Ulster University

Decoding mental imagery from electroencephalography (EEG) and applications of AI-enabled wearable neurotechnology for communication and rehabilitation

Prof Damien Coyle

Professor of Neurotechnology

Turing AI Fellow, 2021-2025

Director, Intelligent Systems Research Centre,

Ulster University, Northern Ireland, UK

Part 1: Brain-computer interface (BCI) and motor imagery basics

Part 2: Spinal injury : Competing at Cybathlon

Part 3: Brain Injury : Communication and Cognitive Profiling in Disorders of Consciousness

Part 4: Stroke : Rehabilitation

Part 5 : Post traumatic stress disorder : Alleviating symptoms with neurofeedback

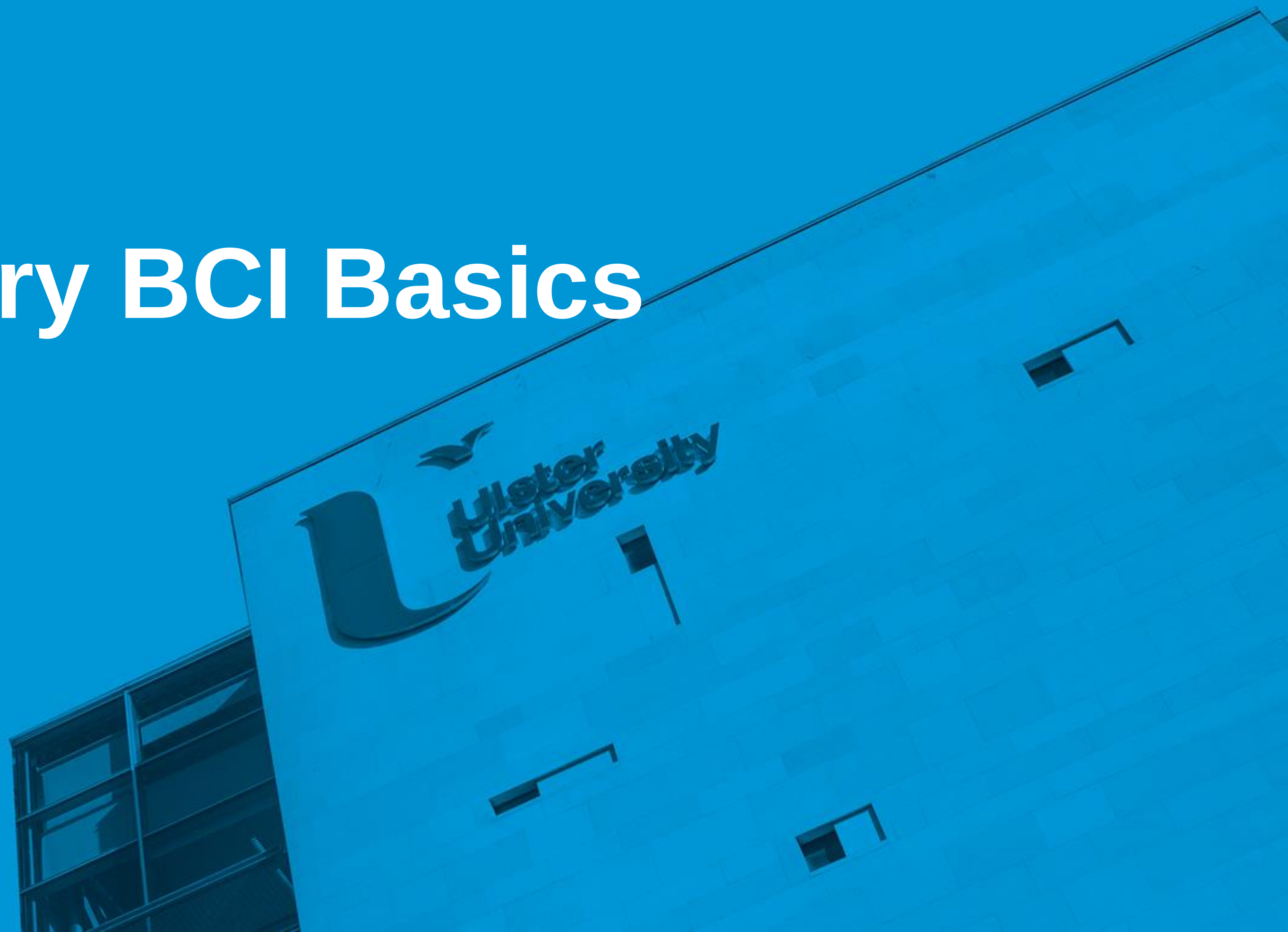
Part 6: Decoding upper and lower 3D limb movement from EEG

Part 7: Prospects for Direct Speech BCI with Imagined-speech

Part 8 : Emotion and Shape imagery classification from EEG

Part 8: Other type of BCIs

Part 1: Motor Imagery BCI Basics



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

Three pillars

Machine Learning

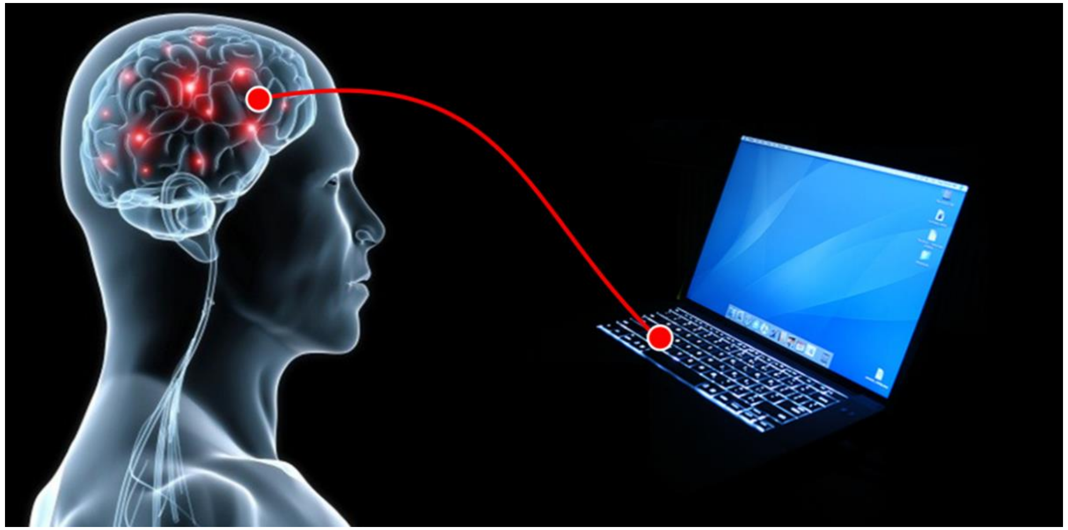
Training

Application

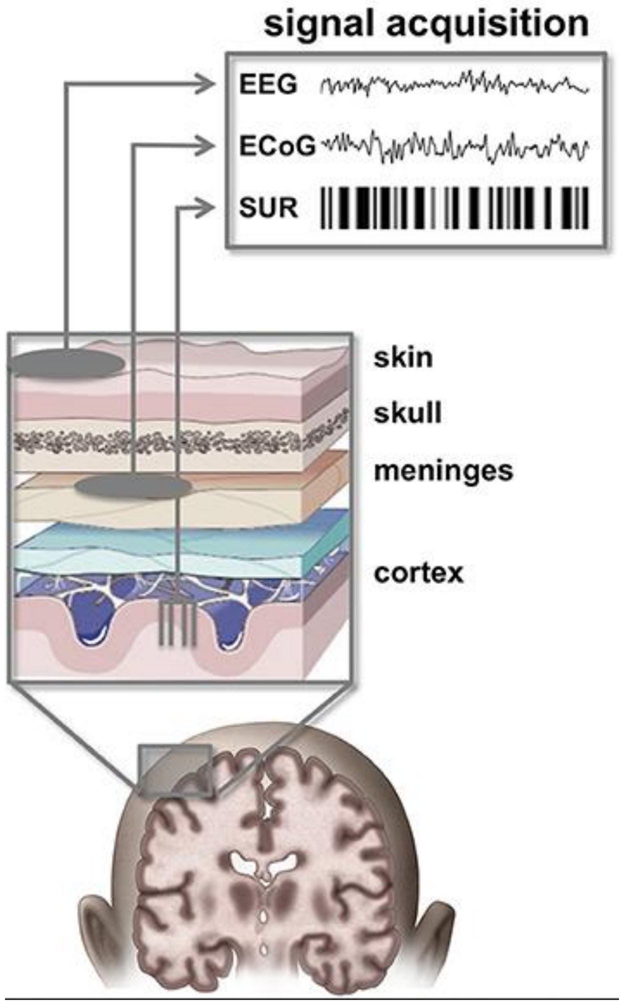
Performance

Brain-Computer Interface

BCI

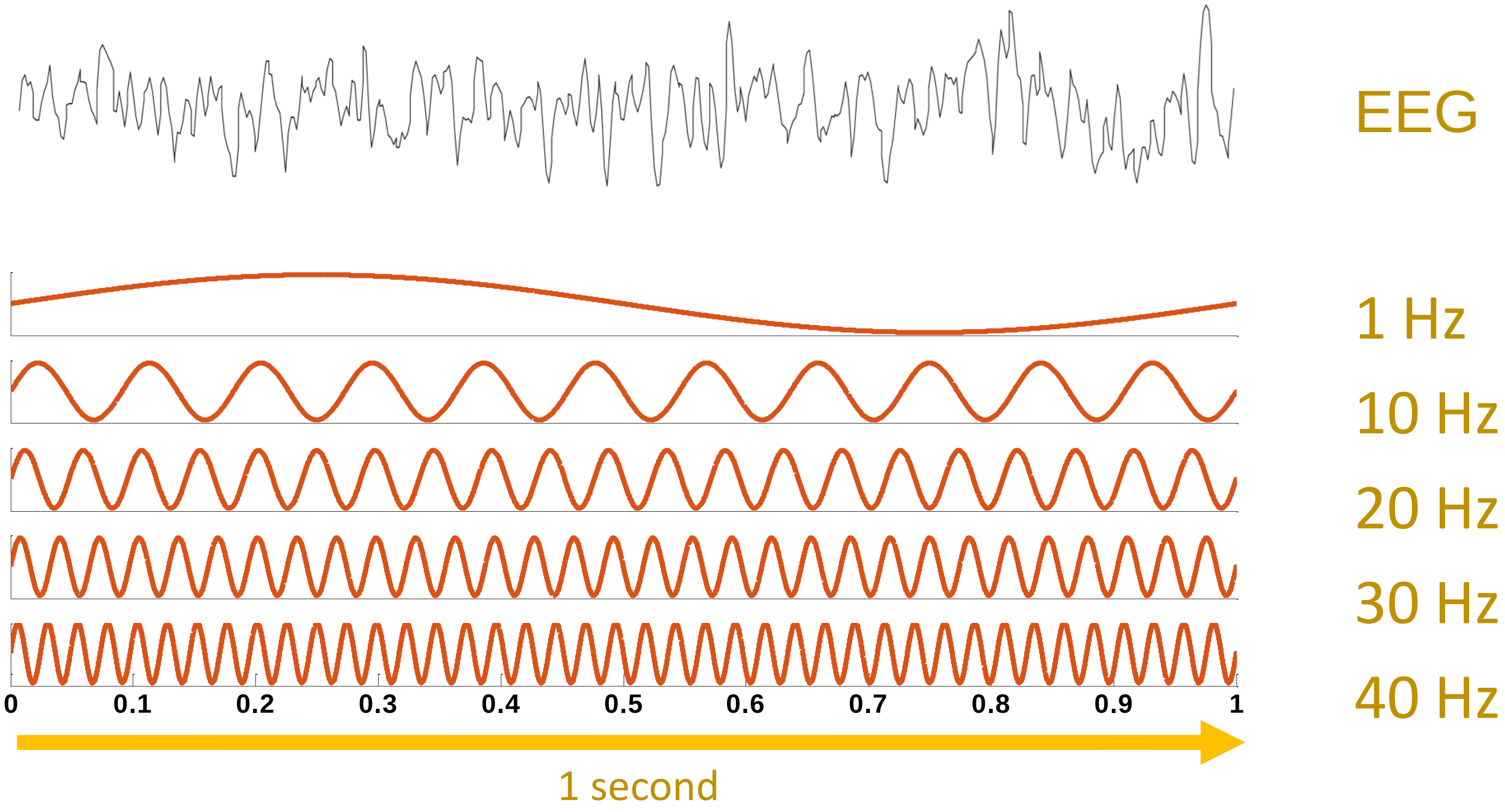


Neural Interface		Physical Interface
INTENT	→ Command	ACTION
PERCEPT	← Coding	STIMULUS

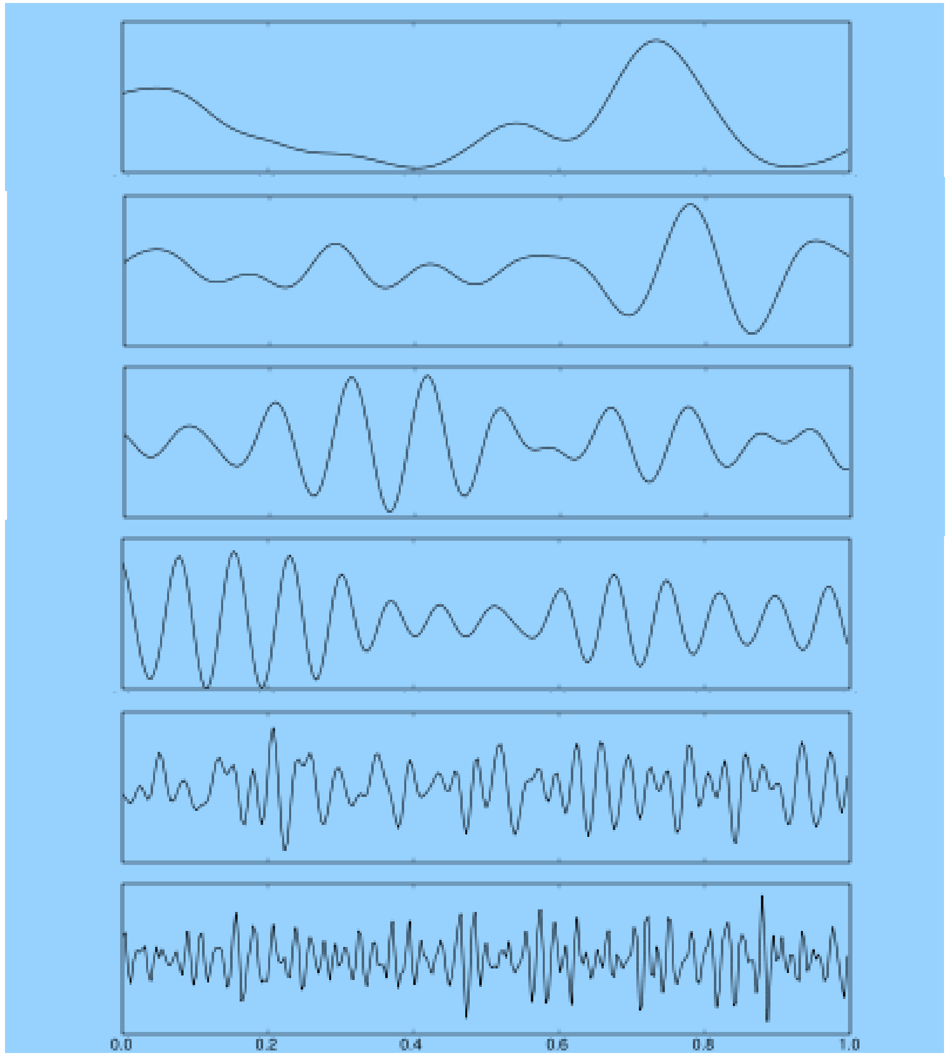


EEG and Frequency (Hz)

Ulster University



Brain Rhythms/Oscillations

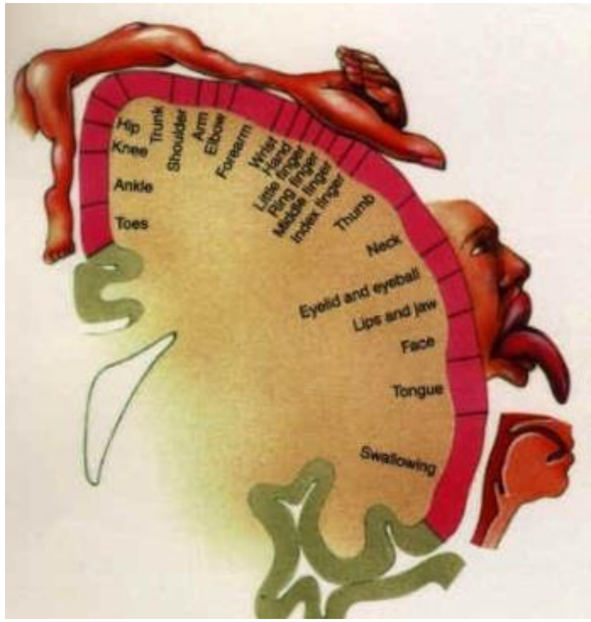


1 second

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

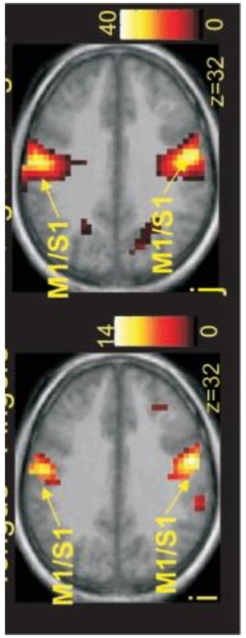
HOMONCULUS: The little guy

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

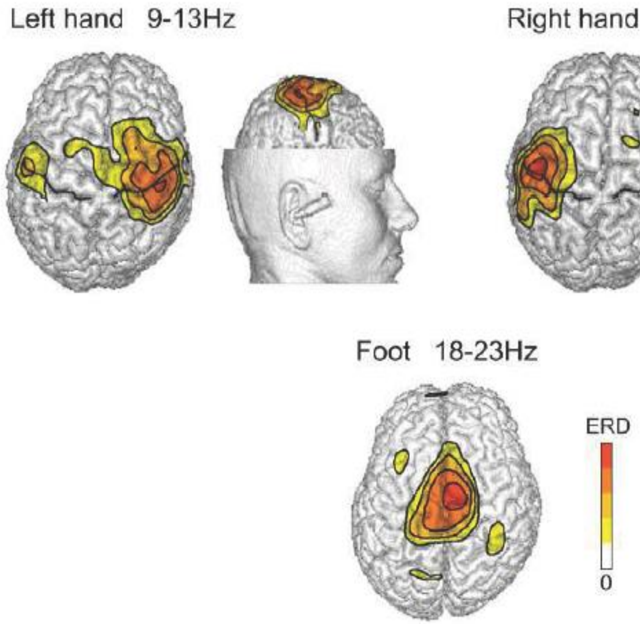


Movement and Imagined Movement

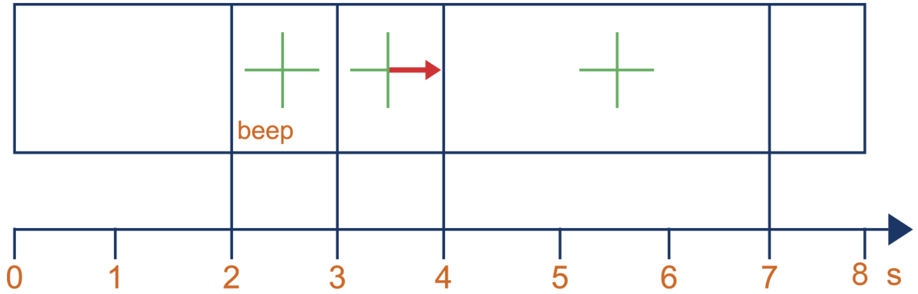
- Tongue

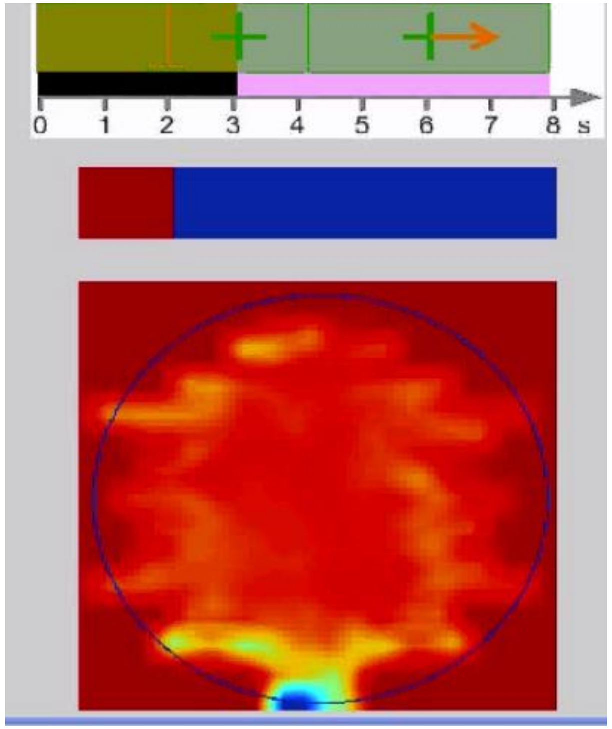


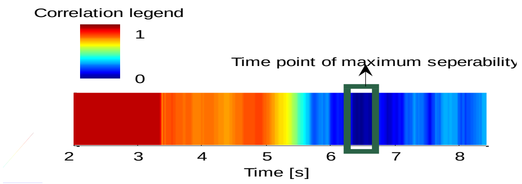
- Execution
- Imagery
- *(Ehrsson et al, 2003)*



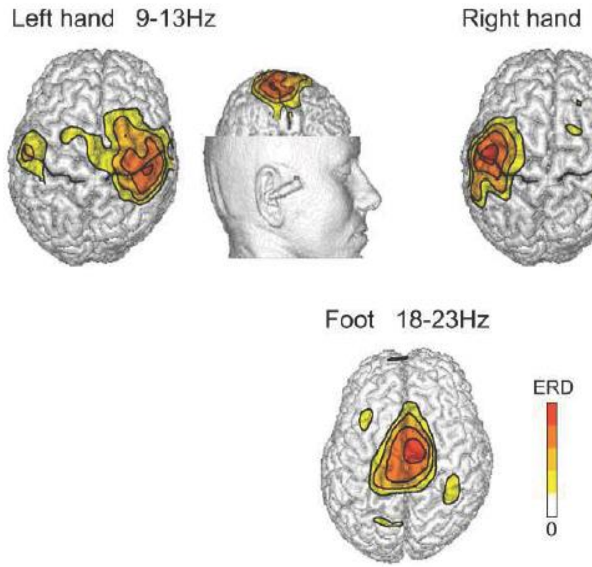
(Pfurtscheller et al, 2001)



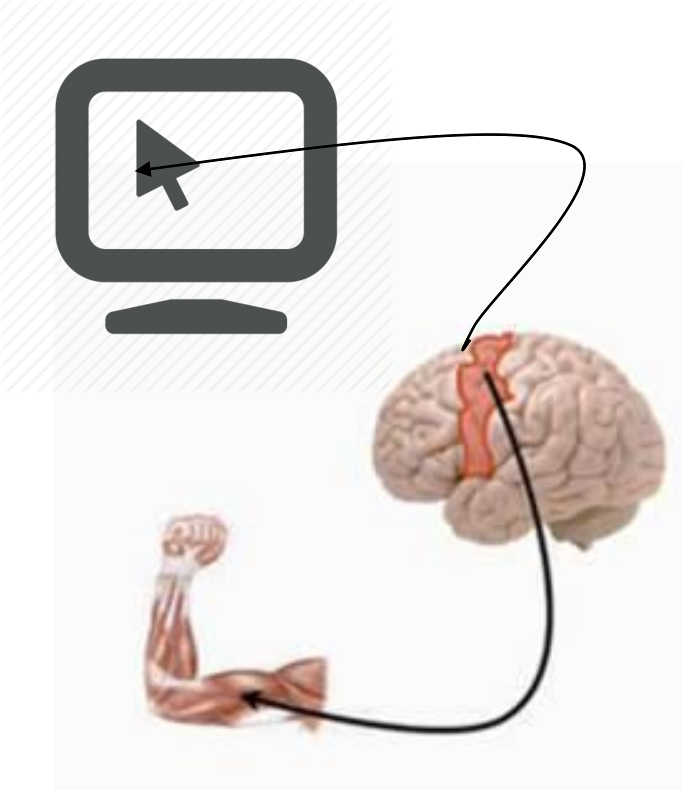




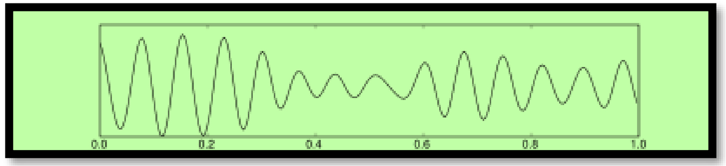
Why motor imagery for BCI?



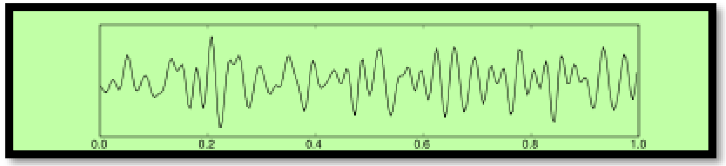
(Pfurtscheller et al, 2001)



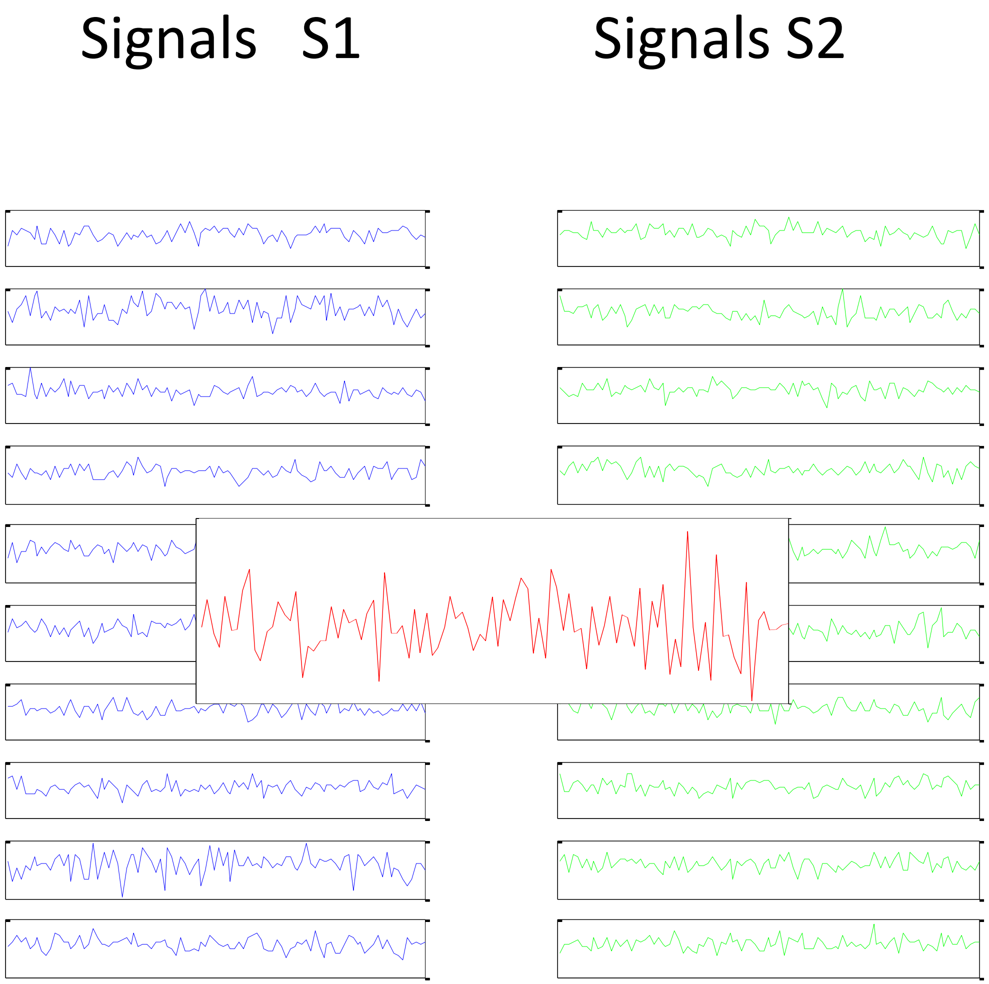
- Mu



- Beta

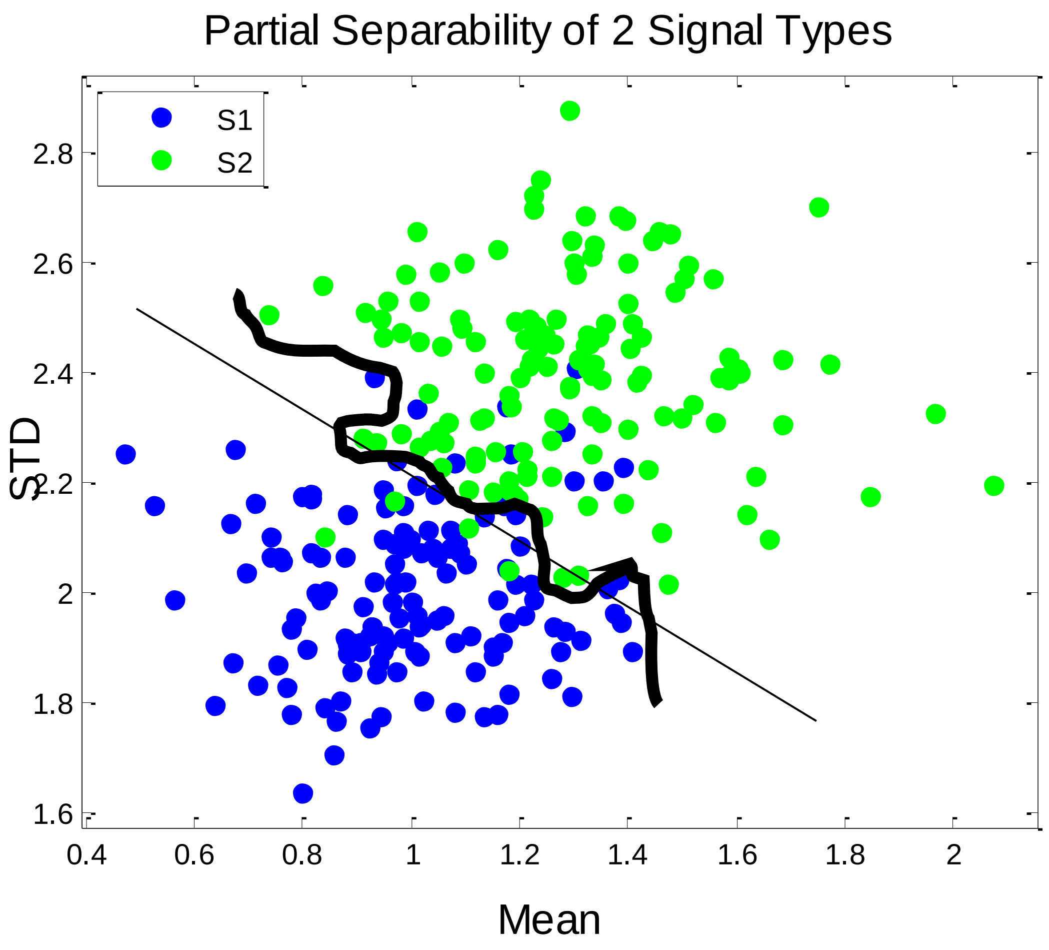


Feature Extraction and Classification



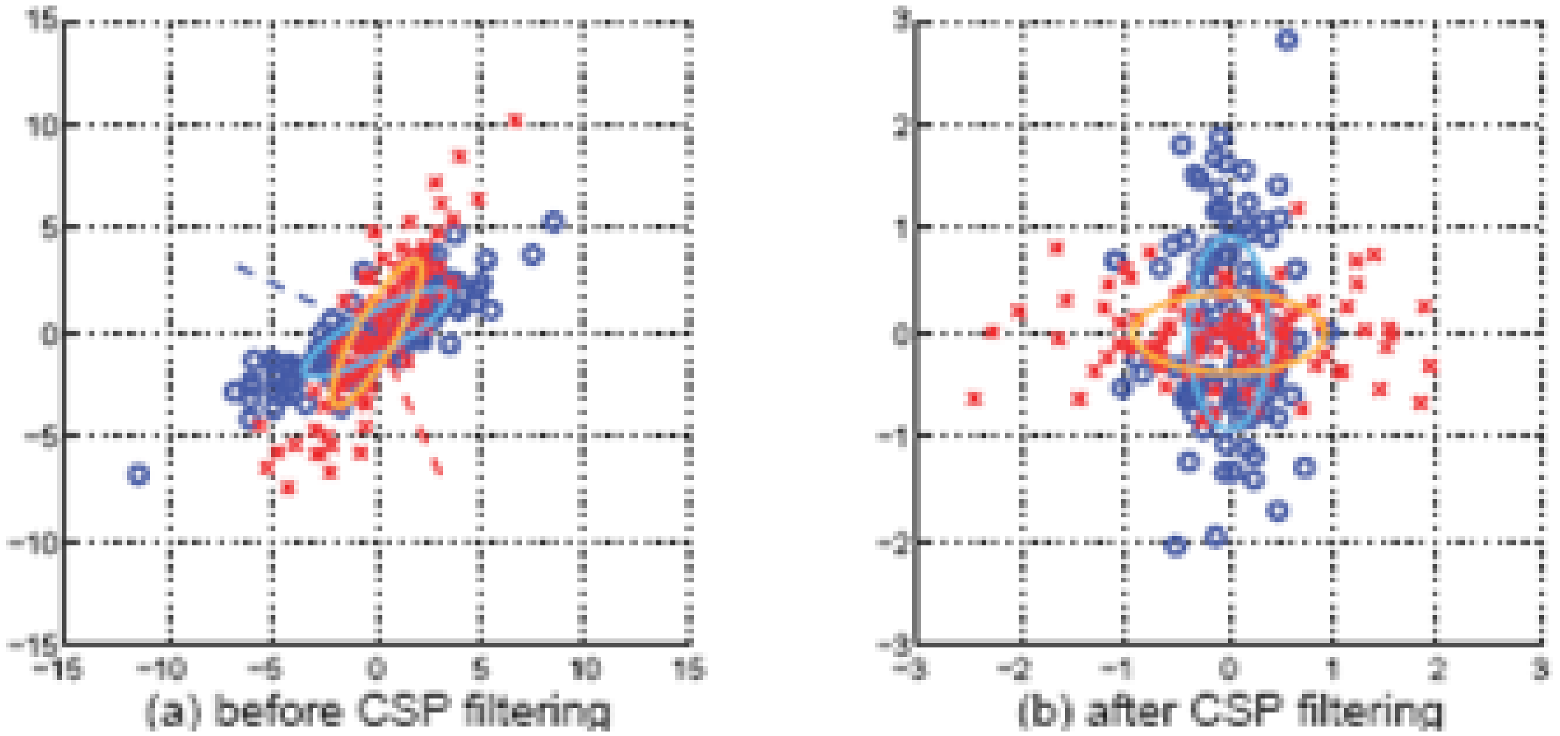
- Too much data to consider
  - High data dimensionality
- No visible Differences
  - Separability
- Need to reduce data and make the data more separable

Scatter Plot of features and separating hyperplane



- Extracted from 274 signals
- The majority of features can be separated into one of two classes easily using a linear separating plane
- A nonlinear separating plane may improve the separation

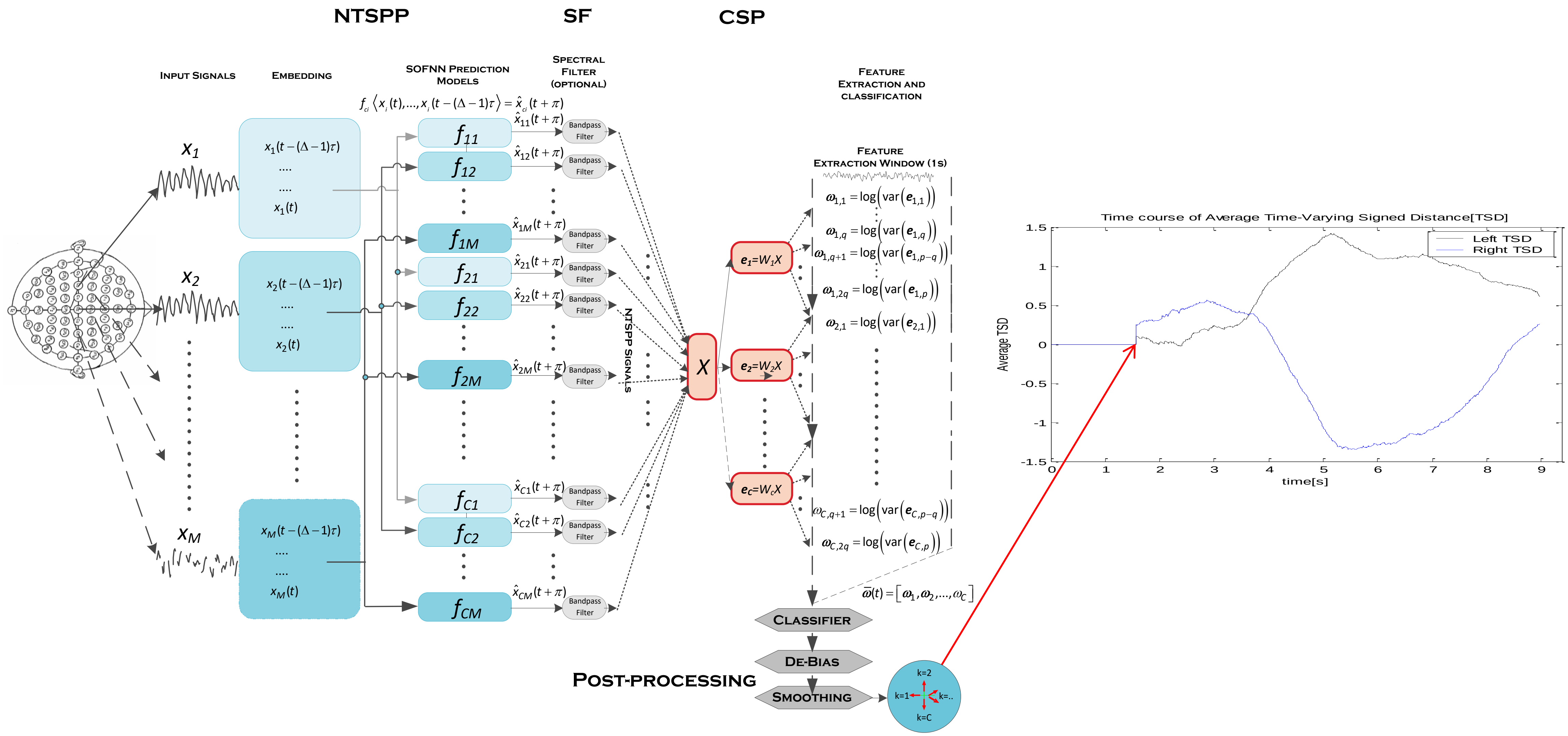
Common spatial patterns



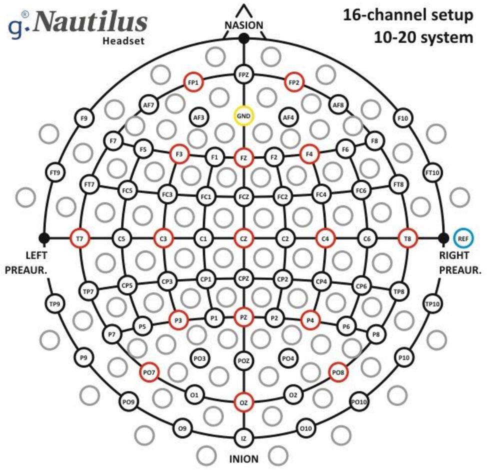
Blankertz et al. [8]

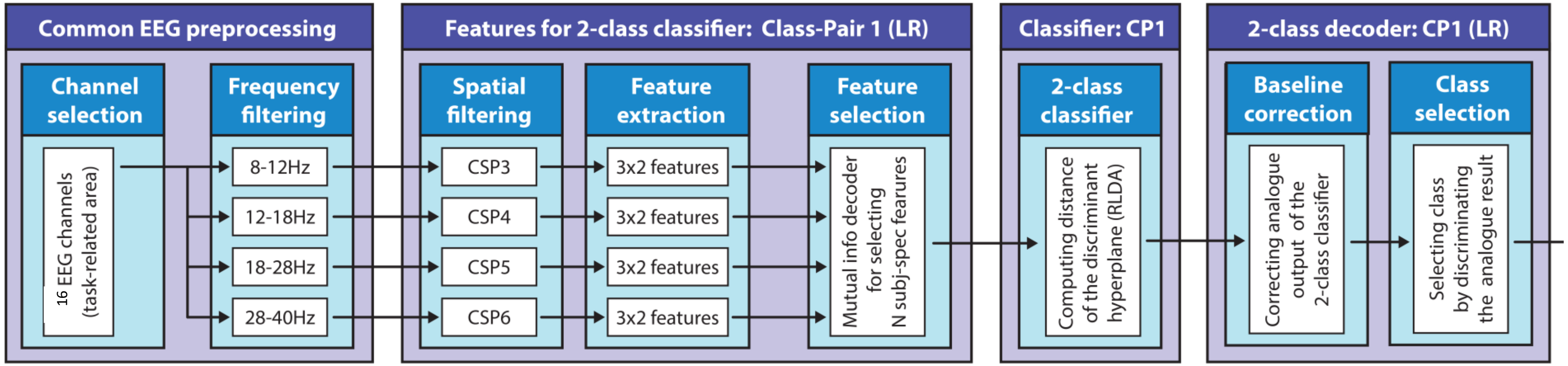
Neural Time Series Prediction Pre-processing

Multistage Signal Processing



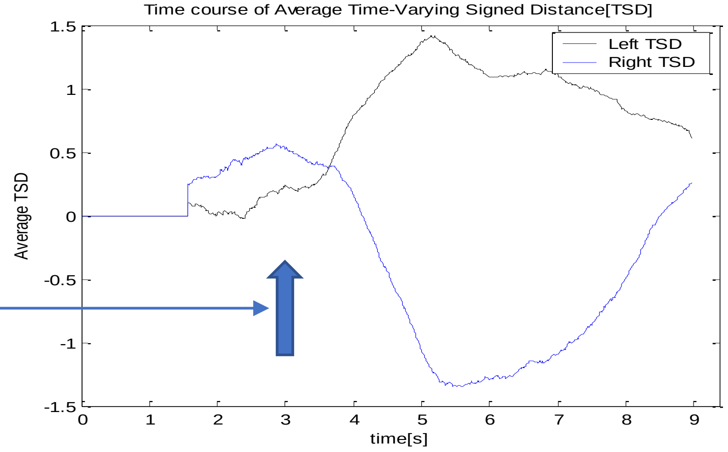
Filterbank Common Spatial Patterns (FBCSP) with Linear Discriminant Analysis (LDA)



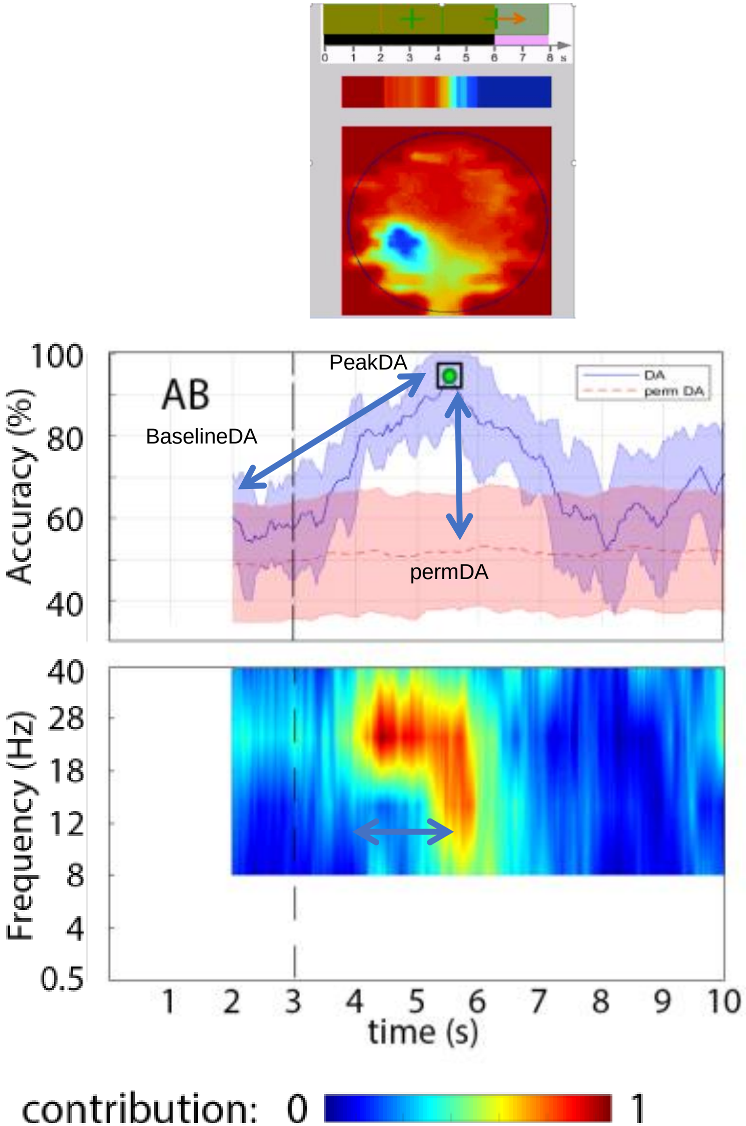


16

Cue to Imagine Movement



Decoding accuracy (DA) and control signals

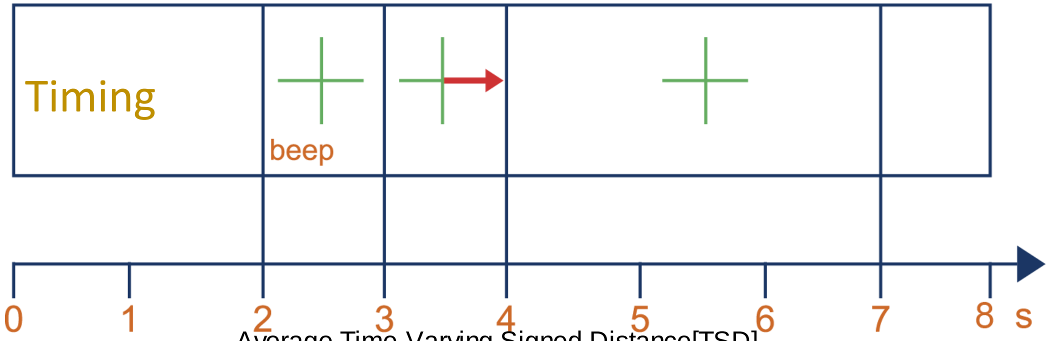


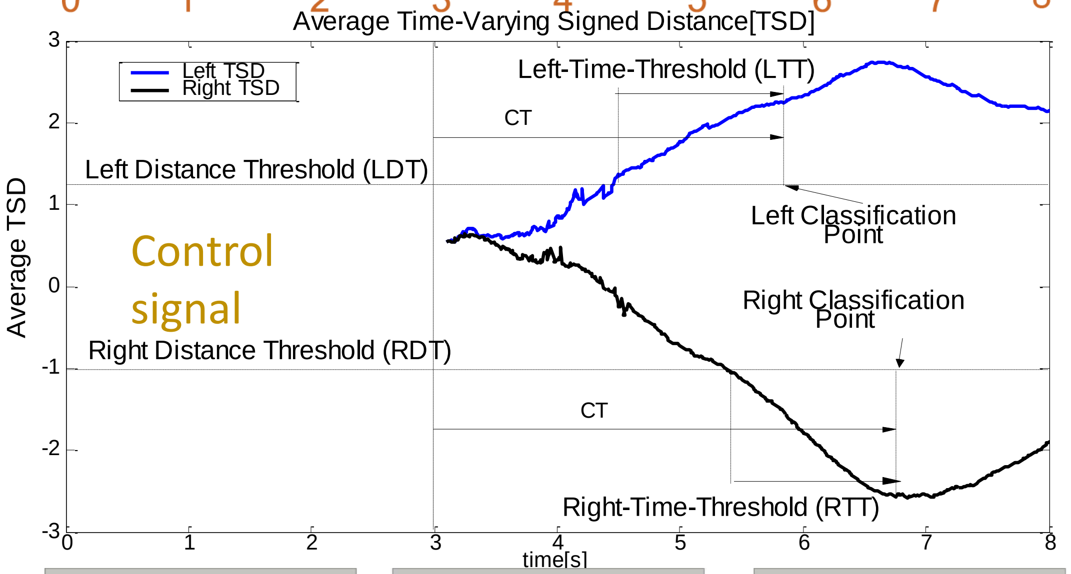
Baseline Vs Peak DA

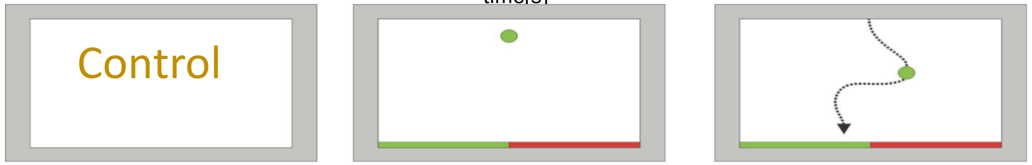
PermDA vs Peak DA

100 permutation tests

Observable change in Corresponding Frequency Contribution within the Decoding Window



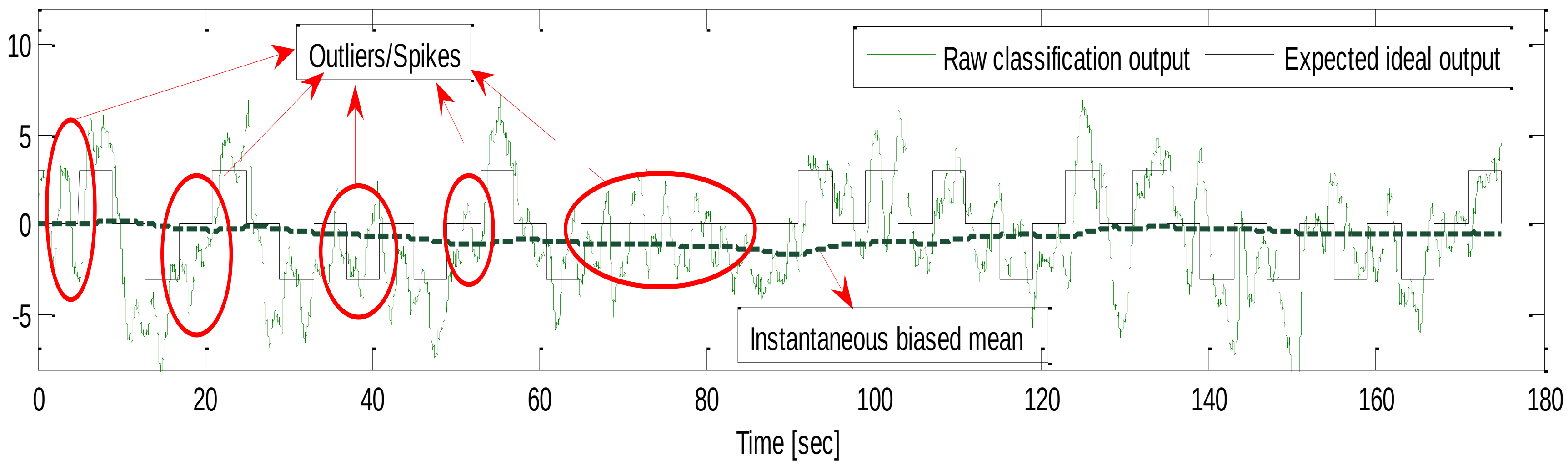




Continuous output analysis

After all that – still problems

-



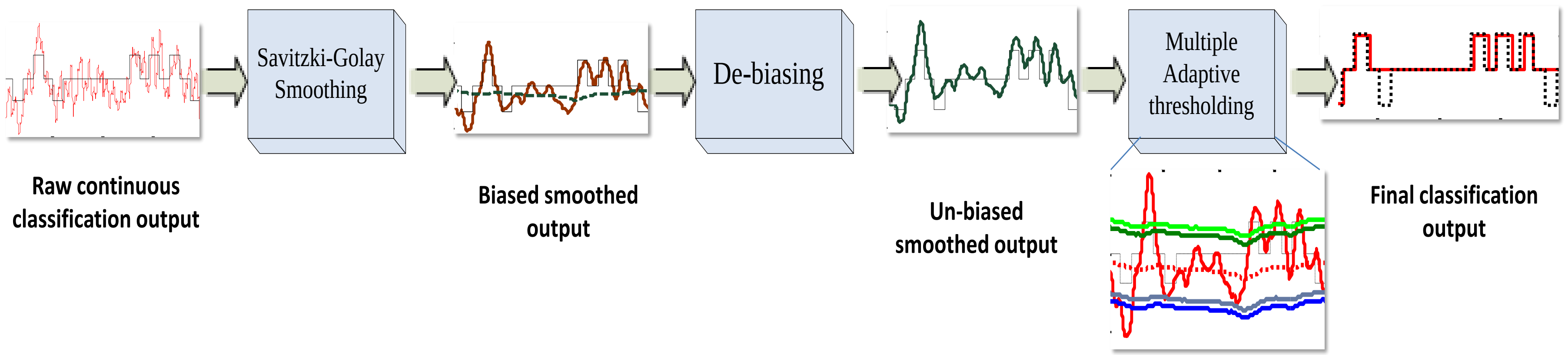
Adaptive post-processing

Savitzky-golay filtering for removing spikes/outliers

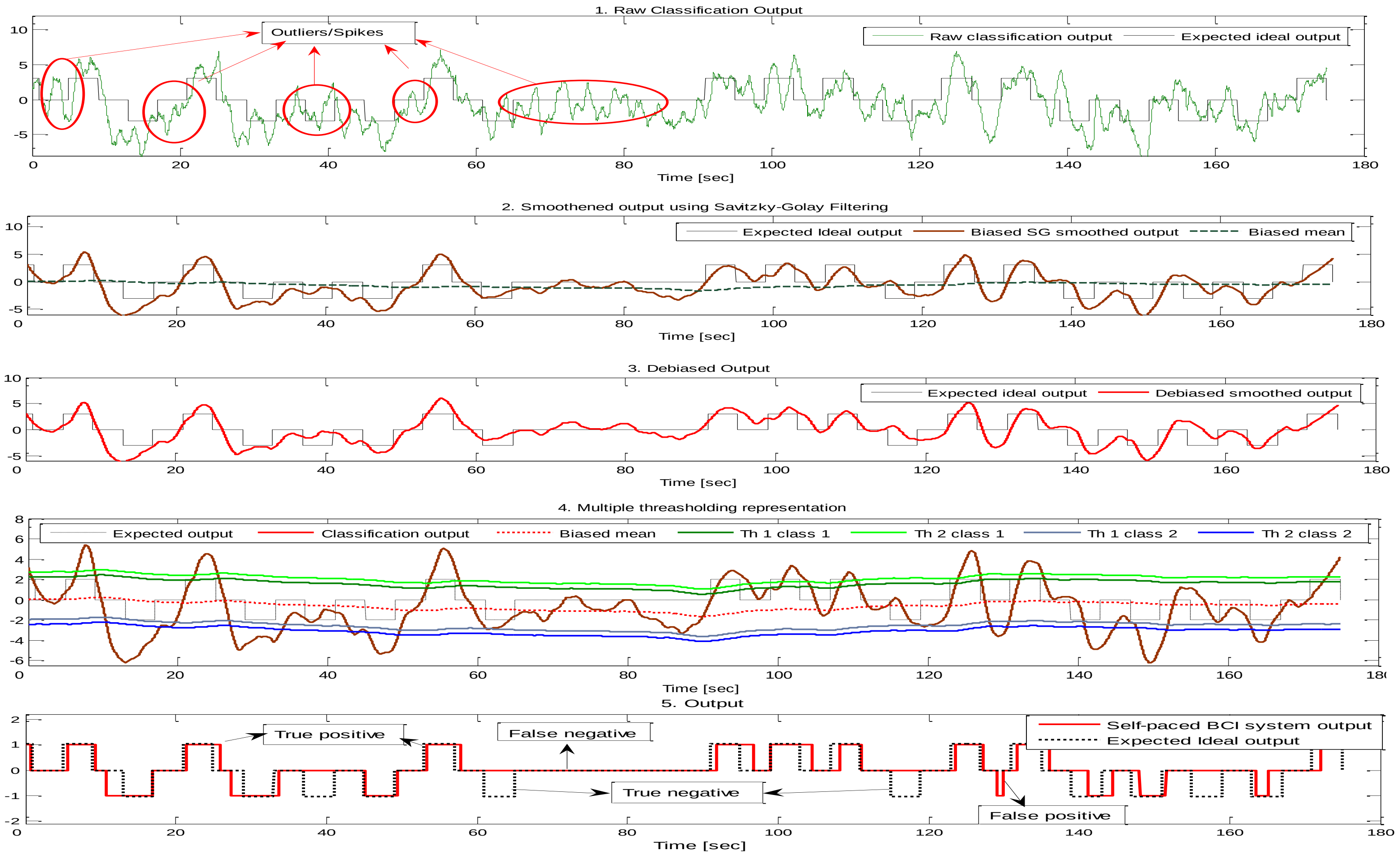
De-biasing to remove instantaneous bias

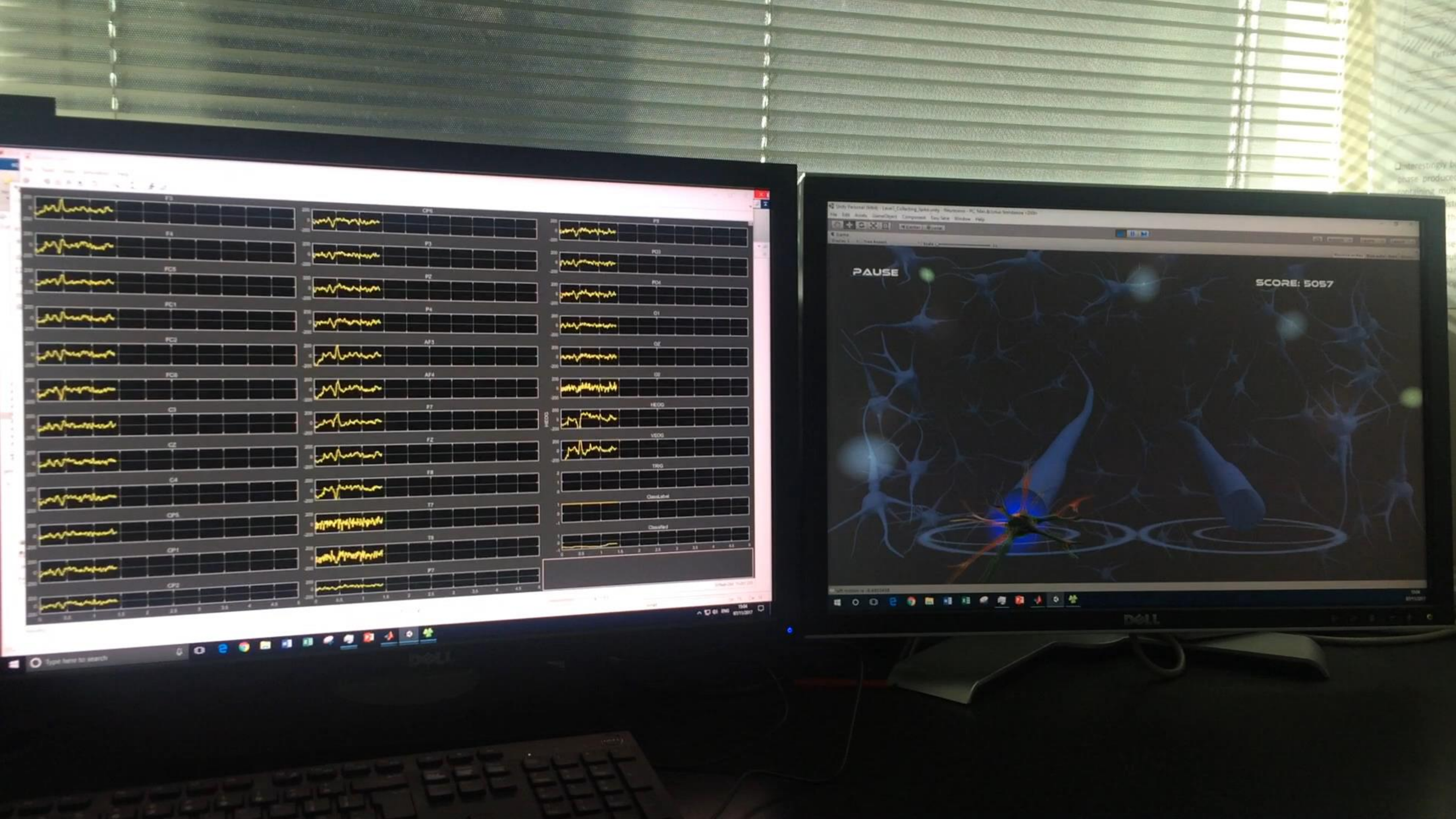
Multiple adaptive thresholding to adapt to different levels of threshold based on gradient information

•

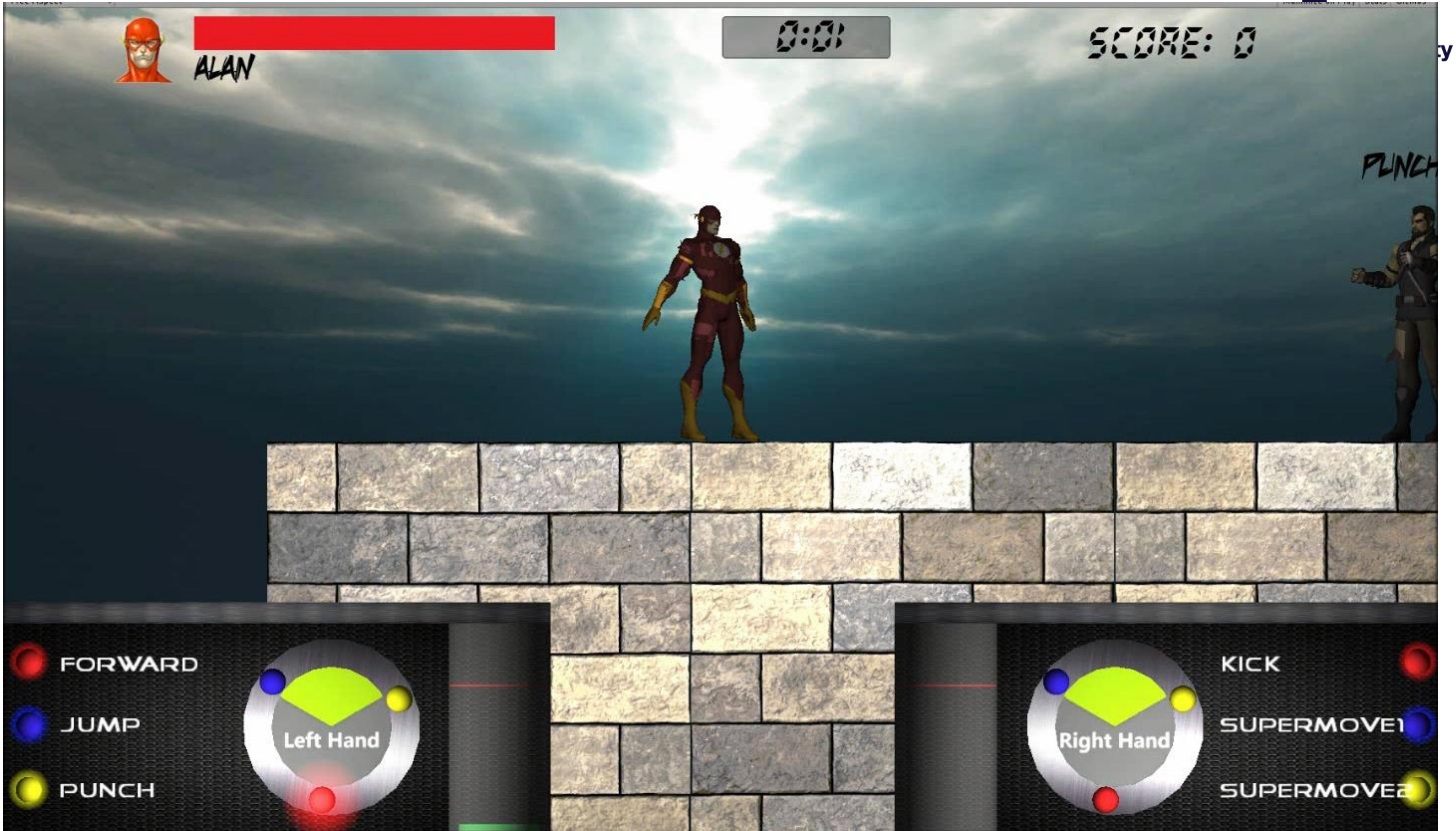


Post processing




PAUSE
SCORE: 5057

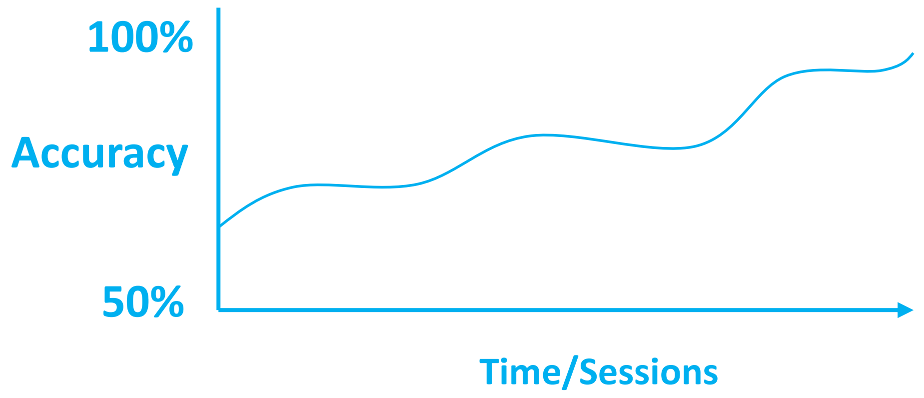
Ulster University


ALAN
0:01
SCORE: 0
PUNCH
FORWARD
JUMP
PUNCH
Left Hand
Right Hand
KICK
SUPERMOVE1
SUPERMOVE2

Motor learning and Real-time Feedback

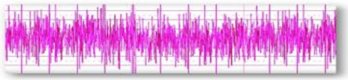
As a person learns to use a BCI, they exhibit similar learning patterns to other motor tasks, such as learning to grasp or write

Feedback is necessary to improve sensorimotor learning and BCI performance

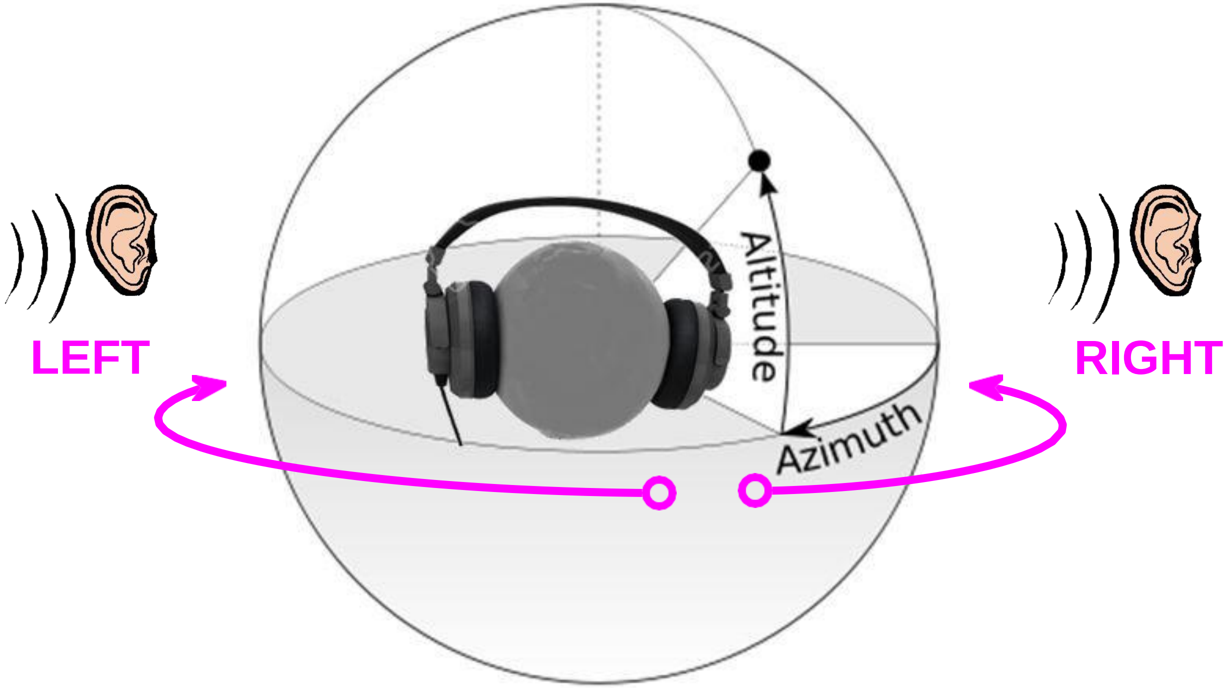


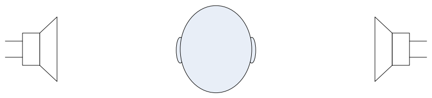
Feedback very important in applying SMR-BCI for PDoC assessment

Auditory Feedback



Pink noise



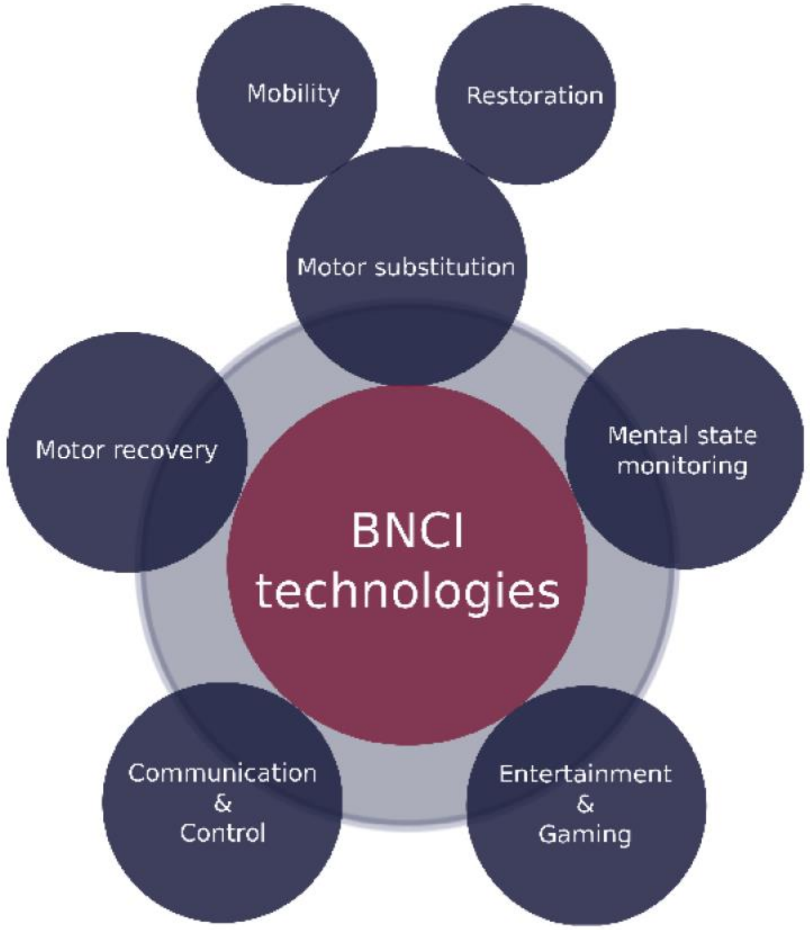


Amplitude panning and stereo Feedback

McCreadie et al 2013, 2014, Coyle et al 2015

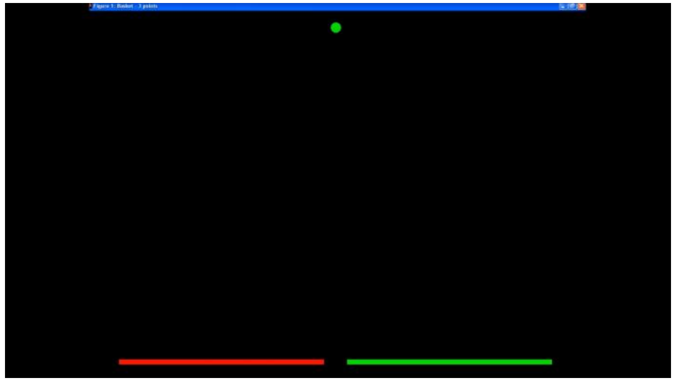
BCI applications >100 Million people

- Disorder of Consciousness (DoC) (280,000)
- Spinal Cord Injury (SCI) (5,000,000)
- Brainstem stroke (2,500,000)
- Ischemic stroke (70,000,000)
- Amyotphic Lateral Sclerosis (ALS) (500,000)
- Guillain-Barré syndrome (70,000)
- Cerebral Palsy (16,000,000)
- Postpolio Syndrome (7,000,000)
- Multiple sclerosis (2,000,000)
- Multiple Dystrophy (1,000,000)

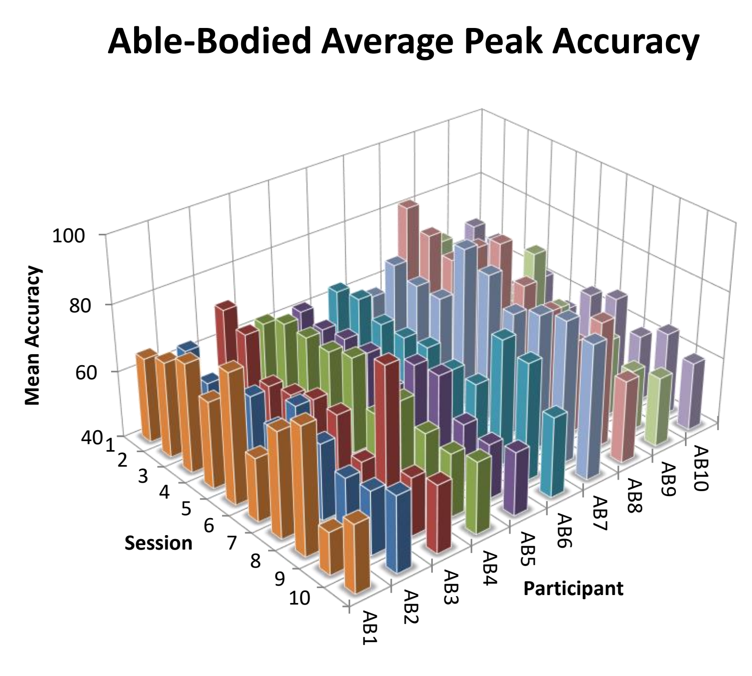


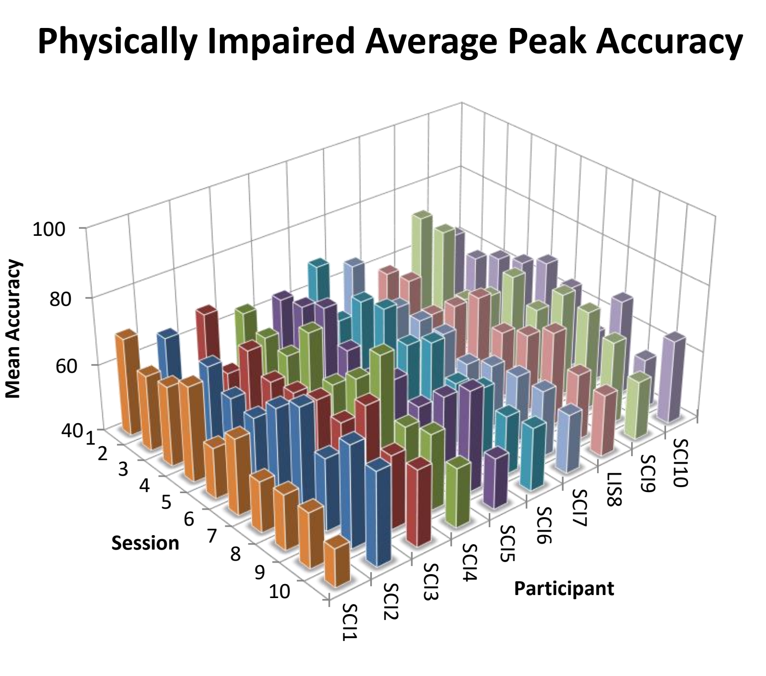
Part 2: Spinal injury : Competing at Cybathlon

Results: Able Bodied vs. SCI

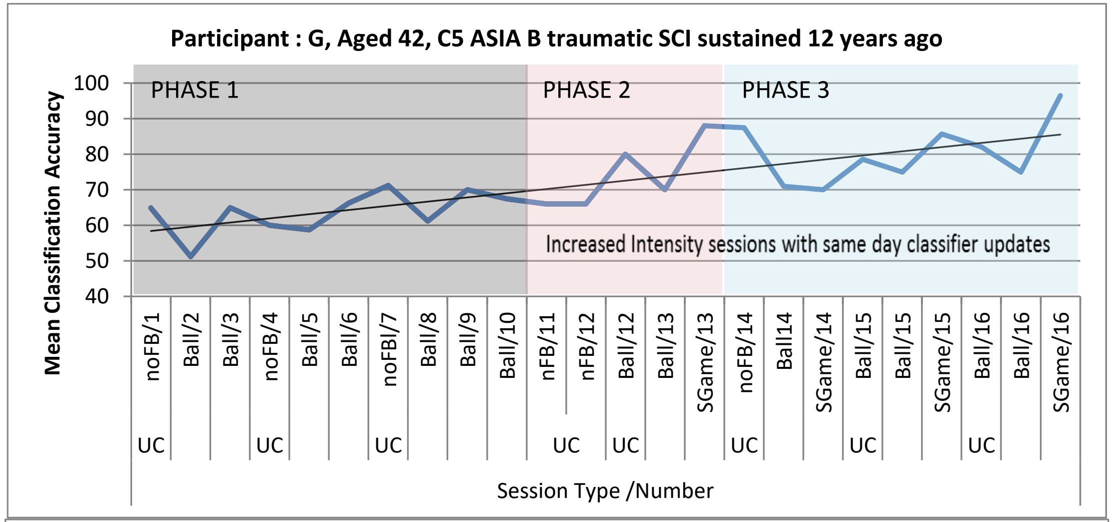


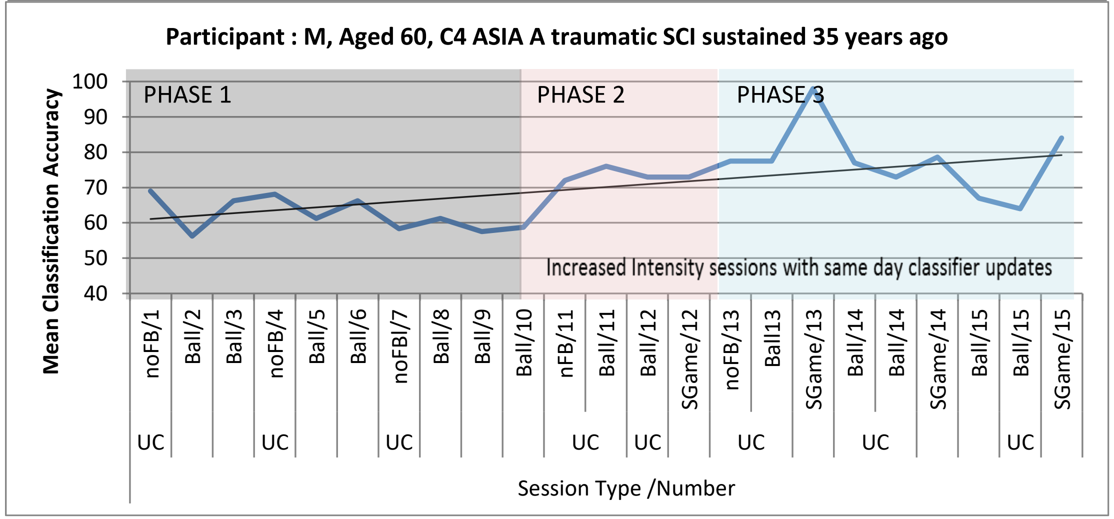
- Accuracy 60-85% across both groups
- Average Acc: AB 65% and SCI 62% (difference not significant)



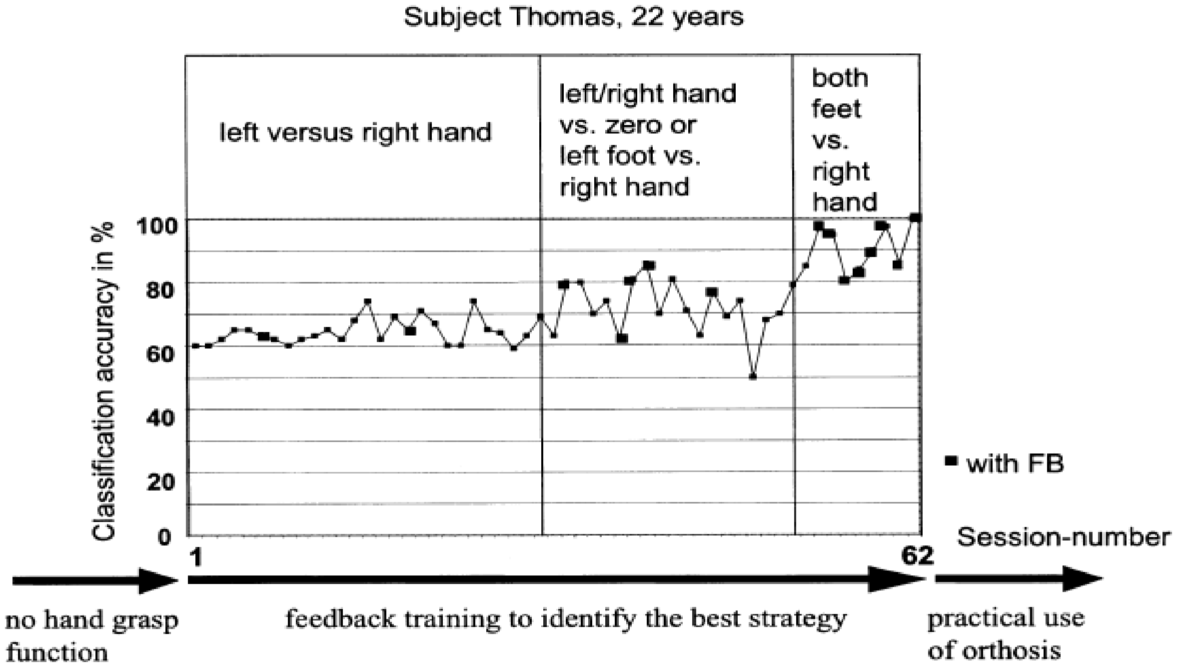


Spinal Cord Injury : Intensive Training





Coyle et al 2015

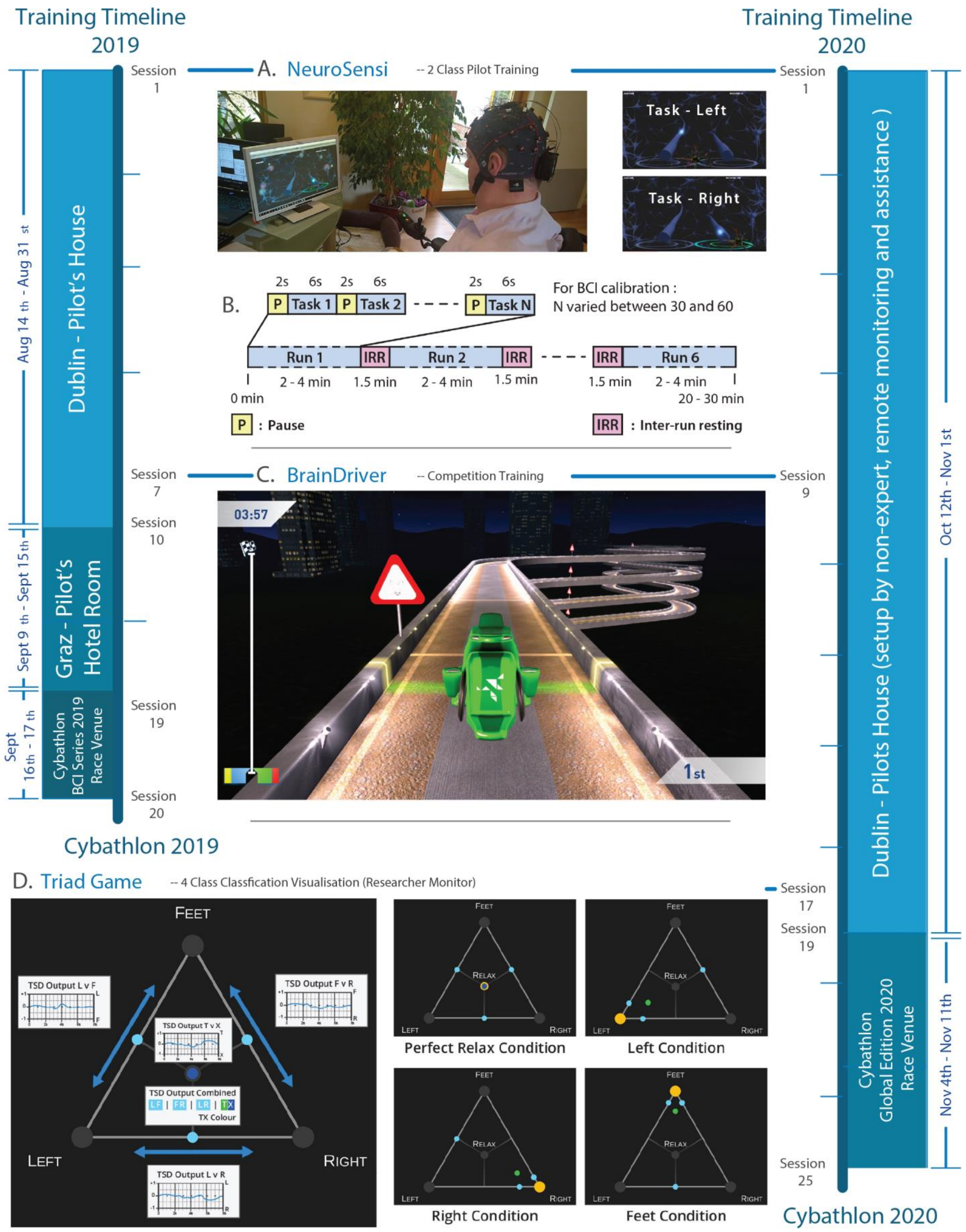


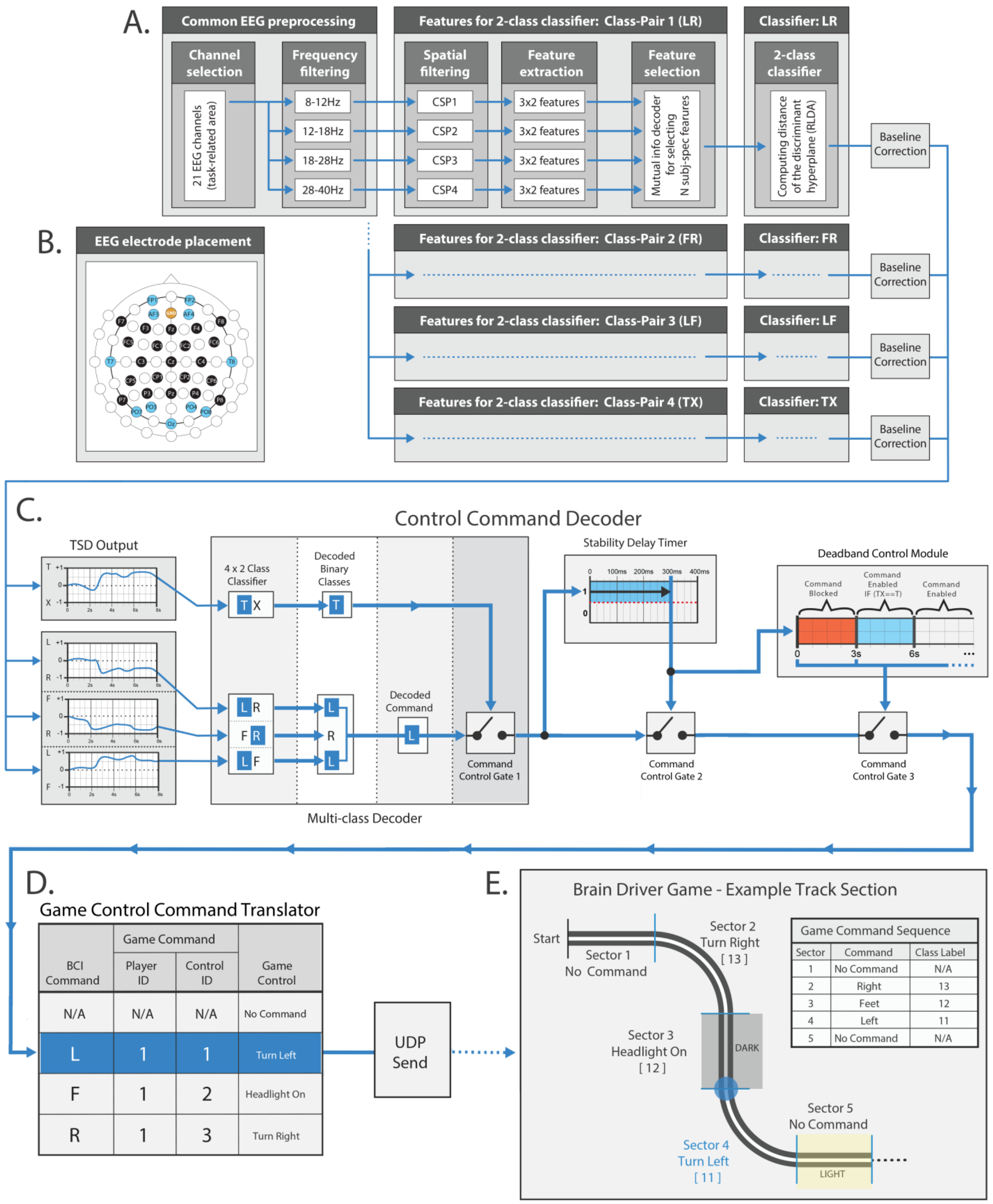
Pfurtscheller et al 2001

CYBATHLON SERIES ETH zürich

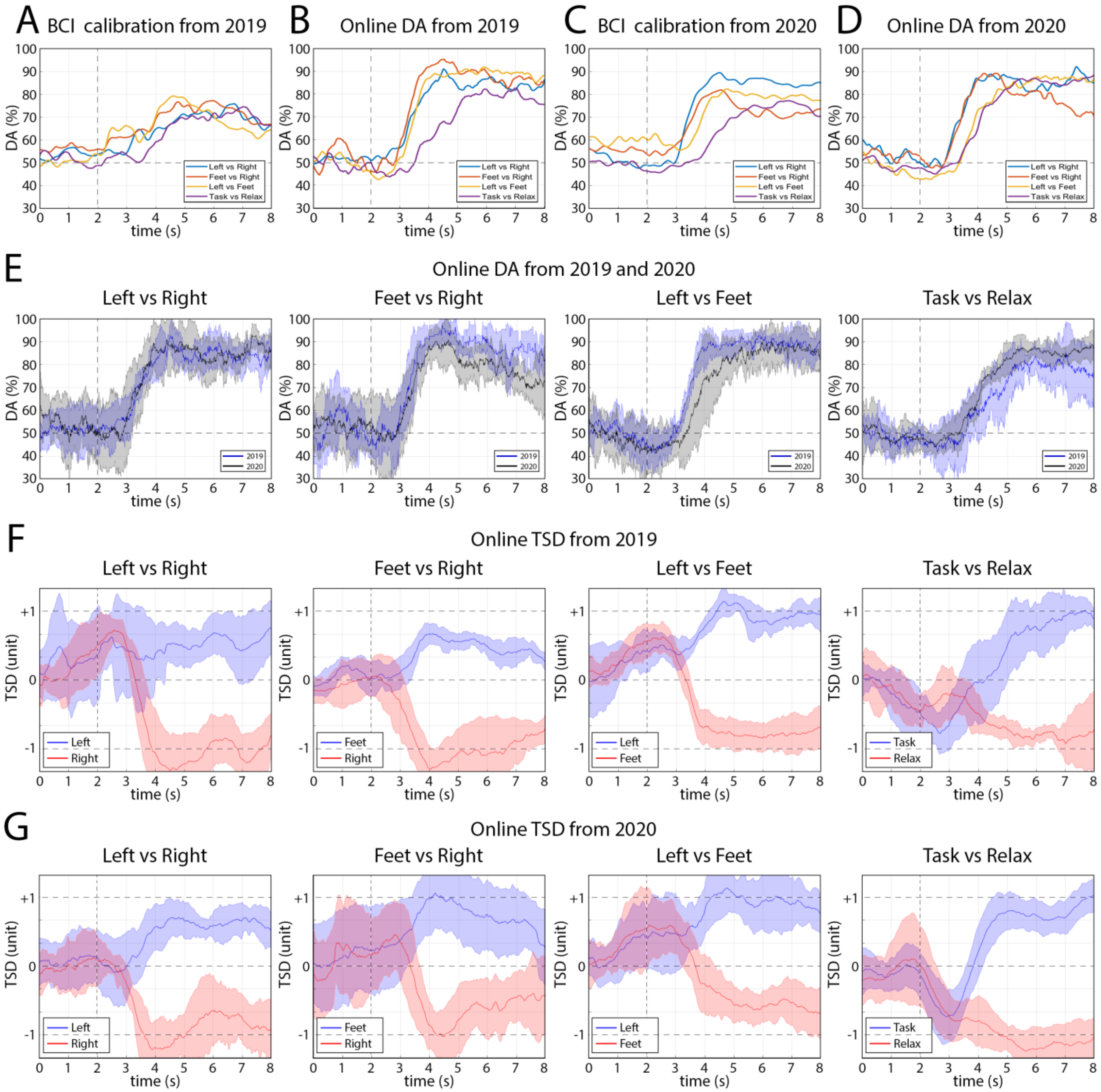
Ulster University

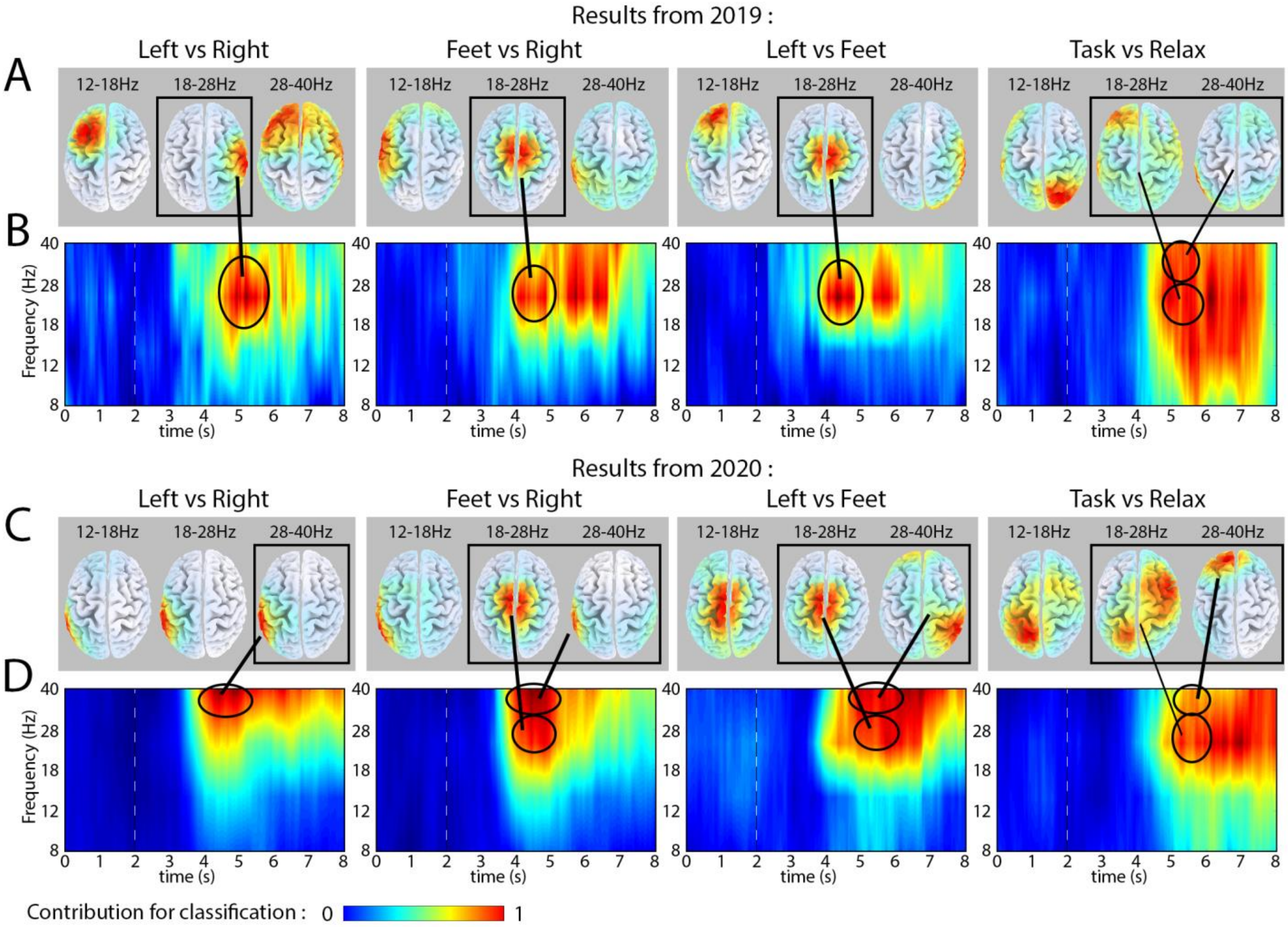
Championship for Athletes with Disabilities

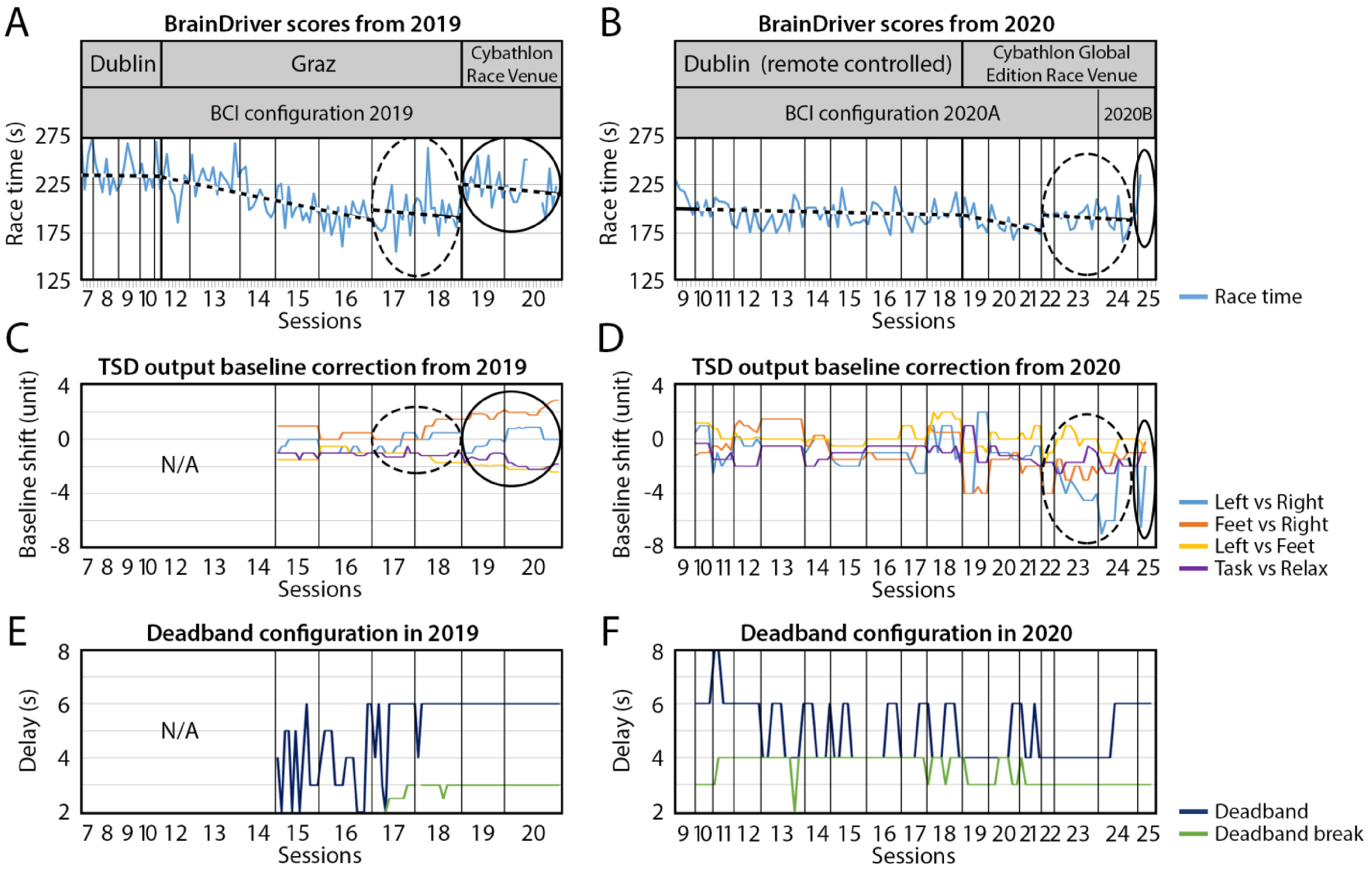

Training Timeline 2019
Training Timeline 2020
A. NeuroSensi
-- 2 Class Pilot Training
Session 1
Task - Left
Task - Right
B.
2s 6s 2s 6s 2s 6s
P Task 1 P Task 2 P Task N
For BCI calibration :
N varied between 30 and 60
Run 1 IRR Run 2 IRR IRR Run 6
0 min
2 - 4 min
1.5 min
2 - 4 min
1.5 min
1.5 min
2 - 4 min
20 - 30 min
P : Pause
IRR : Inter-run resting
C. BrainDriver
-- Competition Training
Session 7
Session 9
Session 10
Session 19
Session 20
03:57
1st
Aug 14 th - Aug 31 st
Dublin - Pilot's House
Sept 9 th - Sept 15 th
Graz - Pilot's Hotel Room
Sept 16 th - 17 th
Cybathlon BCI Series 2019 Race Venue
Cybathlon 2019
Dublin - Pilots House (setup by non-expert, remote monitoring and assistance)
Oct 12th - Nov 1st
Cybathlon Global Edition 2020 Race Venue
Nov 4th - Nov 11th
D. Triad Game
-- 4 Class Classfication Visualisation (Researcher Monitor)
Session 17
Session 19
Session 25
Feet
Left
Right
TSD Output L v F
TSD Output F v R
TSD Output T v X
TSD Output Combined
LF | FR | LR | TX
TX Colour
TSD Output L v R
Relax
Perfect Relax Condition
Left Condition
Right Condition
Feet Condition
Cybathlon 2020


A.
Common EEG preprocessing
Channel selection
Frequency filtering
21 EEG channels (task-related area)
8-12Hz
12-18Hz
18-28Hz
28-40Hz
Features for 2-class classifier: Class-Pair 1 (LR)
Spatial filtering
Feature extraction
Feature selection
CSP1
CSP2
CSP3
CSP4
3x2 features
Mutual info decoder for selecting N subj-spec features
Classifier: LR
2-class classifier
Computing distance of the discriminant hyperplane (RLDA)
Baseline Correction
B.
EEG electrode placement
Features for 2-class classifier: Class-Pair 2 (FR)
Classifier: FR
Features for 2-class classifier: Class-Pair 3 (LF)
Classifier: LF
Features for 2-class classifier: Class-Pair 4 (TX)
Classifier: TX
C.
Control Command Decoder
TSD Output
4 x 2 Class Classifier
Decoded Binary Classes
Decoded Command
Stability Delay Timer
0 100ms 200ms 300ms 400ms
Deadband Control Module
Command Blocked
Command Enabled IF (TX==T)
Command Enabled
0 3s 6s
Command Control Gate 1
Command Control Gate 2
Command Control Gate 3
Multi-class Decoder
D.
Game Control Command Translator
BCI Command
Game Command
Player ID
Control ID
Game Control
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
Start
Sector 1 No Command
Sector 2 Turn Right [13]
Sector 3 Headlight On [12]
DARK
Sector 4 Turn Left [11]
Sector 5 No Command
LIGHT
Game Command Sequence
Sector Command Class Label
1 No Command N/A
2 Right 13
3 Feet 12
4 Left 11
5 No Command N/A

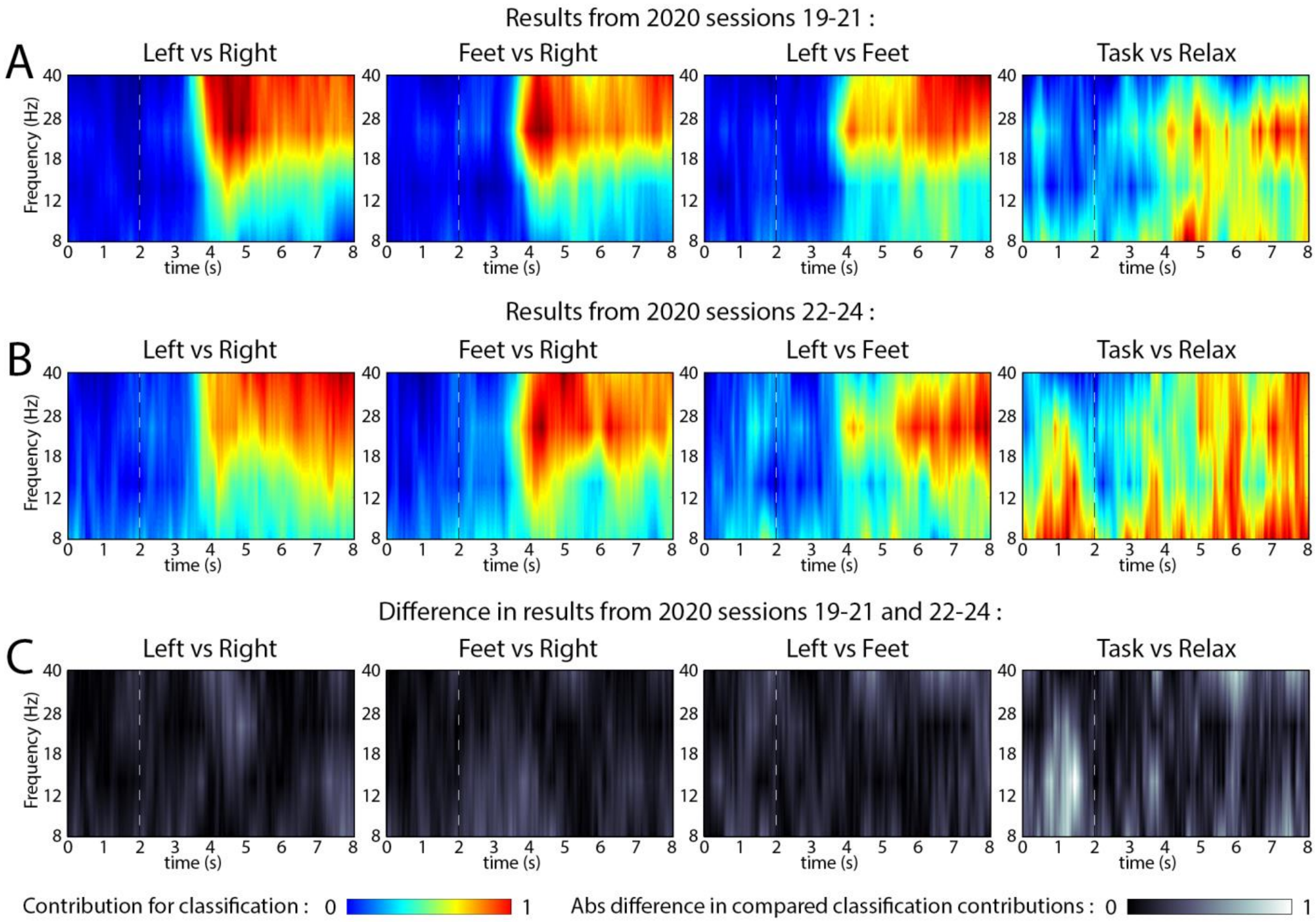
ity


A BCI calibration from 2019
B Online DA from 2019
C BCI calibration from 2020
D Online DA from 2020
DA (%)
time (s)
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
E Online DA from 2019 and 2020
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
2019
2020
F Online TSD from 2019
G Online TSD from 2020
TSD (unit)
Left
Right
Feet
Task
Relax


Results from 2019 :
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
A
B
12-18Hz
18-28Hz
28-40Hz
Frequency (Hz)
time (s)
Results from 2020 :
C
D
Contribution for classification : 0 1



Ulster University



Results from 2020 sessions 19-21 :
A
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
Frequency (Hz)
time (s)
Results from 2020 sessions 22-24 :
B
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
Frequency (Hz)
time (s)
Difference in results from 2020 sessions 19-21 and 22-24 :
C
Left vs Right
Feet vs Right
Left vs Feet
Task vs Relax
Frequency (Hz)
time (s)
Contribution for classification : 0 1
Abs difference in compared classification contributions : 0 1

Cybathlon Conclusion

Effective training strategy, BCI approach and optimisation

Pilot has developed into a BCI expert (>90% accuracy), even though he has been tetraplegic for 37 years

Race day performances were mainly not competitive

Impacted by changes in cognitive state, possibly due to heightened arousal arising from competition day pressure on the pilot.

Recommendations

Helping the pilot to maintain consistent cognitive states is of critical importance to ensure race day performances competitive.

Supplemented by adaptive BCI strategies that can autonomously adapt to cognitive state changes to maintain performance.

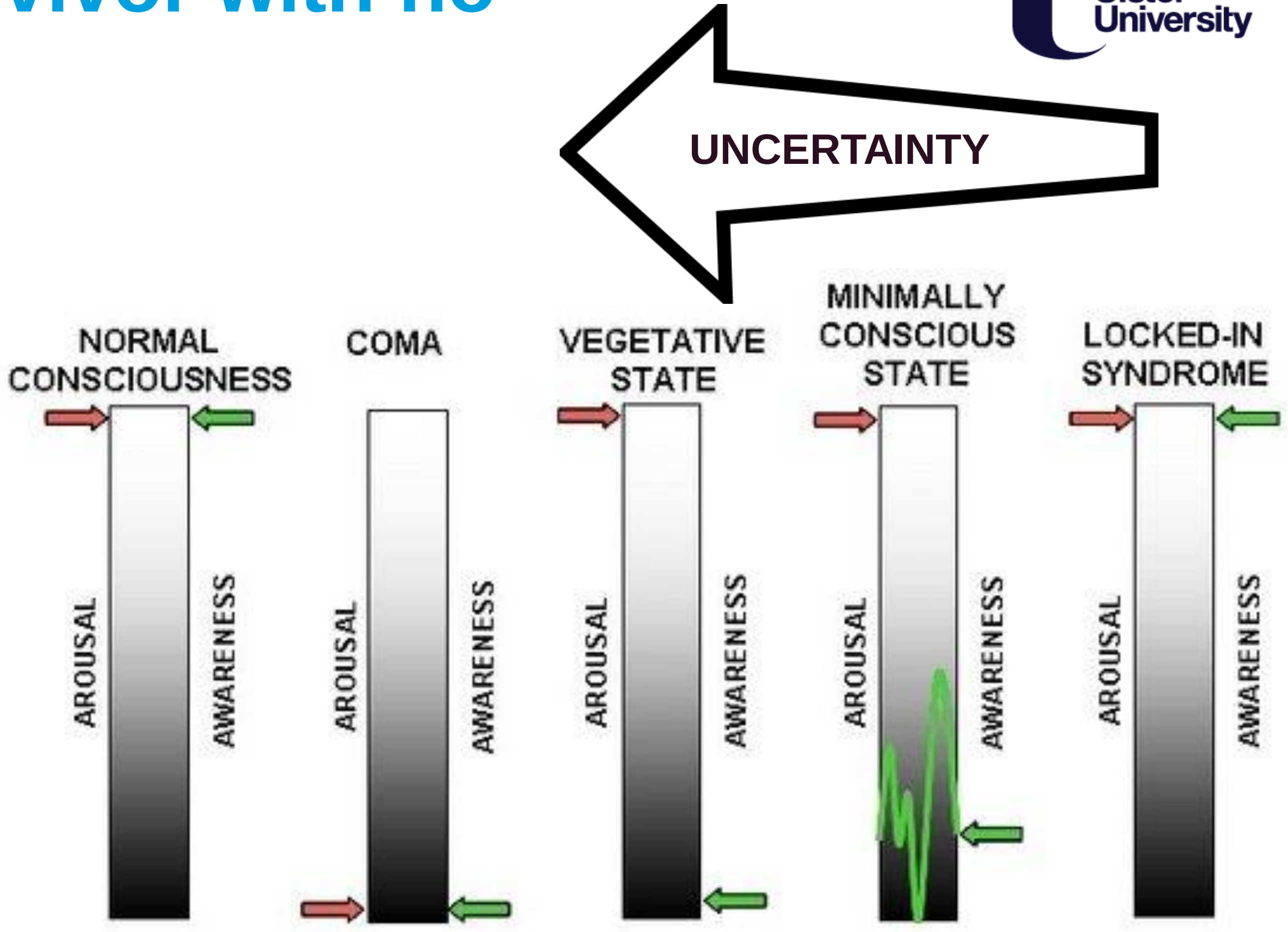
We will focus on this and compete again at the CYBATHLON Edition in 2024.

Ulster University

Part 3: Brain Injury : Communication and Cognitive Profiling in Disorders of Consciousness

Meet Eoin, a brain injury survivor with no means of communication

Prolonged disorders of consciousness



UWS

UNRESPONSIVE
WAKEFULNESS
SYNDROME

Challenges and Motivation

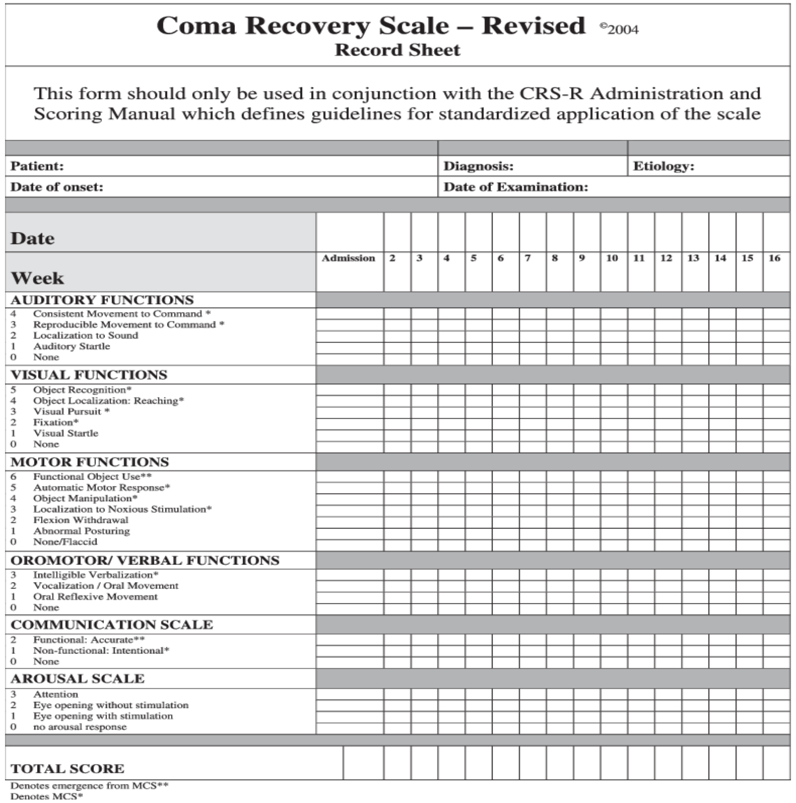
Many consciousness scales are insufficient for complete and accurate diagnosis because

- they require overt motor responses
- may provide snapshot measures of activity.

UWS or MCS diagnosis probable when there are no overt behavioural responses to external stimuli.

43% of patients who receive a diagnosis of VS/MCS are often reclassified after prolonged assessment

Current methods: Neuropsychometric testing



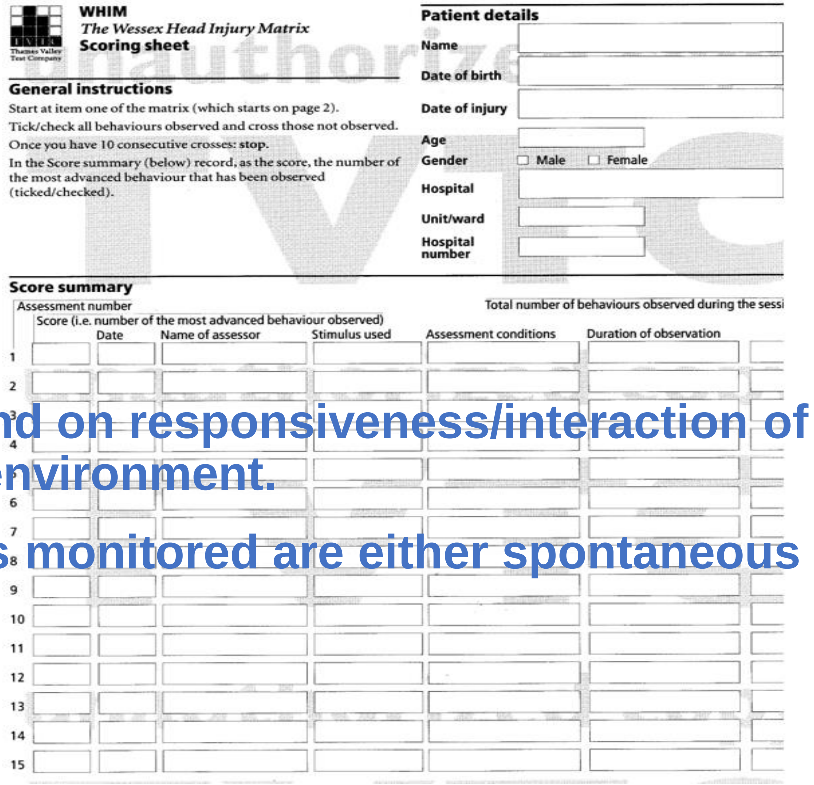
Coma Recovery Scale – Revised ©2004
Record Sheet

This form should only be used in conjunction with the CRS-R Administration and Scoring Manual which defines guidelines for standardized application of the scale

Patient: | Diagnosis: | Etiology:
Date of onset: | Date of Examination:

Date / Week	Admission	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
AUDITORY FUNCTIONS																
4 Consistent Movement to Command *																
3 Reproducible Movement to Command *																
2 Localization to Sound																
1 Auditory Startle																
0 None																
VISUAL FUNCTIONS																
5 Object Recognition*																
4 Object Localization: Reaching*																
3 Visual Pursuit *																
2 Fixation*																
1 Visual Startle																
0 None																
MOTOR FUNCTIONS																
6 Functional Object Use**																
5 Automatic Motor Response*																
4 Object Manipulation*																
3 Localization to Noxious Stimulation*																
2 Flexion Withdrawal																
1 Abnormal Posturing																
0 None/Flaccid																
OROMOTOR/ VERBAL FUNCTIONS																
3 Intelligible Verbalization*																
2 Vocalization / Oral Movement																
1 Oral Reflexive Movement																
0 None																
COMMUNICATION SCALE																
2 Functional: Accurate**																
1 Non-functional: Intentional*																
0 None																
AROUSAL SCALE																
3 Attention																
2 Eye opening without stimulation																
1 Eye opening with stimulation																
0 no arousal response																
TOTAL SCORE																

Denotes emergence from MCS**
Denotes MCS*



WHIM
The Wessex Head Injury Matrix
Scoring sheet

Thames Valley Test Company

Patient details
Name
Date of birth
Date of injury
Age
Gender ☐ Male ☐ Female
Hospital
Unit/ward
Hospital number

General instructions
Start at item one of the matrix (which starts on page 2).
Tick/check all behaviours observed and cross those not observed.
Once you have 10 consecutive crosses: stop.
In the Score summary (below) record, as the score, the number of the most advanced behaviour that has been observed (ticked/checked).

Score summary
Assessment number
Score (i.e. number of the most advanced behaviour observed)
Total number of behaviours observed during the sessi

Assessment number	Score	Date	Name of assessor	Stimulus used	Assessment conditions	Duration of observation
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						

Both depend on responsiveness/interaction of an individual with their environment.

Behaviours monitored are either spontaneous or stimulus induced

Considered most sensitive scale to distinguish UWS & MCS

6 sub scales testing: audition, vision, motor, oromotor/verbal, yes-no communication and arousal.

(Giacino et al., 2004; Seel et al., 2010a).

Most commonly used instrument in the UK, followed by SMART & CRS-R.

62 item hierarchical scale of defined behaviours considered sequentially more advanced

(McCann, Delargy, & Cornall, 2014).

Assessment criteria

According to PDOC National Clinical Guidelines patients should demonstrate at least one of the following sustained over time to be classed as MCS:

- ➔ **Functional interactive communication:**
  Correct yes/no responses to 6/6 basic situational questions on 2 consecutive evaluations
- ➔ **Functional object use:**
  Generally appropriate use of at least two different objects on 2 consecutive evaluations.

Challenges with current best practice

These operational definitions may still be problematic for certain groups of patients including those who:

- have no motor control
- have specific language deficits
- are blind and/or deaf
- are fully aware but confused.

Such individuals may be fully aware, but unable to produce consistent behavioural responses…

Brain-Computer Interfaces

May mitigate need for consistent behavioural responses that rely on motor control

May provide alternative to behavioural response monitoring.

BCI for PDoC assessment

BCIs may enable patients with PDoC to learn to wilfully modulate sensorimotor rhythms (SMR)

SMR-BCIs could enable movement-independent patient assessment and/or communication strategies.

SMR-BCI was evaluated in a three-stage protocol for PDoC.

Stage I assessed awareness and capacity to modulate brain activity intentionally.

Stage II facilitated SMR-BCI learning/learning via stereo-auditory feedback.

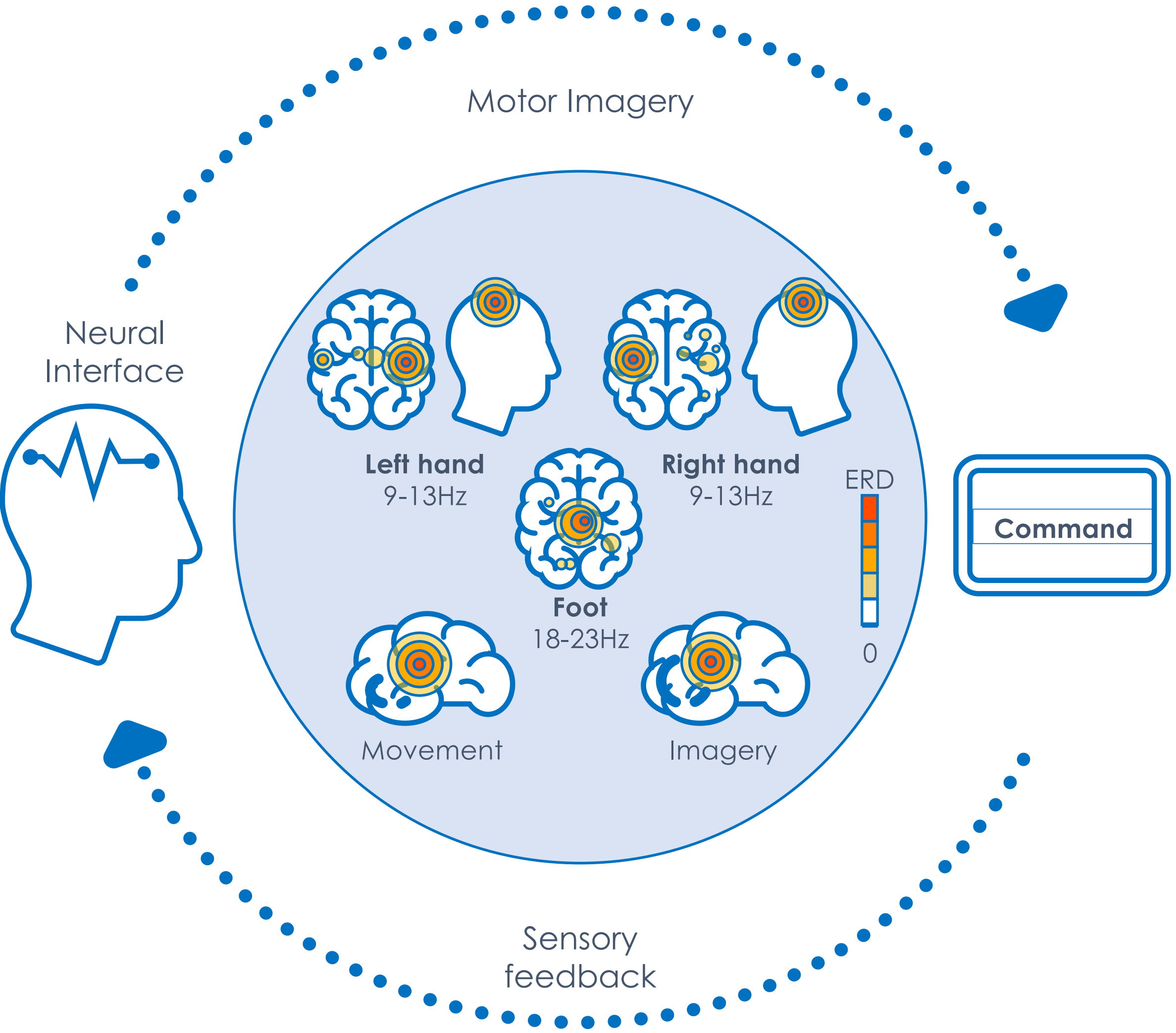
Stage III evaluated patient response to categorized, closed questions (yes/no)

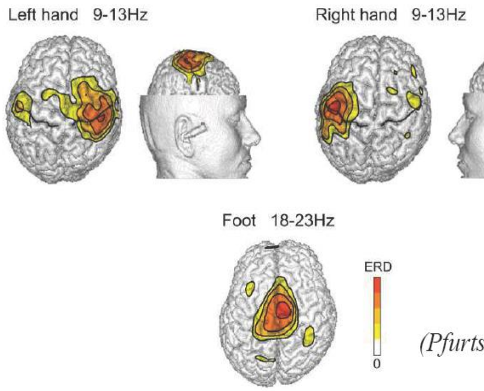
Hypothesis – real-time feedback improves patient responses

Hypothesis – evaluating average responses to categorised questions may enable cognitive profiling

24 patients : unresponsive wakefulness syndrome (**UWS,** n=9), minimally conscious state (**MCS,** n=11)) and locked-in syndrome (LIS, n=4) patients, who each participated in 10-12, 1-hour sessions.

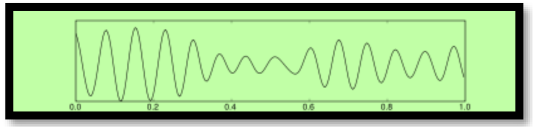
Motor imagery for PDoC assessment?



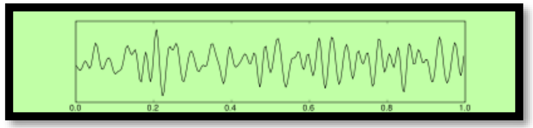


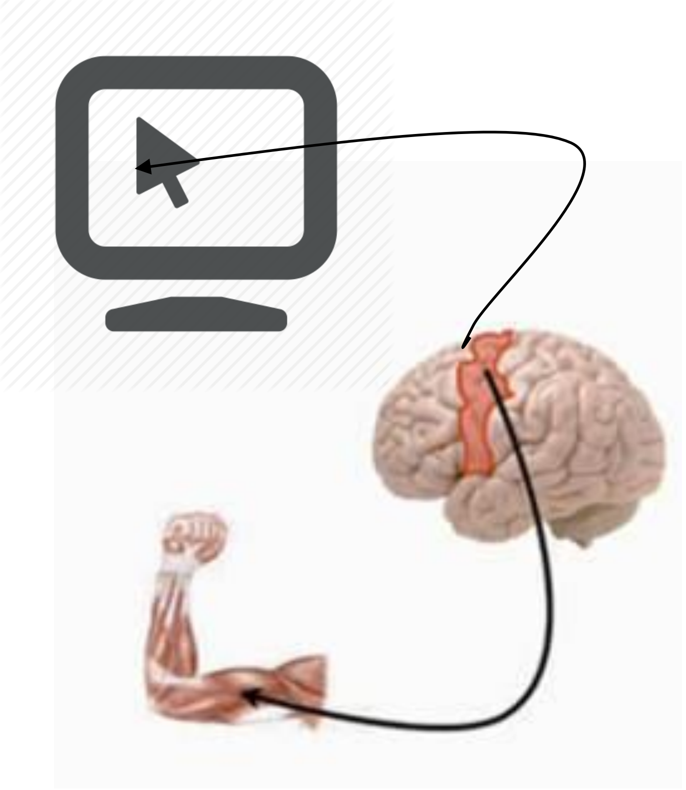
(Pfurtscheller et al, 2001)

- Mu

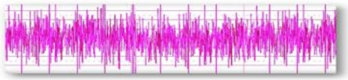


- Beta

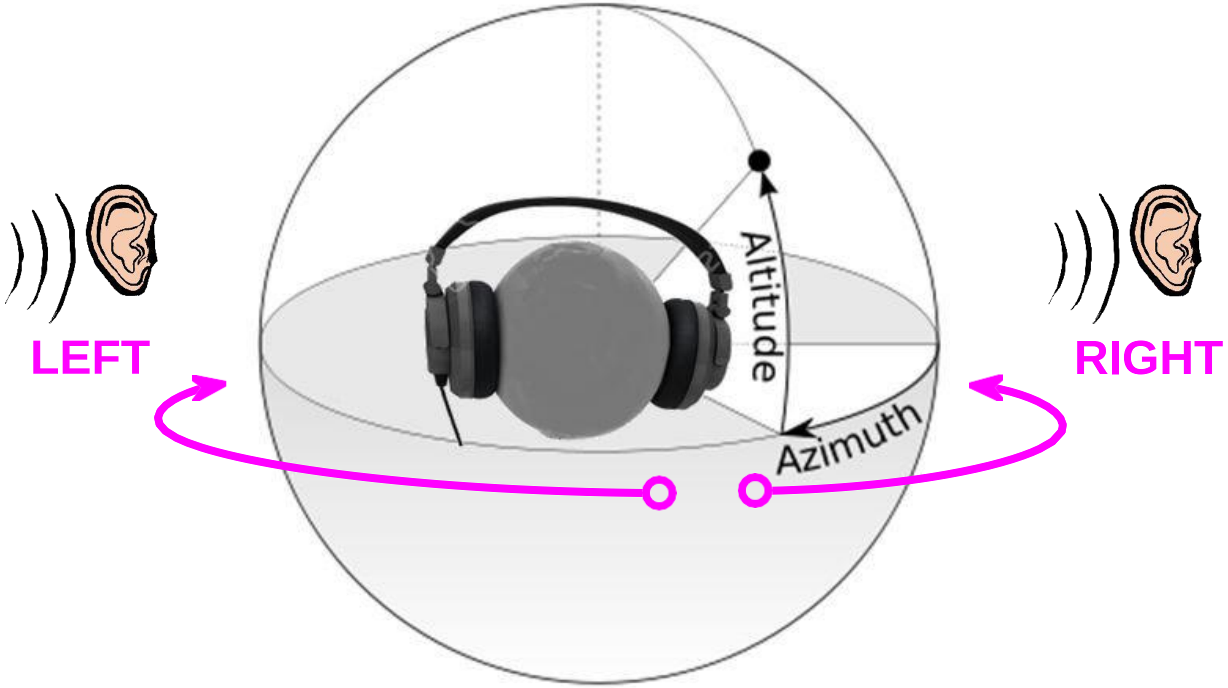


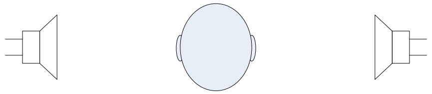


Auditory Feedback



Pink noise





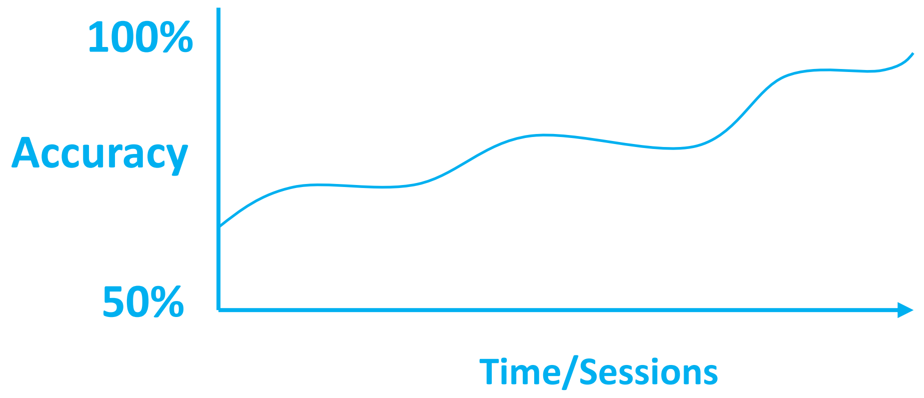
Amplitude panning and stereo Feedback

McCreadie et al 2013, 2014, Coyle et al 2015

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



Feedback very important in applying SMR-BCI for PDoC assessment

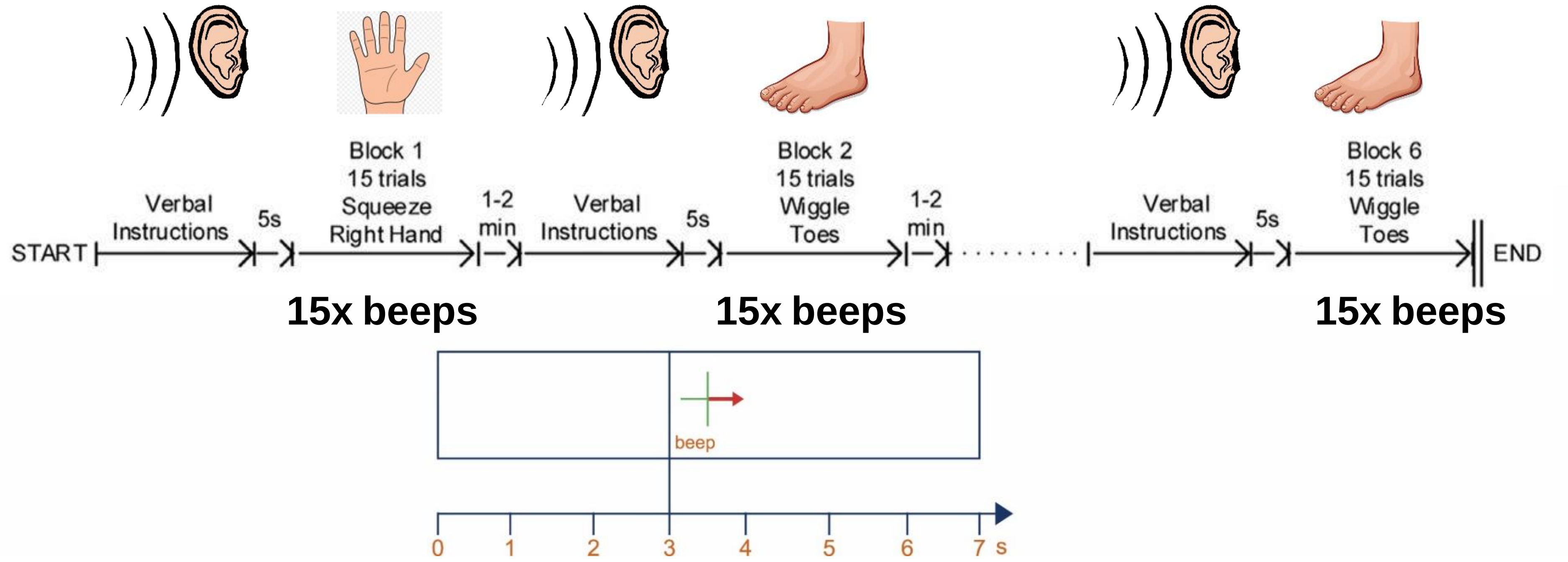
Study protocol

- **Initial assessment**
- **Auditory feedback training**
- **Question & Answer system**

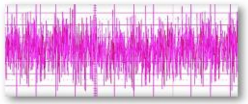
Initial Assessment

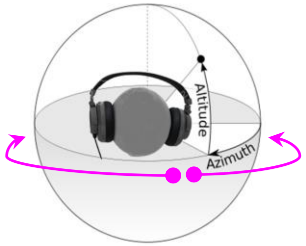
“Every time you hear a beep, imagine that you are lifting your right/left-hand.”

“Every time you hear a beep, try to imagine that you are lifting both feet.”



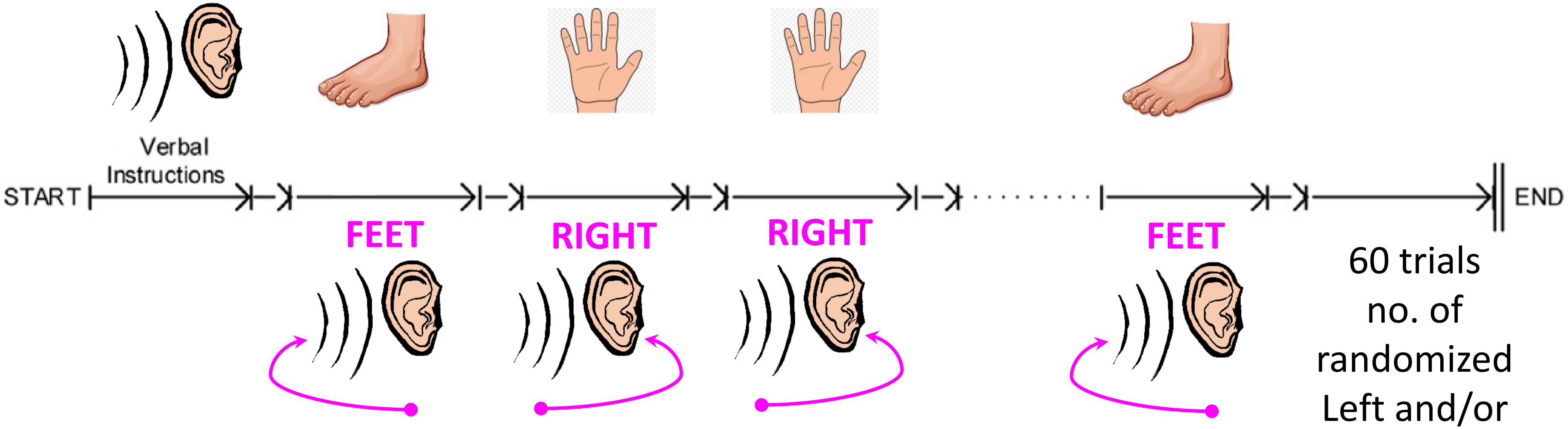
Audio Feedback





➔ **Auditory feedback training**

- pink noise **-**
music samples



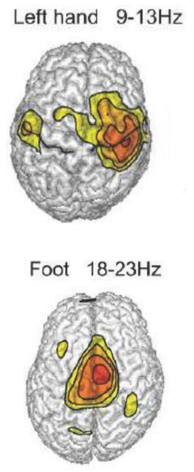
60 trials
no. of
randomized
Left and/or
Right
and/or Feet

Q&A system

Based on:

- Functional communication section of annex 1a of National clinical Guidelines
- Montreal Cognitive Assessment

01	**Biographical**	Is your name "X"? Are you a man?
02	**Situational**	Are you in bed? Are you at home?
03	**Abstract reasoning/logic**	Are mice bigger than elephants? Is water wet?
04	**Numbers & Letters**	Are A-B-C-D letters? Is 2-2 = 0?

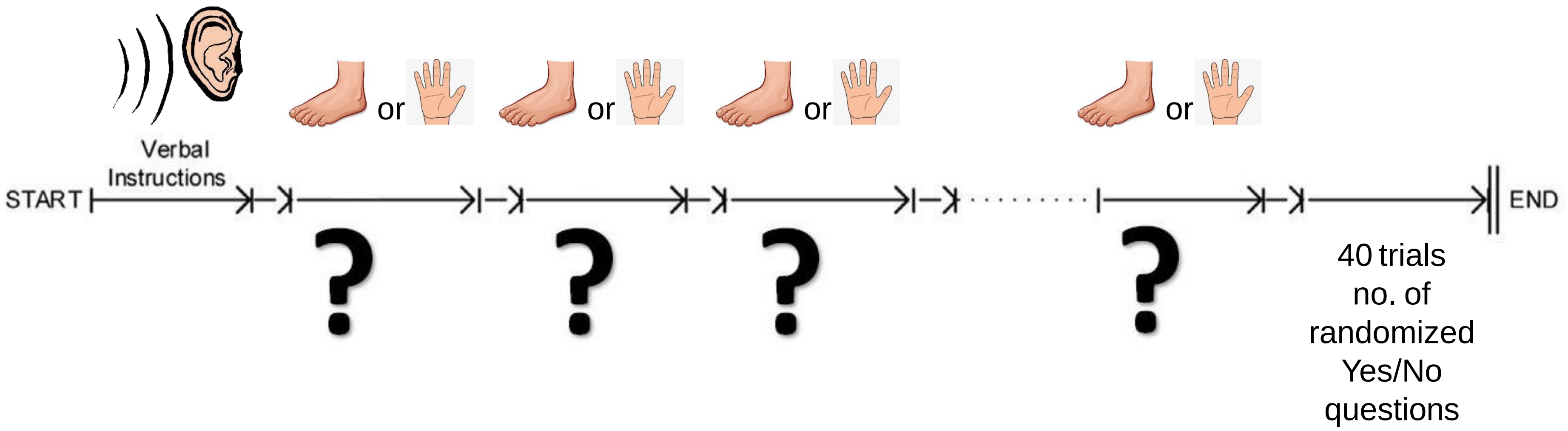


Yes

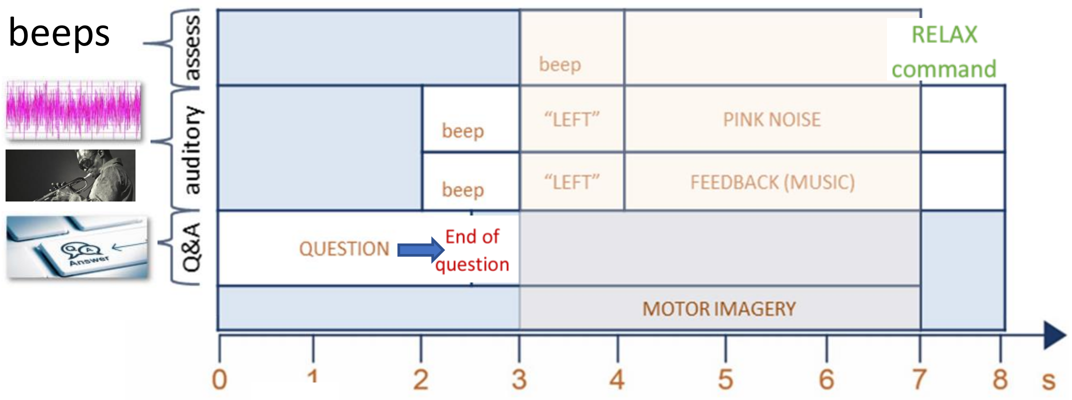
No

Define Questions (40+ in each category) 20/yes 20/no → Agree Yes/No Answers with Family Members → Record familiar voice reading questions aloud → Play back questions to participant (40 per run) (repetitive random sequence)

Q&A Assessment

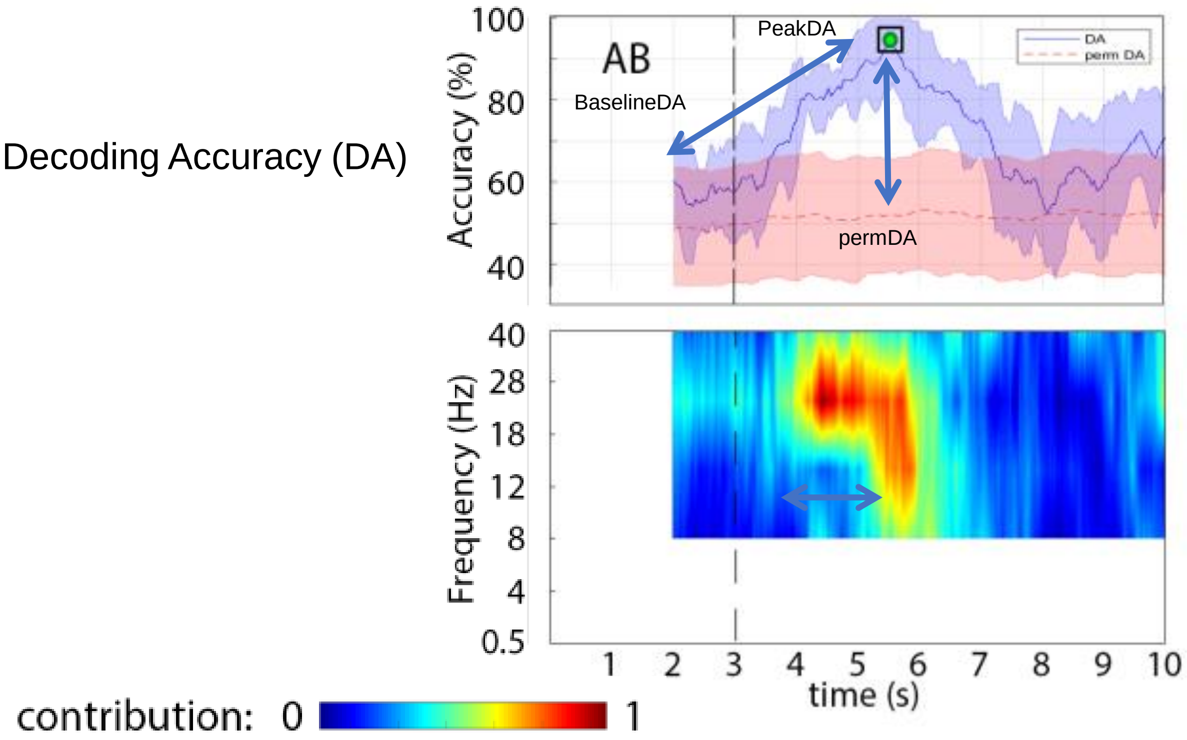


Runs and Evaluation



	Run>>>	1	2	3	4
Stage I	Session 1	A1	F(PN)	-	-
	Session 2	A2	T	F(PN)	-
Stage II	Sessions 3 - 4	T	T	F(PN)	F(M)
	Sessions 5 - 6	T	F(M)	F(M)	F(M)
Stage III	Sessions 7 - 8	T	F(M)	Q&A	Q&A
	Sessions 9 - 10	F(M)	F(M)`	Q&A	Q&A

Decoding Accuracy (DA)



Baseline Vs Peak DA

PermDA vs Peak DA

100 permutation tests

Observable change in Corresponding Frequency Contribution within the Decoding Window

A=Assessment
T = Training
F(PN) = Feedback (Pink Noise)
F(M) = Feedback (Music)
Q&A = Question and Answer

Participant info

24 patients

9 unresponsive wakefulness syndrome (UWS)

11 minimally conscious state (MCS)

4 locked-in syndrome (LIS)

2 able-bodied (AB)

ID	Inter ID	Sex	Age	Type of injury	Time since injury (months)	AV CRS-R	AV WHIM
'UWS 1'	1004	M	46	Traumatic	54	.	3.50
'UWS 2'	1009	M	25	Non-traumatic	26	9.00	16.80
'UWS 3'	1011	F	25	Non-traumatic	85	4.50	5.00
'UWS 4'	1019	M	22	Non-traumatic	9	3.73	6.00
'UWS 5'	1026	M	43	Traumatic	90	4.67	3.67
'UWS 6'	1038	M	29	Traumatic	74	4.80	4.20
'UWS 7'	1048	M	34	Non-traumatic	192	5.00	4.78
'UWS 8'	1054	F	64	Traumatic	.	9.00	7.50
'UWS 9'	1056	M	34	Non-traumatic	103	2.83	3.17
'MCS 1'	1001	F	48	Non-traumatic	58	12.00	14.00
'MCS 2'	1003	F	33	Non-traumatic	43	5.00	4.13
'MCS 3'	1006	M	33	Traumatic	21	.	.
'MCS 4'	1008	M	53	Non-traumatic	14	12.70	13.40
'MCS 5'	1010	F	56	Traumatic	35	18.10	16.50
'MCS 6'	1012	M	24	Traumatic	5	7.27	8.45
'MCS 7'	1023	M	29	Non-traumatic	.	19.00	26.00
'MCS 8'	1025	M	49	Non-traumatic	23	11.20	16.45
'MCS 9'	1041	M	18	Non-traumatic	6	13.60	24.00
'MCS 10'	1045	F	35	Non-traumatic	19	9.00	12.29
'MCS 11'	1059	M	44	Traumatic	30	.	21.00
'LIS 1'	1029	F	44	Non-traumatic	6	0.00	1.00
'LIS 2'	1030	F	27	Non-traumatic	36	15.00	17.00
'LIS 3'	1035	F	34	Non-traumatic	11	14.00	14.00
'LIS 4'	1057	M	28	Traumatic	25	19.00	6.00
'AB 1'	3000	M	23	AB	.	.	.
'AB 2'	3001	M	20	AB	.	.	.

Sessions and Patient Progression

Assessment
1-2 sessions

Training with audio
5-7 Sessions

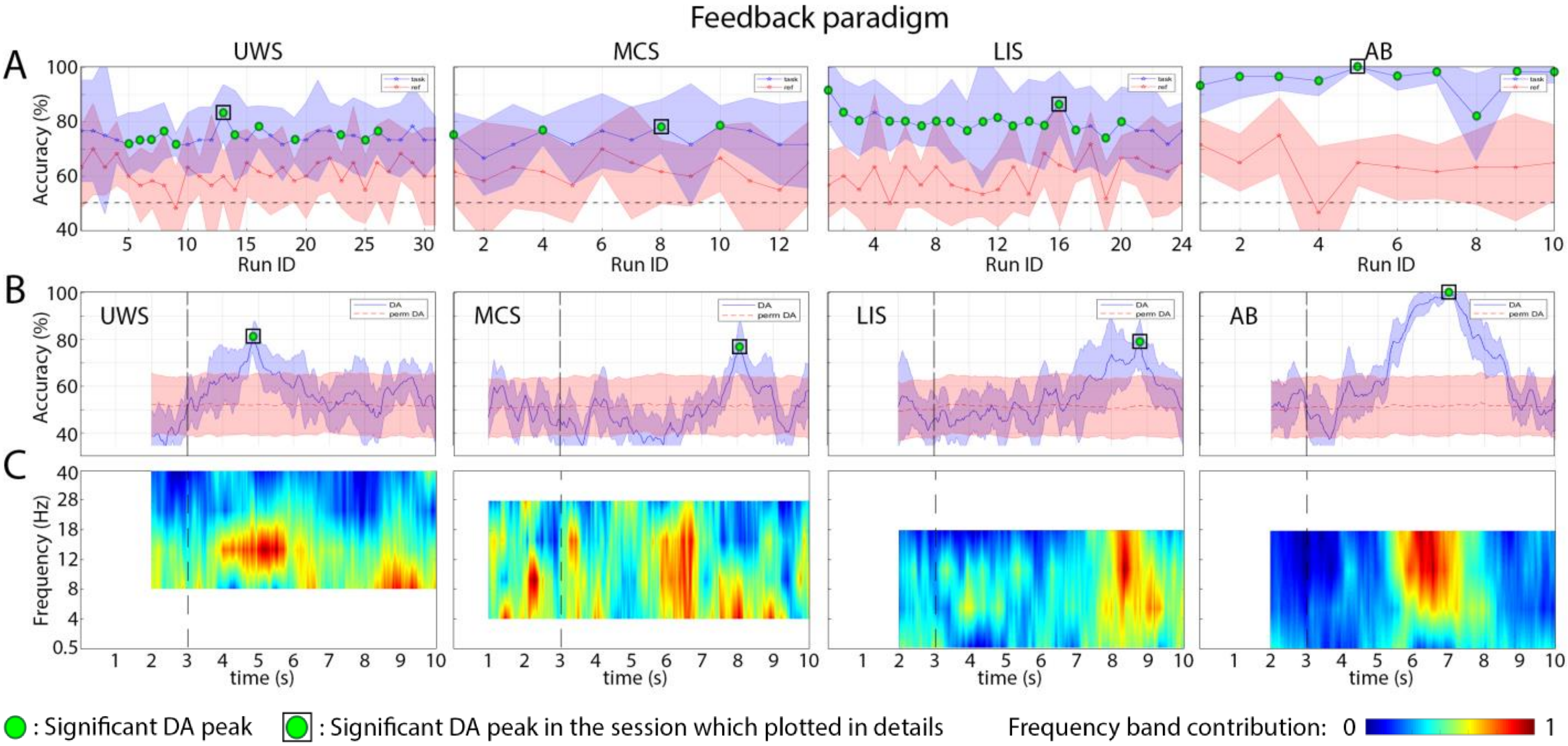
Closed Q&A
2-5 sessions

24 Patients
9 UWS
11 MCS
4 LIS

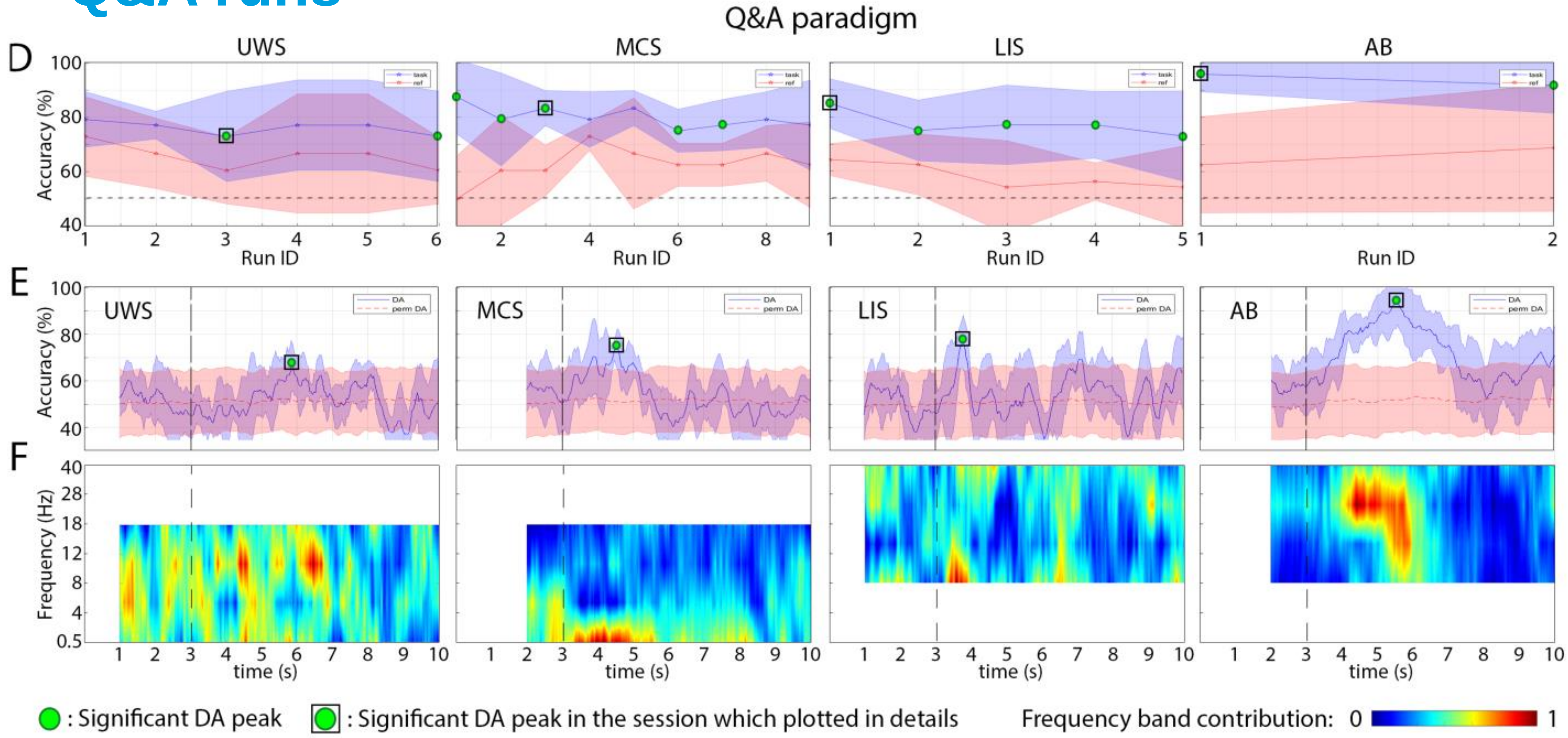
15 Patients
5/9 UWS
7/11 MCS
3/4 LIS

12 Patients
3/5 UWS
6/11 MCS
3/4 LIS

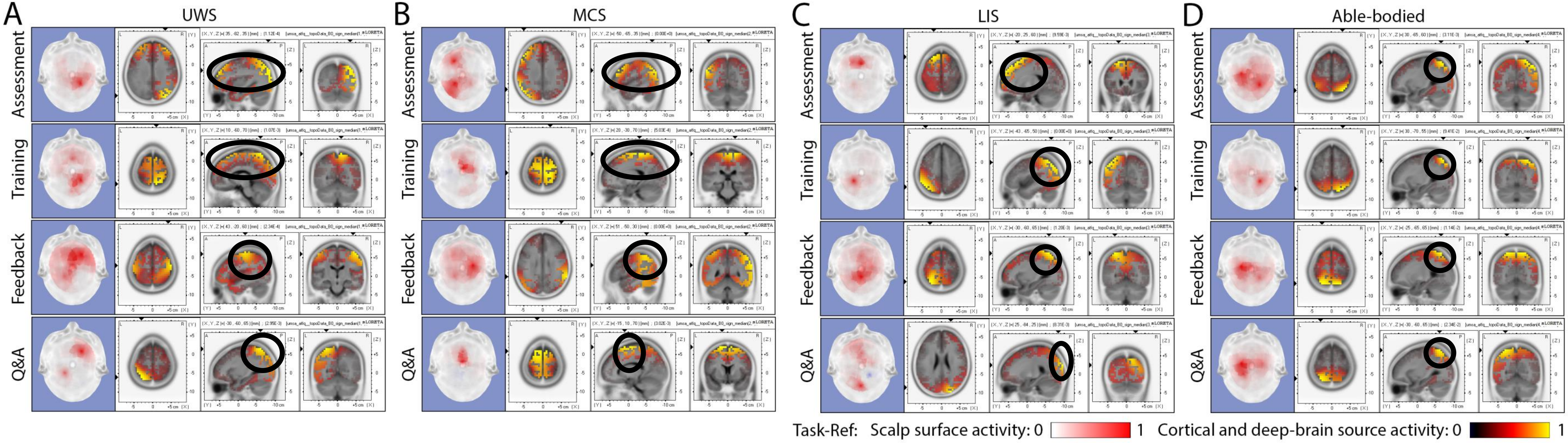
Induvial subject results example – Audio feedback



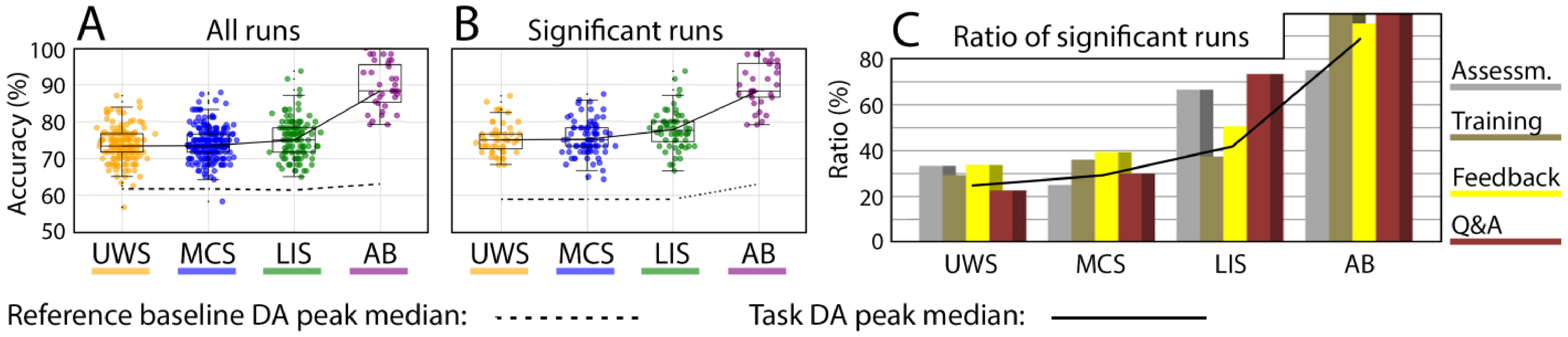
Individual subject results example – Q&A runs



Task-related brain activity patterns



Group DA for each diagnostic category



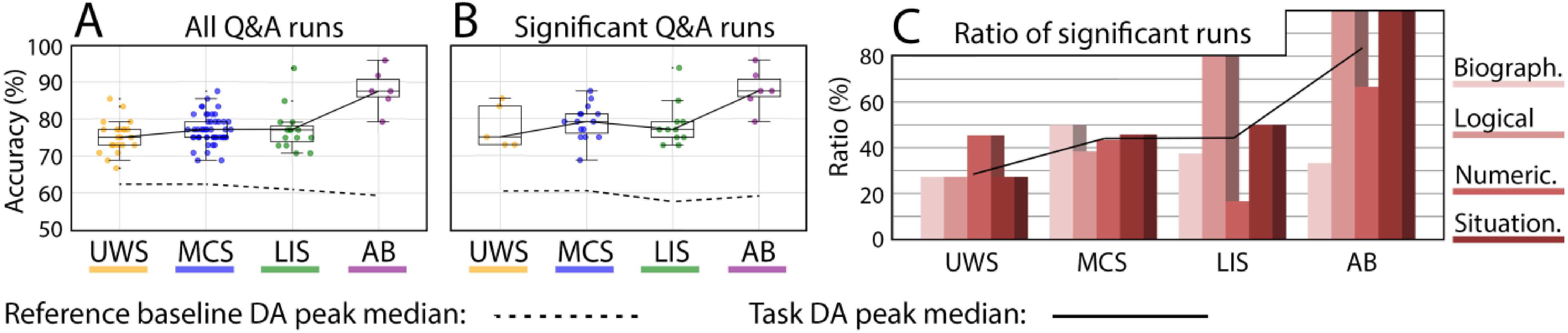
Group differences revealed ($F_{(3,134.9)} = 81.47$, $p < .001$): LIS responded significantly higher than UWS ($p = .023$).

Accuracy across groups was correlated with diagnostic category

Ratio of significant runs is indicative that with further training BCI may be used to augment patient assessment/diagnosis

WHIM and CSR-R scores conducted before each session were not correlated with DA.

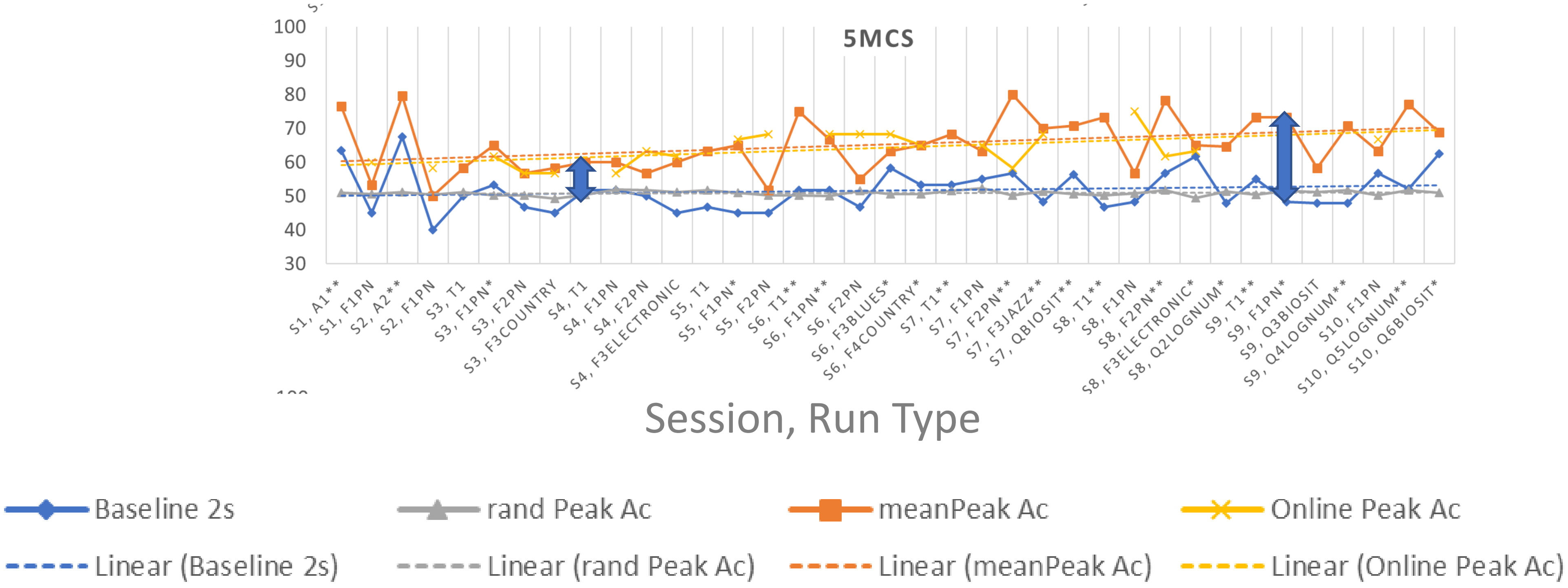
Group Accuracy for each question category



Non-significant differences were found across question categories

Ratio of significant runs indicates with training and feedback + more Q&A sessions the average DA results may be used to assess cognition

Intensive training - minimally conscious state



Dayan et al 2019

Summary

Stage I - Assessment:

5/9 UWS, 7/11 MCS and 3/4 LIS demonstrated significant capacity to modulate brain activity in stage I

Stage II - Training/auditory feedback:

All patients in stage II/III had significant responses and appeared to engage with feedback – auditory feedback essential

Accuracies are significantly above chance level but remain low for BCI control - more feedback sessions may improve

Accuracies are correlated with diagnosis category and may be used to for diagnosis but insignificant differences between UWS/MCS

Scores from standard PDoC assessments conducted before each session were not correlated with DA.

Stage III – Q&A

Revealed all patients responded significantly to questions.

Non-significant differences were found across question categories but ratio of significant runs shows promise for profiling cognition

More patient data and many more Q&A sessions required for through statistical analysis

Conclusion

Motor imagery BCI may augment assessment in DoC to establish consciousness levels

Auditory feedback has an impact on performance and training in PDoC

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

Large Neurotechnology Trial

Partners

Rep of Ireland

- National Rehabilitation Hospital of Ireland
- St Conal's Campus Rehabilitation Unit, Letterkenny, Ireland

Northern Ireland

- Belfast Health and Social Care Trust
- Western Health and Social Care Trust
- Southern Eastern Health and Social Care Trust
- Southern Health and Social Care Trust
- Northern Health and Social Care Trust

England

- Barnsley Hospital NHS Foundation Trust
- The Walton Centre NHS Foundation Trust
- Hull and East Yorkshire Hospitals NHS Trust
- Northern Lincolnshire and Goole NHS Foundation Trust
- Imperial NHS Trust

Scotland

- Lothian NHS Trust

UK – Private

- Woodland Neuro rehab Center, York (Christchurch Group)
- Glenside Care, Salisbury
- Royal Hospital for Neuro-disability, Putney London

Ulster University

Part 4: Stroke : Rehabilitation

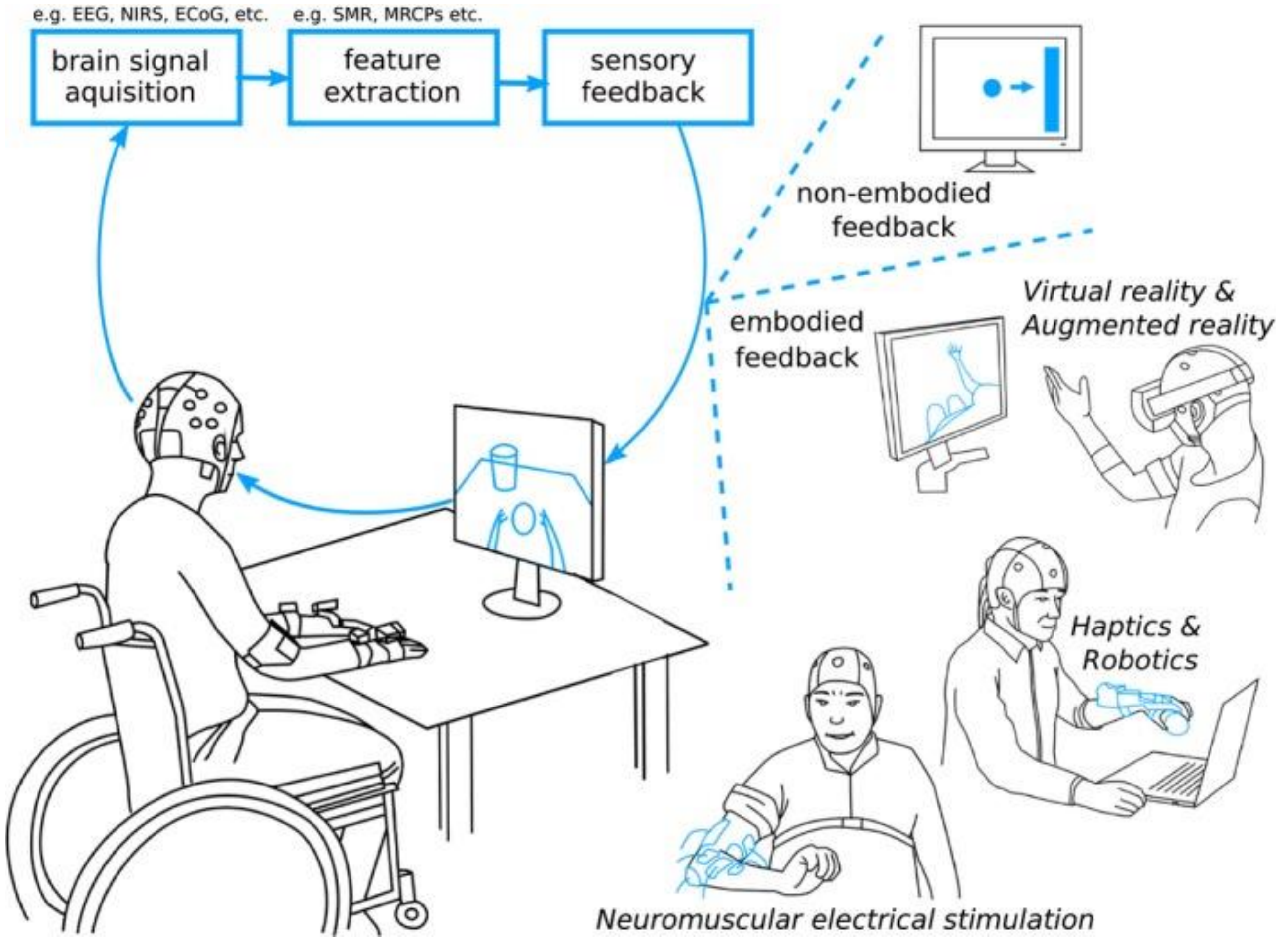
Stroke Rehabilitation

with BCI based Neurofeedback

Movement imagery (MI) relies on the same brain areas as movement
(Miller et al, 2010)

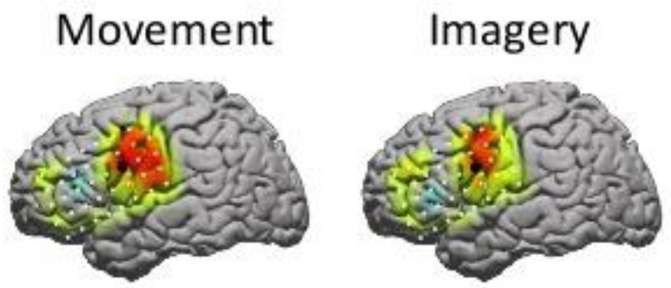
Repeated practice of MI can induce plasticity in the brain
(Jackson et al 2001)

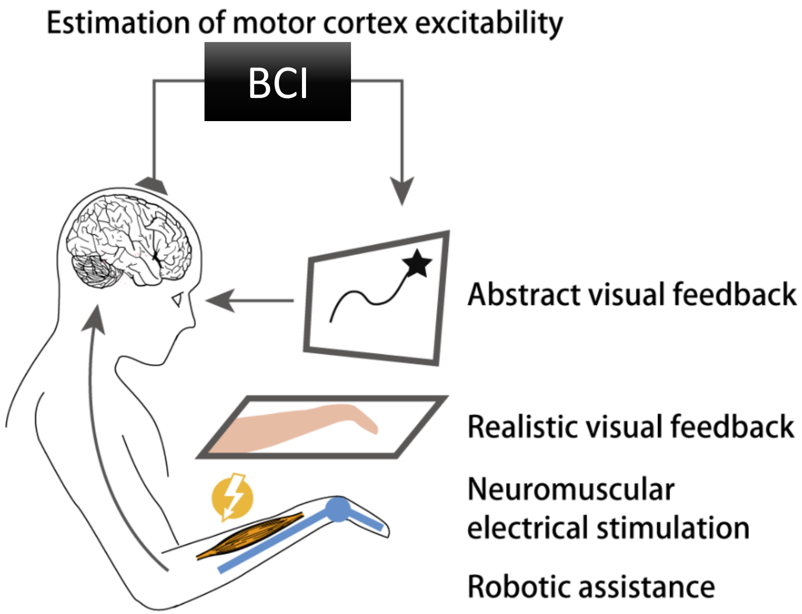
Combing MI and BCI can augment rehabilitation gains
(Aung et al, 2011, Prasad et al, 2011)



Cervera et al, 2019

Why use BCI in stroke rehab therapy?





Study	BCI Modality	Feedback Mechanism	Partipants	Sessions	Average FMA Gain
Meng et al. 2008, Tam et al. 2011	EEG	BCI FES	5	20	-0.4
Prasad et al. 2010	EEG	BCI Visual	5	12	6.2
Broetz et al. 2010	EEG MEG	BCI Robot	1	NA	4
Ang et al. 2010, 2014	EEG	BCI Robot	11	12	4.5
Caria et al. 2011	EEG MEG	BCI Robot	1	20 20	11
Mihara et al. 2013	NIRS	BCI Visual	10	6	6.6
Biasiucci et al. 2013	EEG	BCI FES	2	10	9.5
Ramos-Murguialday et al. 2014	EEG	BCI Robot	16	20	3.4
Ang et al. 2014	EEG	BCI Robot	6	18	7.2
Ang et al. 2015b	EEG	BCI Robot - tDCS BCI Robot	10 9	10	5 5.4

Total #stroke subjects: 76 Average FMA Improvement: 4.93

Compared to robotic rehab: #subjects: 1206, Average FMA Improvement: ~2

Veerbeek, et al, Neurorehabilitation and Neural Repair, September 5, 2016

BCI surpasses other rehab therapies when outcomes measured using Fugel Meyer Assessment (FMA)

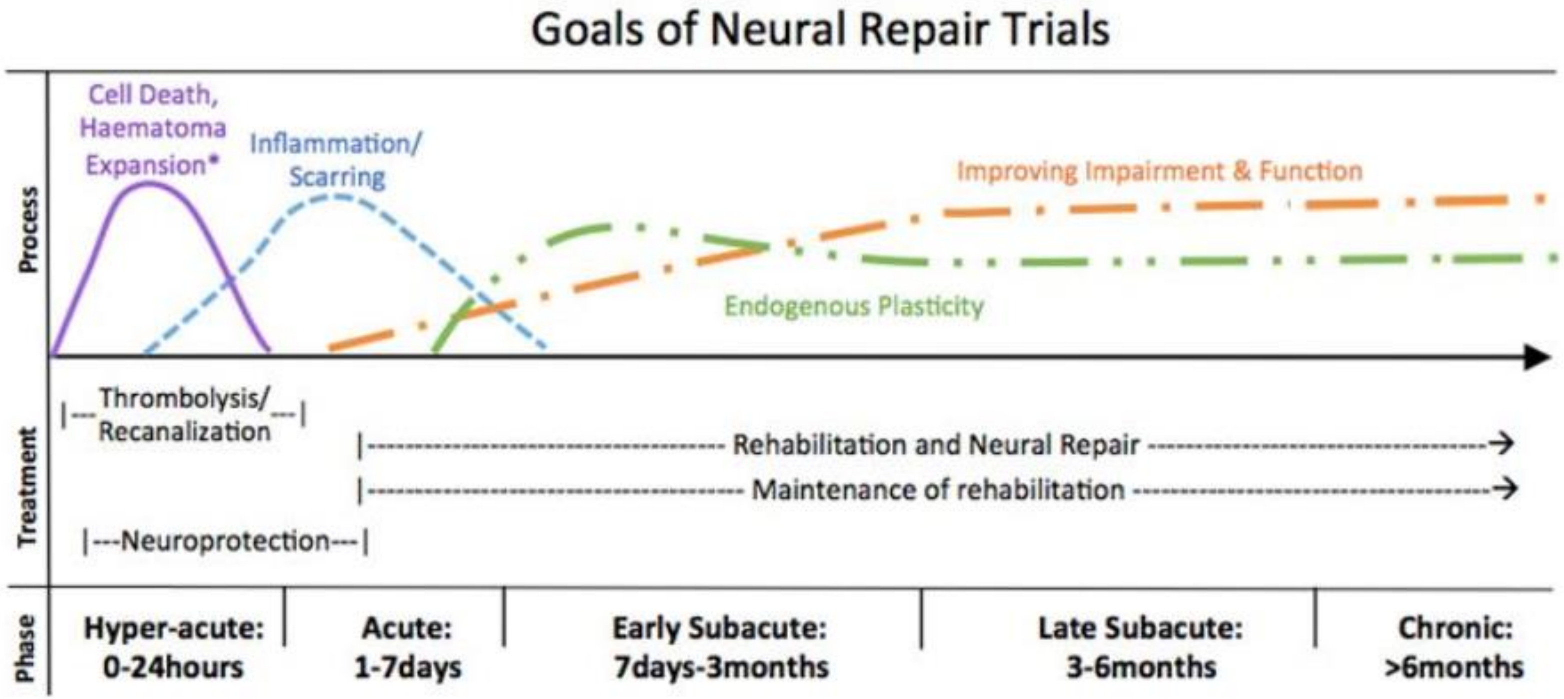
BCI offers a lot of potential

Therapy	Outcome (SMD)	Sample Size
BCI	0.79	235
Mental Practice	0.62	102
Mirror Therapy	0.61	481
Robotics Therapy	0.35	1078
CIMT	0.33	355
Virtual Reality	0.27	363
tDCS	0.11	431

Cervera, et al, Annals of Clinical and Translational Neurology, 25 March, 2018

Neuroplasticity

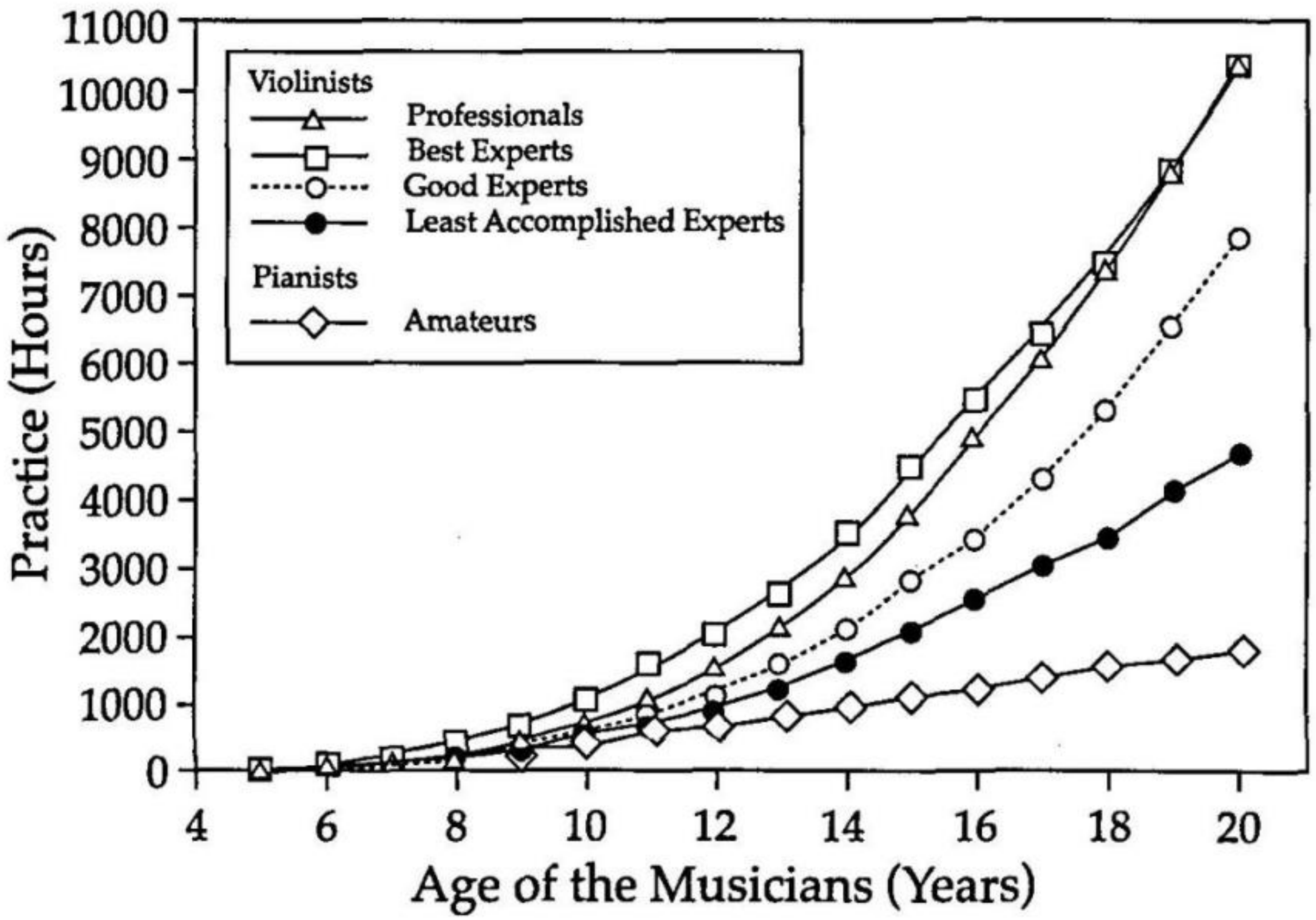
Leff, 2017



The underlying molecular, cellular and brain network processes that mediate neural plasticity vary over time

They probably are time-limited, but does the overall window of neuroplasticity ever shut?

Ericsson's "10,000 hours"



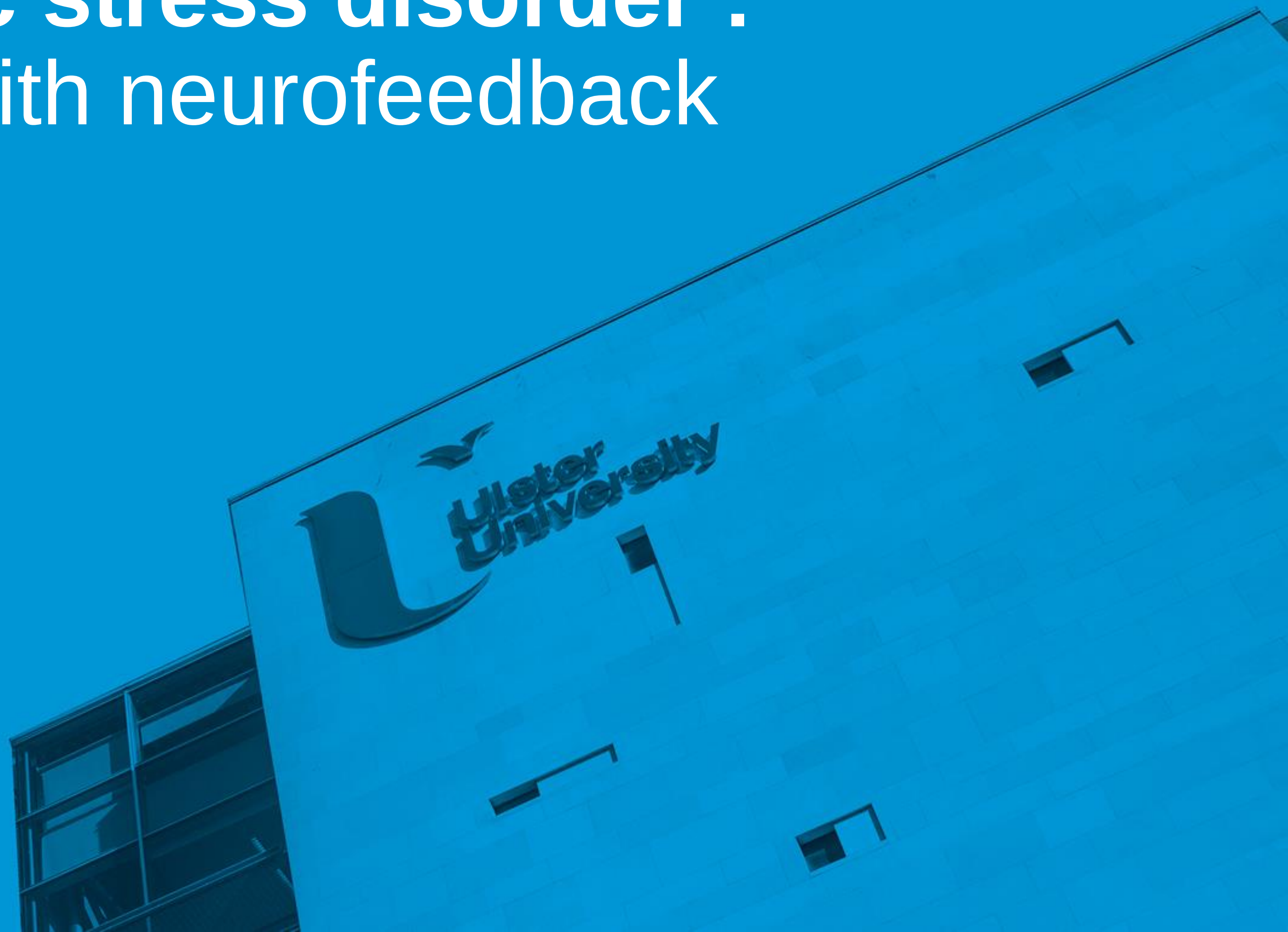
Human expert performance literature may help

Better performance feedback – real-time and regular coaching

Increase the training duration and intensity

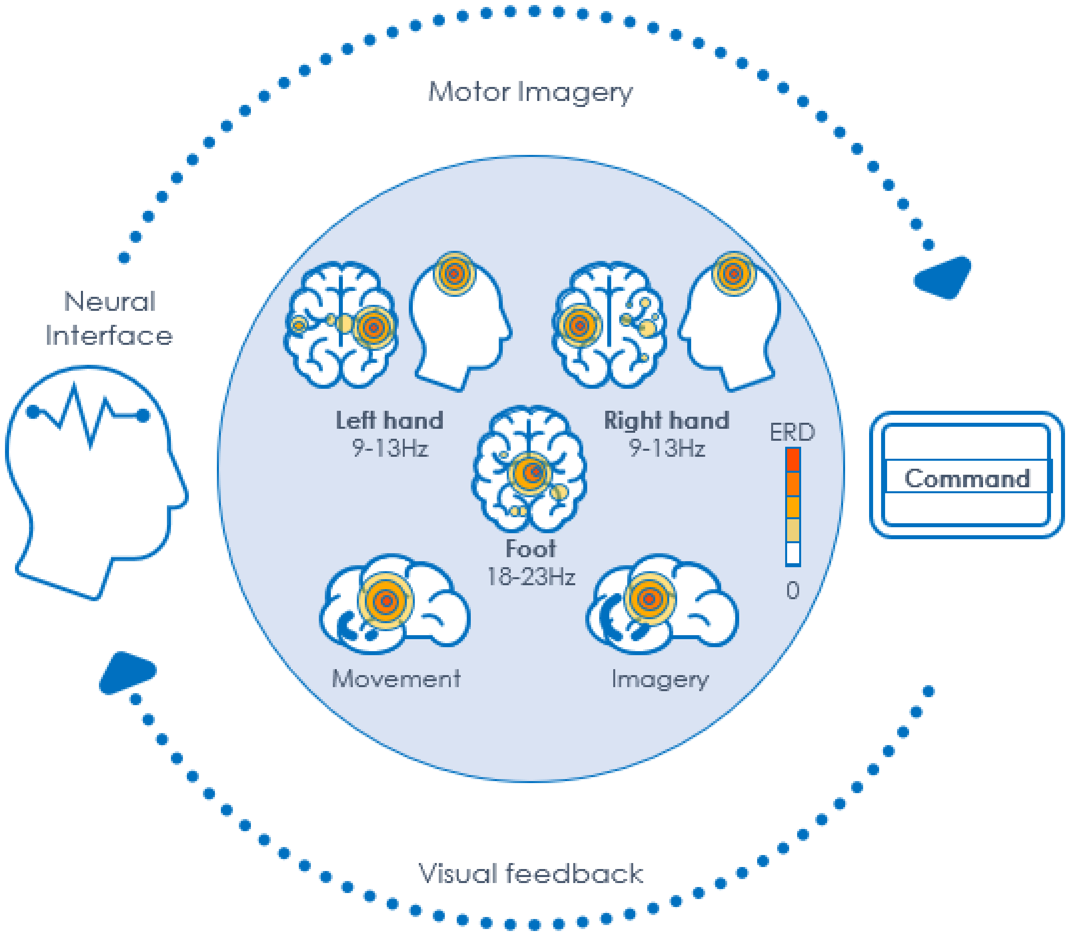
For patients : dedicated, high dose therapy services

Part 5 : Post traumatic stress disorder : Alleviating symptoms with neurofeedback



How effective is neurofeedback and/or motor-imagery training – delivered using low-cost EEG-based wearable headsets – in the reduction of PTSD symptoms?

Motor Imagery BCI vs Neurofeedback



Pilot RCT in Rwanda

29 participants community engagement with women genocide survivors, pregnant during genocide

Intervention

Participants were assigned to three conditions

- Control (*n* = 9)
- Neurofeedback (NF, *n* = 10)
- Motor Imagery BCI (MI-BCI, *n* = 10)

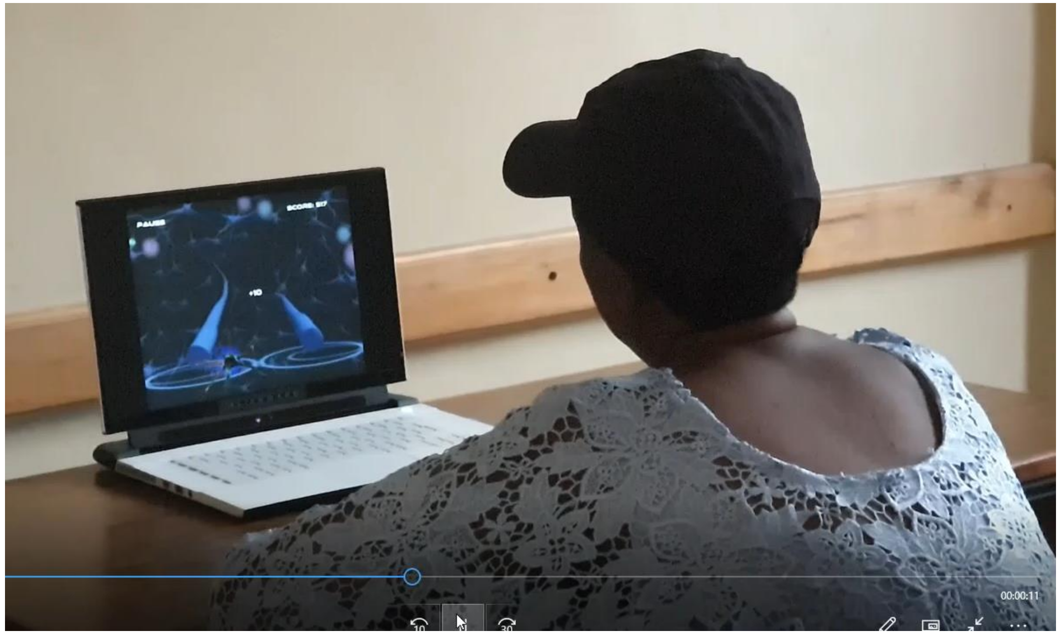
6-7 training sessions for the experiment groups over a three-week period

Outcome measures

- Conduct a clinical interview pre- and post- training

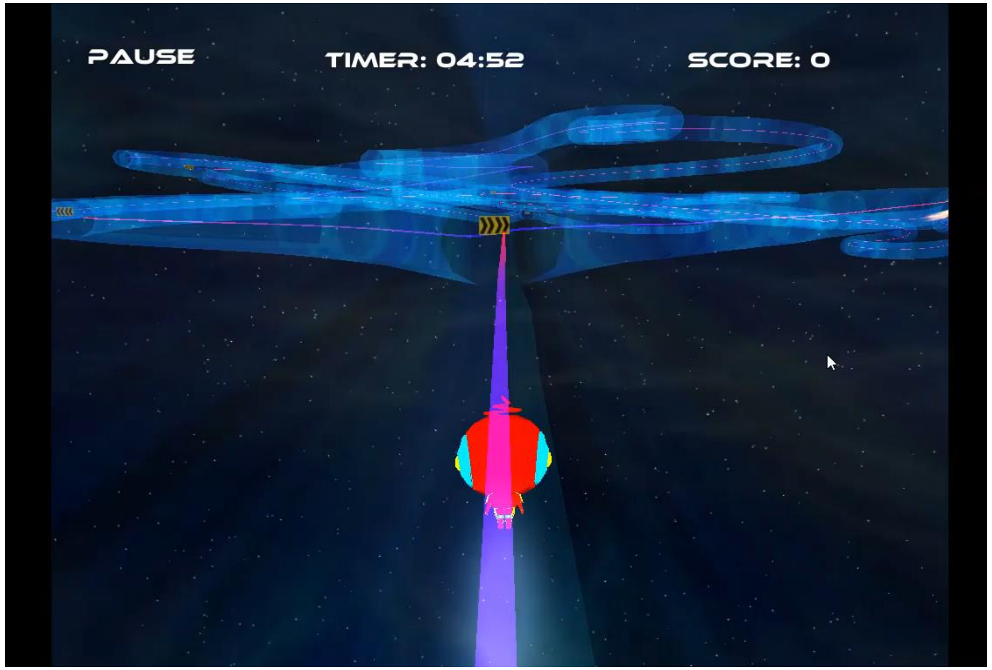
Motor-imagery BCI

Neurofeedback



- From motor-imagery group
- Left- hand vs right-hand imageries

- Used by Neurofeedback group
- Self-regulating alpha rhythms



Pilot Study Findings

Clinical Interviews

Neurofeedback group – reduced symptoms post training

10-item CD-RISC questionnaire (p = .041)

PTSD: PCL-5 DSM 5 (p = .005)

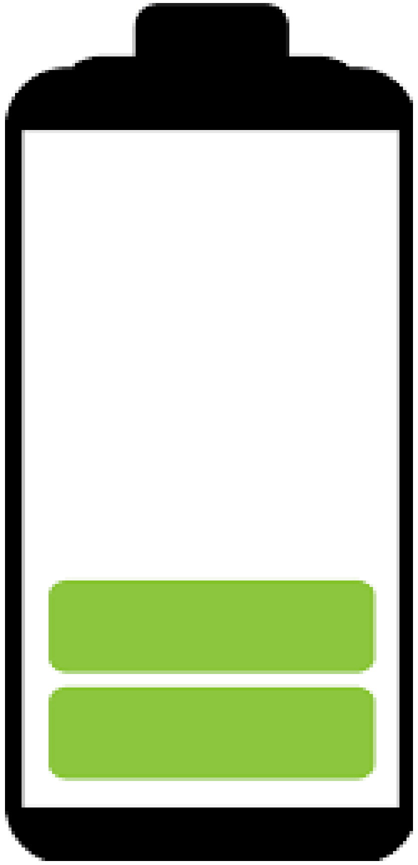
Primary Care PTSD screen for DSM-5 (p = .005)

PTSD Harvard Trauma questionnaire (p = .005)

Large effect sizes; r = - 0.79/ -0.8

Post- training scores fell *below* the cut-off scores for a clinical diagnosis of PTSD

The implication is that neurofeedback training resulted in a clinically relevant reduction in symptom severity

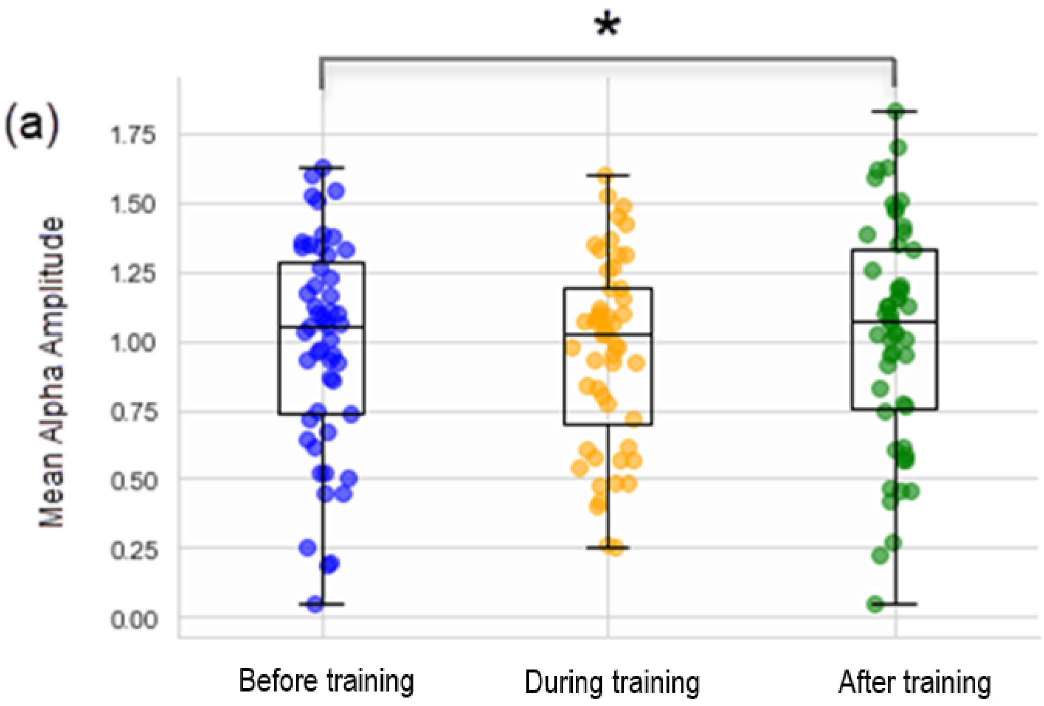


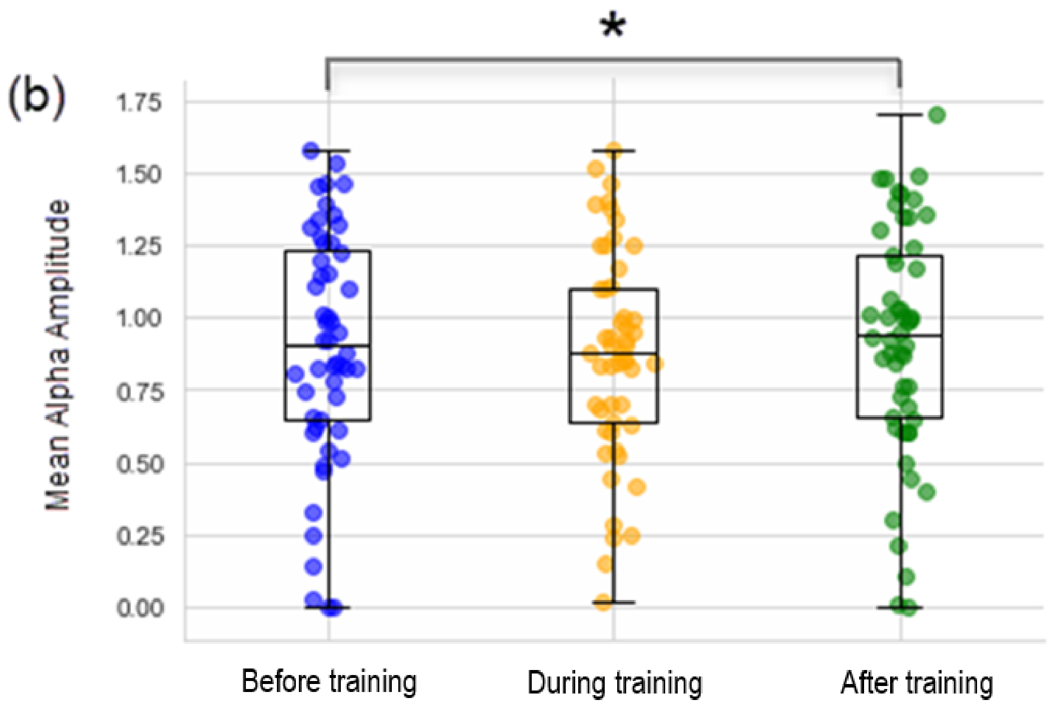
Pilot Study Findings

Ulster University

Neurofeedback group successfully reduced absolute alpha amplitudes during NF training

(a) local: $Z = -2.235$, $p = 0.025$, $r = -0.31$, and **(b)** global: $Z = -2.253$, $p = 0.024$, $r = -0.31$



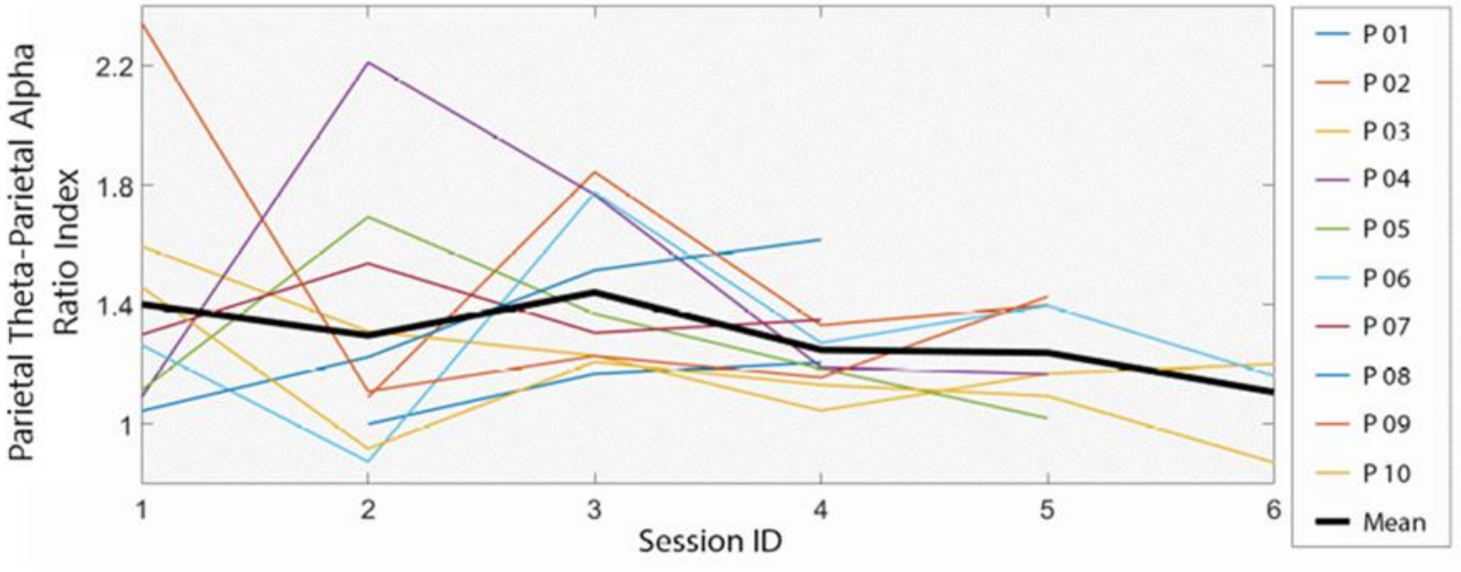


…reduced alpha power on task infers increased alpha desynchronisation, i.e., attenuation, implying improved functional connectivity

Pilot Study Findings

Motor Imagery BCI

While not significant, there was a decrease in the ratio index of parietal theta power to parietal alpha power for each BCI session, for each participant.



…focus on task irrelevant information results in increased parietal theta/alpha power, therefore, a decrease across sessions supports improved CEN function and network switching.

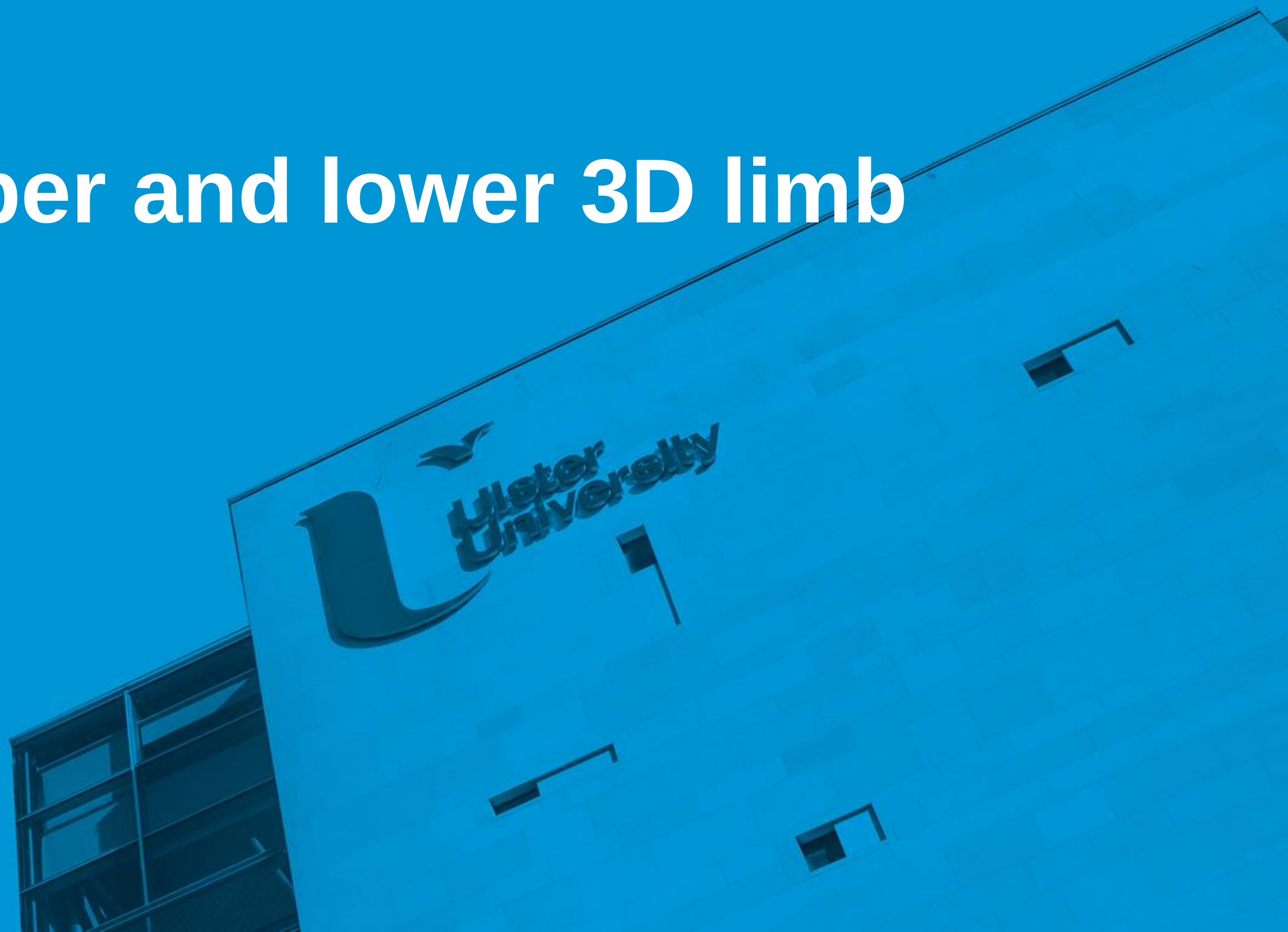
(Emami & Chau, 2020)

Conclusion

- Neurofeedback group demonstrated increased resting-state alpha following each training session…referred to as alpha ‘rebound’, associated with increased calmness/reduced anxiety (Kluetsch et al. 2014).
- While not significant, there was an observed decrease in the ratio index of parietal theta power to parietal alpha power for each BCI session, for each participant.
- Neurofeedback training resulted in a clinically relevant reduction in symptom severity on standard measures of PTSD.

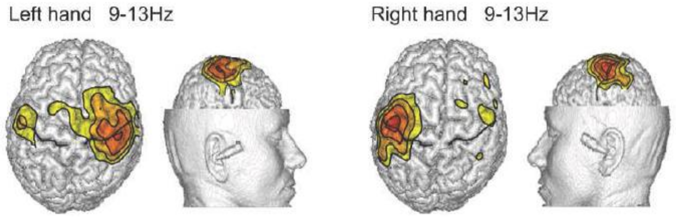
This research has demonstrated a clinically important effect of NF training on symptom severity for PTSD patients within a group of genocide survivors in Rwanda – representing the first evidence of a neurotechnological solution for the treatment of PTSD in Rwanda.

Part 6: Decoding upper and lower 3D limb movement from EEG

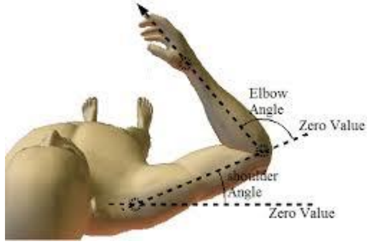


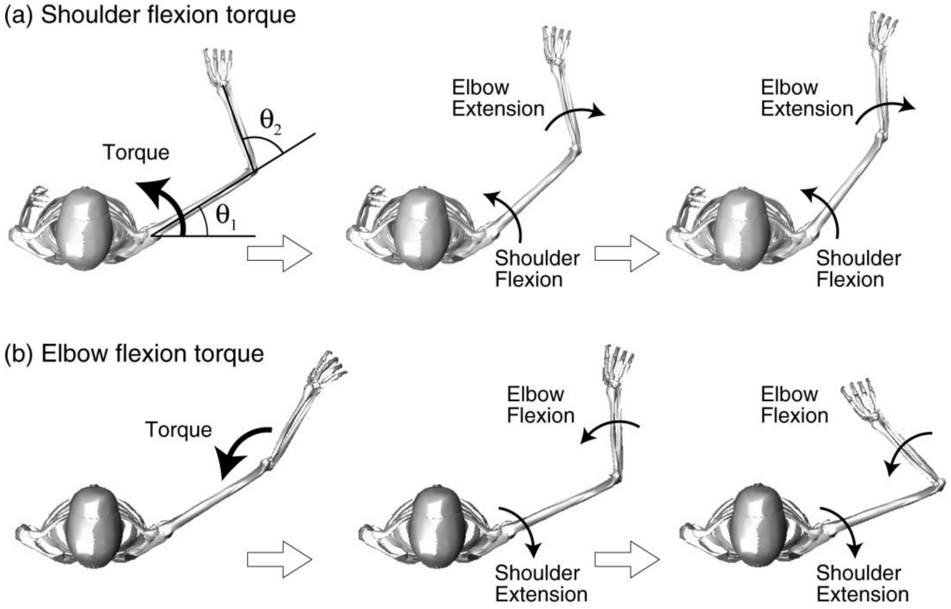
Classical SMR BCI vs 3D hand motion trajectory prediction (MTP) BCI

Classical sensorimotor rhythm (SMR) BCIs

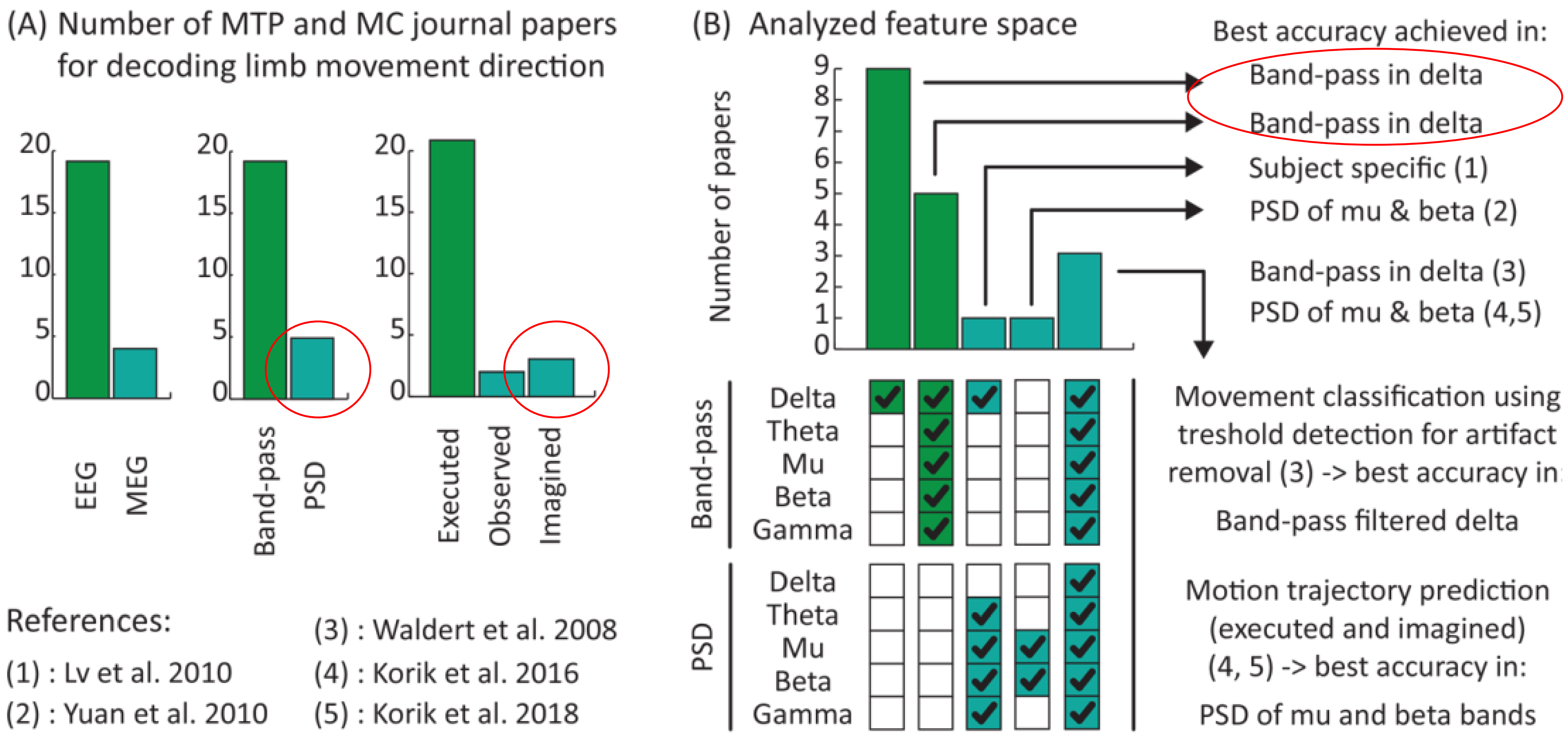


3d hand motion trajectory prediction (MTP)/reconstruction/decoding



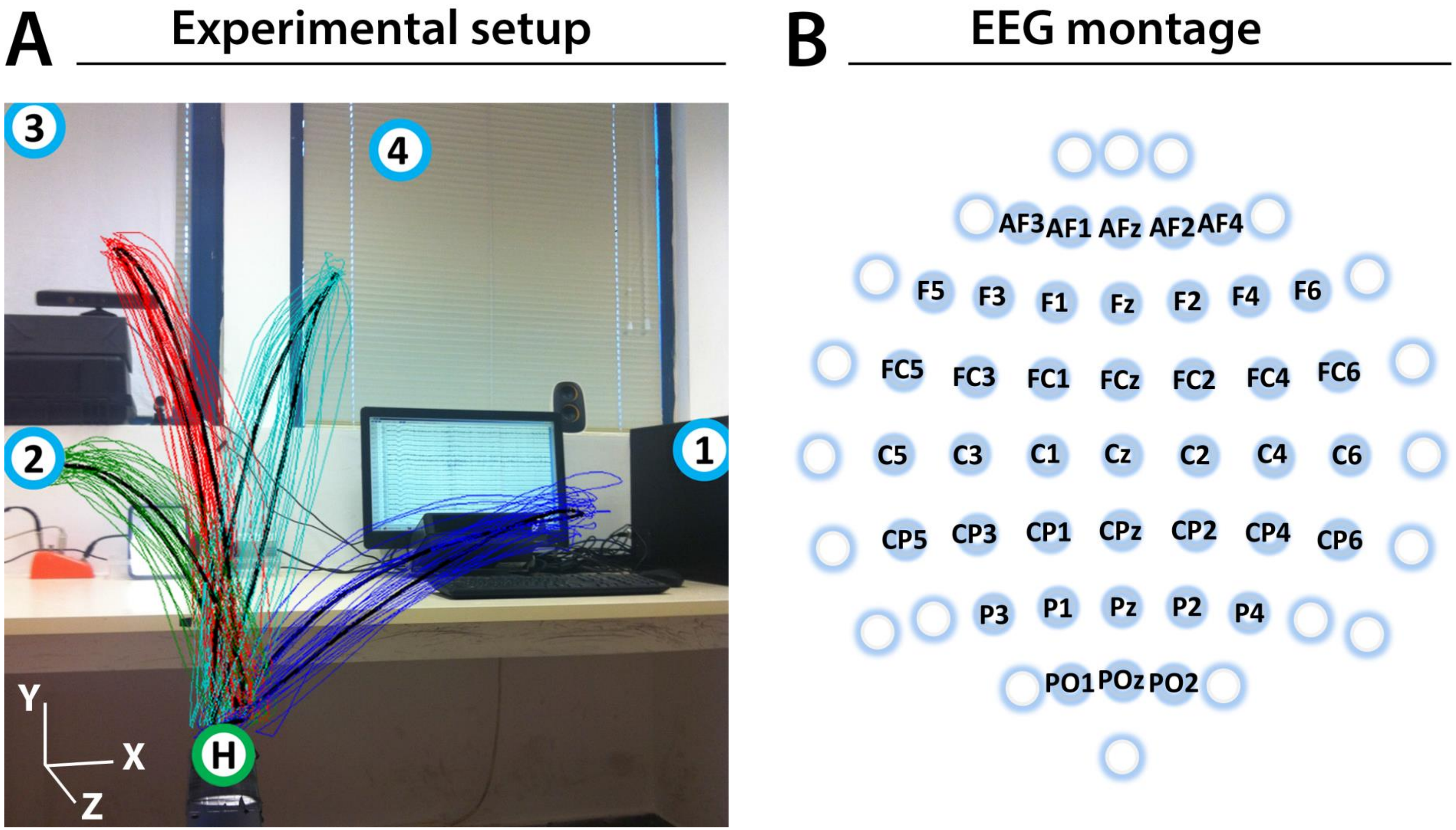


Literature review 2018

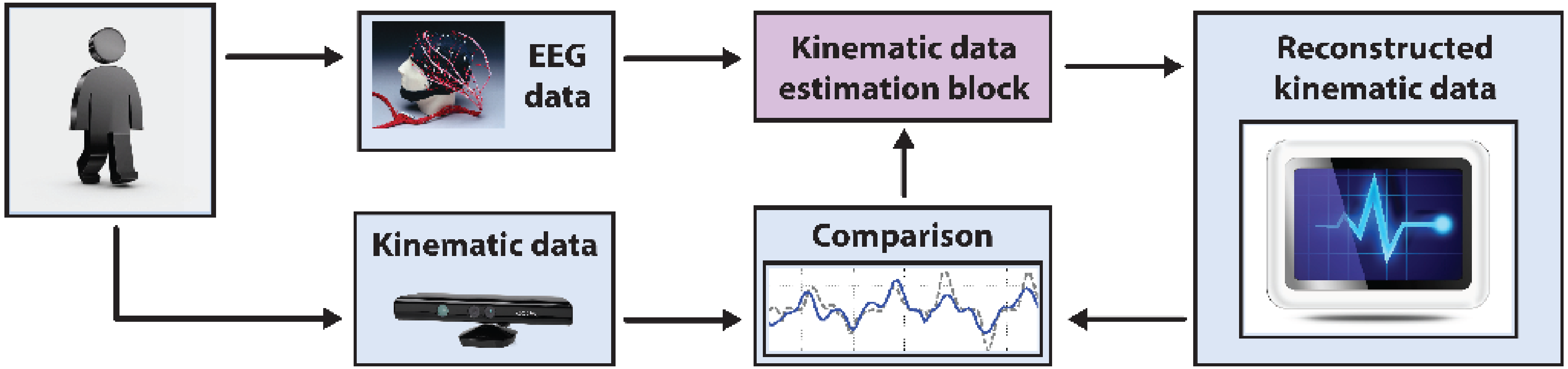


Decoding 3D Trajectory of Arm Movements and Imagined Arm Movements from EEG

Ulster University



Multiple linear regression mLR



mLR based kinematic data estimation:

$$x_i[t] = a_i + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nki} S_n[t-k] + \varepsilon[t]$$

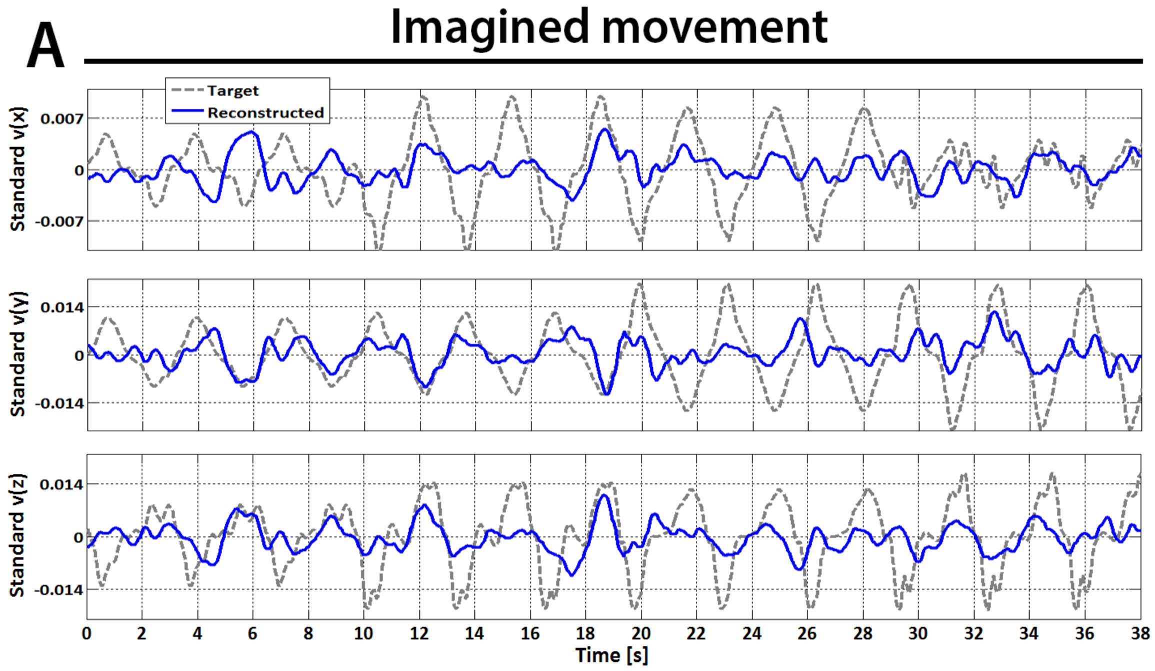
- N : bandpass-filtered EEG channel number
- L : time lag number

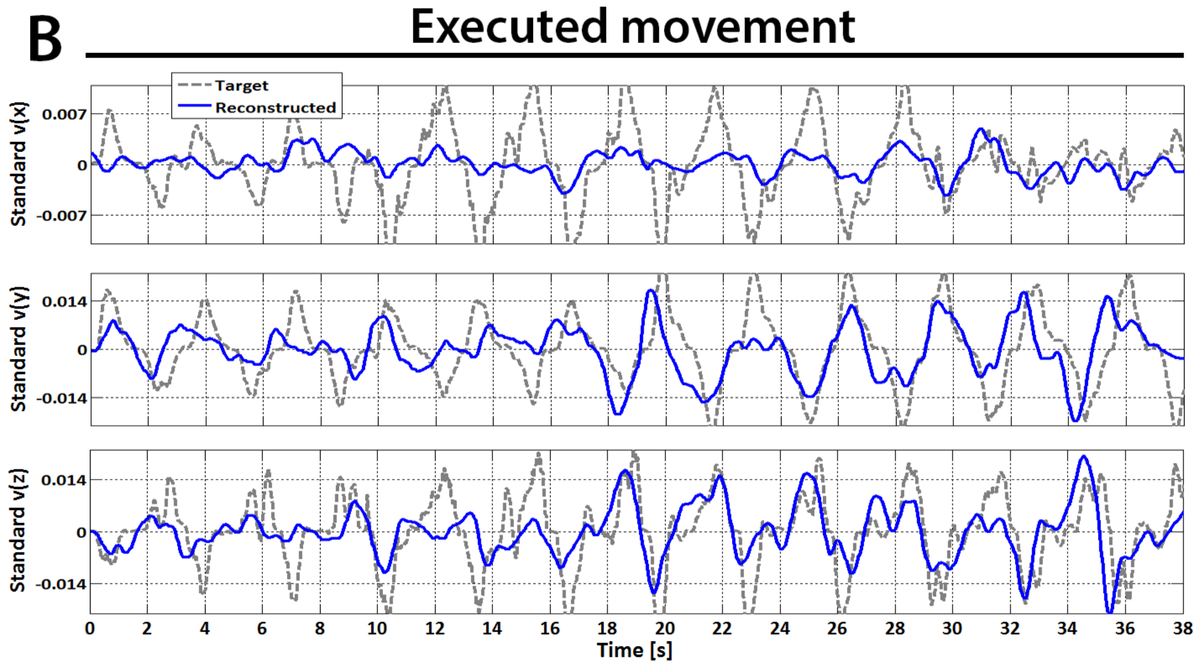
S_n : Standardized temporal differences at sensor n

PTS model: $$S[t] = \frac{v_{PTS}[t] - \mu_{v_{PTS}}}{\sigma_{v_{PTS}}}$$

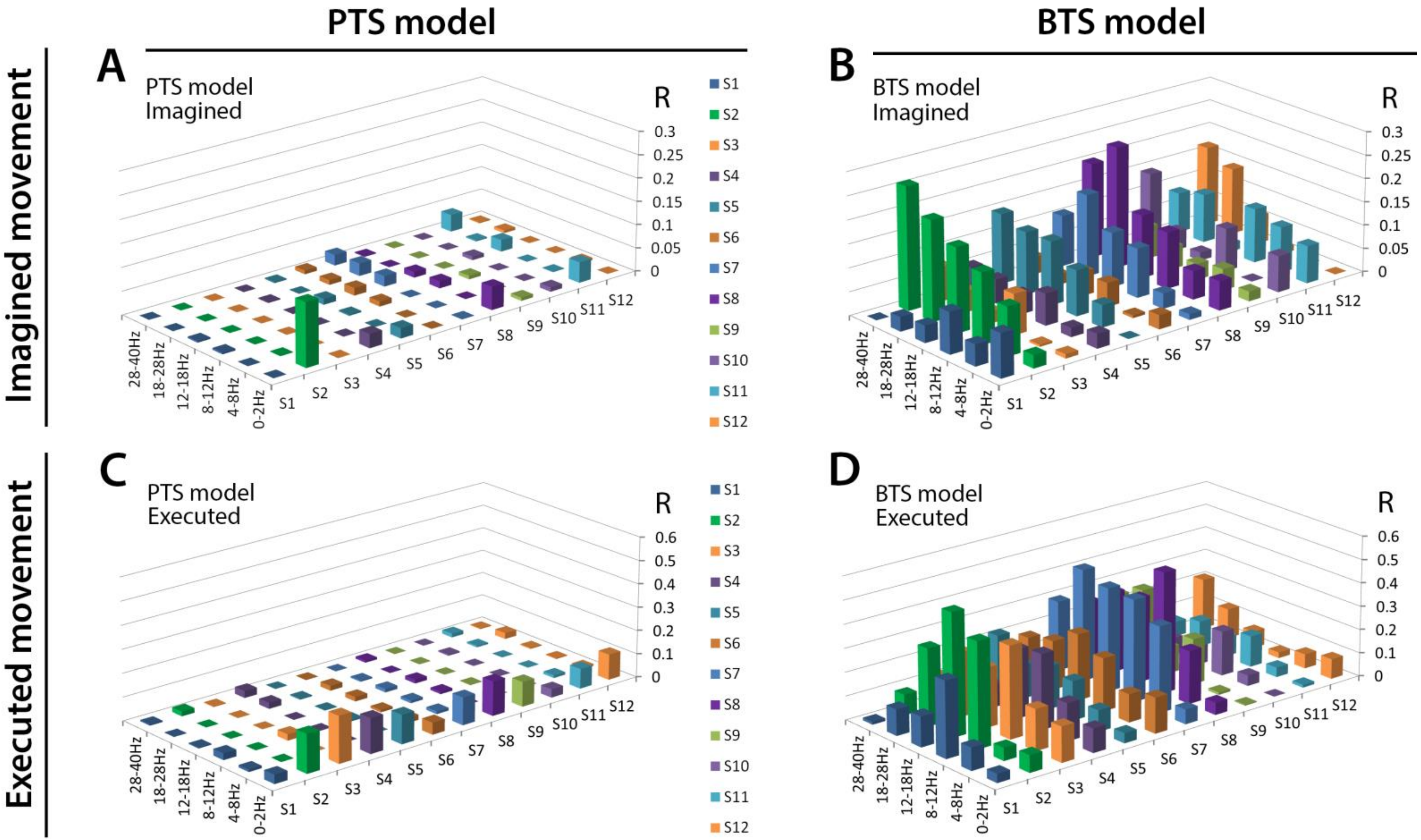
BTS model: $$S[t] = \frac{v_{BTS}[t]}{\sigma_{v_{BTS}}}$$

Reconstructed velocity profiles





Decod

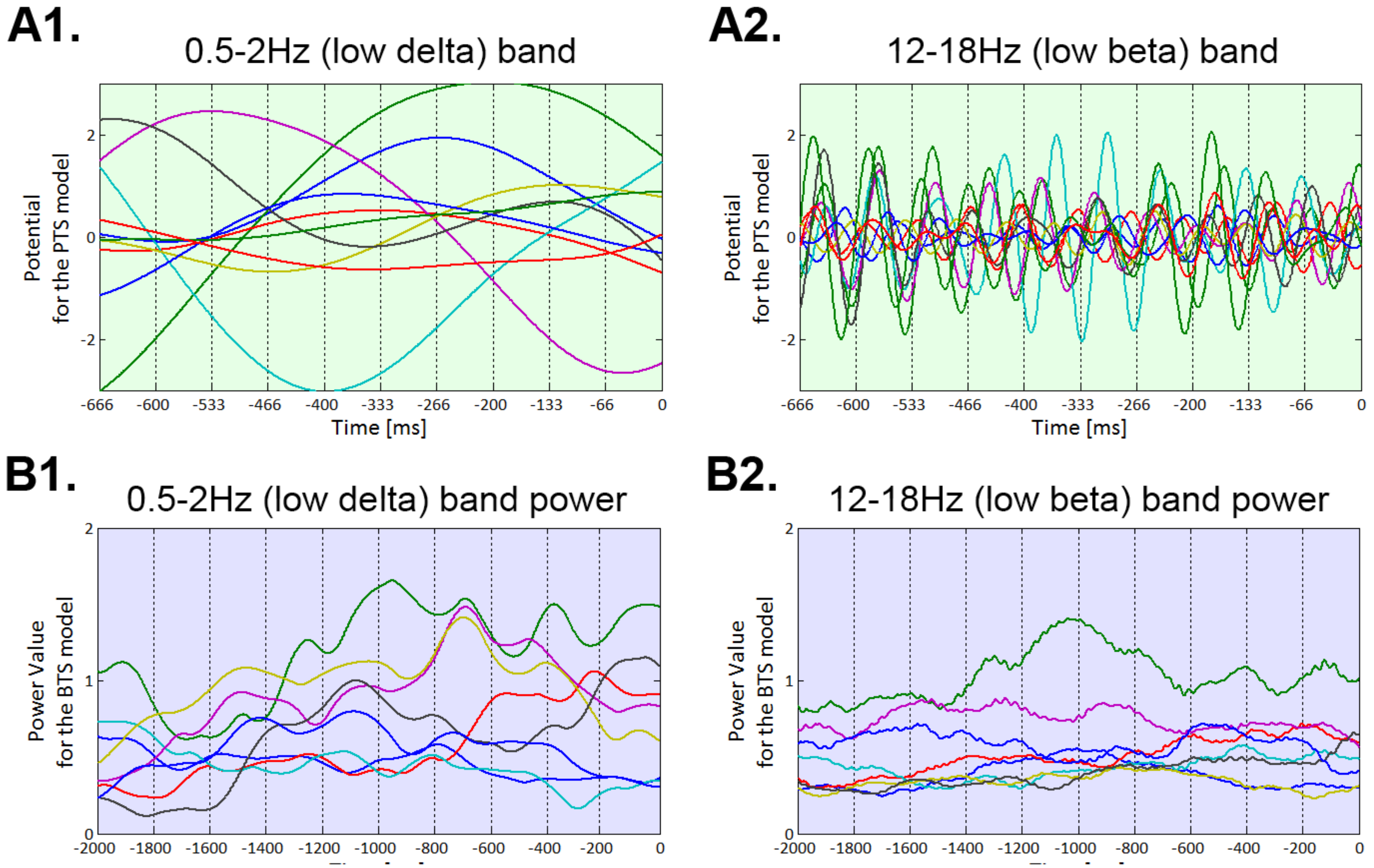

PTS model
BTS model
Imagined movement
Executed movement
A
PTS model
Imagined
R
0.3
0.25
0.2
0.15
0.1
0.05
0
28-40Hz
18-28Hz
12-18Hz
8-12Hz
4-8Hz
0-2Hz
S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
B
BTS model
Imagined
C
PTS model
Executed
0.6
0.5
0.4
0.3
0.2
0.1
D
BTS model
Executed

Potentials (Band pass) vs Band-power (PSD) time-series

PTS model
(Bandpass)

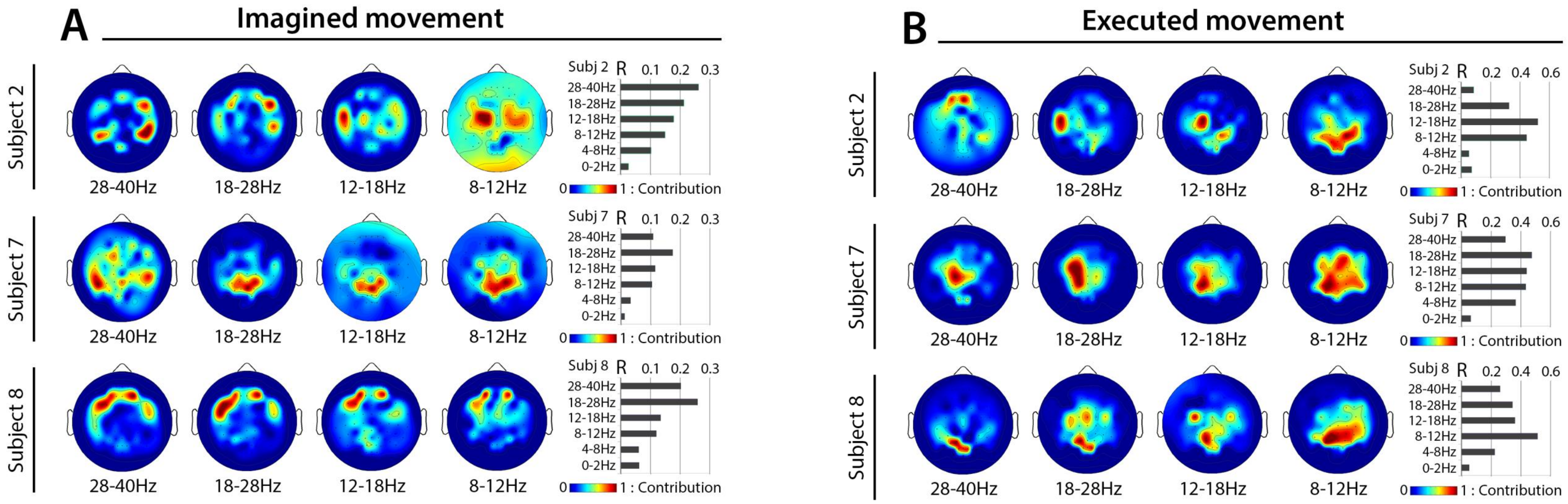
BTS model

(Band
power)

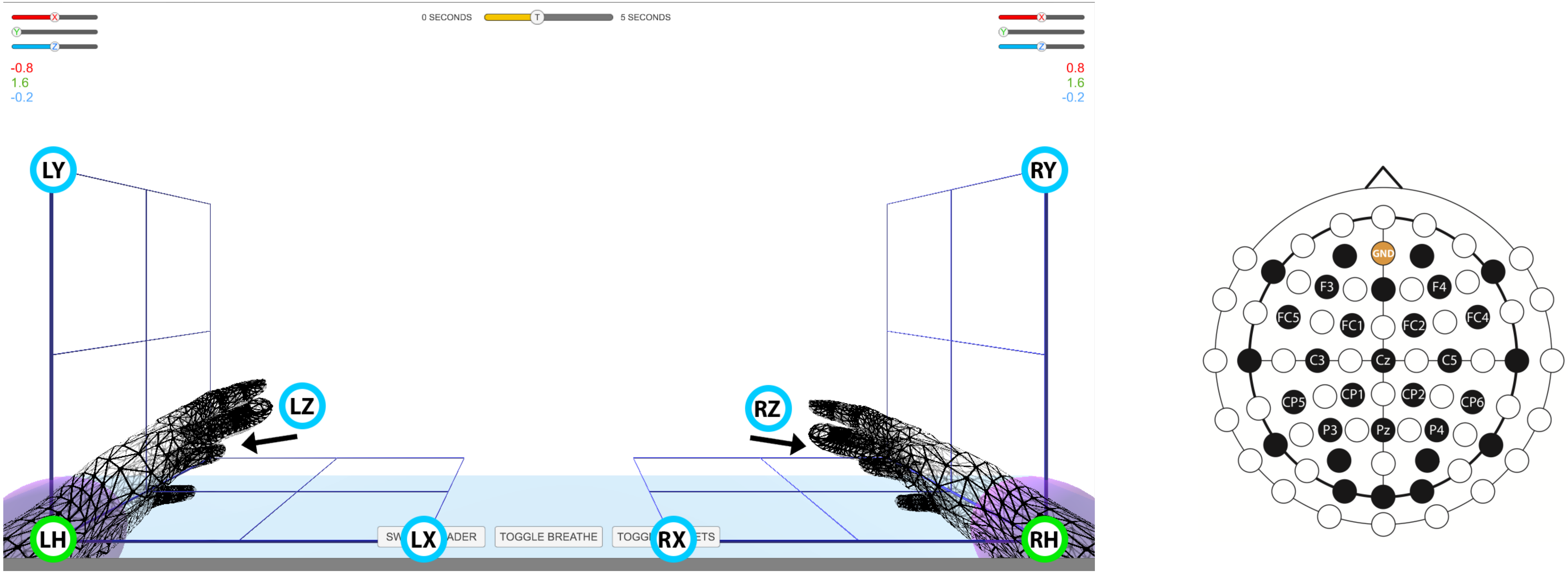


Example of input time-series in two different bands (A): PTS, (B): BTS

Topological maps



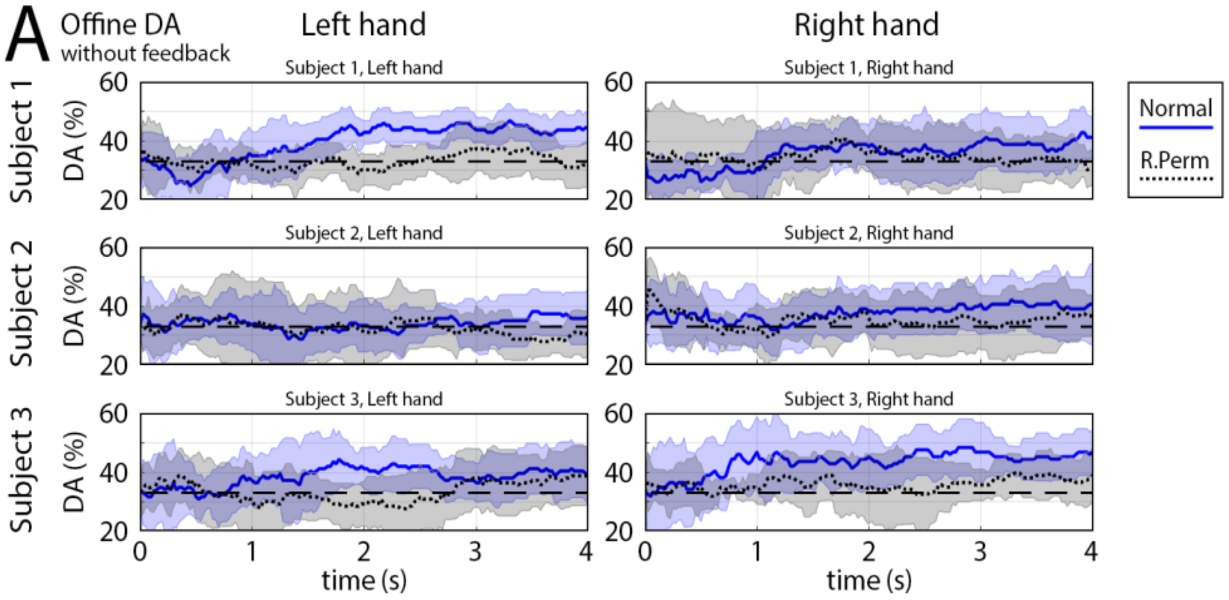
Real-time Control of Virtual Arms?



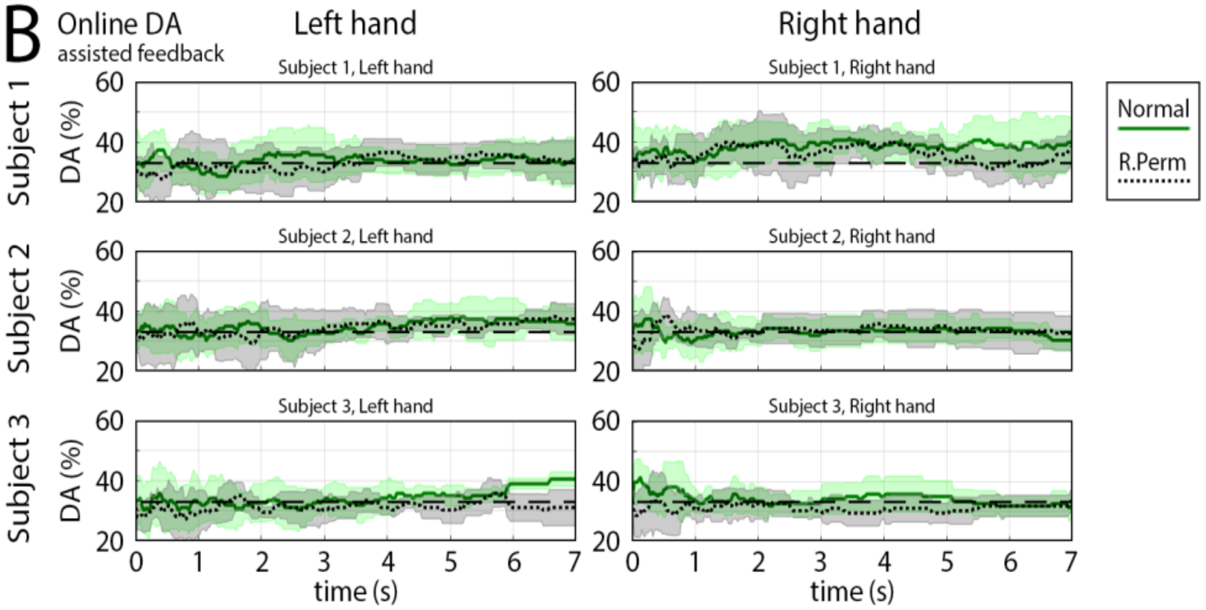
Virtual arm layout and EEG montage

Target Classification

Target Classification : Offline

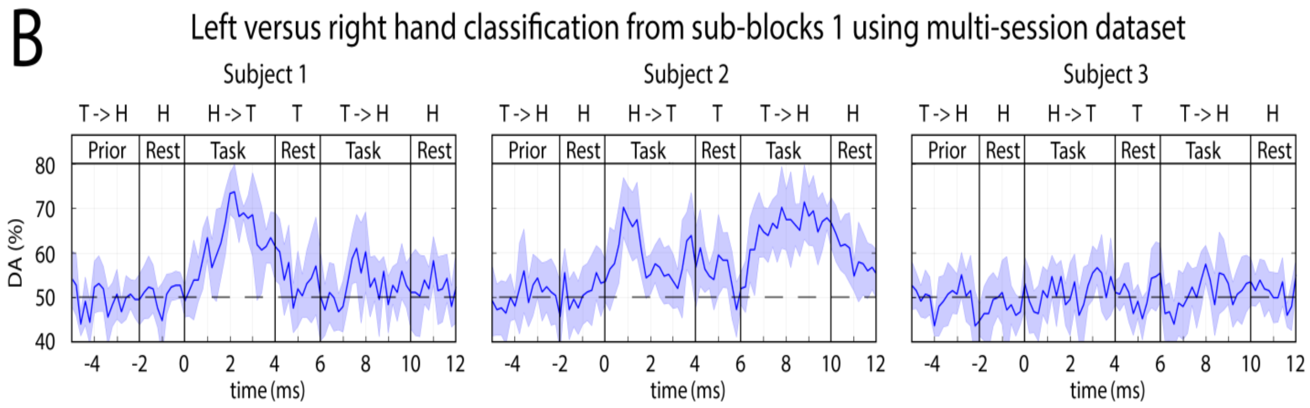


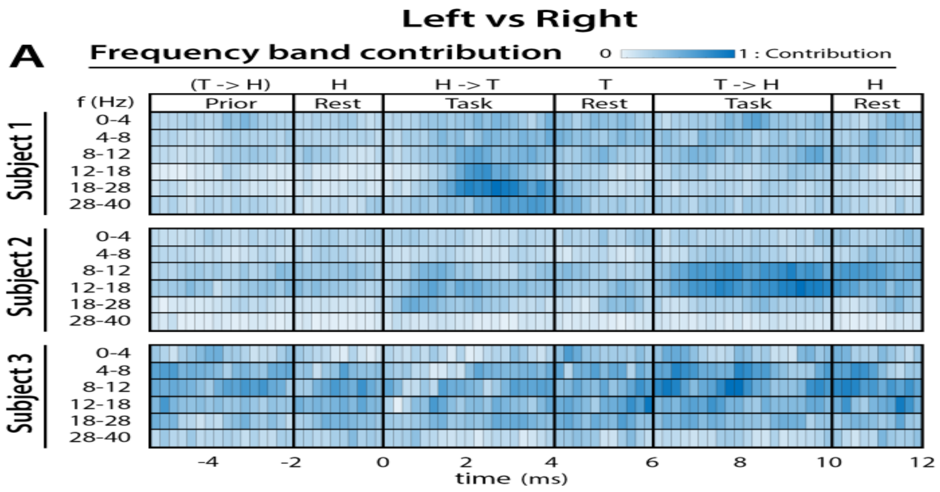
Target Classification : Online



Imagined Movement Classification (Left vs Right)

Time-varying Decoding Accuracy (DA)





Multi-session results calculated using trials from 7 sessions
1 session involved 3x6 trials/arm (i.e., 6 trials towards 3 targets / session)

How do we improve BCI paradigms to enable more and better data collection?

Spatial Computing and Neurotechnology Innovation Hub

SCAN iHub

Ulster University

The Spatial Comupting and Neurotechnology Innovation Hub, SCANi-Hub

Offcially opened by

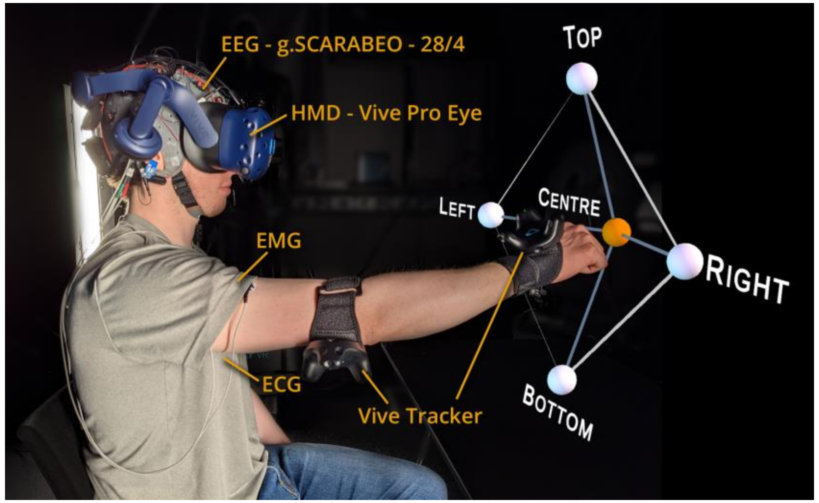
HRH The Princess Royal

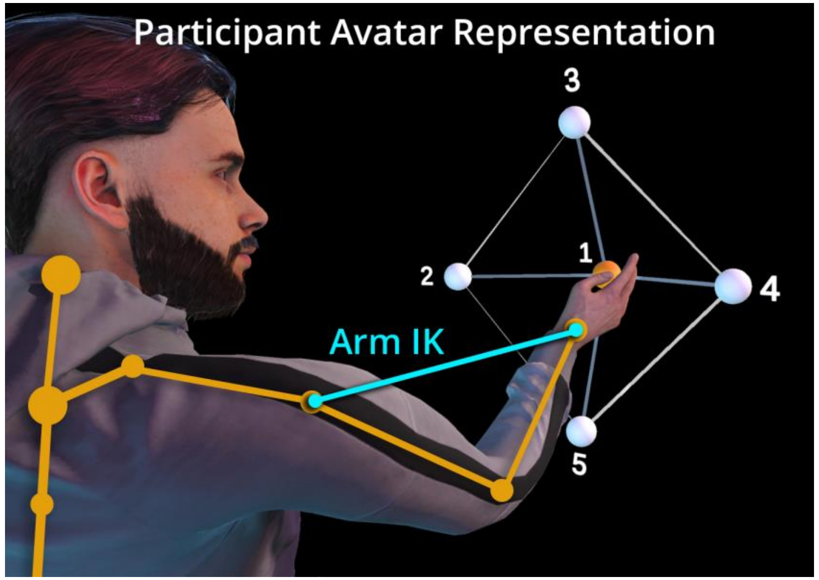
on

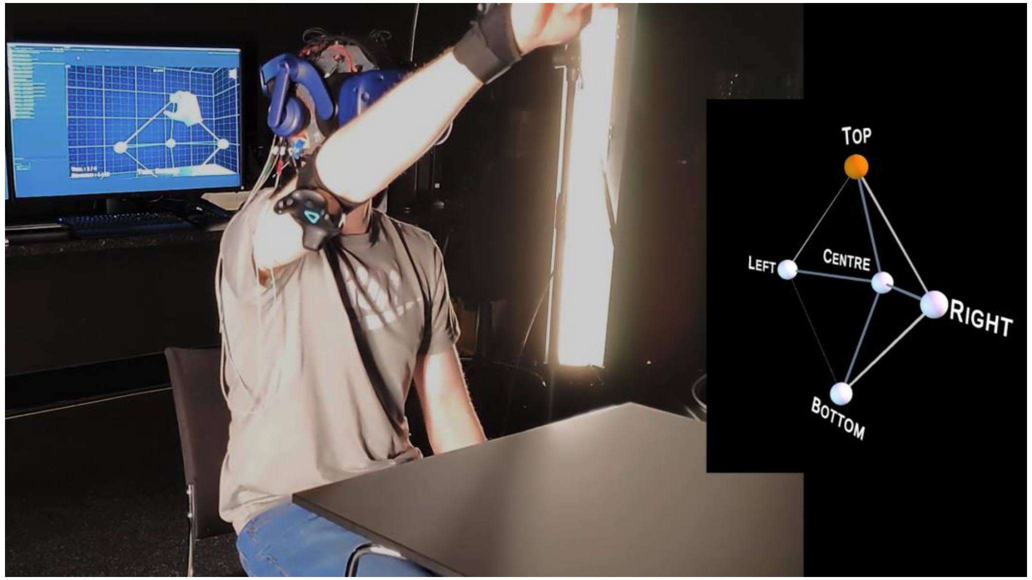
17th January 2020

SCAN iHub

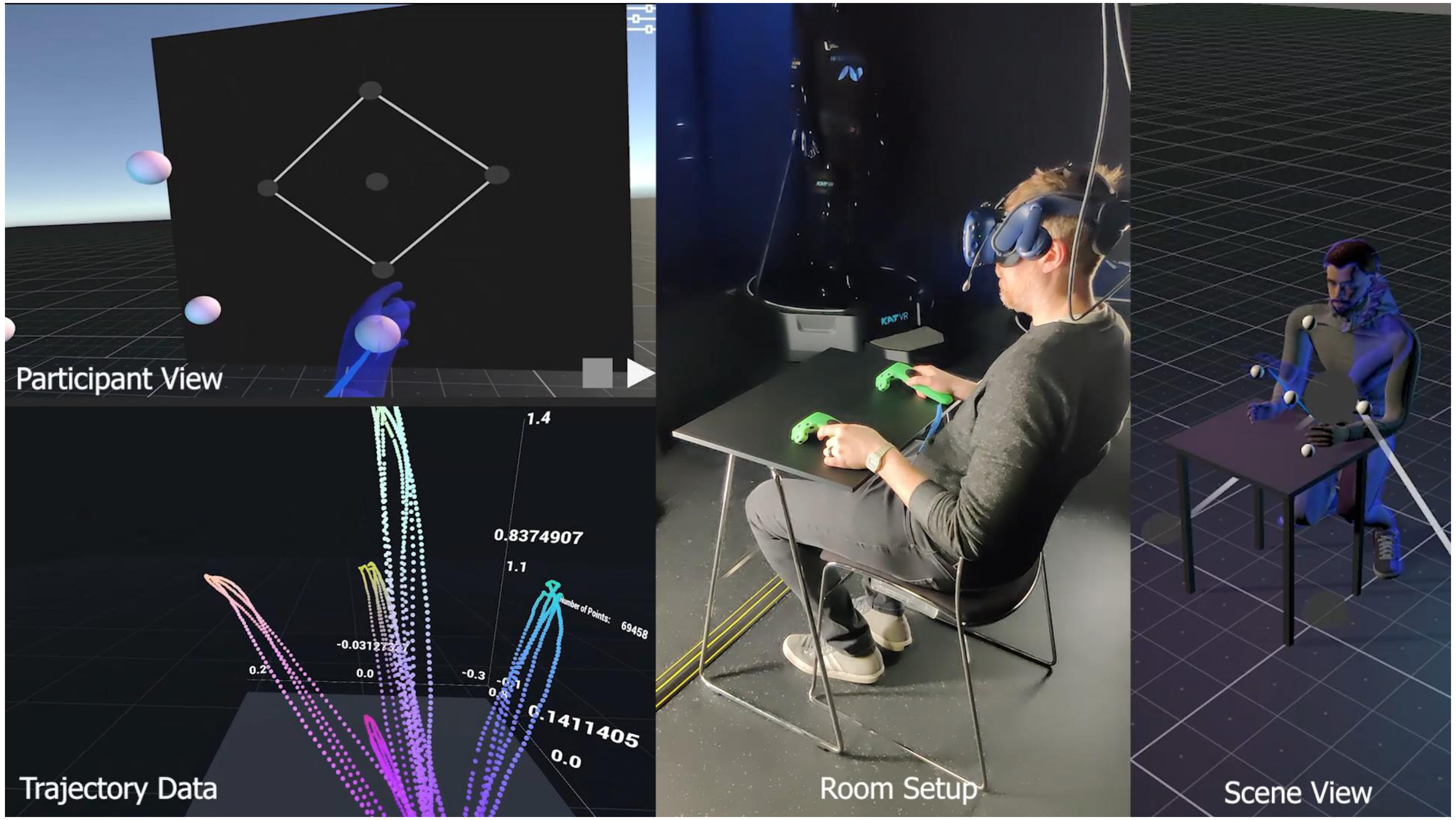
New Experimental Setup





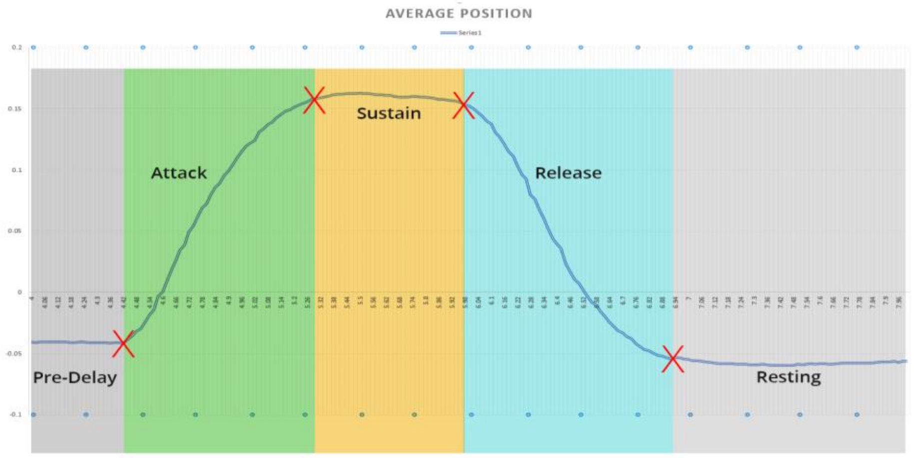


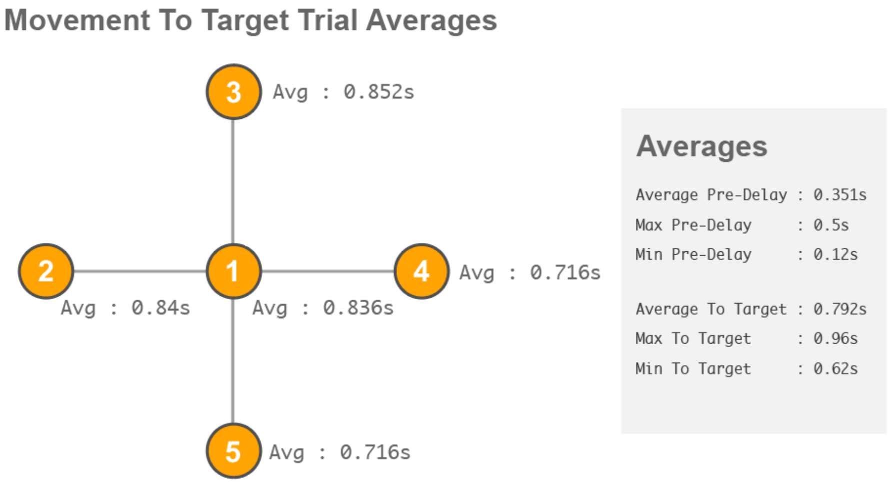
Centre-Out Reach

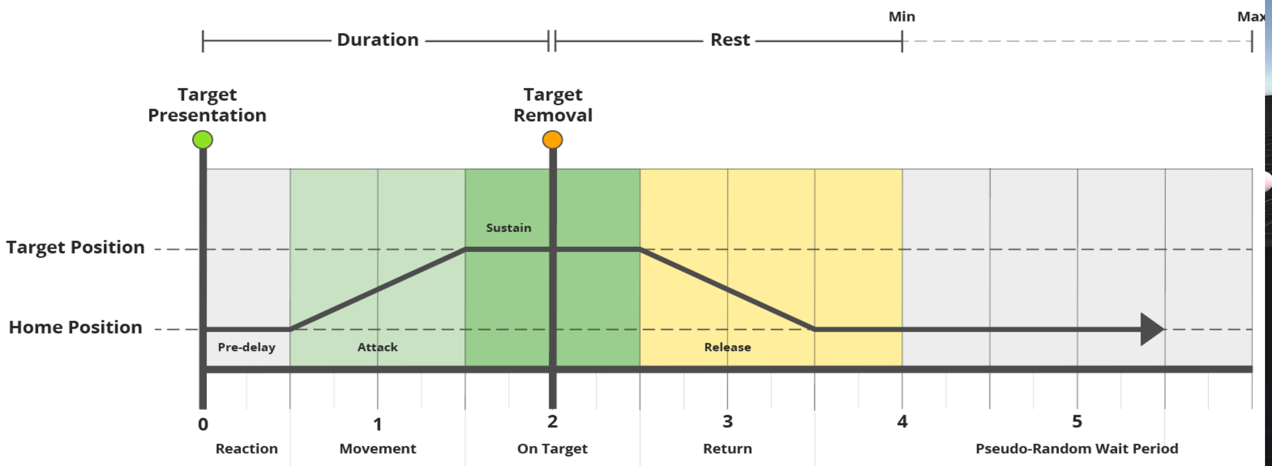


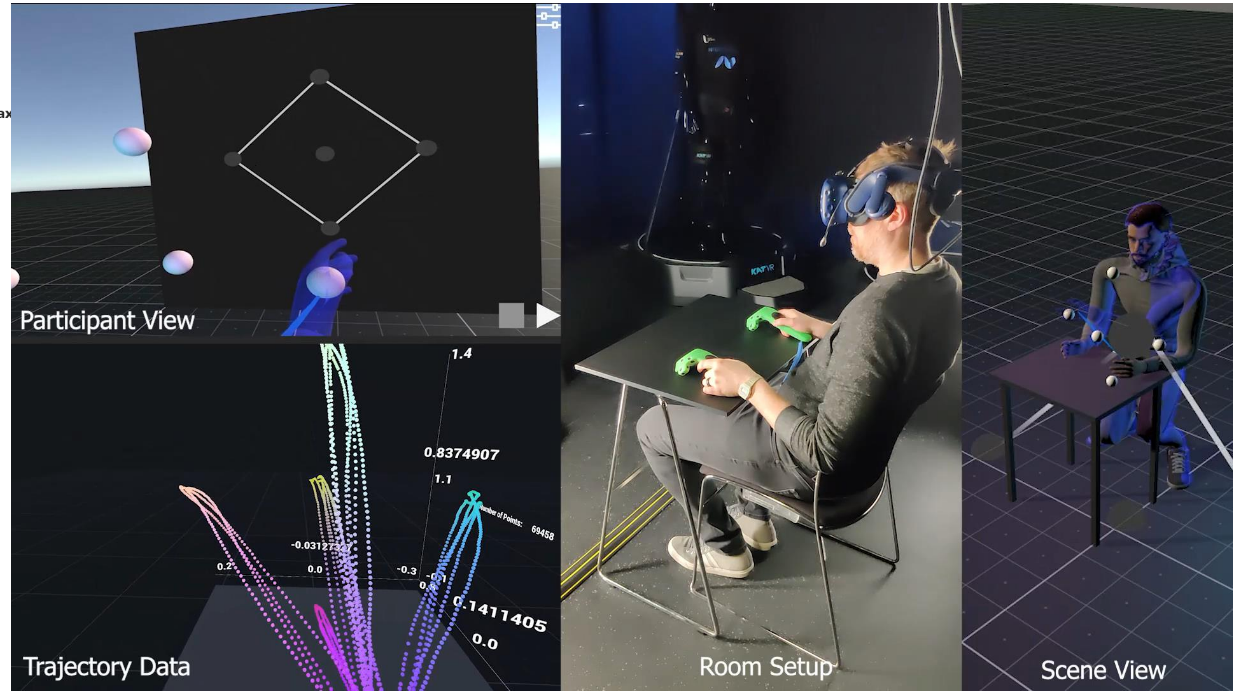
- 2D screen or
- 3D environment
- Avatar representation
- Action Observation
- Trajectory data
- Fixed positions
- BCI
    - Limited to 4/5 target positions

Tracked Hand Movement Envelope

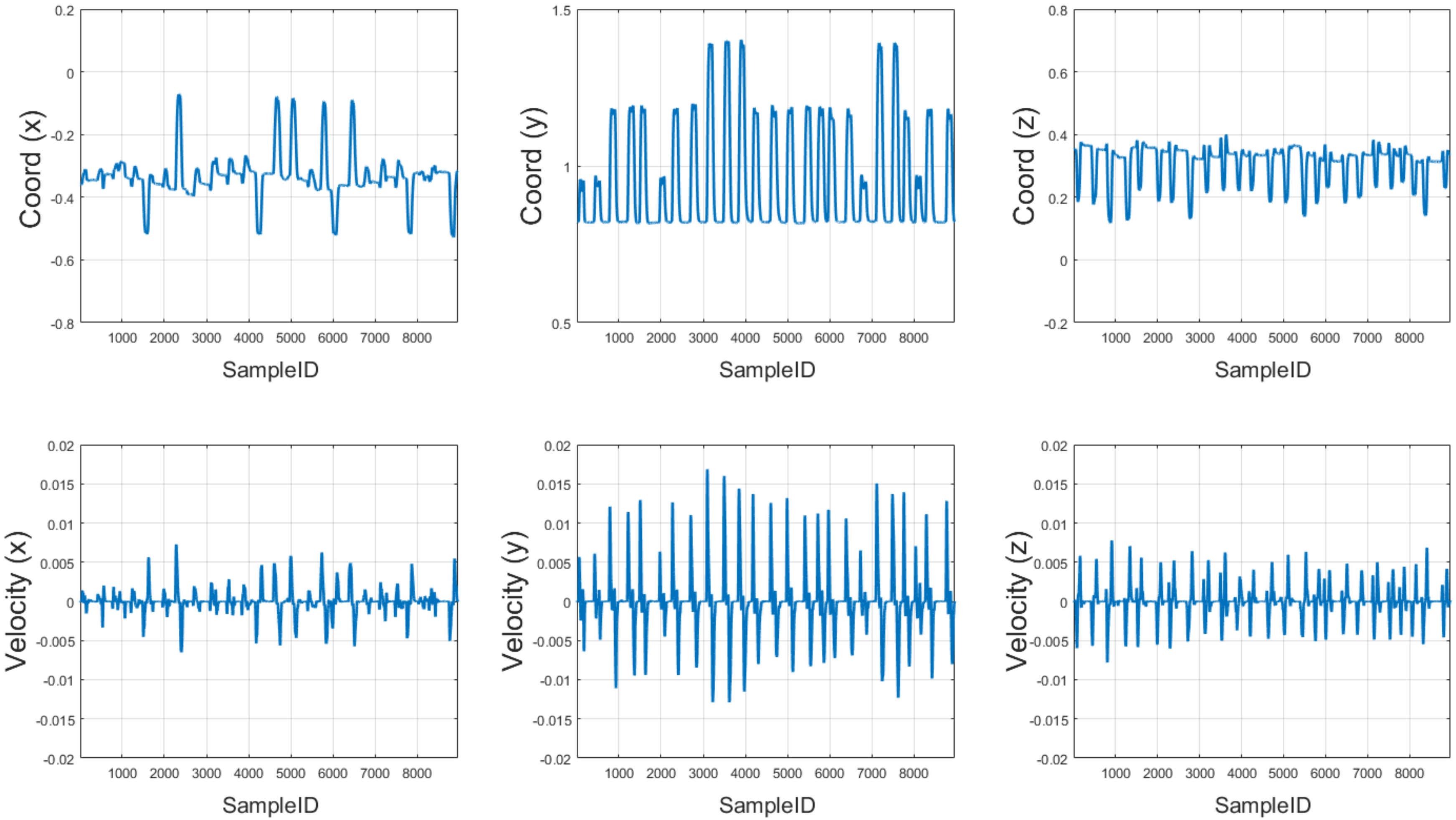






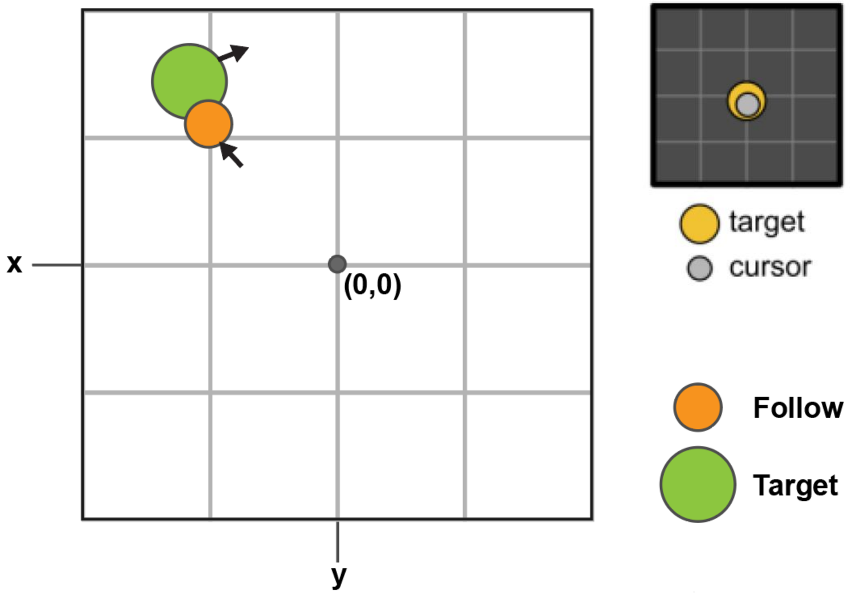


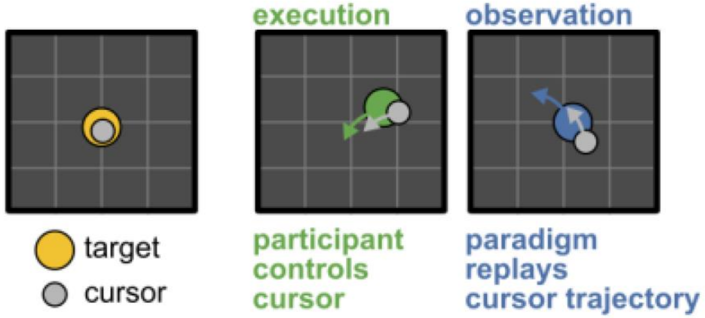
Kinematic data

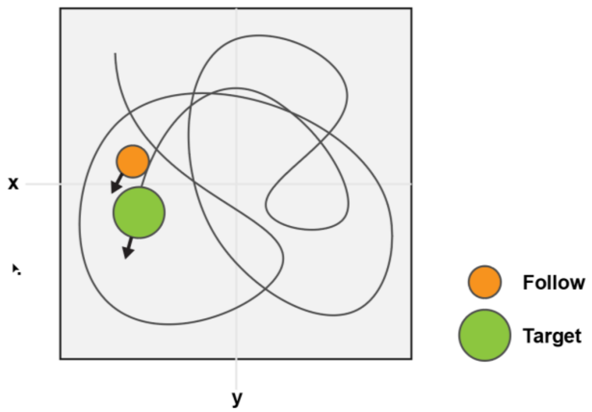


Other paradigms

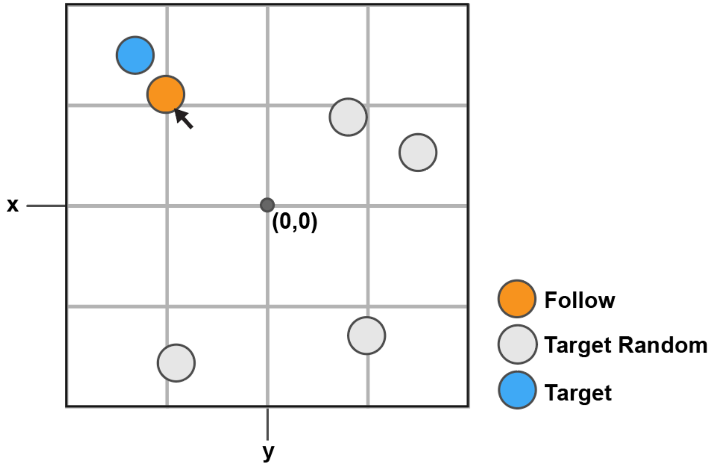
Target Pursuit



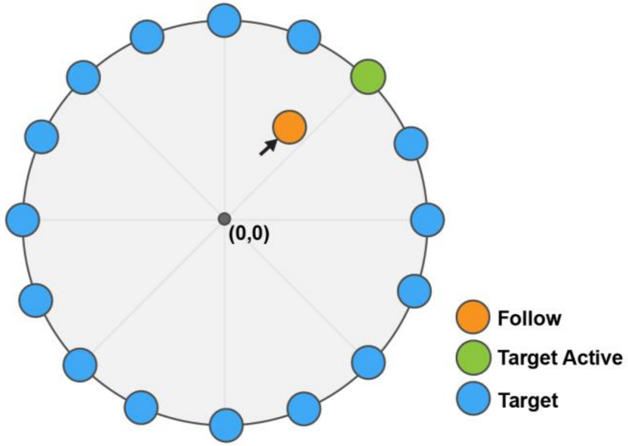


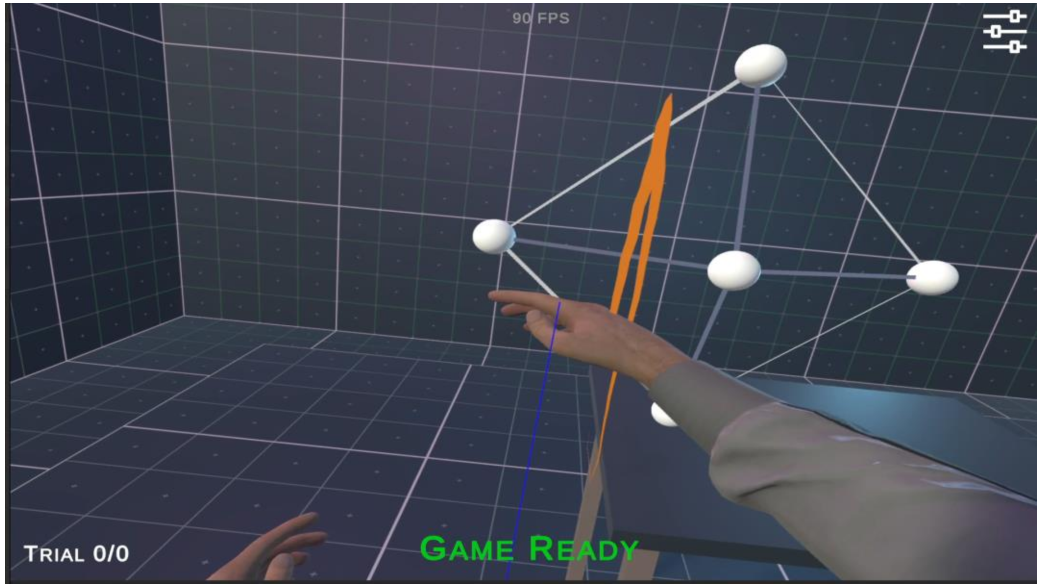


Random Points



Circle Decode





Additional Paradigms

Pursuit – Circle Decode – Random Point

- Extra fidelity in position – more fluid
- Takes into account horizontal / vertical precision
- 2D based planes
  - possibility to adapt for 3D
  - Integrate with avatar rig

BCI Benefits

- Better data for BCI classification
- Higher potential long term for dynamic limb/arm control
- Higher possibility for participant engagement

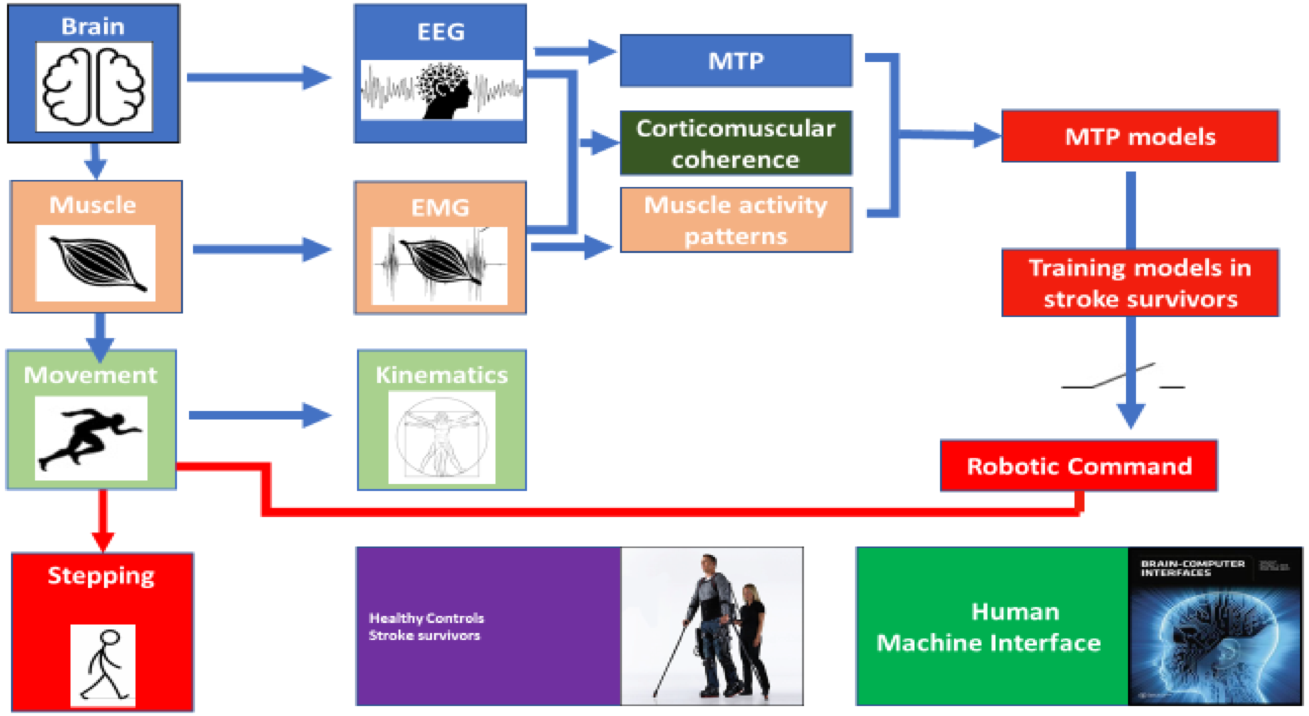
Ulster University

Decoding 3D lower limb movements

EU H2020 RISE Project : PROGAIT

PRO GAIT Physiological and Rehabilitation Outcomes Gains from Automated Interventions in Stroke Therapy

PROGAIT aims to investigate, develop, and evaluate new algorithms and models to support the acquisition to exploitation of neural biosignals in Robotic Gait Rehabilitation post-stroke

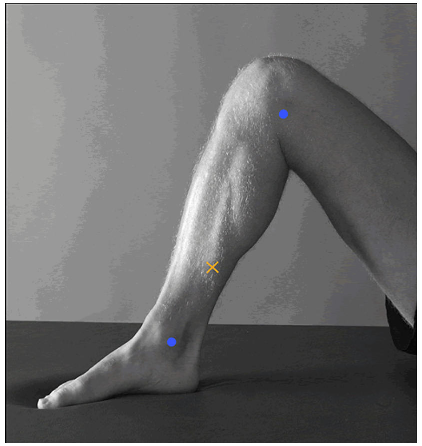


www.ProGait.eu

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 778043

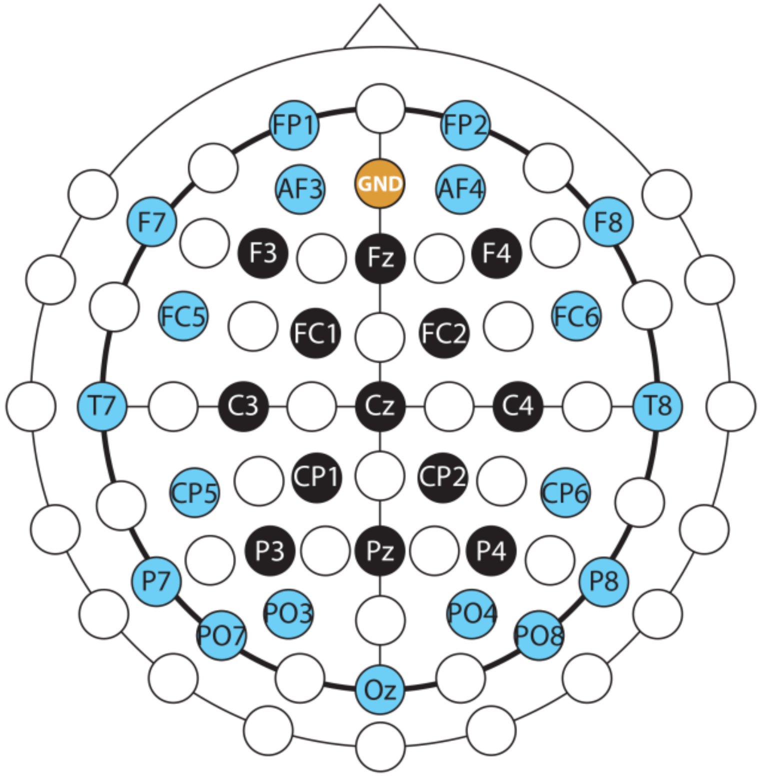
Decoding 3D Trajectory of Lower-limb Movements

Position of tracked markers



- Task:
- Step forward and back

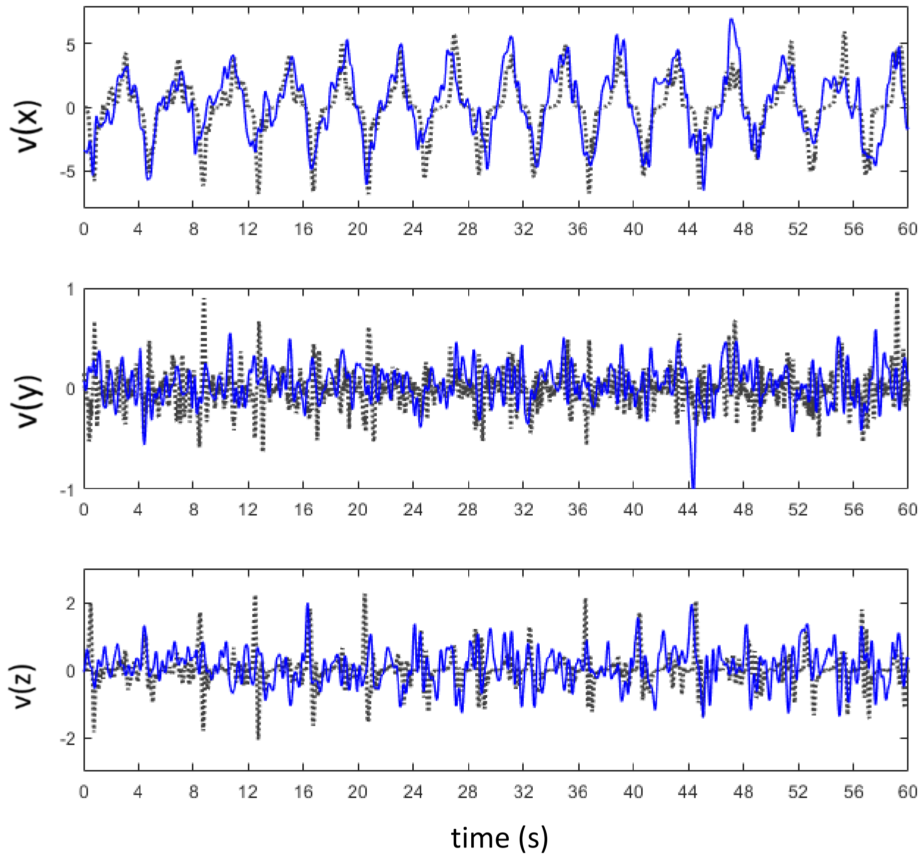
- Timing of the trials:
- Onset of the task: Auditory cue (every 10s)
- Speed of the task: Subject specific (self-selected)
- typical time of steps: forward (1.6s) + back (1.6s) = 3.2s
- 10 run x 10 trials/run -> 100 trials/subject
- Test result validation: 6 fold CV



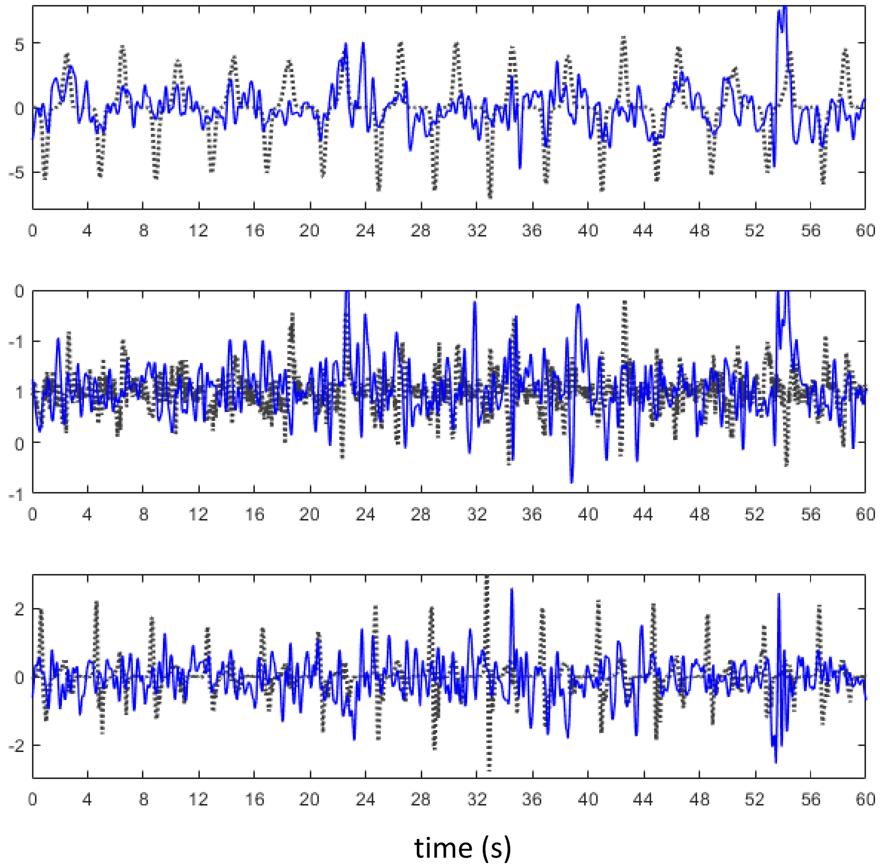
EEG montage

Target and decoded velocity vectors

Subject 1 (the best subject)

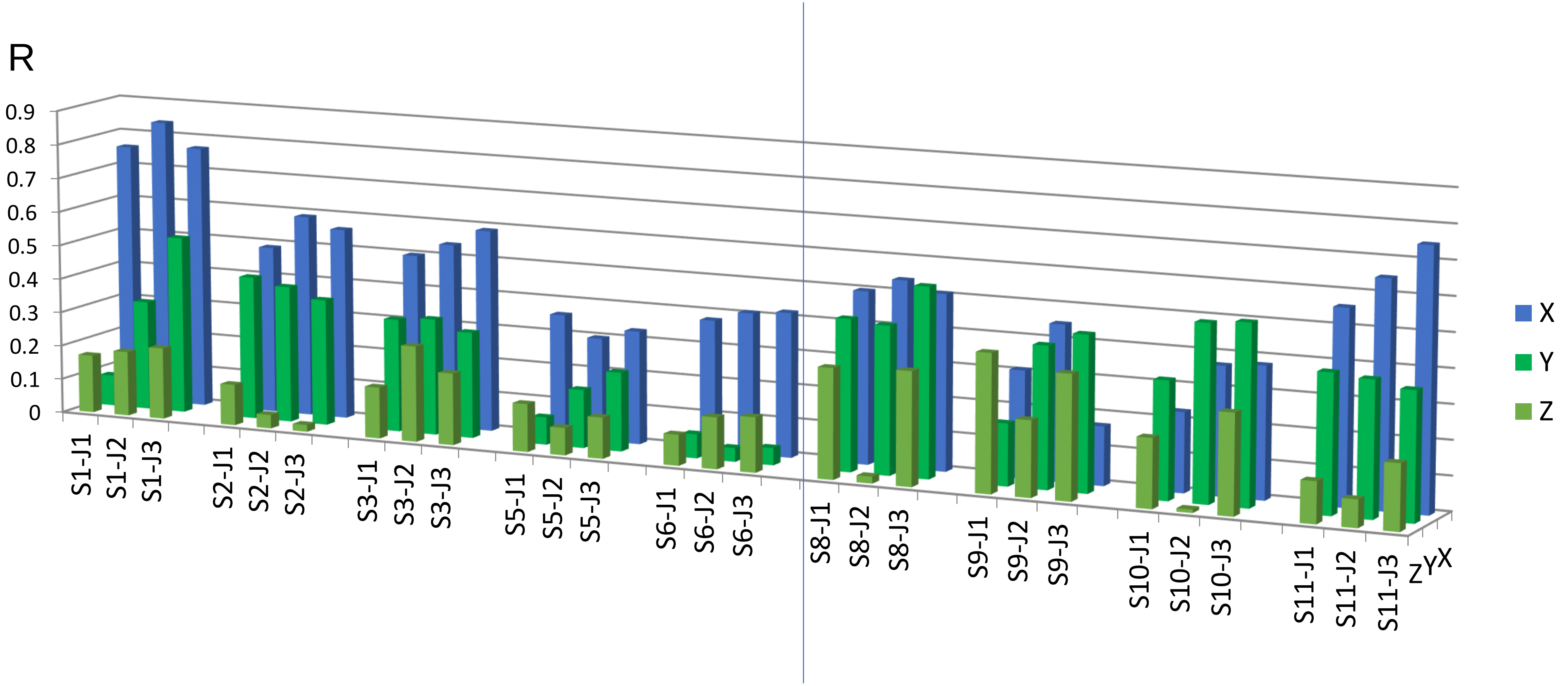


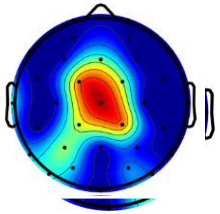
Subject 6 (the worst subject)



Averaged results from 6 test folds

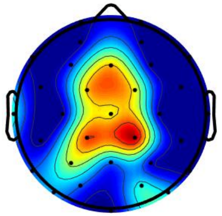
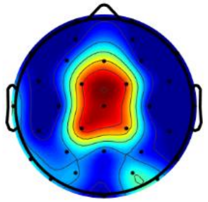
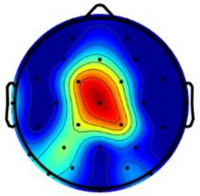
Decoding Accuracy (Pearson Correlation)



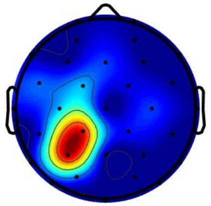
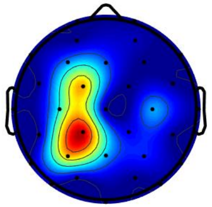
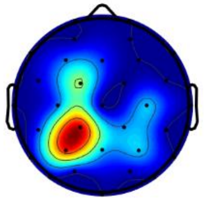


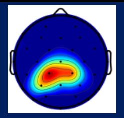
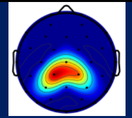
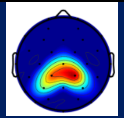
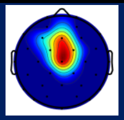
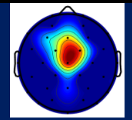
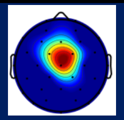
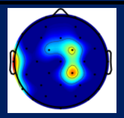
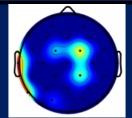
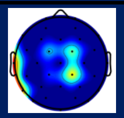
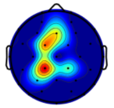
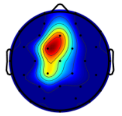
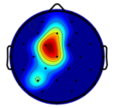
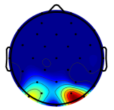
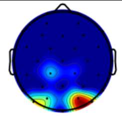
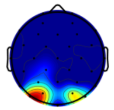
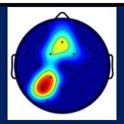
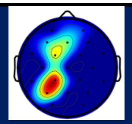
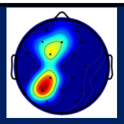
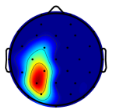
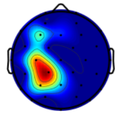
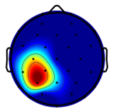
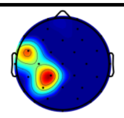
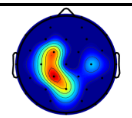
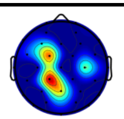
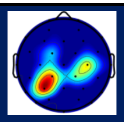
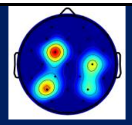
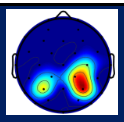
Subject specific topoplots calculated using results from X direction (R>0.4 Highlighted in Blue >>>>)

Averaged topoplots calculated using results from X direction from dataset (group 1)

Joint 1 (Head of the fibula)	Joint 2 (Mid-fibular point)	Joint 3 (Lateral Malleolus)
		

Averaged topoplots calculated using results from X direction from dataset (group 2)

Joint 1 (Head of the fibula)	Joint 2 (Mid-fibular point)	Joint 3 (Lateral Malleolus)
		

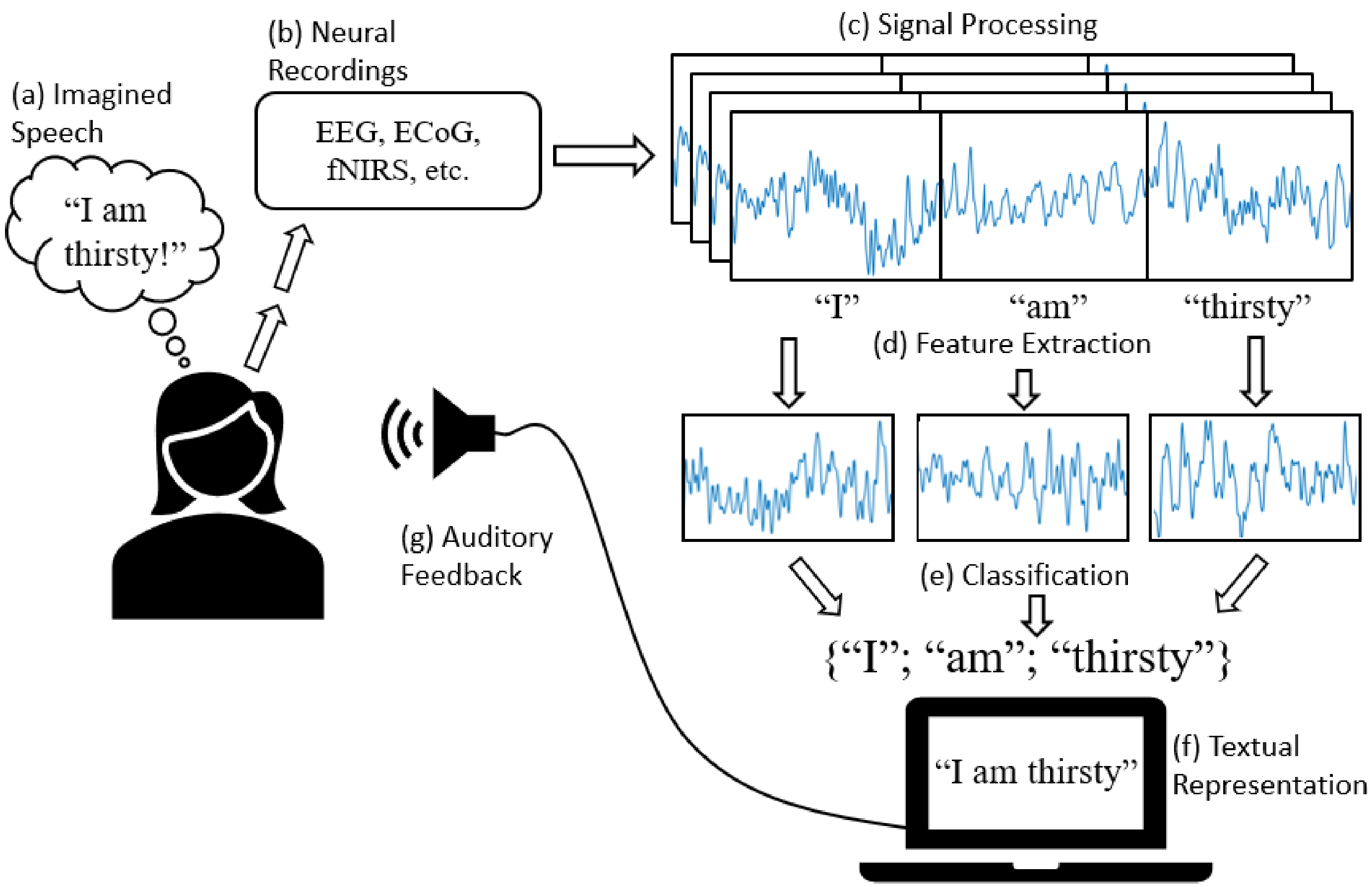
Subj	Joint 1 (Head of the fibula)	Joint 2 (Mid-fibular point)	Joint 3 (Lateral Malleolus)
1			
2			
3			
5			
6			
8			
9			
10			
11			

Lower limb gait rehab with exoskeleton/FES and motion trajectory prediction using BCI

Ulster University

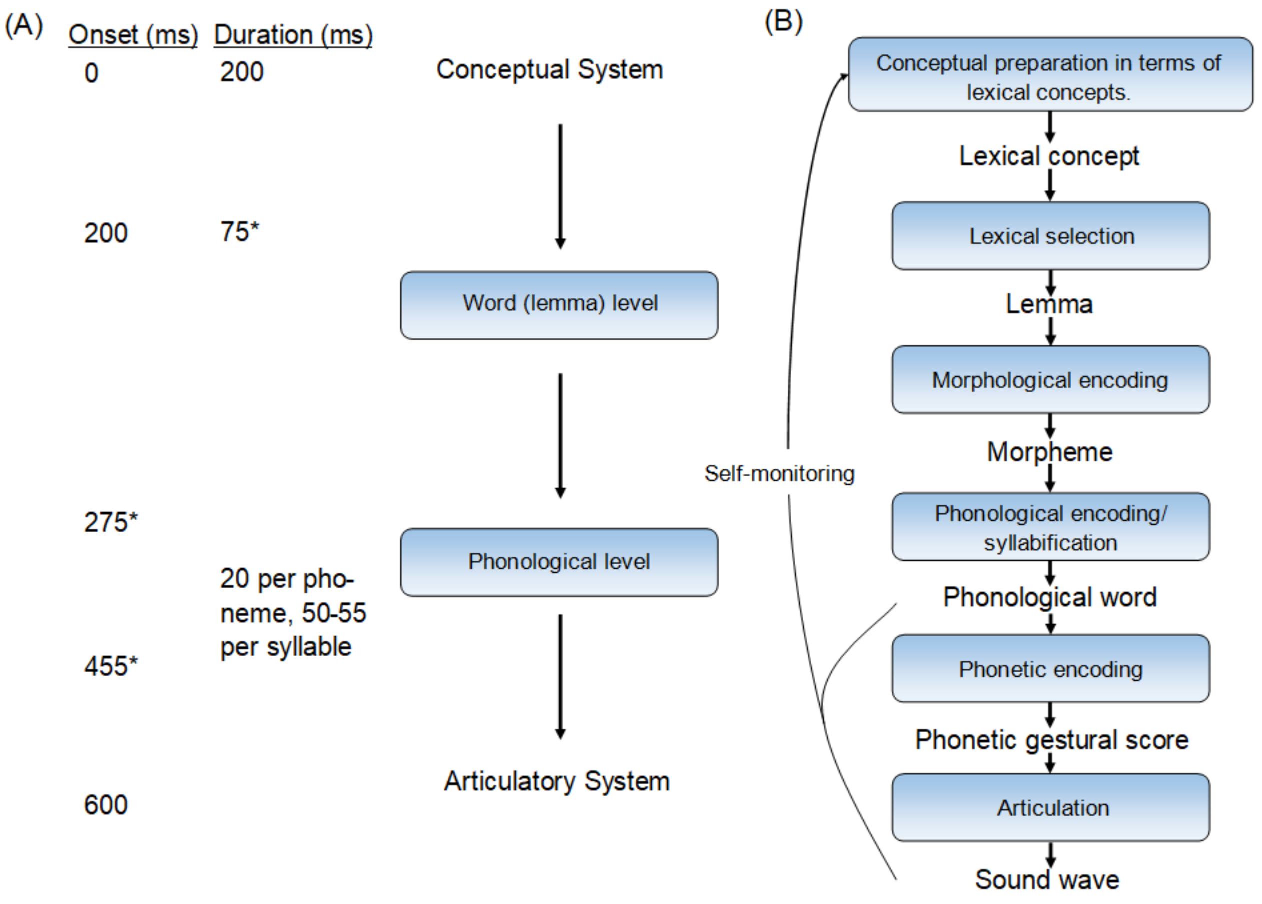
Part 7: Prospects for Direct Speech BCI with Imagined-speech

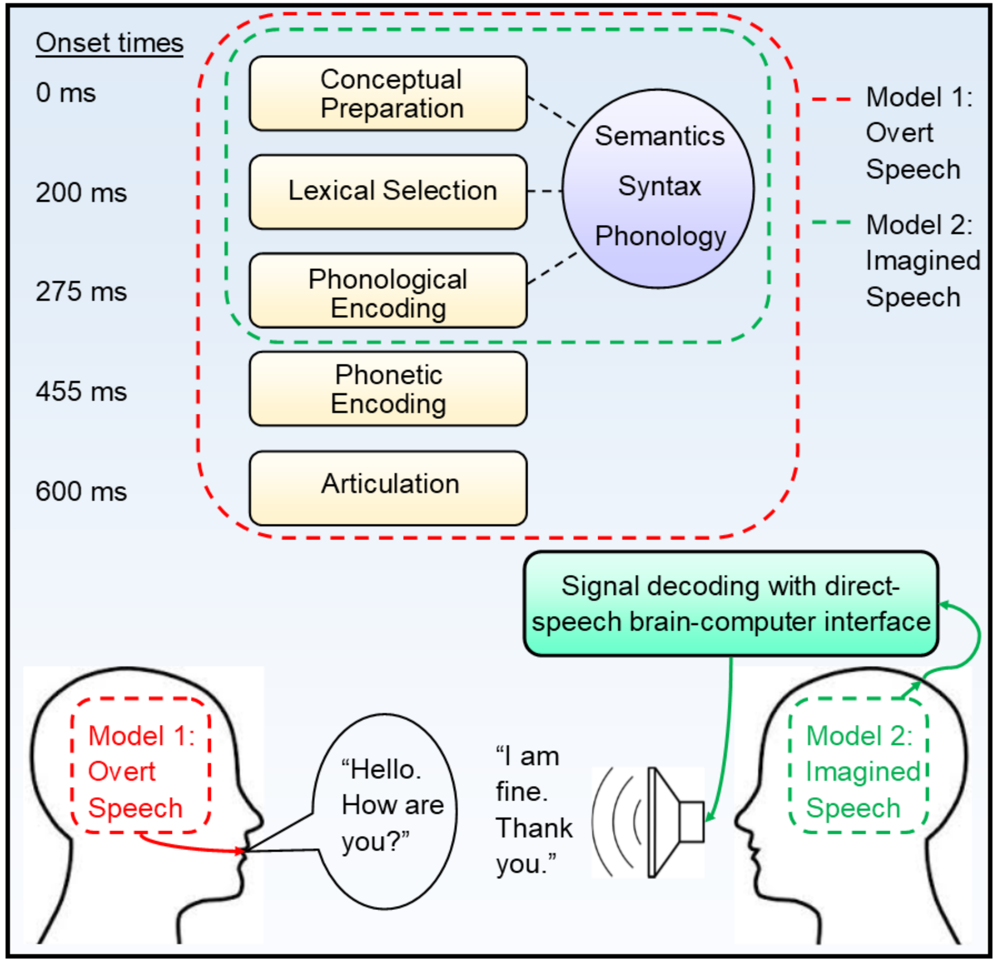
Direct-Speech BCI
Conceptual Design



Direct-Speech BCI

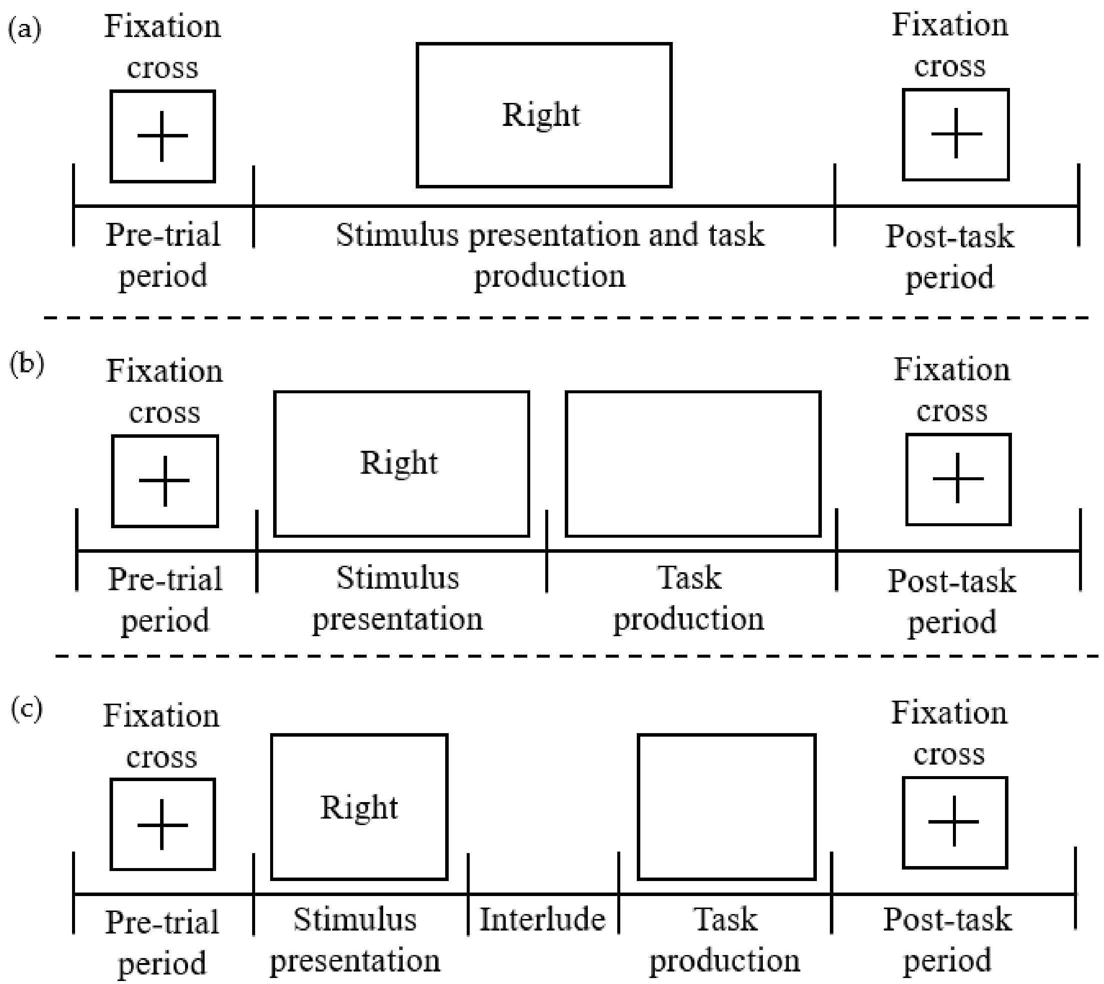
Speech production





Direct-Speech BCI

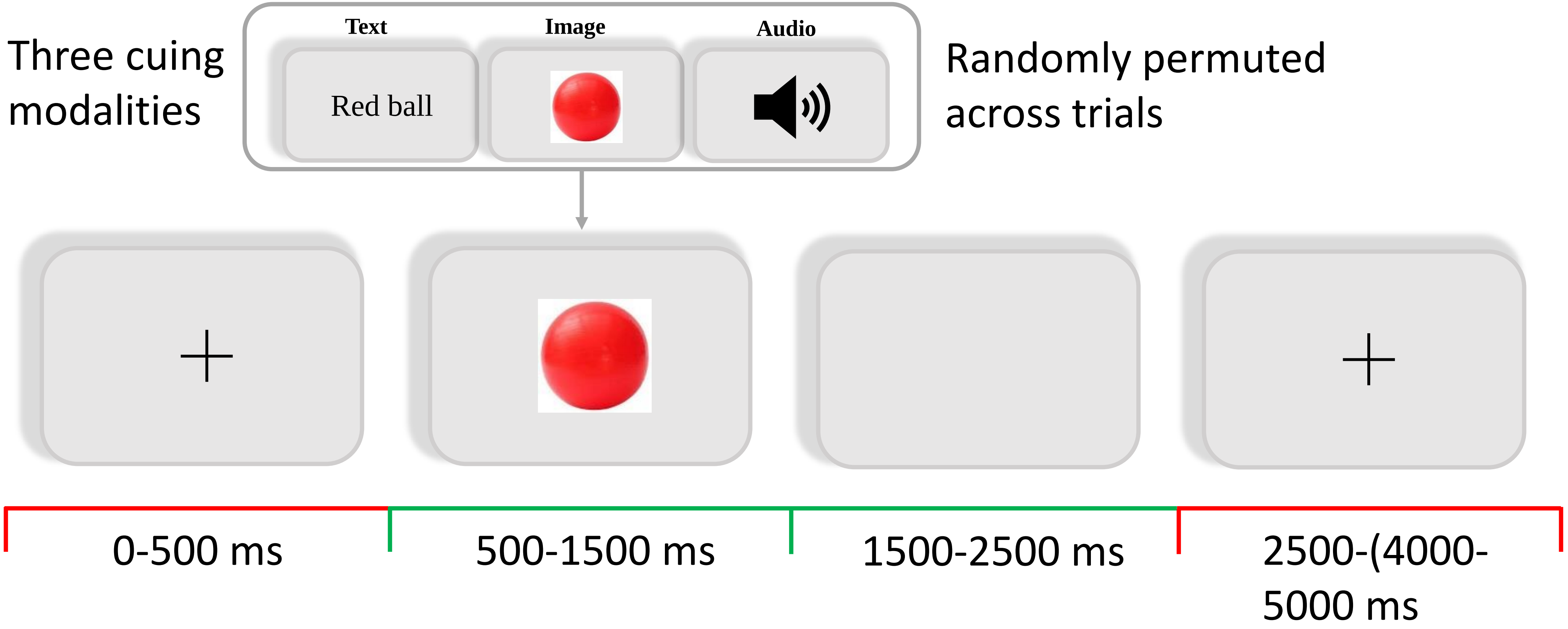
Protocol Design



- Immediate response to cue/prompt
  - Participants not required to hold prompts in working memory
  - Less time required per trial
- Separate cuing and task production periods
  - Speech begins immediately upon removal of the cue
- Temporal interlude between cuing period and task production period.
  - Participants required to hold prompt in working memory

Experimental Paradigm

Multiple Cuing Modalities



Experimental Paradigm

Words selected for linguistic properties

Action Words (Embodiment)

- Embodiment suggests that language mechanisms in the brain support local motor activations that correspond to meaning in words and phrases
- Studies indicate action words (e.g. *kick*, *lick*, *pick*) associated with different body parts elicit increased activity in cortical regions corresponding to muscle groups used to perform that action (e.g. *foot*, *tongue*, *hand*)

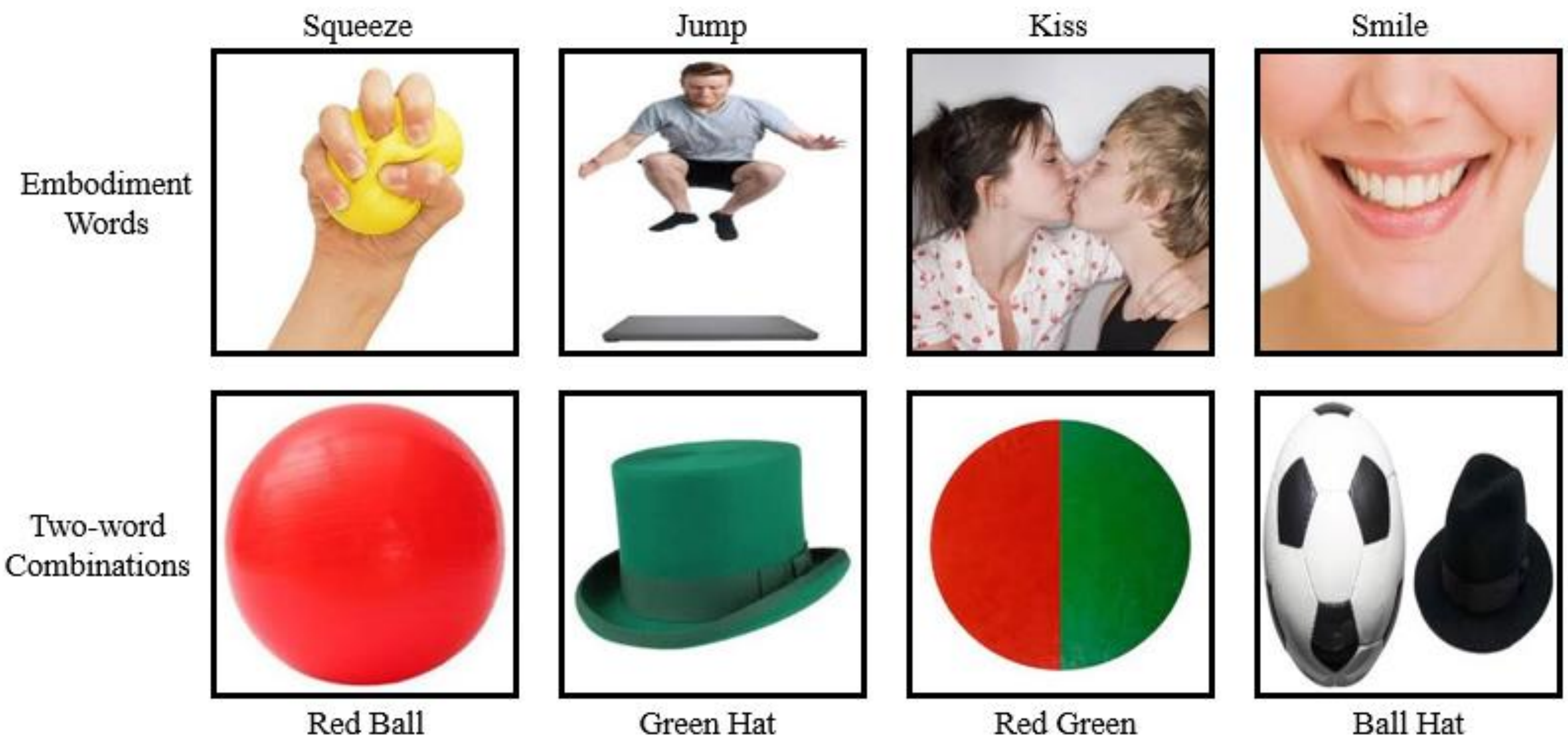
Syntactic Modification vs Lists

- Studies show that lists of words lack the critical computation required to combine them into a single concept
- **Two-word combinations** were selected to facilitate the adjective-noun semantic modification (making the words into a single concept), and two-word lists

---

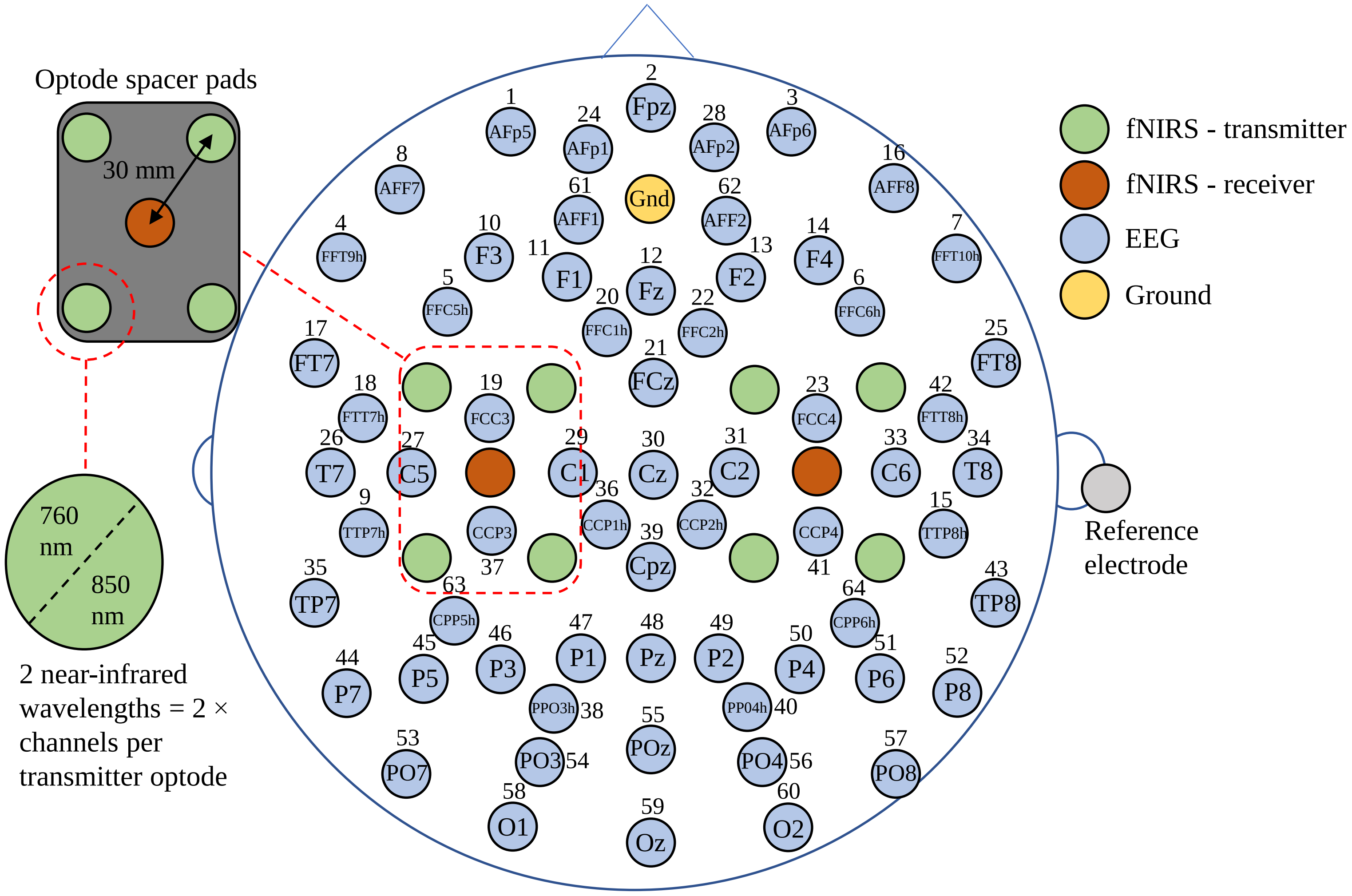
Face-related words	Limb-related words	Syntactic Modification	Lists
“Smile”	**“Squeeze”**	**“Red Ball”**	**“Red Green”**
“Kiss”	**“Jump”**	**“Green Hat”**	**“Ball Hat”**

Selected cues



Methodology

64-channel EEG montage

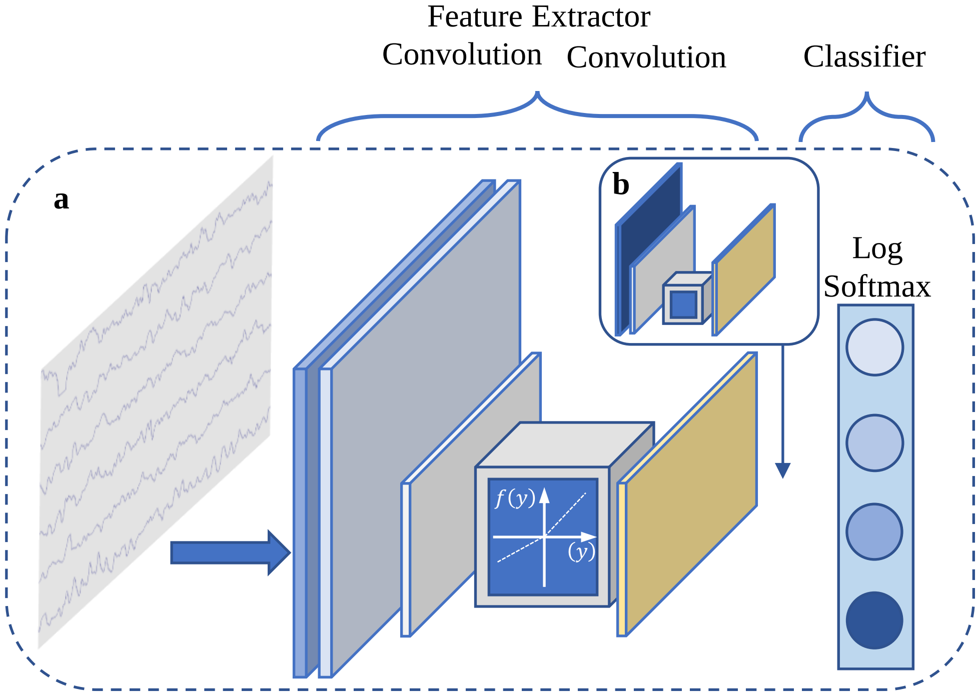


- 19 participants
- 4 sessions per participant (2 overt speech, 2 imagined speech)
- 24 conditions (8 words × 3 cuing modalities)
- 50 trials per condition
- 1200 trials/participant

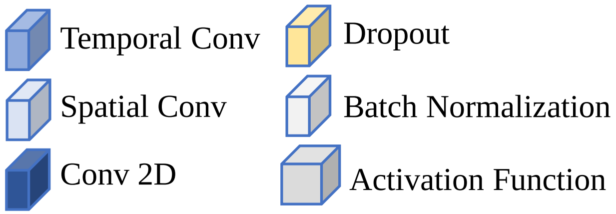
Classification

Convolutional Neural Network

Convolutional Neural Network

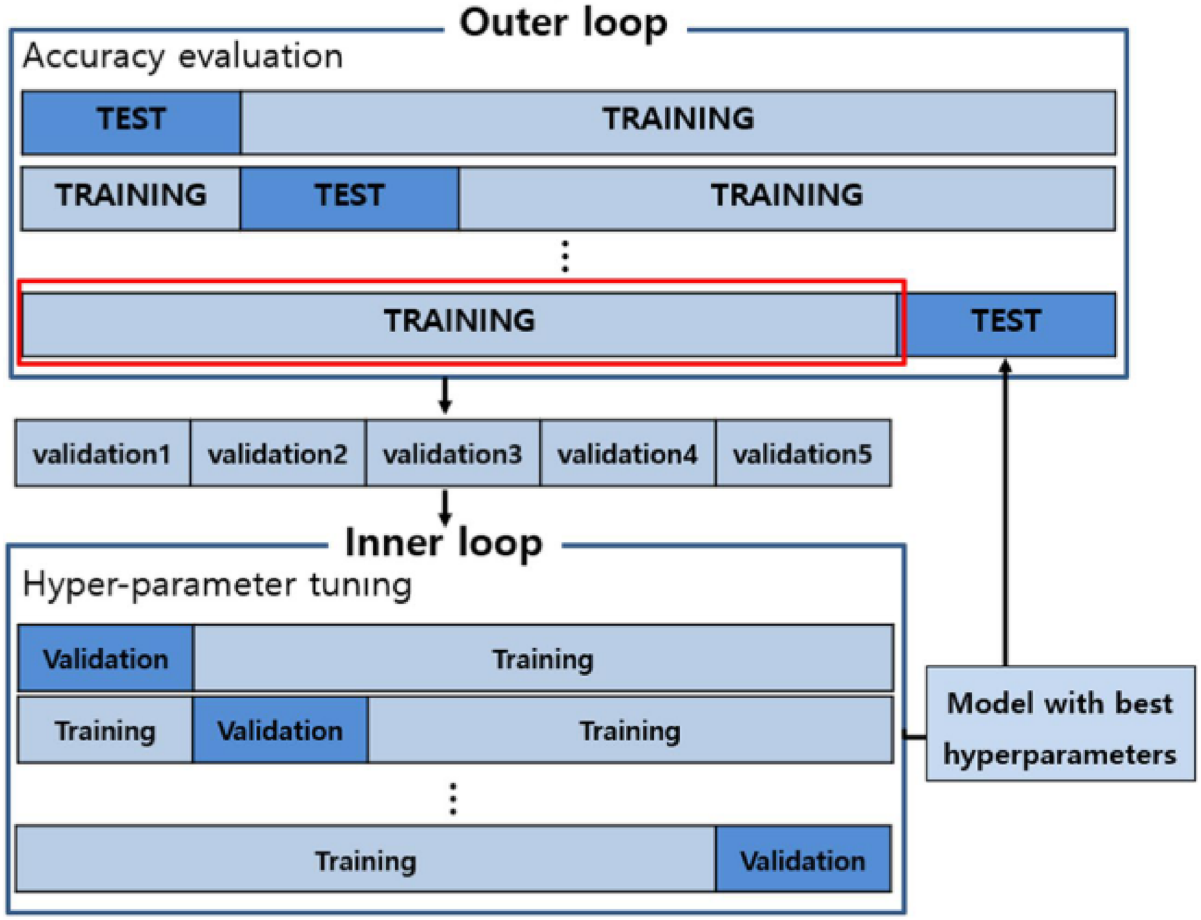


b Structural parameters evaluated with nested cross-validation – 2D convolutional layer, batch normalization, activation function and dropout.



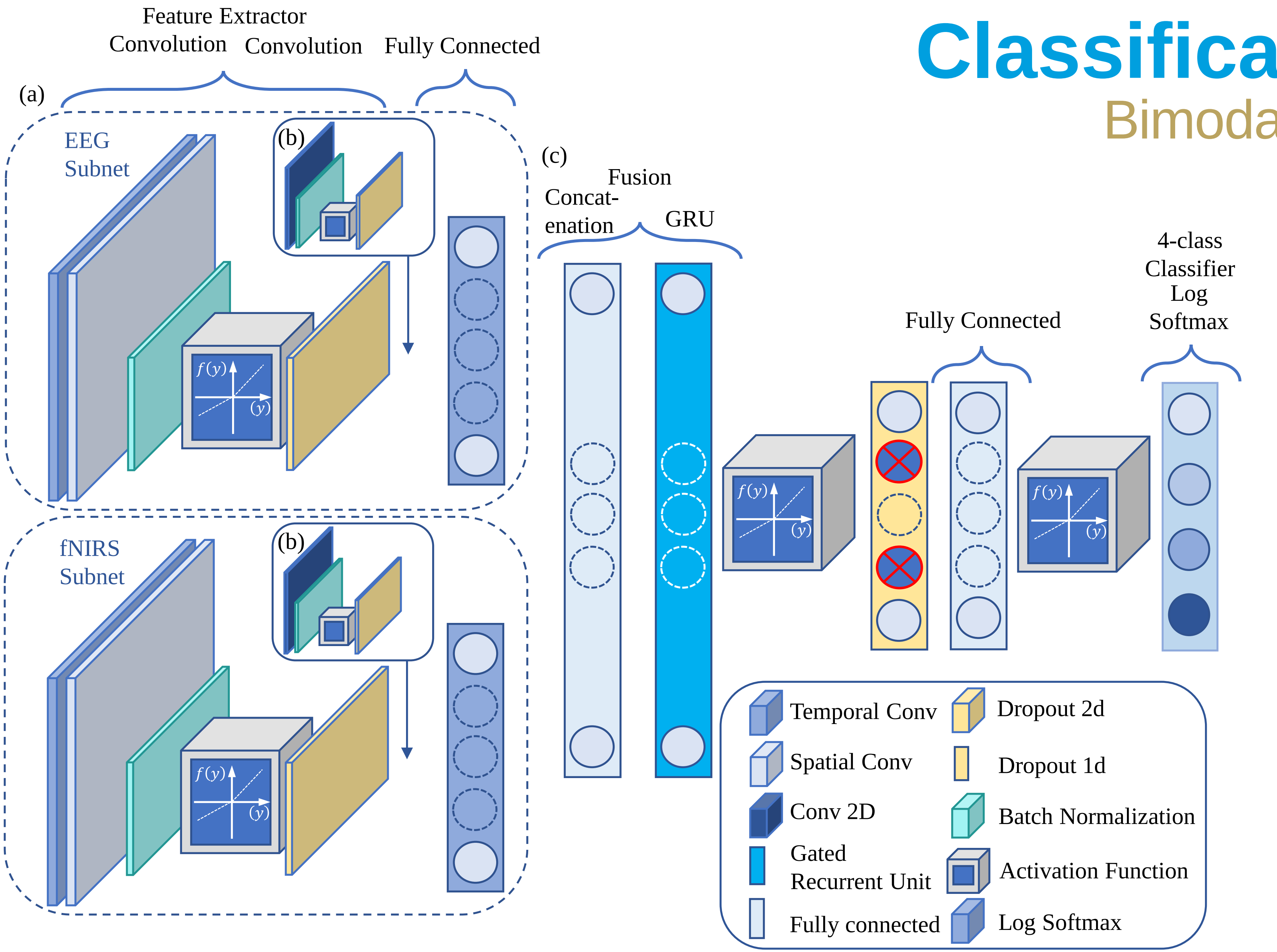
See Cooney et al 2020 for detailed analysis of CNN Hyperparameters

Nested Cross-validation



Classification

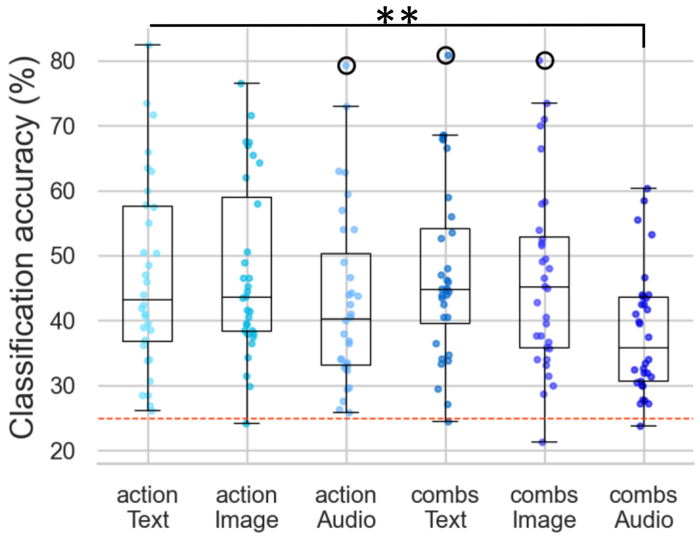
Bimodal CNN



EEG Decoding Accuracy

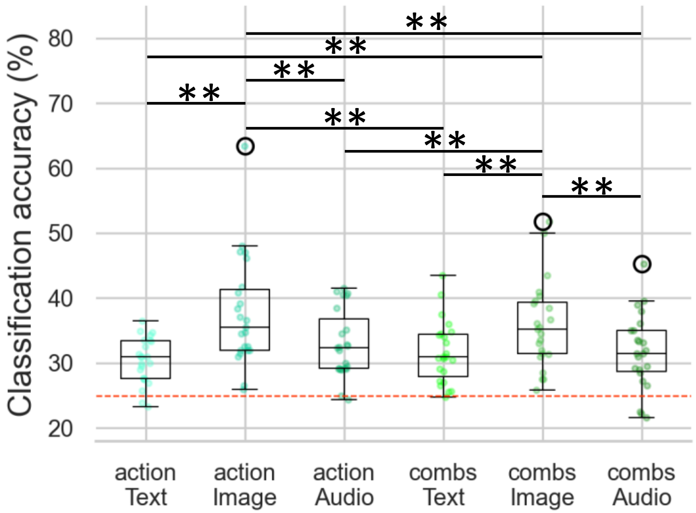
Overt and Imagined Speech

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%

Imagined Speech



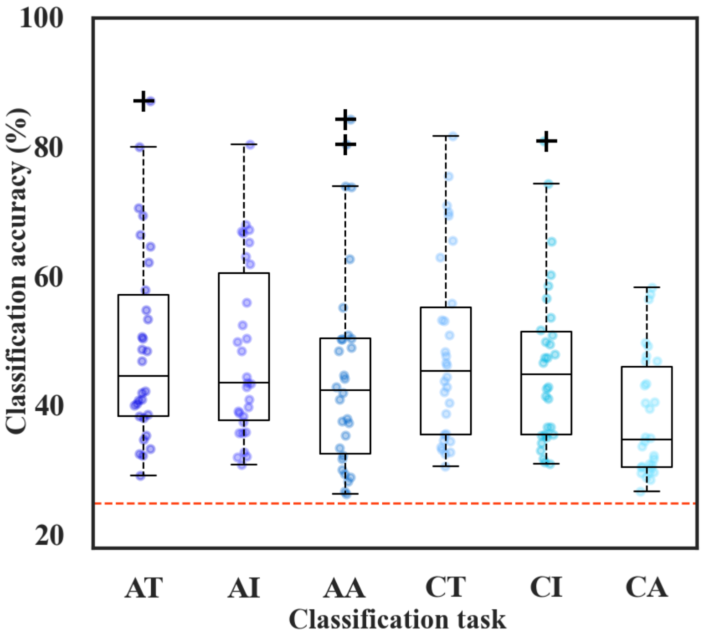
** *p*<0.005

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

Hybrid EEG-fNIRS Decoding Accuracy

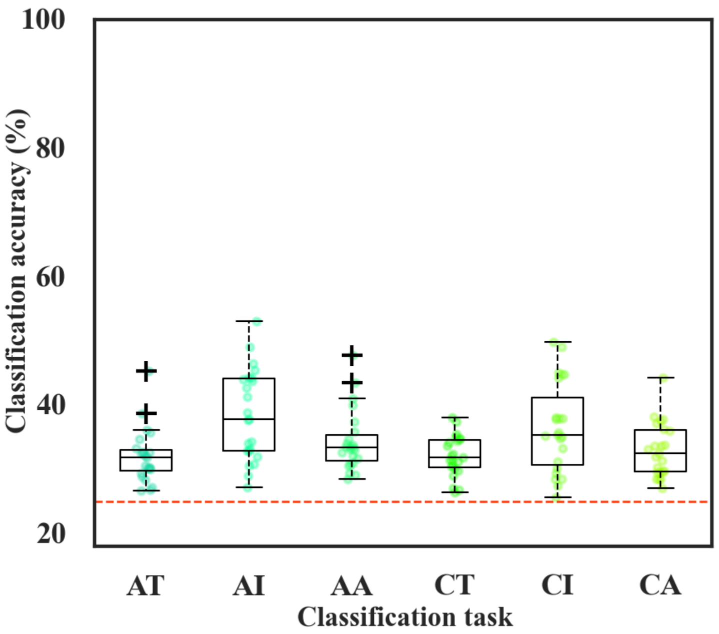
Bimodal Network

Overt Speech



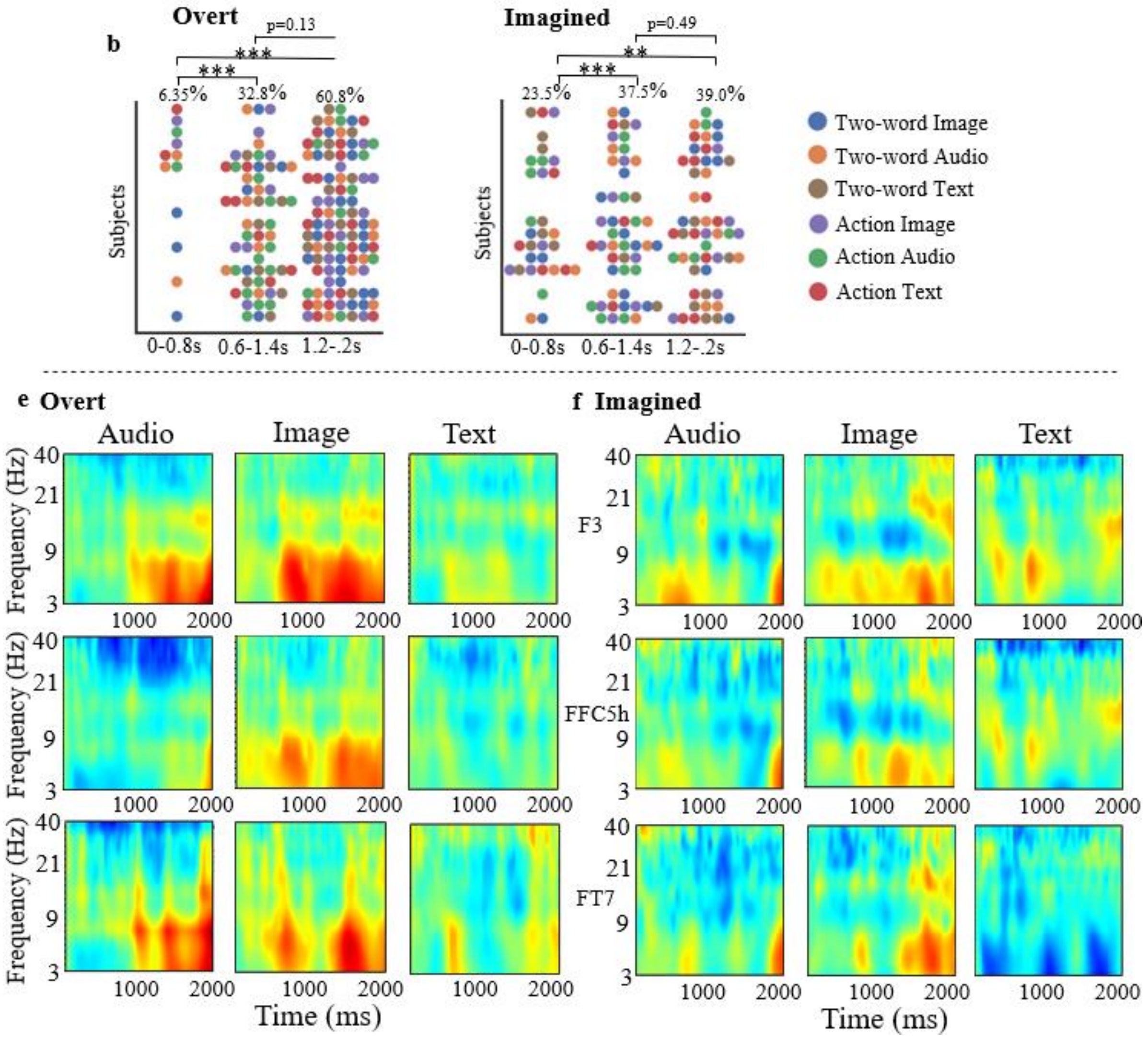
Action Words			Two-word pairs		
Text	Image	Audio	Text	Image	Audio
49.08%	48.10%	45.40%	**48.51%**	46.25%	38.33%

Imagined Speech



Action Words			Two-word pairs		
Text	Image	Audio	Text	Image	Audio
32.03%	**38.46%**	34.35%	32.10%	**36.49%**	32.97%

Time and frequency



Conclusion

- Imagined speech decoding from EEG is possible but presents challenges

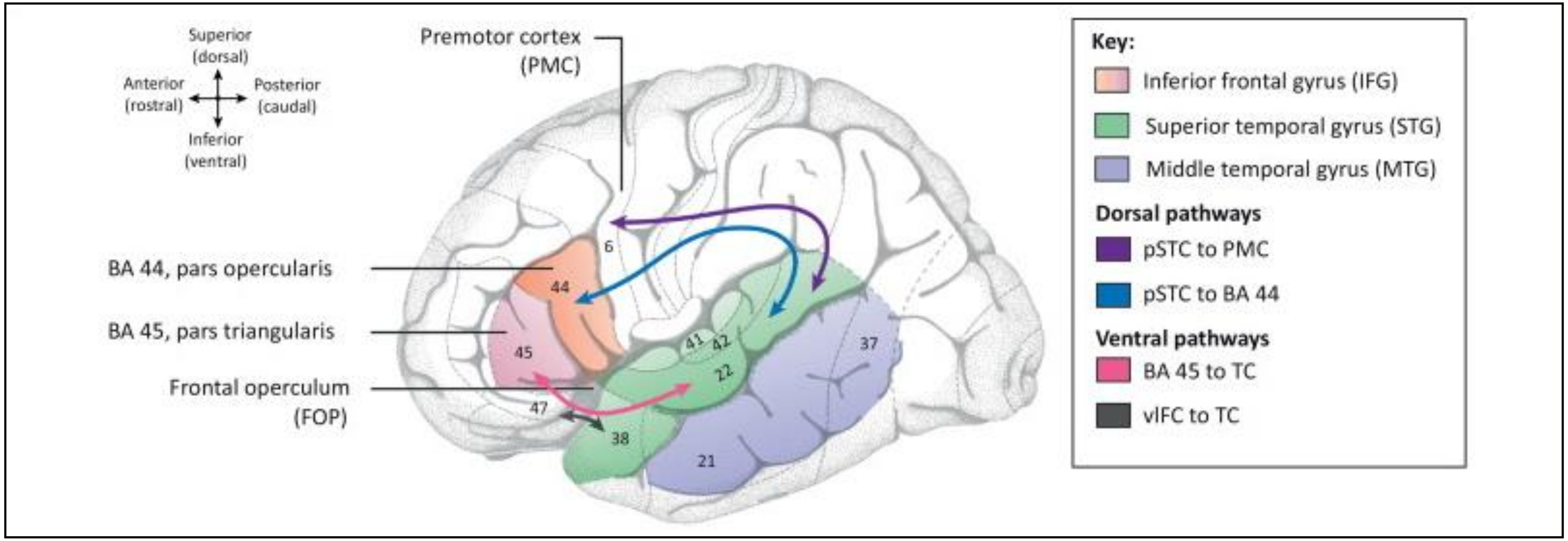
- Overt speech is easier to classify than imagined-speech
  - Despite imagined speech exhibiting attenuated characteristics of overt speech, any a priori assumptions of a direct mapping between the two are incomplete and require further research.
  - BCIs require independence from overt speech/movement

- Imagined speech cued with *images* is easier to classify than with *text* or *audio* cues
  - The effects of stimuli/cues on speech decoding from EEG are highly significant
  - Differential effects of stimuli must be controlled in experimental procedures to elicit imagined speech

- Linguistic properties, semantics and syntax, do not impact accuracy significantly
  - Also insignificant improvement with respect to embodiment or the inclusion/exclusion of a syntactic modifier in two word-pairs.

- Hybrid EEG-fNIRS produced insignificant improvements over unimodal
  - Biomodal CNN architectures offer potential for Hybrid-BCIs

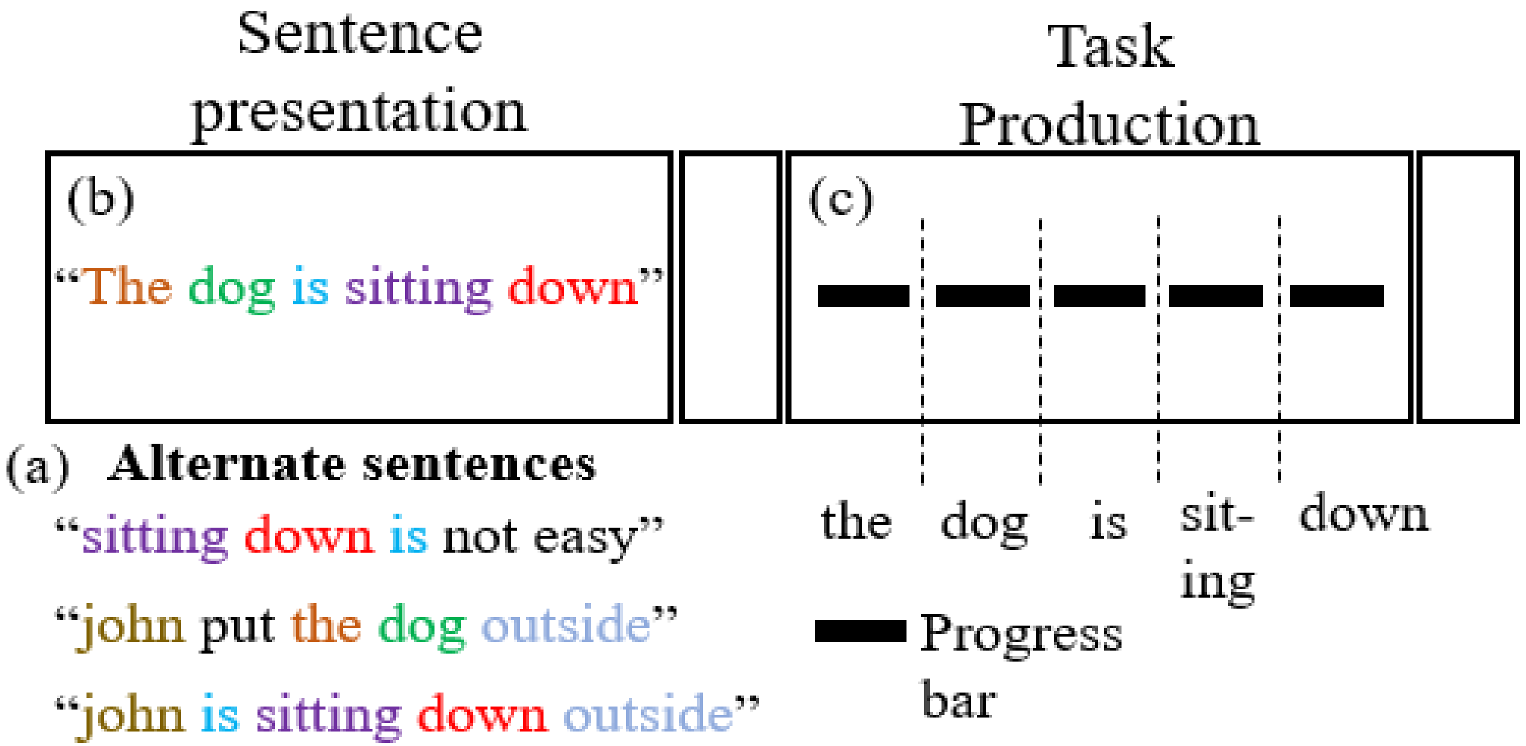
Neuroanatomy of Imagined Speech
Regions of Interest



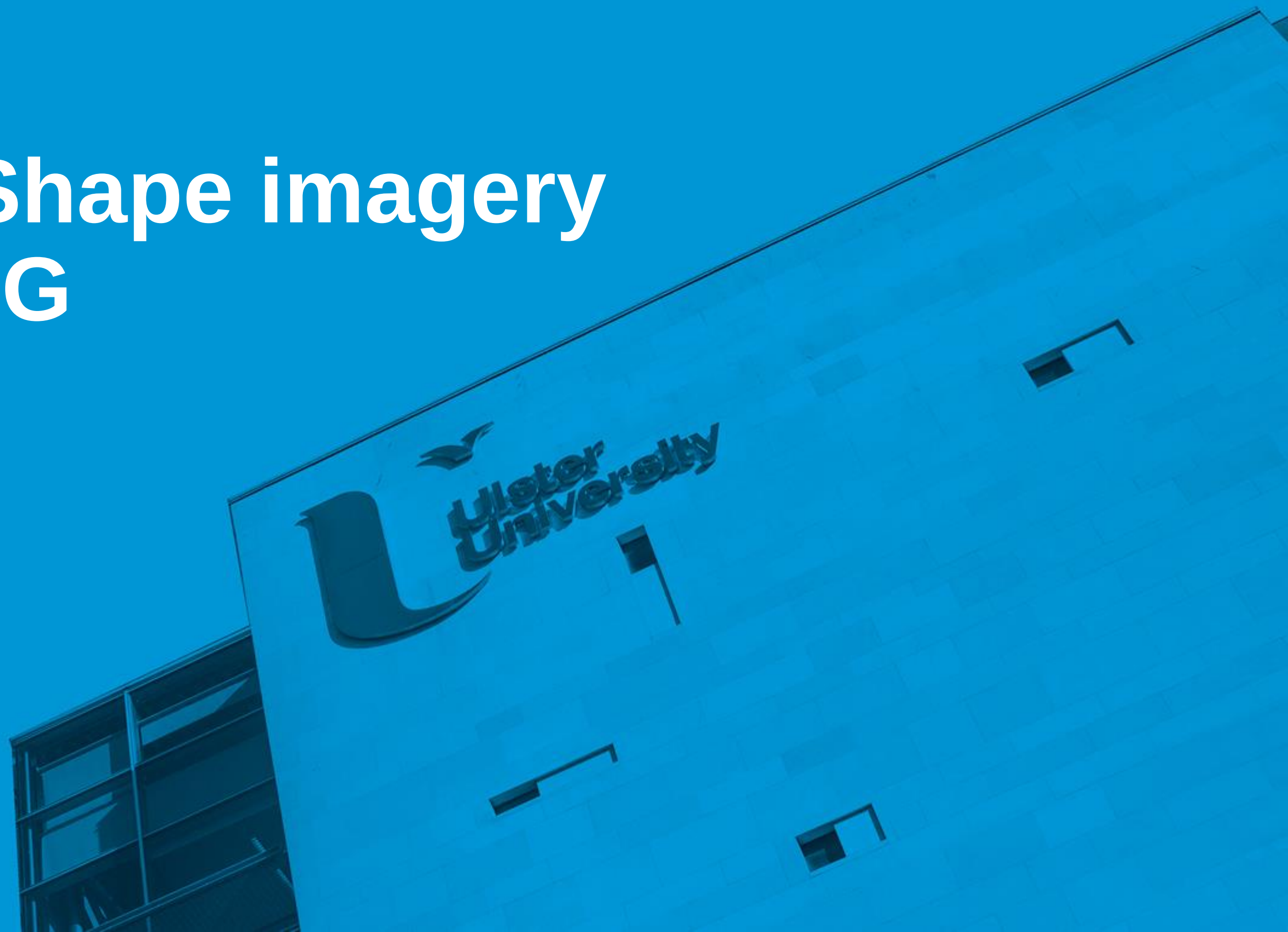
- Targeted electrode placement
- Left-hemispheric regions (in right-handed persons)
- Broca's area, Wernicke's area, etc.
- ROIs corresponding to imagined speech

Berwick et al. 2013

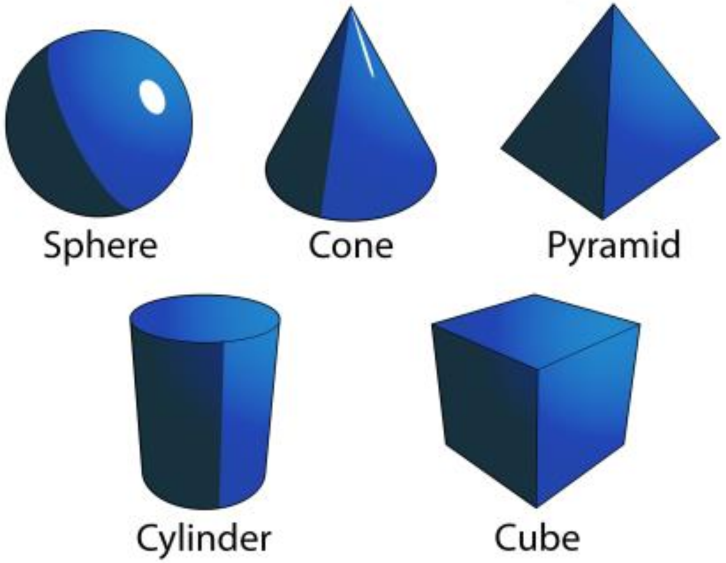
New Paradigms
Innovative Experimentation



Part 8 : Emotion and Shape imagery classification from EEG



Imagined Object/Shape Classification



Timing of the trials:

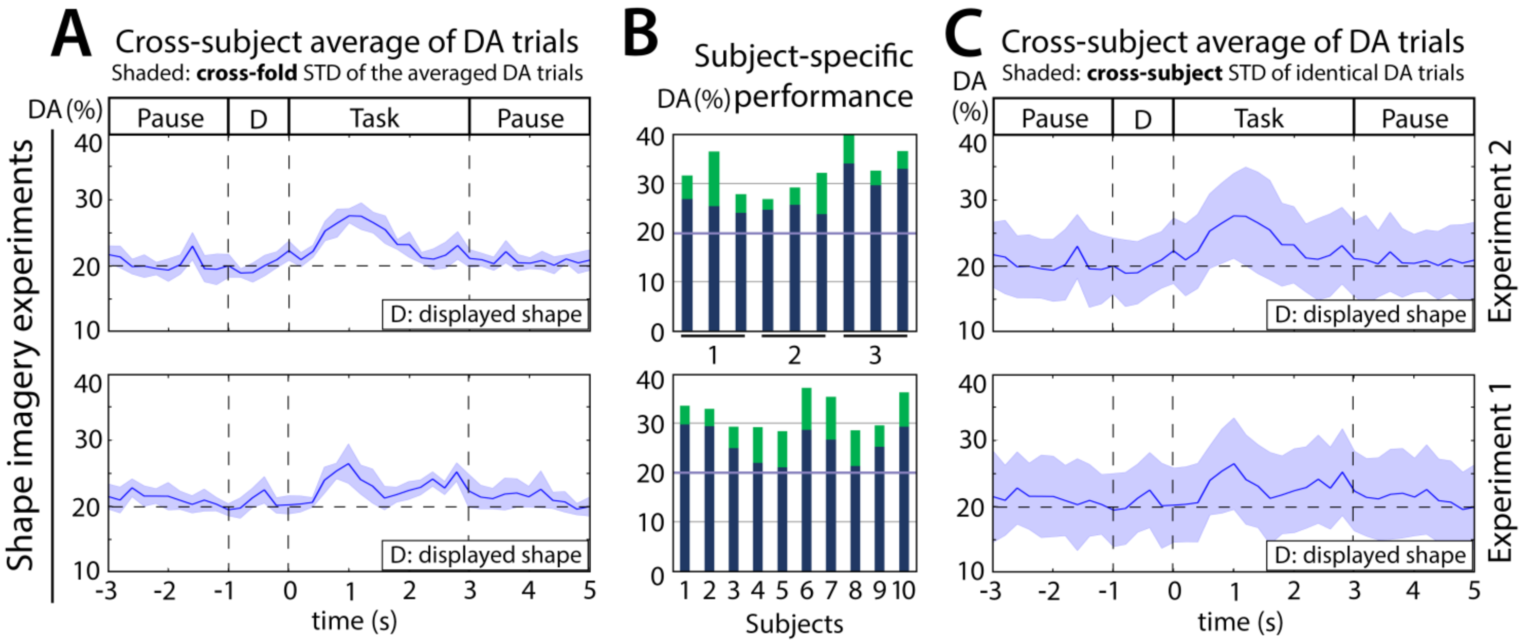
	-4s to -1s	-1s to 0s	0s to 3s	
Function :	Resting period	Display	Shape imagery task	End
Visual info :	Empty screen	Shape	Empty screen	

-4s -1s 0s 3s

Object vs Motor Imagery

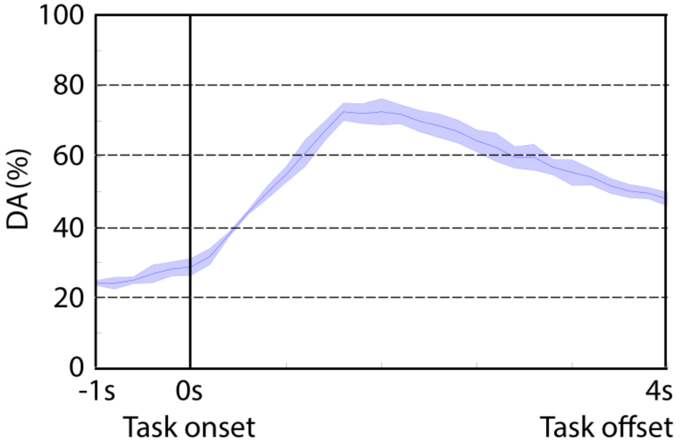
- **Imaged Object:**

5 classes
(20% chance level)



- **Motor Imagery:**

BCI Competition IV 2.a
4 classes (25% chance level)

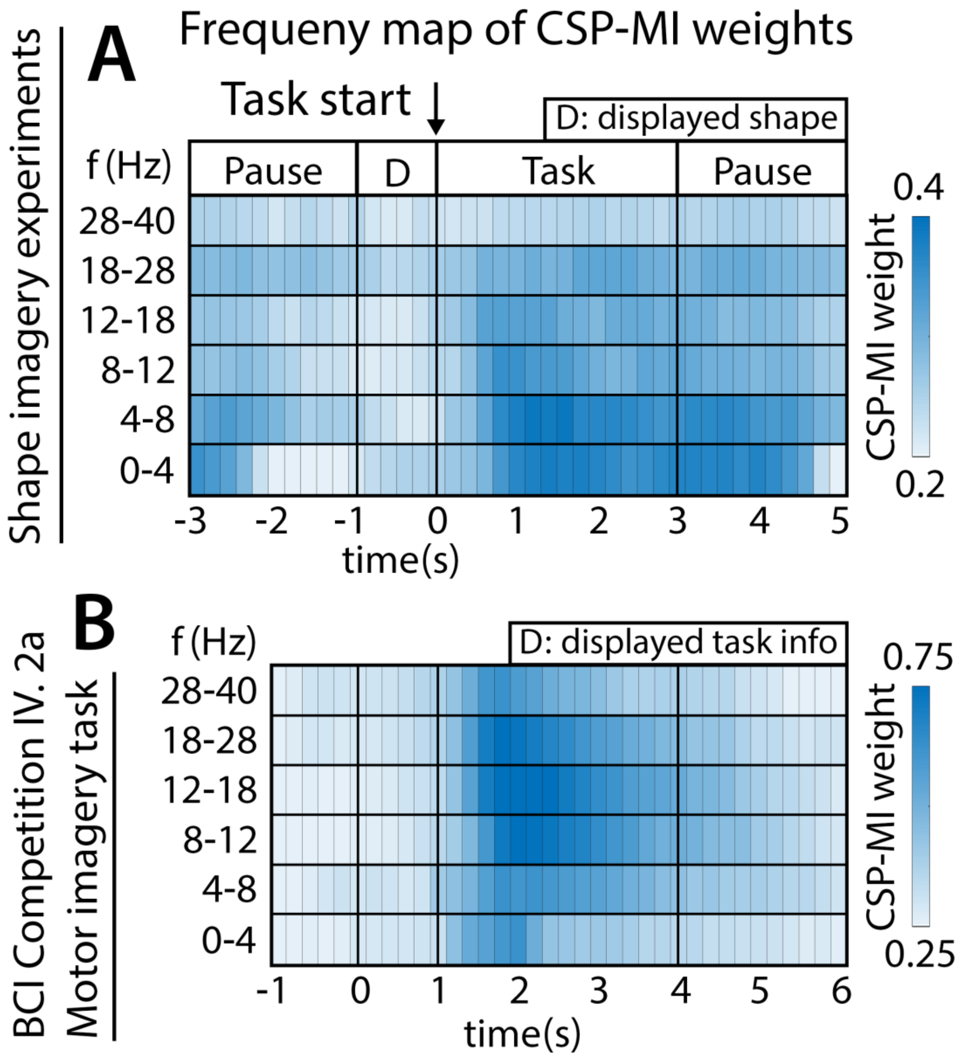


Ulster University

Object vs Motor Imagery

- Imaged Object:

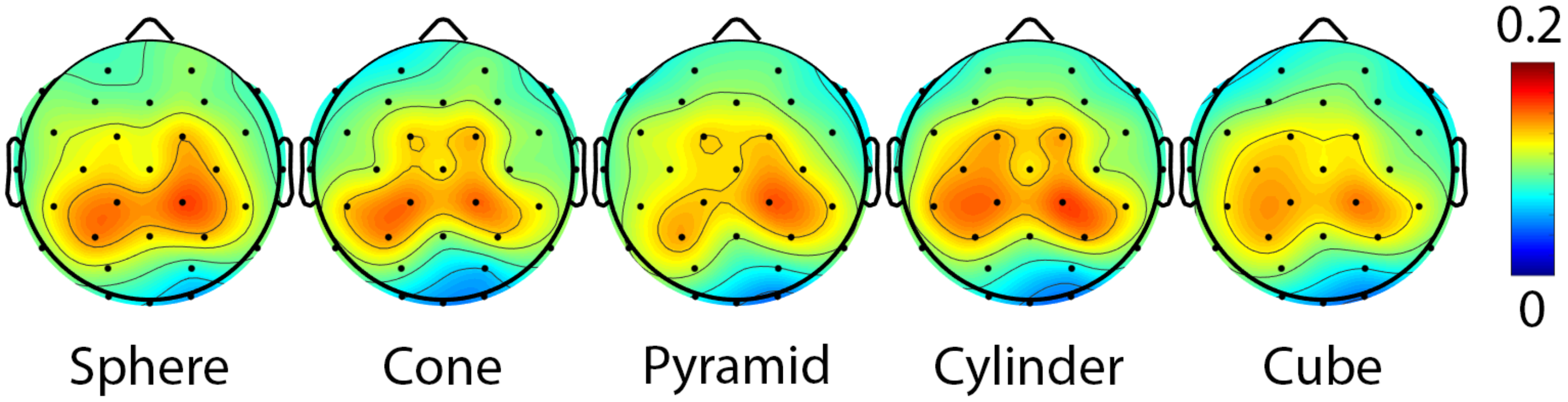
- Motor Imagery:



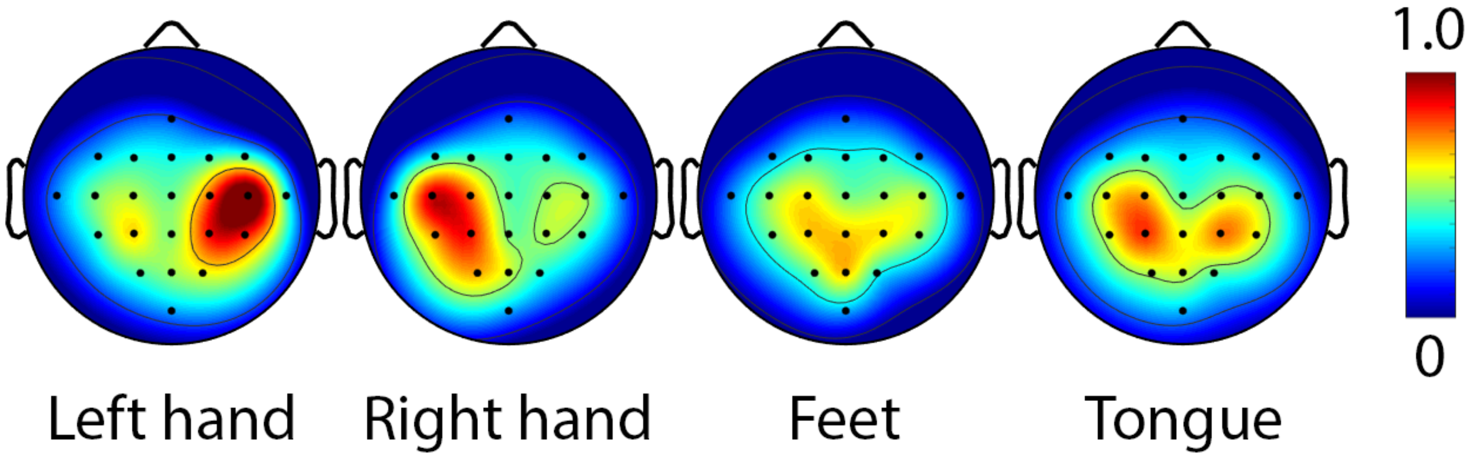
Ulster University

Topographical Analysis

Imaged Object:



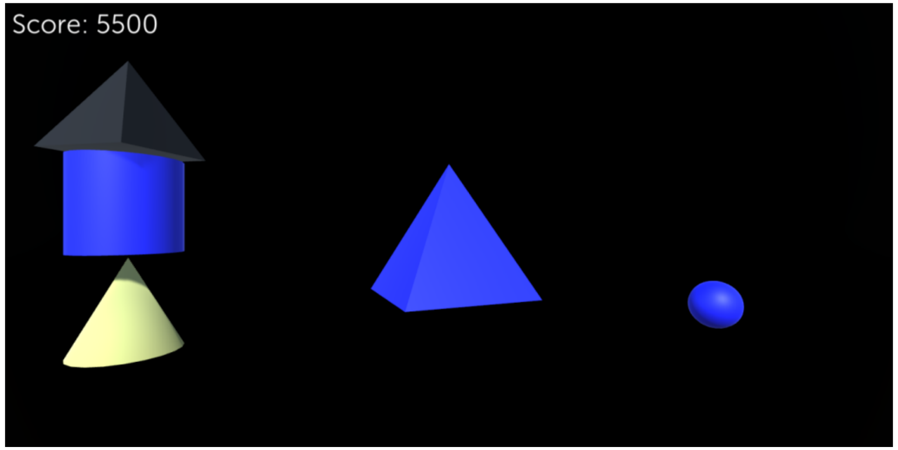
Motor Imagery:



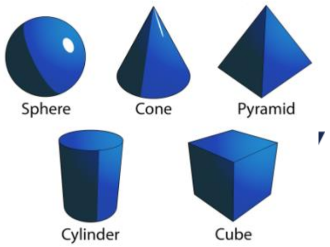
Ulster University

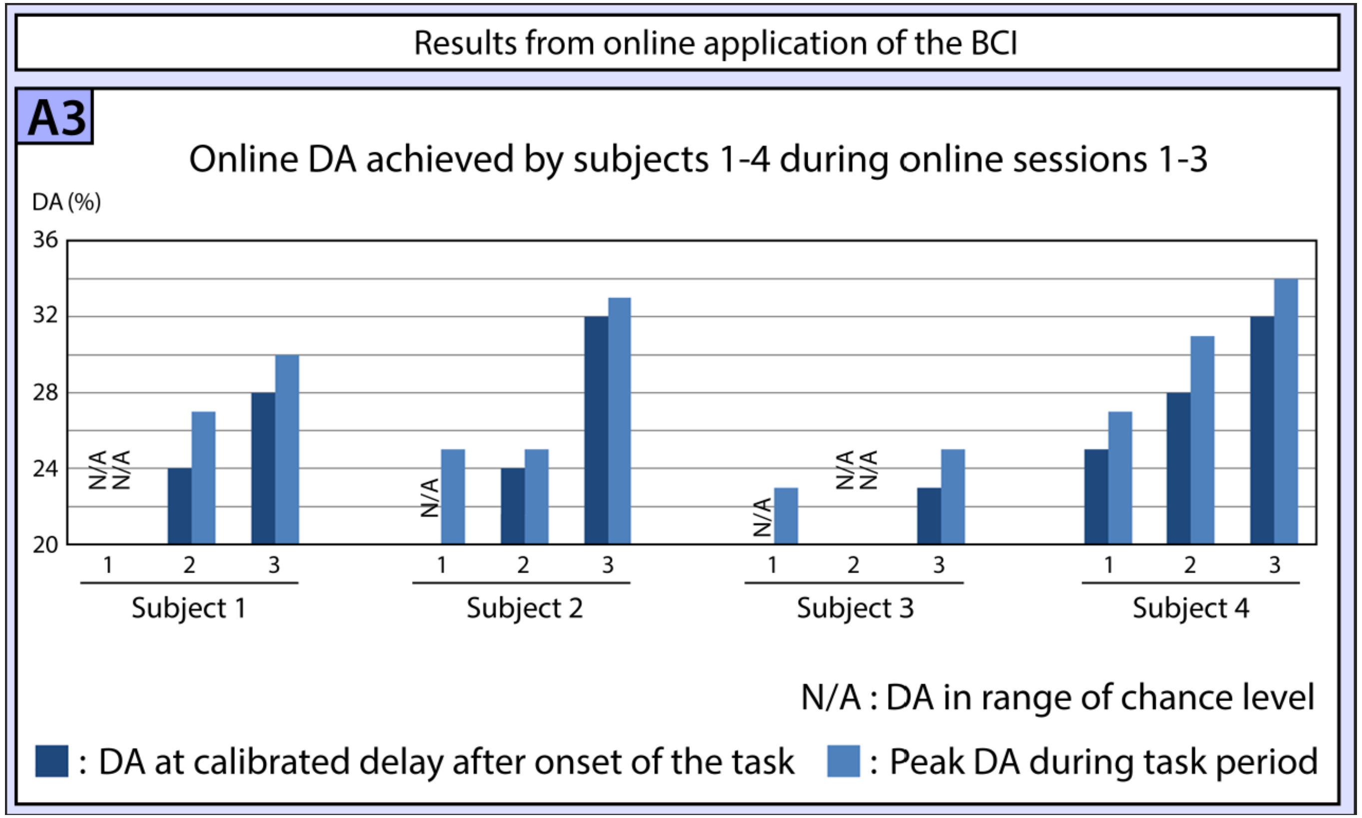
Online Decoding Accuracy

BCI calibration for Online sessions 1-2: based on 2 offline sessions
BCI calibration for Online sessions 3: based on online sessions 1-2



5 classes
(20% chance level)

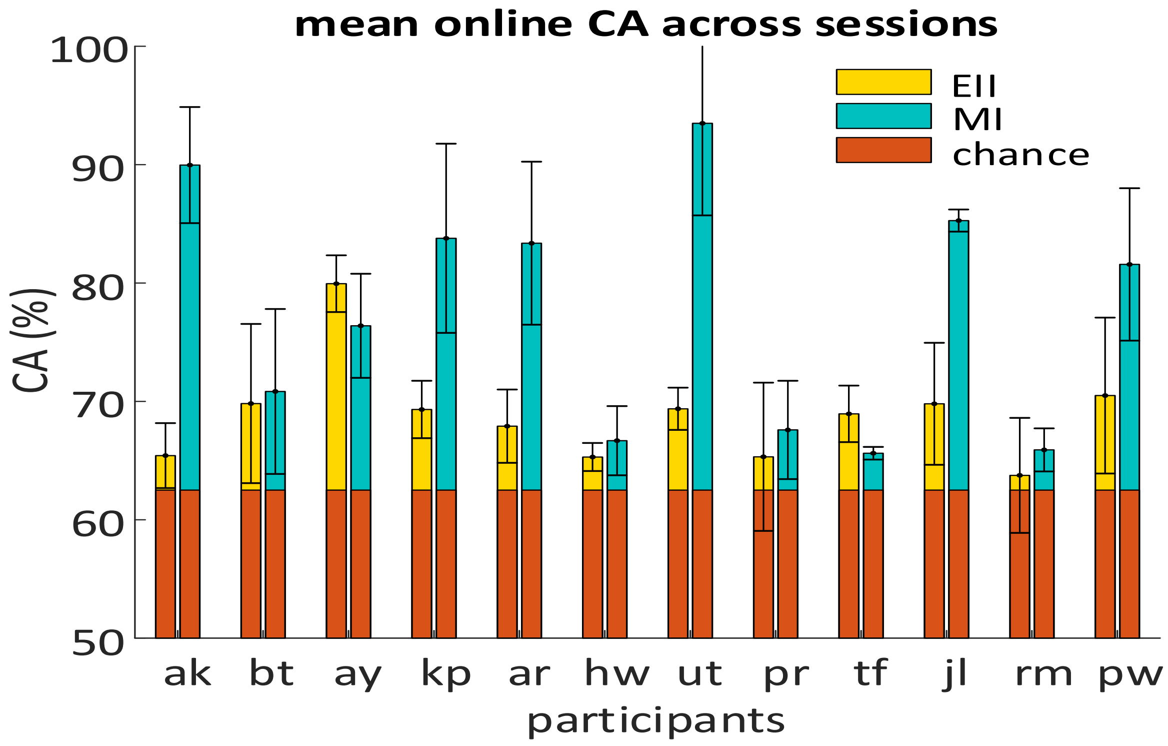


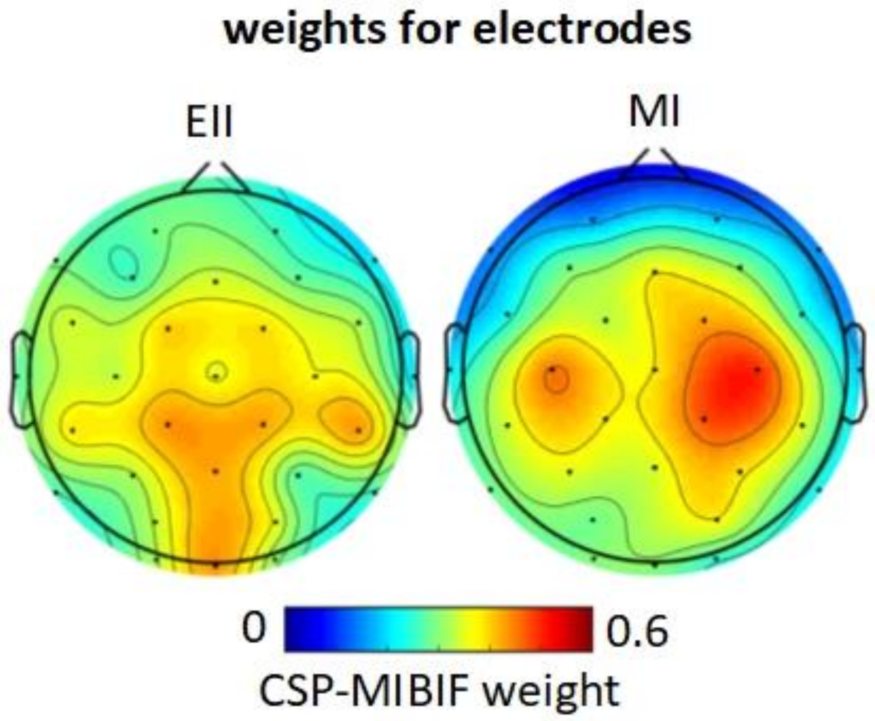


Korik et al, (in review)

Classifying self-induced emotions

Emotion-inducing imagery vs motor imagery



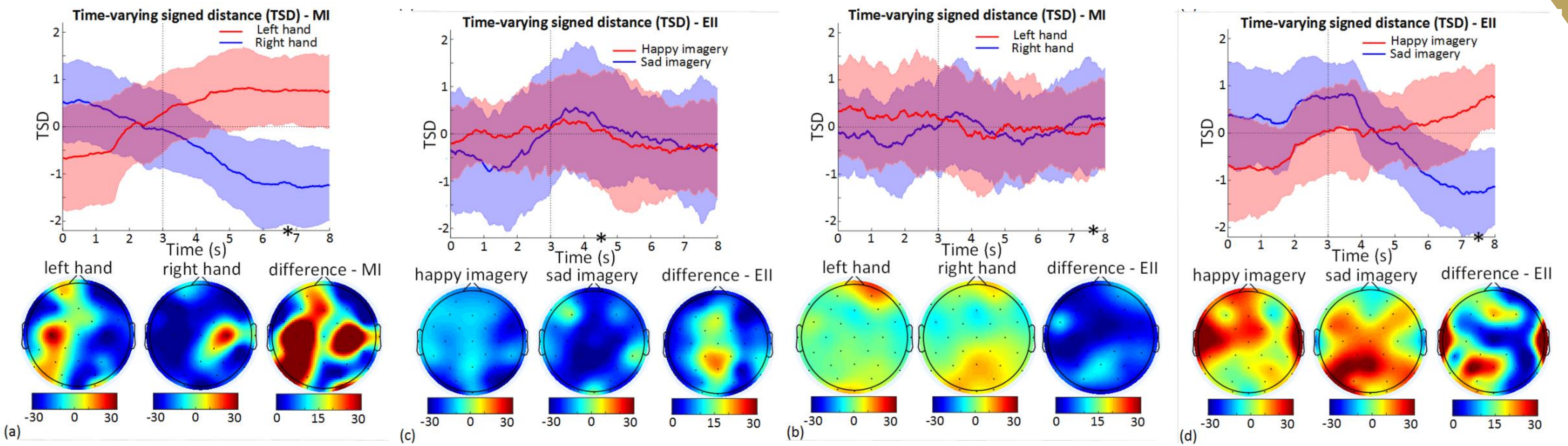


Ulster University

Bigirimana et al, 2020

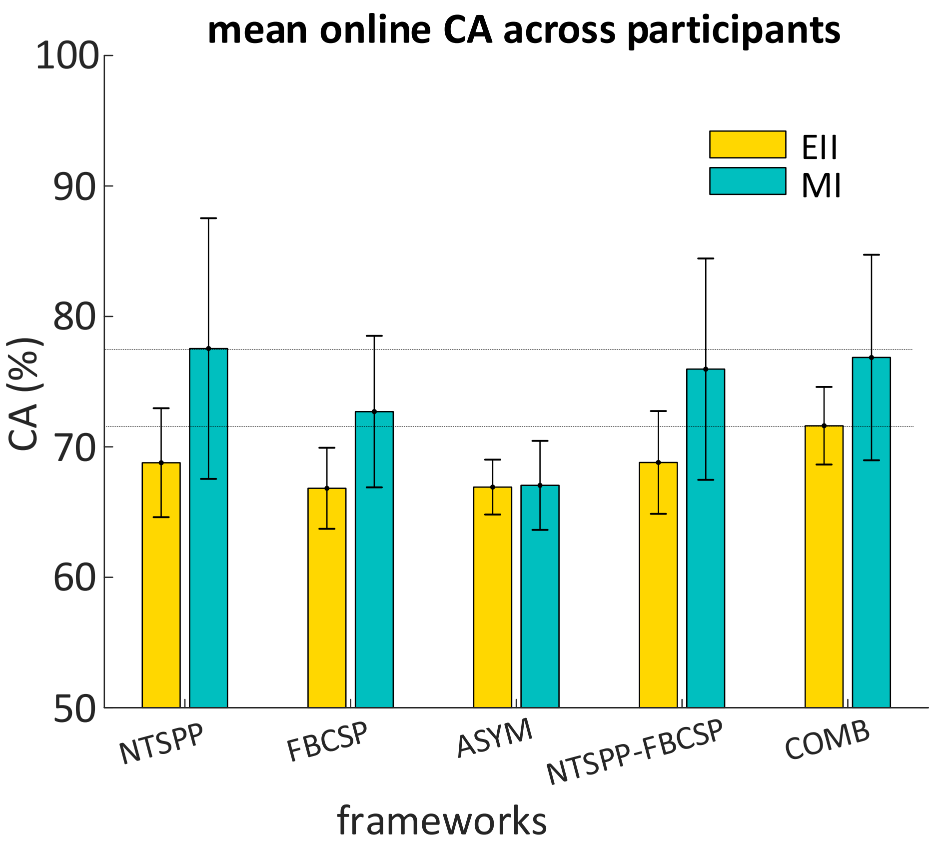
Is there a role for Emotion-inducing imagery?

- Participant with better performance in MI
- Participant with better performance in EII



Ulster University

Emotion-inducing imagery vs motor imagery



- **Correlation between pre-run (resting) EEG bandpower and classification accuracy across sessions**

Scalp locations\BCI	EII	MI	EII	MI	EII	MI	EII	MI	EII	MI	EII	MI	EII	MI
Frontal-middle											*a			
Temporal-left							*t			*g				
Central-right		*g	*a							*b				
Parietal-left		**-t *b *g					*t *-b	*-t			**t			
Parietal-middle						*a	**-a	*a						
Parietal-right	*b						*t							
Occipital-left	*a	*g				*-b	*-a *g			*t				
Occipital-middle					*-t *b	**t								
Occipital-right						***-g								*-t
Participants IDs	ak		bt		ay		kp		ar		tf		pw	

a = alpha, b = beta, g= gamma, t= theta band *: p < 0.05, **: p < 0.01, ***: p < 0.005 -: negative correlation

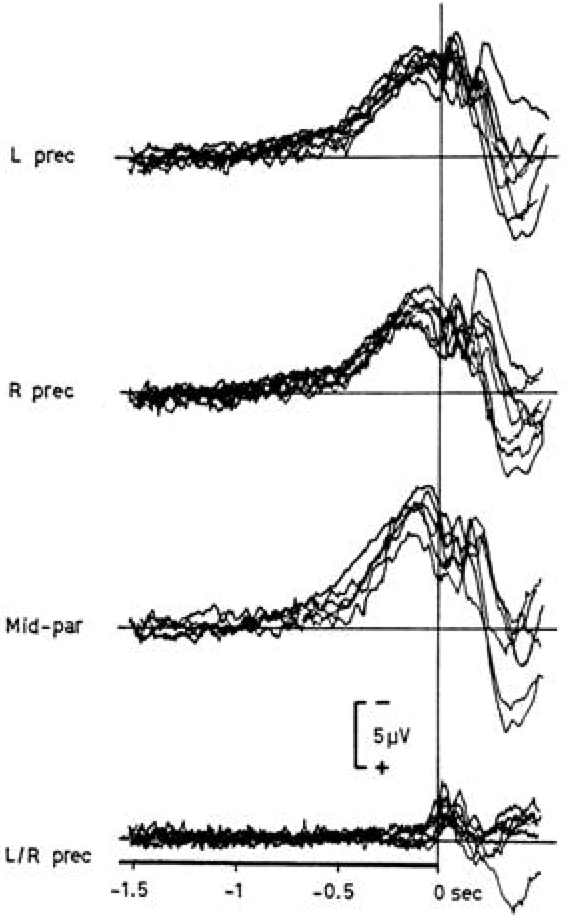
Ulster University

Part 8: Other type of BCIs

Rapid reaction

Bereitschaftspotential (readiness potential)

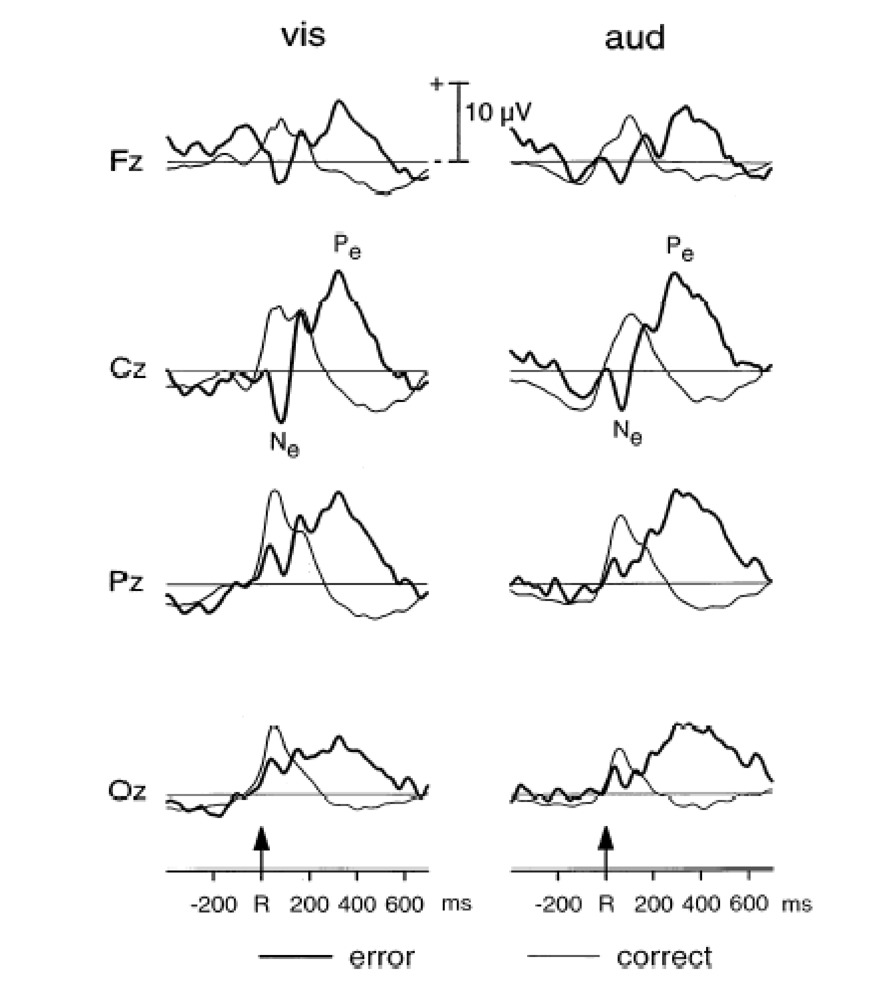
a measure of activity in the motor cortex of the brain leading up to voluntary muscle movement.



Rapid error correction

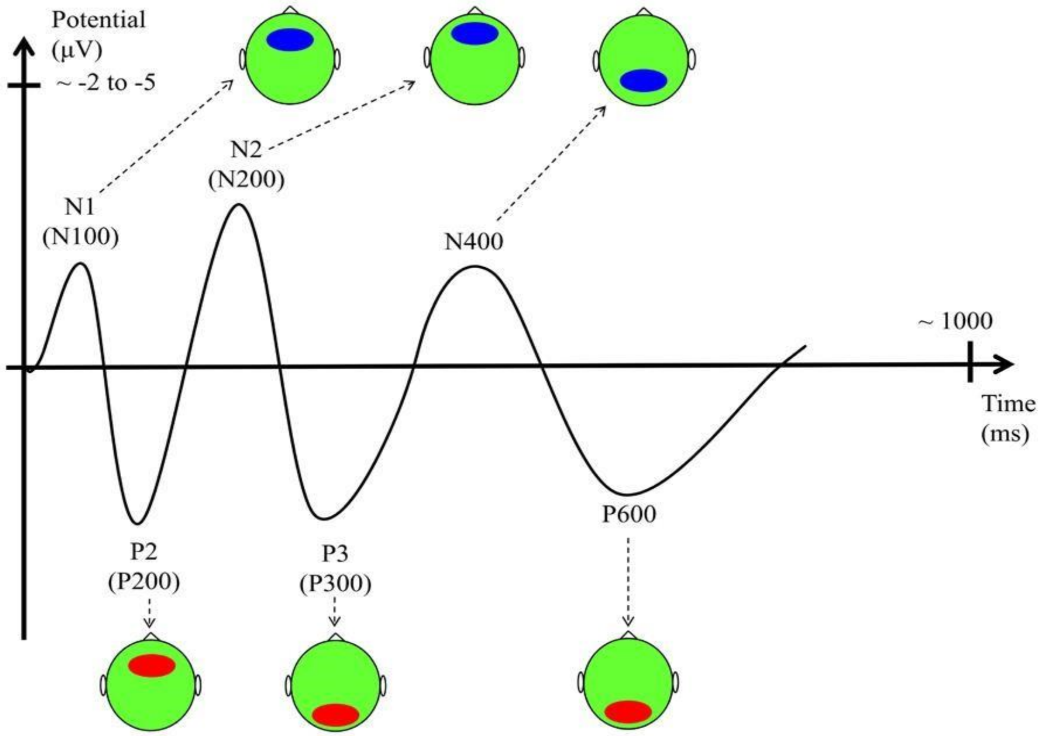
Error-Related Negativity - The Brain's **"Uh Oh"** Signal when an error is made

This is a negative shift in the EEG seen immediately after a subject thinks s/he just made a mistake.



Visual evoked potentials (VEPs)

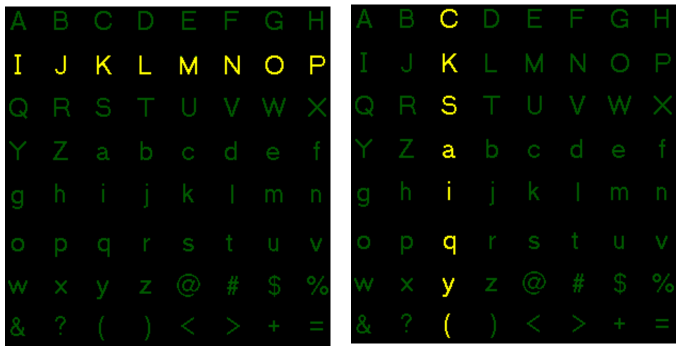
Stimulus

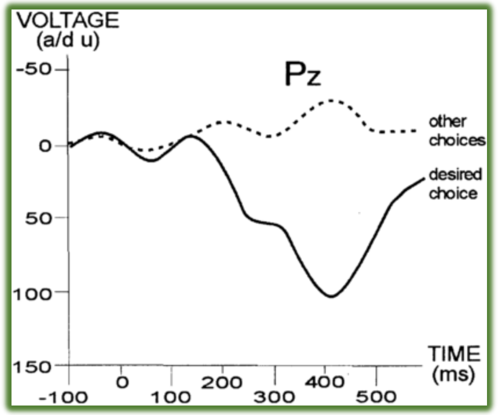


Component	Behavioral counterpart
N1	Pre-attentive perceptual processing
P2	Pre-attentive perceptual processing
N2	Stimulus detection
P3	Stimulus categorization and memory updating
N4	Semantic/conceptual processing
P6	Syntactic processing

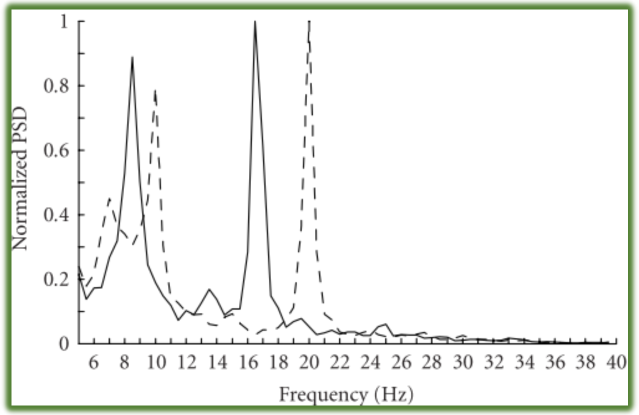
Visual evoked potential

- P300 speller

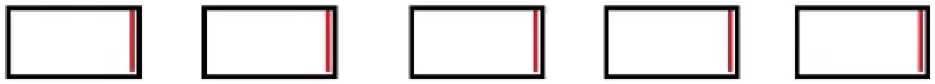


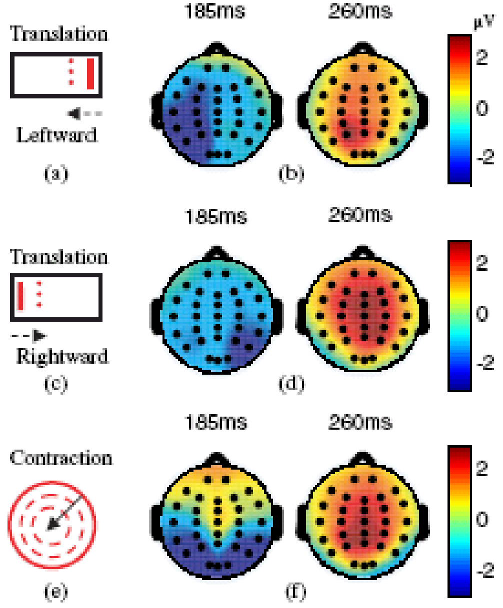


Steady-state VEPs

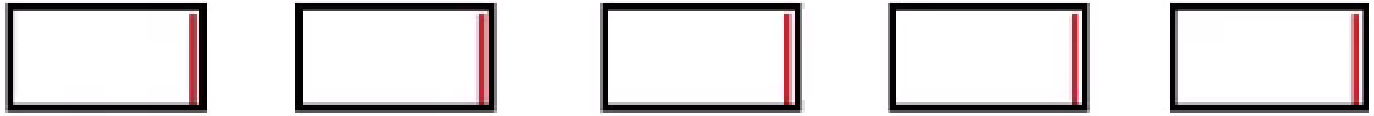


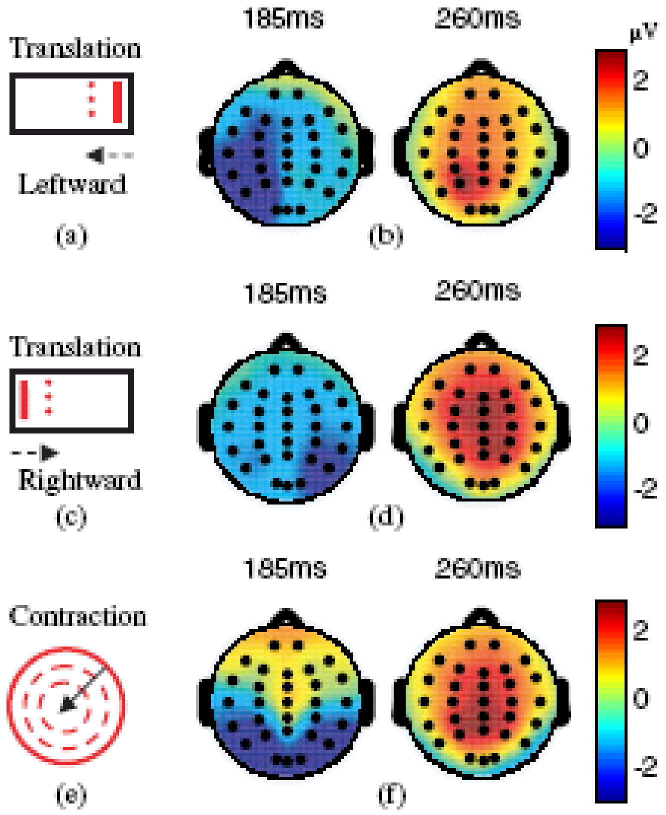
Motion onset VEPs





Motion onset visual evoked potentials

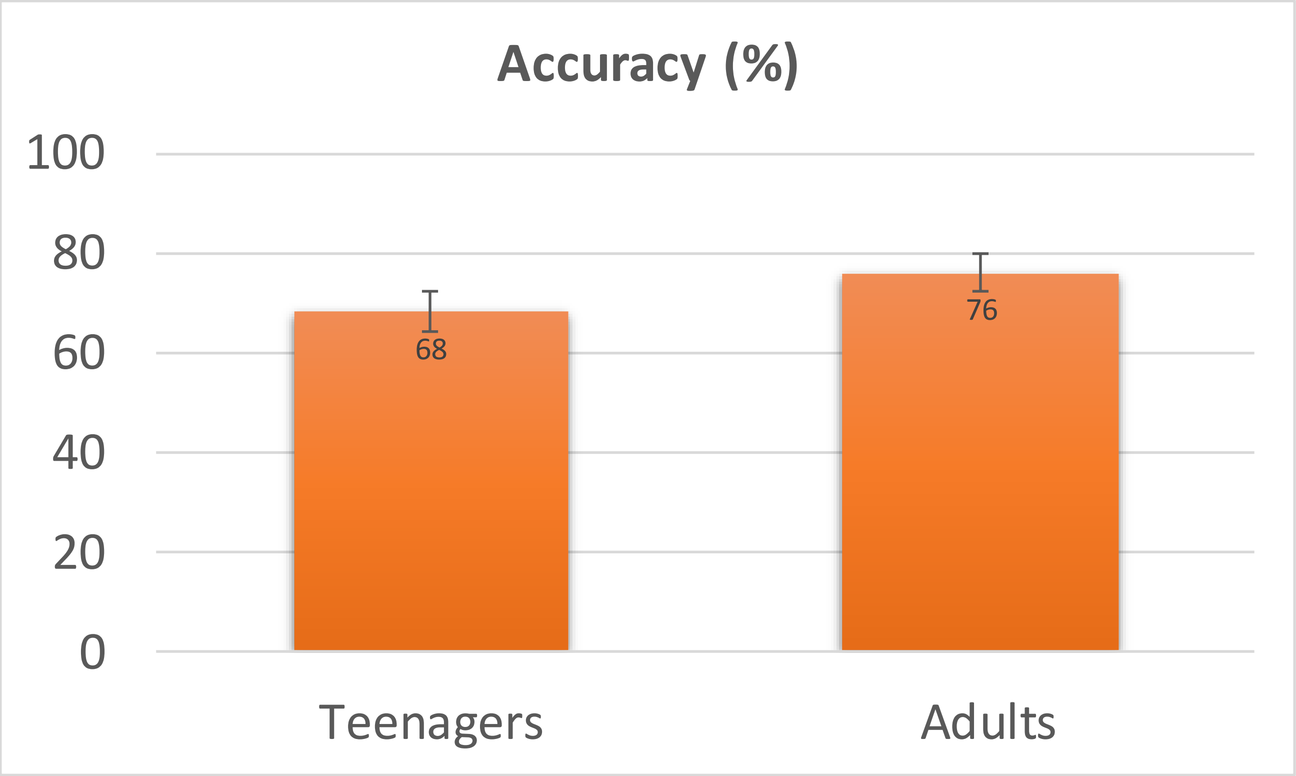




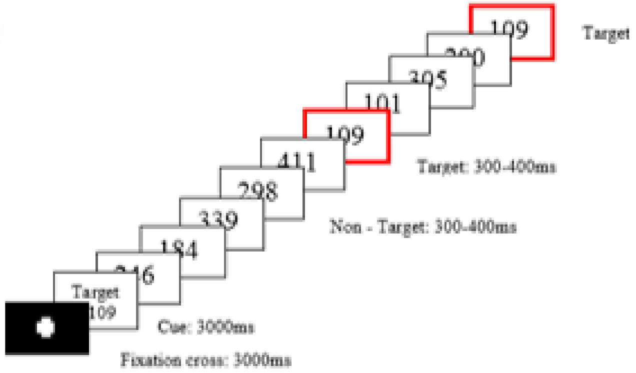
Car racing with mVEP

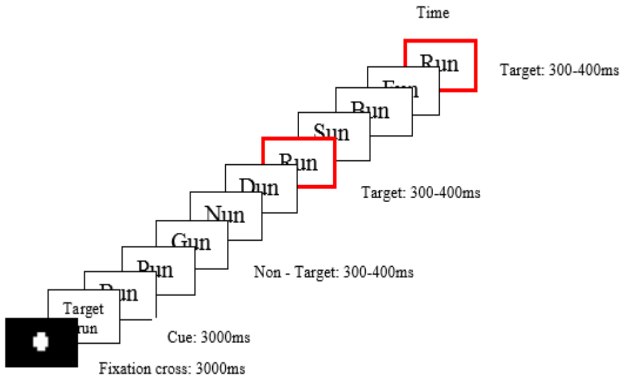
Adults vs Teenager

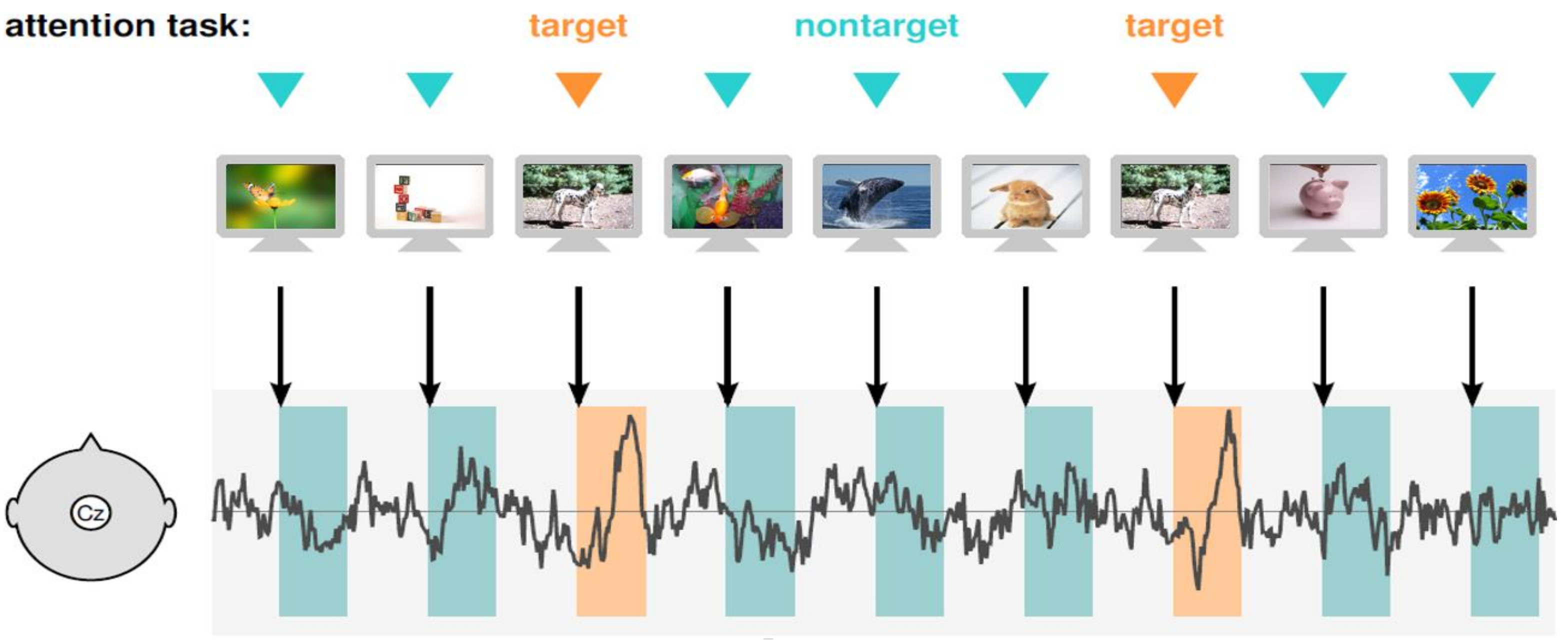
Adults vs Teenager



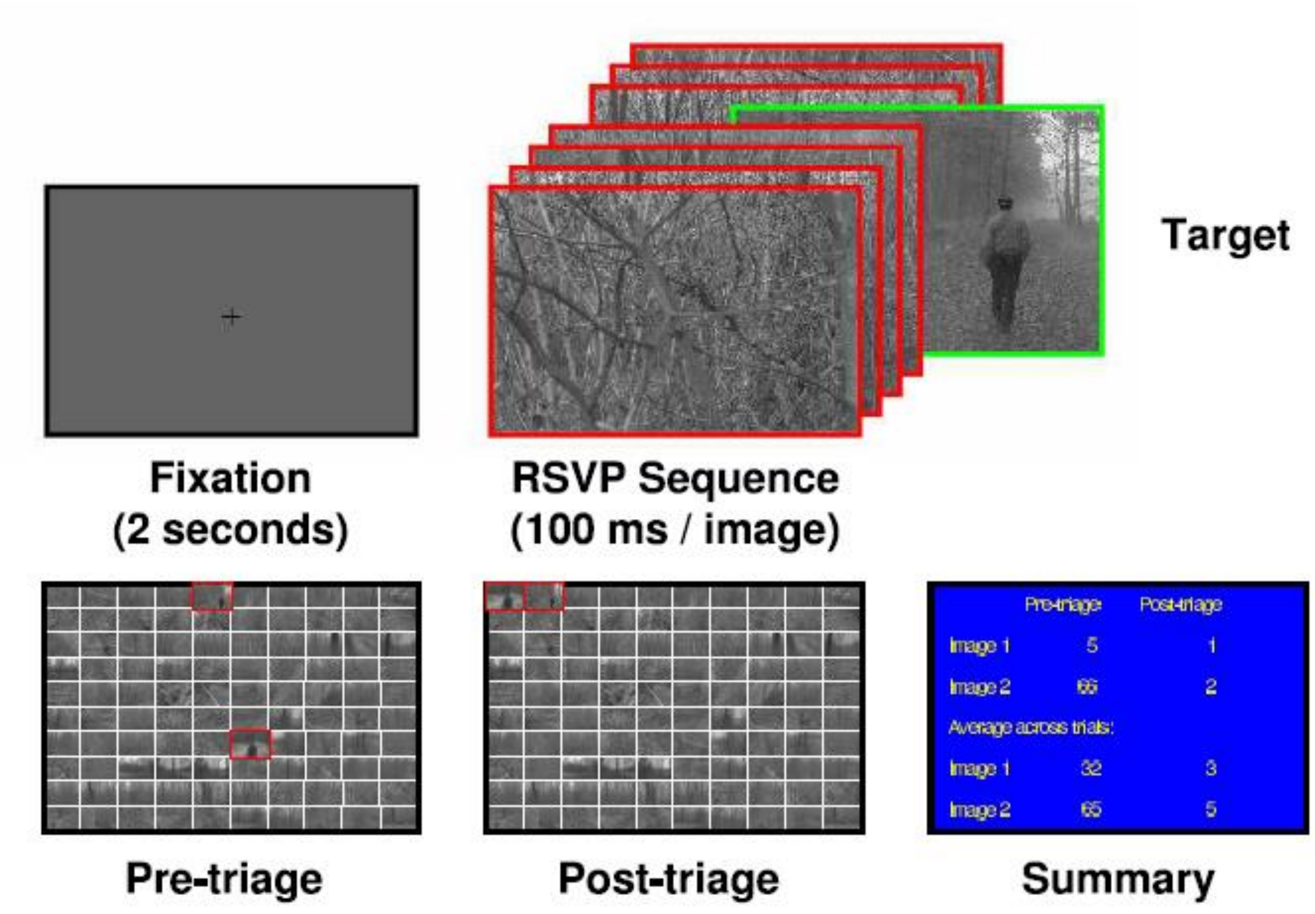
Rapid Serial Visual Presentation







Human Machine Symbiosis



Applications

Face recognition

Categorization

Surveillance – counter intelligence

Medical image sorting – clinical diagnosis

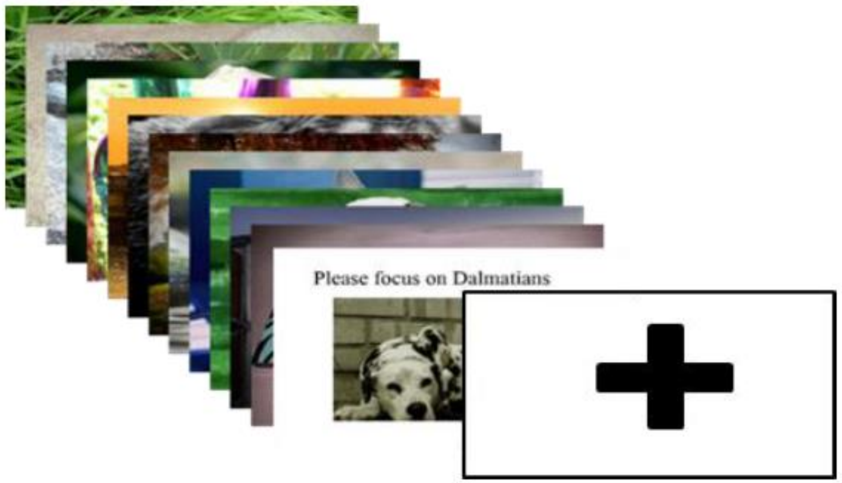
Lees et al, J. Neural Eng., 2018

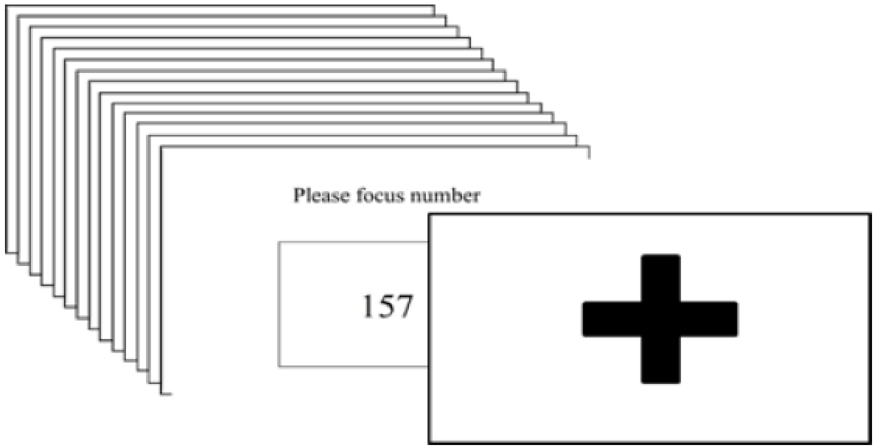
Assessing human performance in decision making under uncertainty

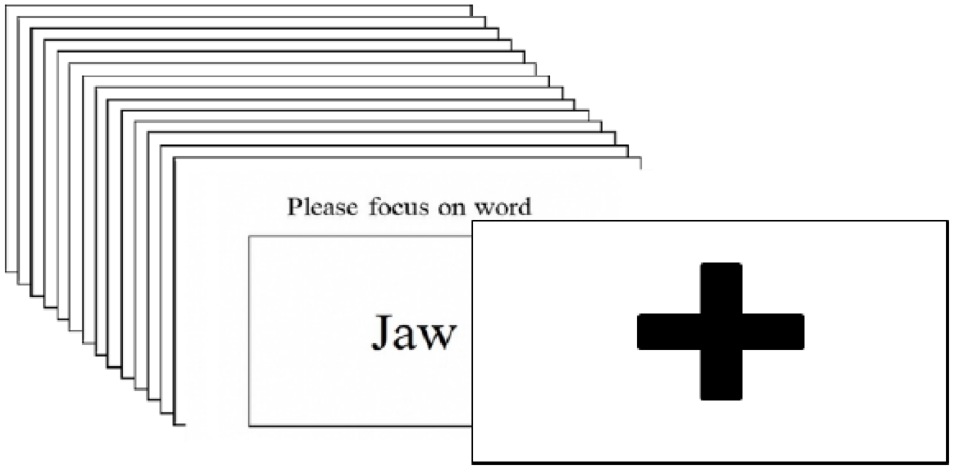
Data analytics and data labelling

Human machine cooperation in sorting challenging datasets – unstructured/unlabelled

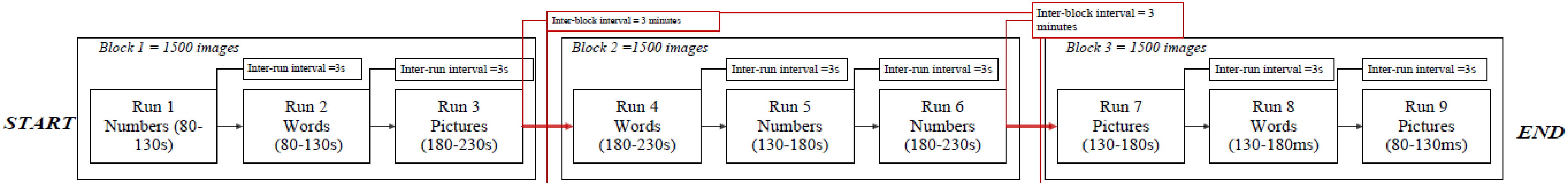
Data analytics/Image triage



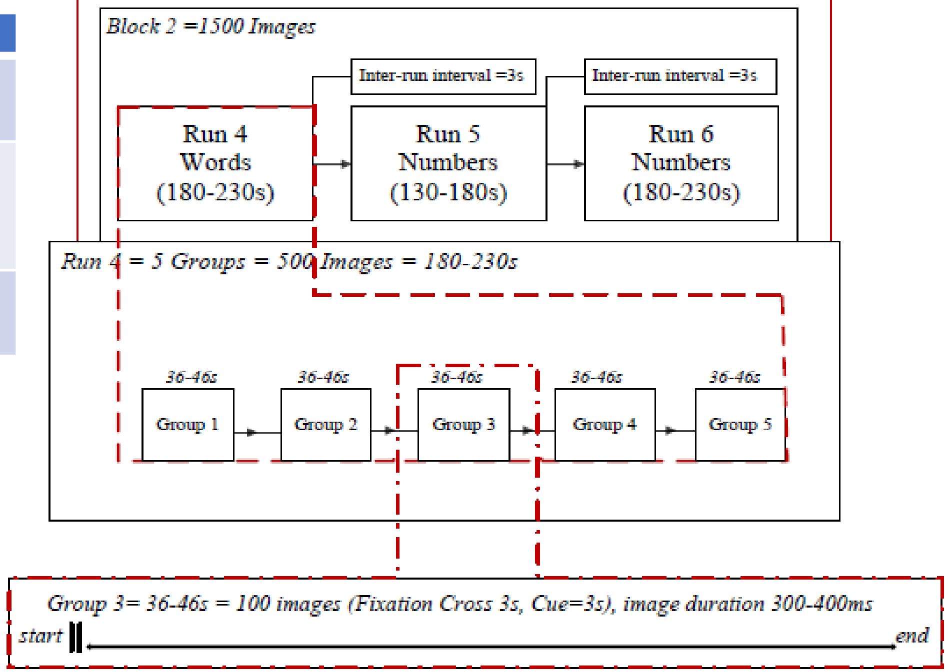


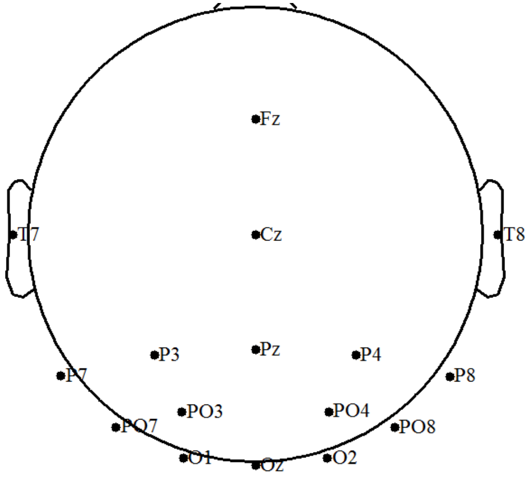


Paradigm

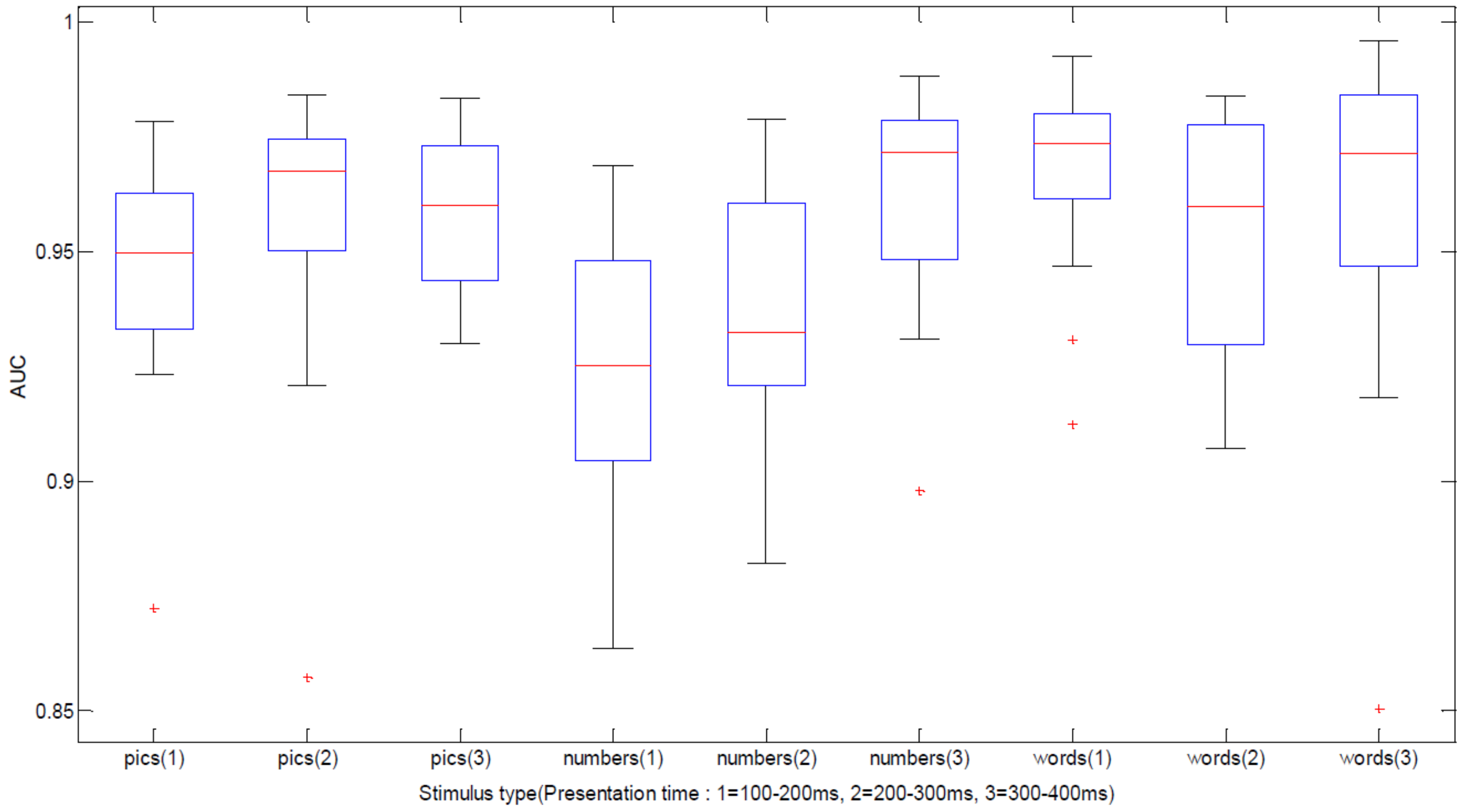


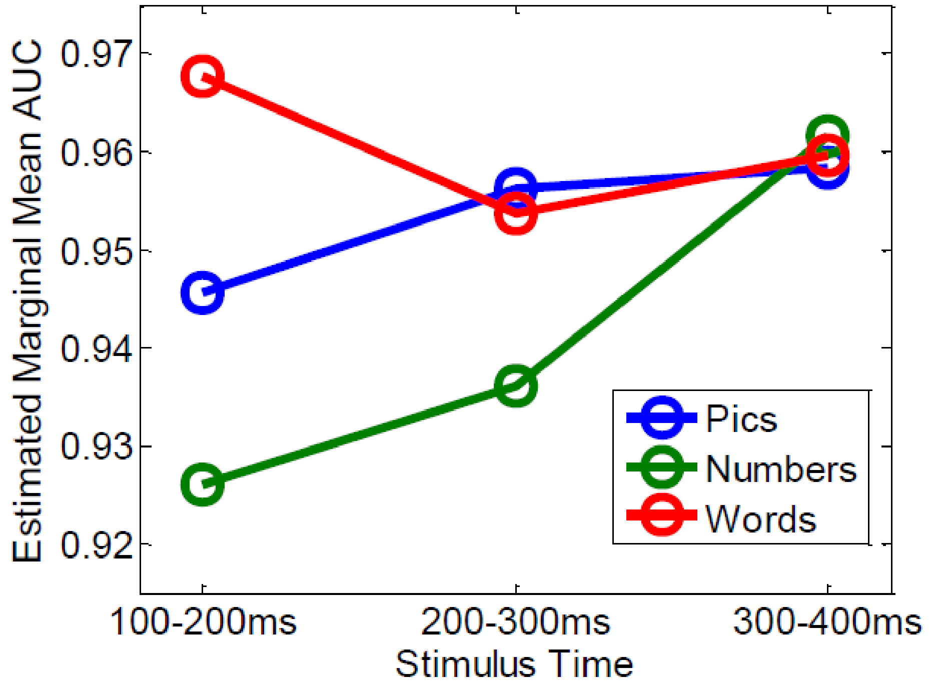
	Run1	Run 2	Run 3
Block 1	Word (300-400ms)	Picture (300-400ms)	Number (300-400ms)
Block 2	Number (100-200ms	Word (200-300ms)	Picture (100-200ms)
Block 3	Picture (200-300ms)	Number (200-300ms)	Word (100-200ms)





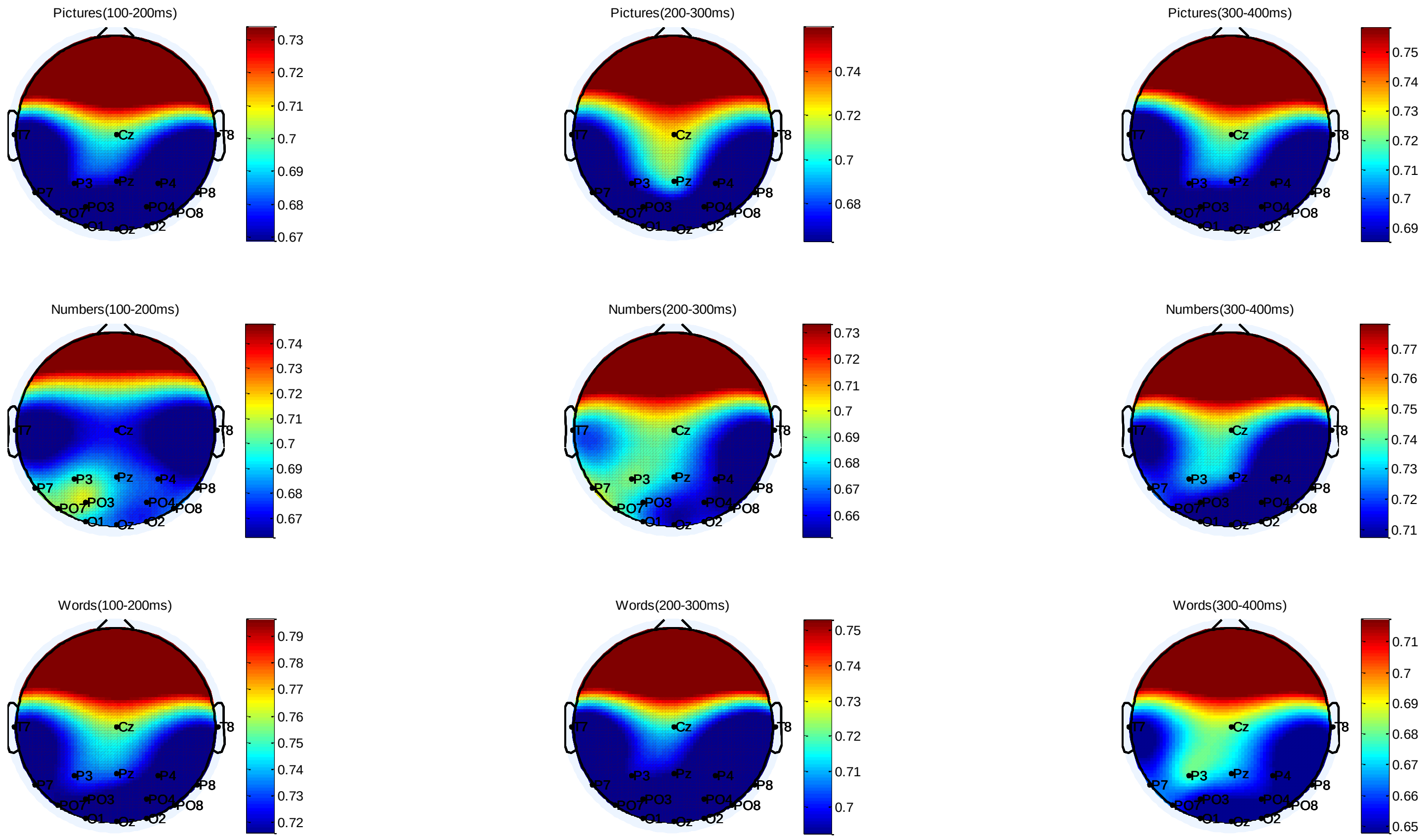
Numbers are more difficult to detect at faster rates

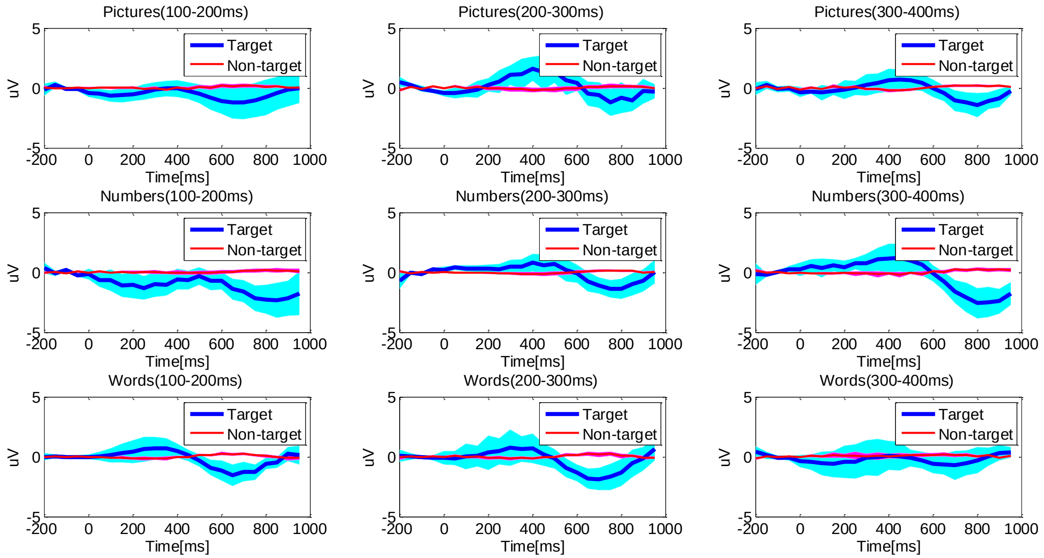




Lees et al, J. Neural Eng., 2020

Number are processed differently





Summary

- *Pictures, numbers and words* could be detected at fast presentation rates, up to 10Hz with high accuracy.
- Numbers are more challenging at faster rates – additional cognitive load, memory requirements
- When using RSVP paradigm for data analytics should bare this in mind
- First step in developing RSVP-BCI for image triage using different information modalities
- **We can study human performance with this paradigm – how humans process multimodal data**
- **We can use RSVP-BCI for data analytics where machines may fail**

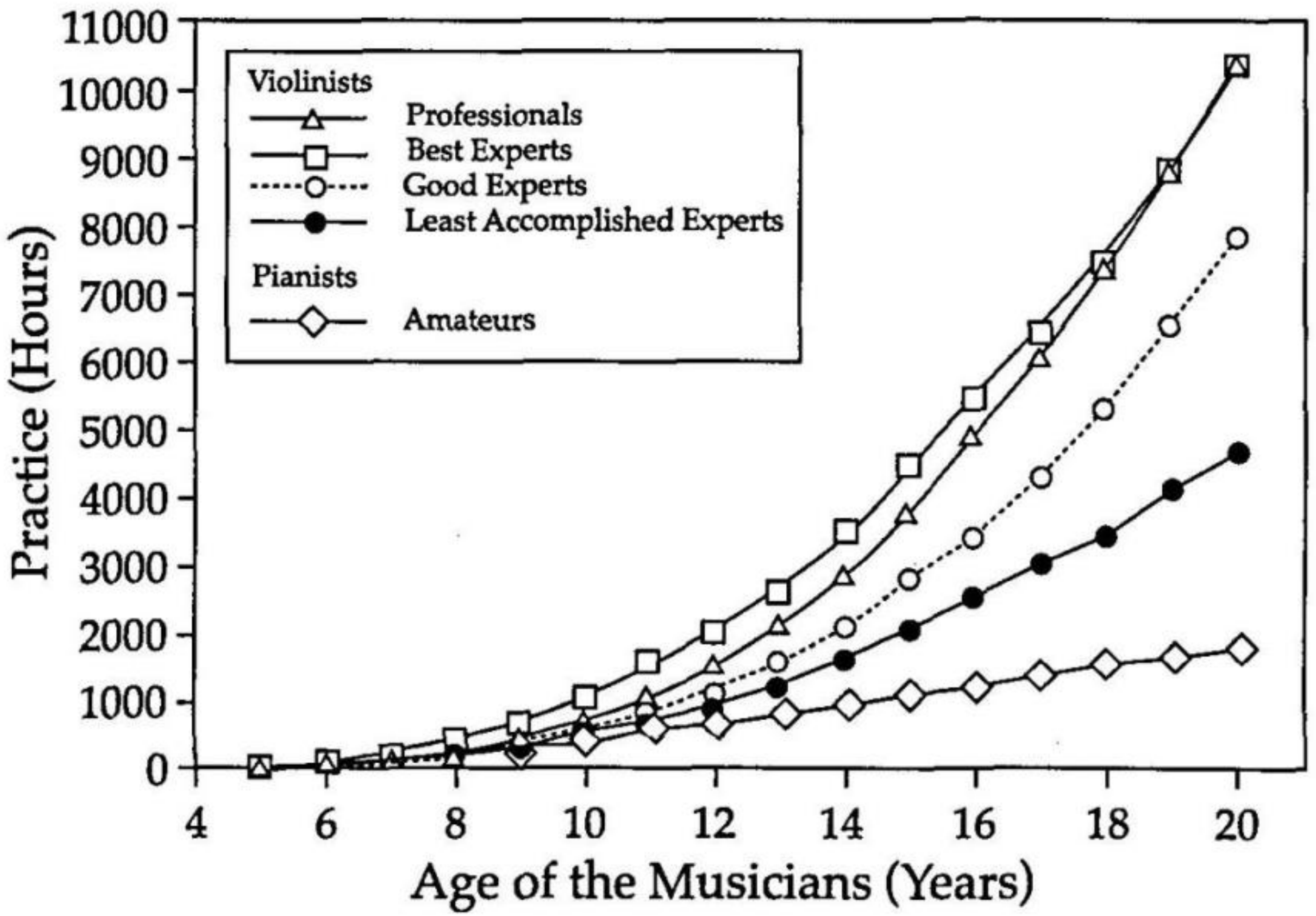
Challenges and prospects for brain-computer interface and neurotechnology

Emotions and affective states

- Fatigue
- Mood
- Stress
- Anxiety
- Joy

Ulster University

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

For patients e.g., dedicated, high dose therapy services

University

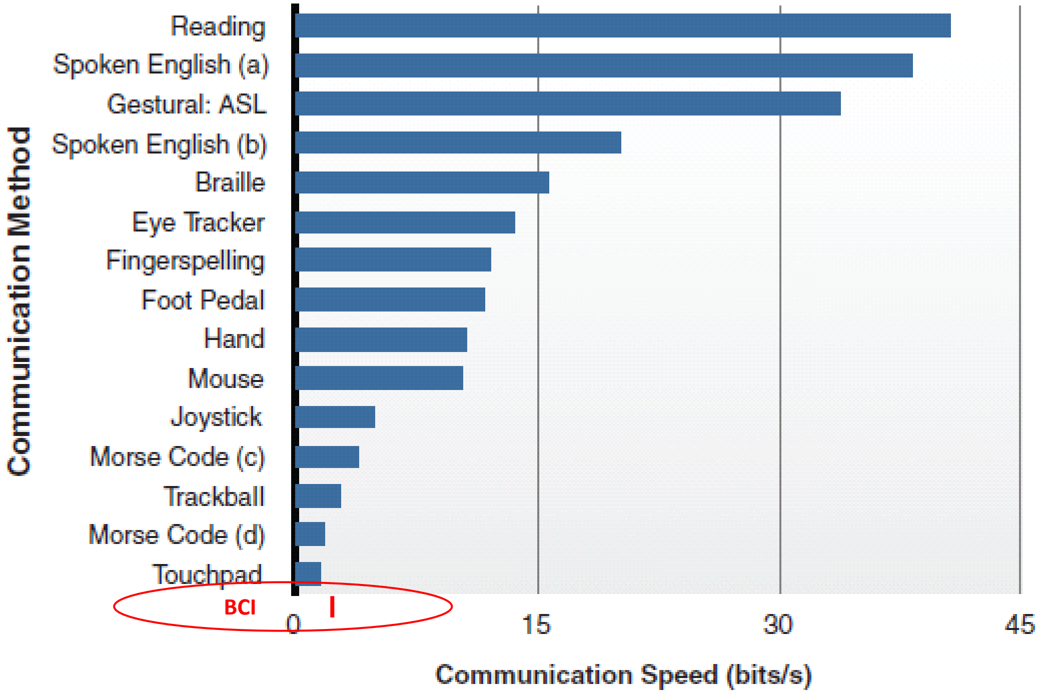
- Ericsson et al, Psychological Review, 1993

Challenges

- Signal quality and noise
- Non-stationarity of signals – brain complexity
- Hardware limitations – wearability, ease of use,

Robustness

- The inconsistency of movement control provided by movement BCIs is probably the single greatest impediment of their practical use – until this problem is resolved it will remain largely research (lab based) endeavour



- McFarland et al., J. Neural Eng., 2010

Ulster University

Hardware – wearable?

Emotiv

Enobio

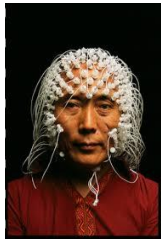
gTec - g.Nautilaus

OpenBCI

BrainwaveBank

Neursky – Thinkgear

Interaxon Muse



Electrical Geodesics Inc

Cognionics

Ant Neuro

EasyCap

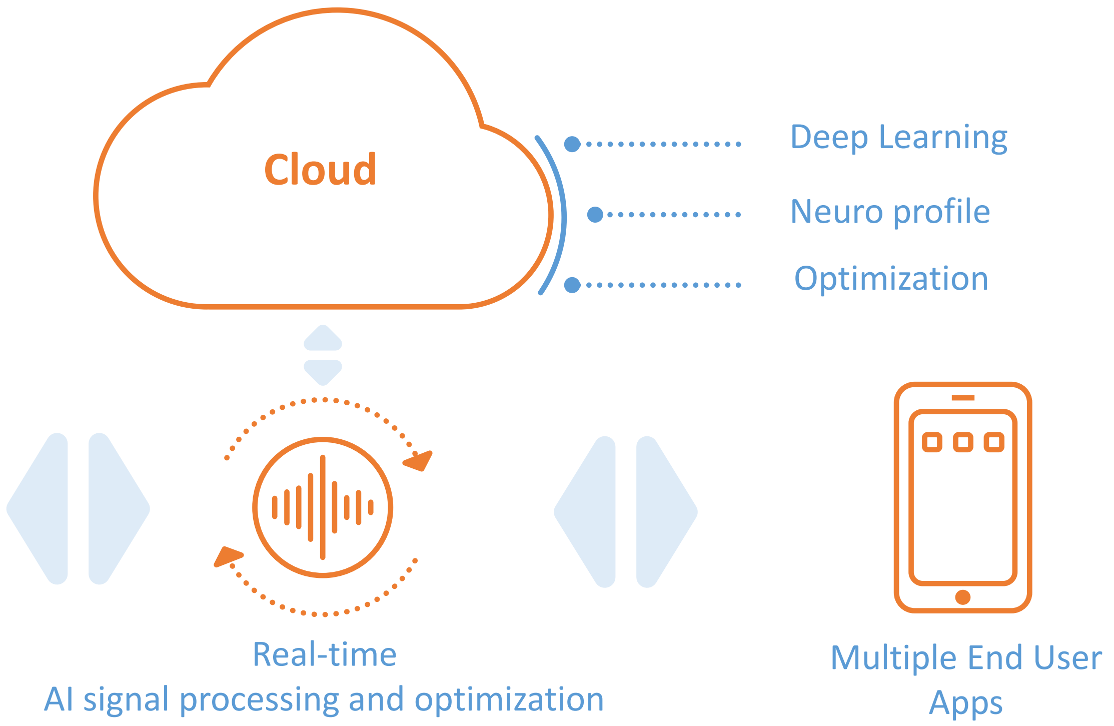
Wearable sensing

Brain Products

NEUROCONCISE

Neurotech Platform

NOW AVAILABLE



IET AWARDS
The Institution of Engineering and Technology
INNOVATION
WINNER 2018

Killer app for BCI?

Clinical utility is clear

The brain twitter interface?

First person shooter game?

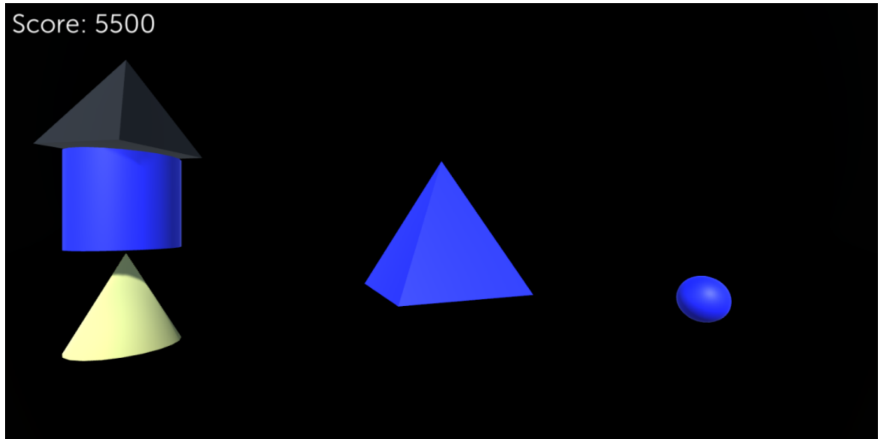
AR/VR hybrid

Blockchain – cloud minds?

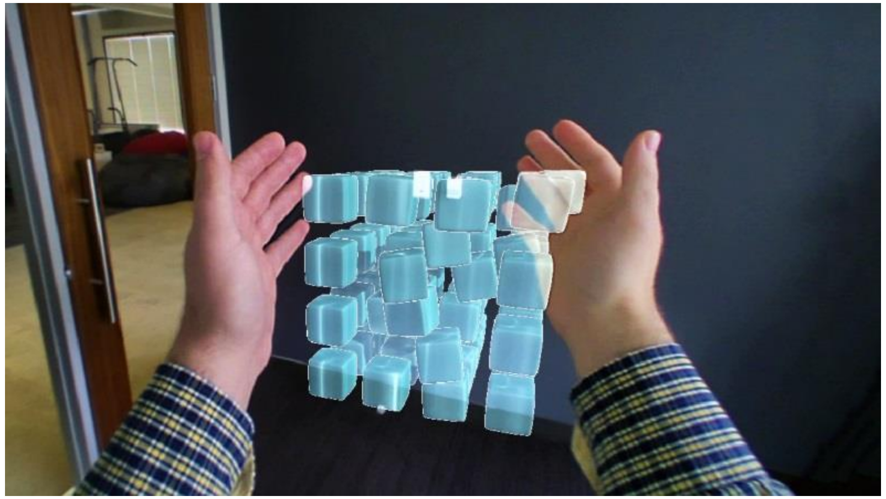
Rapid reaction and human enhancement?

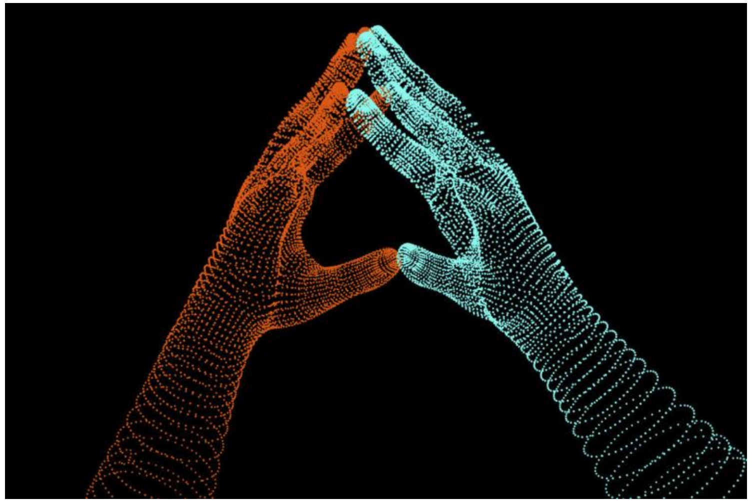
Better paradigm – Virtual/Augmented Reality and Games

2D Monitor



Augmented reality



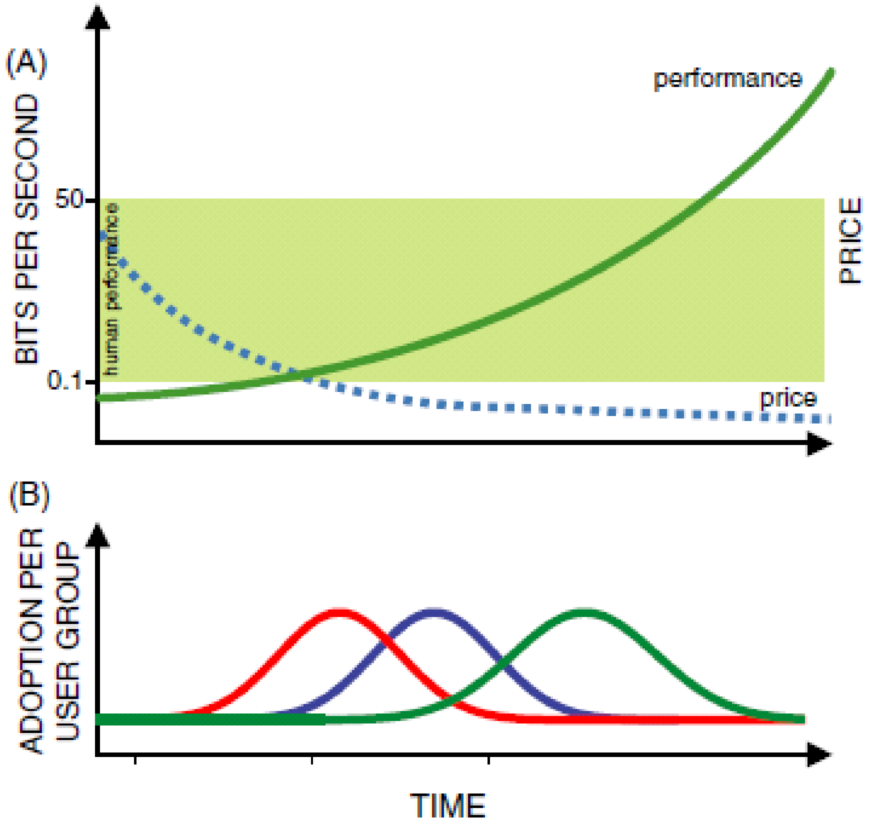


Driving forces for neurotechnology

- People with restricted abilities
- Aging population, increasing demand to repair the nervous system
- Consumer demand
- Health and wellness monitoring and entertainment
- Human desire to learn, improve and advance
- Robotics, artificial intelligence and computing advances
- Capitalism

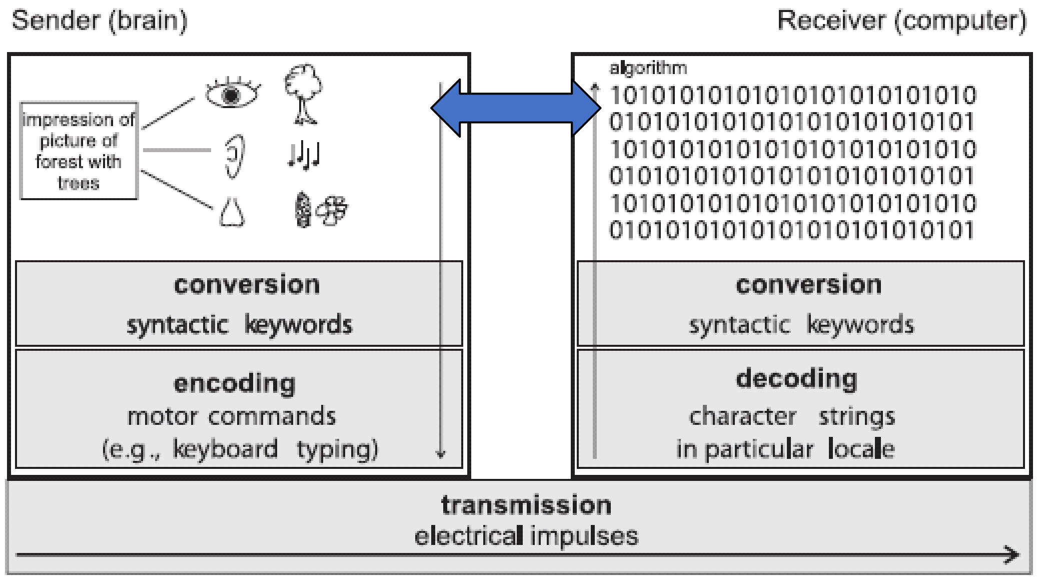
Ulster University

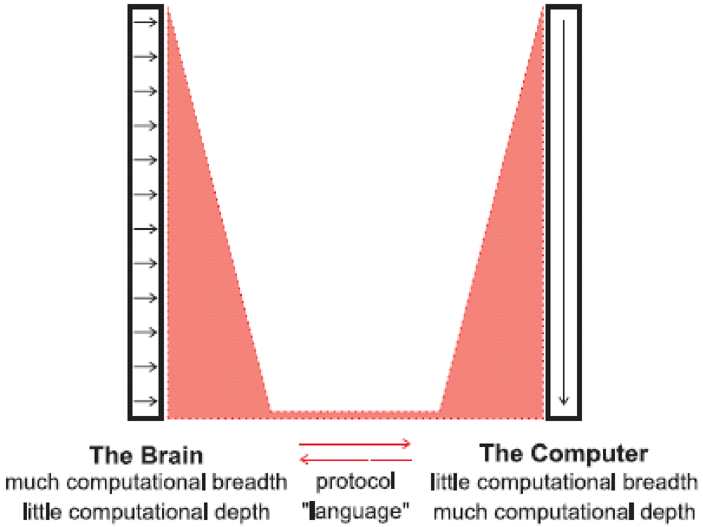
Technology diffusion



Ulster University

Brain-Computer Symbiosis





- Schalk, J. Neural Eng., 2008

Conclusion

Decoding imagined movement is challenging

Executed movement less so

Need to gain a better understanding of dynamics associated with imagined movement

Can executed movement be used as proxy for imagined movement in BCI experiments?

What frequency band are best for imagined movement?

Virtual reality offers significant scope to develop better paradigms

Need to engage participants – potentially with gamification in VR

How many motor imagery trials/repetitions are enough for 3D decoding with EEG?

Conclusion

Brain–computer interface use is a skill that user and system acquire together

Man-machine learning dilemma requires time

Continual adaptation and learning

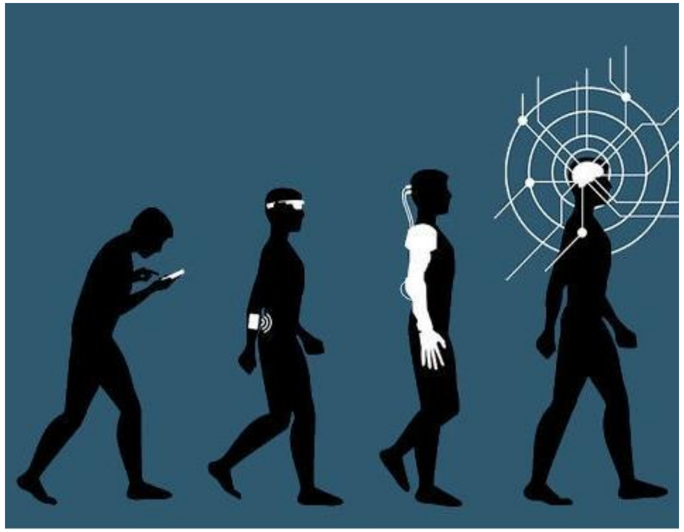
AI Machine/deep learning is essential

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



Thank you

Thanks to all PhD Researchers colleagues, collaborators, funders, and study participants

Ulster University

Ulster
University