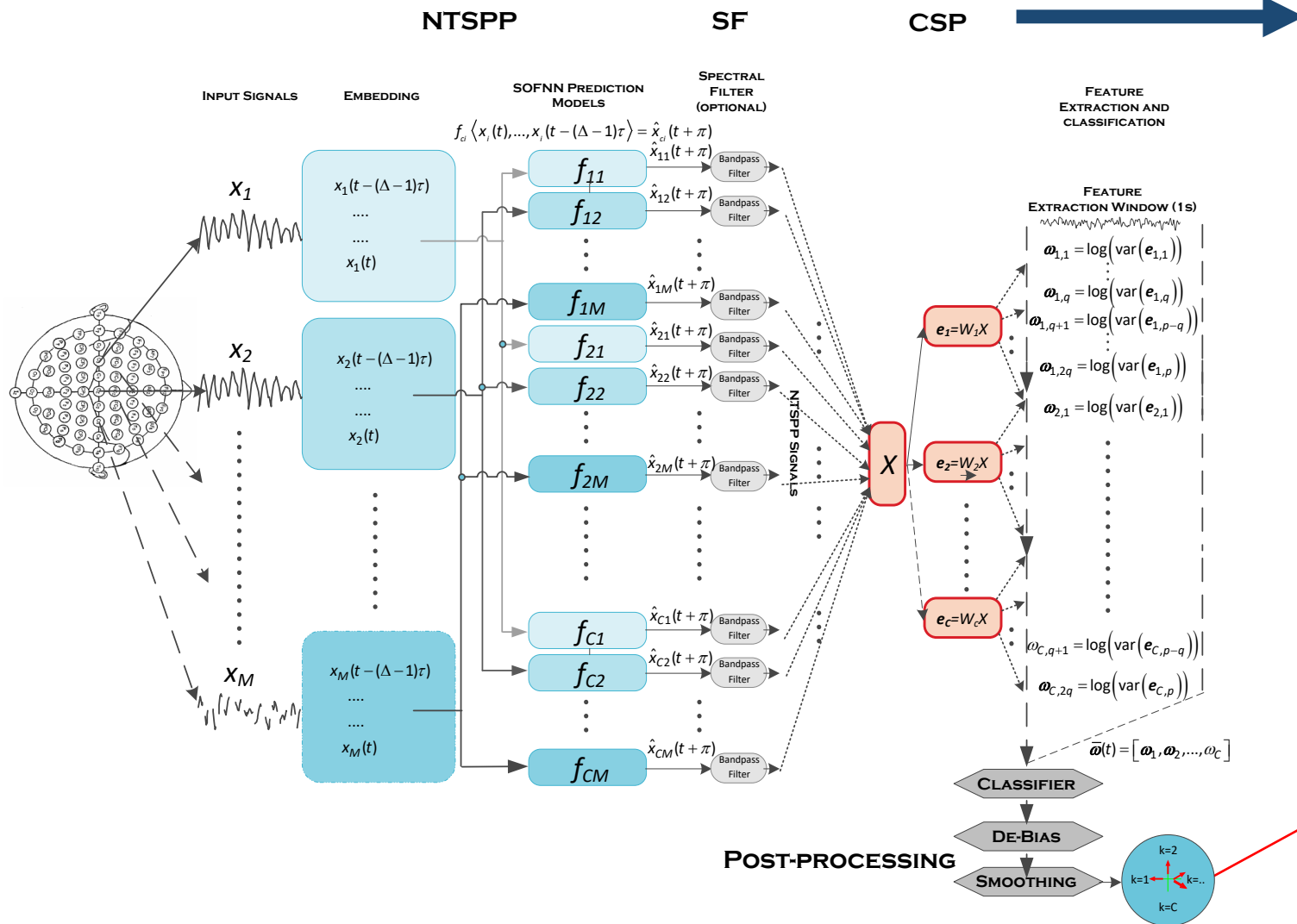


- Beta

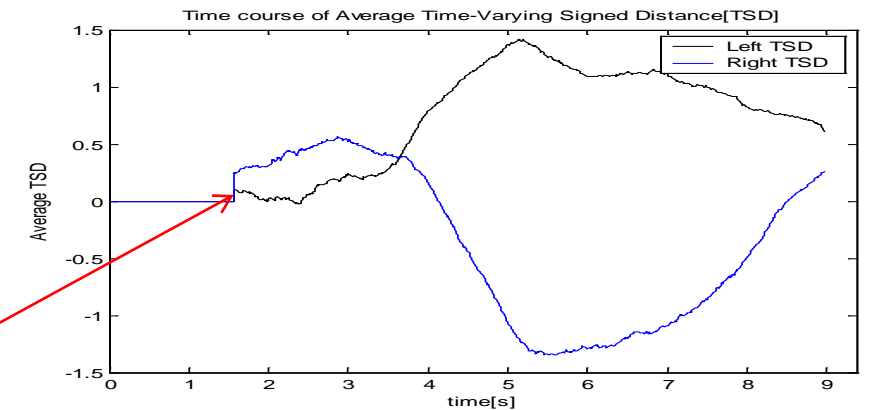


Neural Time Series Prediction Pre-processing

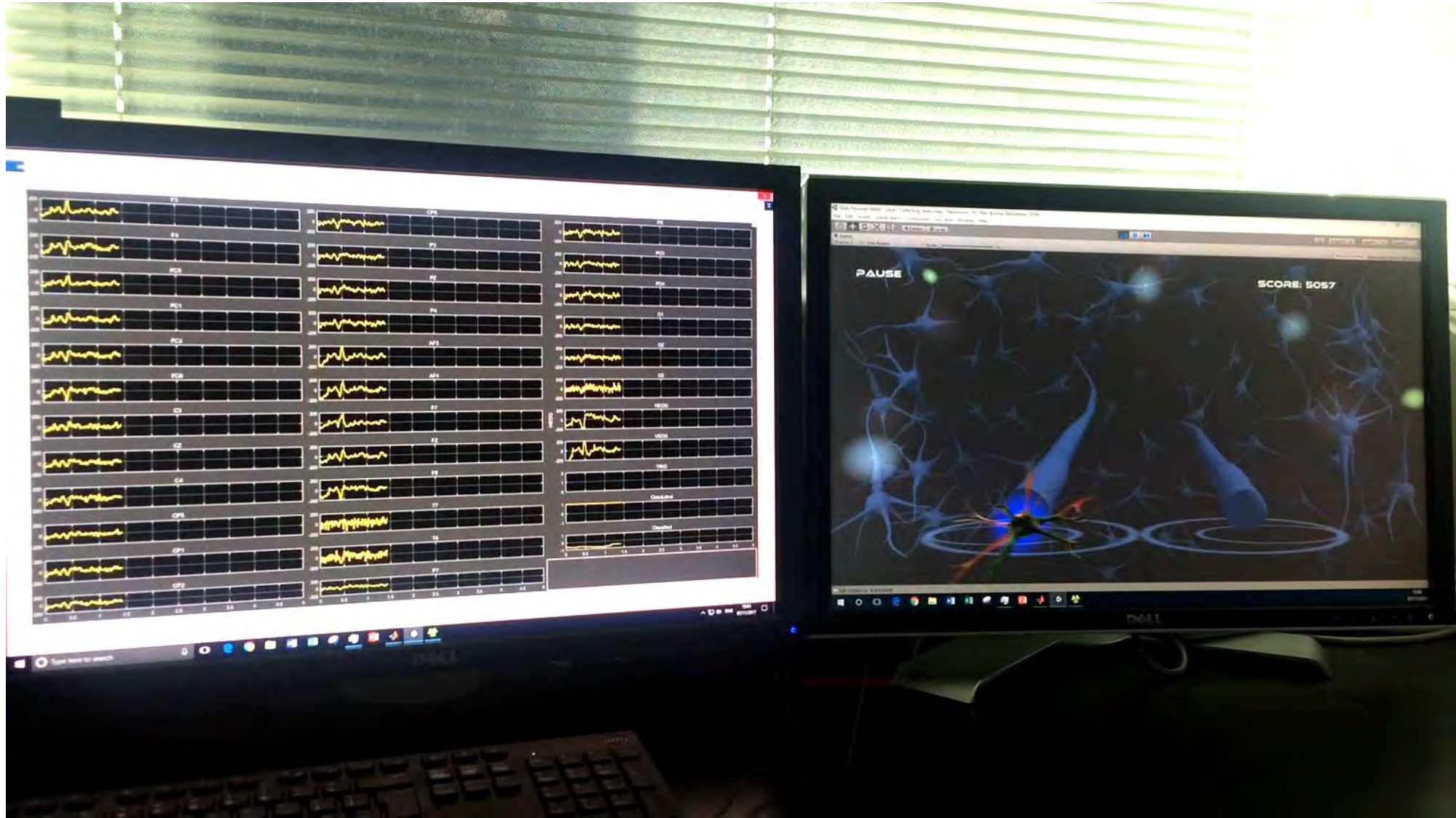
Multistage Signal Processing



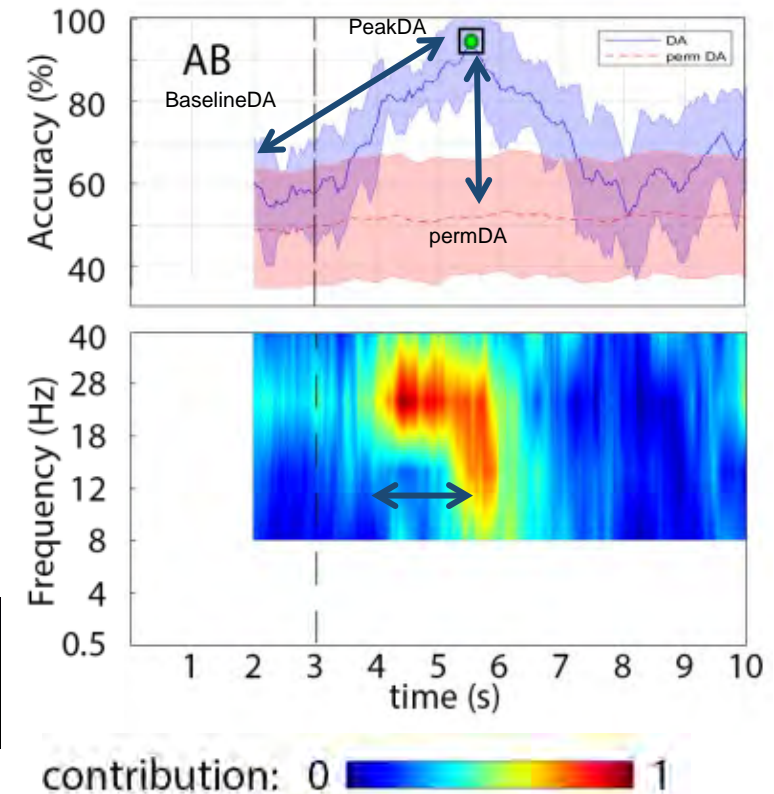
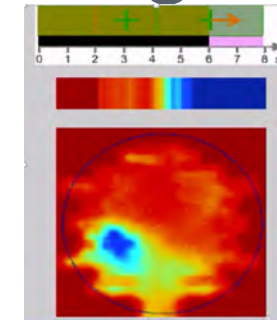
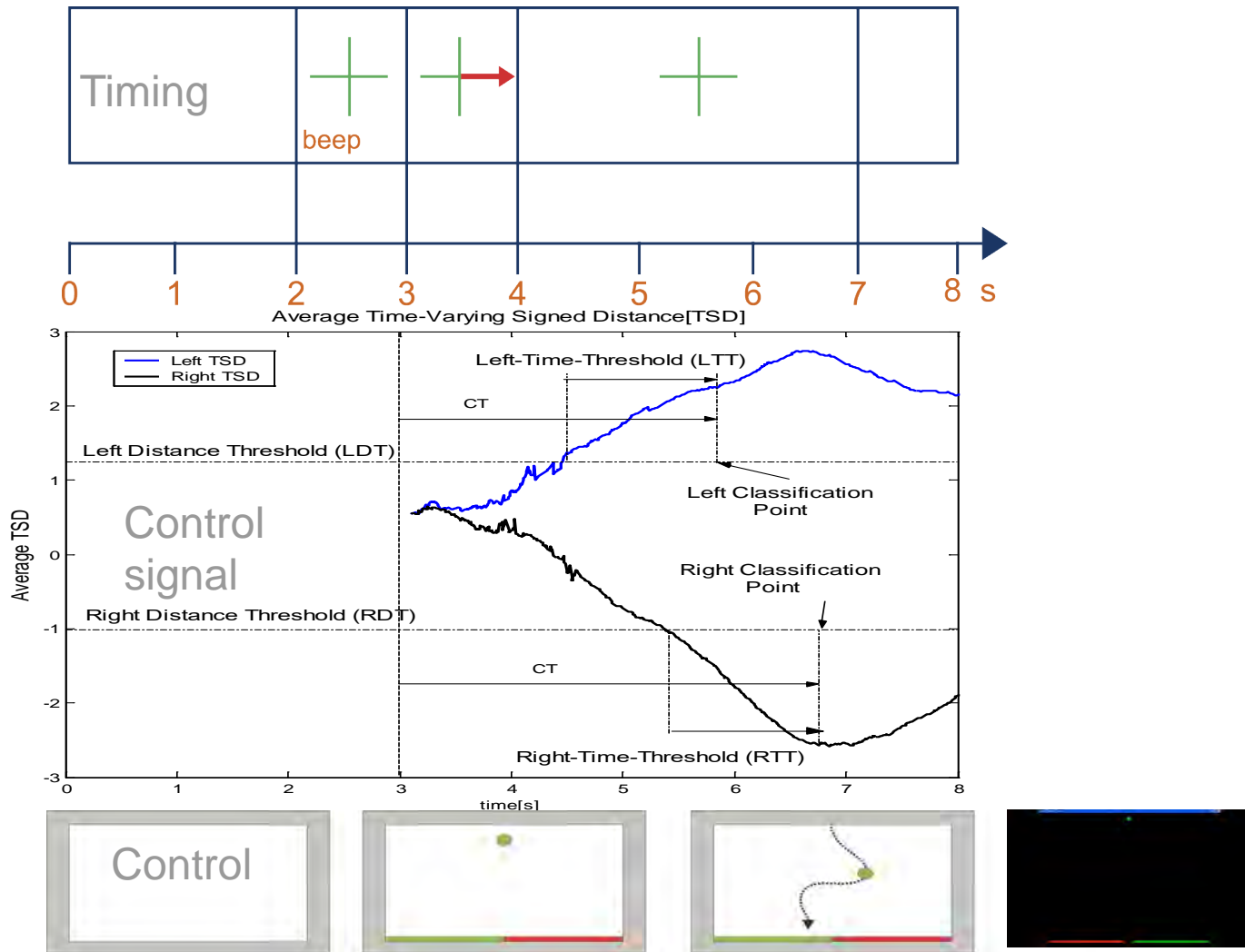
Blankertz et al 2008



Imagined Movement Neurogaming (Motor Imagery BCI)



Decoding accuracy (DA) and control signals



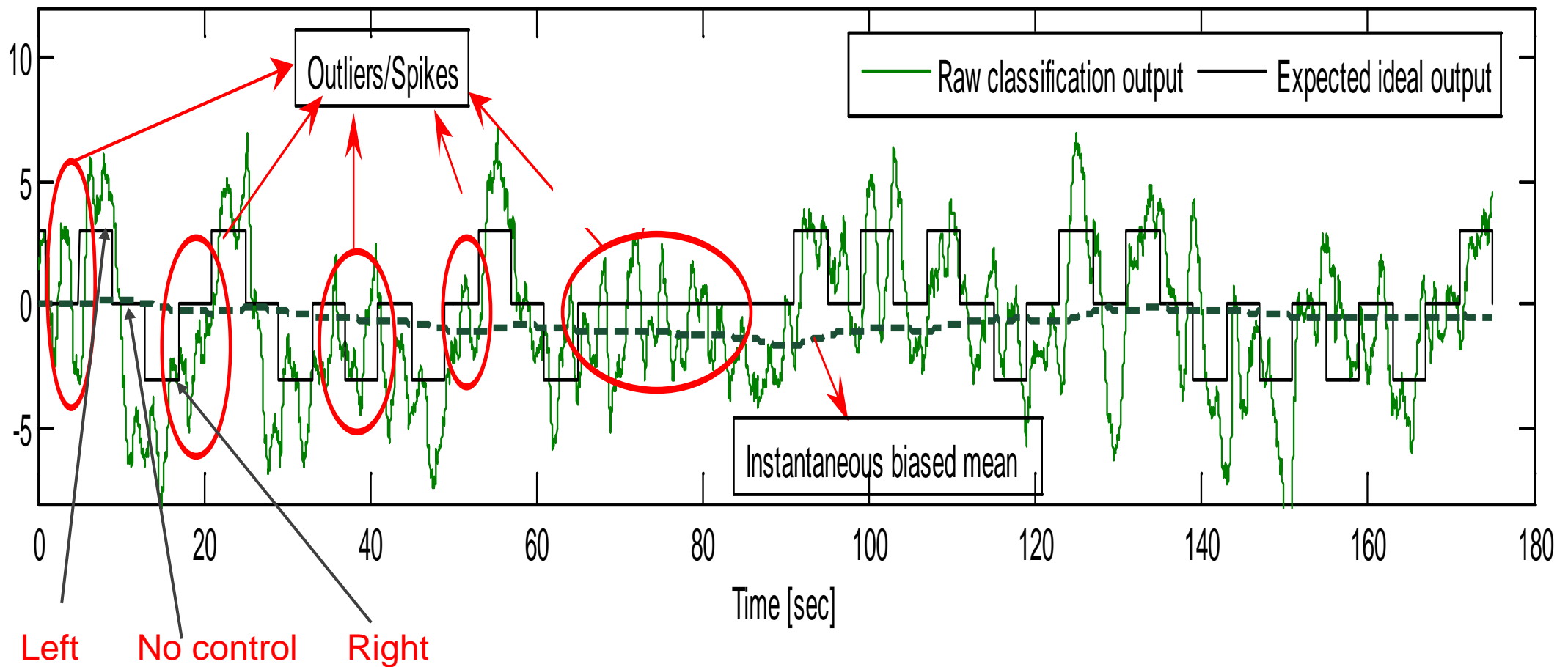
Baseline Vs Peak DA

PermDA vs Peak DA

100 permutation tests

Observable change in Corresponding Frequency Contribution within the Decoding Window

Continuous output analysis

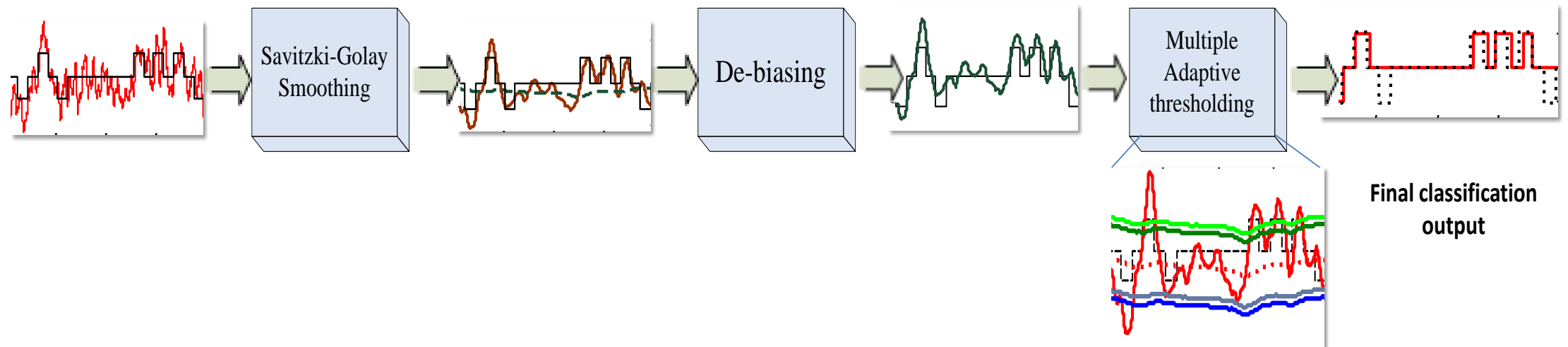


Adaptive post-processing

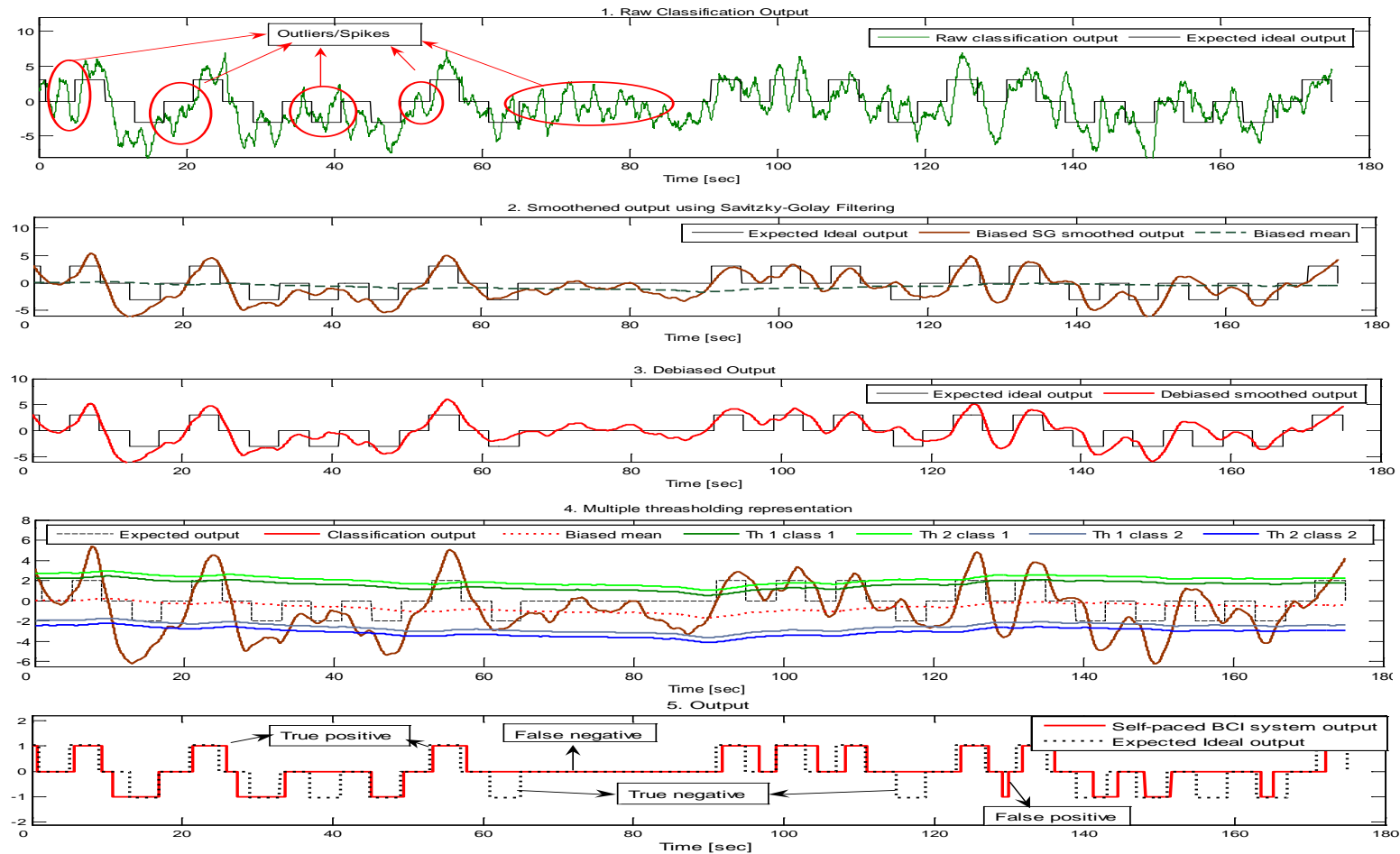
Savitzky-golay filtering for removing spikes/outliers

De-biasing to remove instantaneous bias

Multiple adaptive thresholding to adapt to different levels of threshold based on gradient information

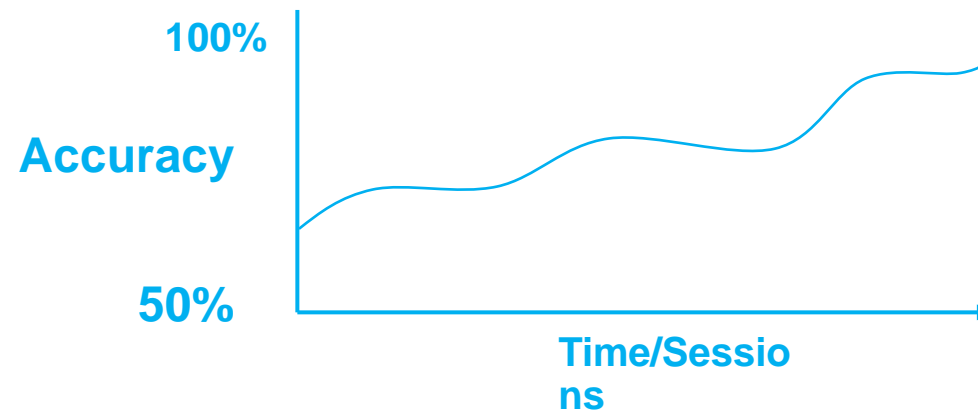


Post processing results



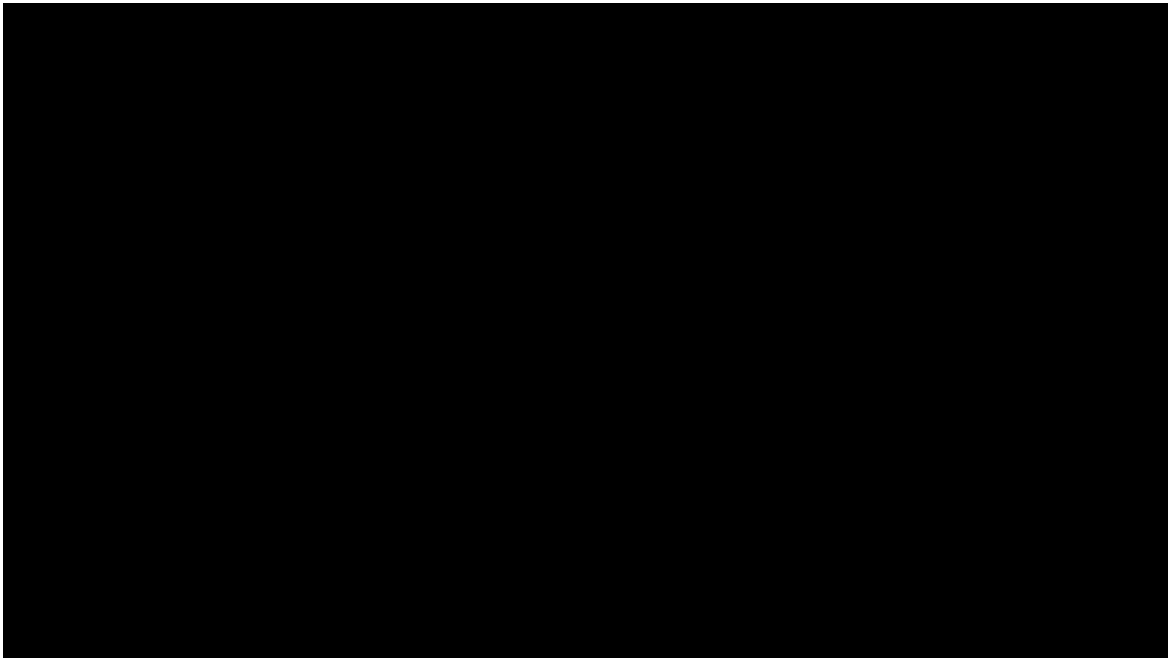
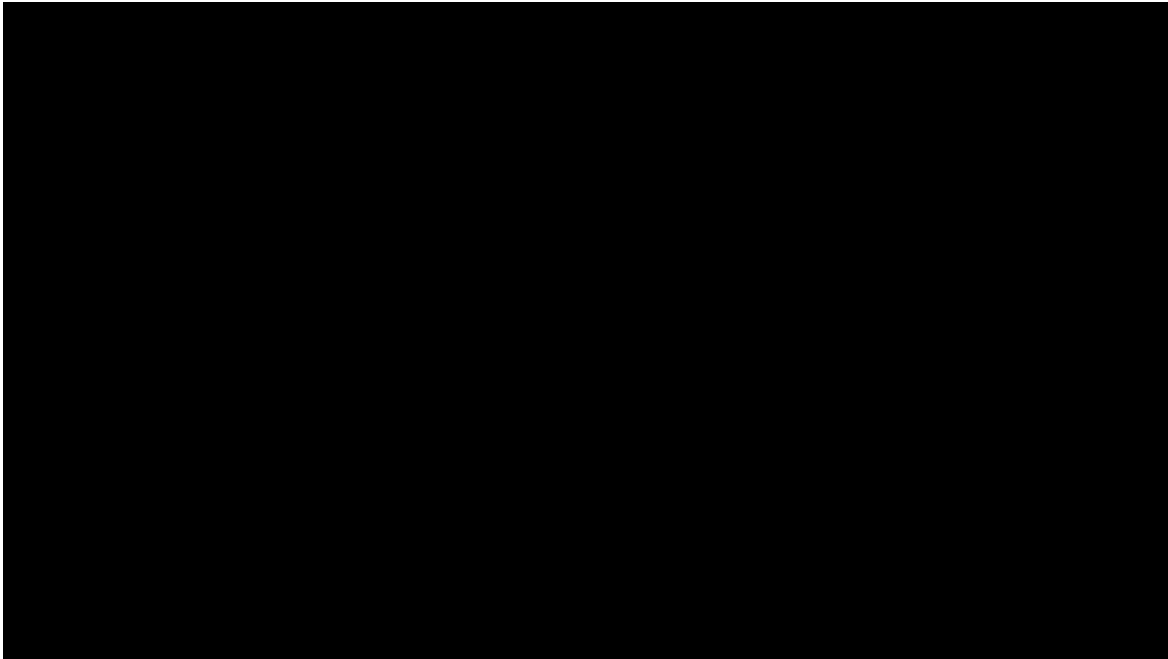
Motor learning and Real-time Feedback

- As a person learns to use a BCI, they exhibit similar learning patterns to other motor tasks, such as learning to grasp or write
- Feedback is necessary to improve sensorimotor learning and BCI performance

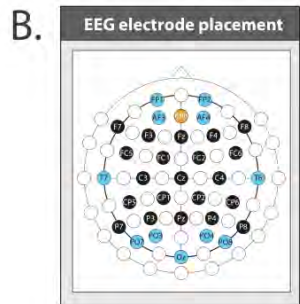
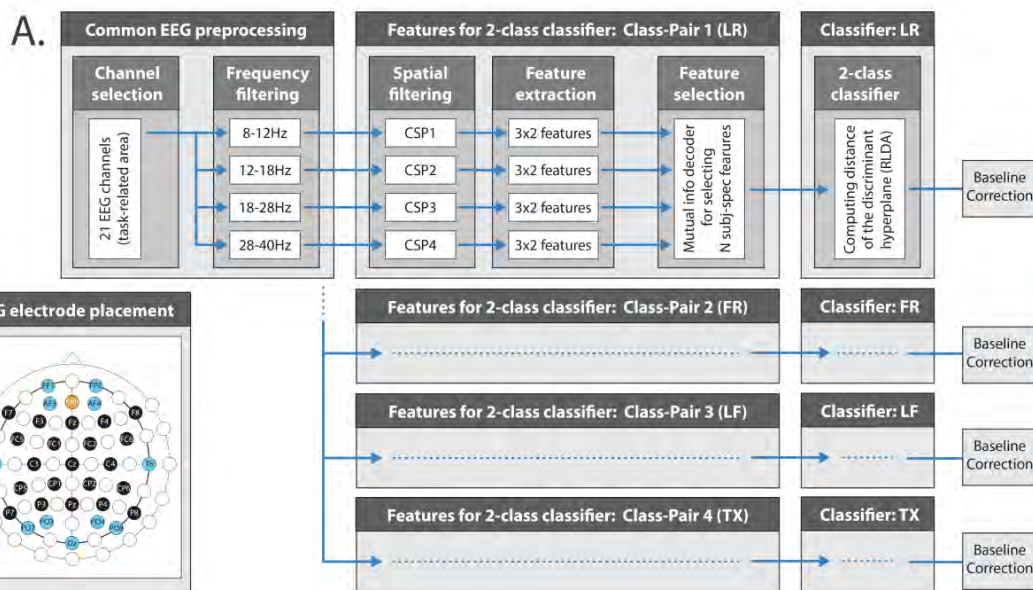




CYBATHLON
ETH zürich



2019 (3rd place)



Four x 2-class classifiers

1. Left hand vs Right Hand (LR)



2. Left hand vs Feet (LF)

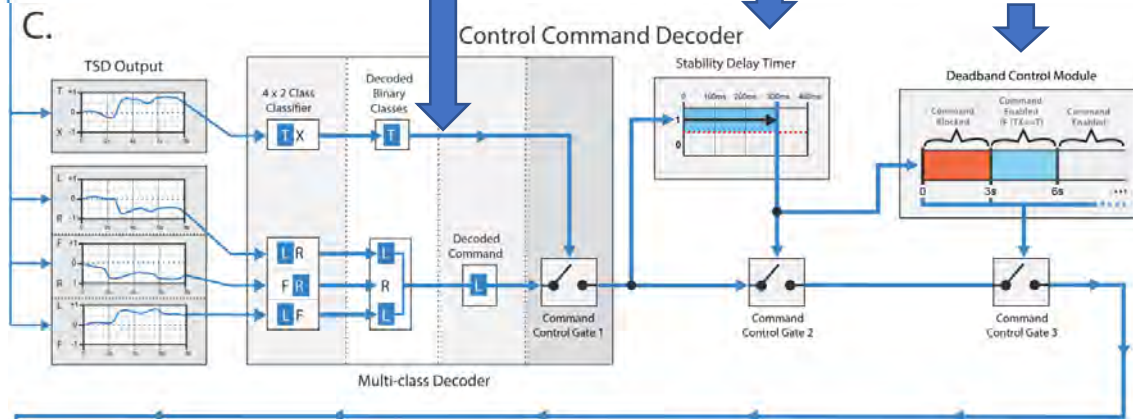


3. Feet vs Right Hand (FR)



4. Task vs Relax (TX)

Decide which command →



D. Game Control Command Translator

BCI Command	Game Command		Game Control
	Player ID	Control ID	
N/A	N/A	N/A	No Command
L	1	1	Turn Left
F	1	2	Headlight On
R	1	3	Turn Right

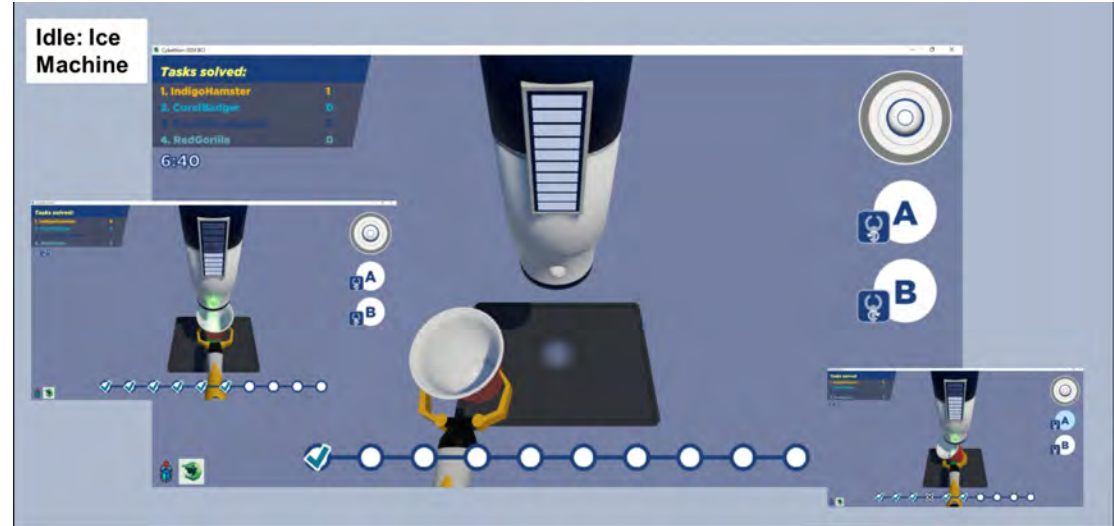
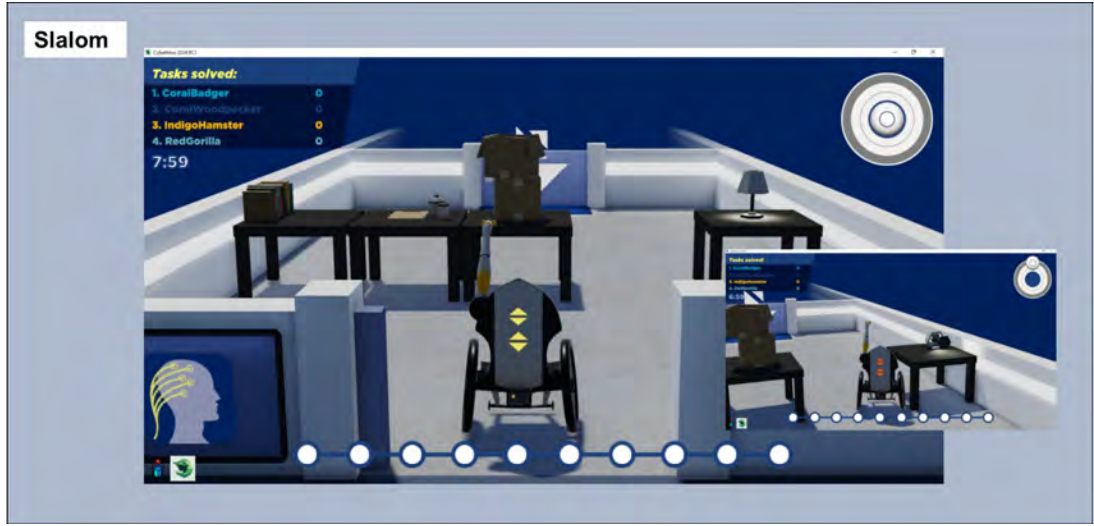
UDP Send

E. Brain Driver Game - Example Track Section



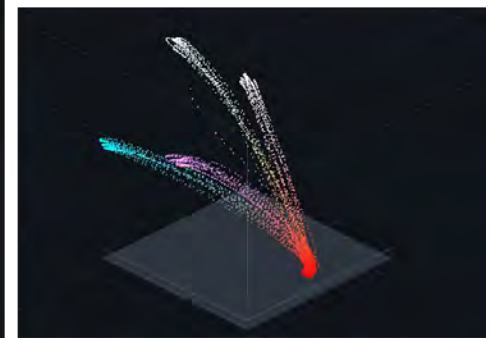
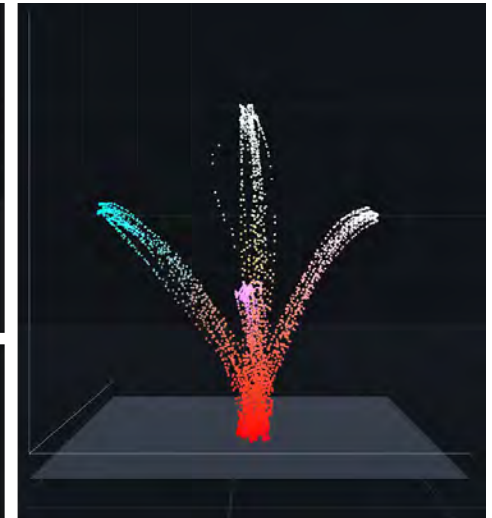
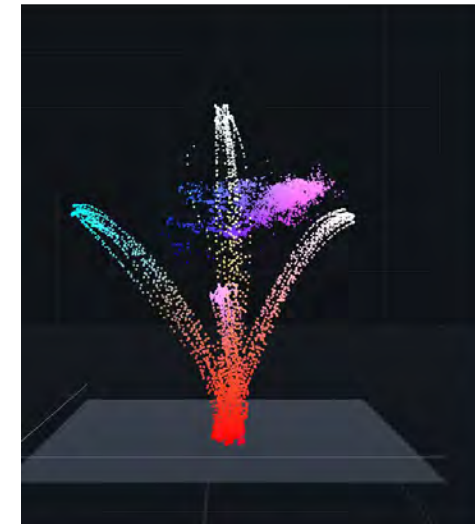
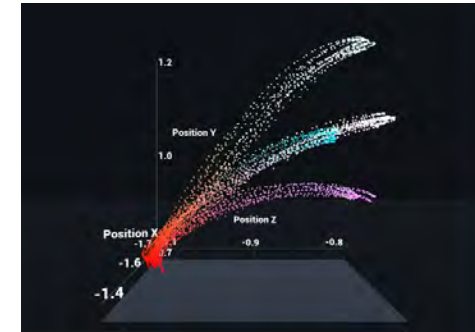
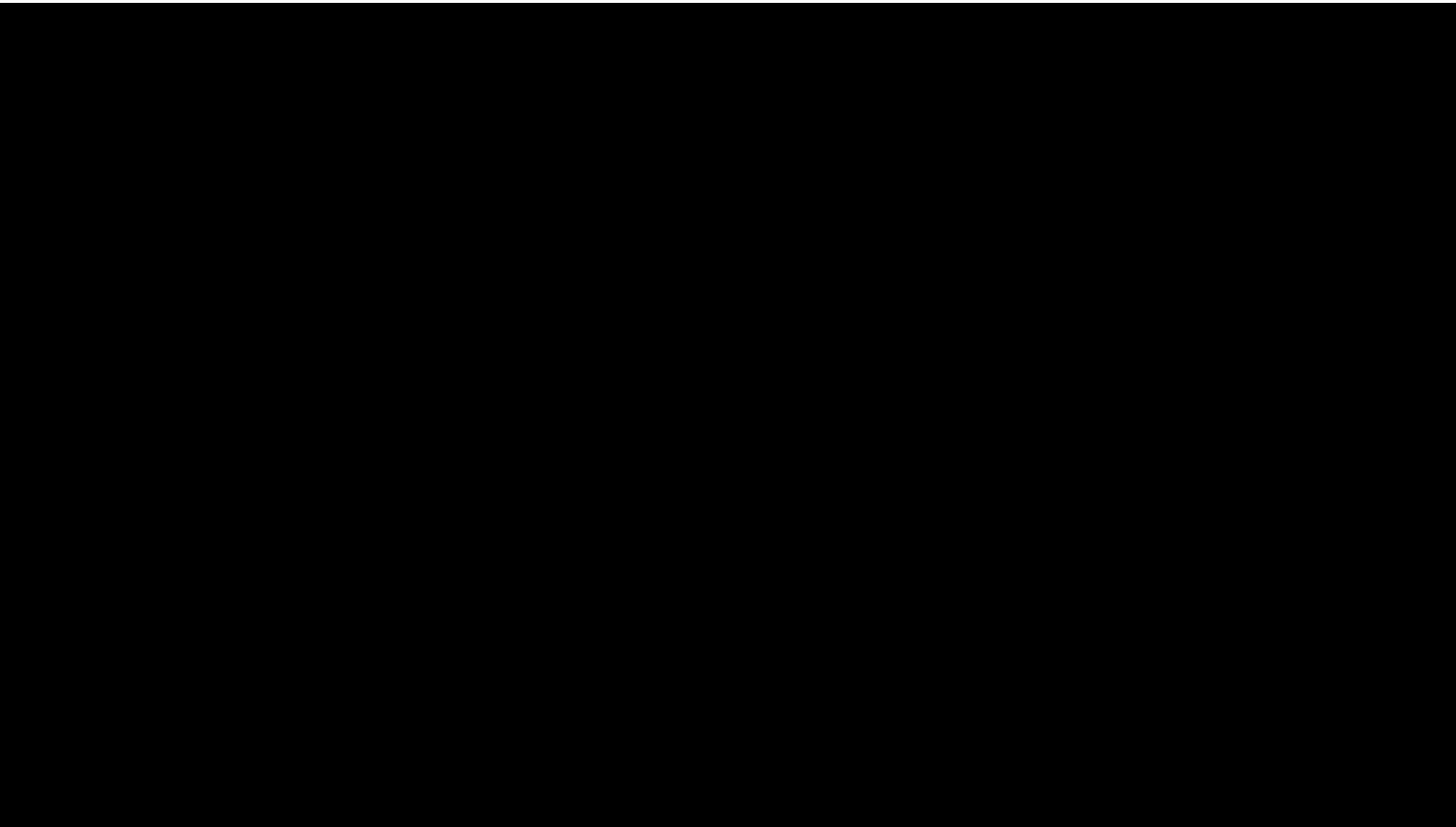
CYBATHLON 2024

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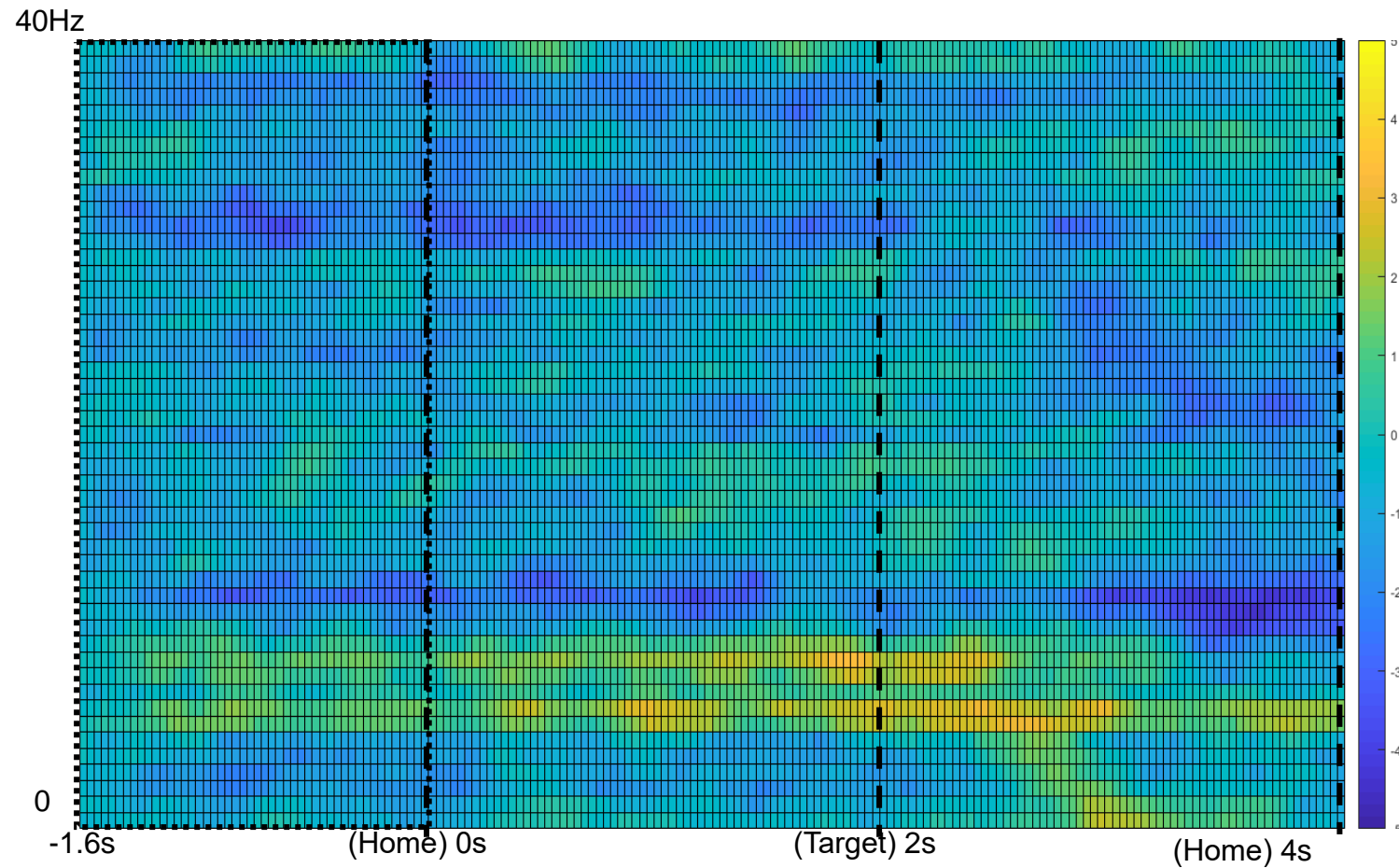


What if we could decode imagined 3D limb movement in multiple directions from EEG?

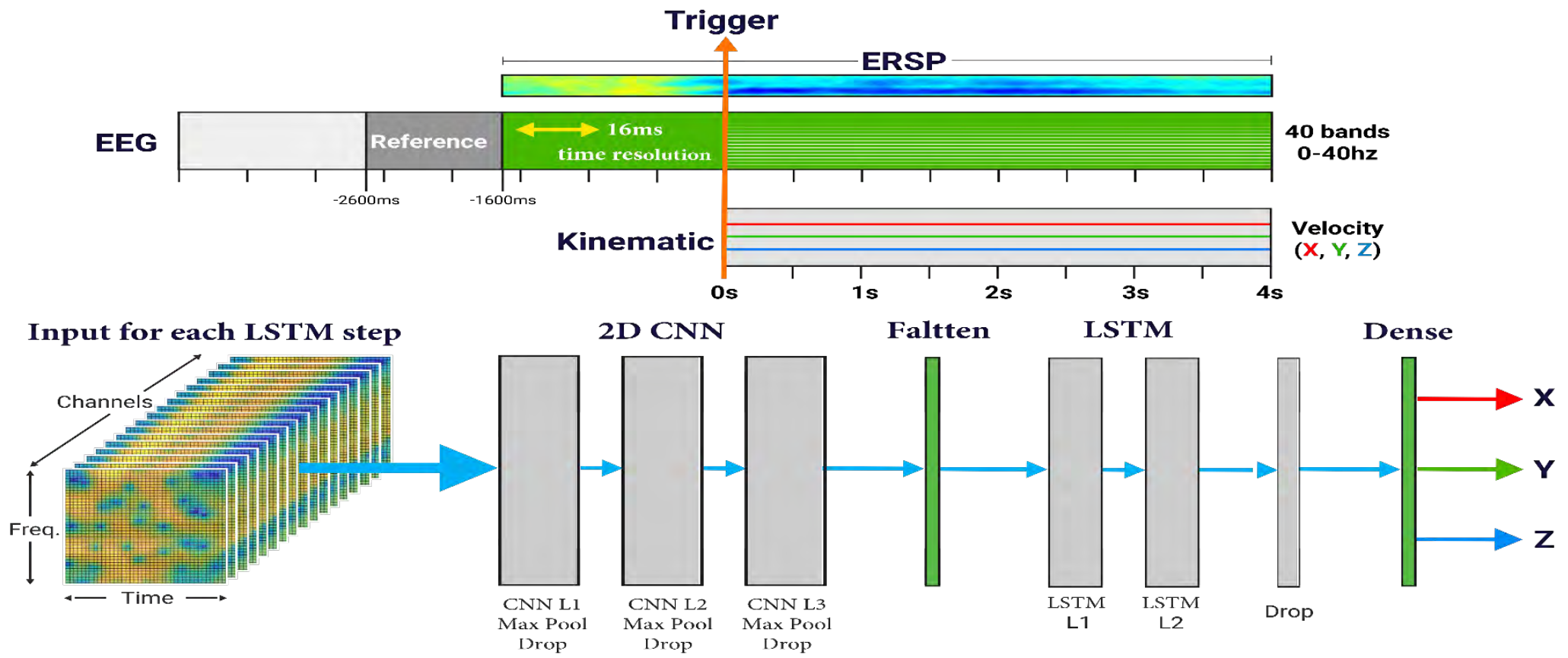
- Embodied Limb Movement – MI Training Environment



ERSP

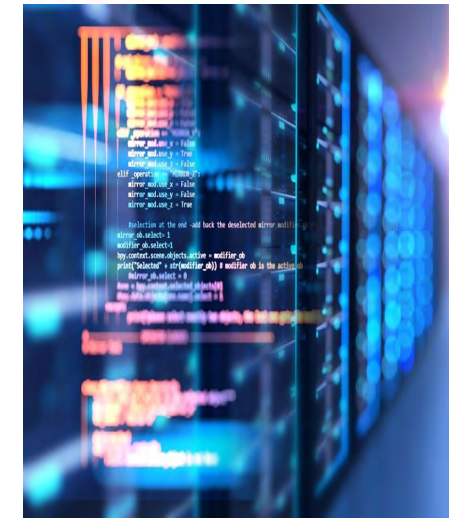


CNN-LSTM Framework



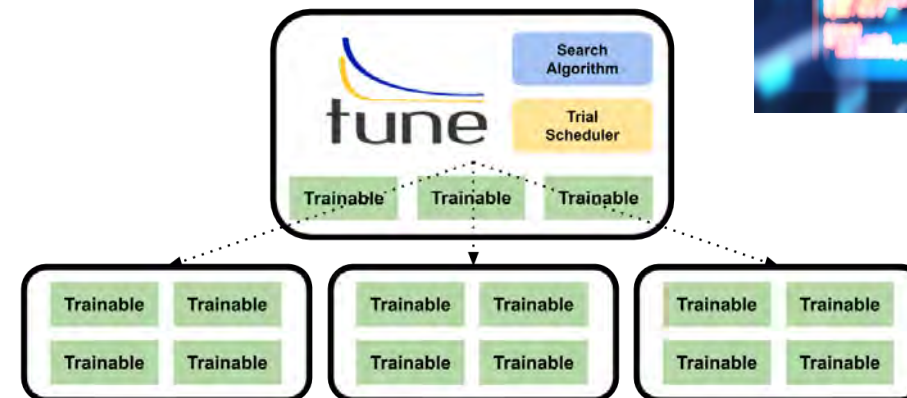
Massively-parallel-hyperparameter-optimization

- **40,000 hyperparameter combinations** with a high-end **PC** (20 mins/option) takes **556 days**
- With **12 GPU** units for 42 times repeated **ASHA/RayTune** optimization the time decreases to **14 hours**

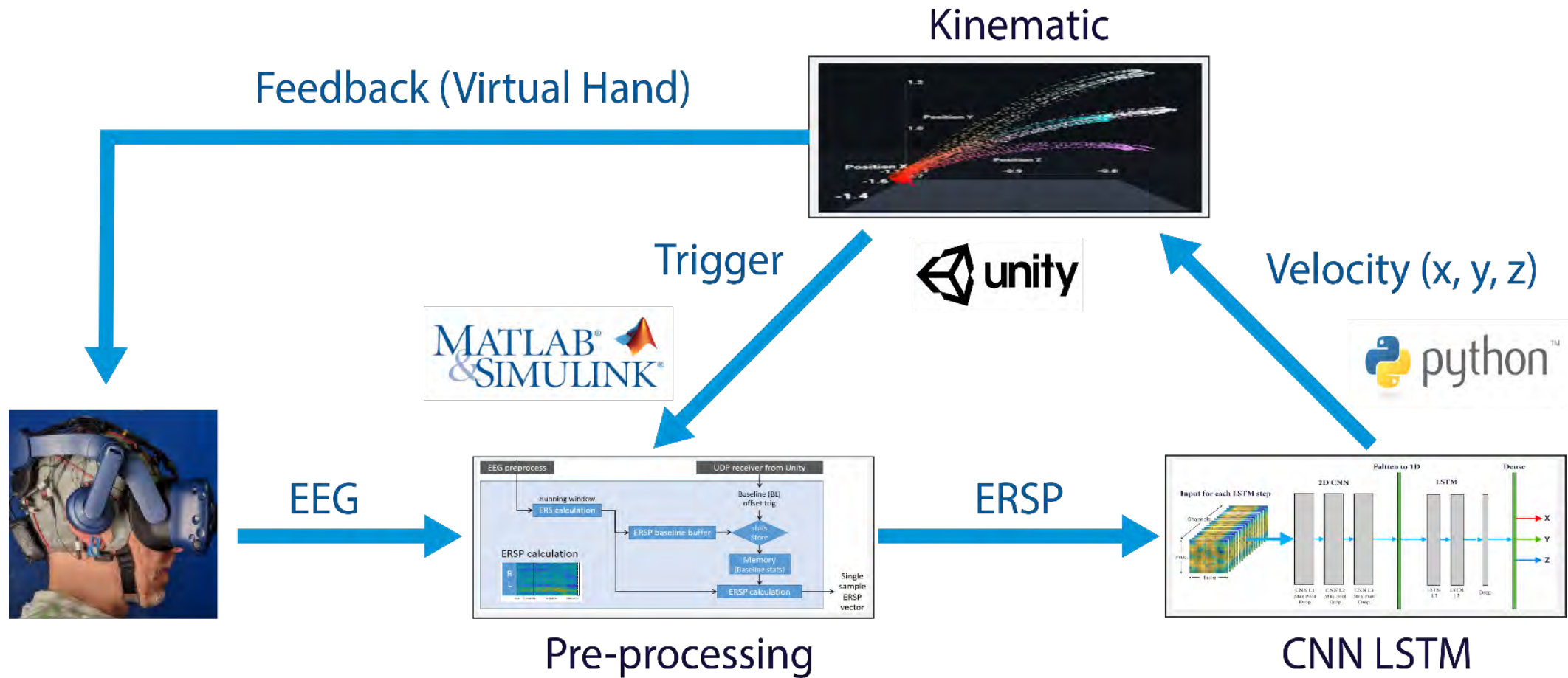


Asynchronous Successive Halving (ASHA)

	Configurations Remaining	Epochs per Configuration
Rung 1	27	1
Rung 2	9	3
Rung 3	3	9
Rung 4	1	27

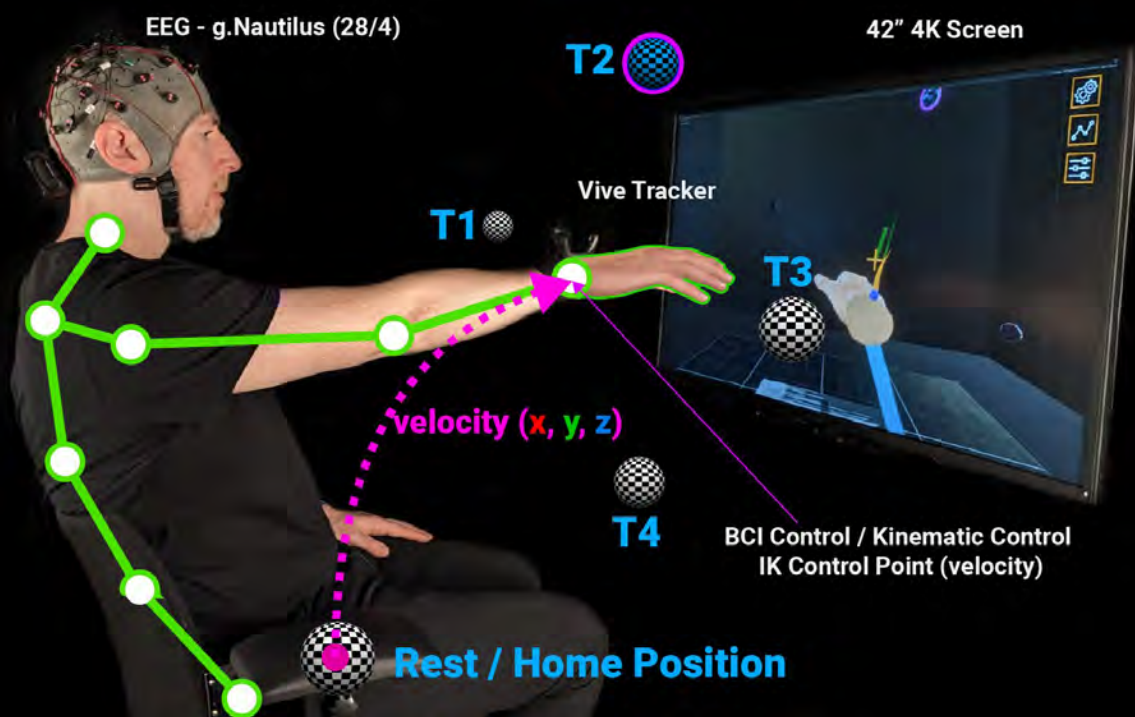


Online real-time BCI framework

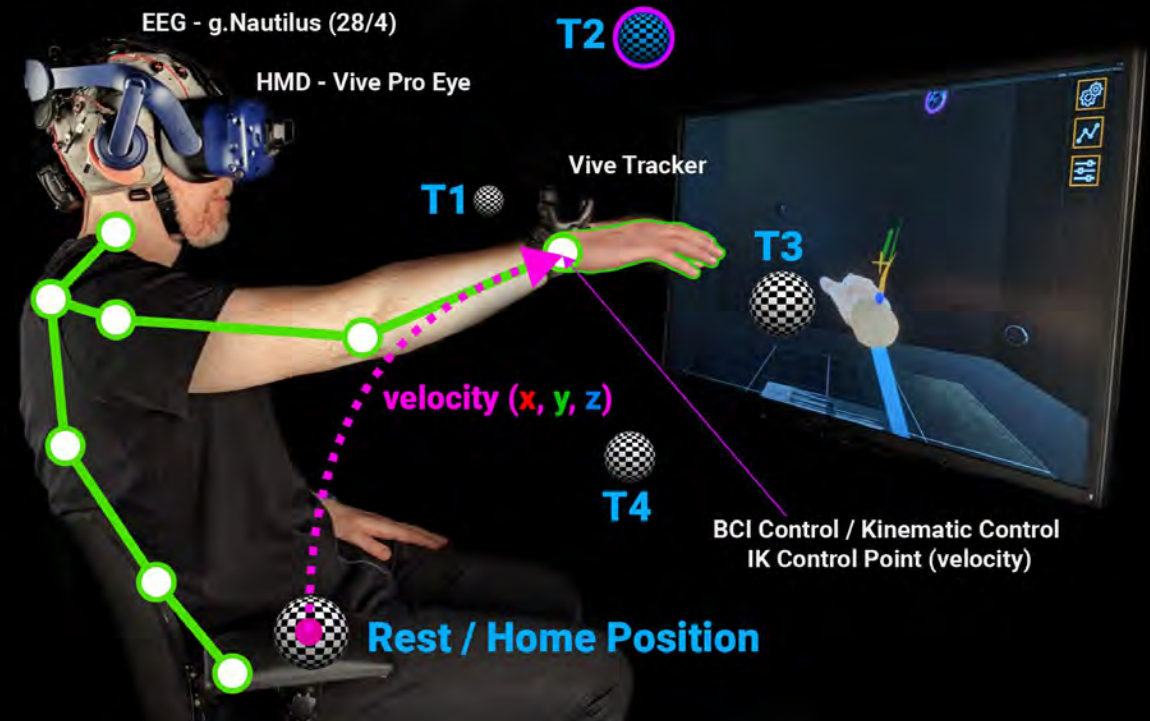


Is spatial feedback better than 2D?

Test it with 10 subjects : 10 x 2 hour sessions each subject



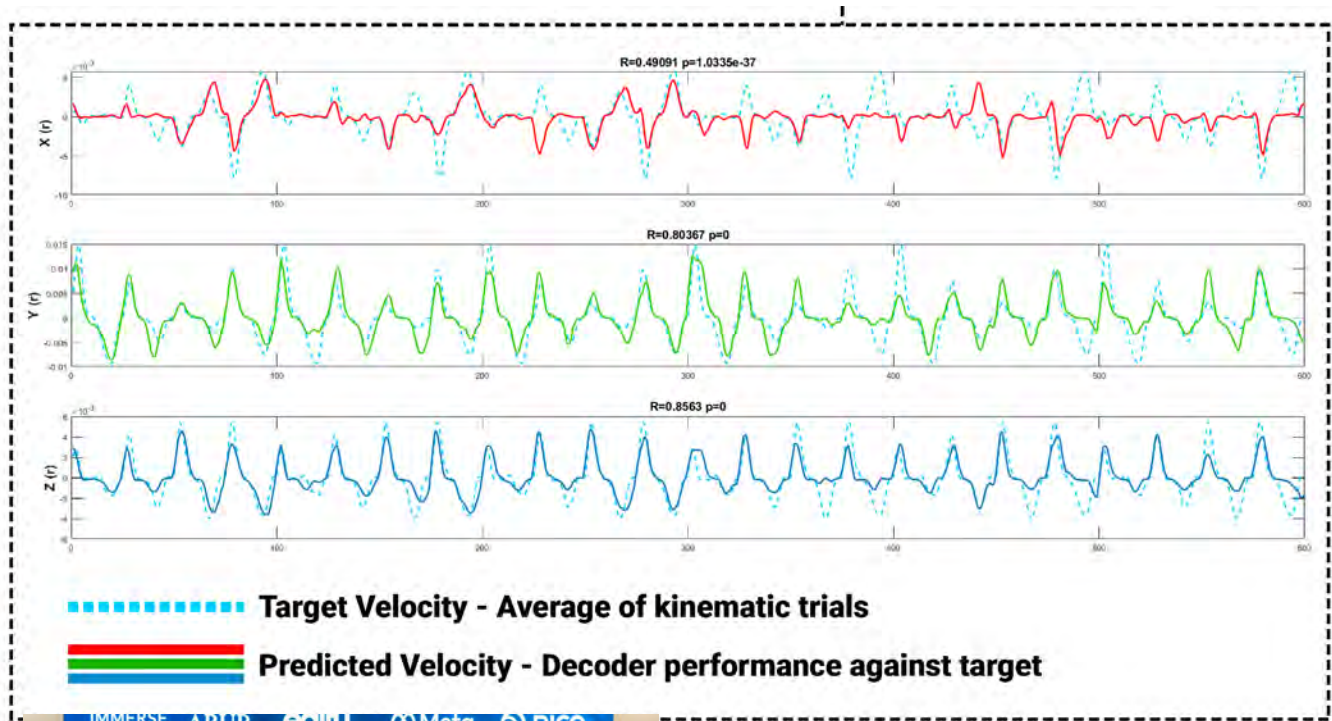
2D Screen (5 sessions)



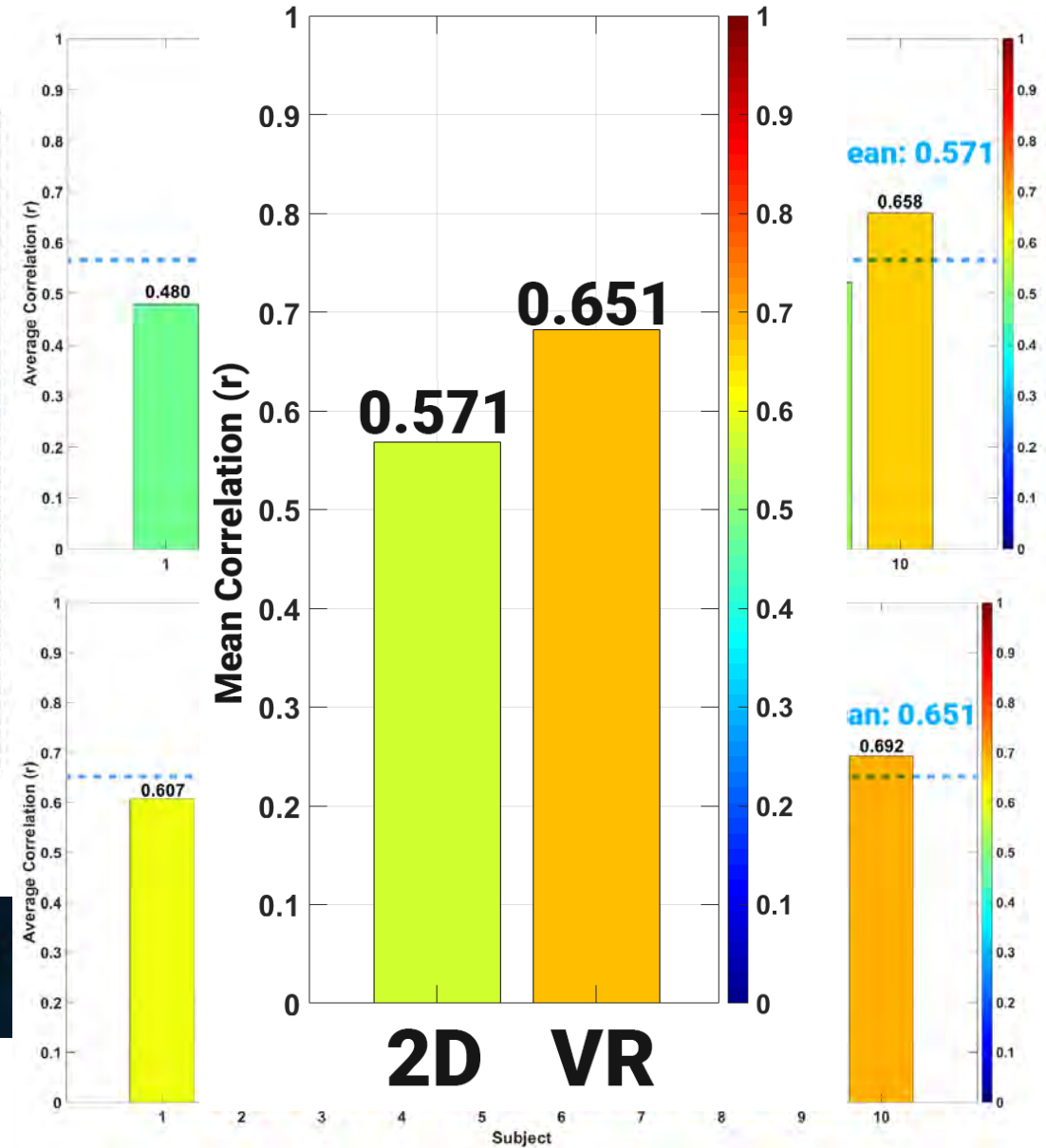
VR Embodied (5 sessions)

Decoding imagined 3D limb movements

VR feedback is better



Immerse UK Awards
Connecting Students To Industry



Feedback Modalities - Embodiment

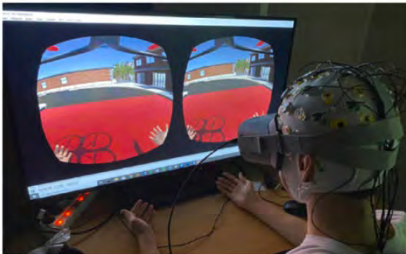
- Closed loop system - type of feedback important
- XR – Embodiment - Sense of Presence
- Effectiveness – task dependant
 - Embodied visual feedback is optimal for natural limb motion training and interactions



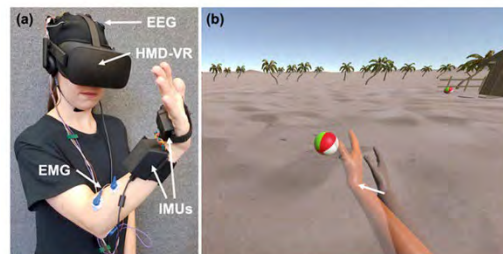
Skola, et al (2019)



Vourvopoulos, et al (2019)



Choi, et al (2020)



Juliano, et al (2020)

Virtual / Augmented Reality (XR)



3D / Spatial Audio

Haptic Feedback

Tactile



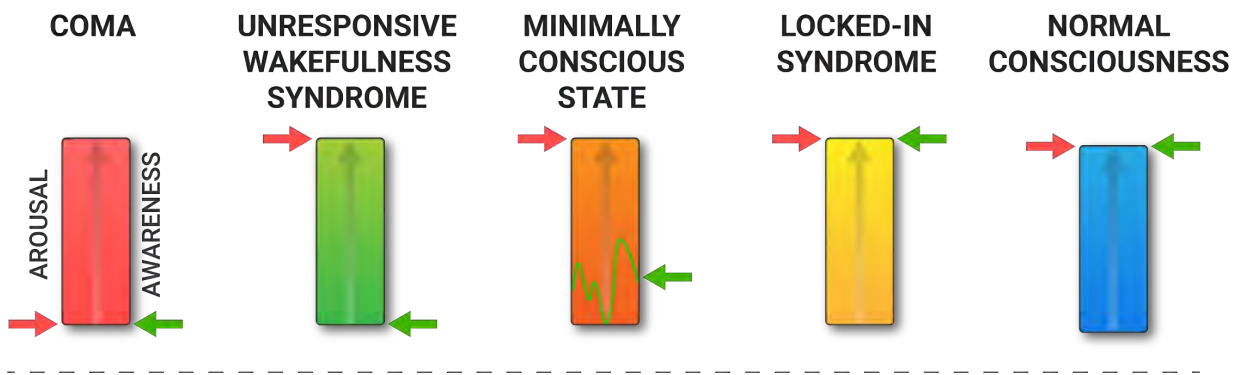
Kinaesthetic



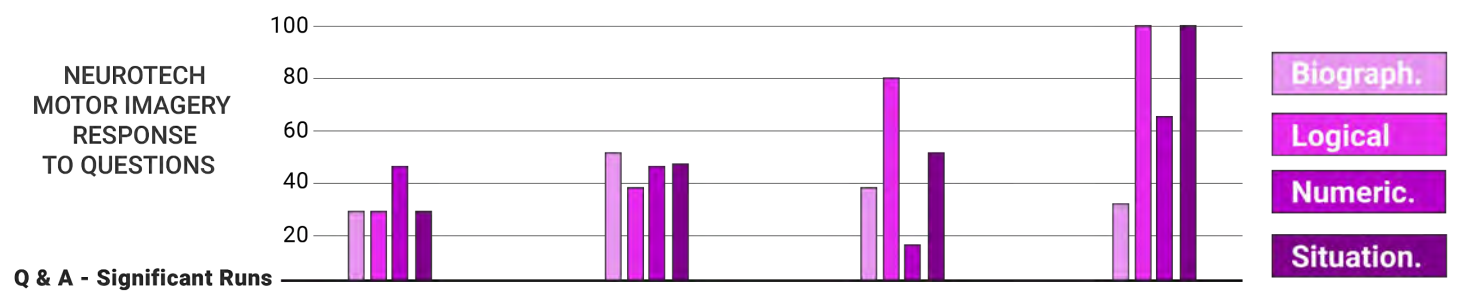
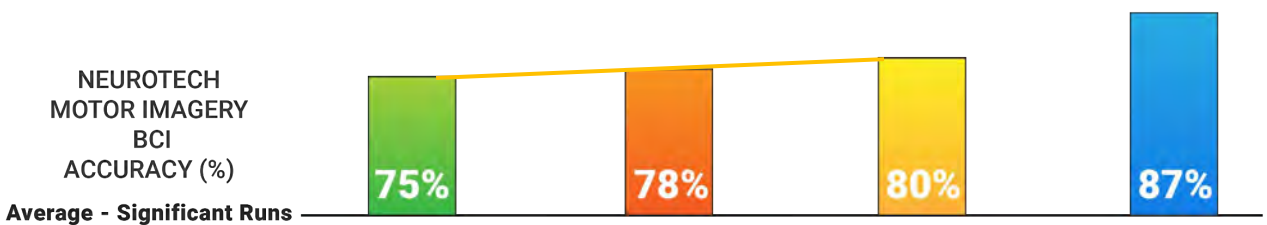
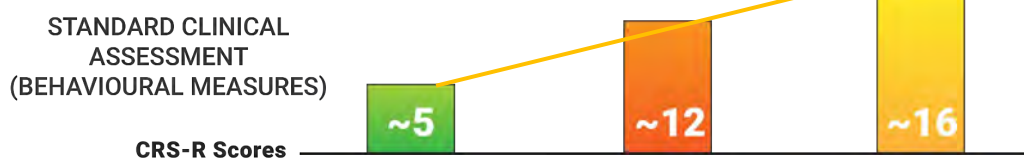
Clinical applications

Use motor imagery BCI to assess awareness in prolonged disorders of consciousness

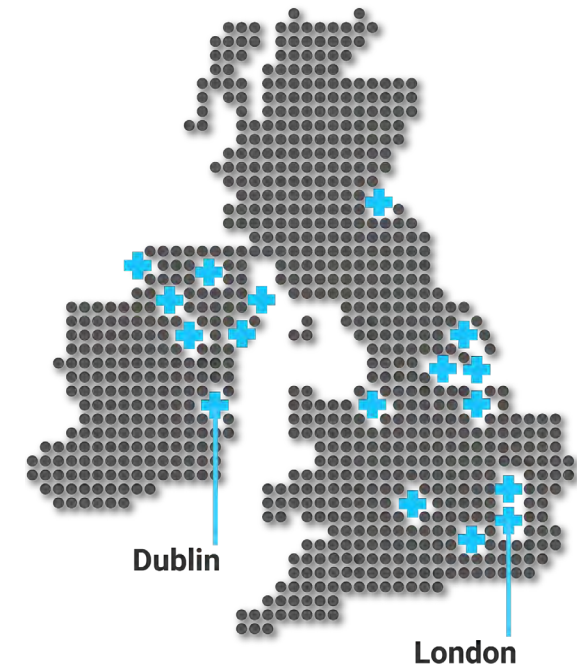
People with unresponsive wakefulness syndrome (UWS) or minimally conscious state (MCS) after brain injury can modulate brain activity



- BCI provide new information that differ from and therefore may augment standard clinical assessment
- Answering questions with motor imagery may be feasible after an extended period of BCI learning through feedback
- After training average response to repeated questions may be used for neuropsychometric testing/cognitive profiling



- 30 patients completed in ongoing trial involving 17 hospitals/NHS trusts
- NCT03827187



Decoding lower limb movements or intention to move

For improved **robotic assist gait therapy (RAGT)** after stroke

Can exoskeleton assisted gait be refined with BCI?

Can neuroplasticity be enhanced through targeting feedback (sensory or robotic assisted) to target spatial and spectral neural features more reliability throughout the gait cycle?



Post traumatic stress disorder : Alleviating symptoms with neurofeedback

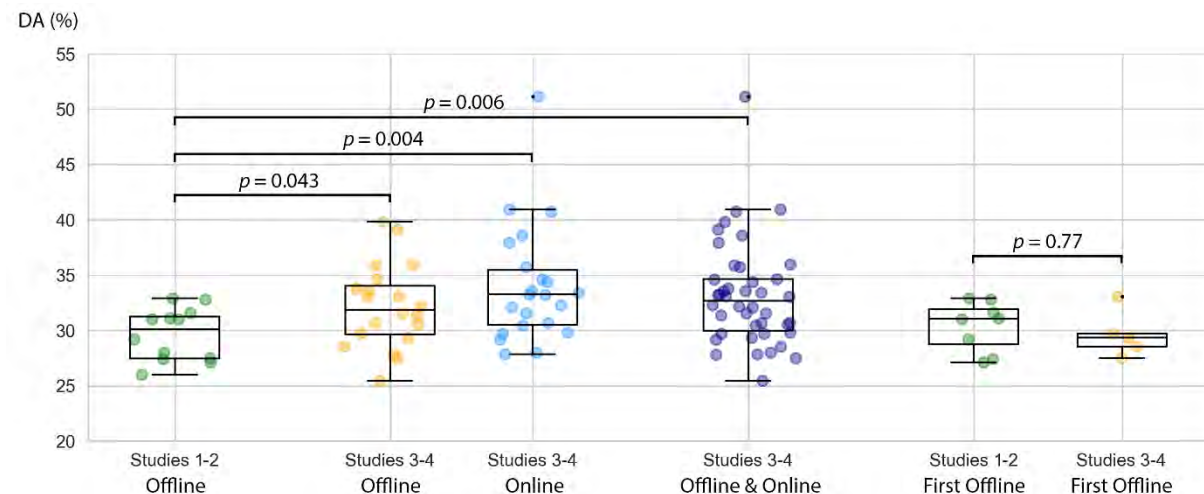
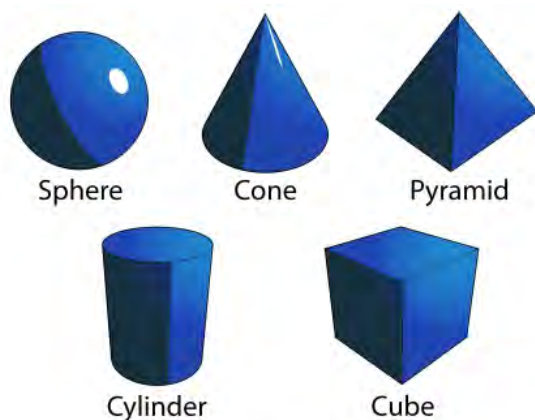


Self-regulating alpha rhythms



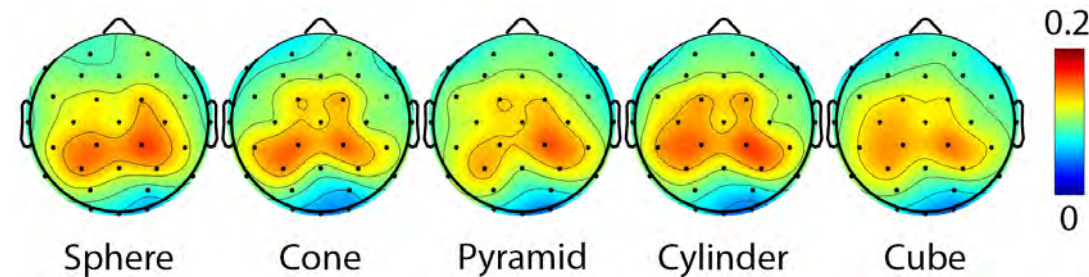
More challenging BCIs

Shape/object imagery classification

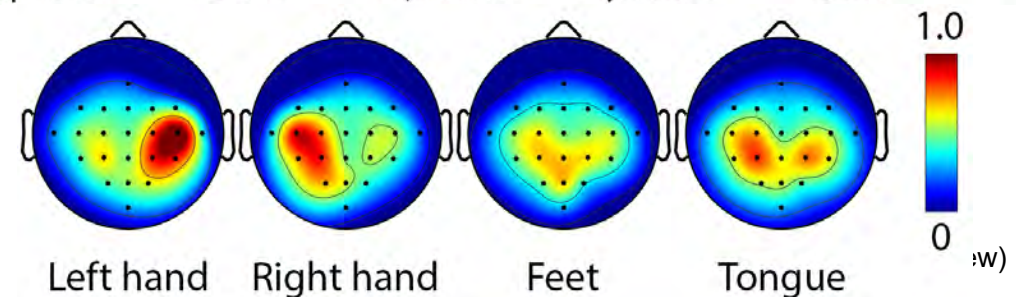


- Gamification improves results

Imaged Object:



Motor Imagery:



Imagined speech decoding

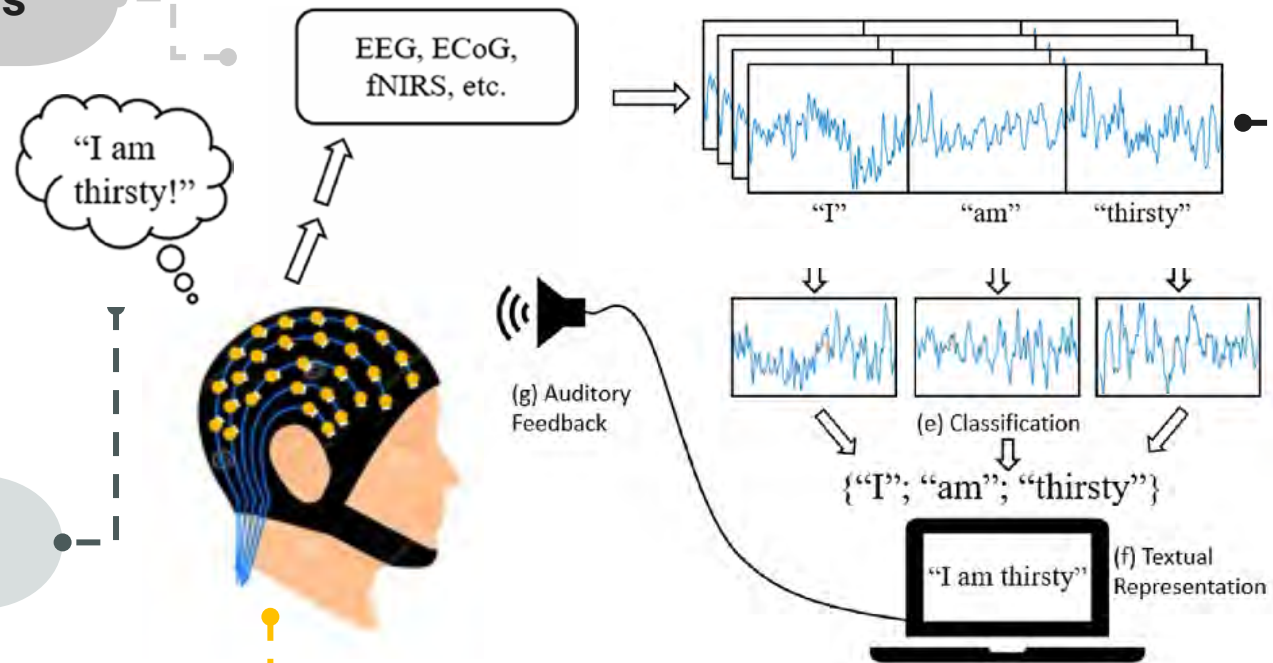
Neural Recordings

Signal Processing

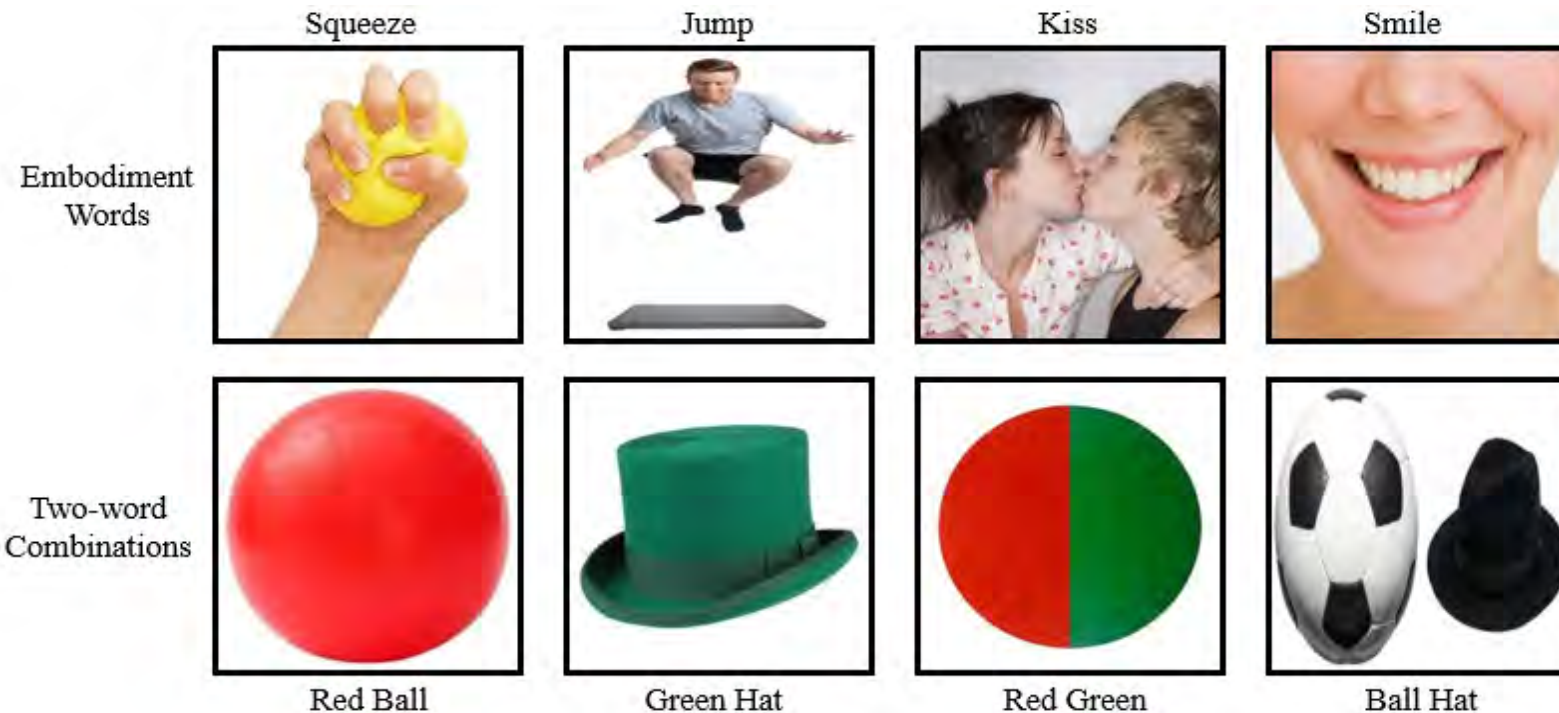
Imagined Speech

BCI Cap

Classification Methods



Selected cues

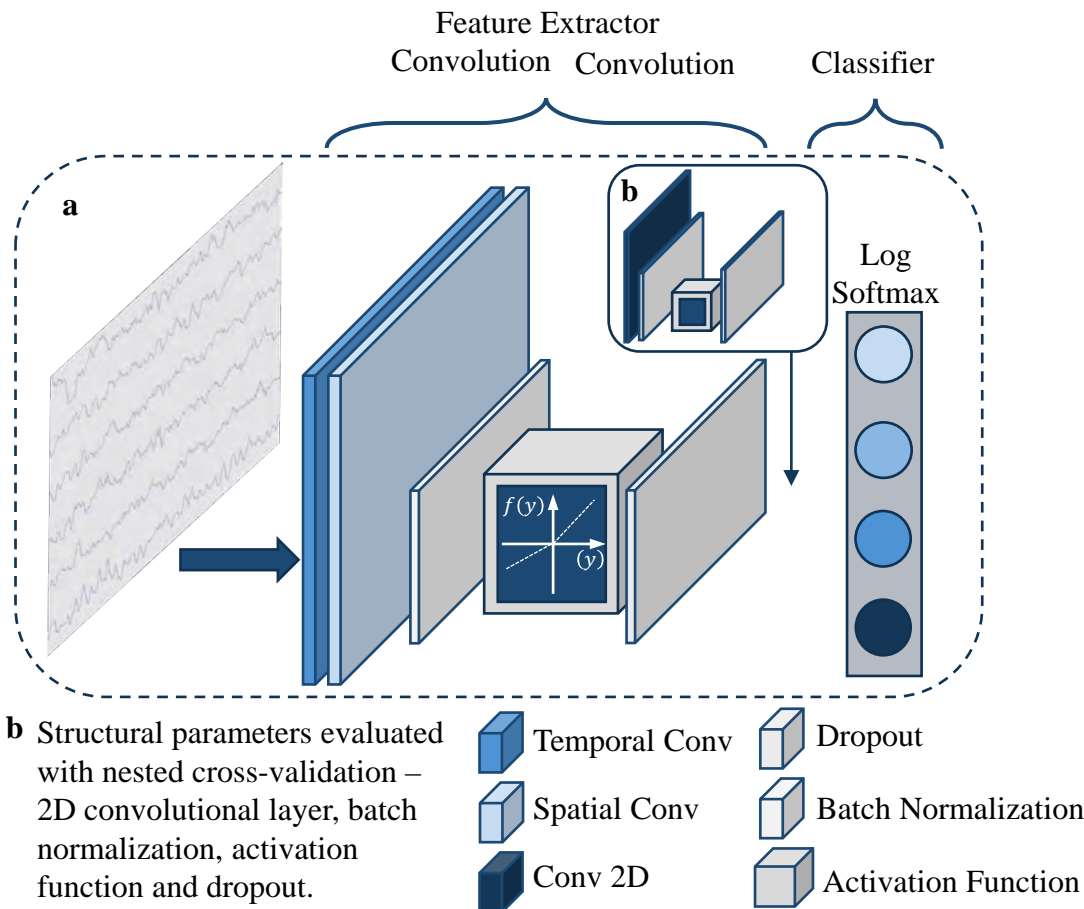


- Text, Image, Audio stimuli

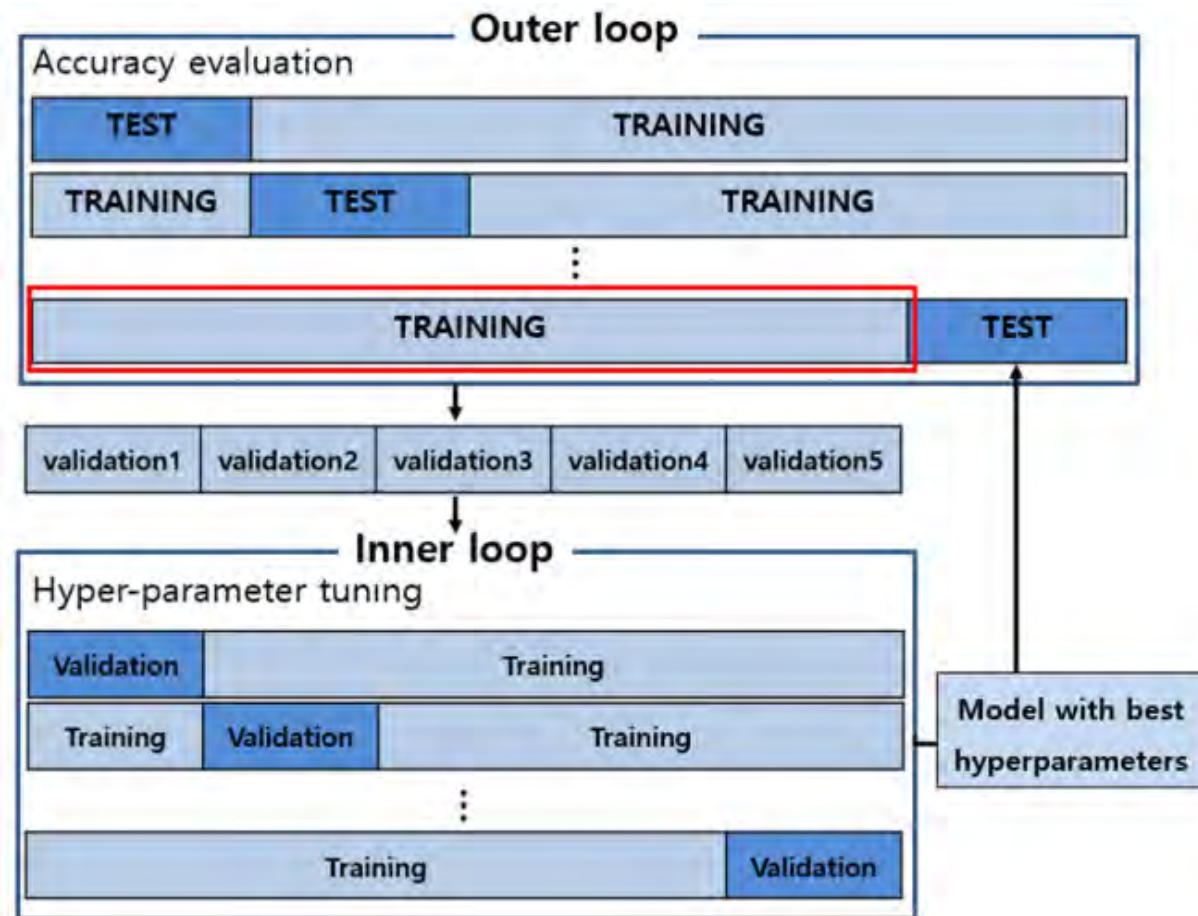
- 19 participants
- 4 sessions per participant (2 overt speech, 2 imagined speech)
- 24 conditions (8 words × 3 cuing modalities)
- 50 trials per condition
- 1200 trials/participant

Classification

- Convolutional Neural Network



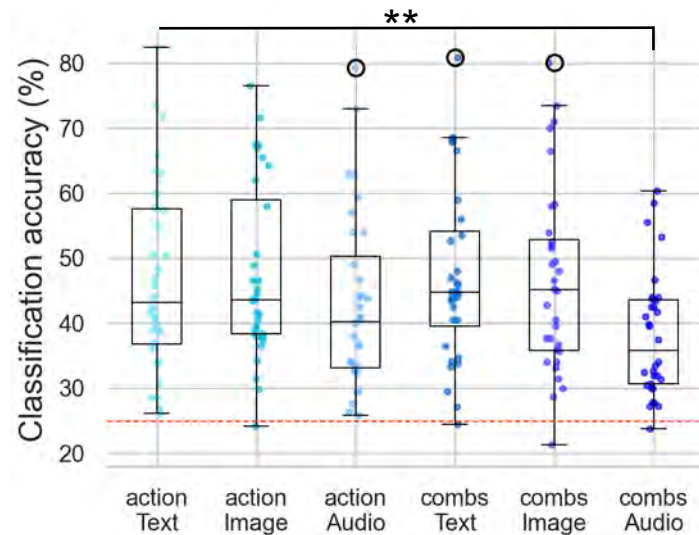
- Nested Cross-validation



See Cooney et al 2020 for detailed analysis of CNN Hyperparameters

EEG Decoding Accuracy

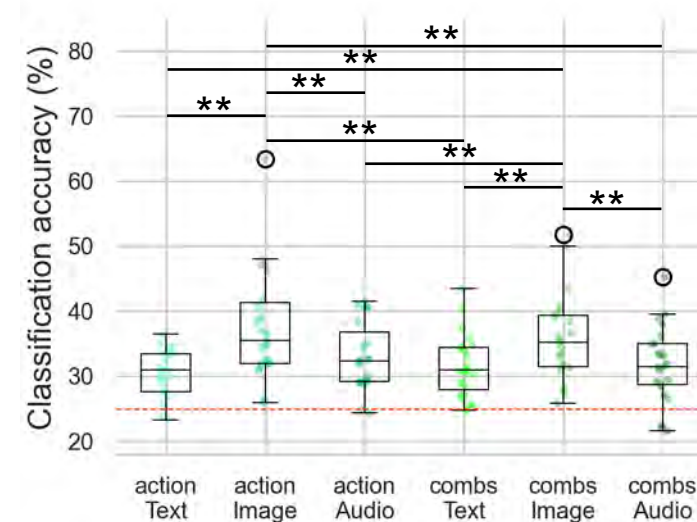
- Overt Speech



Action Words			Two-word pairs		
Text	Image	Audio	Text	Image	Audio
46.92%	47.45%	43.04%	47.38%	46.55%	38.02%

Overt and Imagined Speech

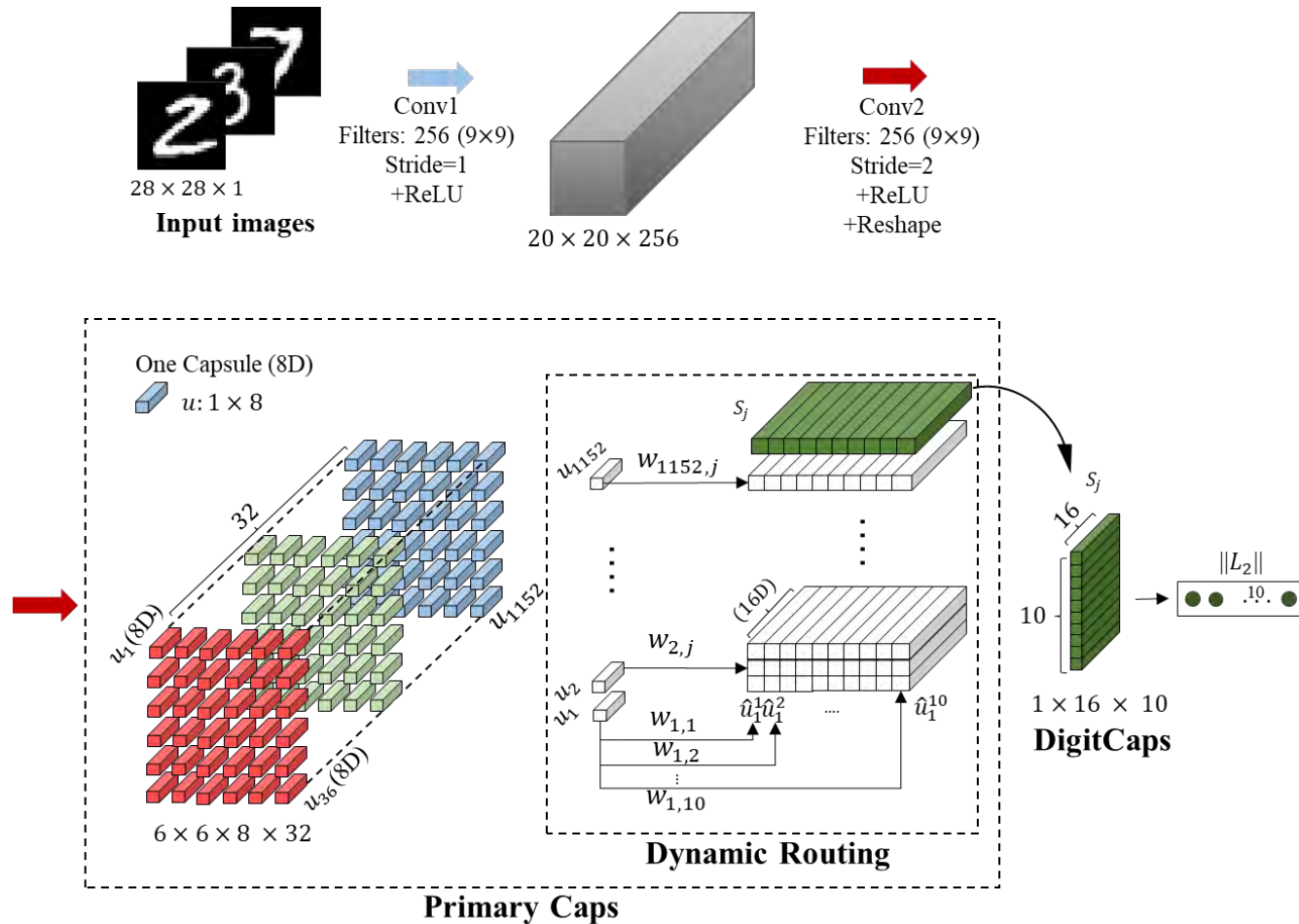
- Imagined Speech



** $p < 0.005$

Action Words			Two-word pairs		
Text	Image	Audio	Text	Image	Audio
30.21%	37.97%	33.13%	31.83%	36.09%	31.81%

Capsule Network (CapsNet)



1. **Hierarchy of Information:** Unlike CNNs, which rely on fixed patterns of features, CapsNets aim to **capture hierarchical relationships in data**. They seek to understand not only what features are present but also how they relate to each other.
2. **Capsules:** In a CapsNet, the fundamental building blocks are called "capsules." Each capsule represents a group of neurons working together to detect specific patterns or features in an image. These capsules work in a hierarchical manner.
3. **Dynamic Routing:** Capsules communicate with each other using a process called "dynamic routing." This means that capsules at one level in the hierarchy send information to capsules at the next level based on the agreement or compatibility of the detected features. This allows CapsNets to **better handle variations in pose, orientation, and spatial relationships between objects in an image**.
4. **Pose and Transformation Information:** Capsules not only detect features but also encode information about the **pose (position and orientation) and transformation (changes in position or size)** of these features. This additional information is valuable for understanding the spatial arrangement of objects in an image.
5. **Primary Capsules:** The lowest level of capsules, often referred to as "primary capsules," process local image features, like edges or corners, and pass this information to higher-level capsules.
6. **Routing by Agreement:** Dynamic routing involves iterative computations to determine which higher-level capsules should receive information from lower-level capsules. This process helps the network focus on relevant features and suppress irrelevant ones.
7. **Final Classification:** Capsule Networks typically include one or more capsules responsible for the final classification of objects in the image. These capsules consider the collective information from lower-level capsules to make a more informed decision about the presence and identity of objects.

CapsNet

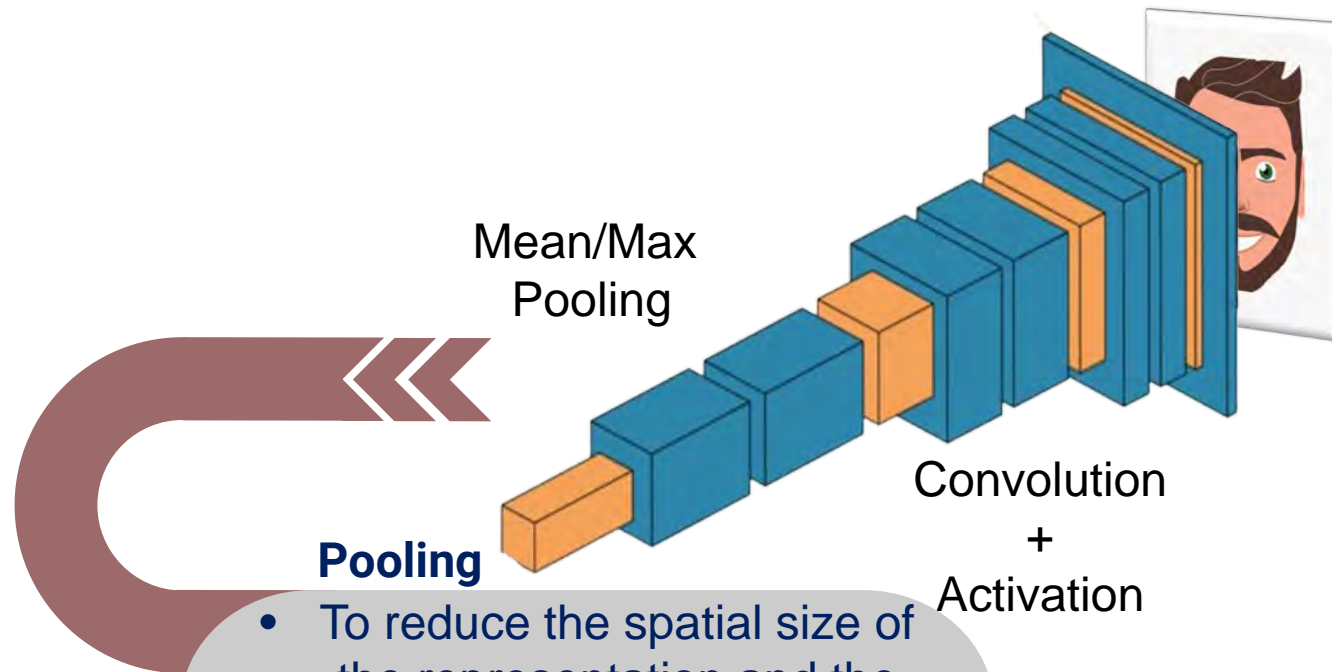
It is NOT a Face!



- Encapsulate neurons
- Vector representation of neurons

Capsule Neural Network (CapsNet)

Preserving spatial information, minimizing loss of features due to pooling, and fewer training data.



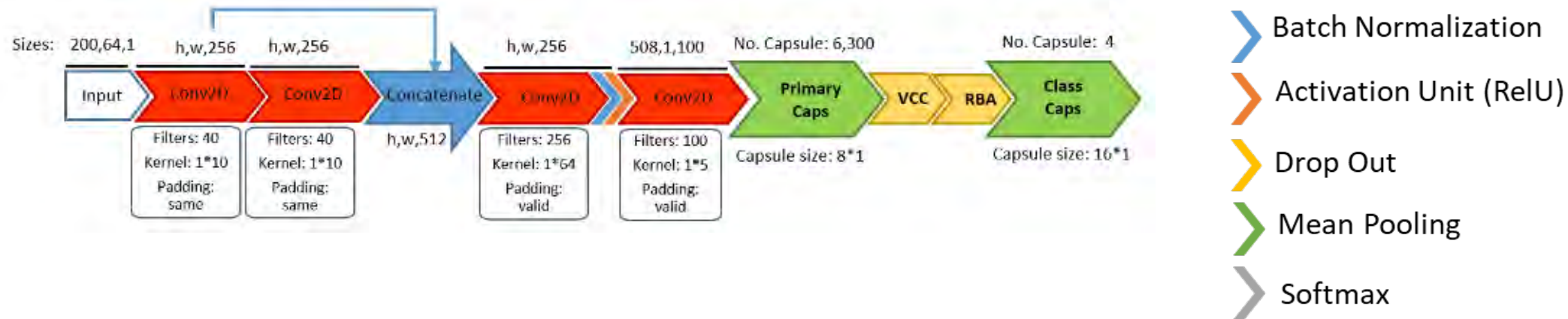
- To reduce the spatial size of the representation and the number of parameters and computation



It is a Face! It is a Face!

Hmmm, I'm not sure!

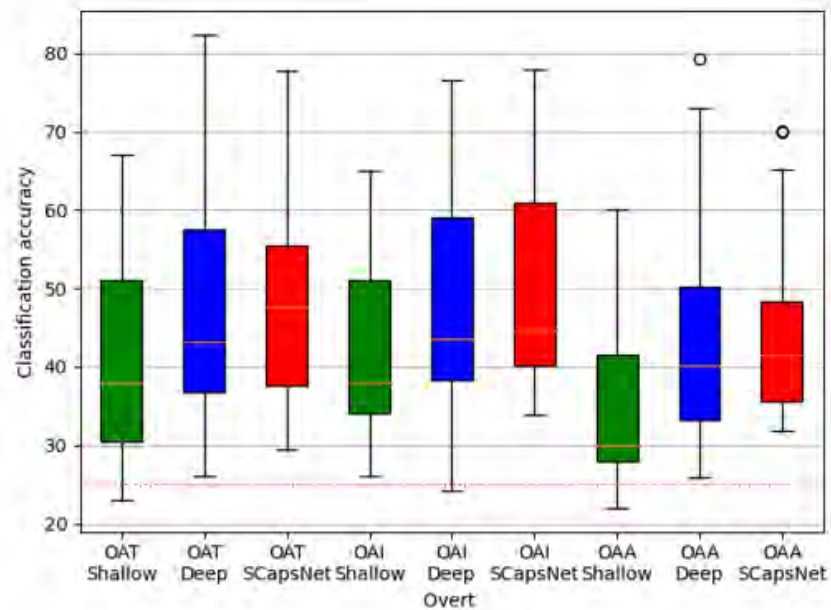
Speech-CapsNet using Deep Features-Guided CapsNet



- using multi-level feature maps to characterize features more accurately in ClassCaps.
- Vector's Convolution Connection (VCC) to minimise trainable parameters and accelerate calculations.
- a deeper DR to support the hierarchical connection of the capsules with shared transformation matrices.

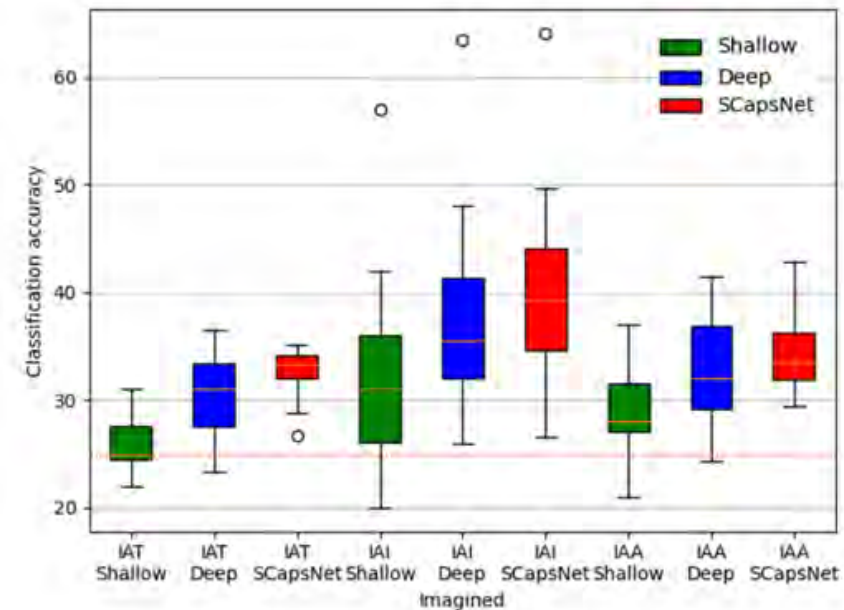
SCapsNet Outperforms shall and deep CNN

- Overt Speech



(a)

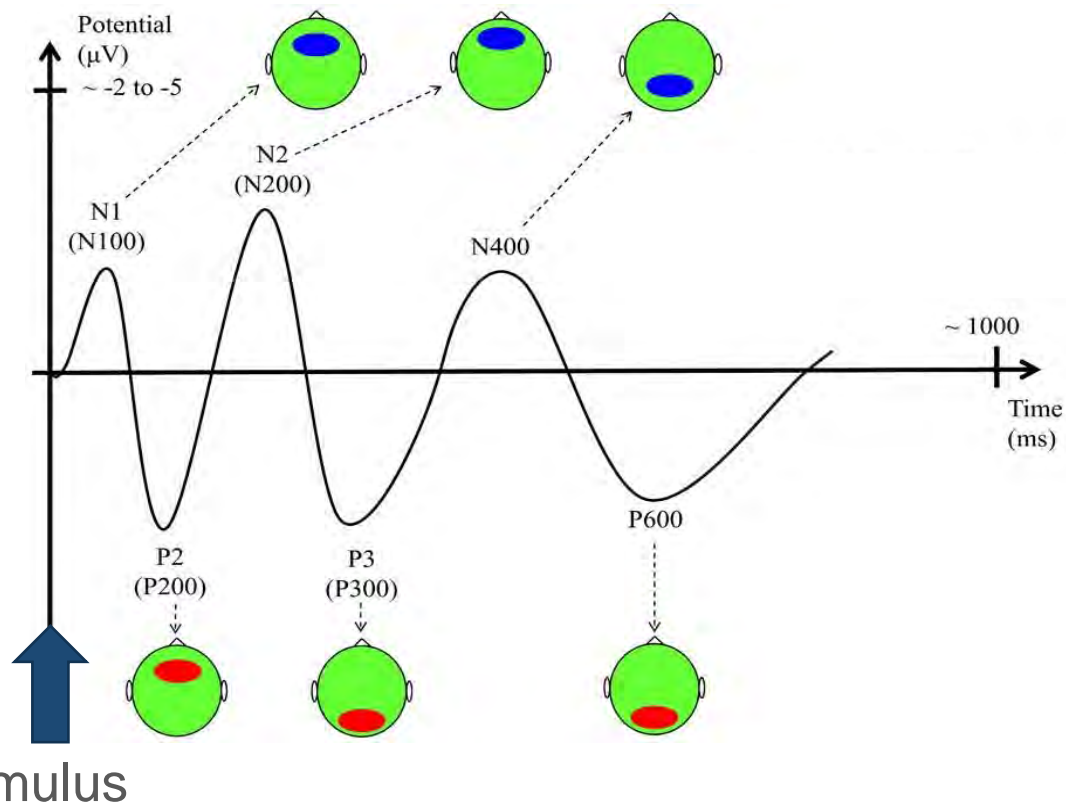
- Imagined Speech



(b)

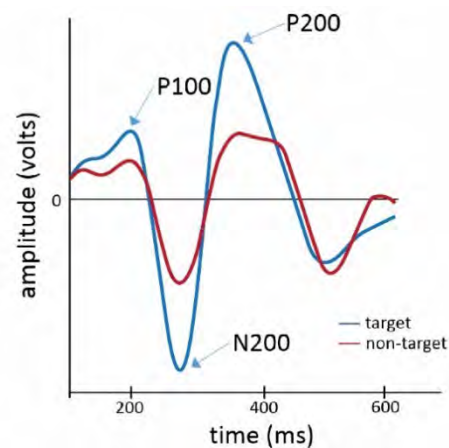
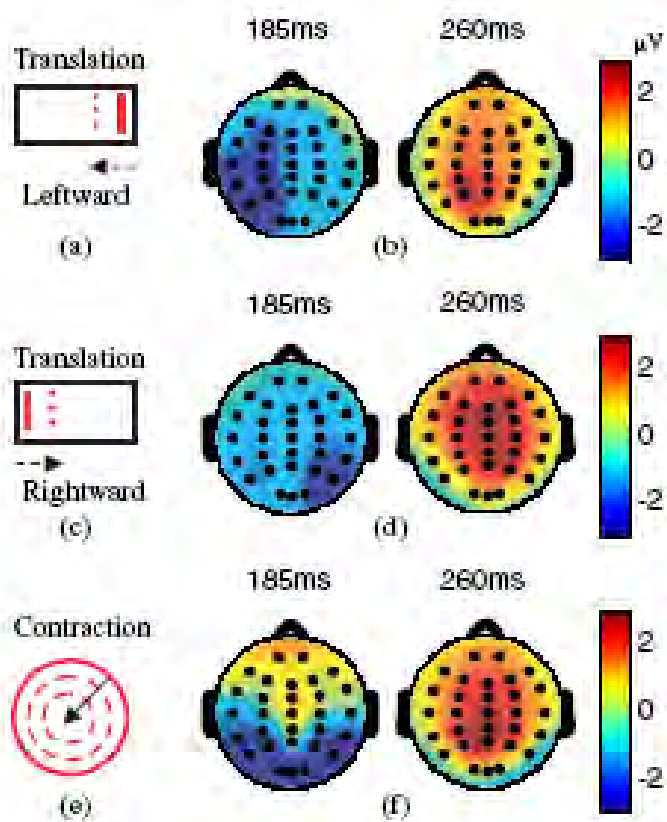
Faster reaction for neurogaming

Event related potentials (ERPs)

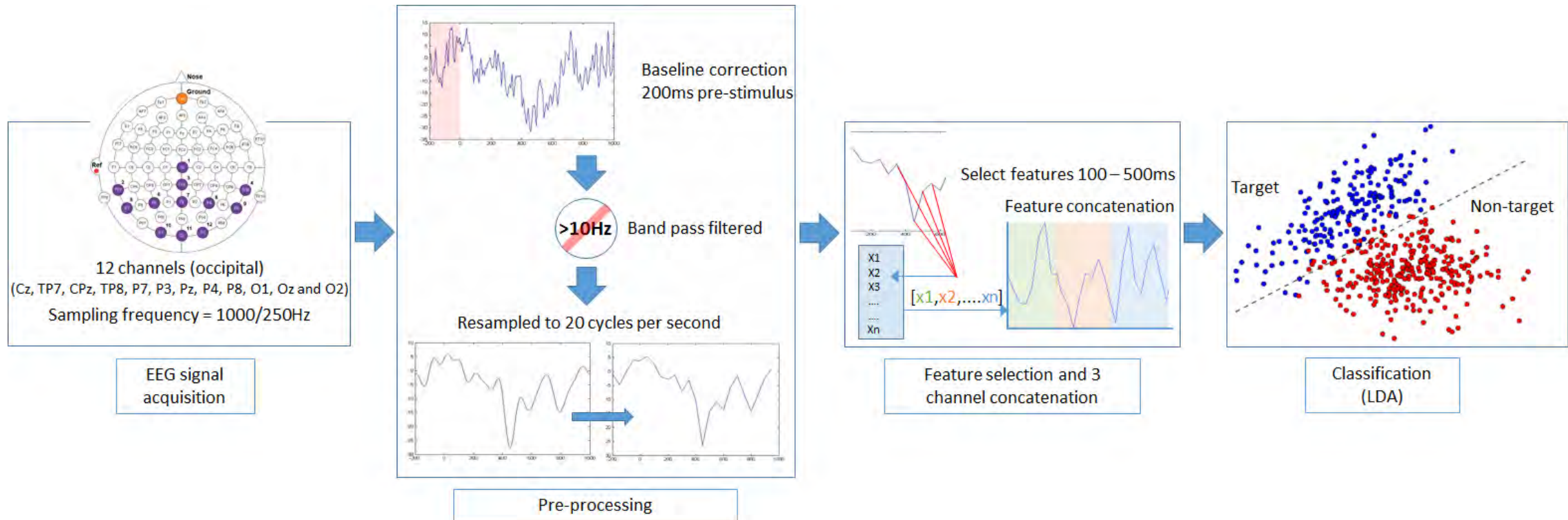


Component	Behavioral counterpart
N1	Pre-attentive perceptual processing
P2	Pre-attentive perceptual processing
N2	Stimulus detection
P3	Stimulus categorization and memory updating
N4	Semantic/conceptual processing
P6	Syntactic processing

Car racing with motion onset visual evoked potentials



Basic Feature Extraction and Classification





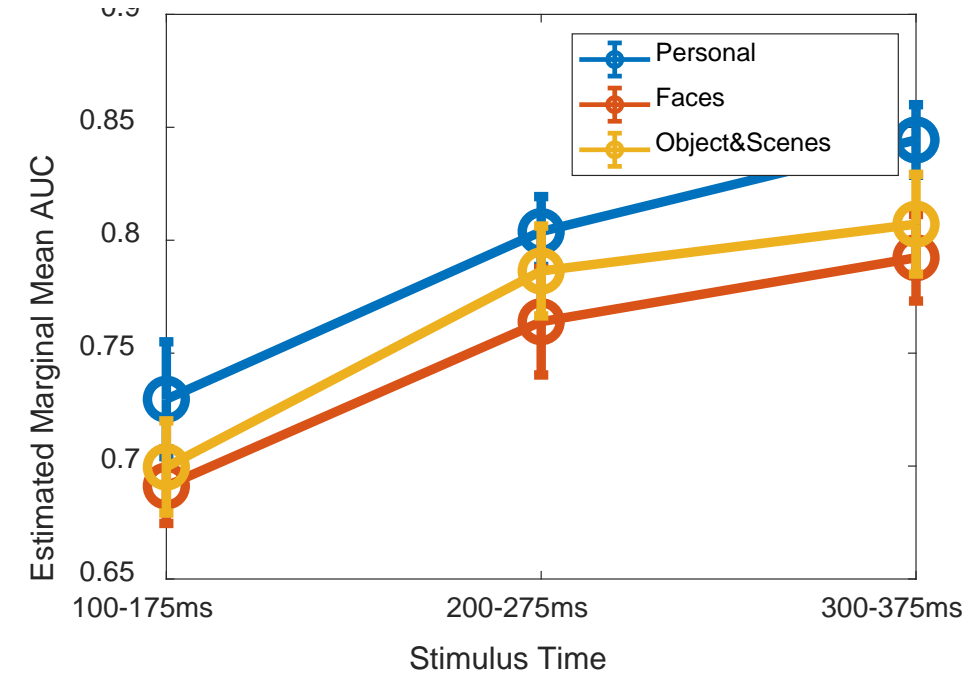
Detecting threat perception from event-related potentials

(participants $N = 28$, 31-channel EEG).

Rapid Serial Visual Presentation (RSVP) paradigm.

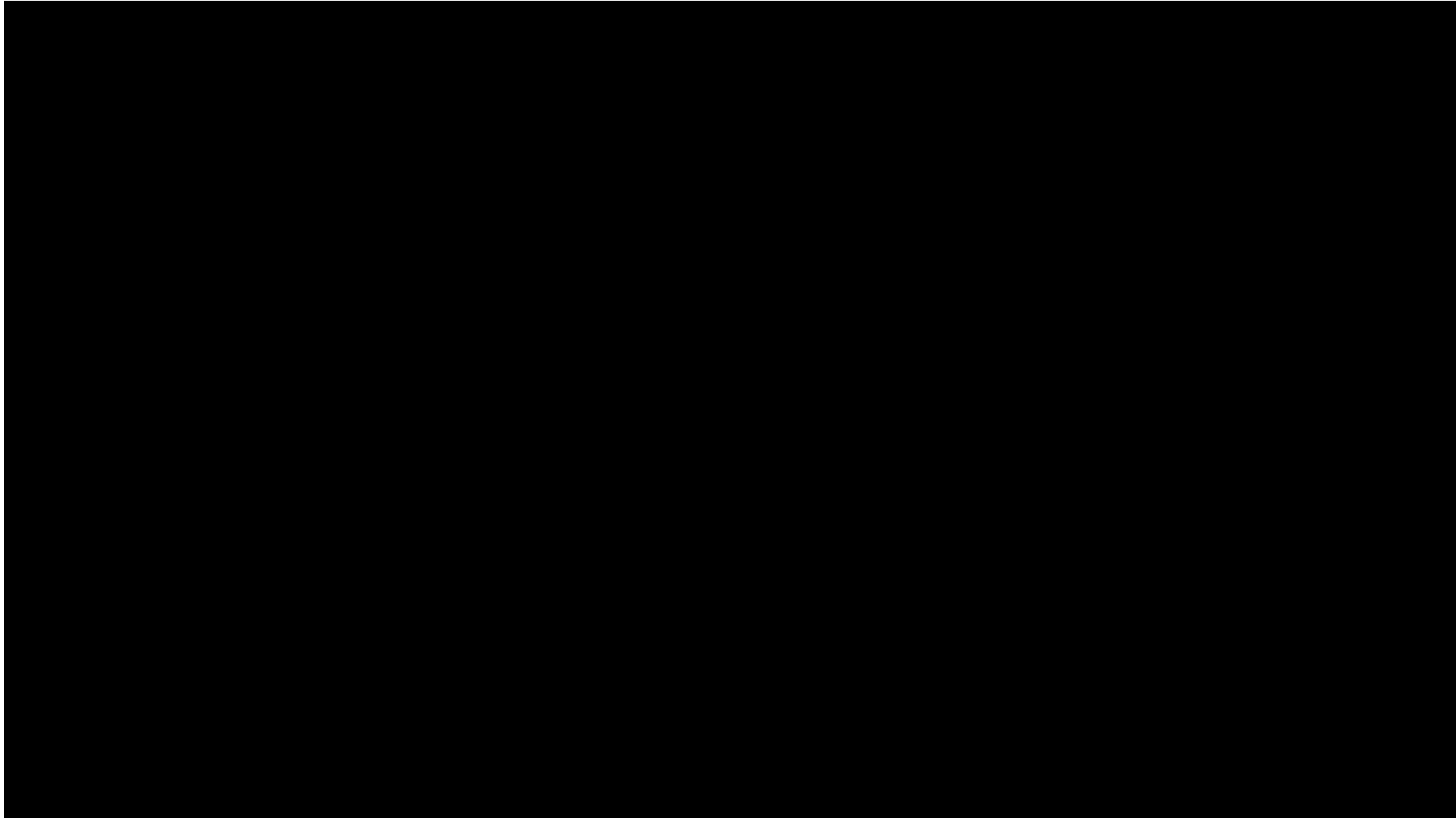


threat vs non-threat



Personal threats are easier to detect from ERPs than Faces/Object/Scenes and distractors

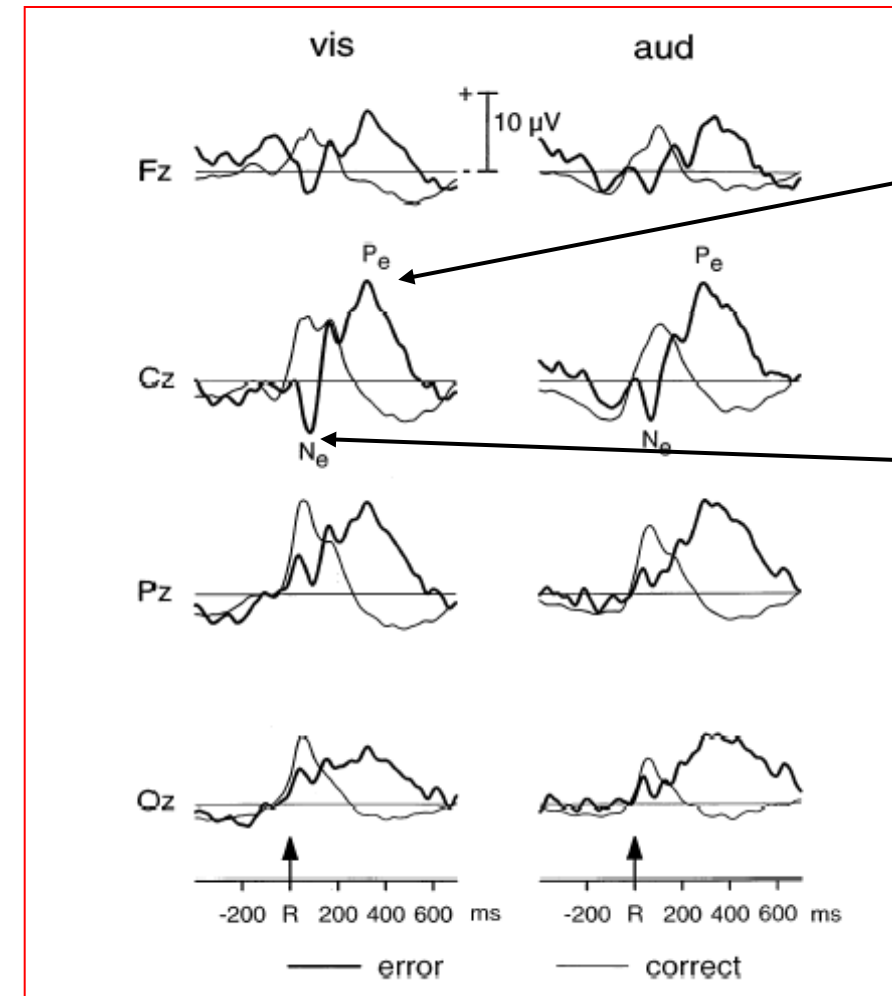
Realtime threat perception detection





Rapid error correction

- Error Potentials
- Error-Related Negativity - The Brain's "Uh Oh" Signal when an error is made
- This is a negative shift in the EEG seen immediately after a person thinks s/he just made a mistake.

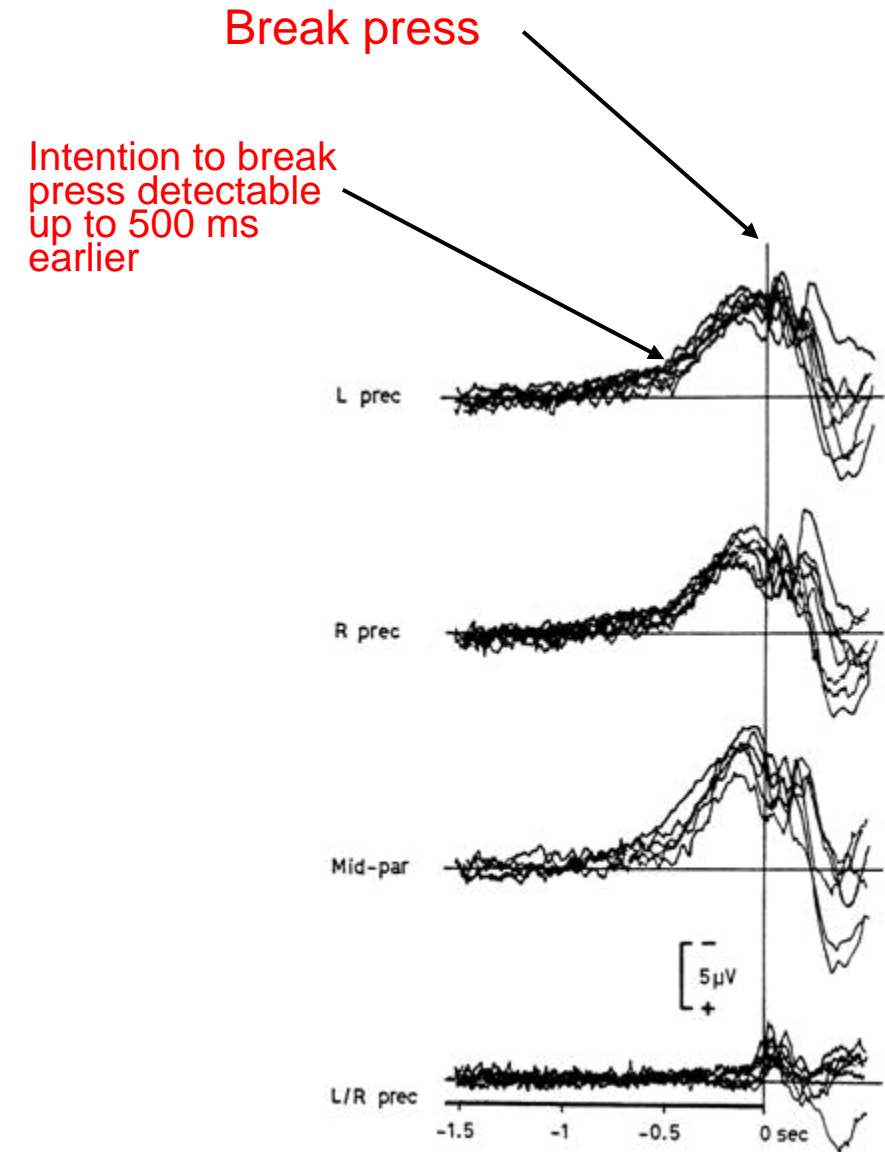


Positive potential at 200-400ms

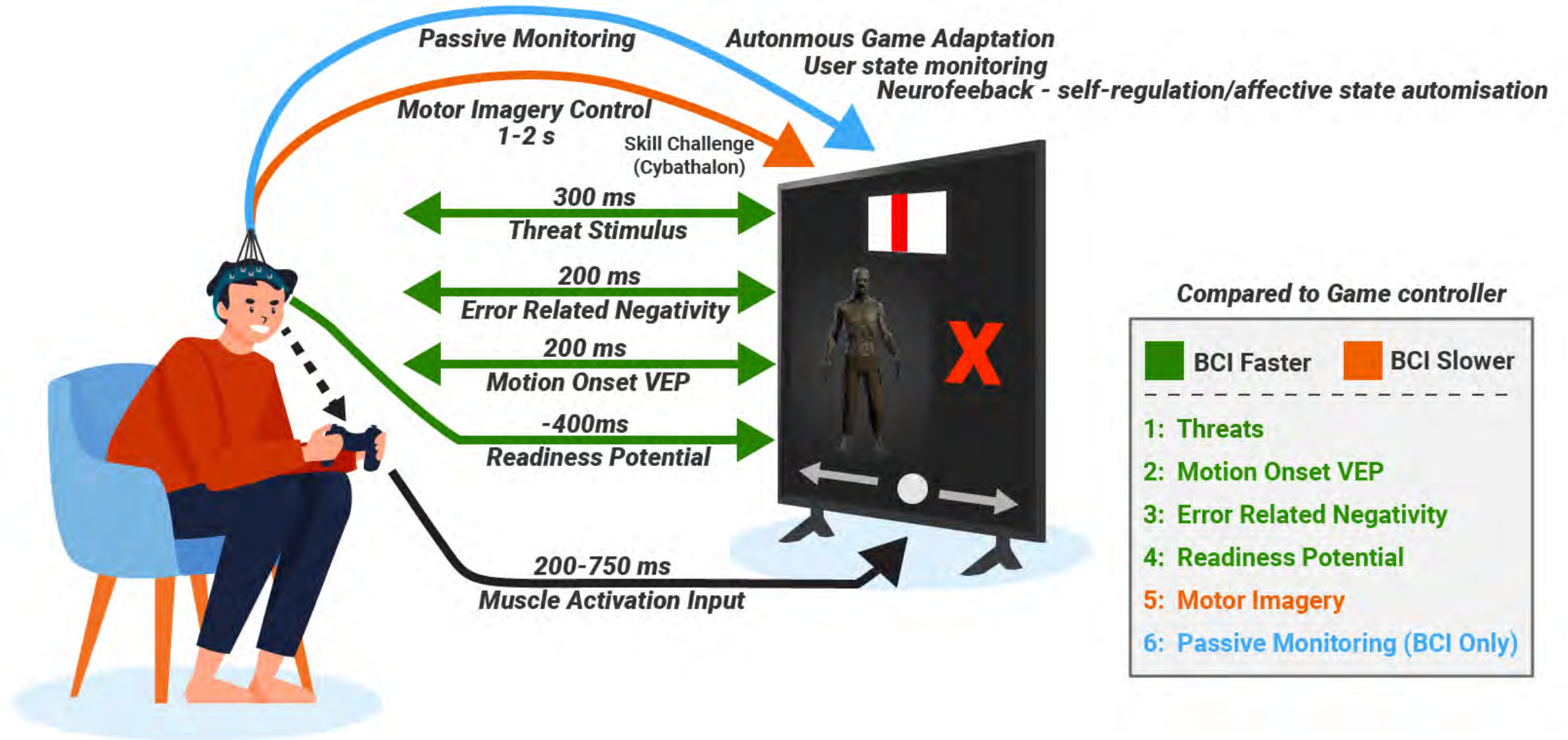
Negative potential at 50-100ms

Rapid reaction

- Bereitschaftspotential (readiness potential)
- a measure of activity in the motor cortex of the brain leading up to voluntary muscle movement.



Faster reaction – case study Neurogaming



Challenges and prospects for brain-computer interface based neurogaming

Emotions and affective states

- Fatigue
- Mood
- Stress
- Anxiety
- Joy

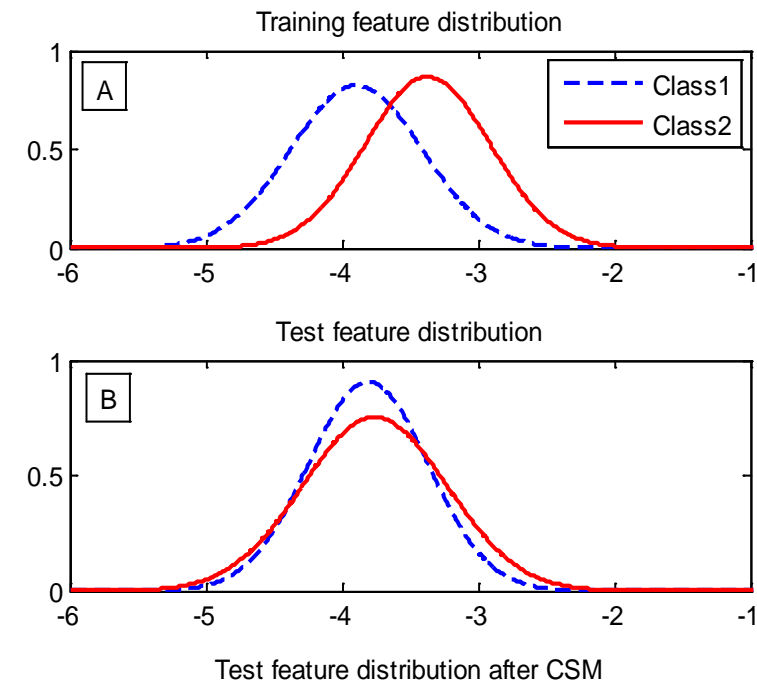


Non-stationarity and covariate shift

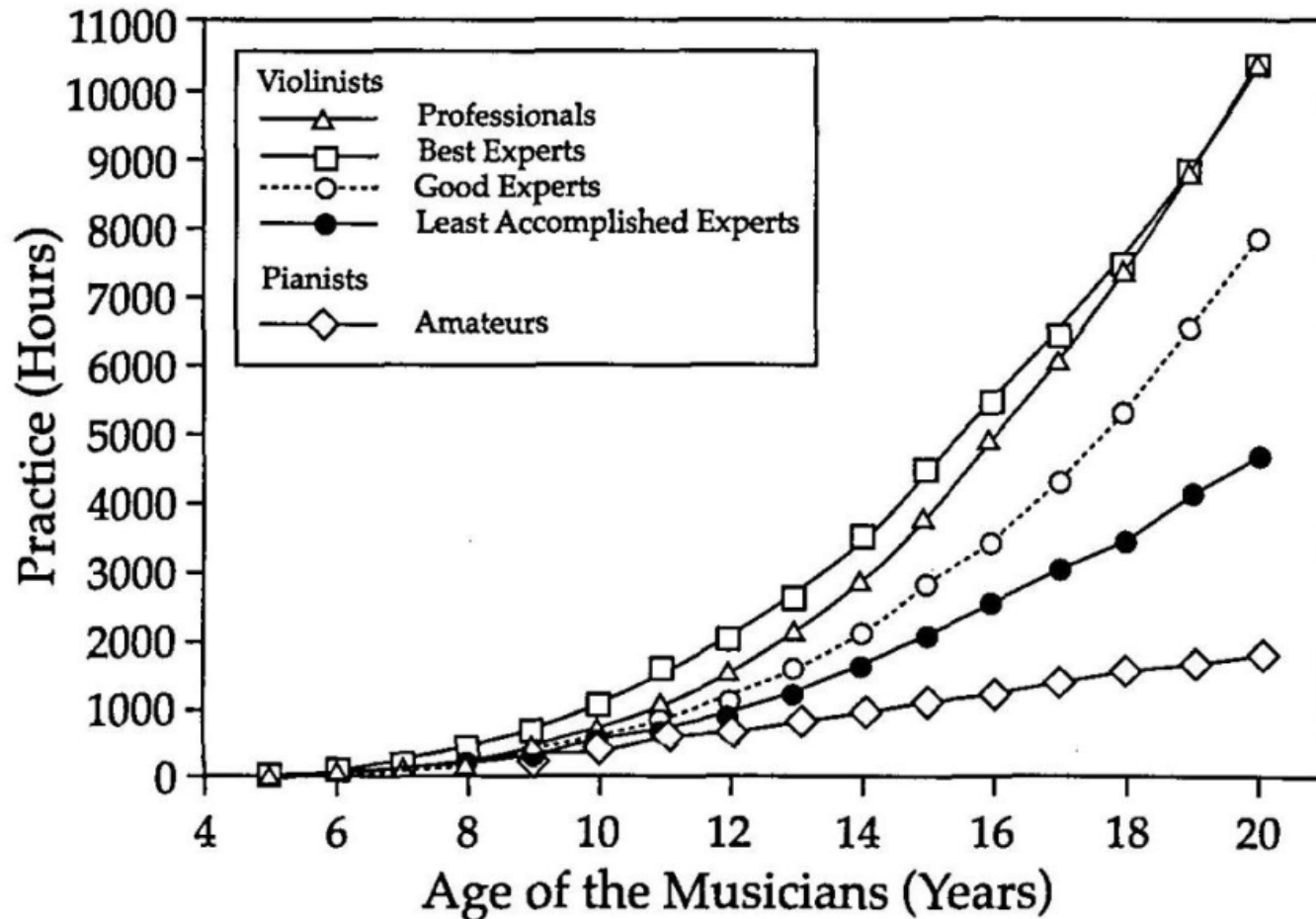
Distribution of input variables (covariates) in a dataset changes between the training and test datasets.

Solutions include

- Data space Adaption
- Features space adaptation
- Adaptive classifiers
- Post processing on classifier output
- When and how often to adapt classifier etc ? (MMLD)



Ericsson's "10,000 hours"



Human expert performance literature may help

Better performance feedback – real-time and regular coaching

Increase the training duration and intensity

How long does it take to learn BCI control with right AI?

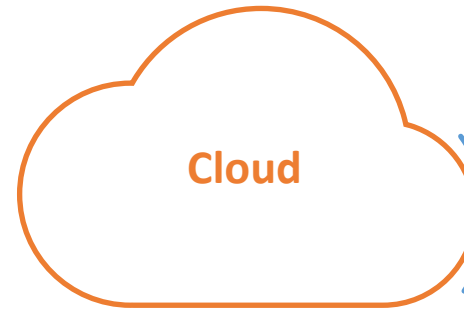
Human-Machine Learning Dilemma – requires adaptation of the AI as the Human Learns and adapt there brain patterns and strategies

- Ericsson et al, Psychological Review, 1993



NEUROCONCISE

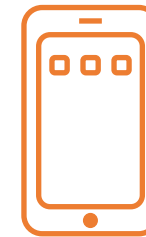
Neurotech Platform



- Deep Learning
- Neuro profile
- Optimization



Real-time
AI signal processing and optimization



Multiple End User
Apps



INNOVATION
WINNER 2018



Call to Gamers and Game Developers

Neurogames Testing – Free access to wearable neurotechnology

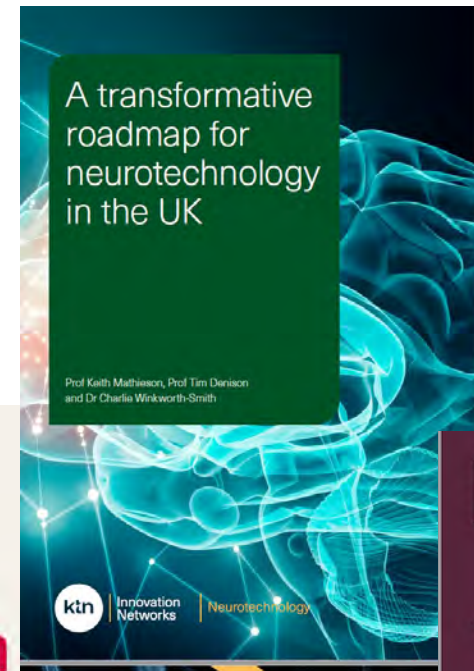


- Are you interested in neurogaming for 1 month in your home/business?
- To experience BCI and neurogaming?
- Determine how far you get and accuracy?
- What level of control and advantage can be achieved?
- Understand various control strategies
- Understand challenges and opportunities
- Compete to be the best in a cohort
- Win a headset to retain
- Provide important feedback
- Get involved in neurogames dev
- Adapt your own games for direct brain control – new markets – accessible games
- Get ahead of the game

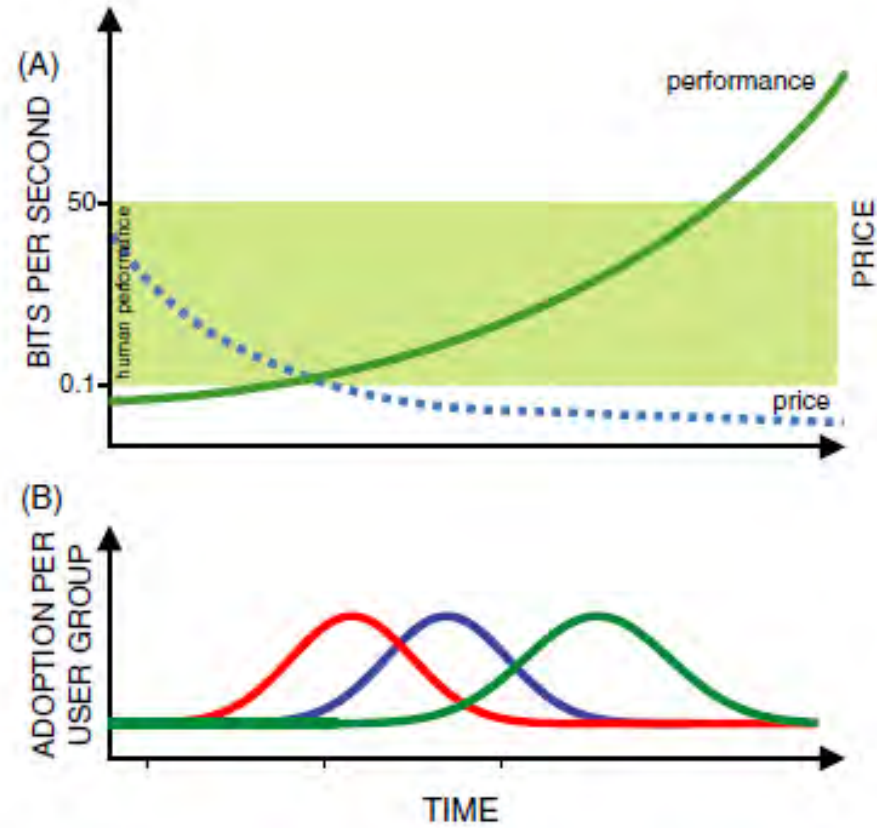


Express Interest – info@neuroconcise.co.uk

The UK is preparing for the impact of neurotechnology



Technology diffusion



Conclusion

- Brain–computer interface use is a skill that user and system acquire together
- Man-machine learning dilemma is challenging
- Requires Continual adaptation and learning
- Signal to noise ratio is limited
- **AI Machine/deep learning** is essential
- More data/user is needed (more users using for longer)
- **Management** – cloud is critical, time and quality of time training (coaching)
- **Modelling** – neuroscience, neurolinguistics, kinematics, engineering
- **Collaboration** – with colleagues, users and patients is key
- We need more AI specialists working on BCI data



Thank you

Questions?

