Bayesian Learning from Multi-way EEG Feedback for Robot Navigation and Target Identification

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Wirth C, Toth J, Arvaneh M. Bayesian learning from multi-way EEG feedback for robot navigation and target identification. Scientific Reports. 2023 Oct 7;13(1):16925.

EPSRC
Engineering and Physical Sciences Research Council

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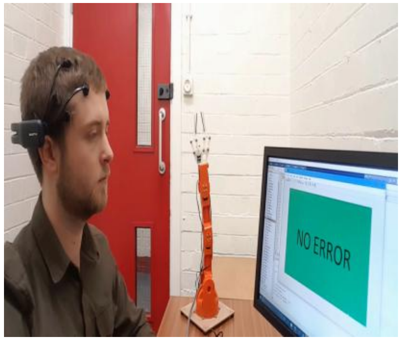
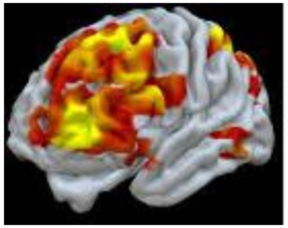
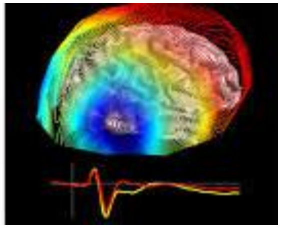
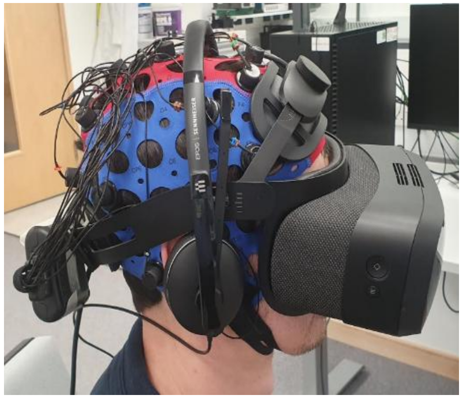
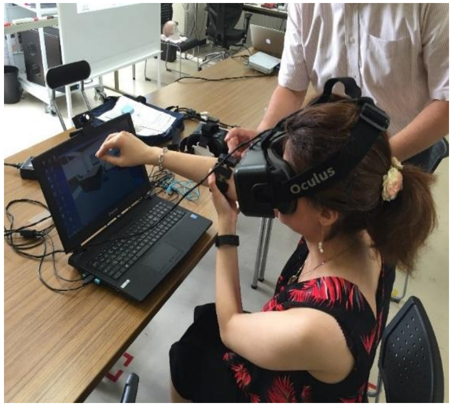
My Research Vision and Ambitions



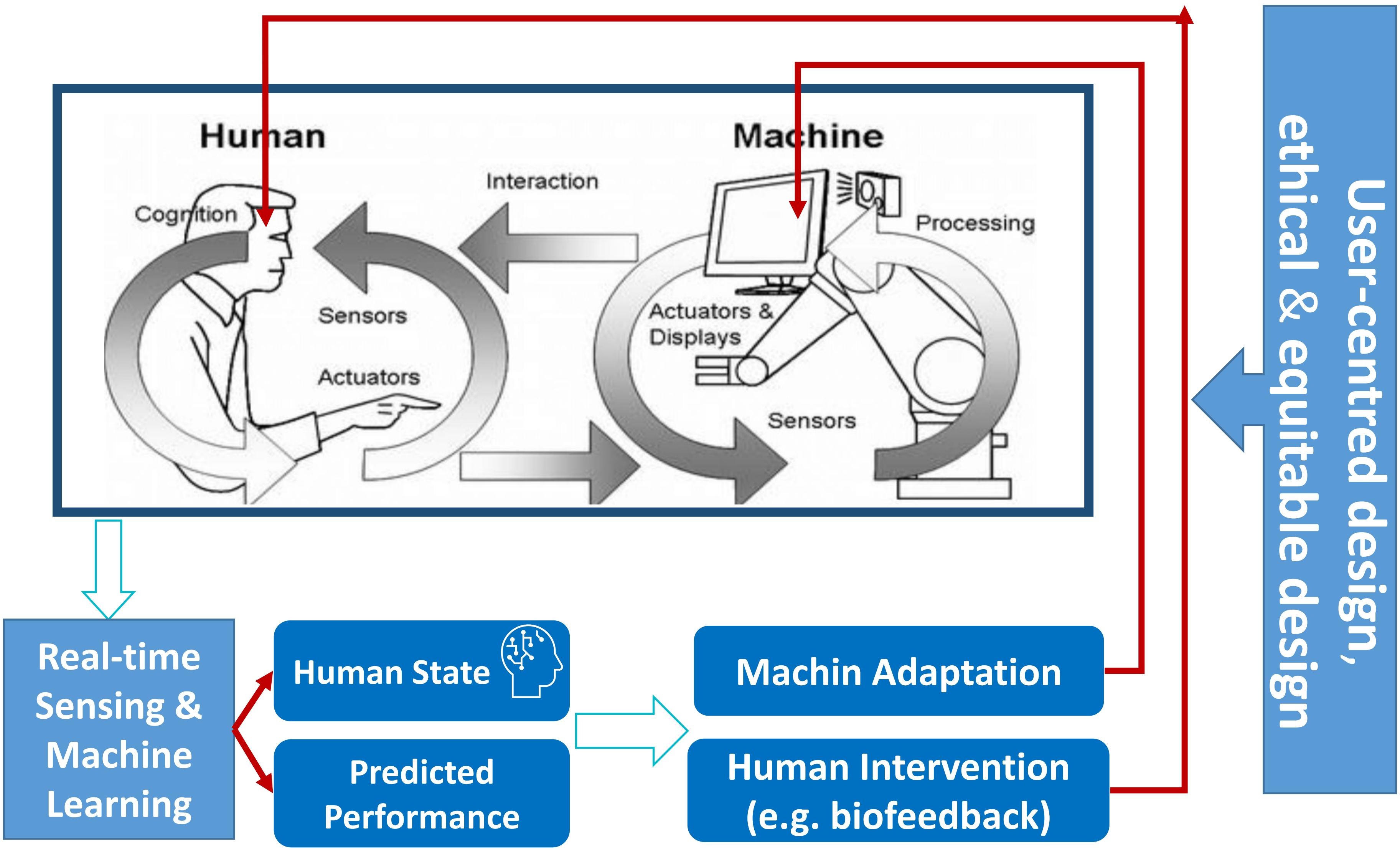




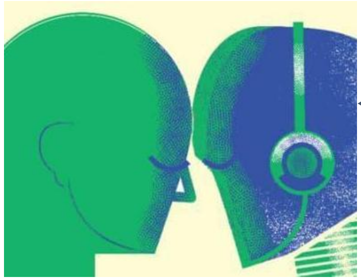




Research vision: to augment human (physical and cognitive) performance by developing user-centred closed-loop neurotechnologies



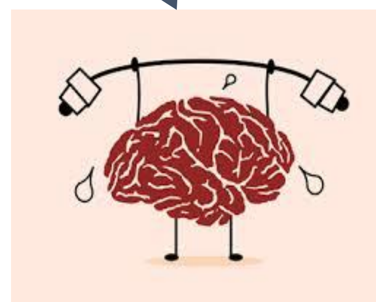
My Main Research Directions



Improving human-machine collaboration
(AI in Wargaming EPSRC £1.2 m, Inclusive Neurotech ARIA £410K)

Monitoring Human States in Real-time
(ElectroTools BBSRC £900K, Haleon £400K, Mind4ACCEL EPSRC £50K)

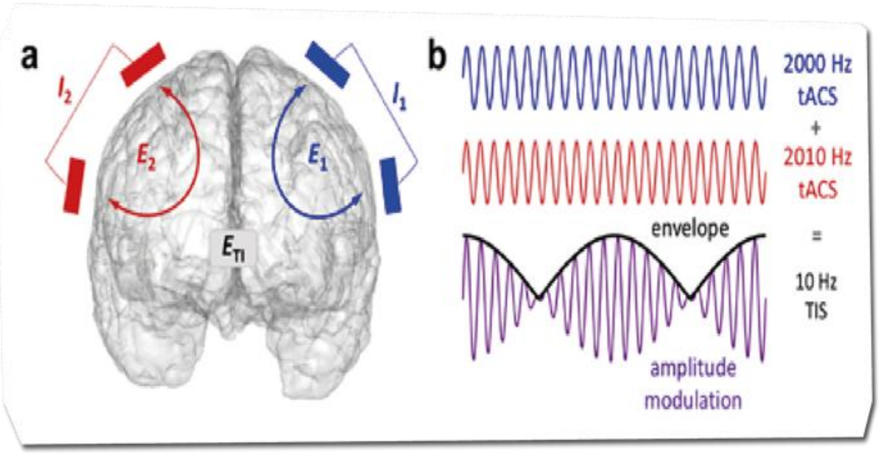
Physical rehabilitation
(TeleRegain funded by MRC IAA, EPSRC IAA & InnovateUK £200K)

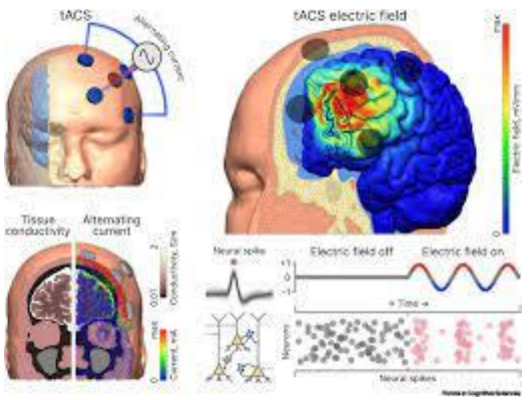


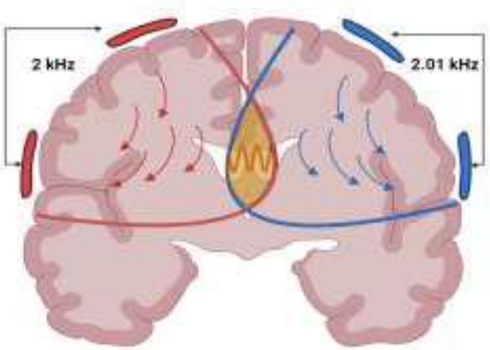
Improving cognitive performance & decision making
(SUPER DSTL £410K, Early Dementia MRC DiMEN £200K)

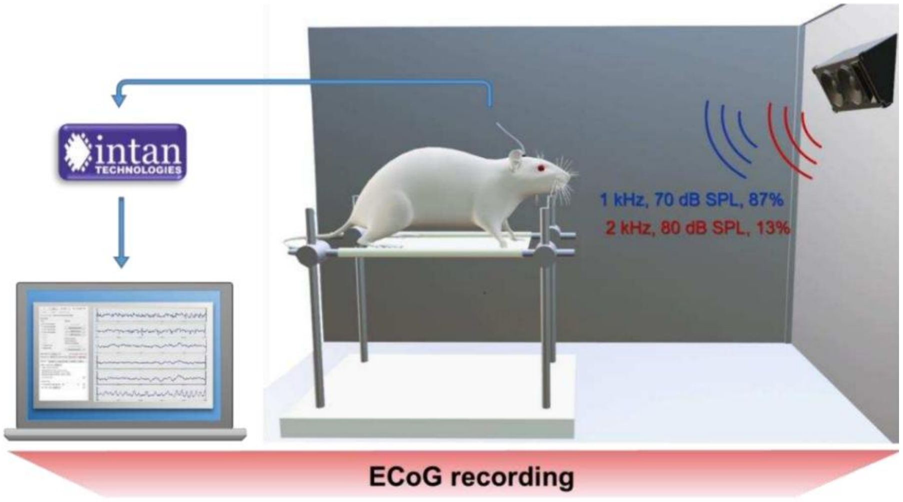
Our Research Spams the Entire Spectrum of TRL 1-6
Theoretical, Experimental, Translational, Clinical Trials

Closed-loop Optimised Non-invasive Deep Brain Stimulation









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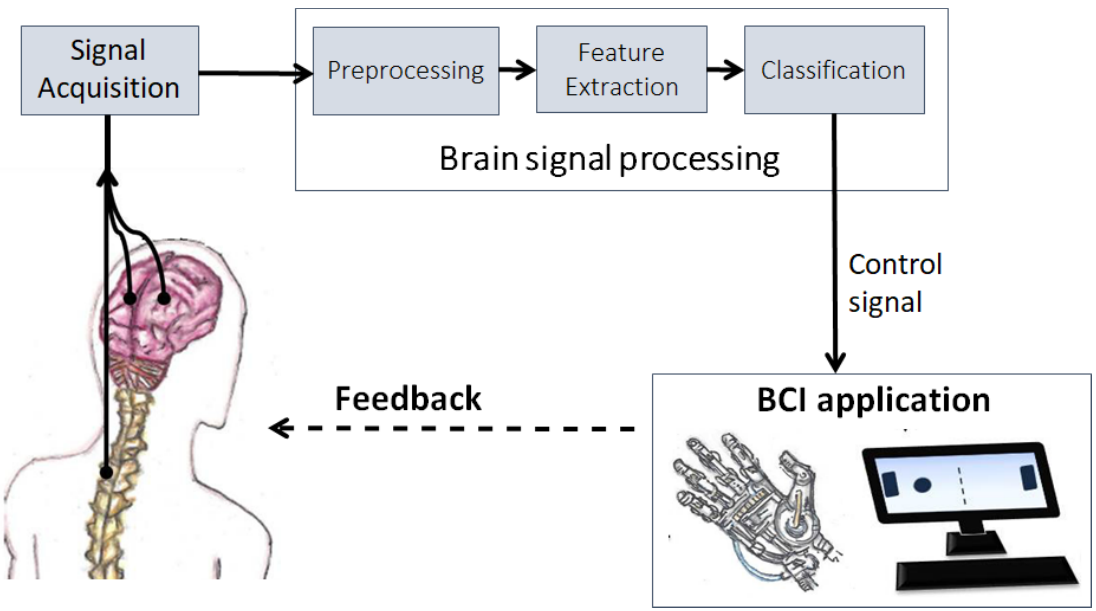
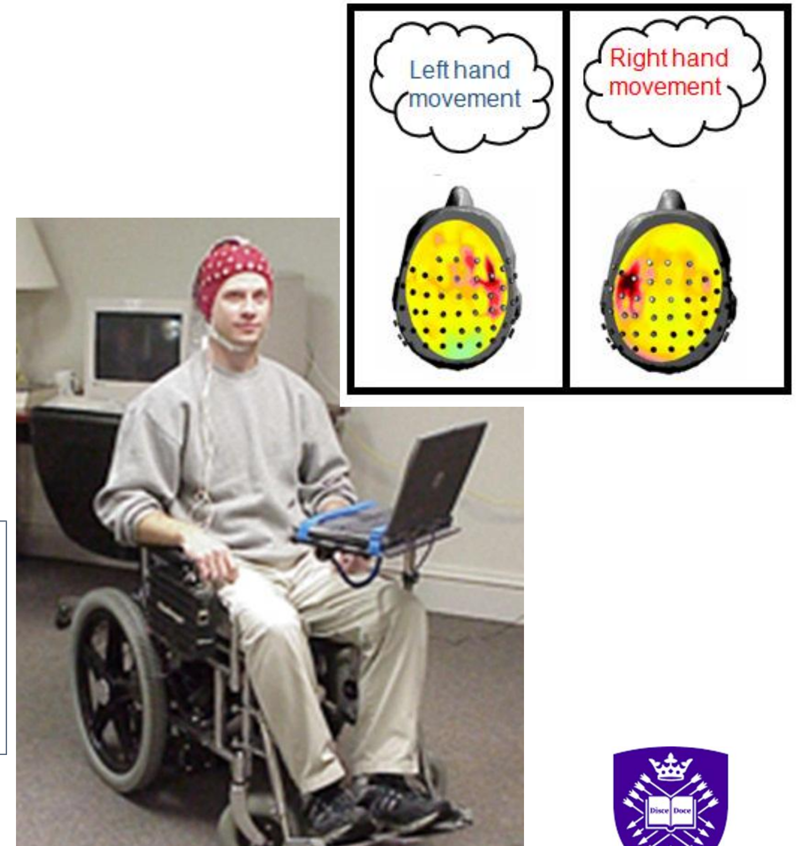
Outline

- Brain-computer interface and its flaws
- Passive BCI and its application for implicit communication
- Implicit control of a navigation robot using BCI
- Future research direction

Brain-Computer Interfaces for Robot Control

BCI uses brain signals as a means of direct communication or control of a computer.





Controlling a wheelchair usi
motor imagery [Leeb07]

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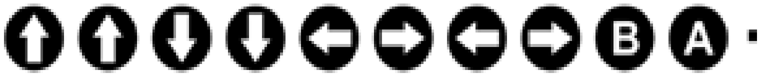
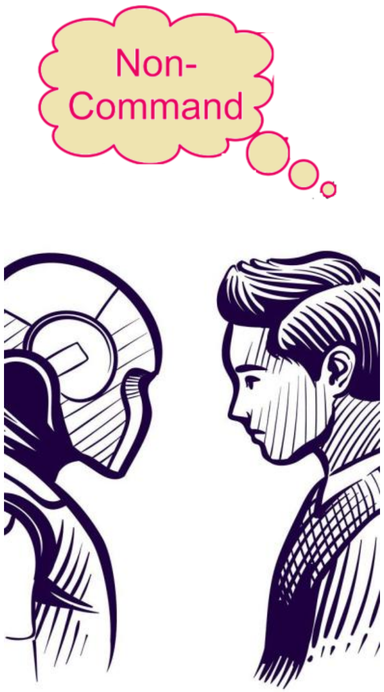
Flaws of existing BCI:

- Most systems require low-level action control
  - e.g. “move right… move right… move forward… grasp…”
  - Low information transfer rate
  - High mental workload



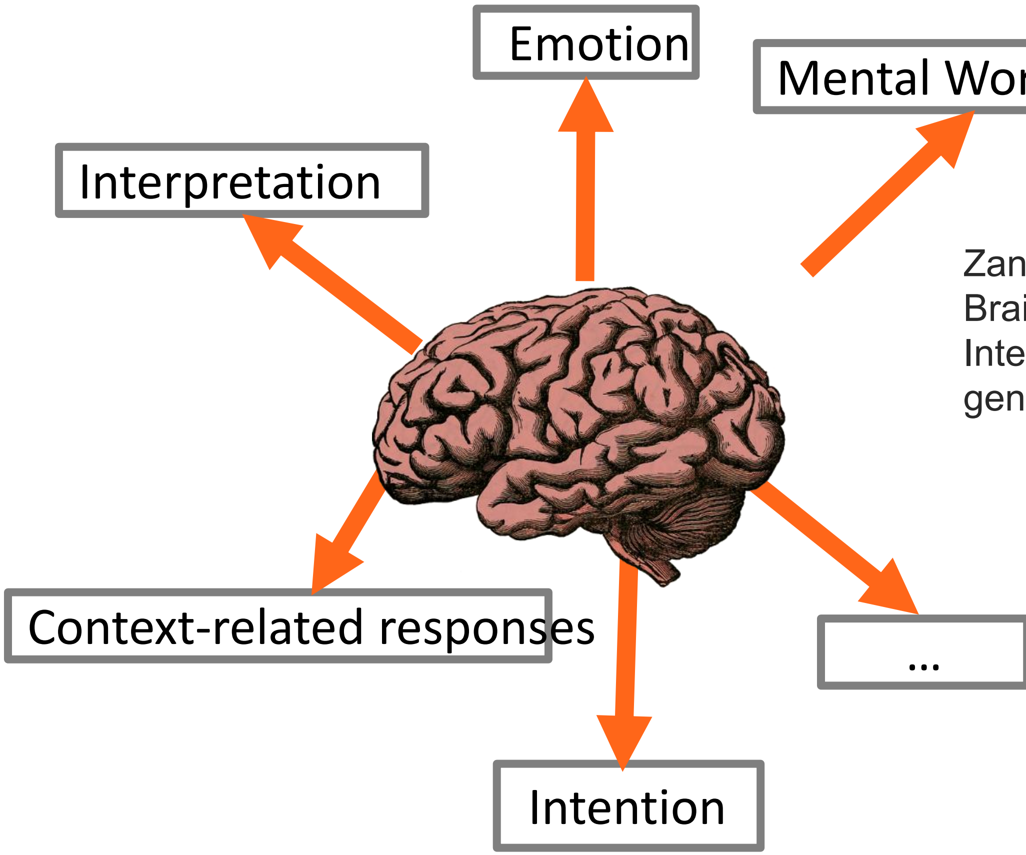
Our aim:



To investigate the feasibility of a more autonomous BCI, where much of the burden is passed from human to machine.

Implicit Control without any commands being intentionally communicated to the system by the user.

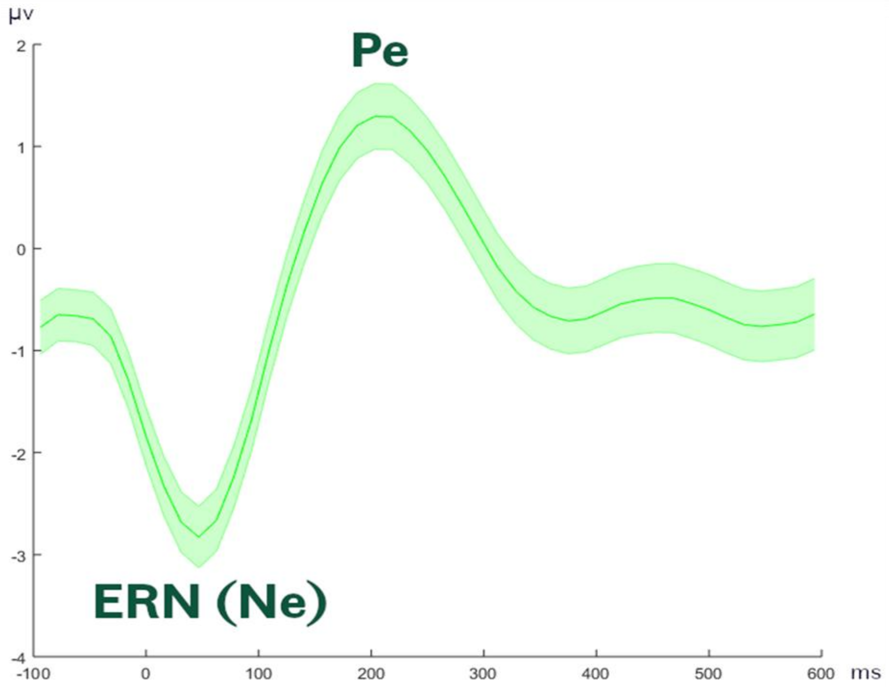
Passive Brain-Computer-Interfaces



Zander, T. O., & Kothe, C. (2011). Towards passive Brain–Computer Interfaces: Applying Brain–Computer Interface technology to Human–Machine Systems in general. Journal of Neural Engineering, 8(2), 025005.

- ✓ Passive BCIs can detect changes in certain aspects of user state in real time.
- ✓ This can be used to establish implicit control to adapt the machine on the fly.

Brain Responses when Observing Errors



- Error-related Potential can be detected in signle-trial basis with accuracy 70%-80%

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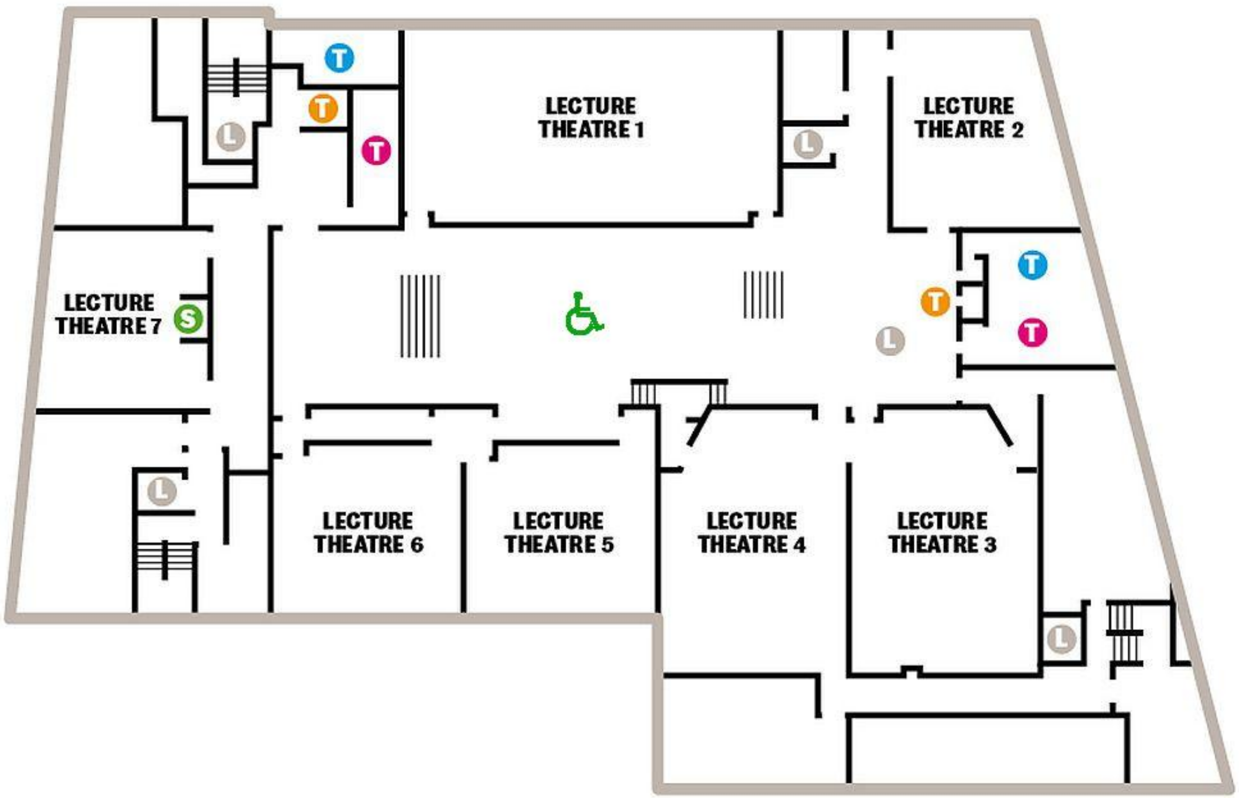
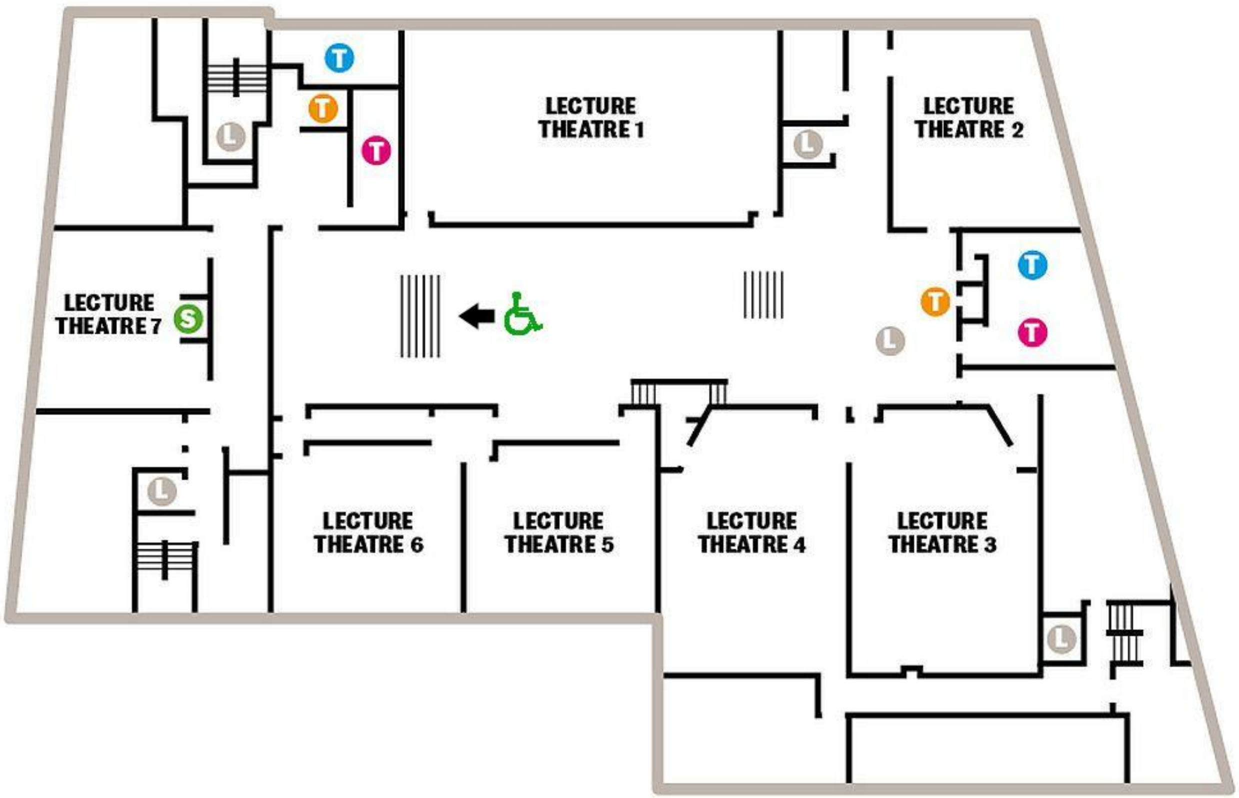


Example of implicit control using EEG error detection and reinforcement learning



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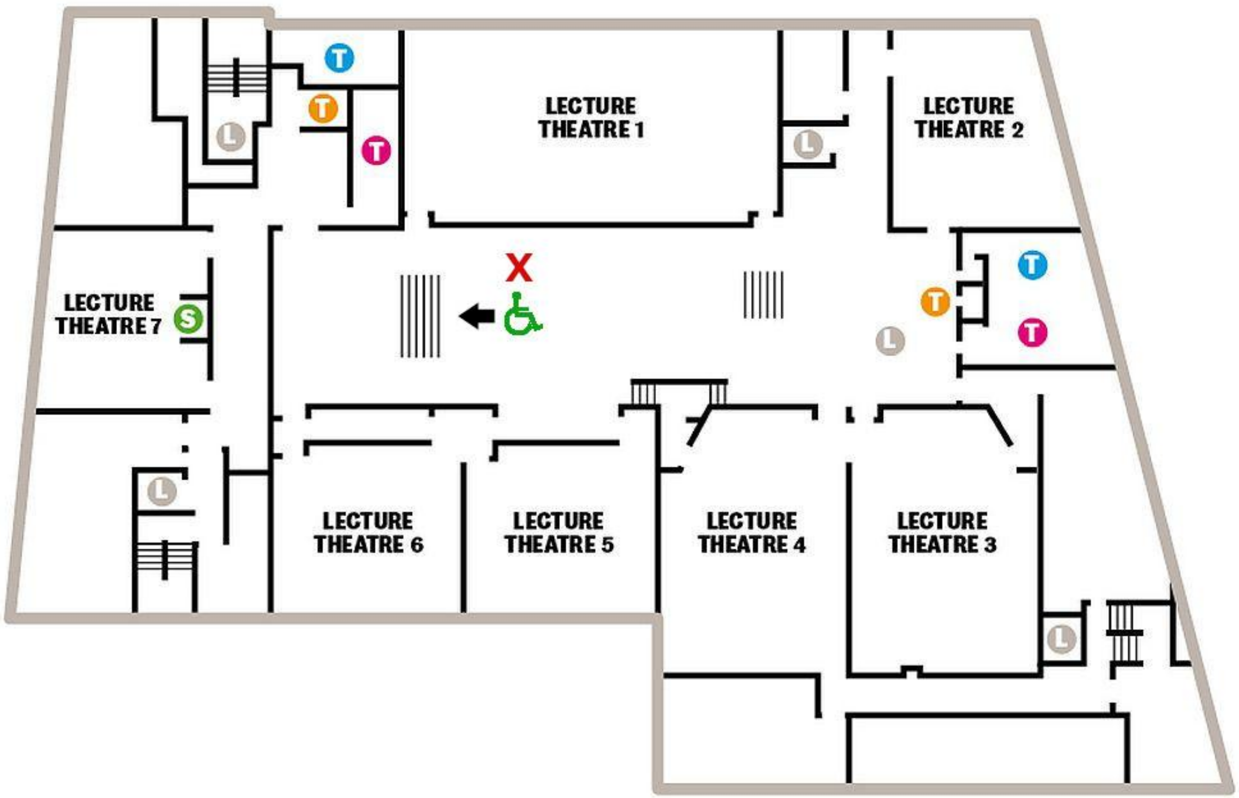

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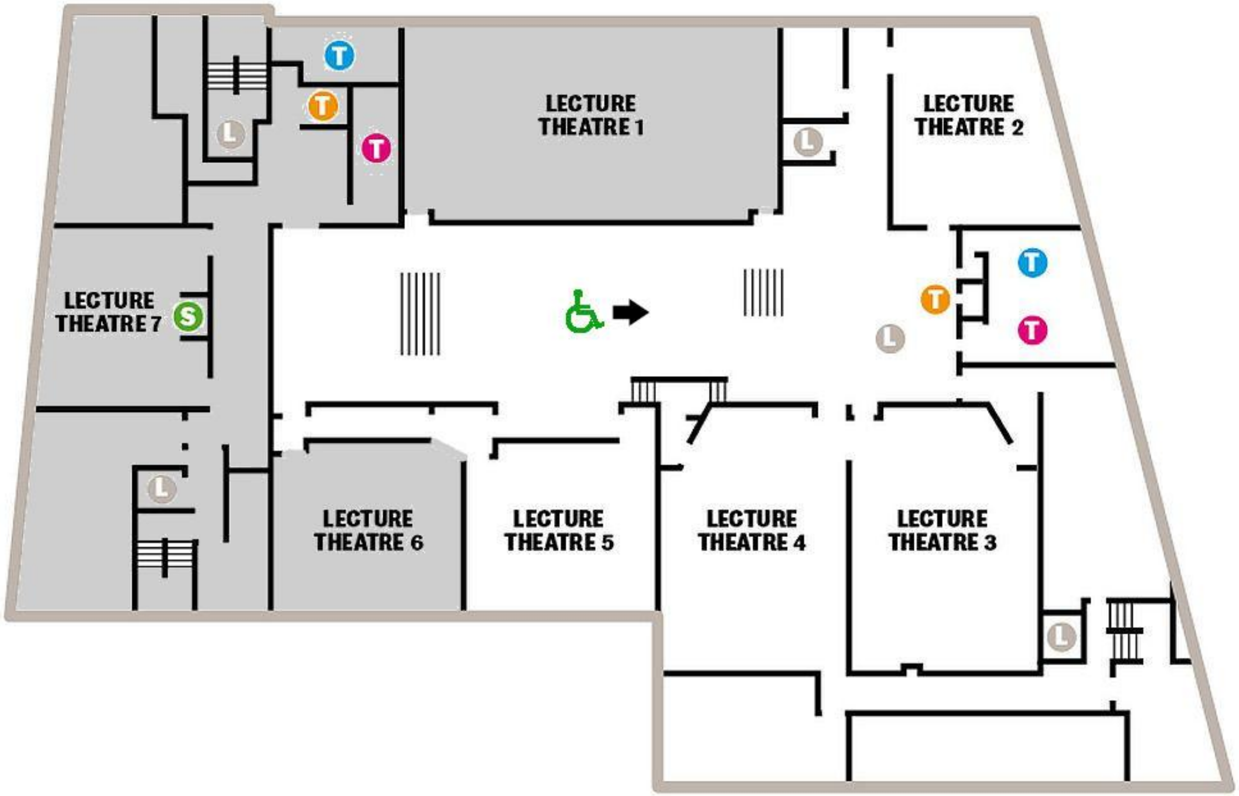

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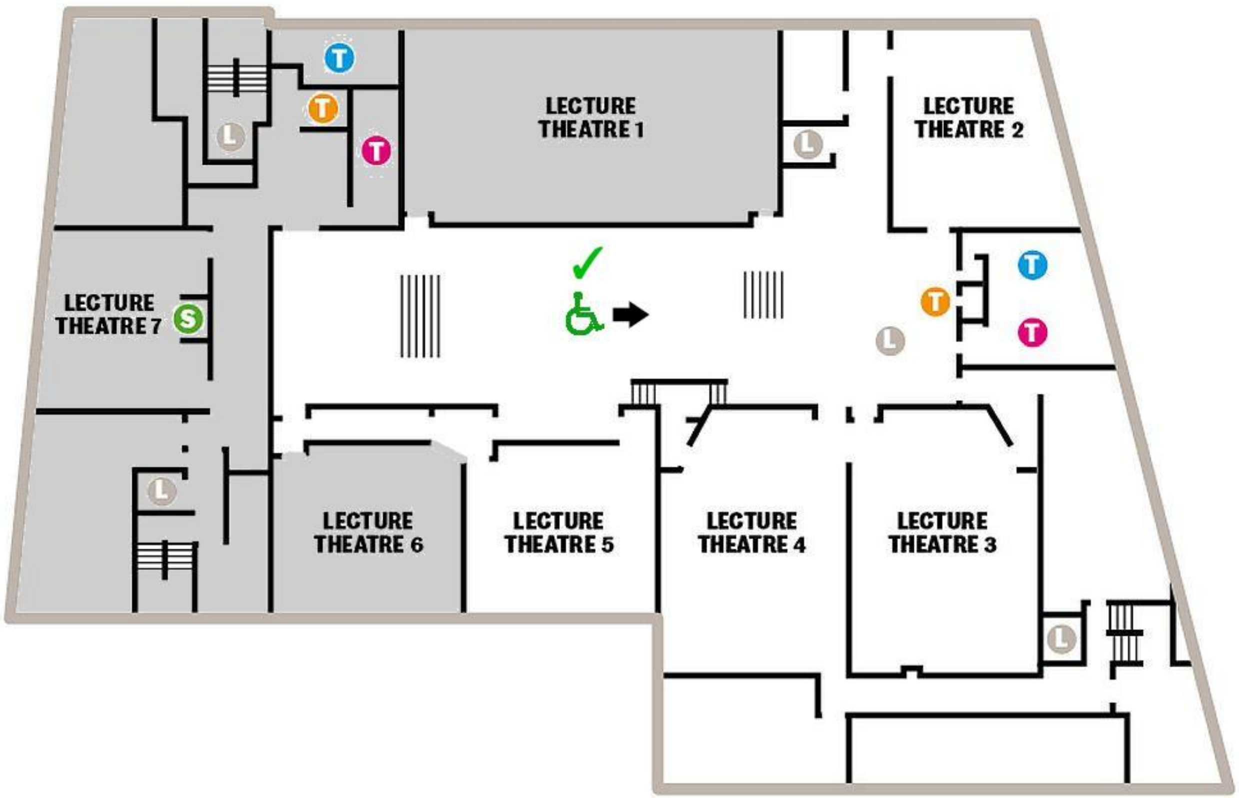

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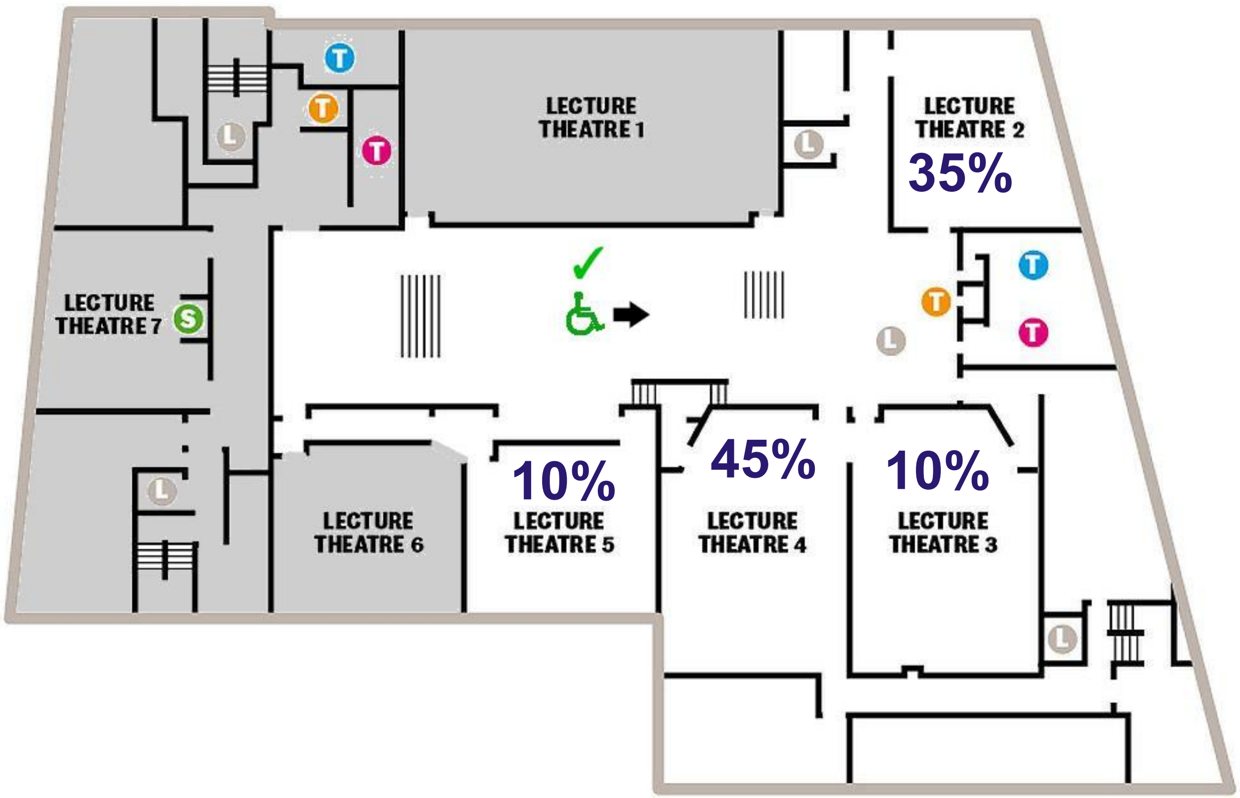
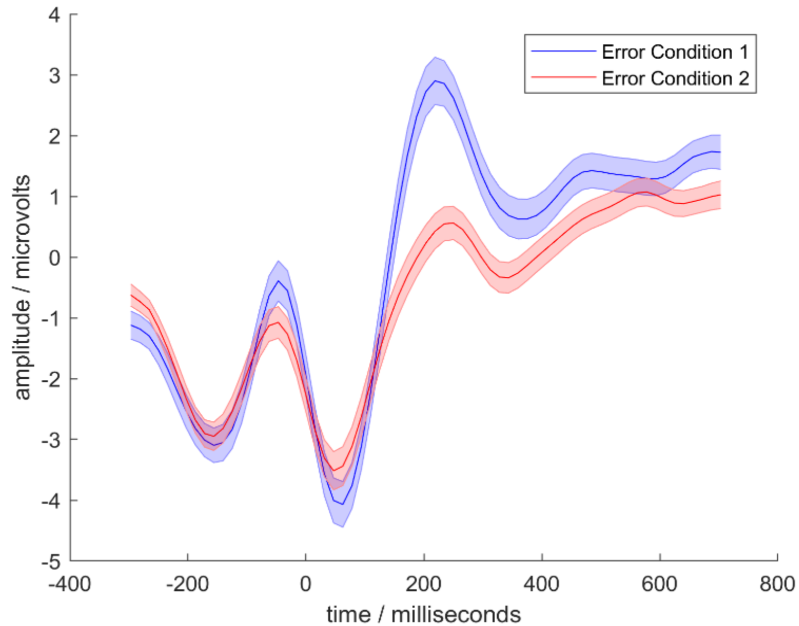


Example of implicit control using EEG error detection and reinforcement learning

Can we have implicit control in greater details?

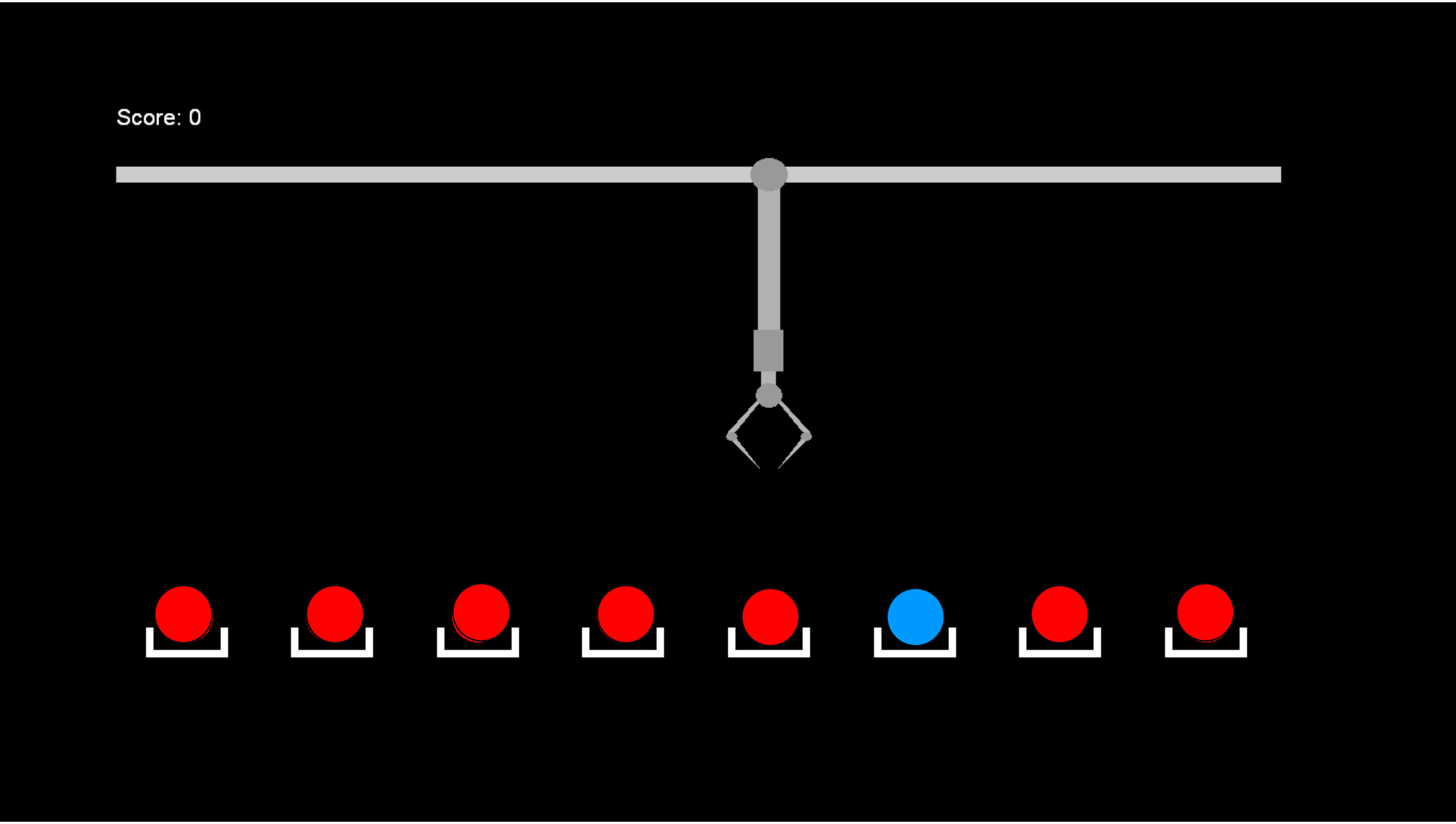
- By going beyond "error or not", we can improve systems further

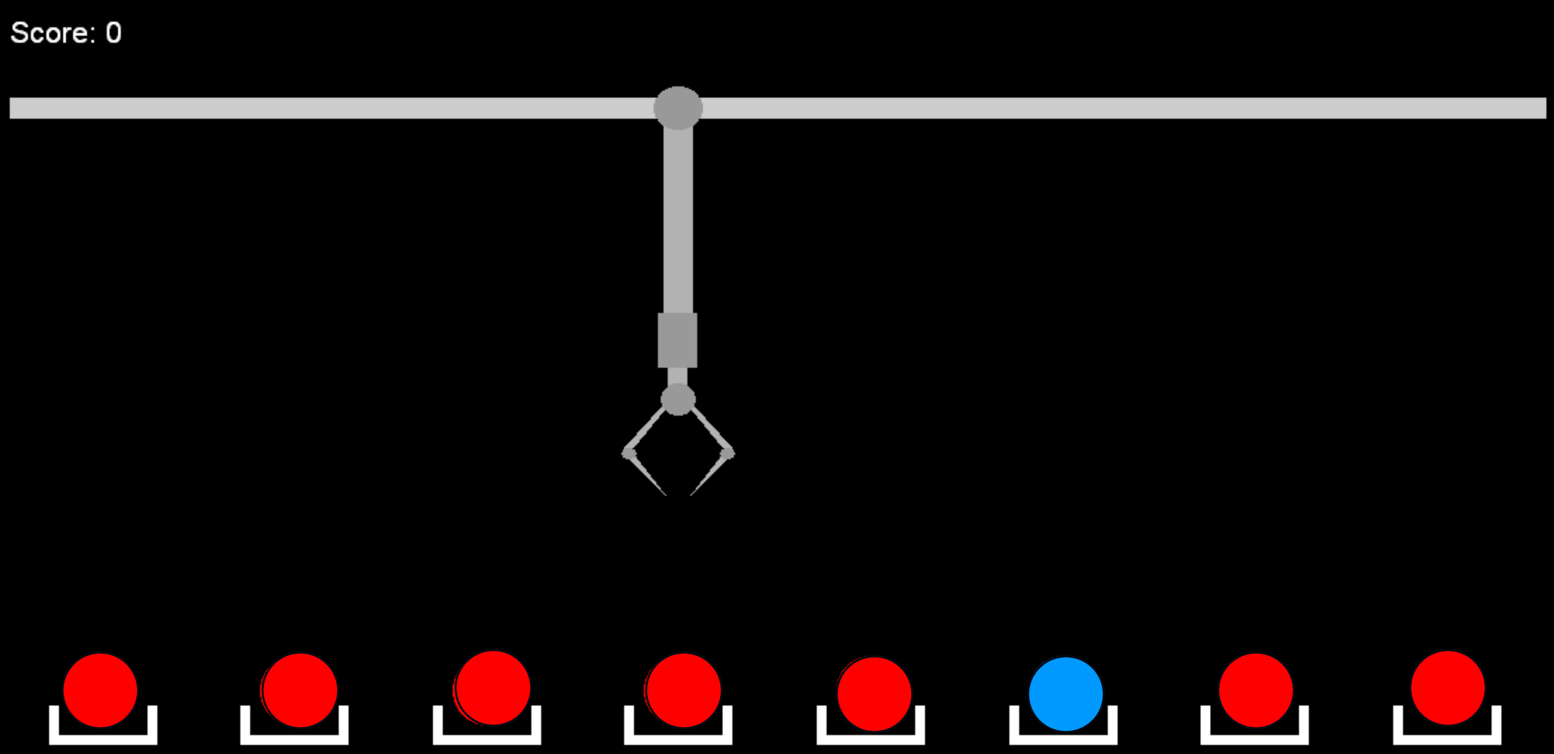


Grand average ErrP at Cz

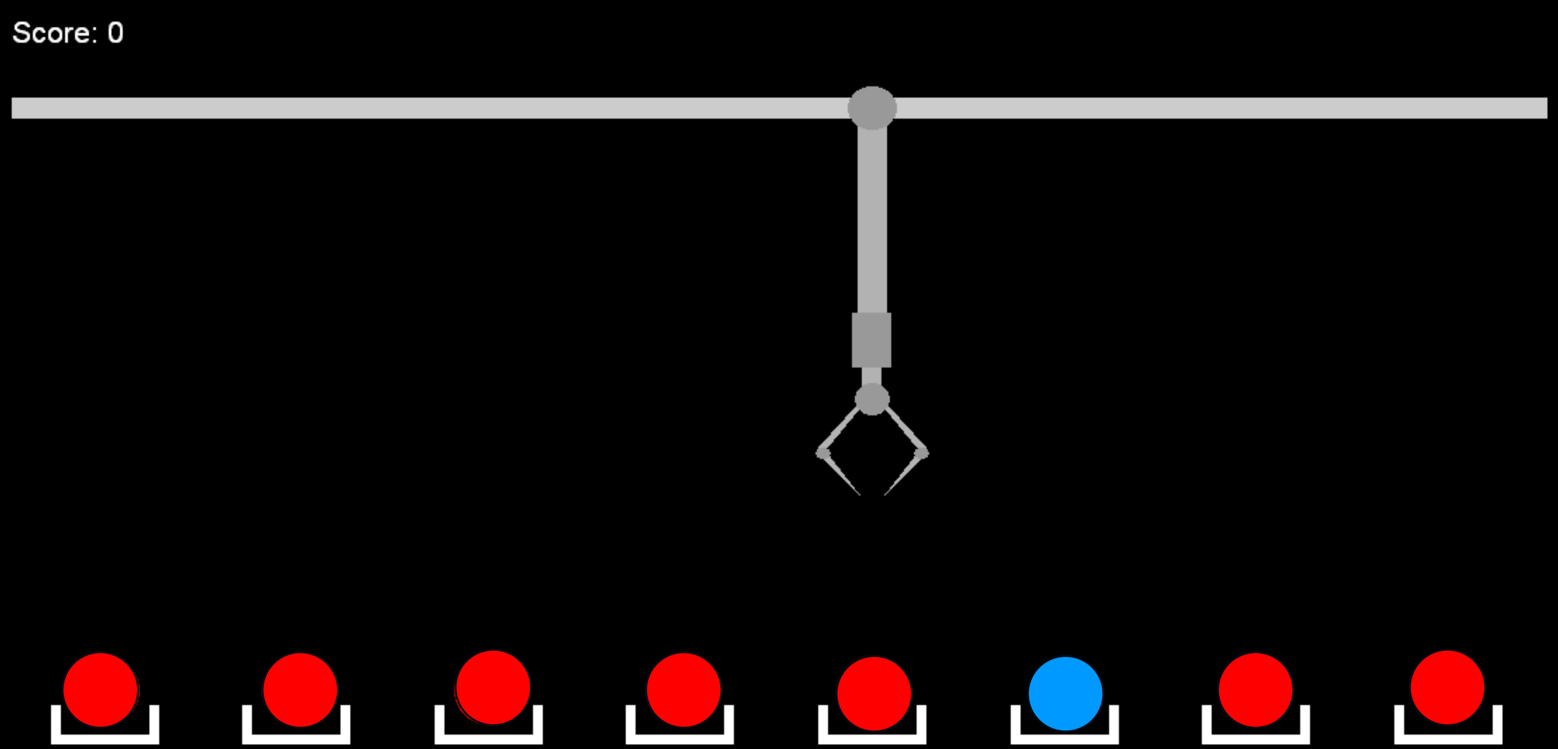
Decision making errors with different severity made by human

- Wirth, C., et al. "Towards error categorisation in BCI: single-trial EEG classification between different errors." *Journal of neural engineering* 17.1 (2019): 016008.

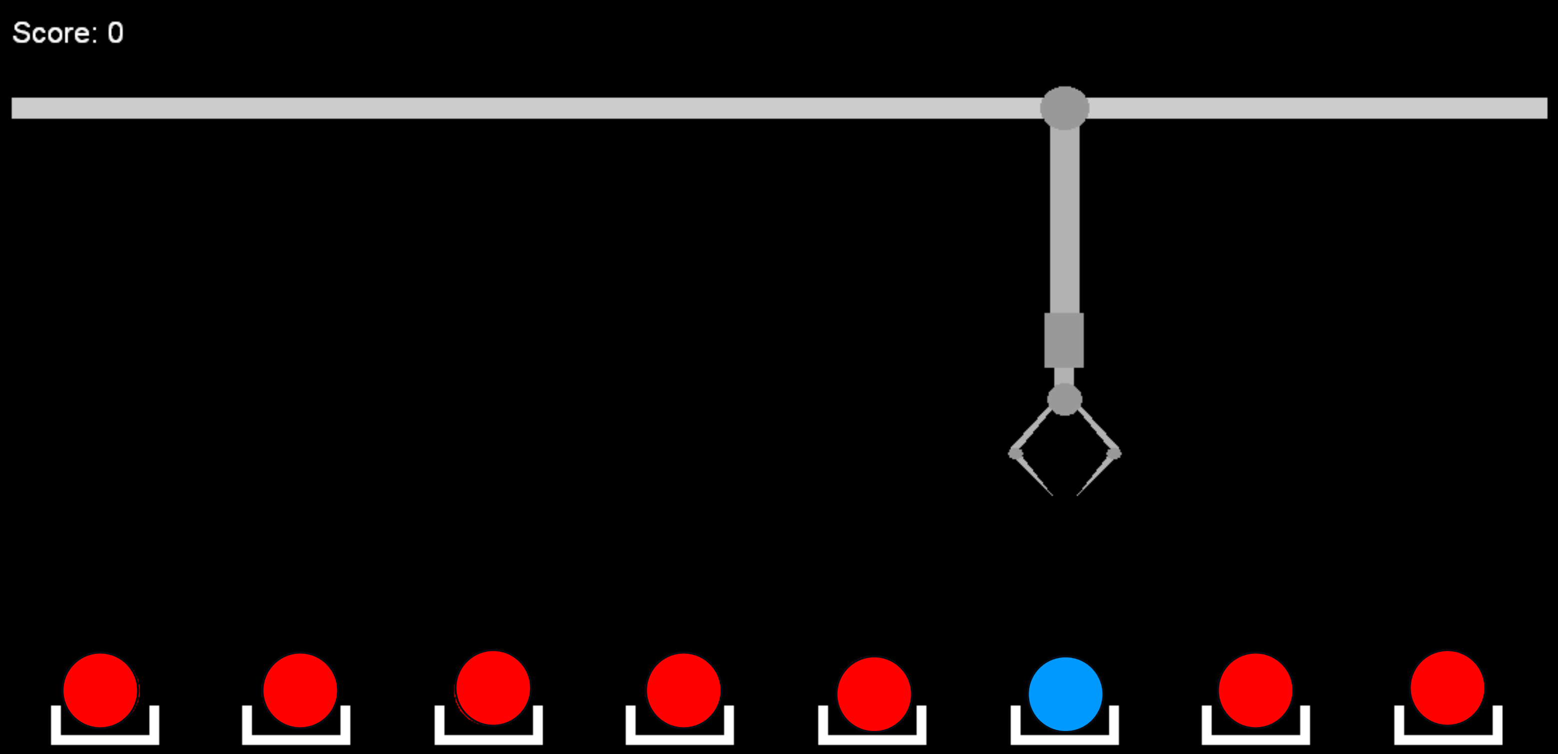

Score: 0



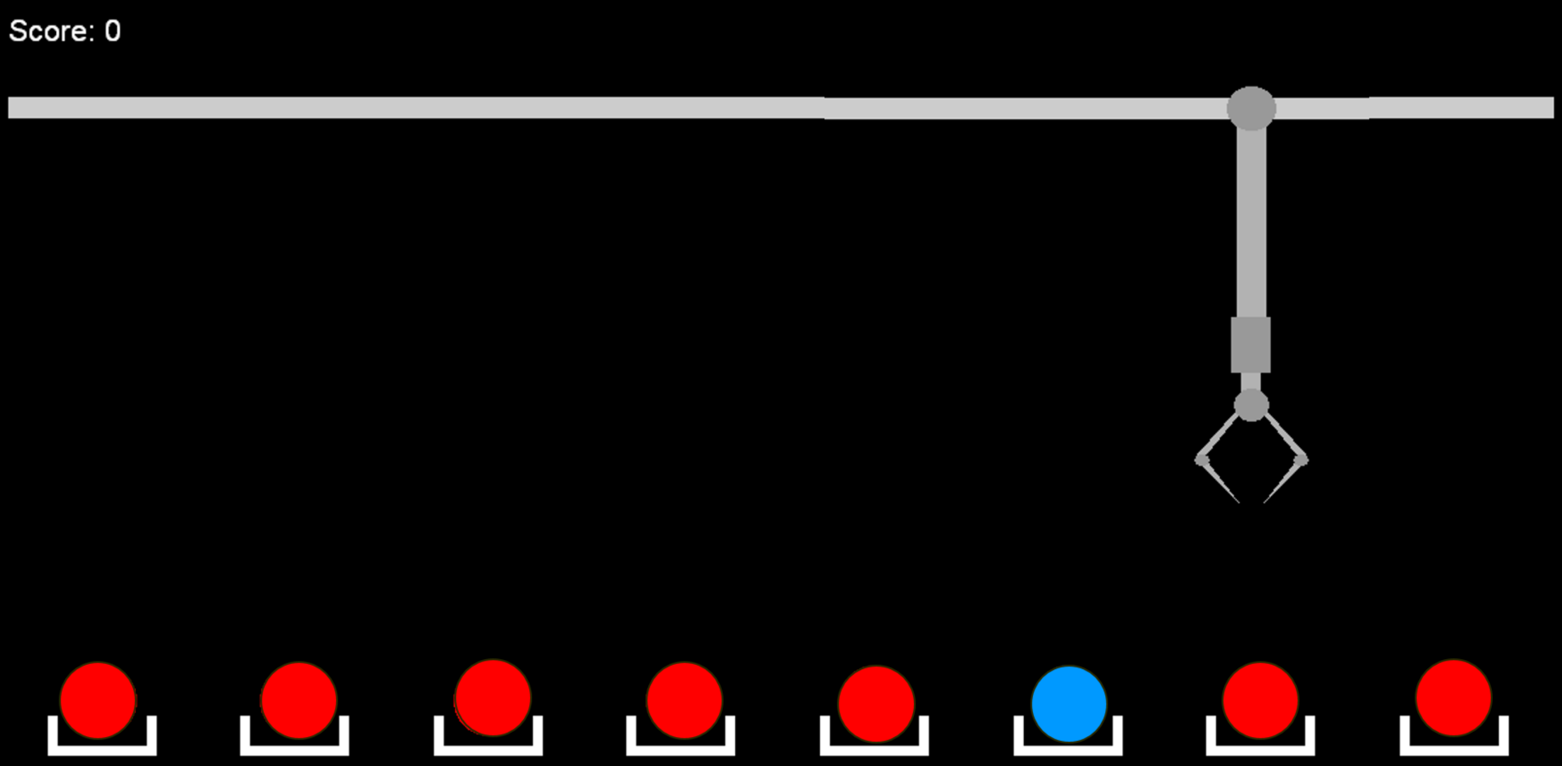
Error type 1: Moving **further from the target**



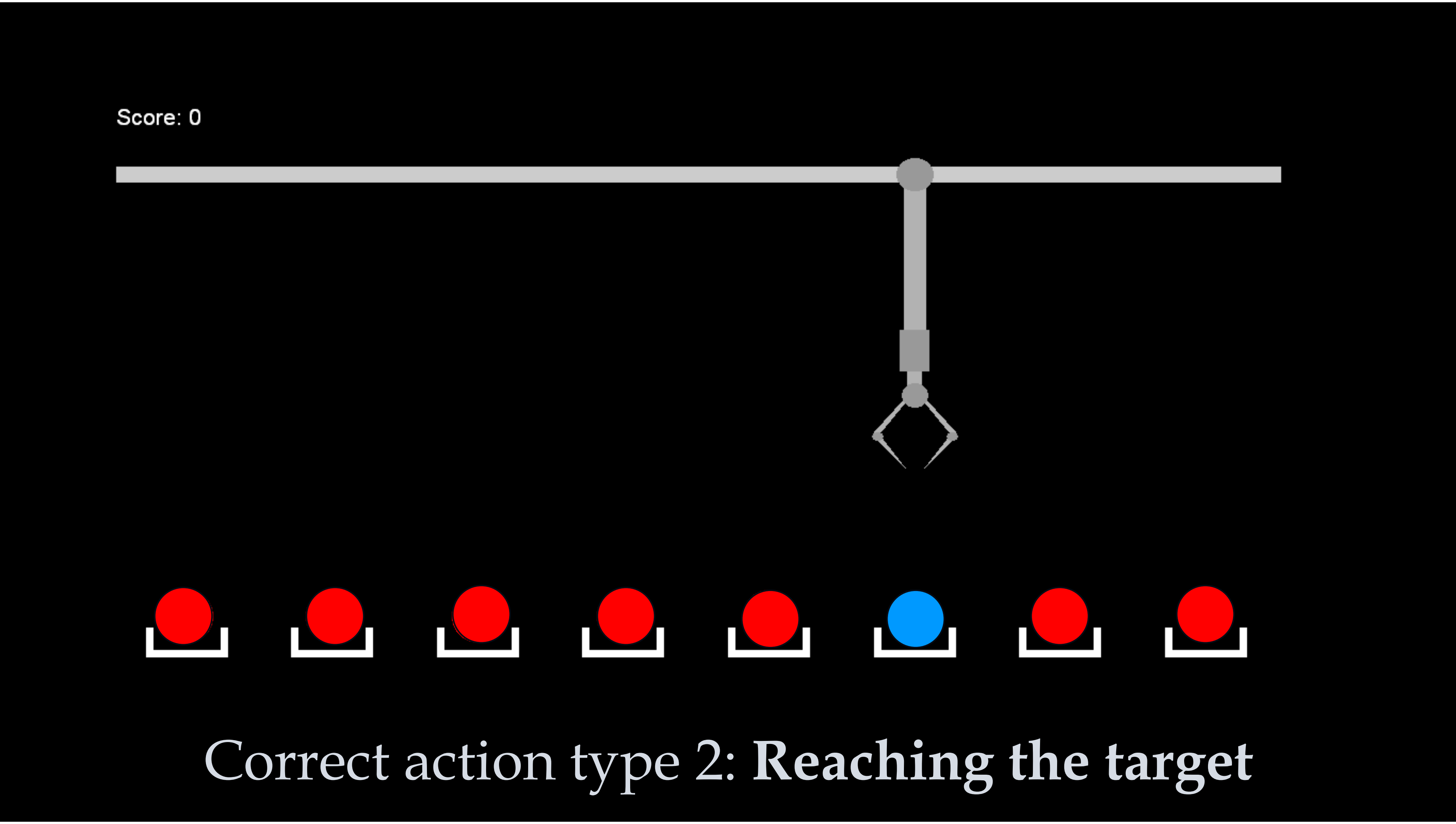
Correct action type 1: Moving **towards the target**

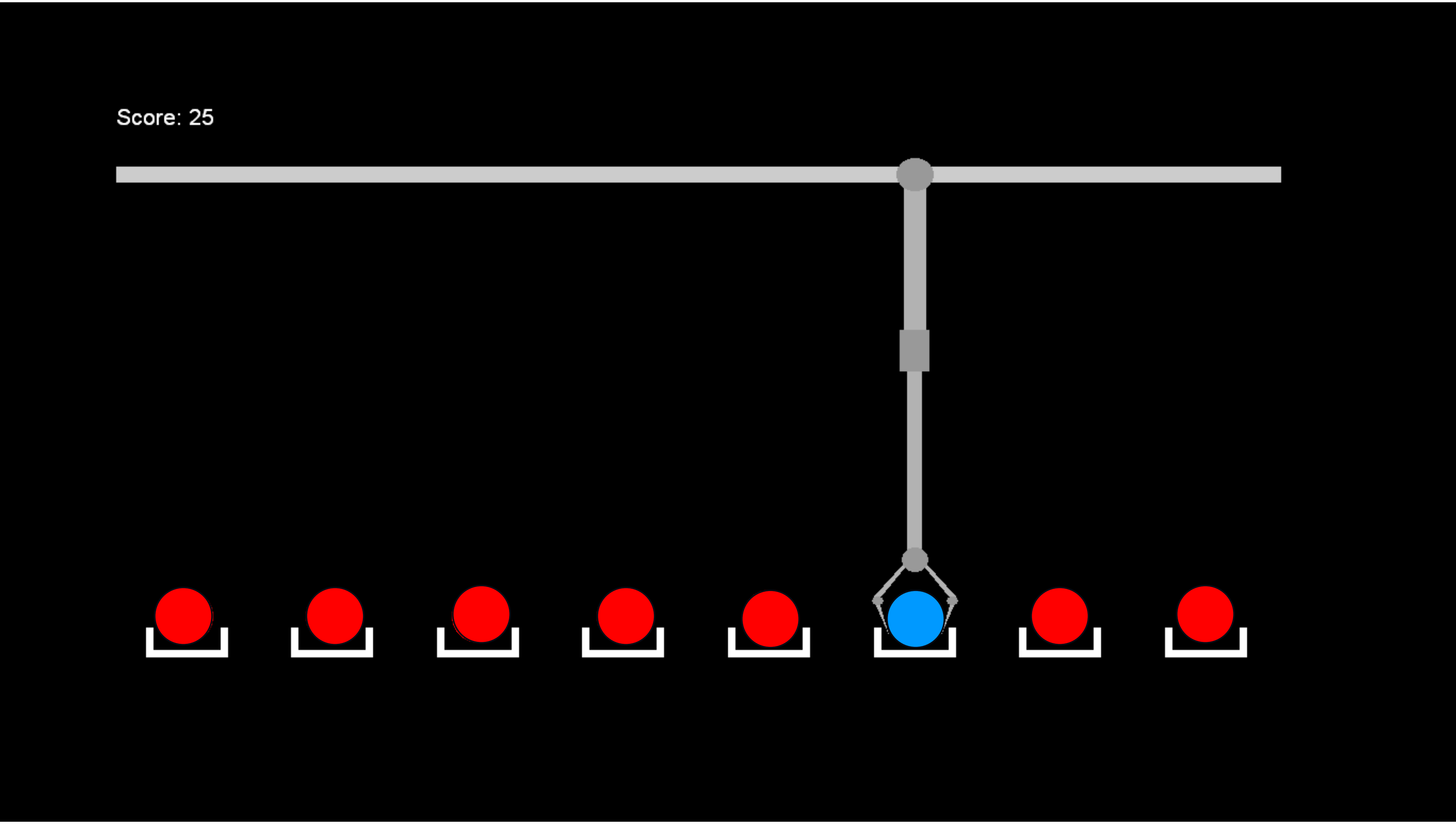


Correct action type 2: **Reaching the target**



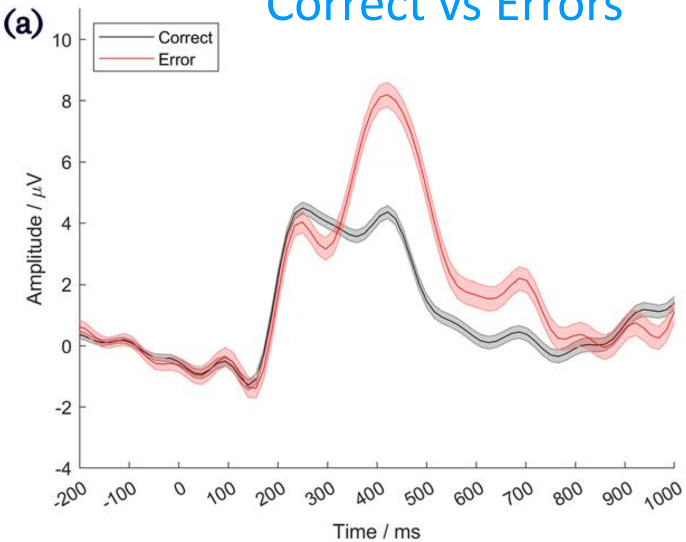
Error type 2: **Stepping off the target** location


Score: 0
Correct action type 2: **Reaching the target**

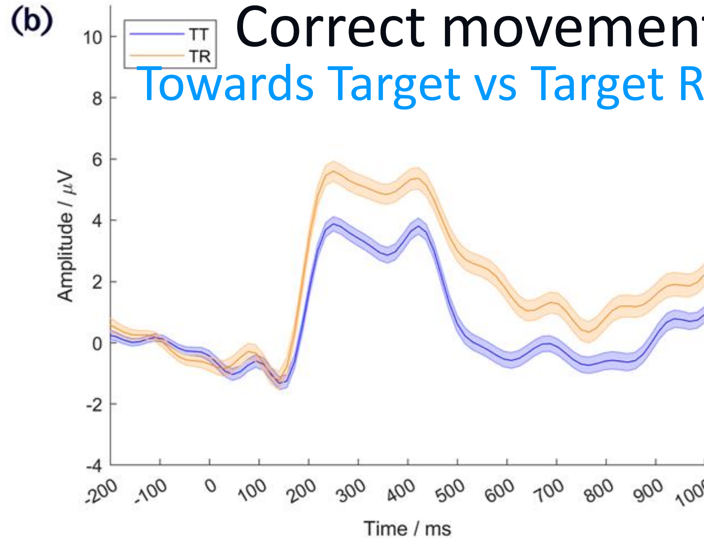

Score: 25

Increasing complexity- EEG from channel Cz

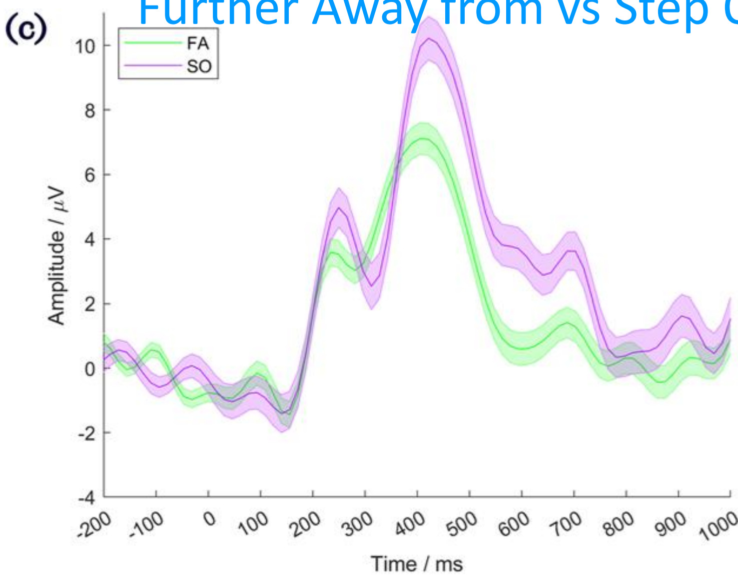
Correct vs Errors



Correct movements:
Towards Target vs Target Reached



Erroneous Movements:
Further Away from vs Step Off the target



EEG data from 14 Participants recorded, while they merely observed robot's actions

Sub-classifying different error types

Classification Challenges:

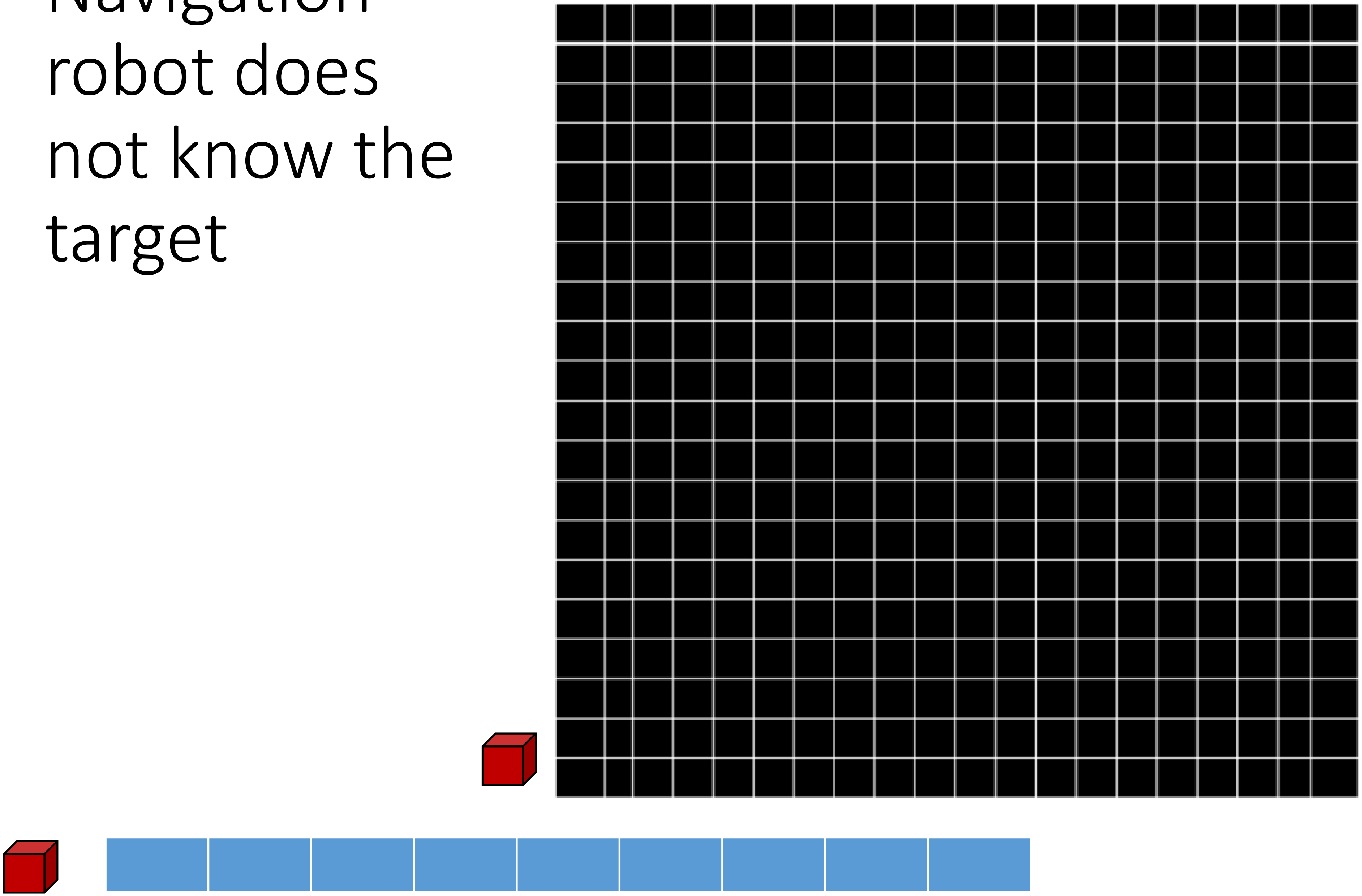
- ✓ Similar signals in noisy data
- ✓ Small training set
- ✓ Imbalance between conditions

Single-trial classification:

- ✓ Down-sampling EEG to 32 Hz, and Oversample smaller class
- ✓ 1-10Hz band-passed EEG amplitudes, 8 electrodes
- ✓ Extracting EEG intervals (200-700ms)
- ✓ Stepwise LDA (minimum 1, maximum 20 features)

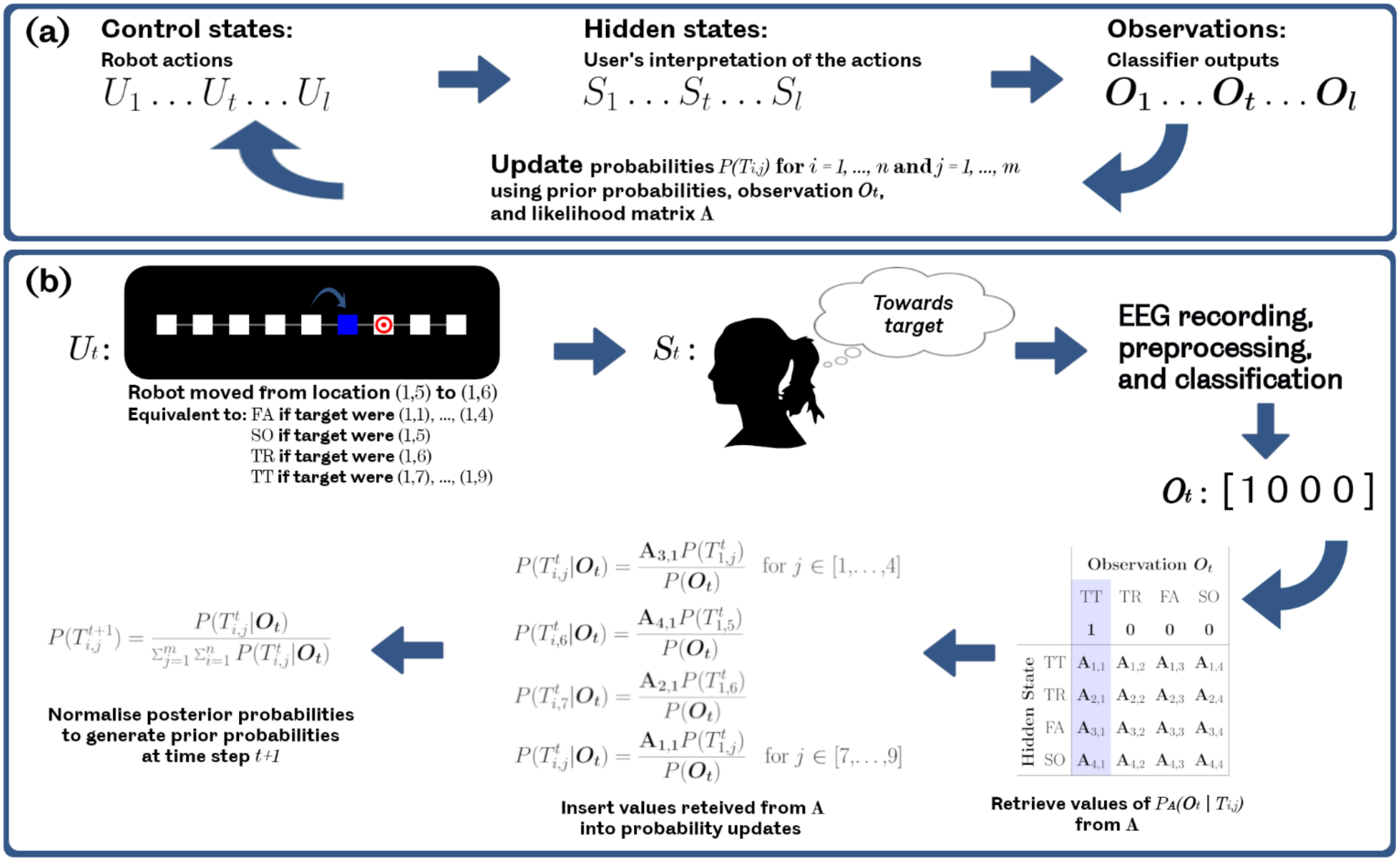
Classification Accuracy		Error 1 vs Error 2	# Significant	Correct 1 vs Correct 2	# Significant
Navigation Task 1	Mean	65.2%	18 of 25 participants	66.5%	All participants
	Max	80.8%		83.7%	
Navigation Task 2	Mean	65.6%	10 of 14 participants	68.0%	all participants
	Max	79.5%		72.4%	

Navigation robot does not know the target

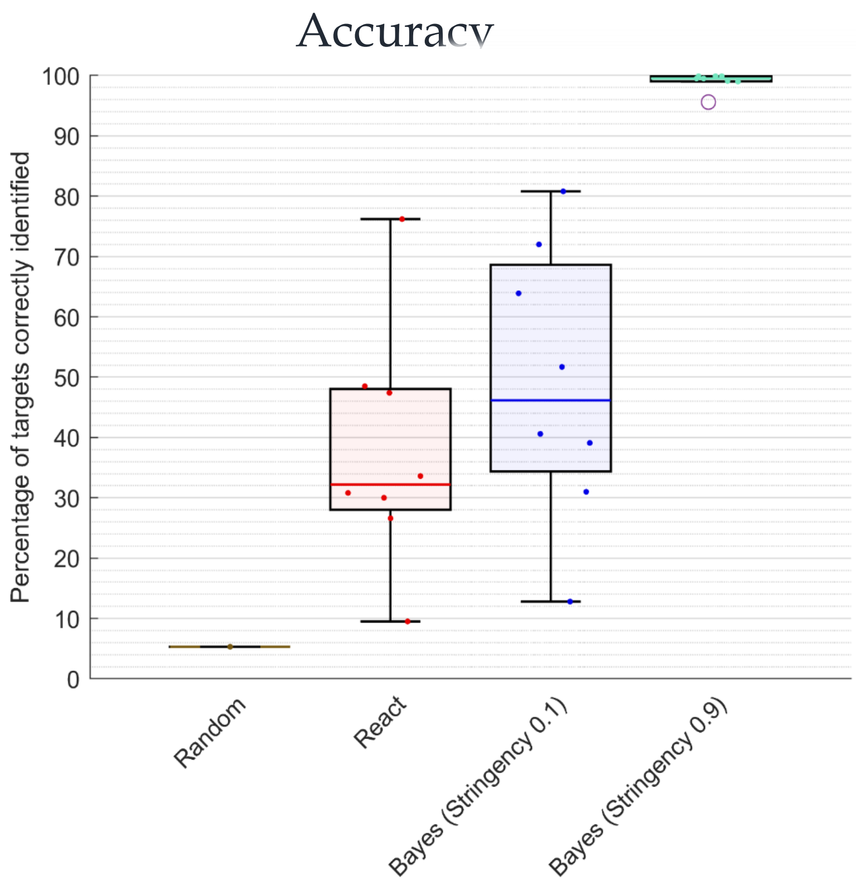


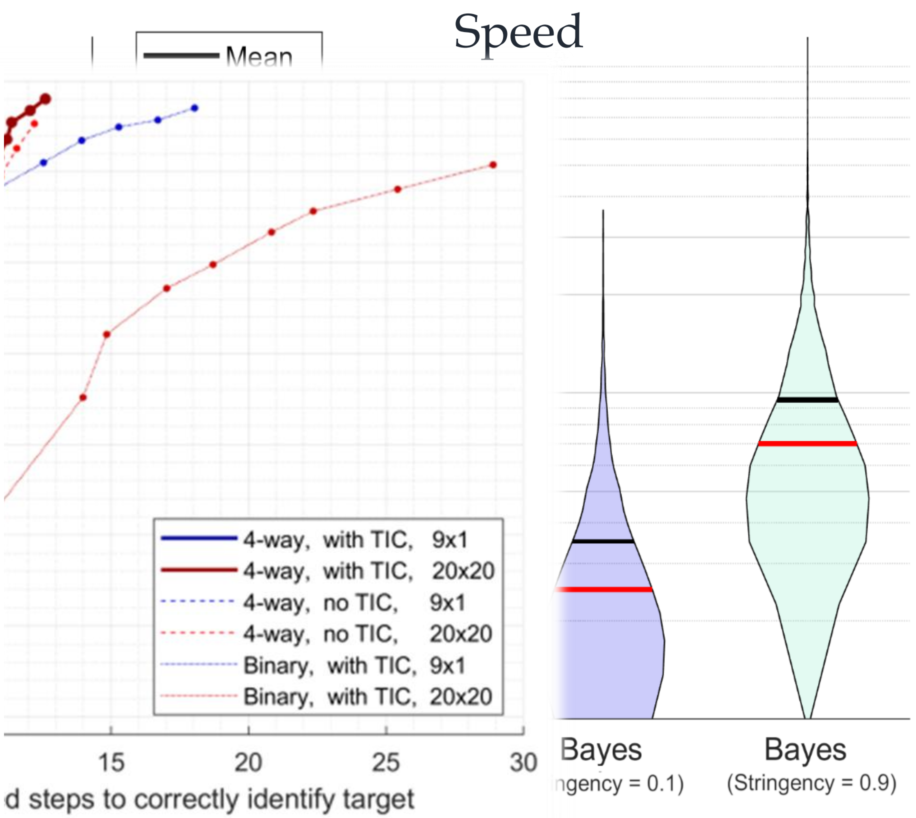
Implicit control of a robot while merely observing its actions

- Bayesian inference builds a model of target probabilities
- Variable *stringency*, determines level of certainty required to identify target



Performance and Scalability of our Solution in Identifying Targets





- Testing efficacy of Bayesian approach against
  - *Random* strategy
  - *React* strategy: using EEG feedback for correction only (no learning)

Impact

- Opened a new horizon on implicit BCI
- Further improving the machine learning models
- Overcoming Challenges of a Human-in-the-Loop Scenario
- Expansion upon the user behaviour model
- Extending to other tasks and applications