

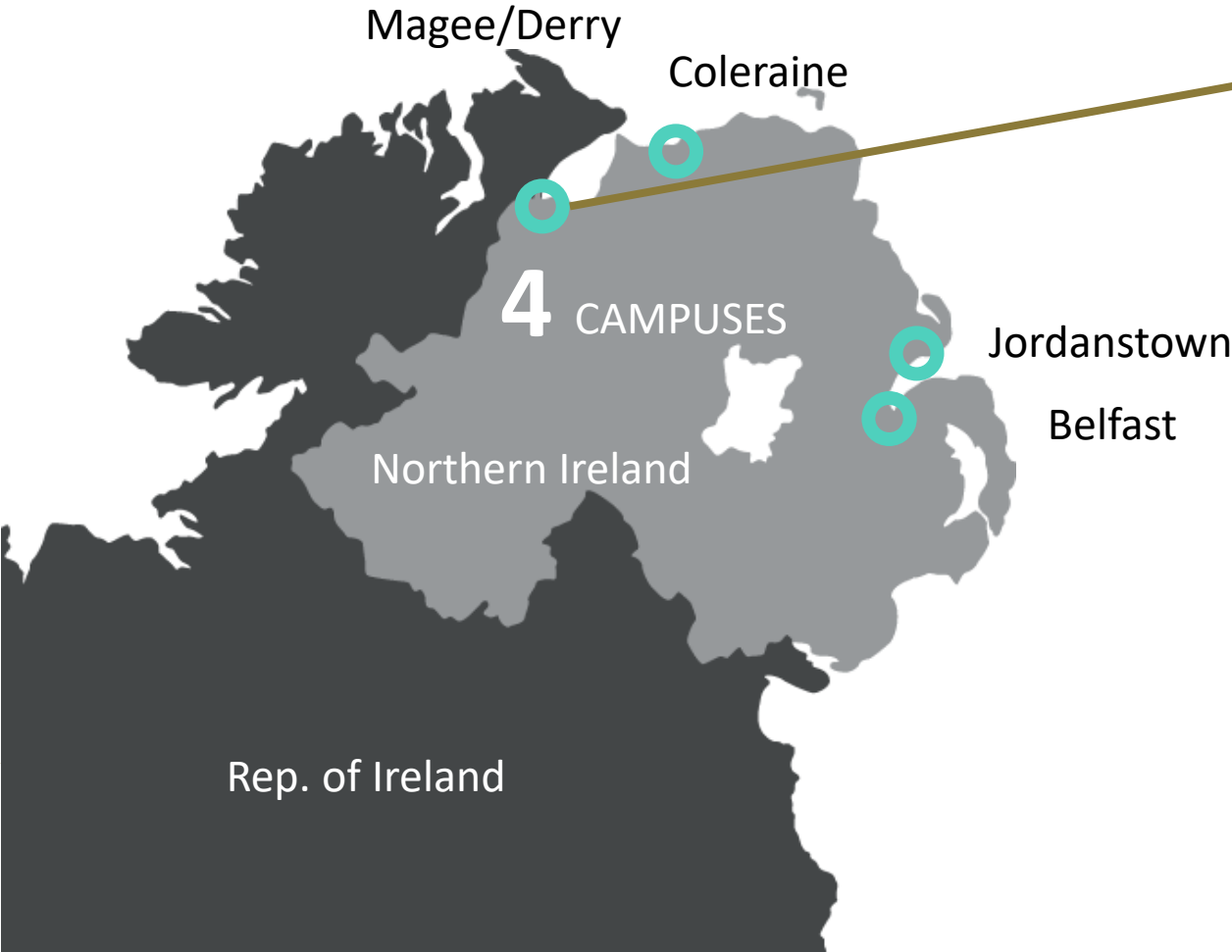
Brain-Computer Interfaces (BCIs) - Decoding Mental Imagery from Electroencephalography (EEG)

*Damien Coyle, Professor of Neurotechnology,
Director, Intelligent Systems Research Centre*



Ulster University

Intelligent Systems Research Centre





Our facilities



Northern Ireland Functional Brain Mapping Facility houses the only magnetoencephalography (MEG) system in Ireland (1 of 10 in the UK).

Spatial Computing & Neurotechnology Innovation Hub



Brain-Computer Interface lab

Advanced cognitive robotics lab



Research themes



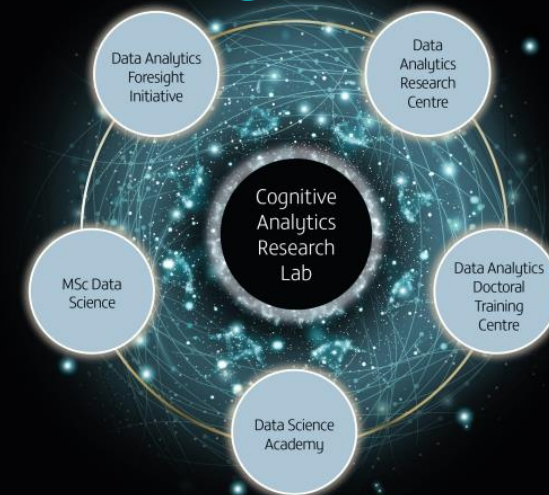
Vision

Our vision is to develop a bio-inspired computational basis for Artificial Intelligence to power future cognitive technologies.

Mission

Our mission is to understand how the brain works at multiple levels, from cells to cognition and apply that understanding to create realistic models and construct technologies that solve the complex issues that face people and society. To accomplish our mission we use a variety of research strategies that include big data and machine learning, brain imaging and neural interfacing, human-computer interaction and robotics.

CARL



Overview

- Brain-computer Interfaces (BCIs) based on **Motor Imagery (some basics)**
- Neurogaming, spinal injury, stroke rehab, disorders of consciousness
- Decoding imagined 3D limbs movements, shapes, emotions and speech from EEG
- Modulating brain activity through imagery is a learned skill that takes time
- Not simply a matter of “mind reading.”
 - Timing, coaching and explanation are important
- Other types of BCI

Three pillars



Three pillars

- Machine Learning/AI
- Training
- Application

=

Performance

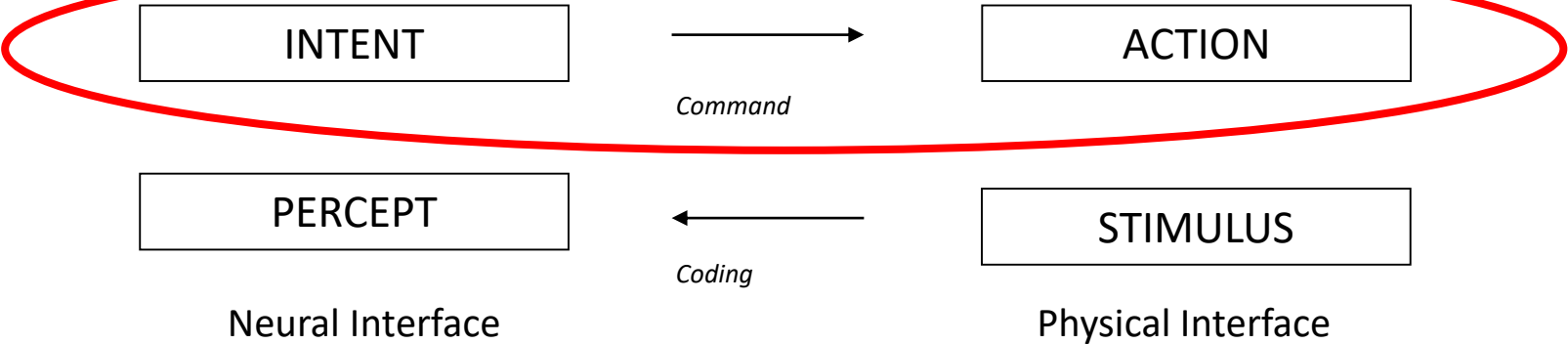
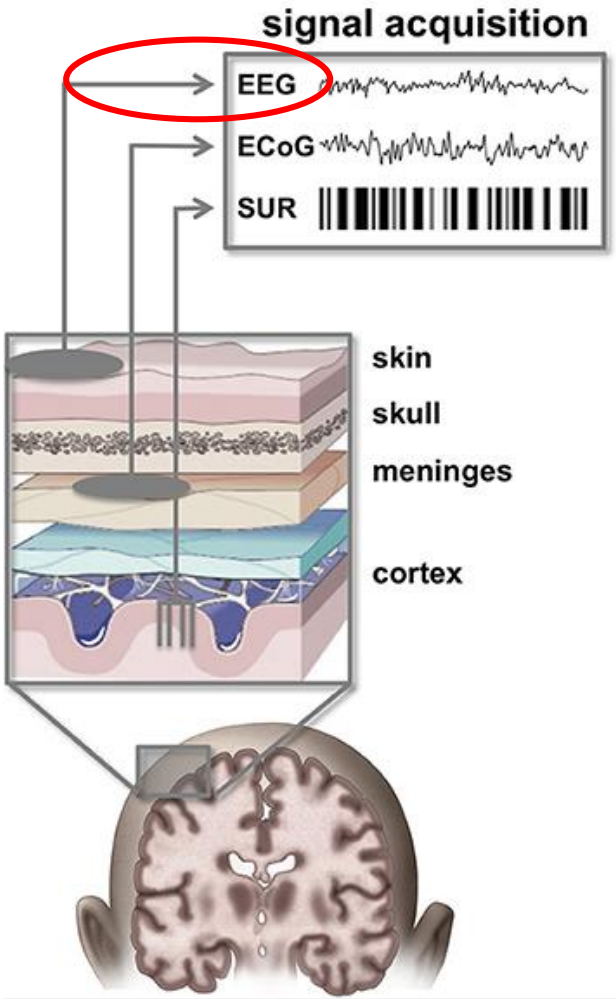
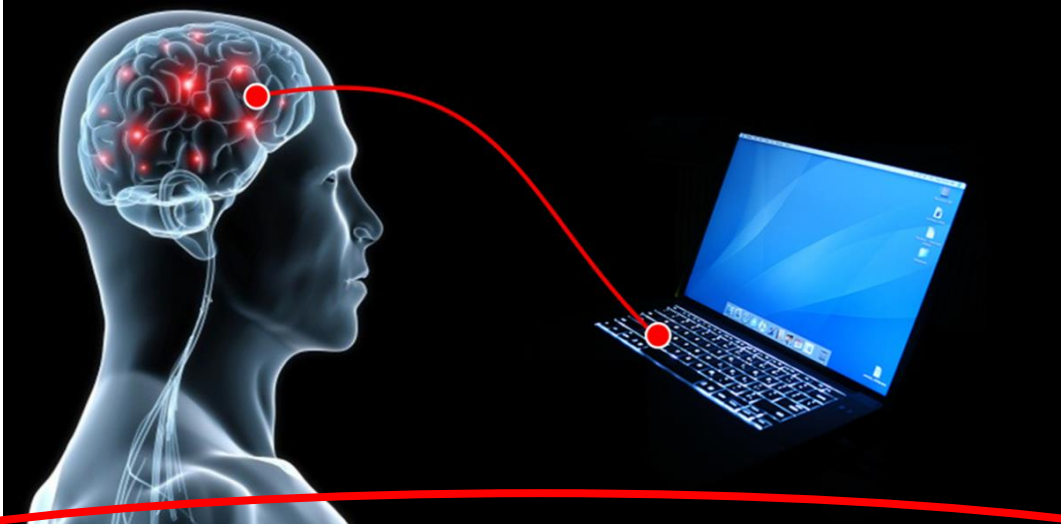


McFarland et al, 2019

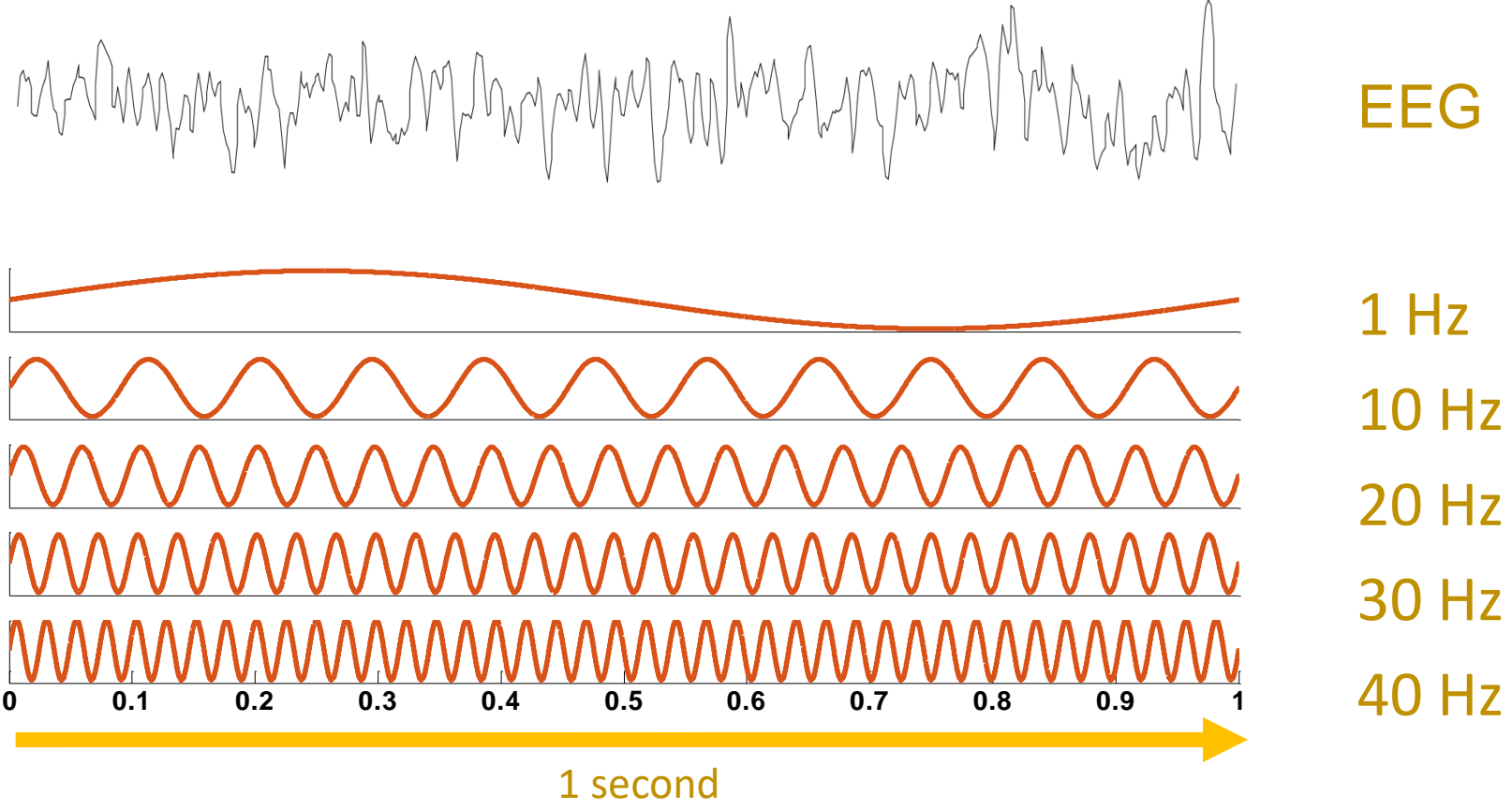


Brain-Computer Interface

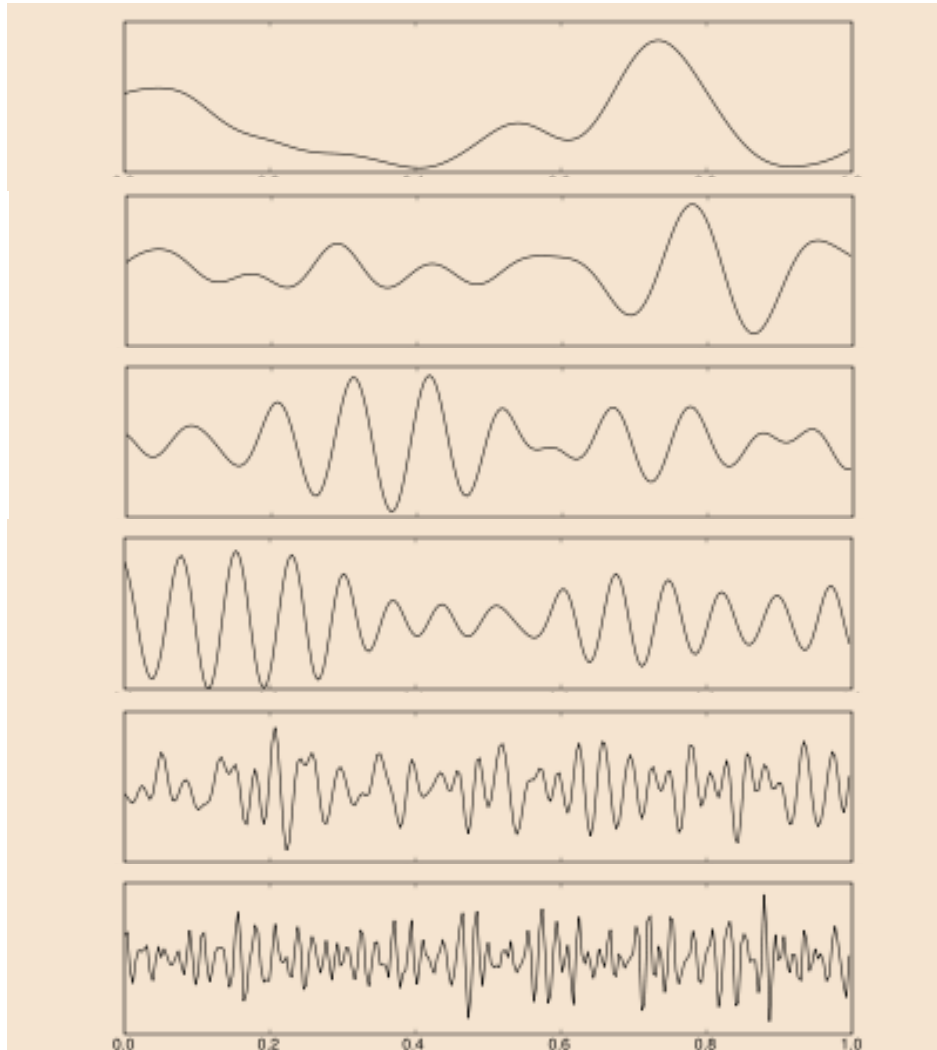
BCI



EEG and Frequency (Hz)



Brain Rhythms/Oscillations

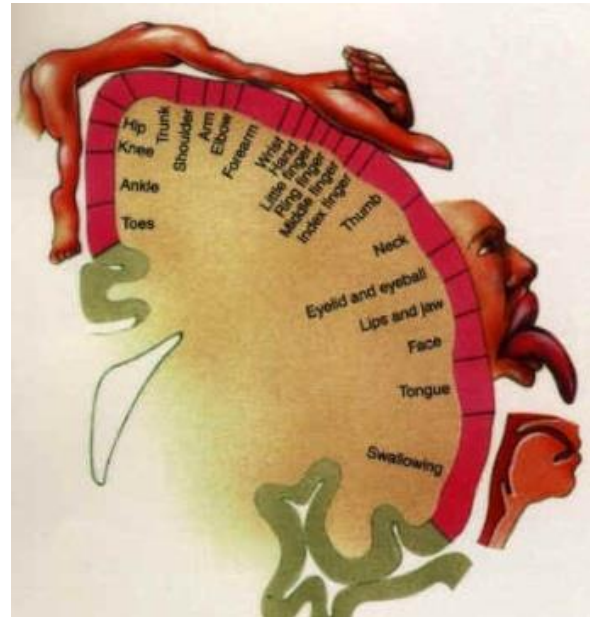


1 second

Name	Hz	Association
Delta(δ)	0.1-4	Deep sleep, comatose state, movement
Theta(θ)	4-7.5	Sleeping, Abnormal in awake adults
Alpha(α)	8-12	Awake but relaxed, eyes closed
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

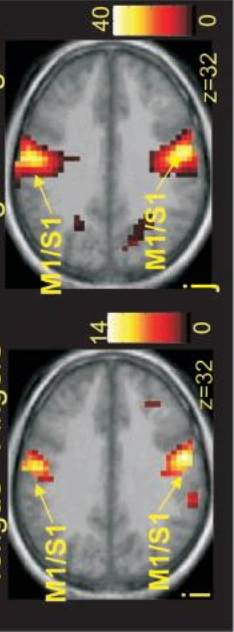
HOMONCULUS: The little guy

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



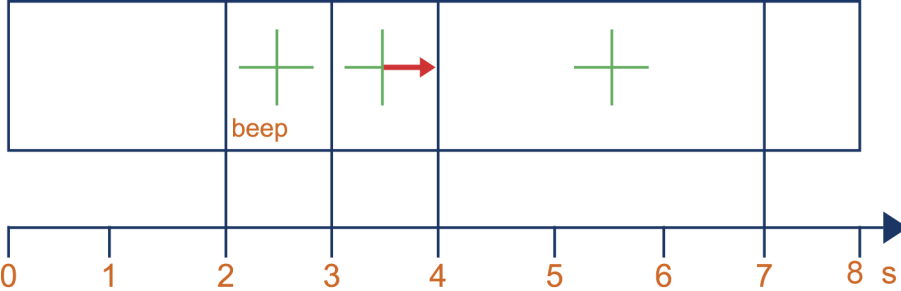
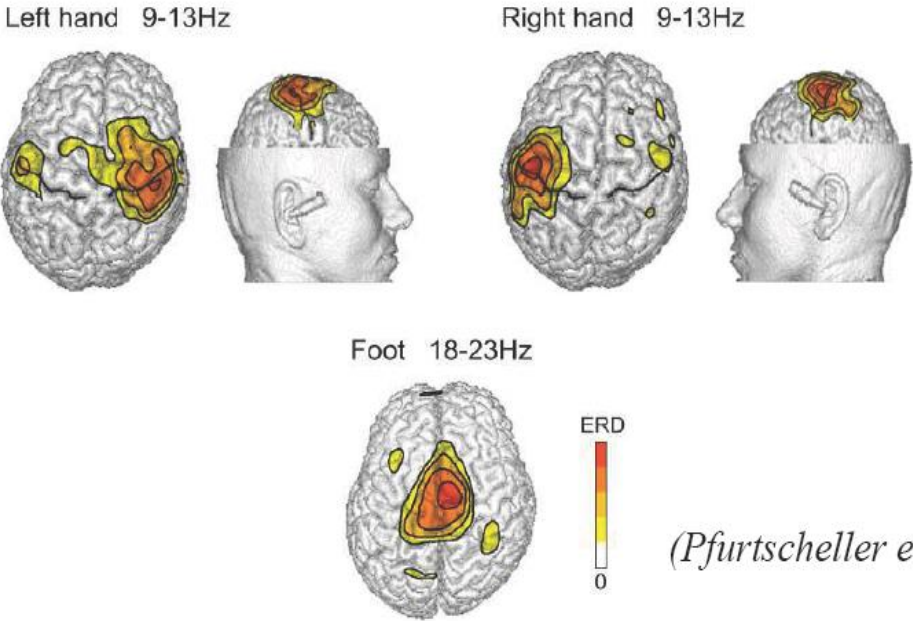
Movement and Imagined Movement

- Tongue



• Execution

• Imagery

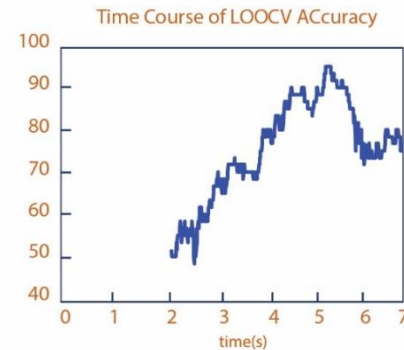
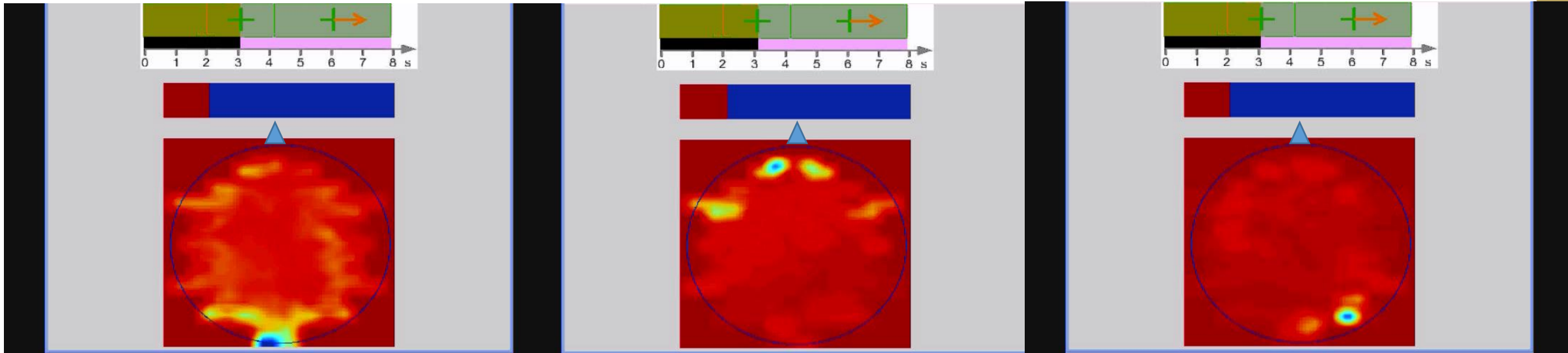
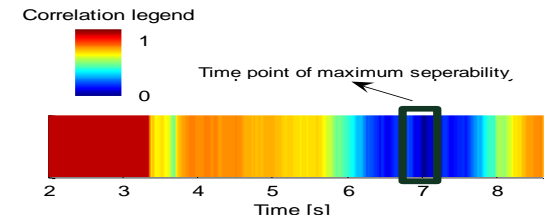
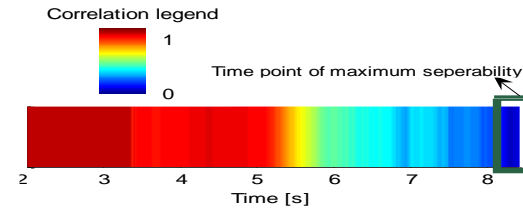
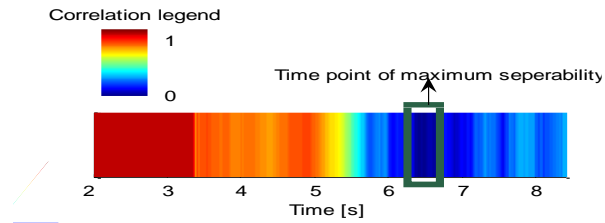


(Pfurtscheller et al, 2001)

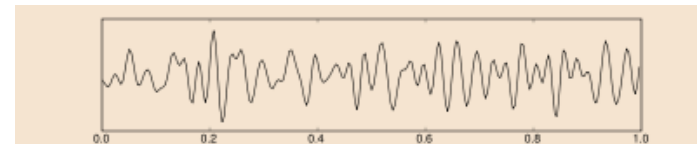
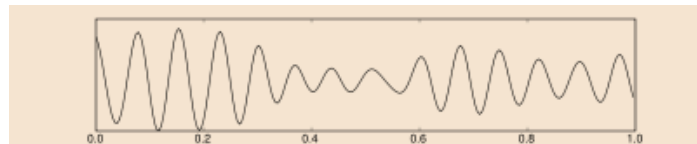
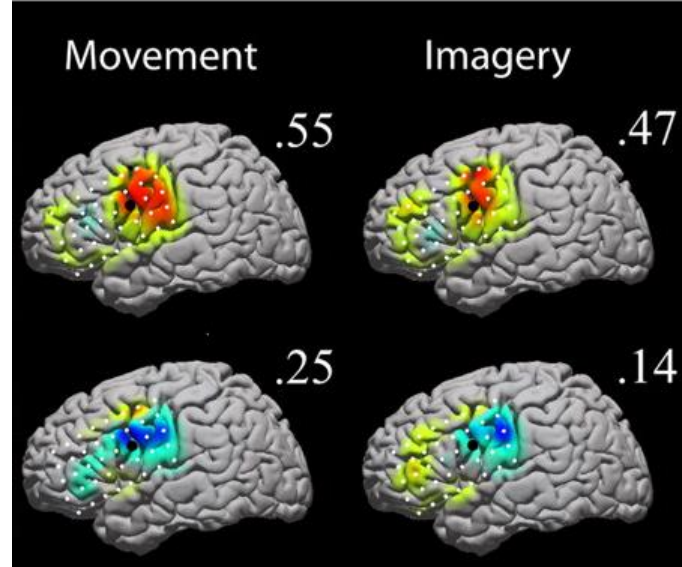
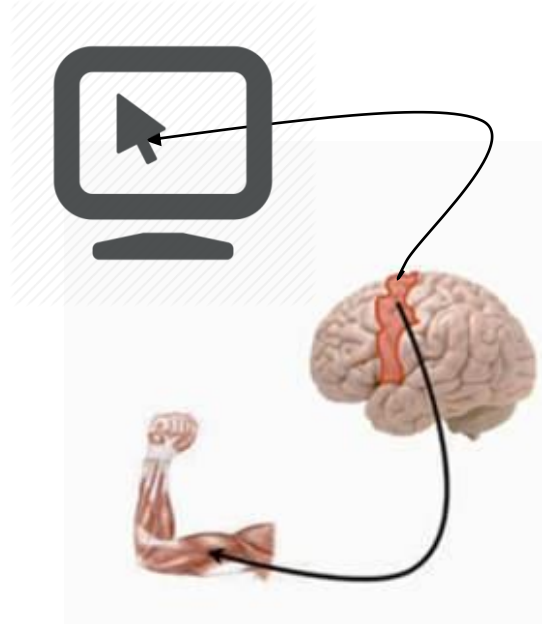
- (Ehrsson et al, 2003)

Differences in motor area response over time

- Char

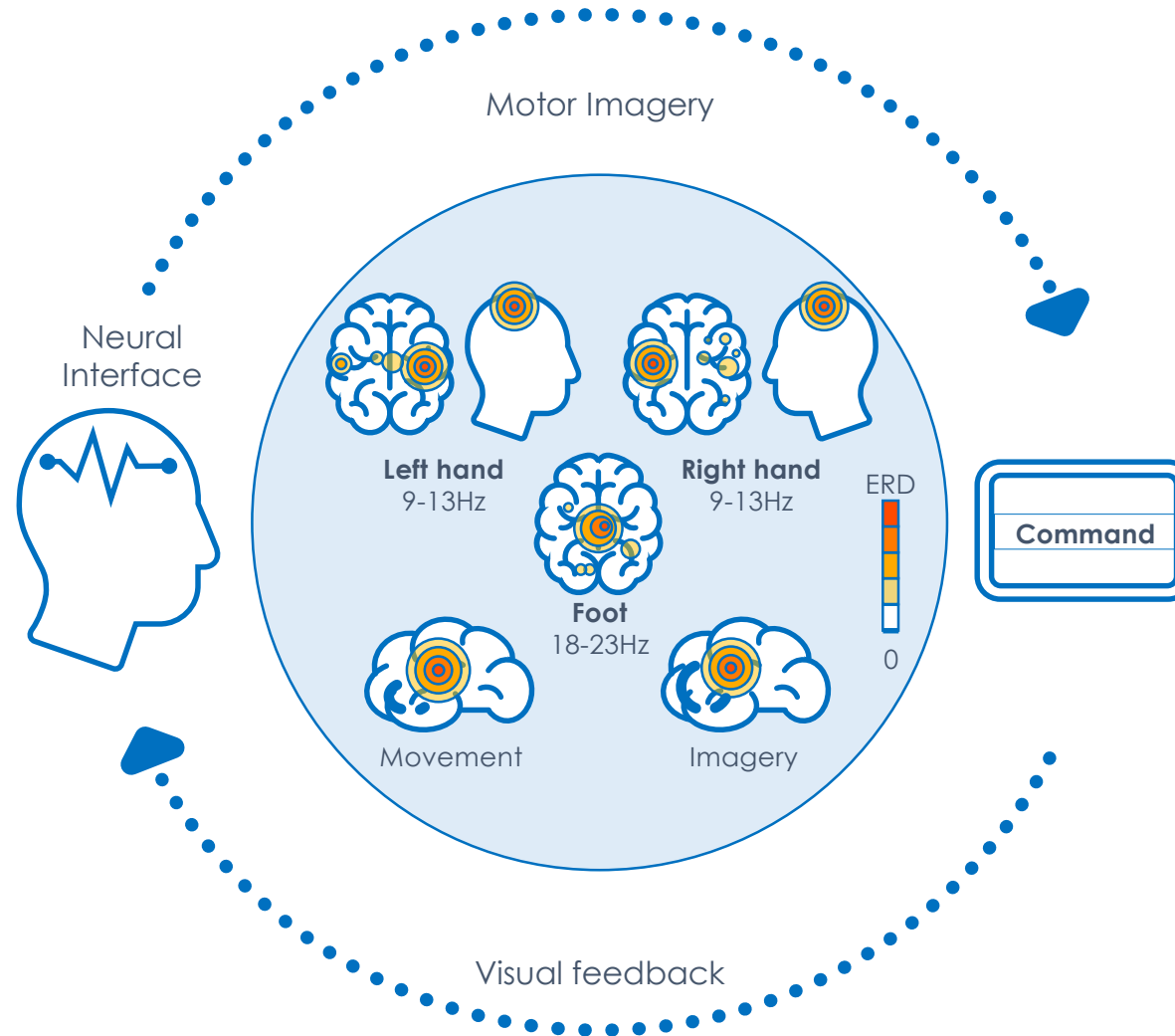


Why motor imagery for BCI?



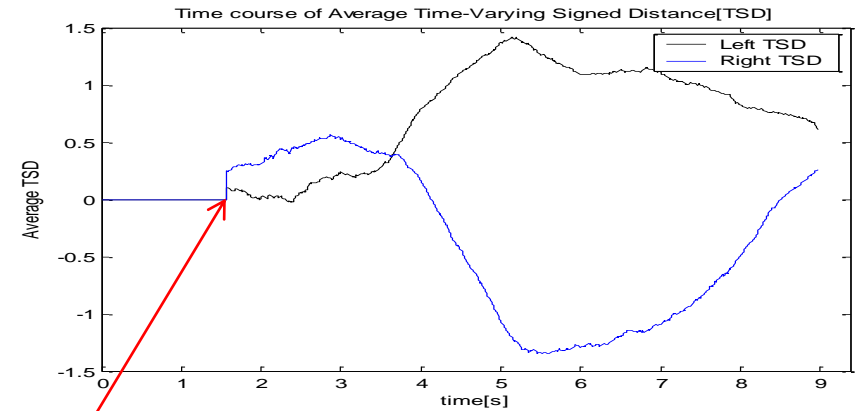
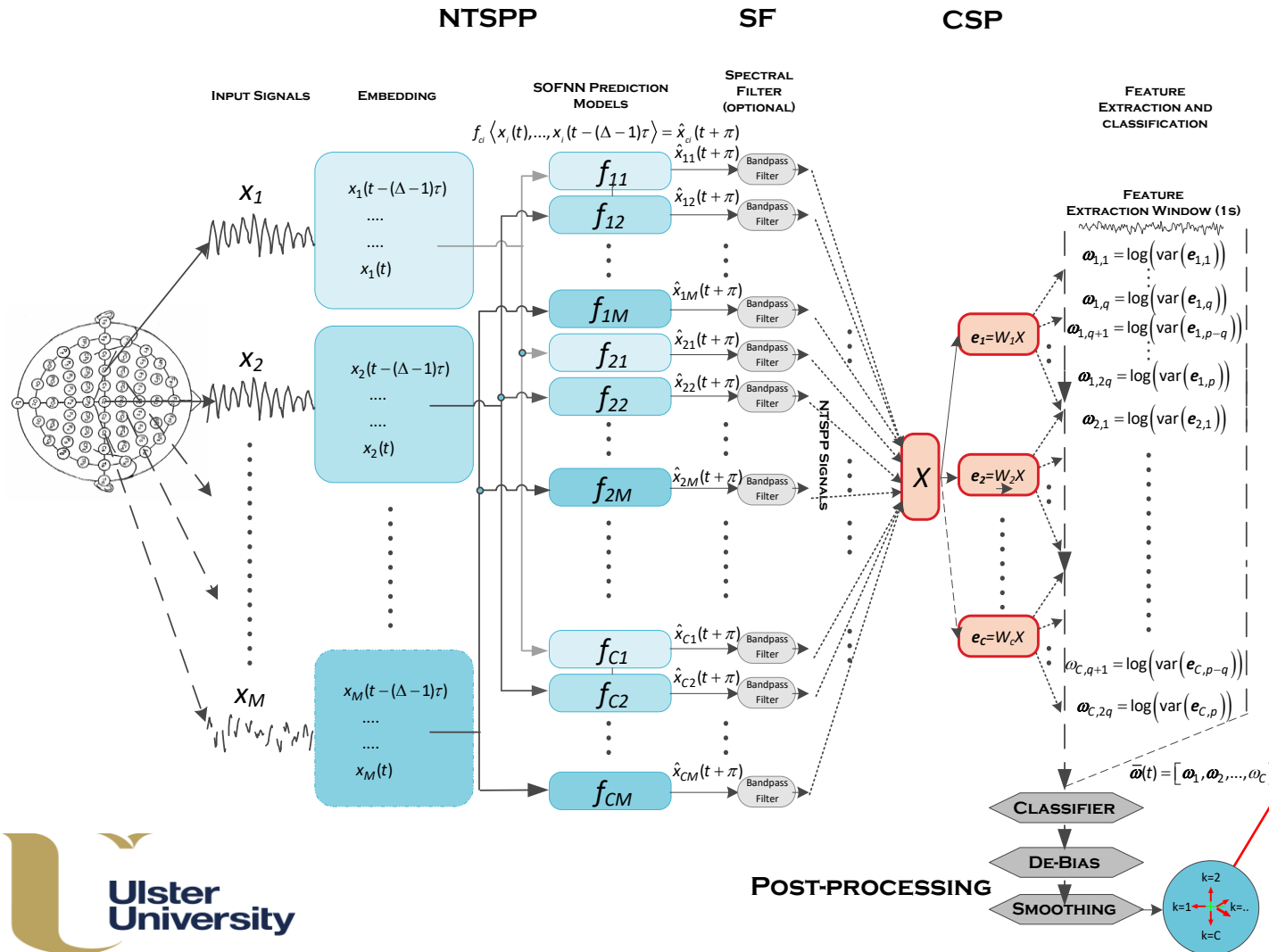
mu

beta



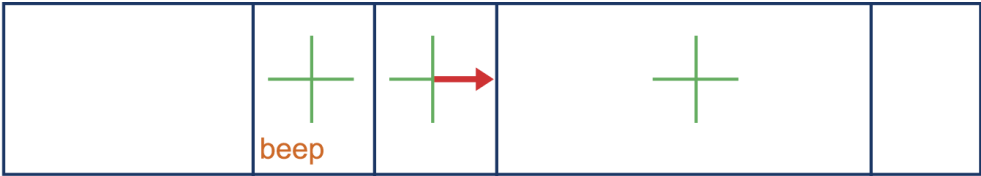
Multistage Signal Processing

Neural Time Series Prediction Pre-processing

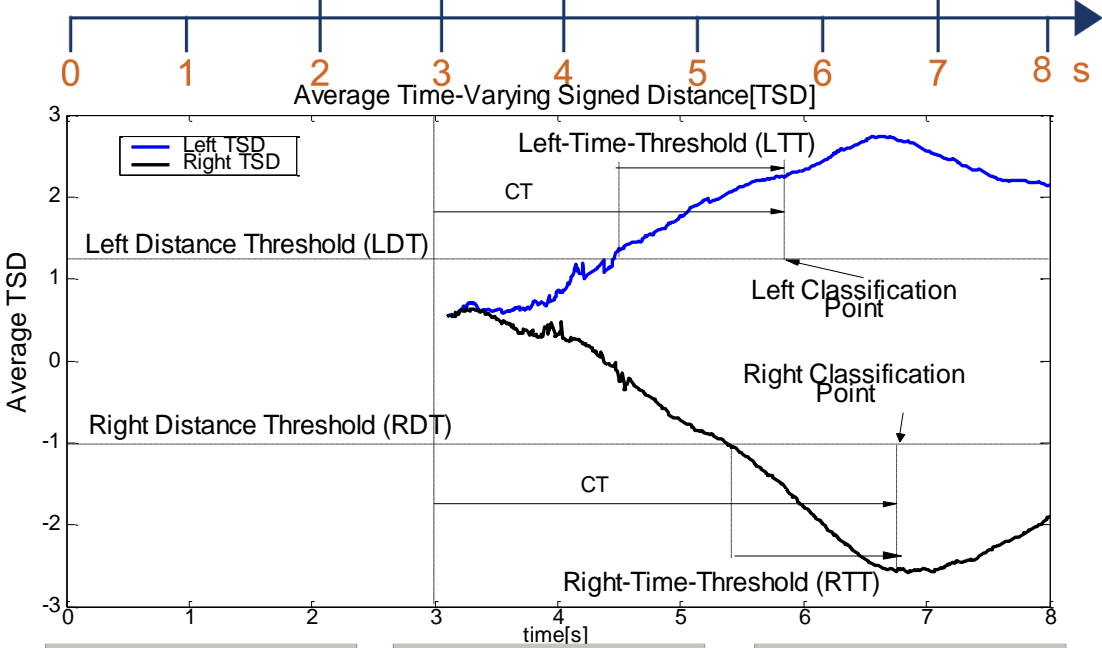


Control signal in BCI

Timing



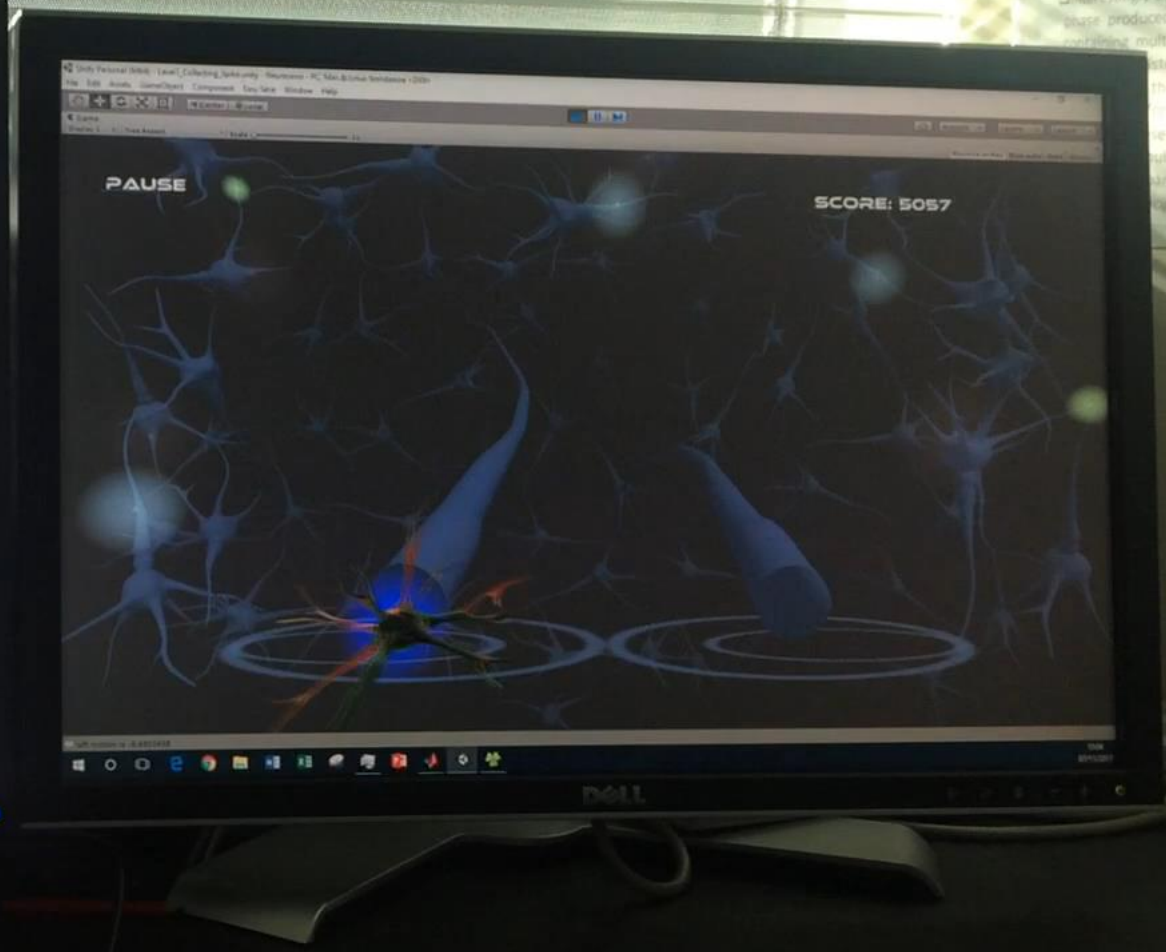
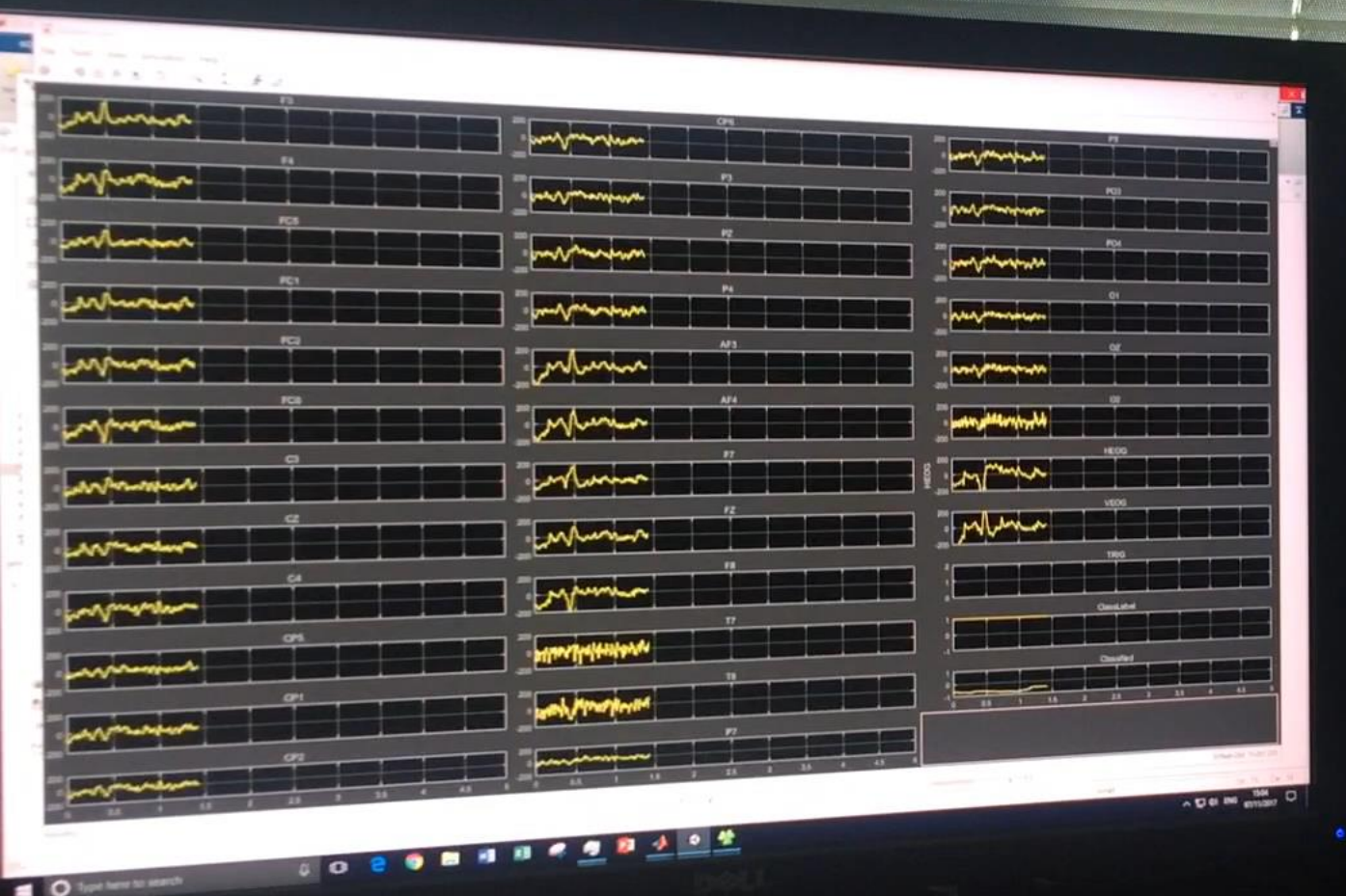
Control signal



Control









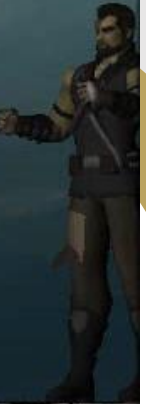
ALAN



0:01

SCORE: 0

PUNCH



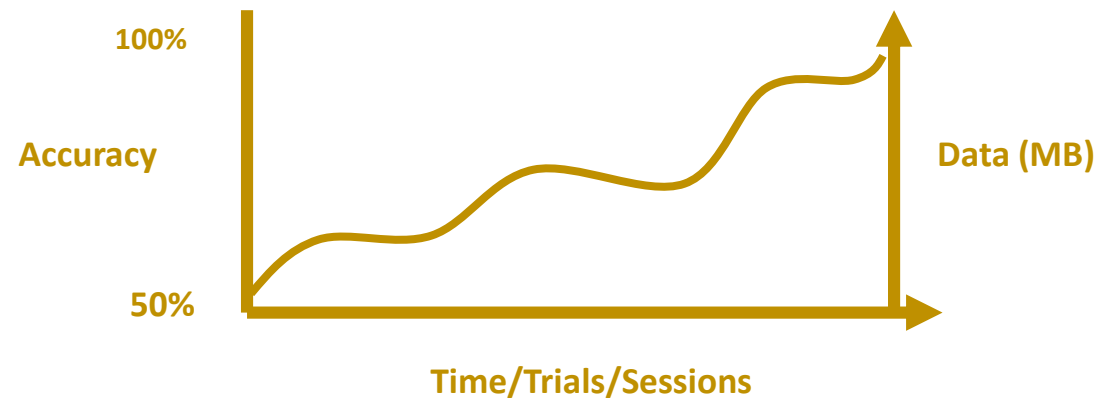
-  FORWARD
-  JUMP
-  PUNCH



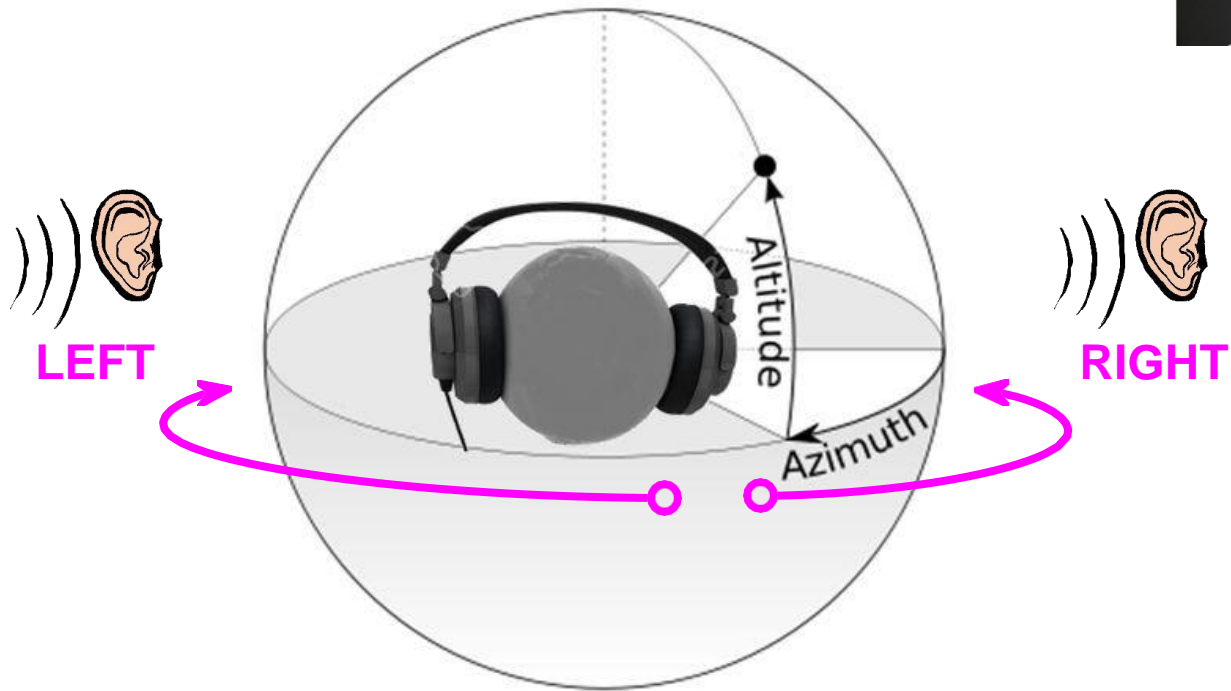
-  KICK
-  SUPERMOVE 1
-  SUPERMOVE 2

Motor learning and Real-time Feedback

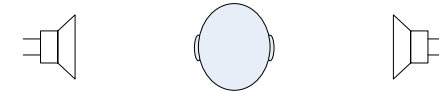
- As a person learns to use a BCI, they exhibit similar learning patterns to other motor tasks, such as learning to grasp or write
- Training with feedback is necessary to improve sensorimotor learning and BCI performance



Auditory Feedback



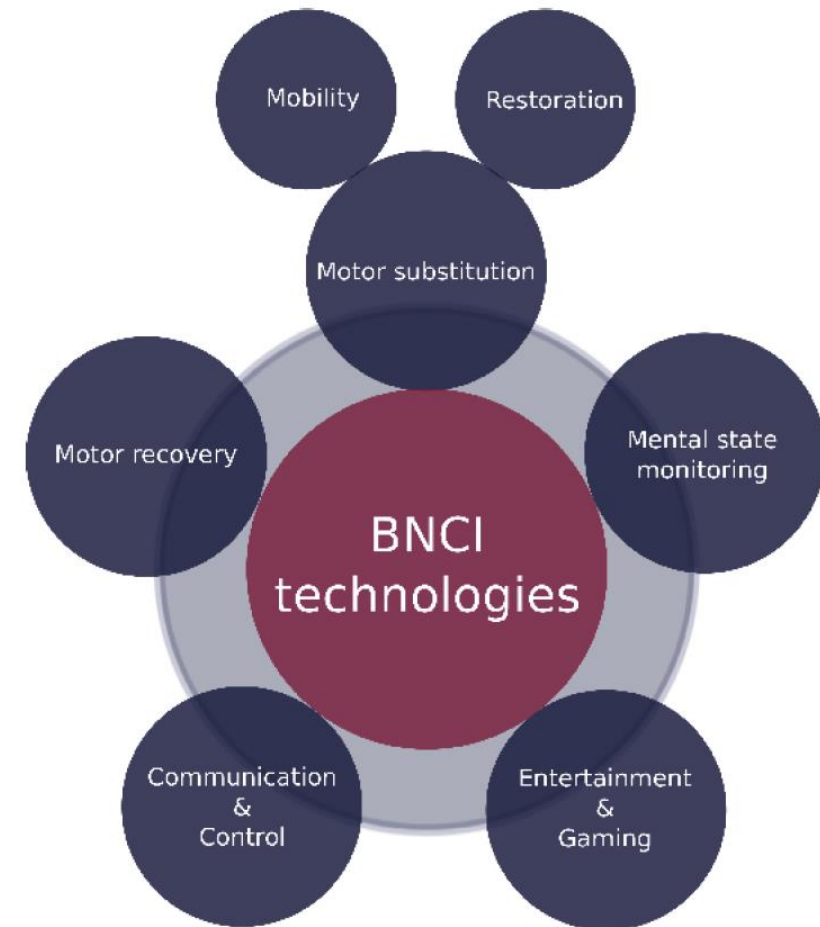
Amplitude panning and stereo Feedback



A screenshot of the 'Azimuth' software control panel. The title 'Azimuth' is displayed in white text on a yellow background. Below the title, there is a list of radio buttons for selecting a sound source: 'None/training', 'Blues', 'Classical', 'Country', 'Electronic', 'Folk', 'Hip-hop', 'Jazz', 'Reggae', 'Rock', 'Trad', 'TEST', and 'PINK NOISE'. To the right of the list, there is a 'Random All Clips' section with a circular gauge and a toggle switch labeled 'off' and 'on'. Below this, there is a volume control slider and a speaker icon. At the bottom right, there is a 'CPU %' display showing '0' and a green bar.

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)
- Amyotrophic 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)

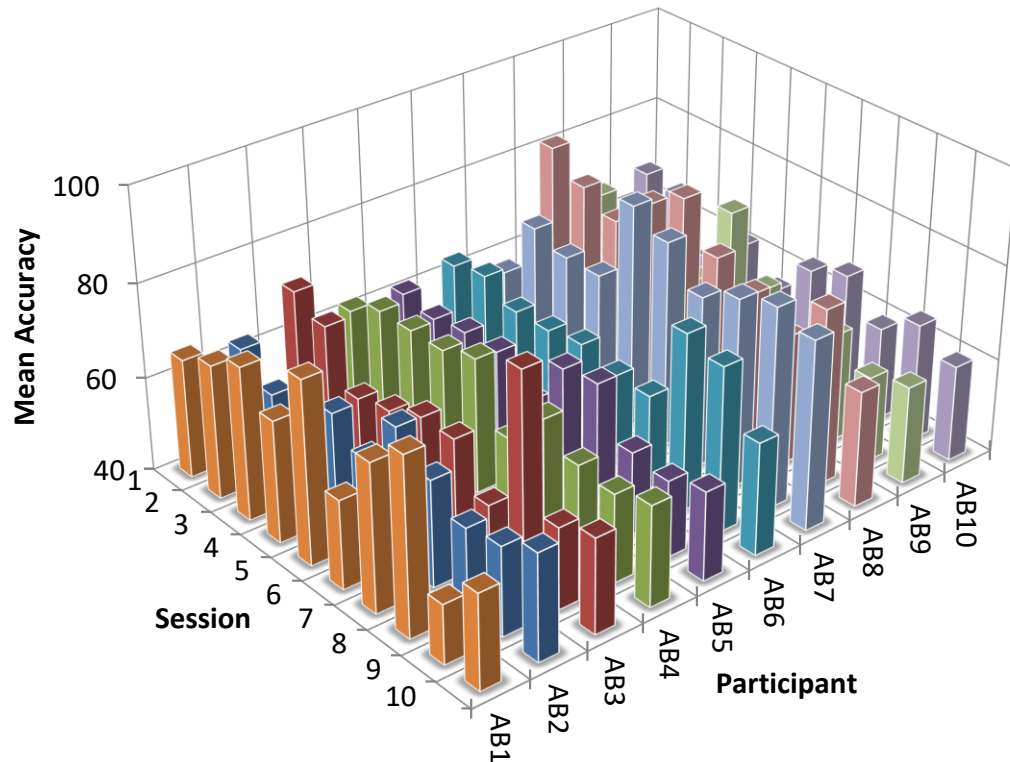


Spinal cord injury

Able Bodied vs. SCI

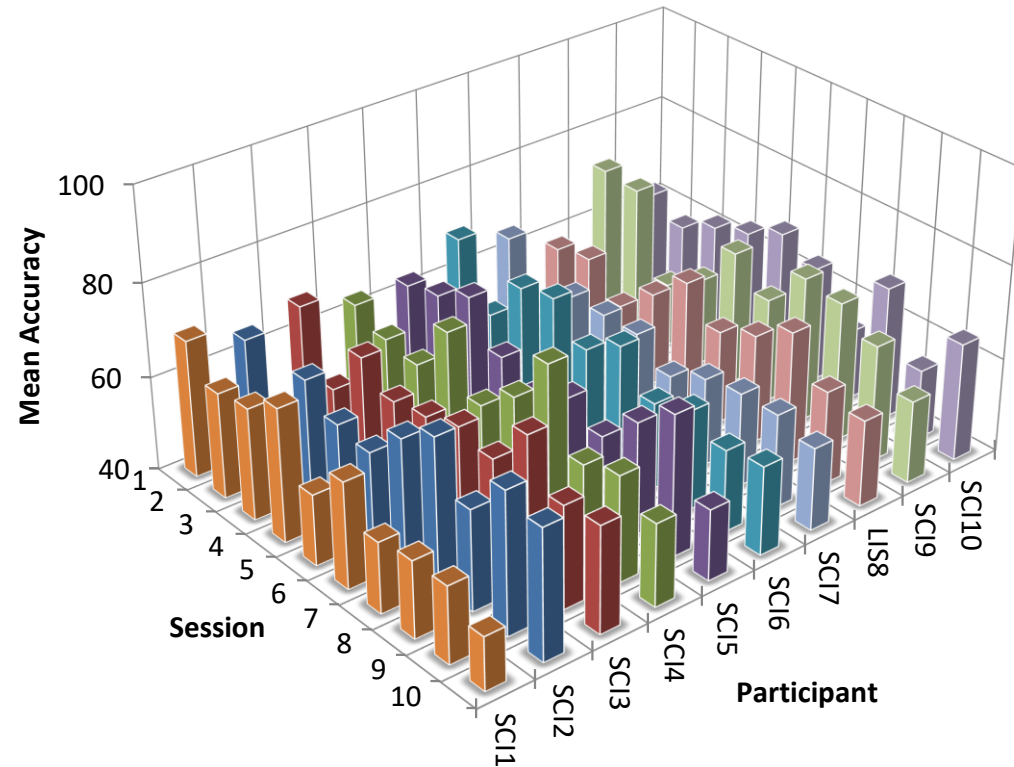
- Accuracy 60-85% across both groups
- Average Acc: AB 65%

Able-Bodied Average Peak Accuracy

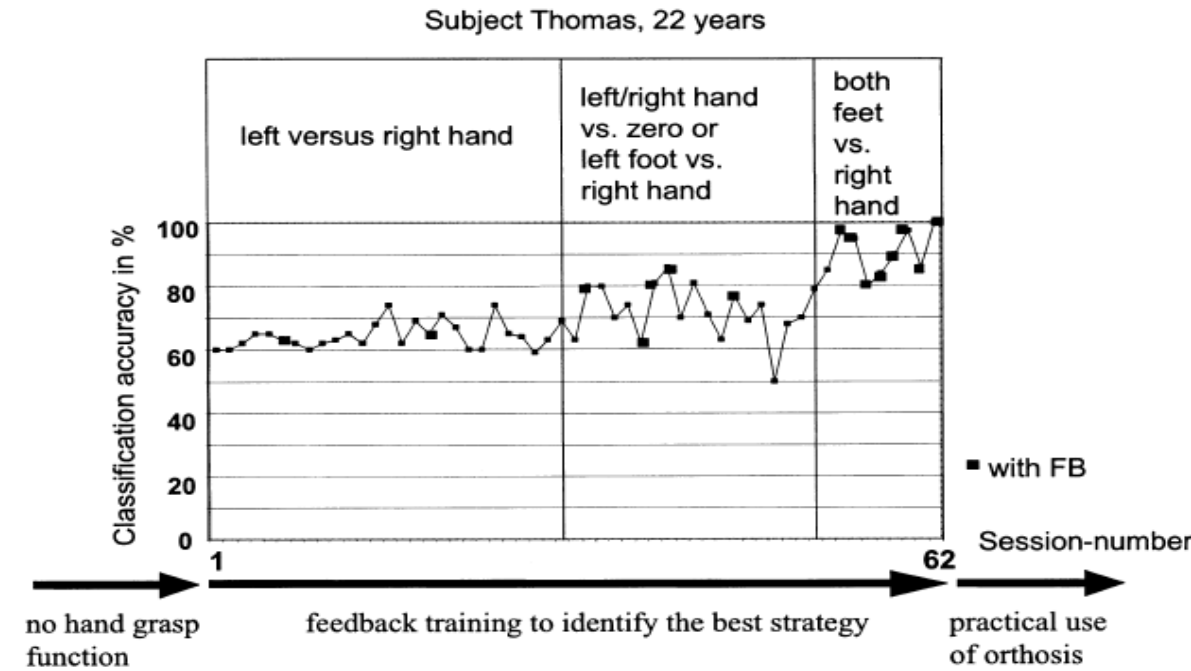
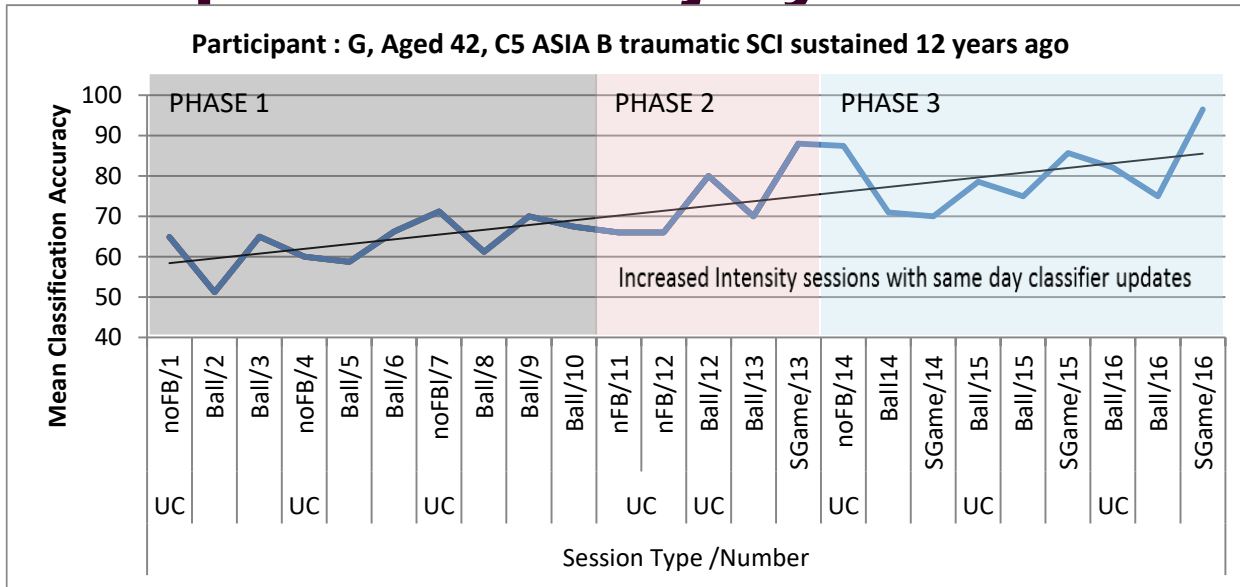


SCI 62% (difference not significant)

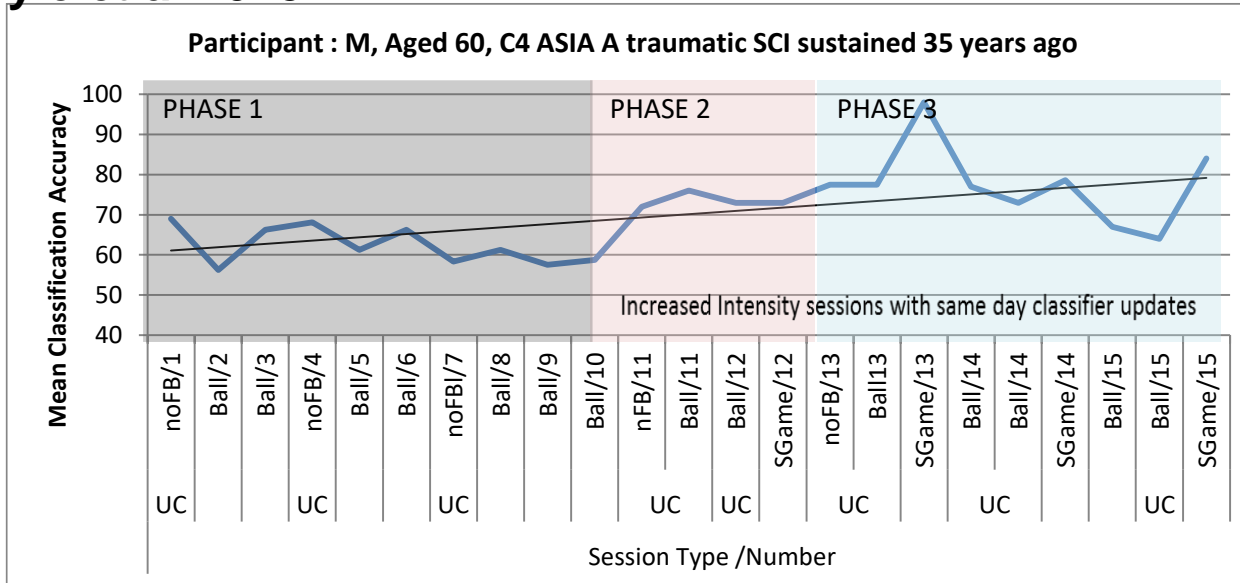
Physically Impaired Average Peak Accuracy



Spinal Cord Injury : Intensive Training



Coyle et al 2015



Pfurtscheller et al 2001

Cyathlon

Championship for Athletes with Disabilities



Brainrunners BCI race



Cyathlon 2016

Championship for Athletes with Disabilities



BCI Final results

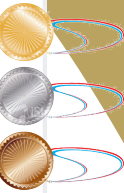
Final times

1st

2nd

3rd

Finalists	Rank	No.	Pilot name	Team name	Country	Distance	Time
A-Finalists	1	10	Numa Poujouly	Brain Tweakers	Switzerland	500	125
A-Finalists	2	6	Toine Welling	BrainGain	Netherlands	500	156
A-Finalists	3	5	David Mark Rose	Brain Stormers	United Kingdom	500	161
A-Finalists	4	1	Eric Anselmo	Brain Tweakers	Switzerland	500	190
B-Finalists	5	13	Evgenii Krasnoperov	Neurobotics	Russia	500	132
B-Finalists	6	8	Owen Collumb	Neurco CONCISE	United Kingdom	500	136
B-Finalists	7	9	Sebastian Reul	Athena-Minerva	Germany	500	146
B-Finalists	8	14	Hong Gi Kim	OpenBMI	Republic of Korea	500	149



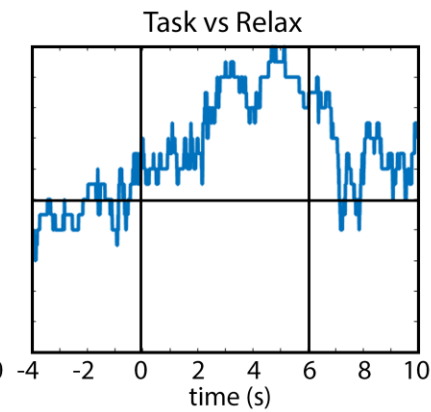
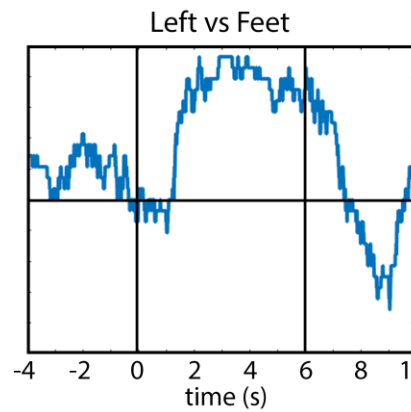
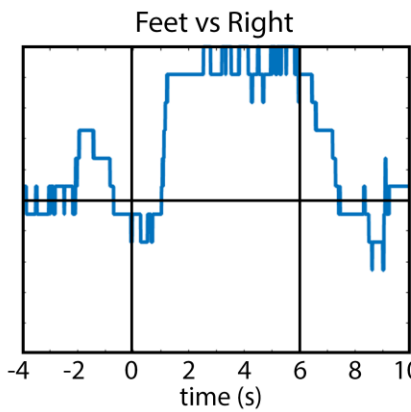
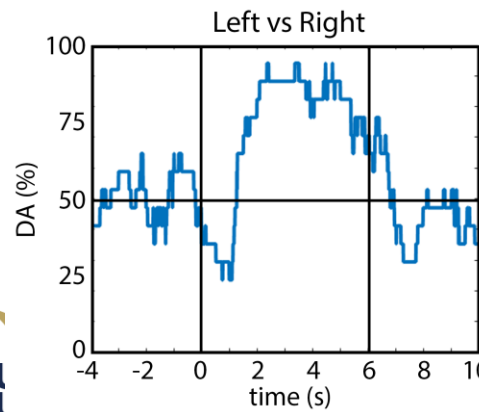
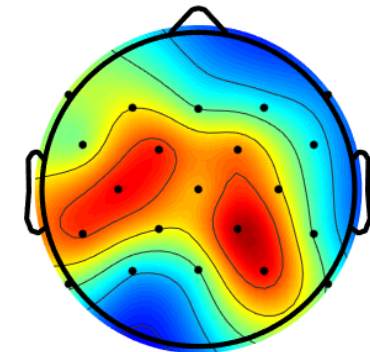
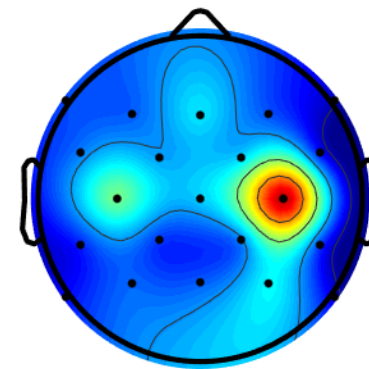
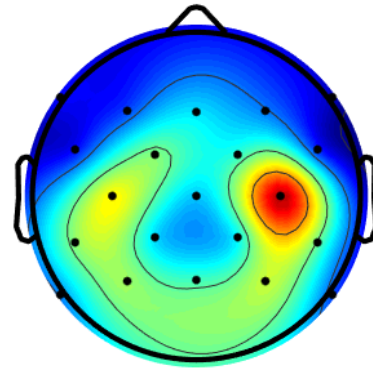
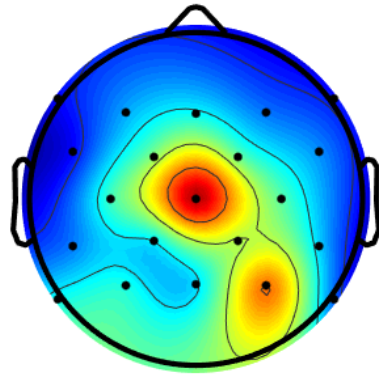
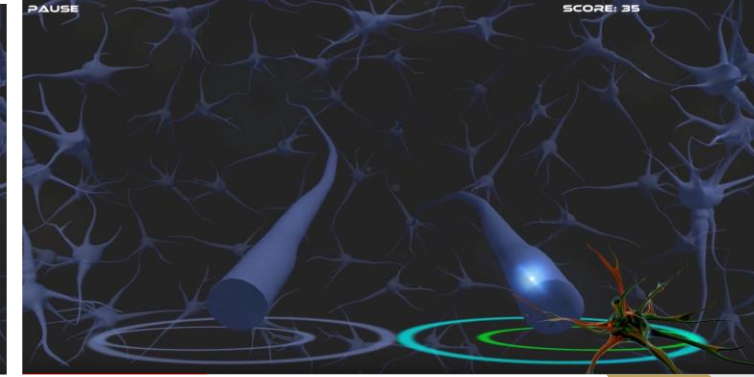
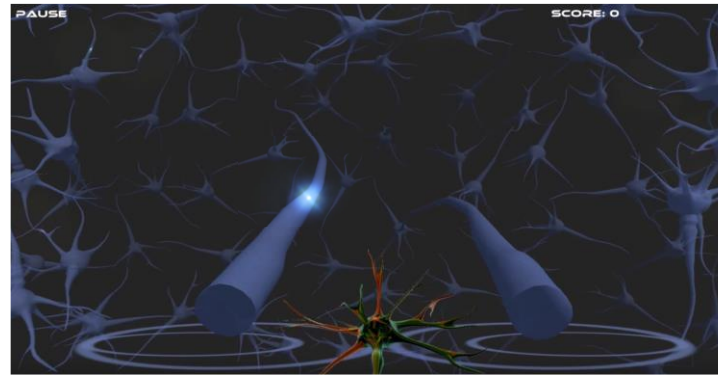
2019



CYBATHLON
SERIES **ETH** zürich

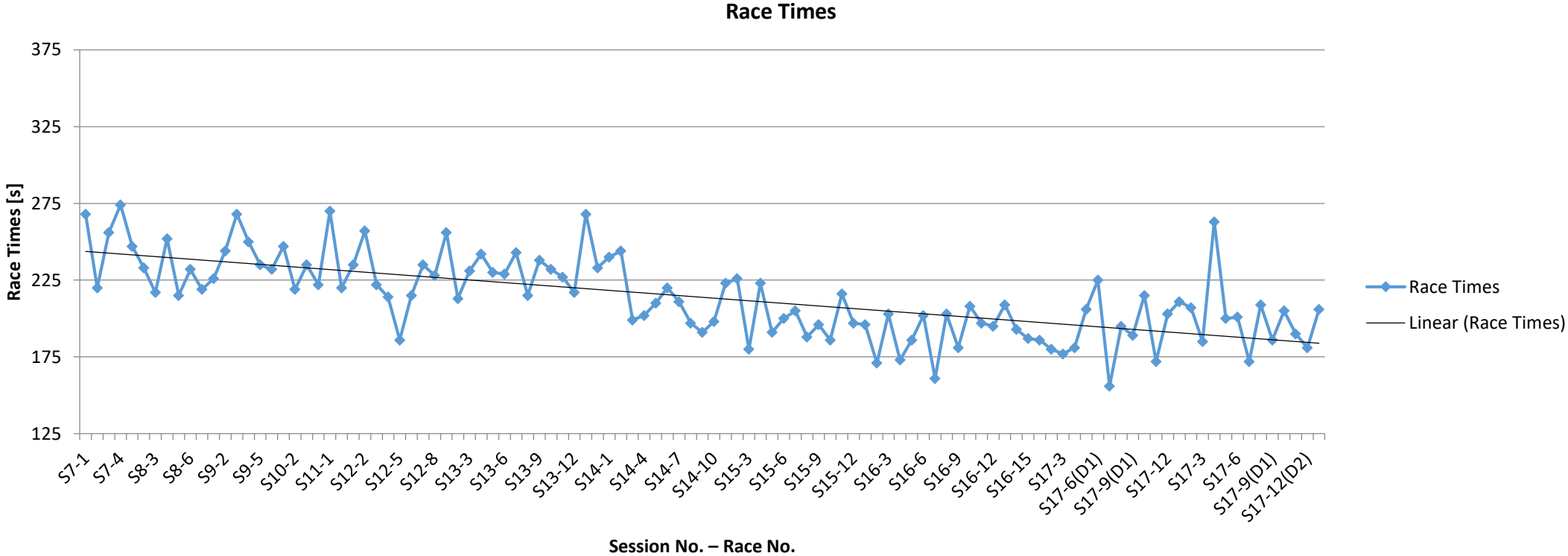


Cyathlon series 2019



Cyathlon : Race times during Training

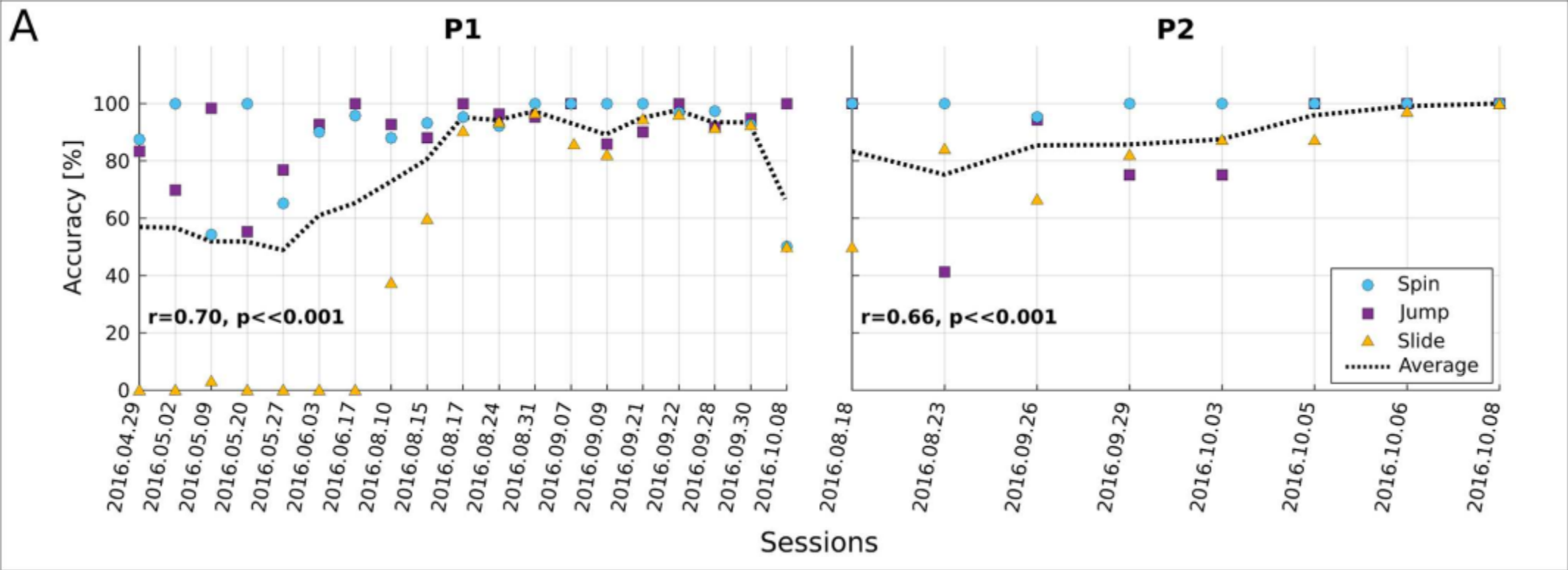
- skill performance is much more dependent on frequent, regular practice than on experience



- August >>>>September 2019



Cyathlon 2016 Winner



Key factors in BCI skill acquisition

- No habits or skills can be developed without many repetitions of the behavior or behaviors that make up that habit or skill.
- Deliberate practice
- Real-time feedback
- Coaching and explanation
- Time engaged, intensity or frequency of practice
- Timing within signal processing
- Timing of commands
- Mental state – baseline



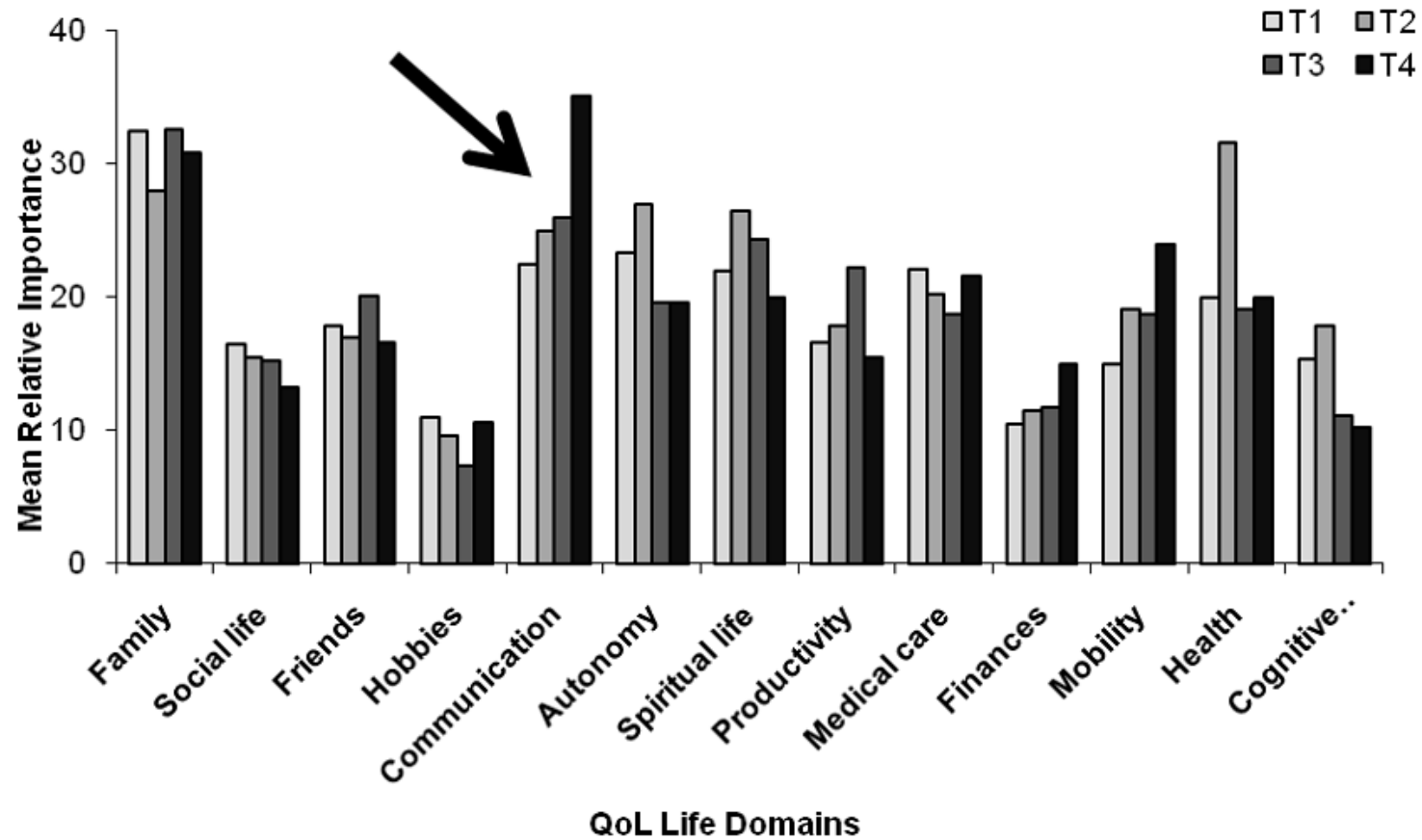
In sum, our empirical investigations and extensive reviews show that the development of expert performance will be primarily constrained by individuals' engagement in deliberate practice and the quality of the available training resources.

Ericsson Ann. N.Y. Acad. Sci. 1172: 199–217 (2009).

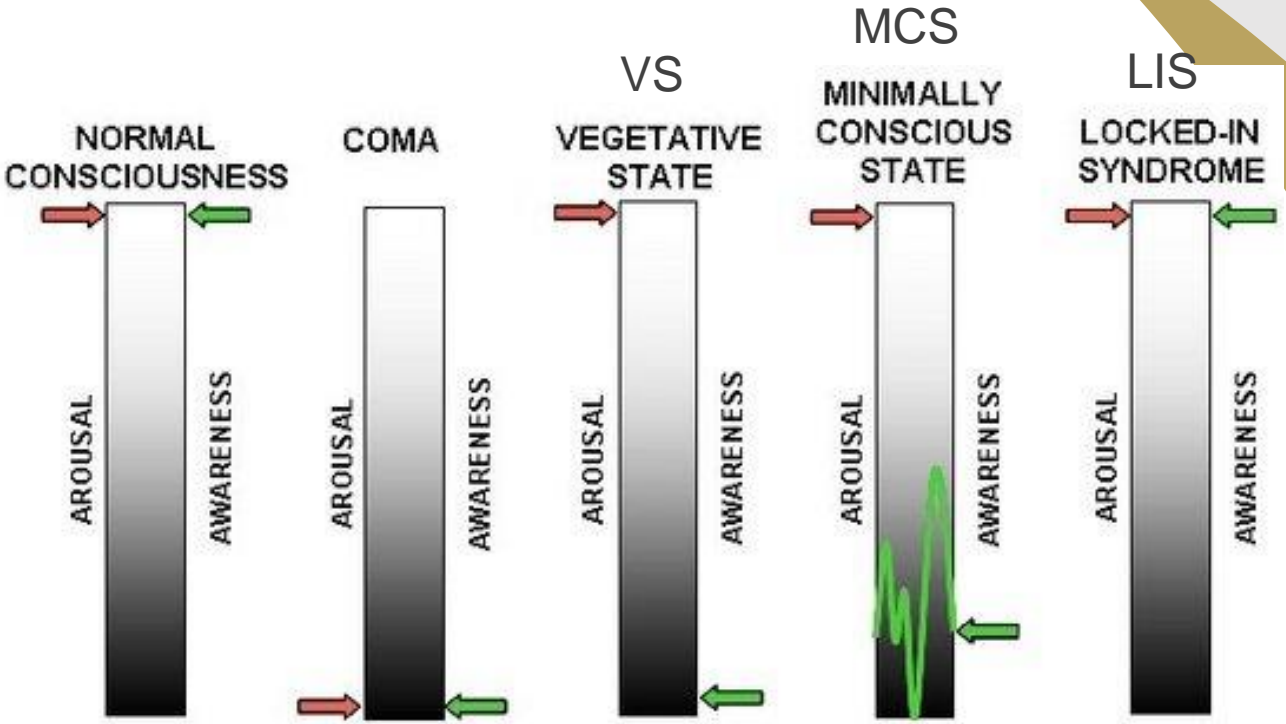
Disorders of consciousness

Quality of Life

Communication – basic need



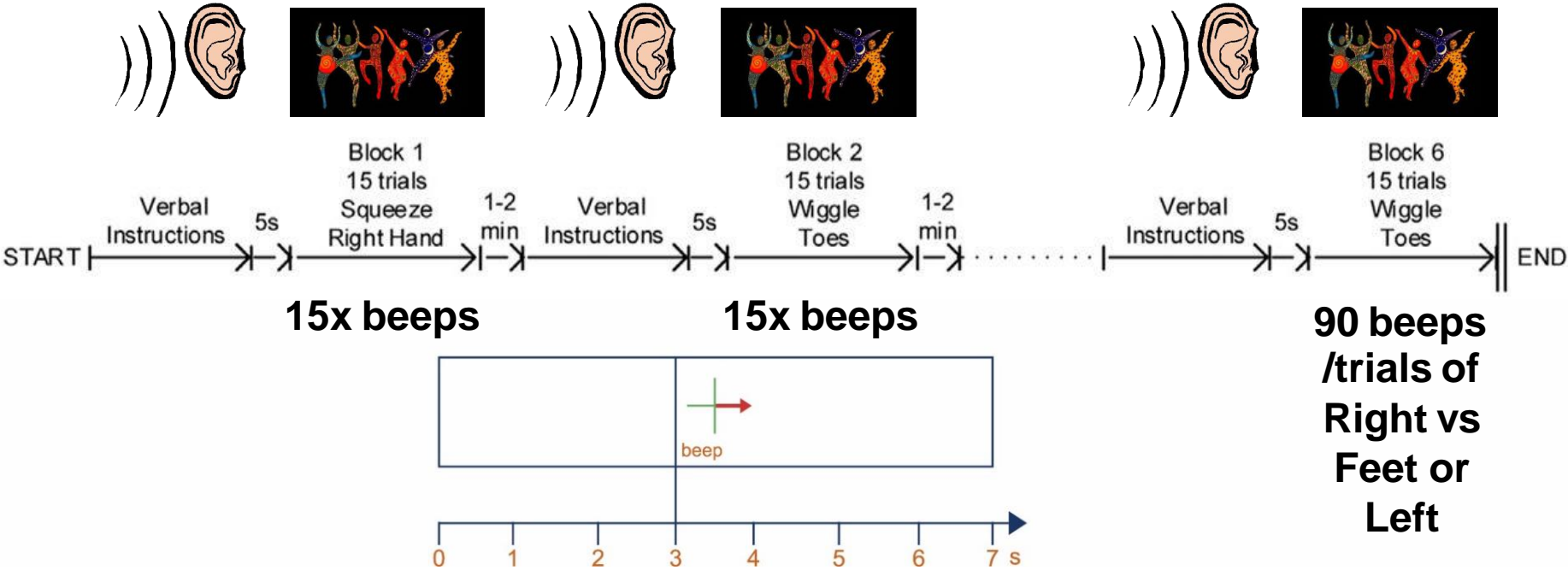
Disorders of Consciousness



UWS
UNRESPONSIVE
WAKEFULNESS
SYNDROME

Initial Assessment

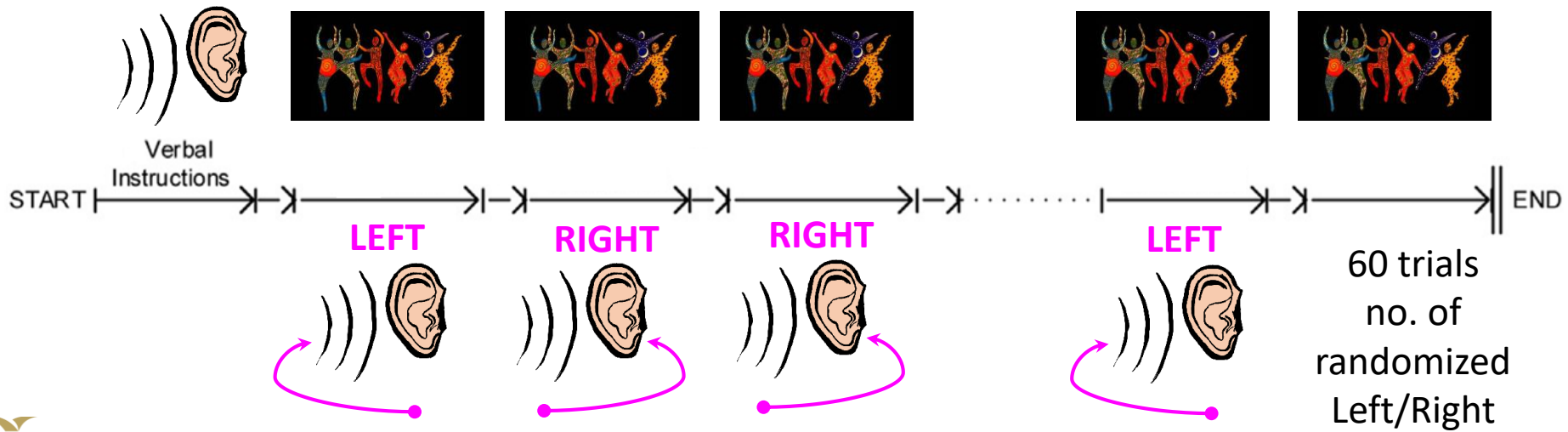
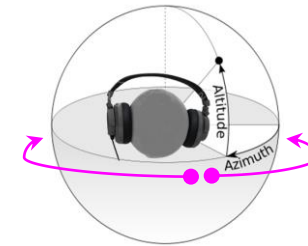
- “Every time you hear a beep, try to imagine that you are squeezing your right-hand.”
- “Every time you hear a beep, try to imagine that you are wiggling your toes.”
-



Audio Feedback

Study Protocol

- **Auditory feedback training** (Coyle et al, AMPR, 2015)
 - pink noise
 - music samples



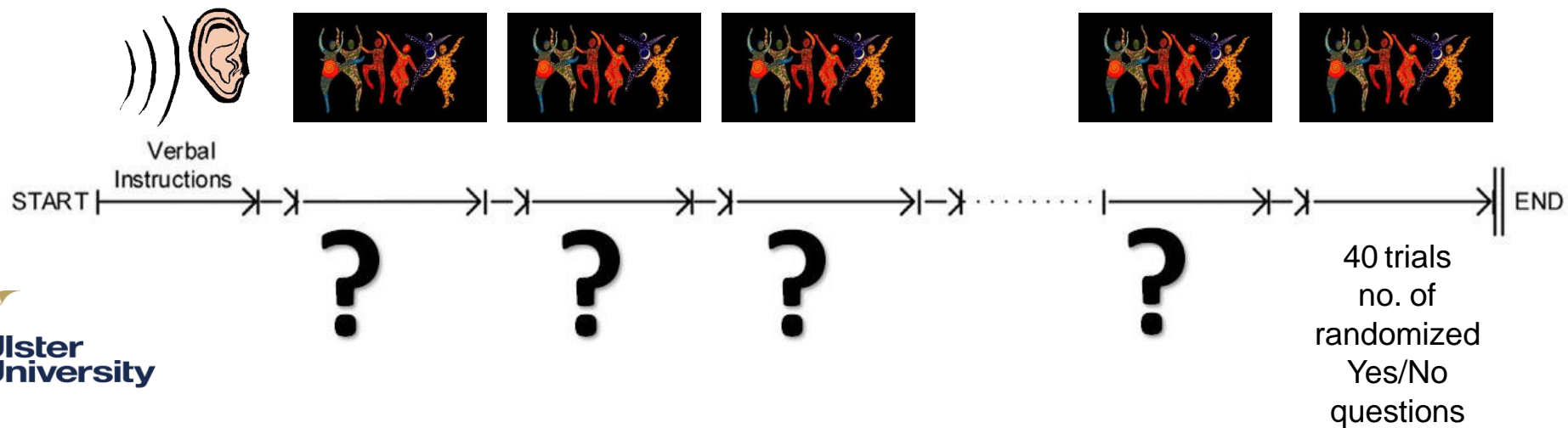
Q&A Assessment

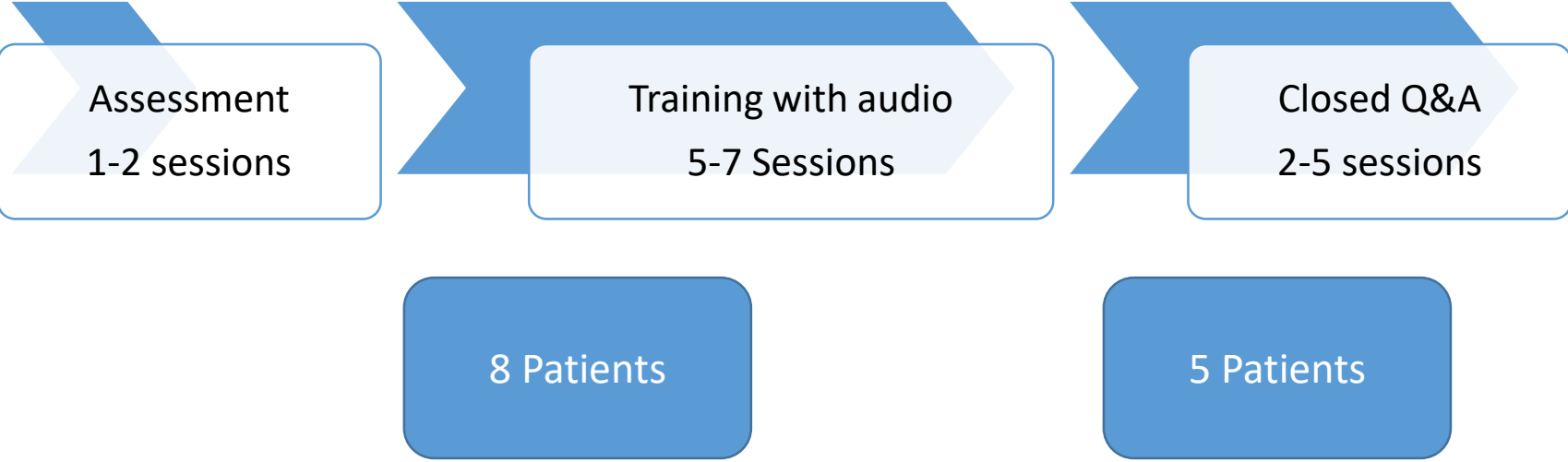
Yes and No

Communicating yes and no by thinking yes and no

Chaudhary et al 2017

- “yes” questions had semantically similar “no” questions
- Biographical and situational questions with known answers
- “Are you 33 years old?” vs “Are you 47 years old?”.
- Record family member and played back to participants.

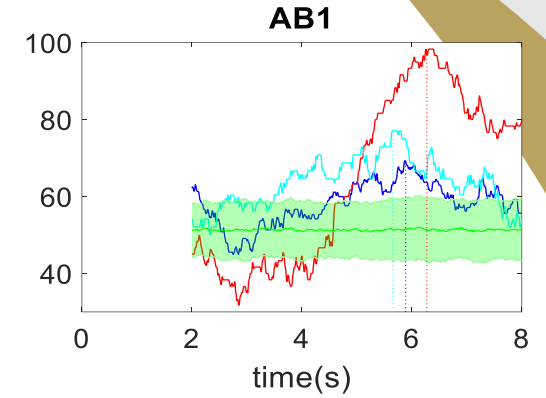
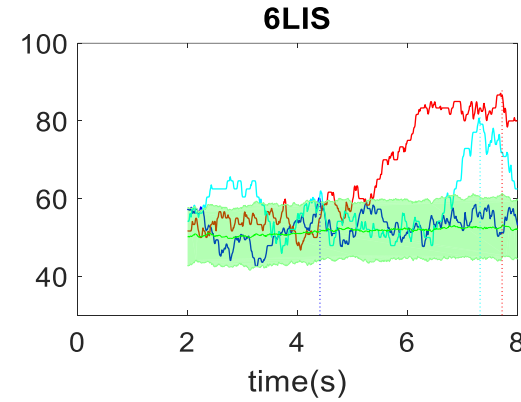
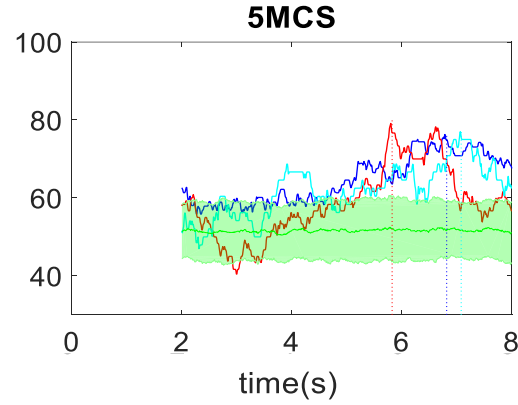
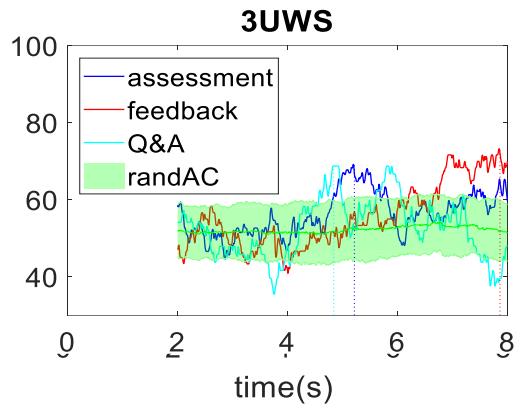
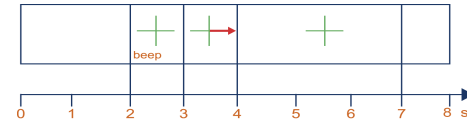




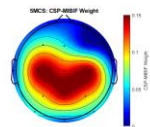
Patient details and results summary

ID	Sex	Age	Type of injury	Time since onset (months)	Av CRS-R	Av WHIM	BCI Top run Performance Accuracy (%)					
							Baseline 2s (A)	Assess	Baseline 2s (F)	Feedback	Baseline 2s (Q)	Q&A
1 UWS	M	34	Non-traumatic	192	5	4	55	63	62	72	-	-
2 UWS	M	34	Non-traumatic	103	3	3	61	61	57	76	-	-
3 UWS	M	29	Traumatic	74	5	4	58	69	47	73	54	69
4 MCS	M	49	Non-traumatic	23	11	16	53	66	52	73	-	-
5 MCS	F	56	Traumatic	35	18	17	67	80	57	80	52	77
6 LIS	F	34	Non-traumatic	11	-	-	52	60	50	88	52	81
7 LIS	M	28	Traumatic	25	-	-	71	73	58	75	58	67
8 LIS	F	27	Non-traumatic	36	-	-	70	78	40	68	56	88
1AB	M	20	-	-	-	-	61	69	45	98	42	79
2AB	M	23	-	-	-	-	65	78	52	88	50	79
Average of BCI Top run Performance Accuracy (%):							61	68	52	79	52	77

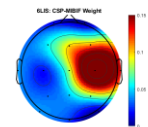
Diagnosis vs accuracy



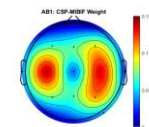
• Feet vs Left



Feet vs Right

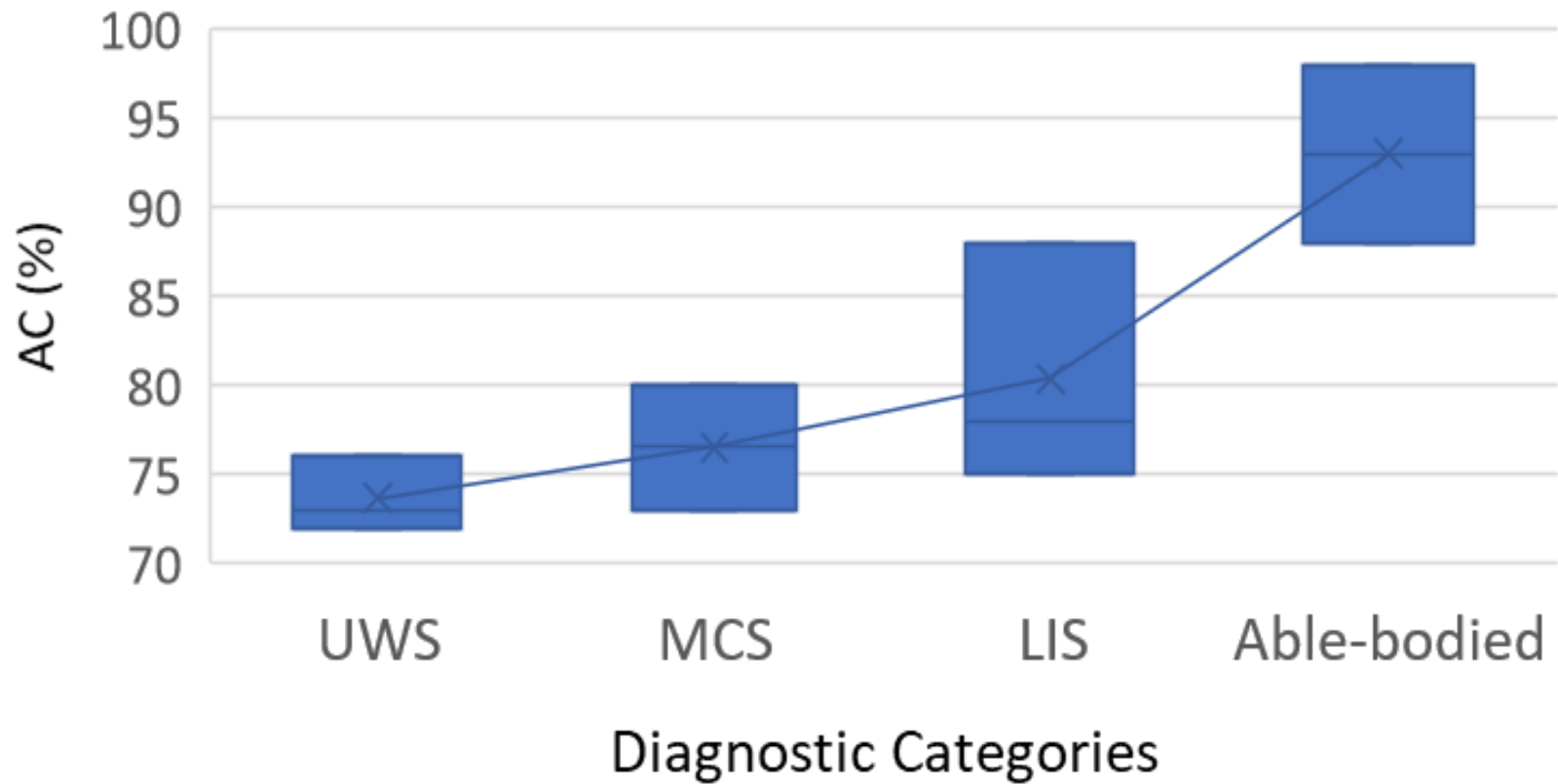


Left vs Right



Left vs Right





Large Neurotechnology Trial

Prolonged disorders of consciousness



Partners

- **Rep of Ireland**
 - National Rehabilitation Hospital of Ireland
 - St Conal's Campus Rehabilitation Unit, Letterkenny, Ireland
- **UK – NHS/HSC**
 - 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
 - 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 NHSTrust
 - Lothian NHSTrust
- **UK – Private**
 - Woodland Neuro rehab Center, York (Christchurch Group)
 - Glenside Care, Salisbury
 - Royal Hospital for Neuro-disability, Putney London

Research questions

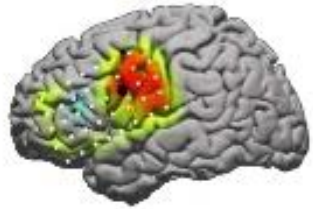
- Can the neural correlates of motor imagery act as a sensitive biomarker for global consciousness state?
- Can neurotraining enable effective use of motor imagery BCI as a communication channel?
- Is there therapeutic benefits from engaging in neurotraining?

Stroke rehabilitation - Upper Limb

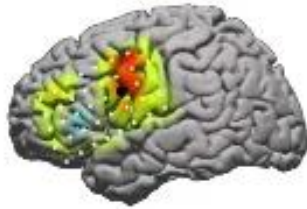
Stroke Rehabilitation

with BCI based Neurofeedback

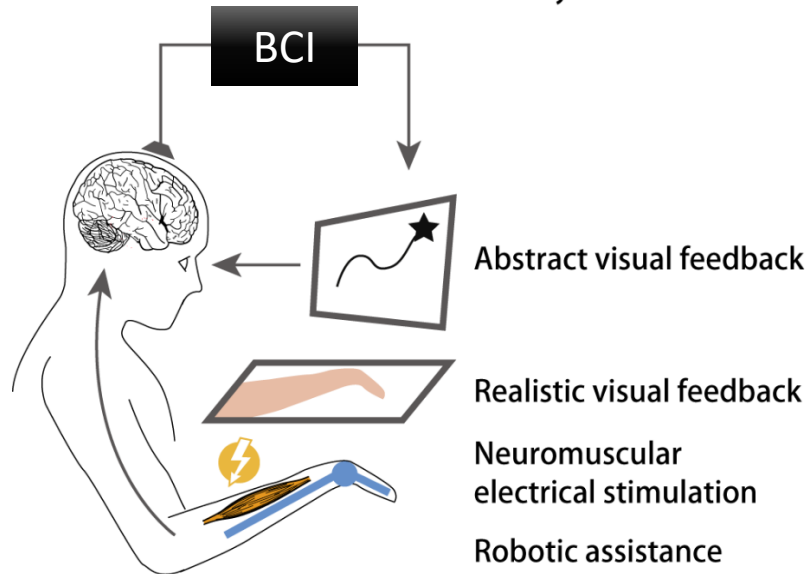
Movement



Imagery



Estimation of motor cortex excitability



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

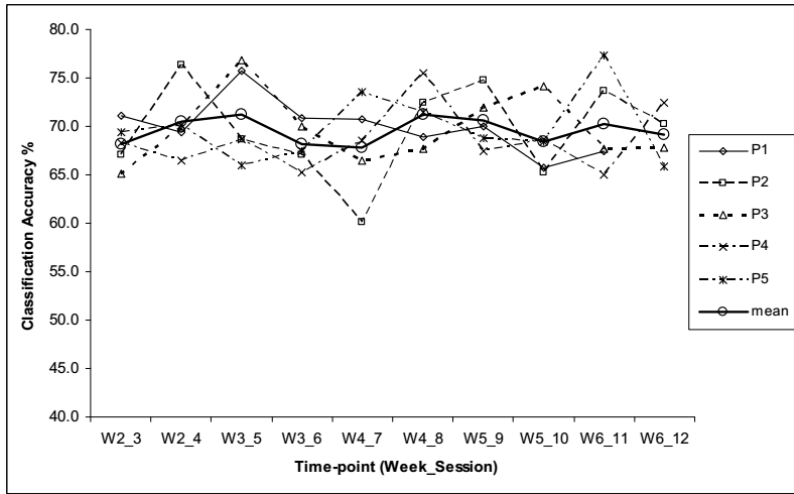
Average FMA Improvement: 4.93

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

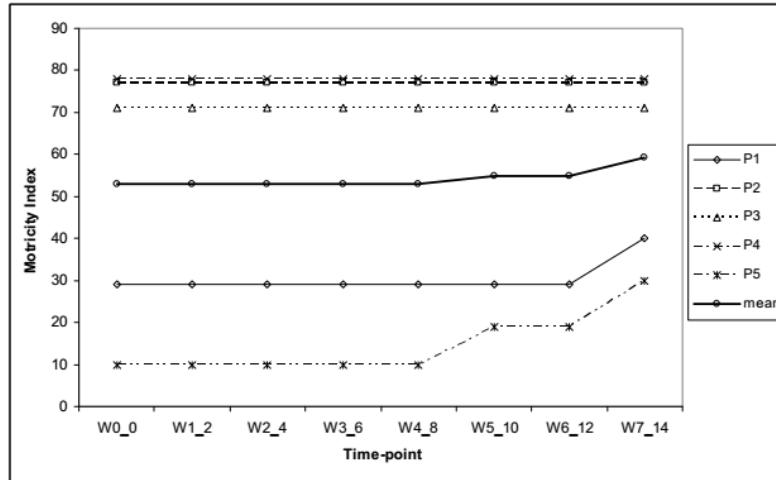
Veerbeek, et al, Neurorehabilitation and Neural Repair, September 5, 2016

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

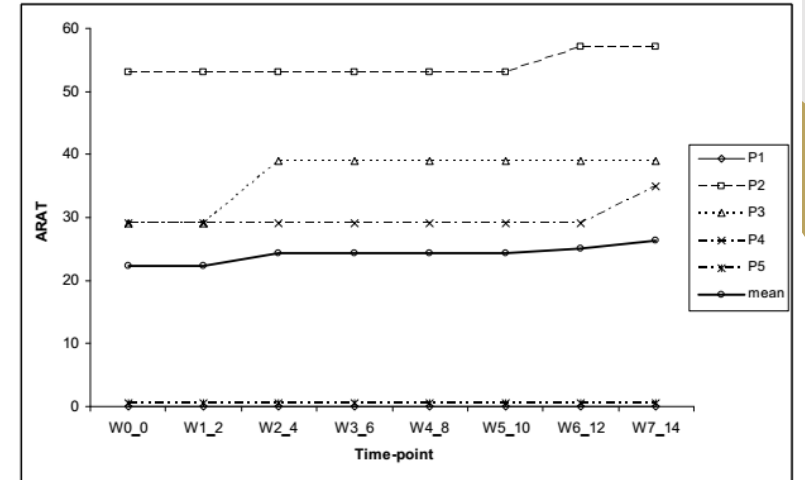
Practice = functional gains



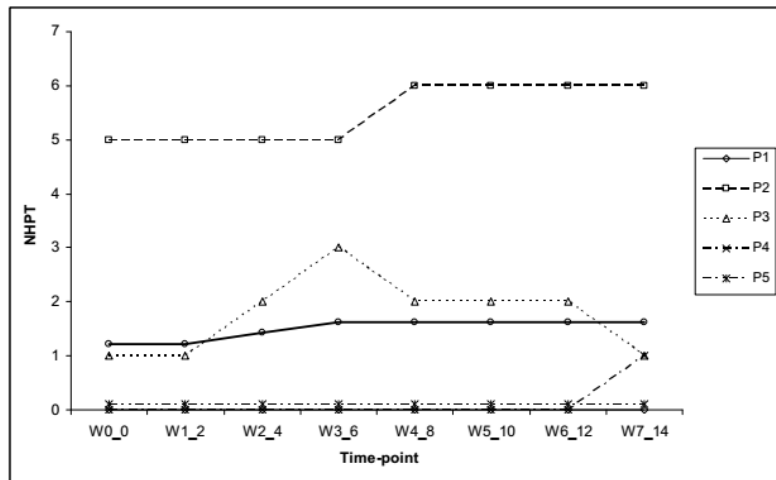
(a)



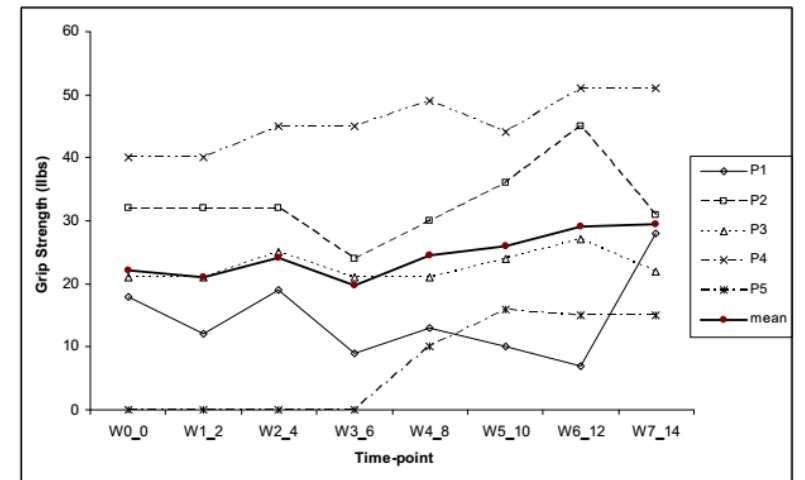
(b)



(c)

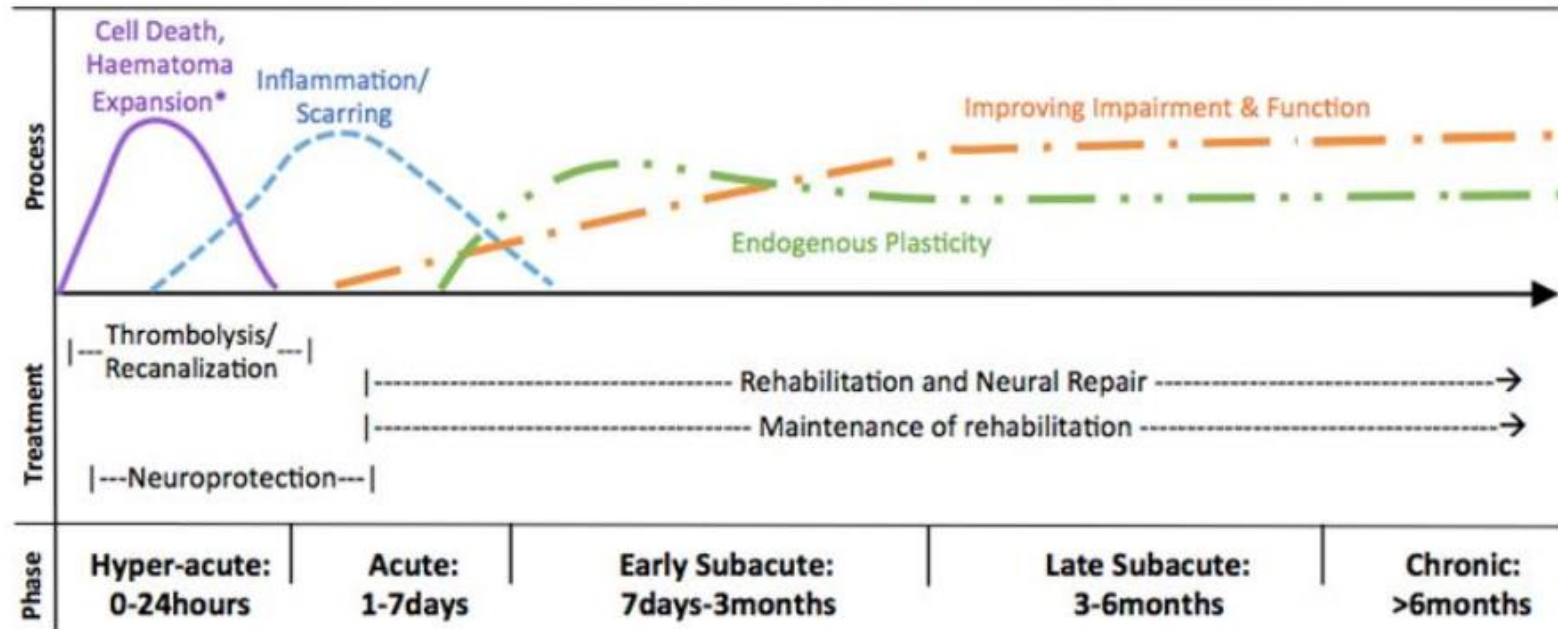


(d)



- Prasad, Coyle et al, 2010

Goals of Neural Repair Trials



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?



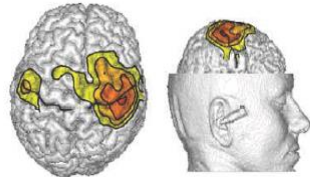
Decoding 3D movement and imagined movement

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

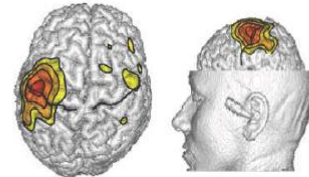
Classical sensorimotor rhythm (SMR) BCIs



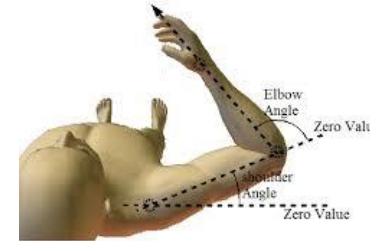
Left hand 9-13Hz



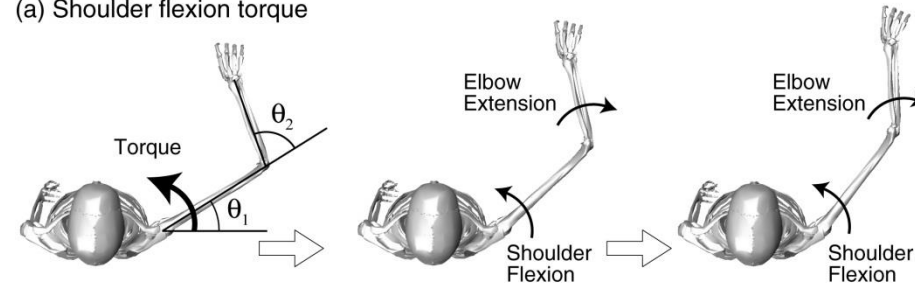
Right hand 9-13Hz



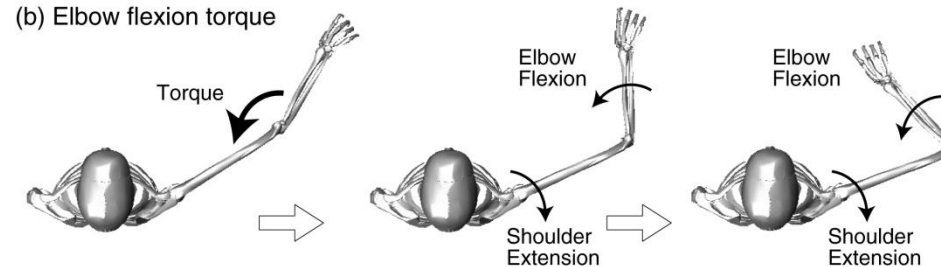
3d hand motion trajectory prediction (MTP)/reconstruction/decoding



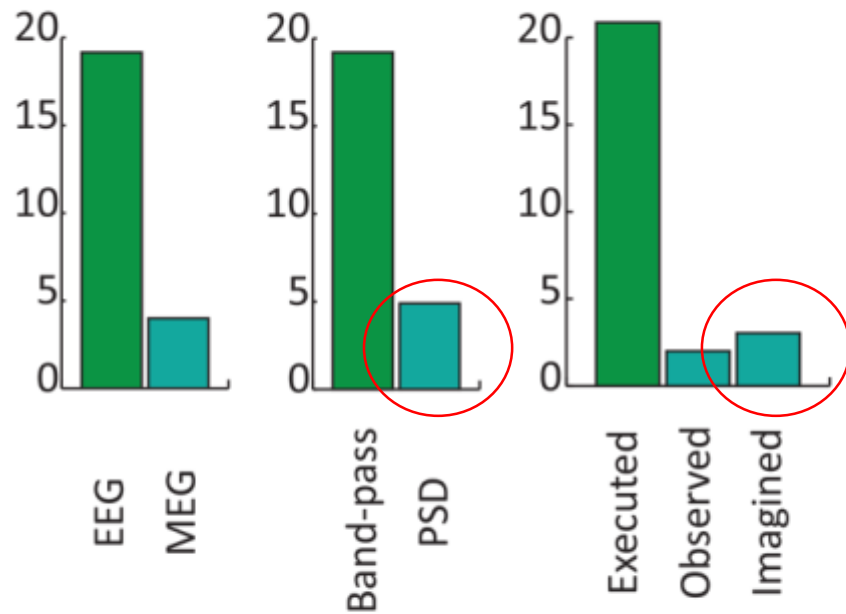
(a) Shoulder flexion torque



(b) Elbow flexion torque



(A) Number of MTP and MC journal papers for decoding limb movement direction



References:

(1) : Lv et al. 2010

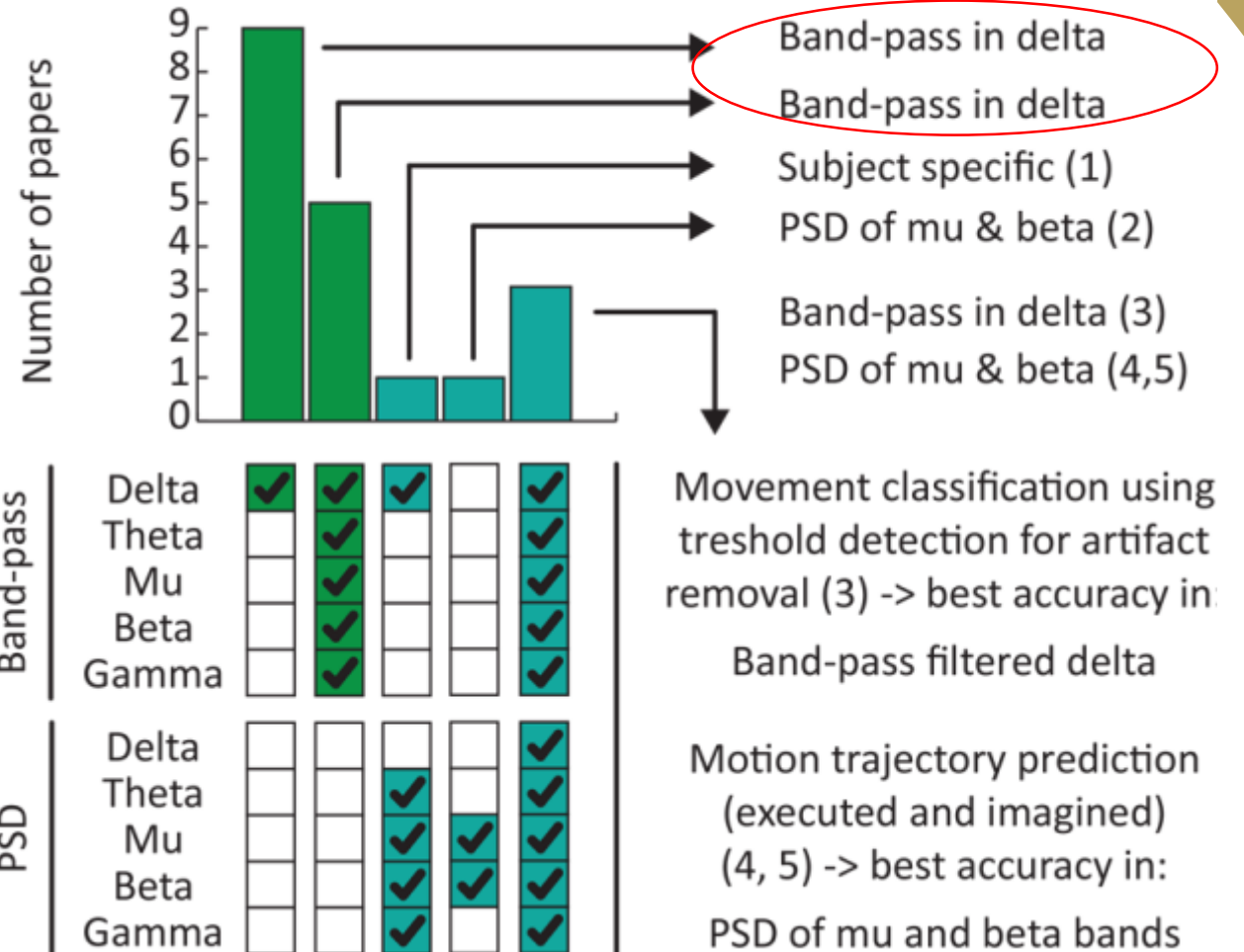
(2) : Yuan et al. 2010

(3) : Waldert et al. 2008

(4) : Korik et al. 2016

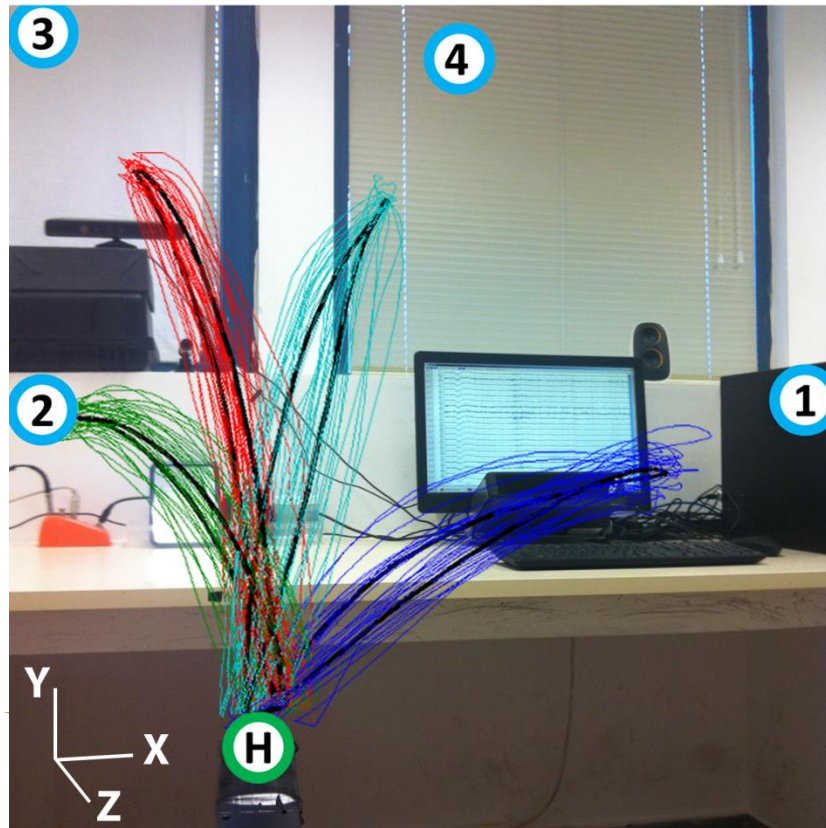
(5) : Korik et al. 2018

(B) Analyzed feature space

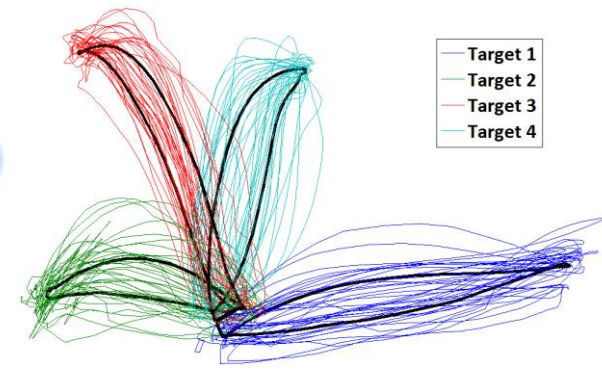
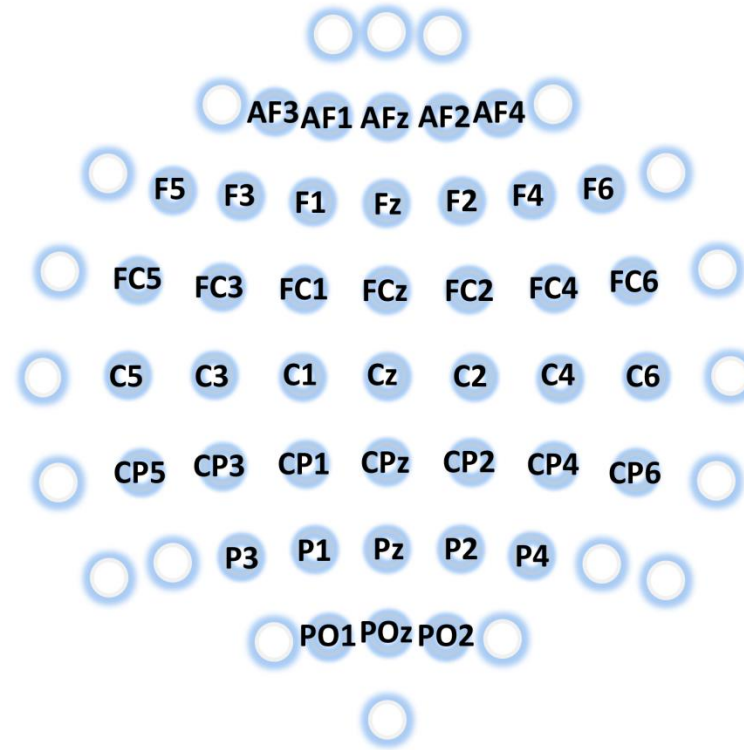


Decoding 3D Trajectory of Arm Movements and Imagined Arm Movements from EEG

A Experimental setup



B EEG montage

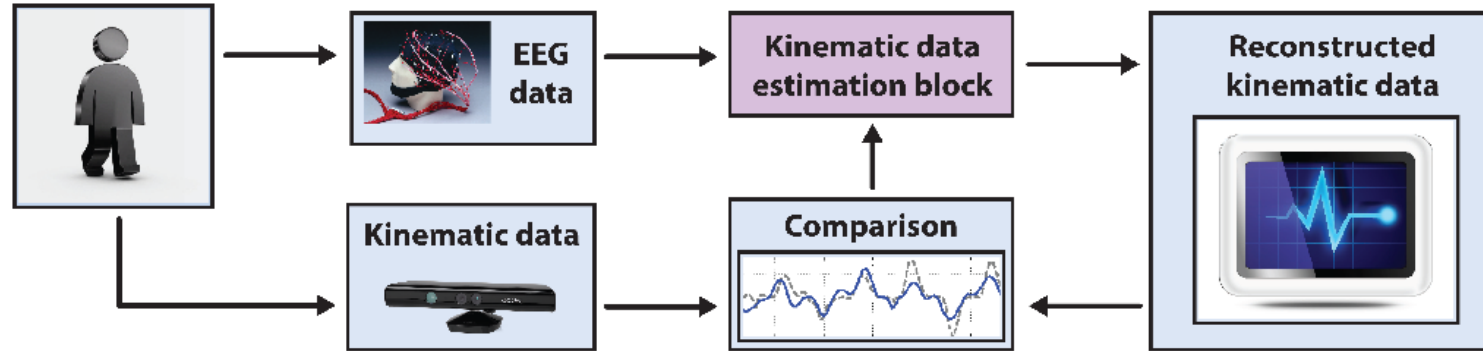


Movement

Target 1

Limb Movement Trajectory Prediction

Multiple linear regression mLR



- mLR based kinematic data estimation:

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

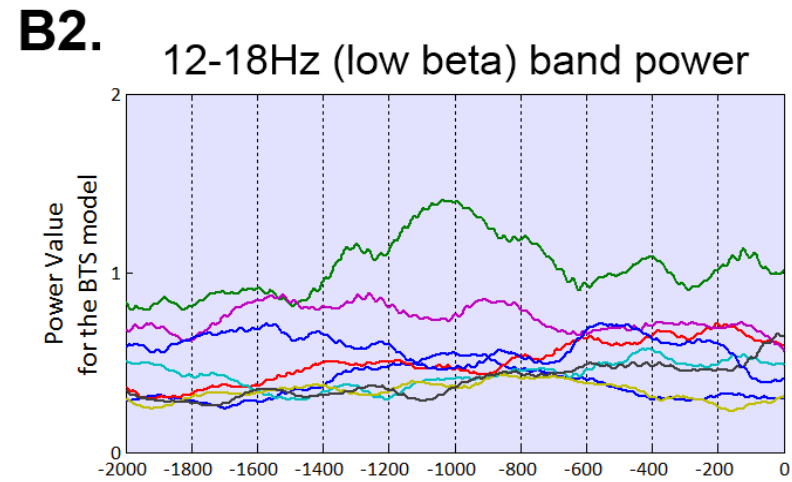
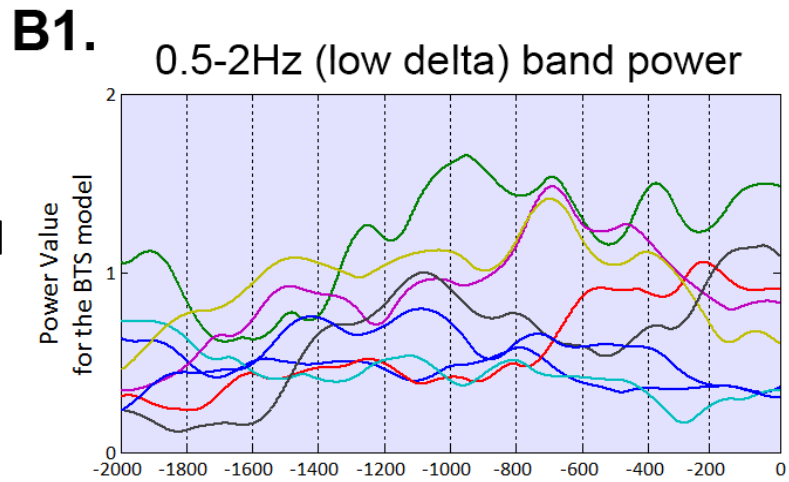
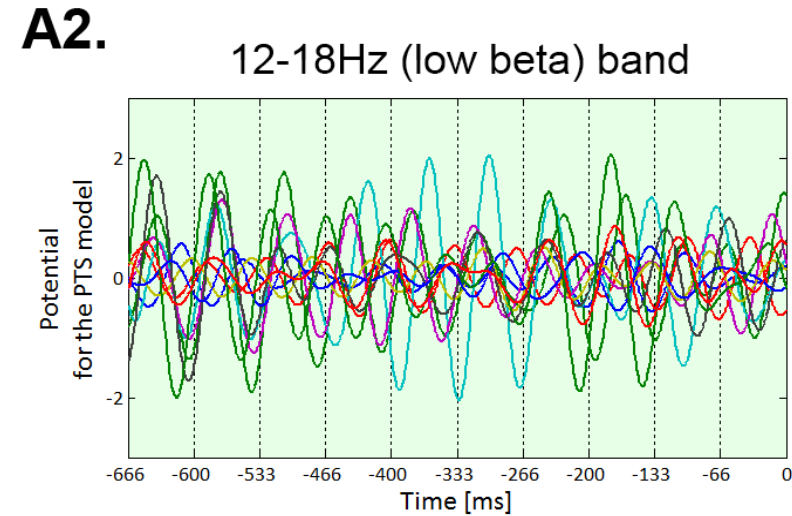
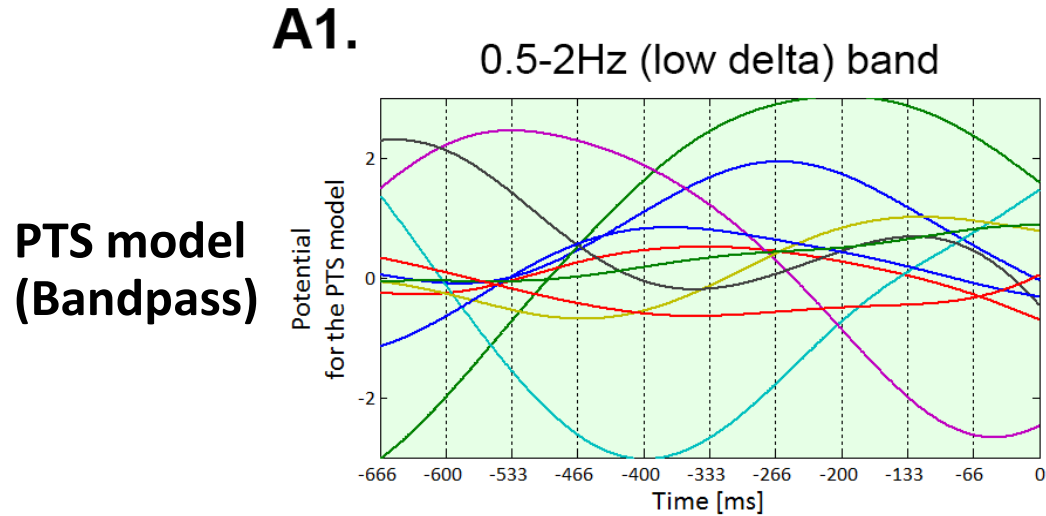
- N : bandpass-filtered EEG channel number
- L : time lag number

S_n : Standardized temporal differences at sensor n

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

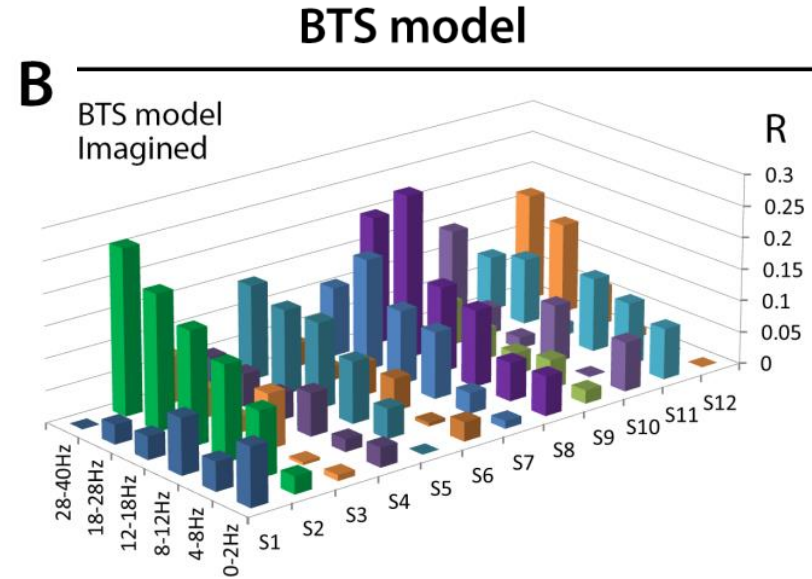
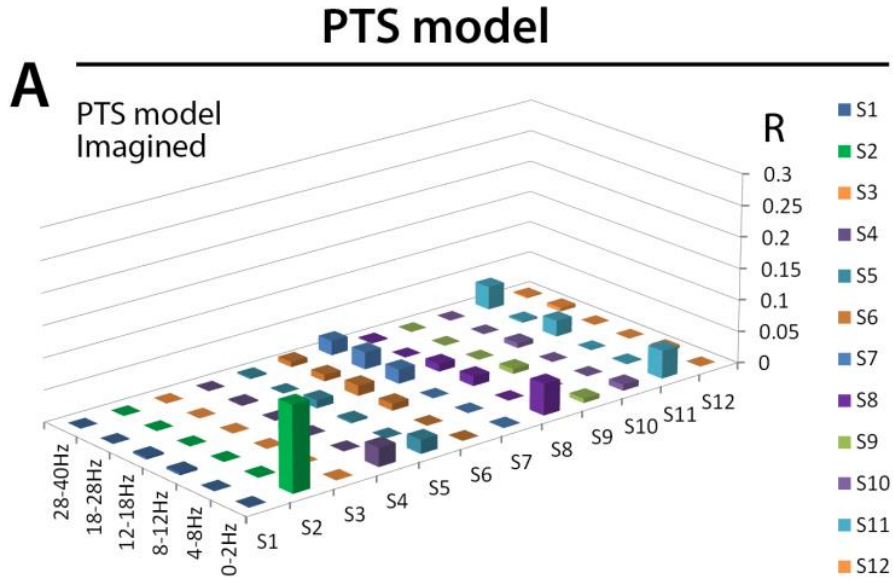
BTS model:
$$S[t] = \frac{v_{BTS}[t]}{\sigma_{v_{BTS}}}$$

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

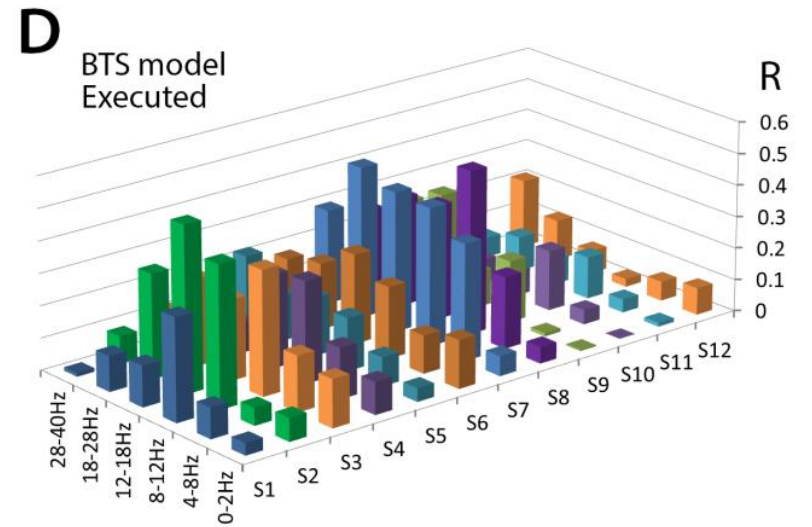
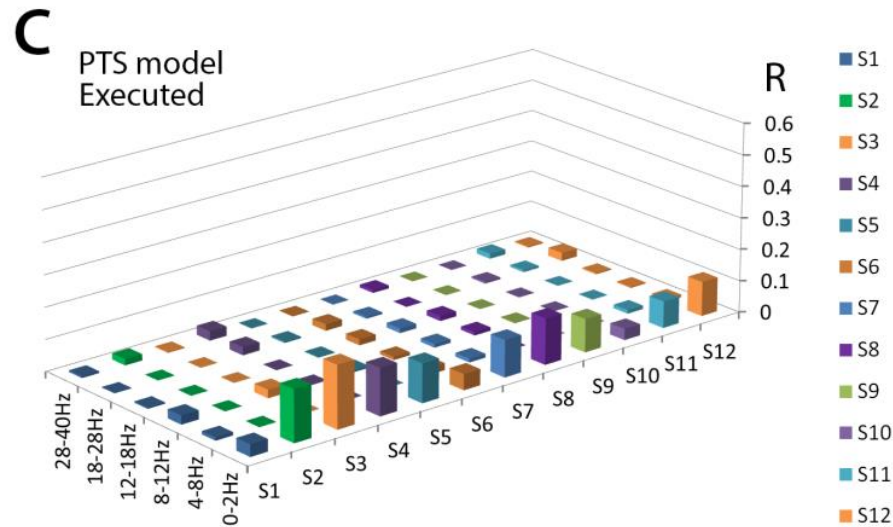


Decoding Accuracy (Pearson Correlation)

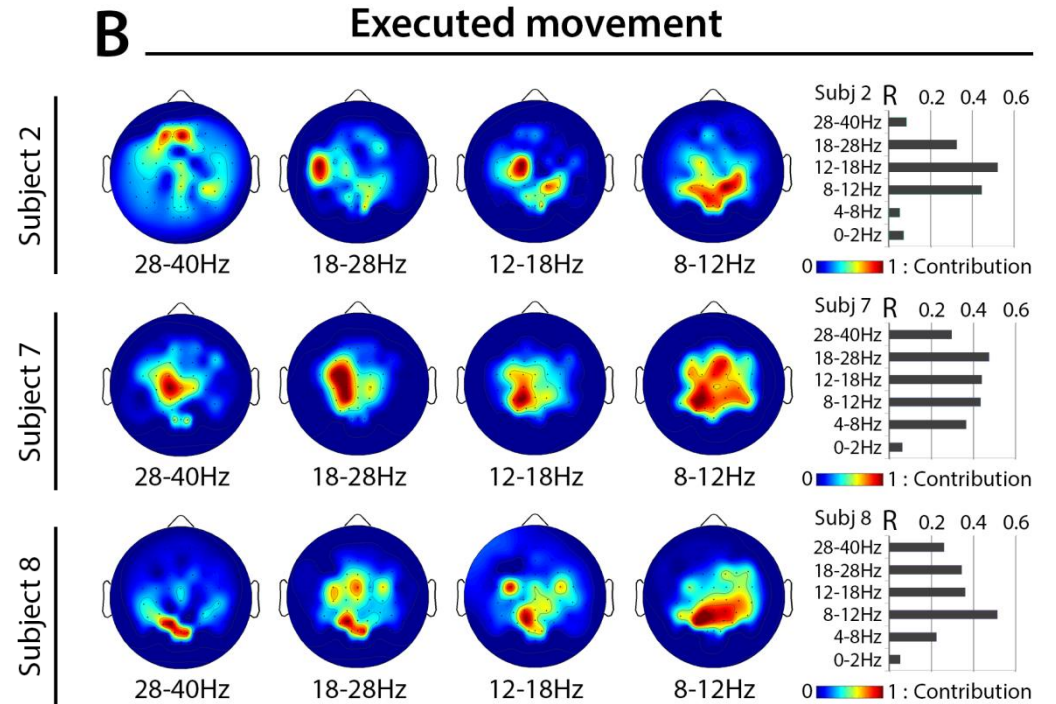
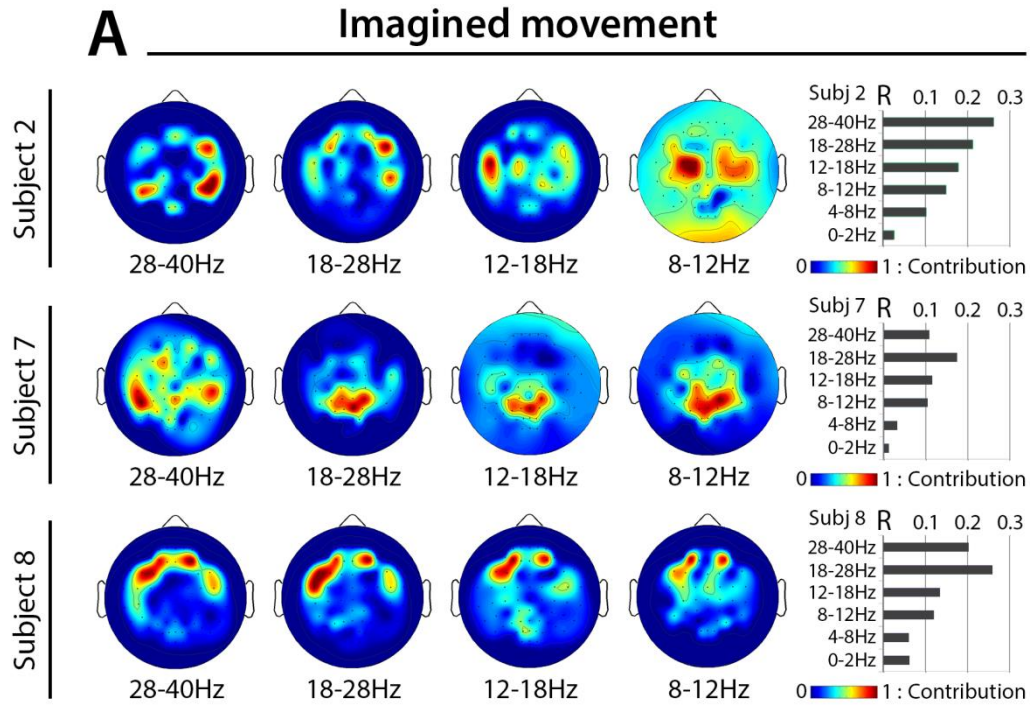
Imagined movement



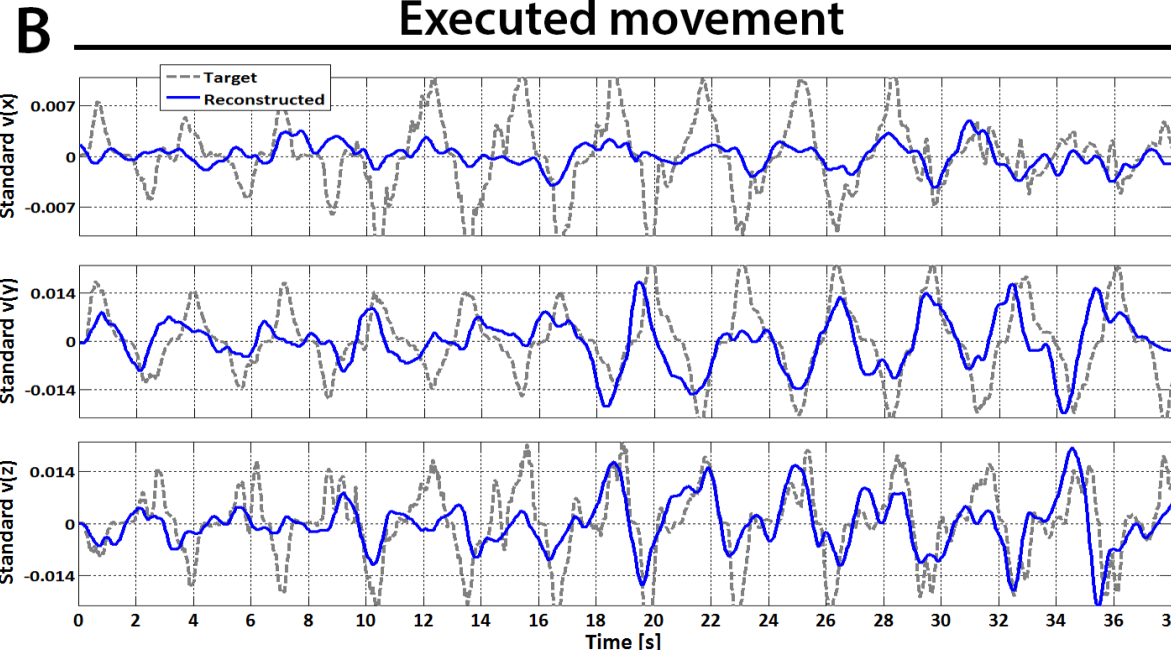
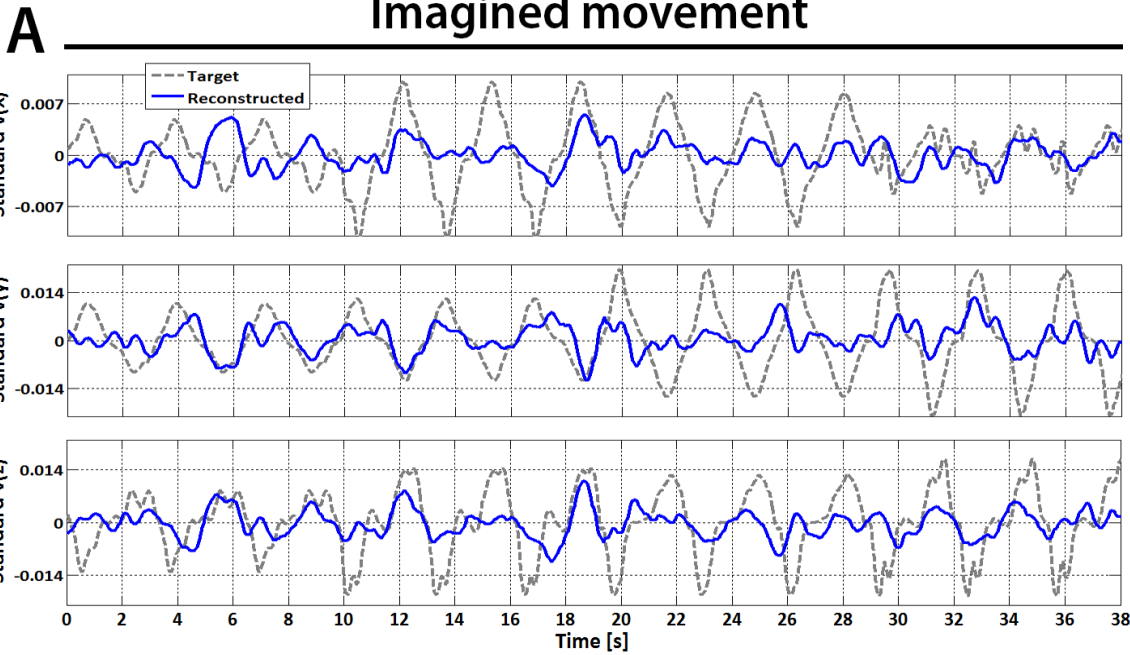
Executed movement



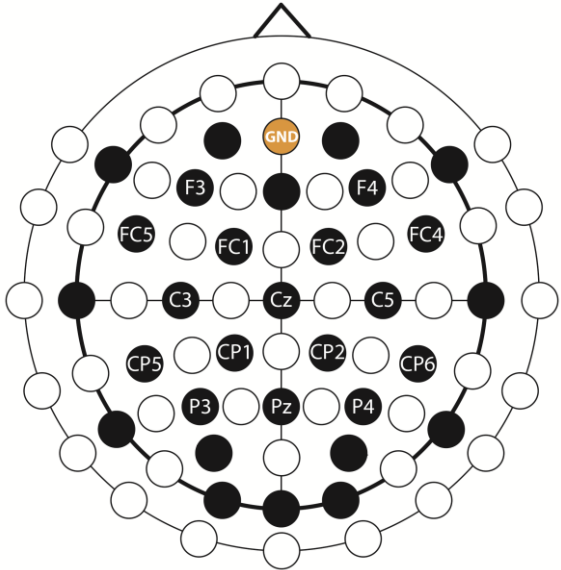
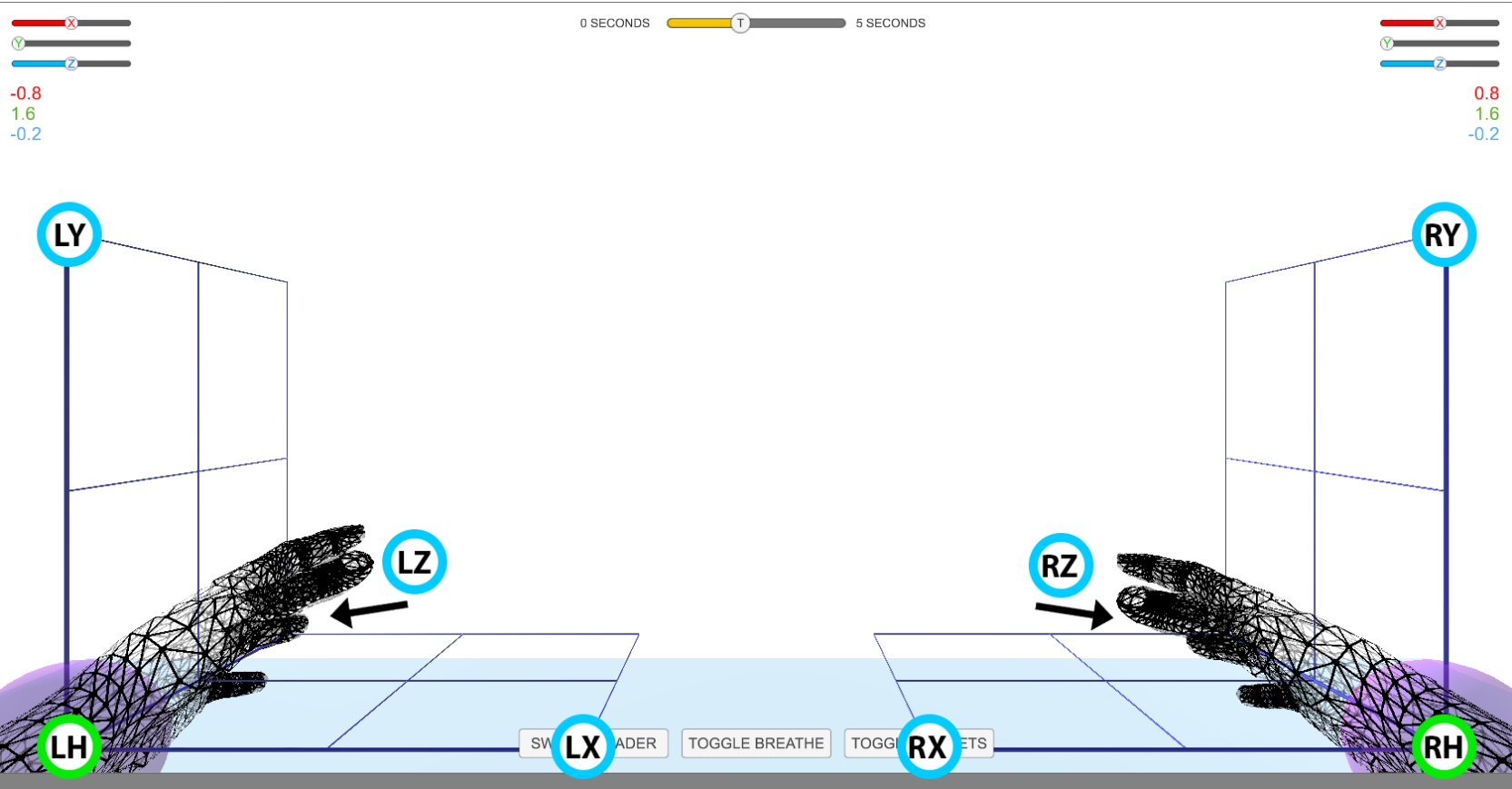
Topological maps



Reconstructed velocity profiles



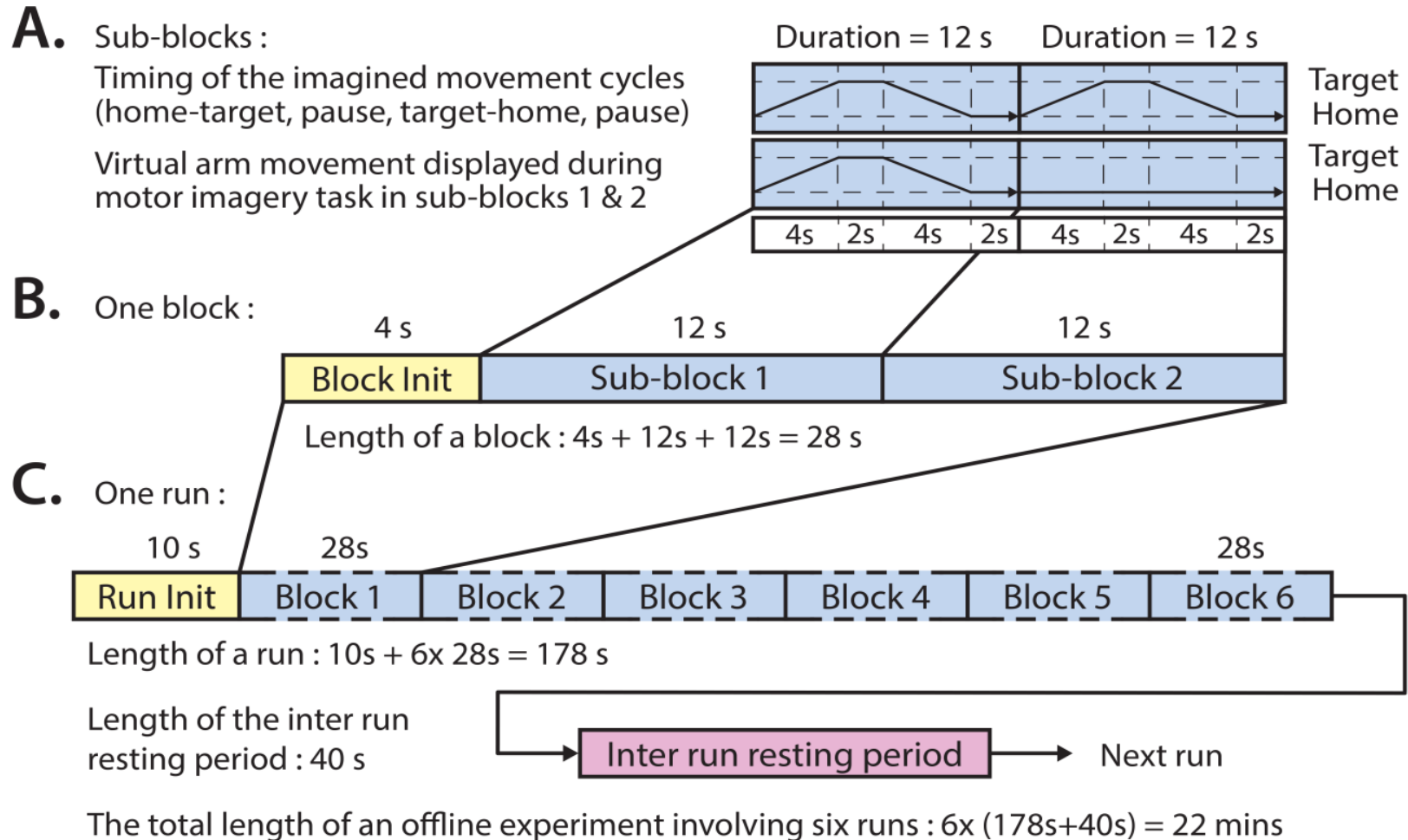
Real-time Control of Virtual Arms?



Timing of the Offline Experiment

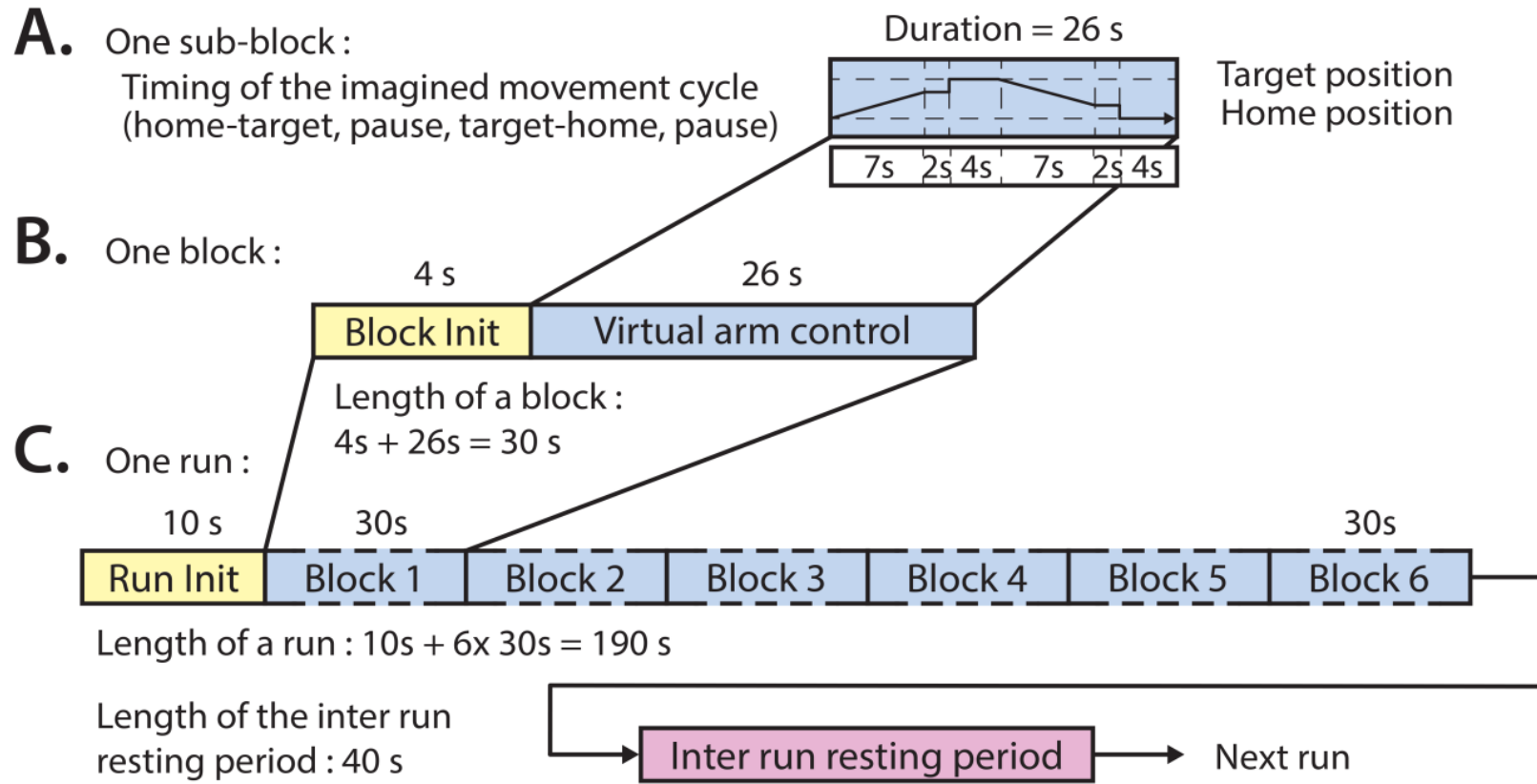
Offline experiment

Issue: low number of trials (6 trials/target/experiment)



Timing of the Online Experiment

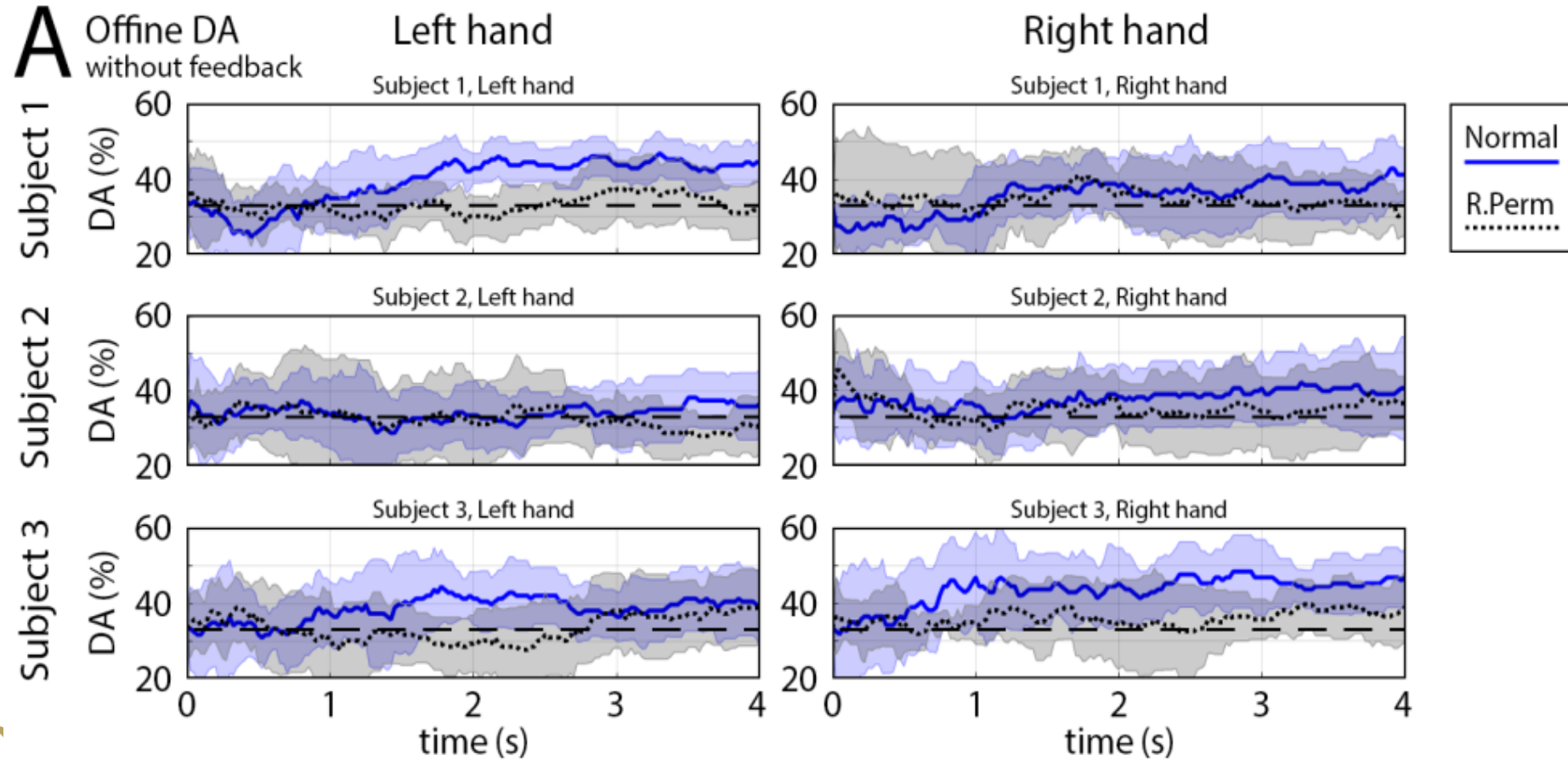
Online experiment



The total length of an online experiment involving six runs : $6 \times (190s + 40s) = 23 \text{ mins}$

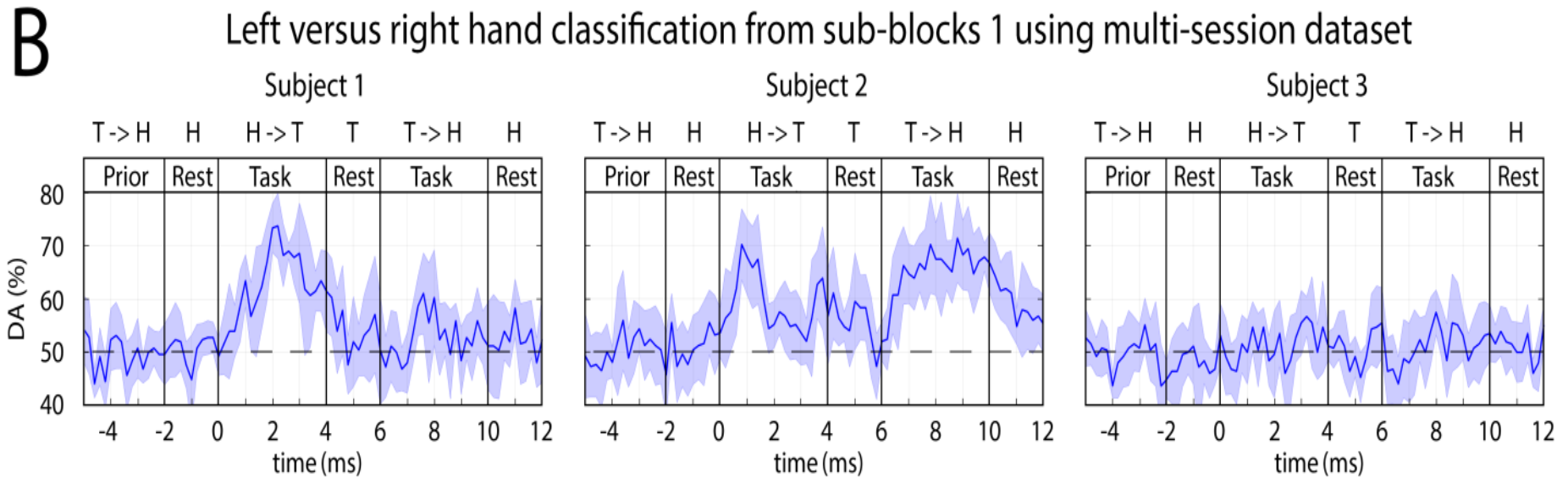
Issue: low number of trials (6 trials/target/experiment)

Target Classification



Imagined Movement Classification (Left vs Right)

Time-varying Decoding Accuracy (DA)

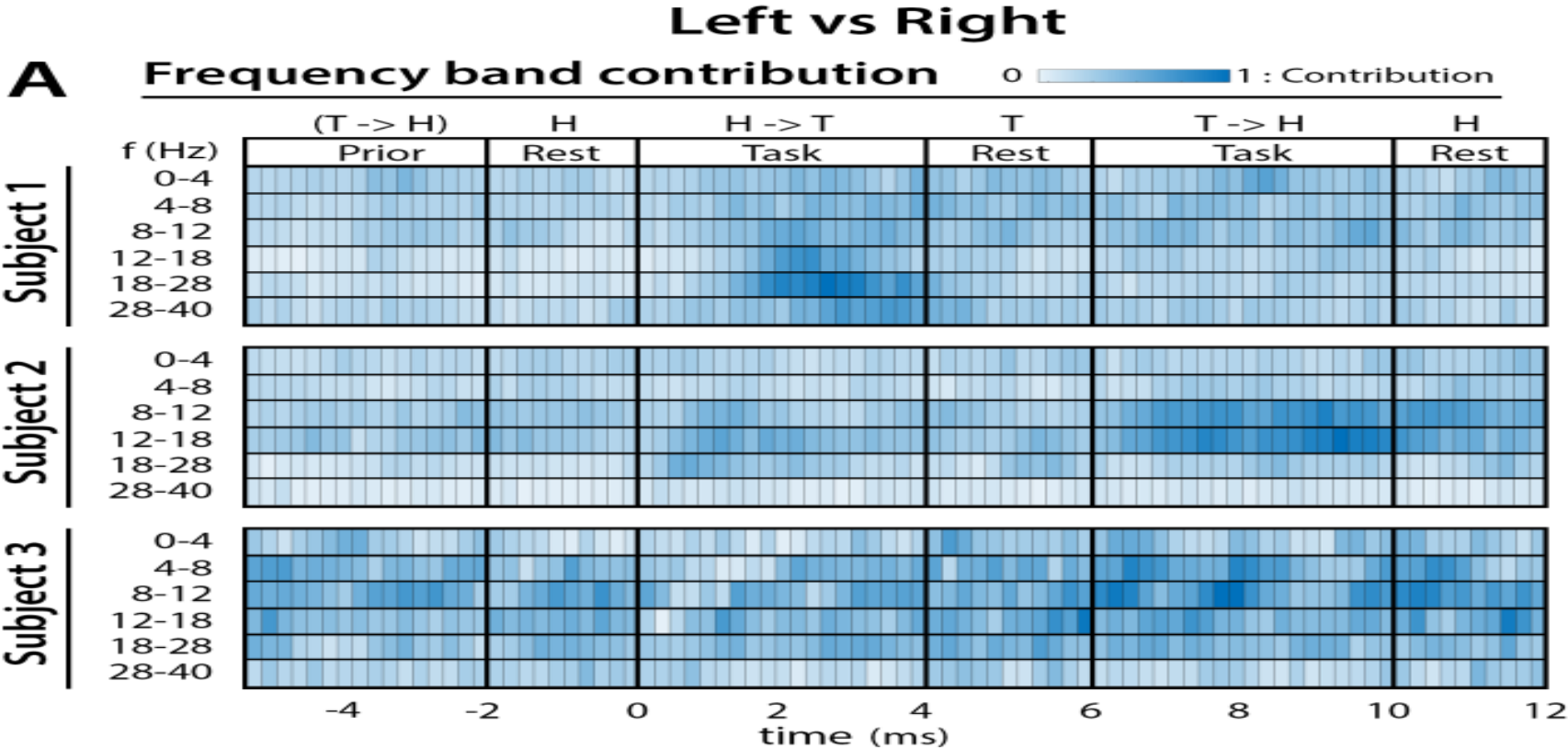


Multi-session results calculated using trials from 7 sessions

1 session involved 3x6 trials/arm (i.e., 6 trials towards 3 targets / session)

Imagined Movement Classification (Left vs Right)

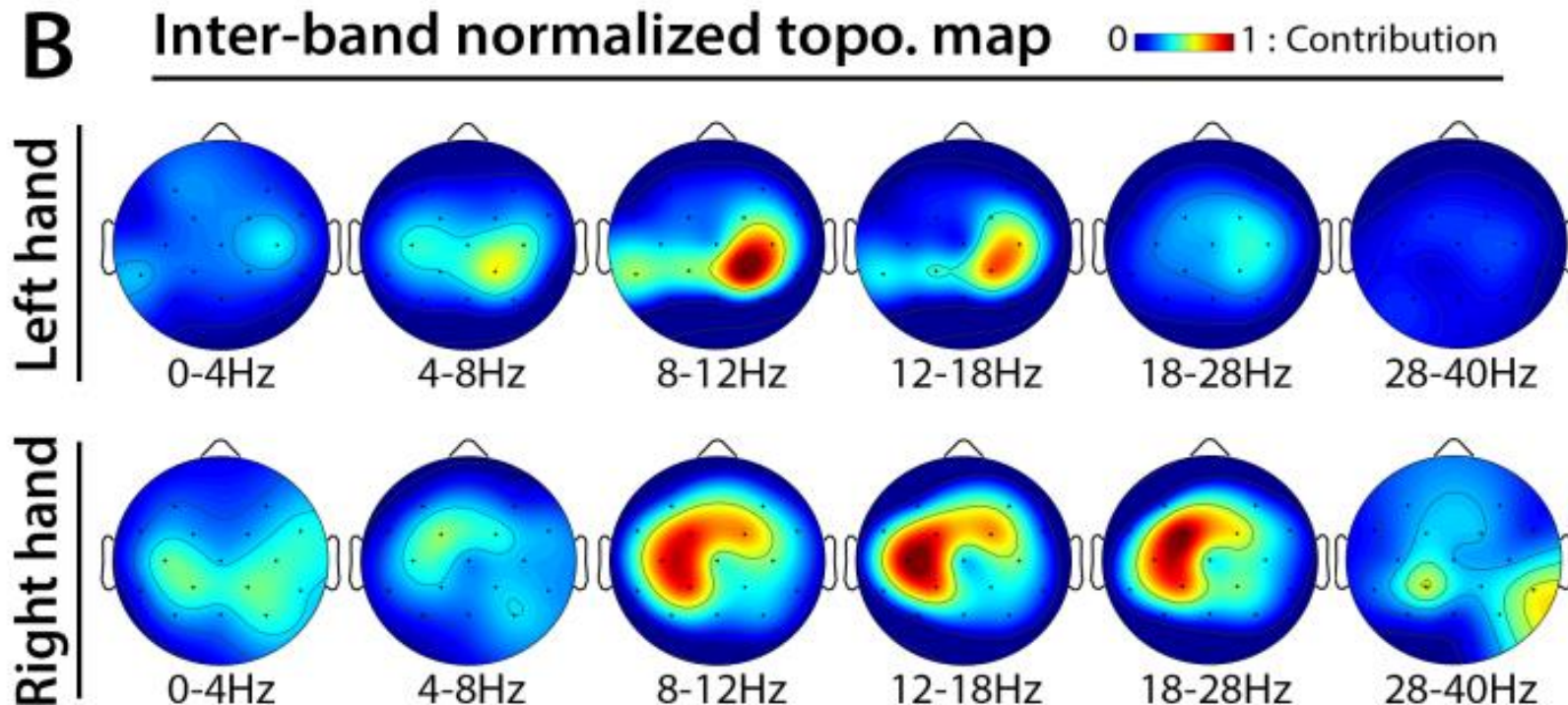
Frequency Analysis (map of CSP-MI weights)



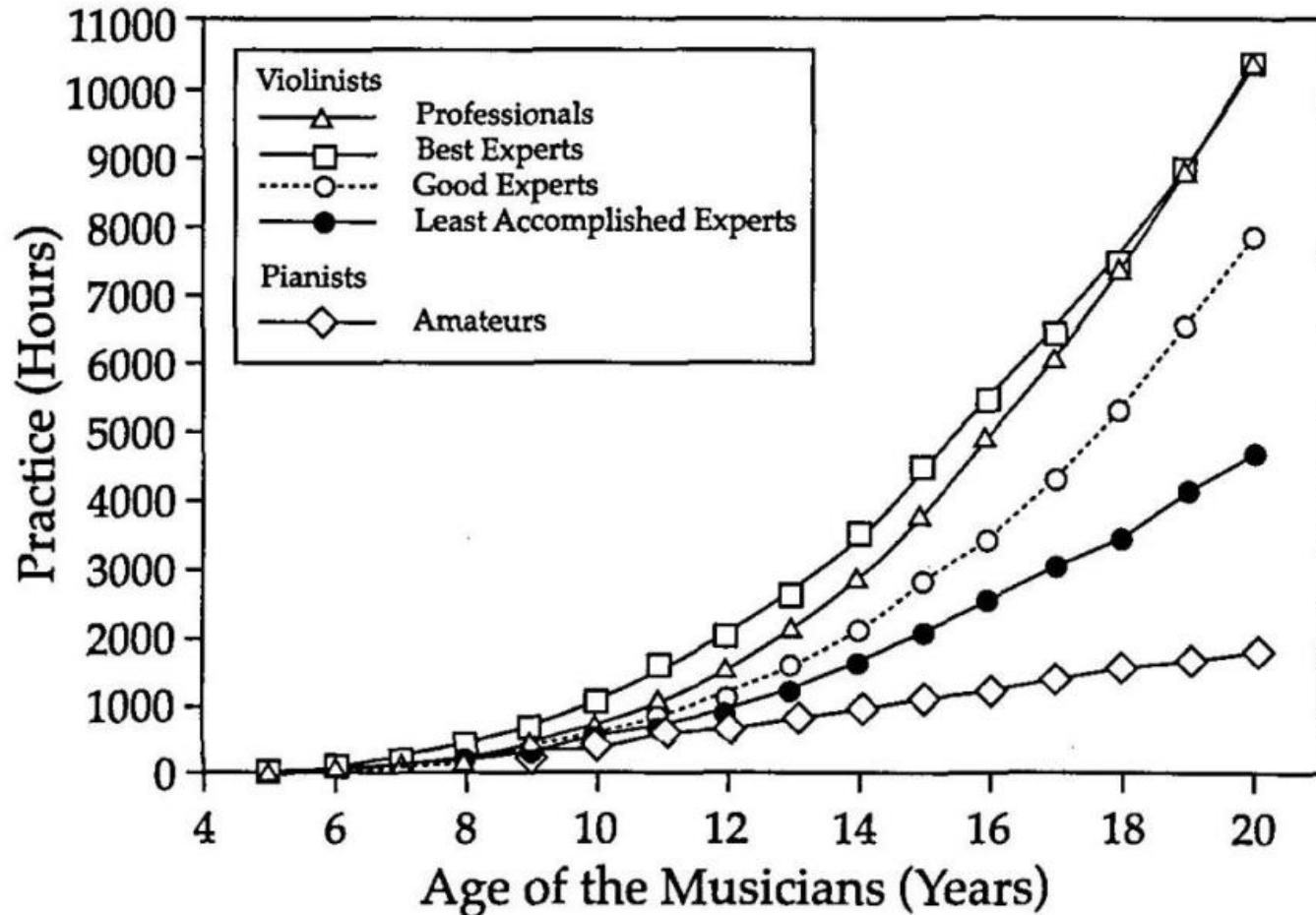
Multi-session results calculated using trials from 7 sessions
 1 session involved 3x6 trials/arm (i.e., 6 trials towards 3 targets / session)

Imagined Movement Classification (Left vs Right)

Topographical Analysis (map of CSP-MI weights)



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

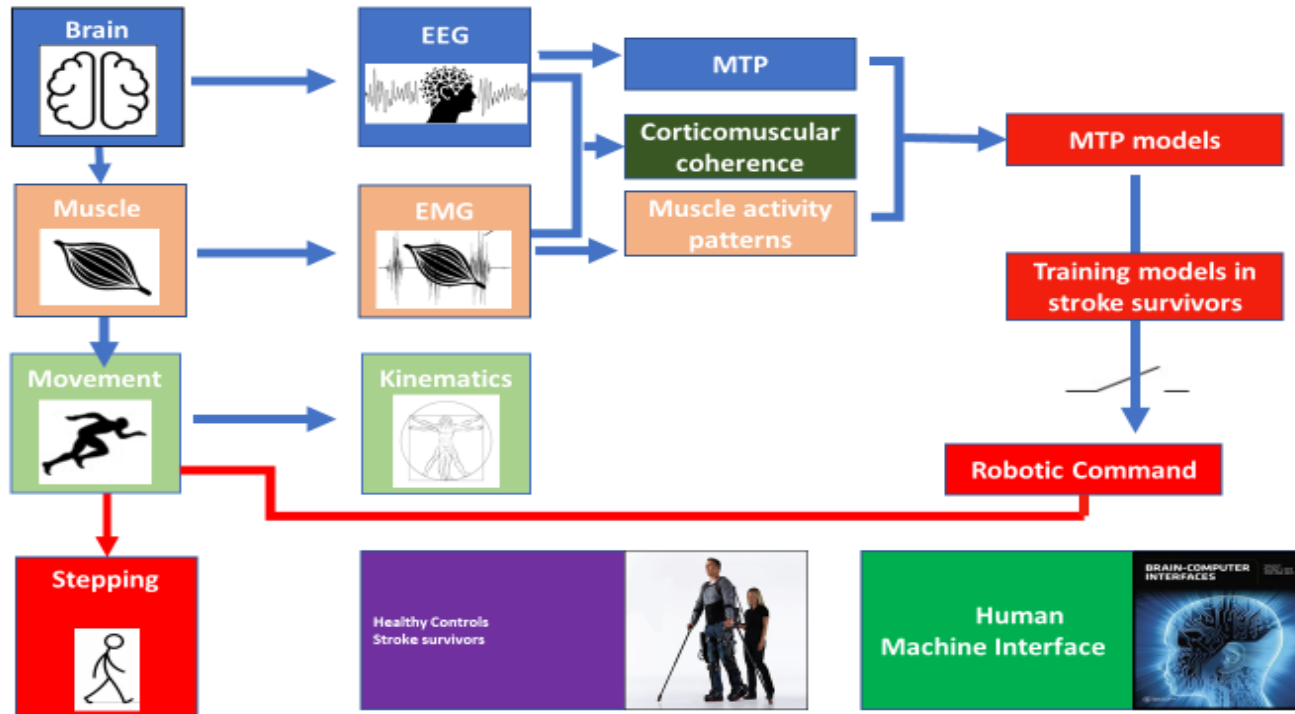
For patients e.g., dedicated, high dose therapy services

Decoding 3D lower limb movements

EU H2020 RISE Project



- 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



UNIVERSITÀ
DEGLI STUD
DI PADOVA



www.ProGait.eu



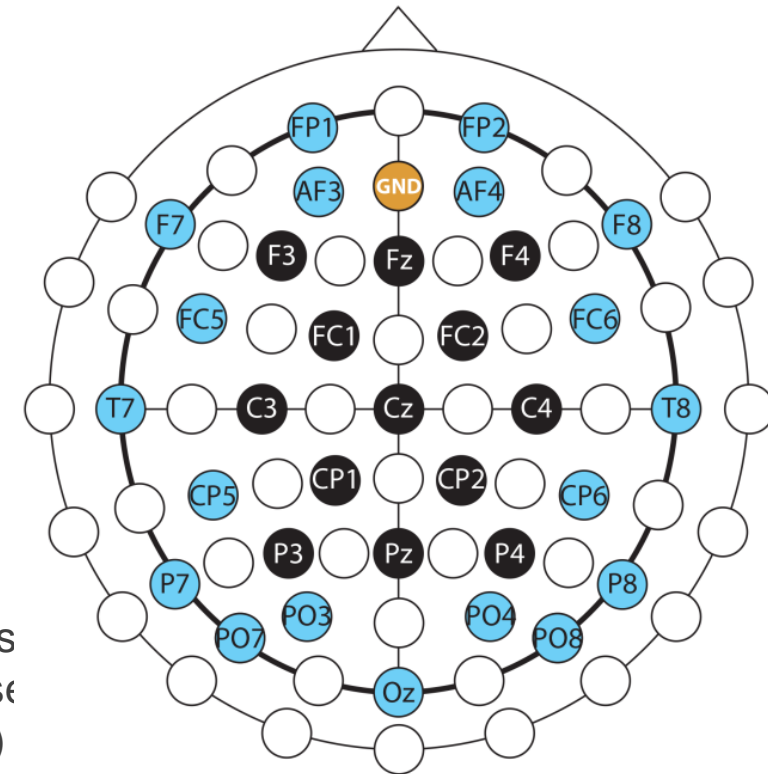
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 778043

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)
- 10 run x 10 trials/run -> 100 trials/subject
- Test result validation: 6 fold CV



EEG montage

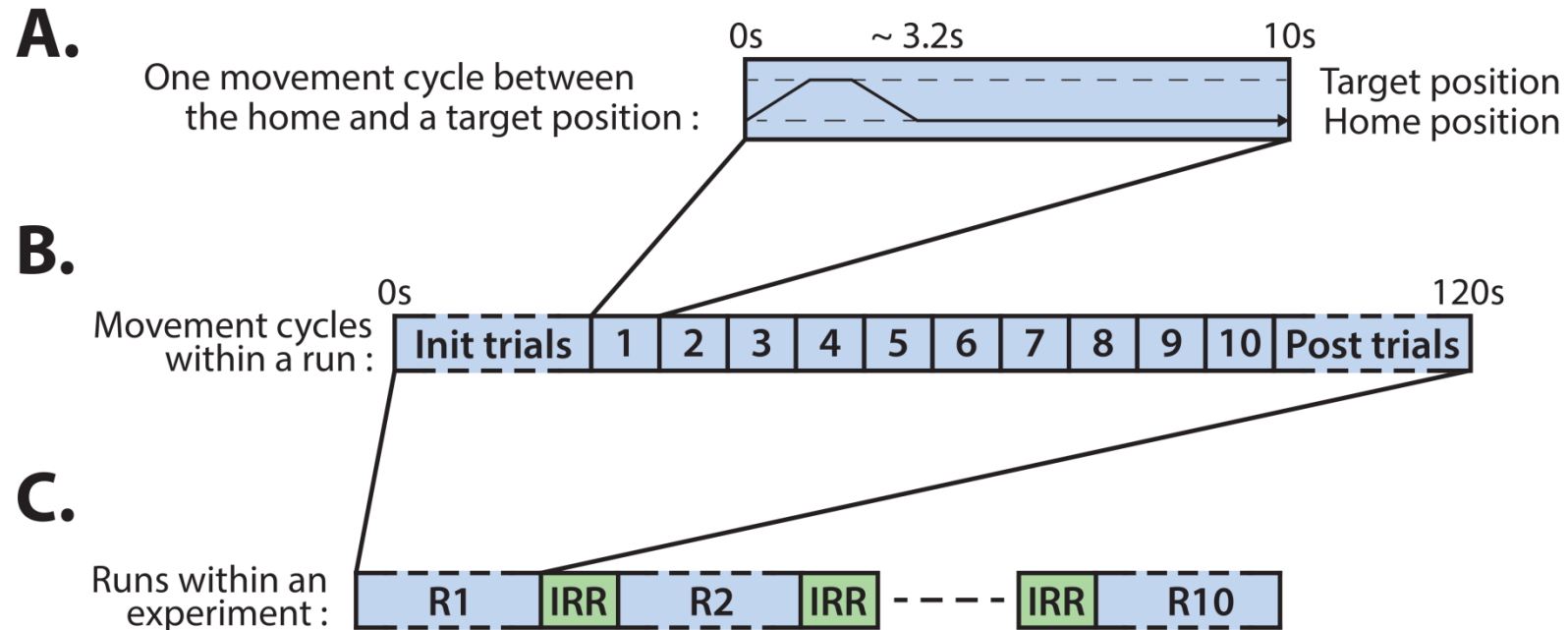
Decoding 3D Trajectory of Lower-limb Movements

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

Task:

- Step forward and back



R... : Run

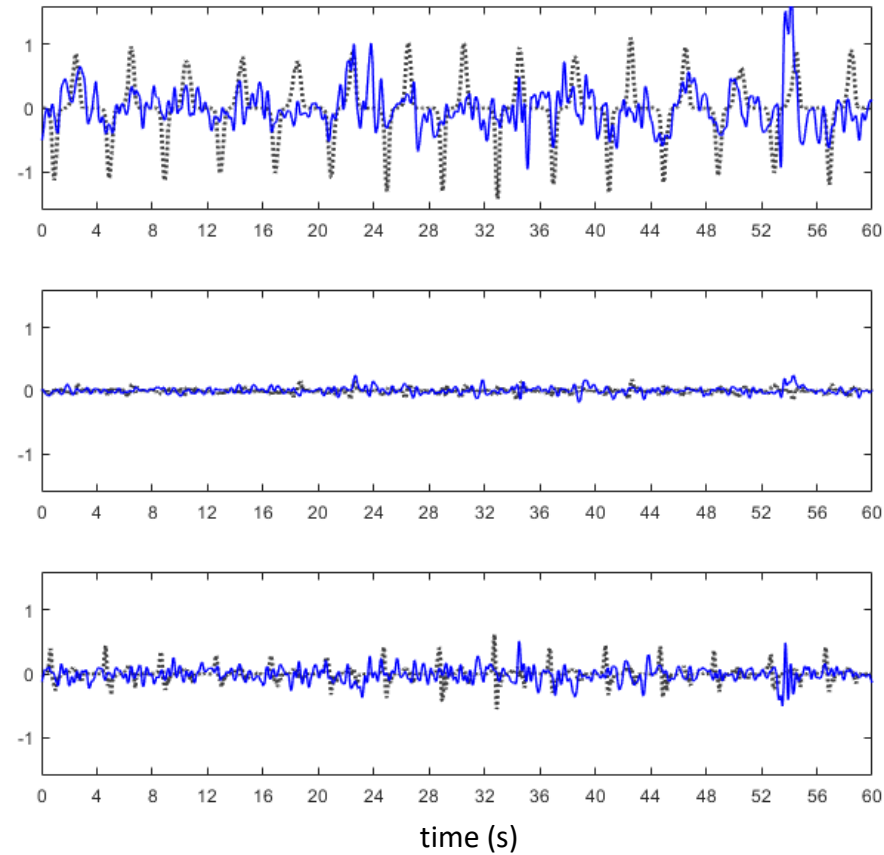
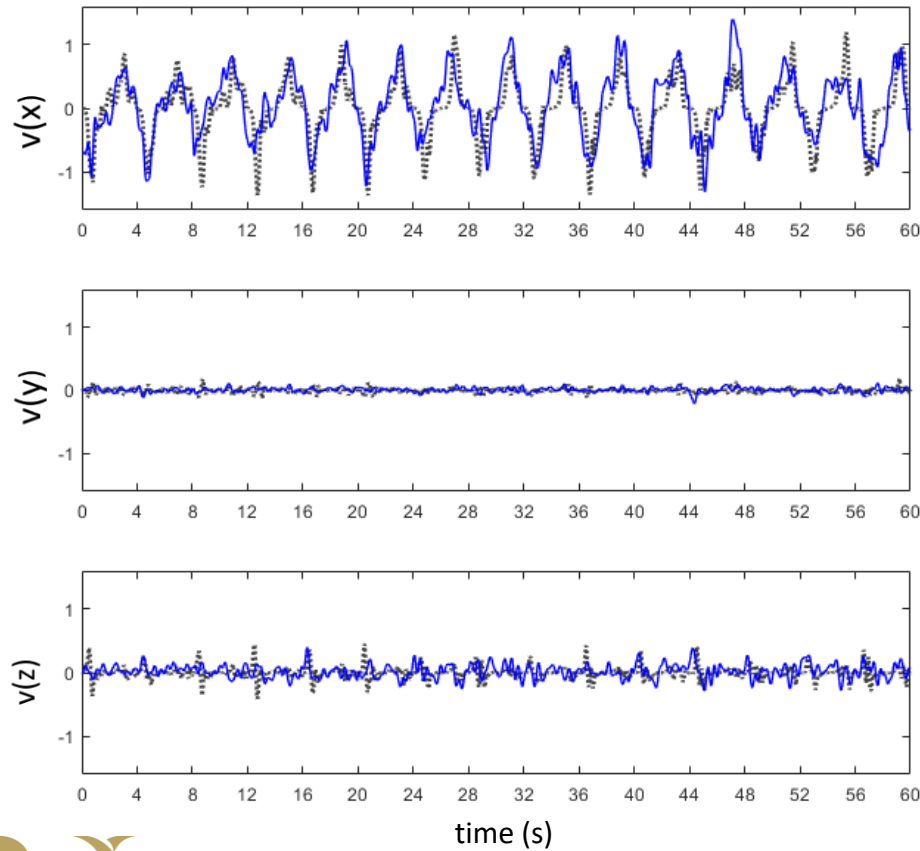
IRR : Inter-run resting period

The total length of the experiment with executed movements: 10x (2min+IRR)

Target and decoded velocity vectors

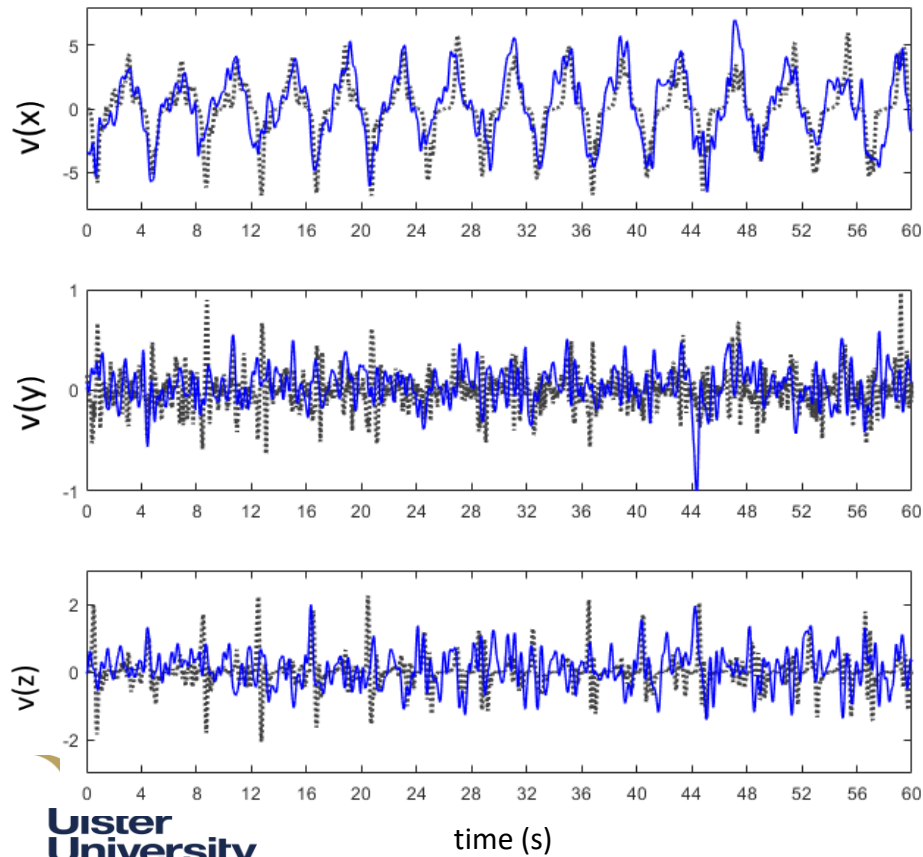
Subject 1 (the best subject)

Subject 6 (the worst subject)

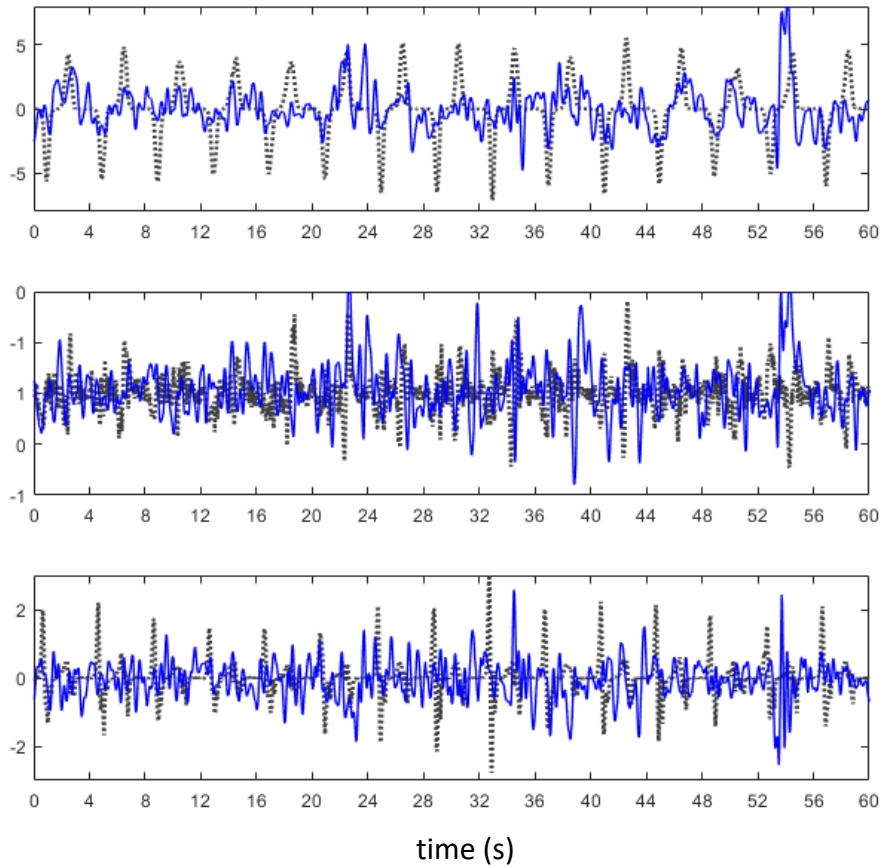


Target and decoded velocity vectors

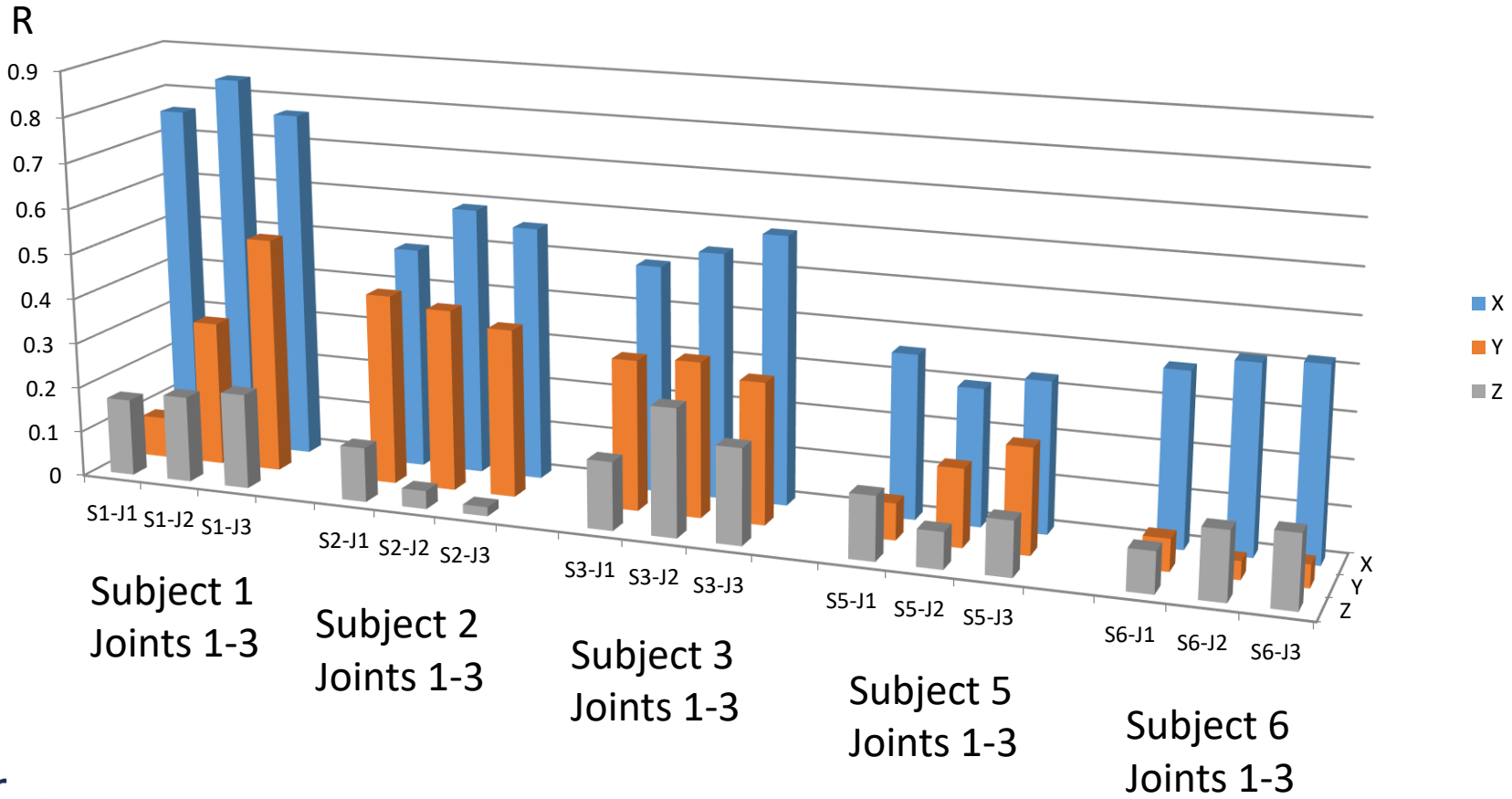
Subject 1 (the best subject)



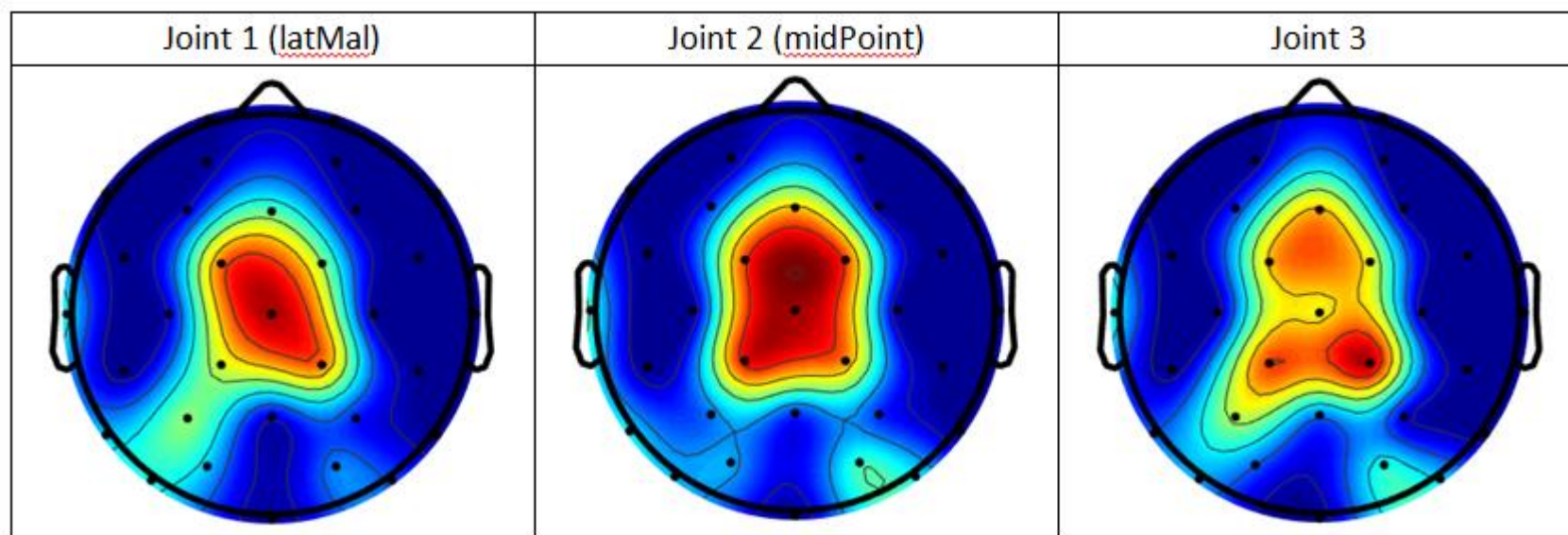
Subject 6 (the worst subject)



Decoding Accuracy (Pearson Correlation)

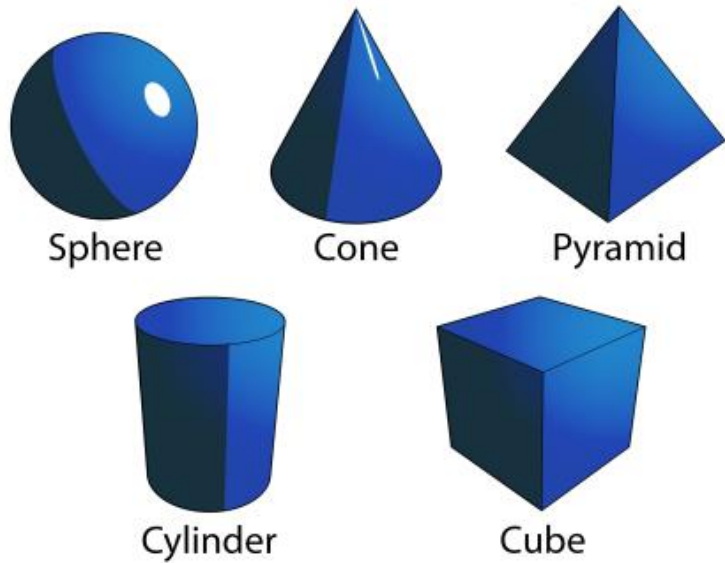


Topographical Analysis



Imagined shape classification

Imagined Object/Shape Classification



Timing of the trials:

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

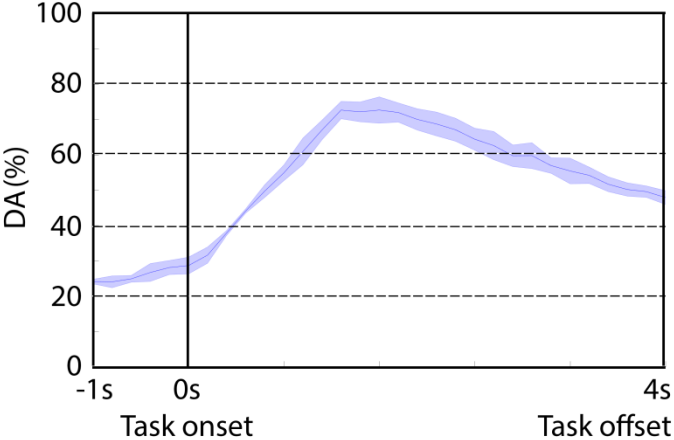
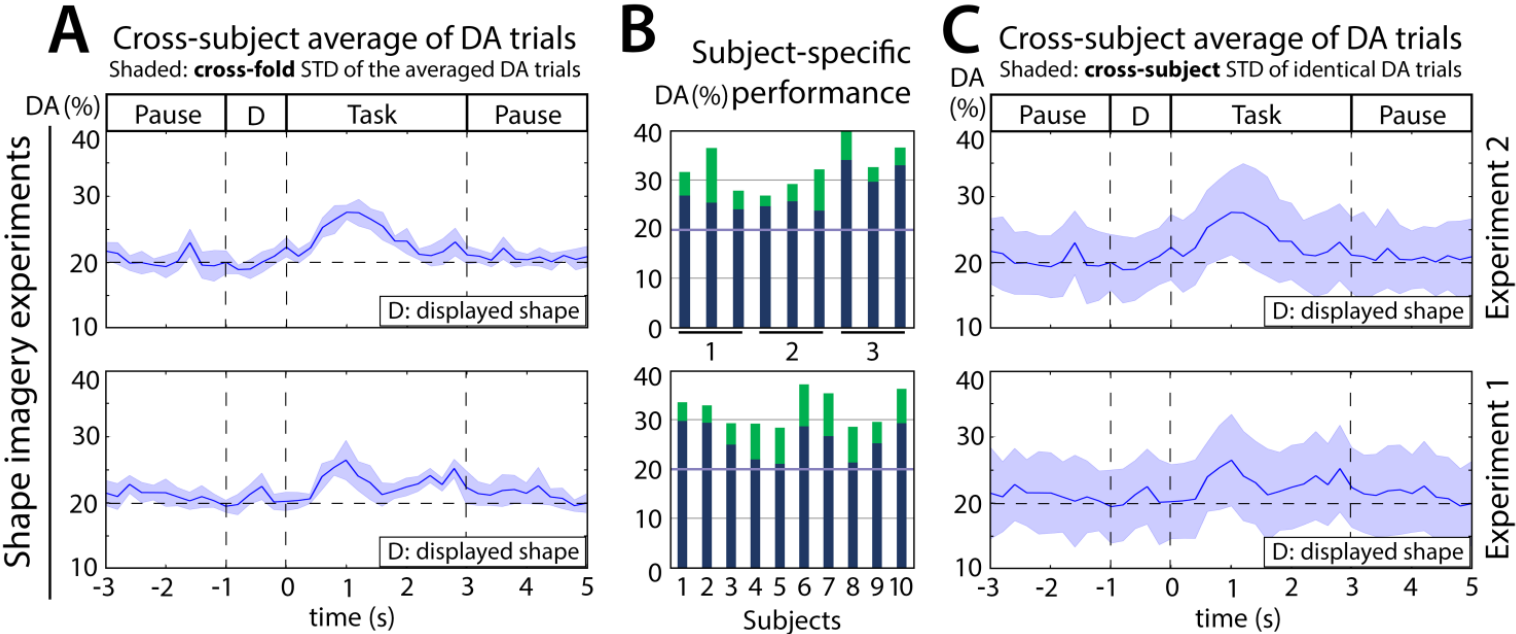
Object vs Motor Imagery

- Imaged Object:

5 classes
(20% chance level)

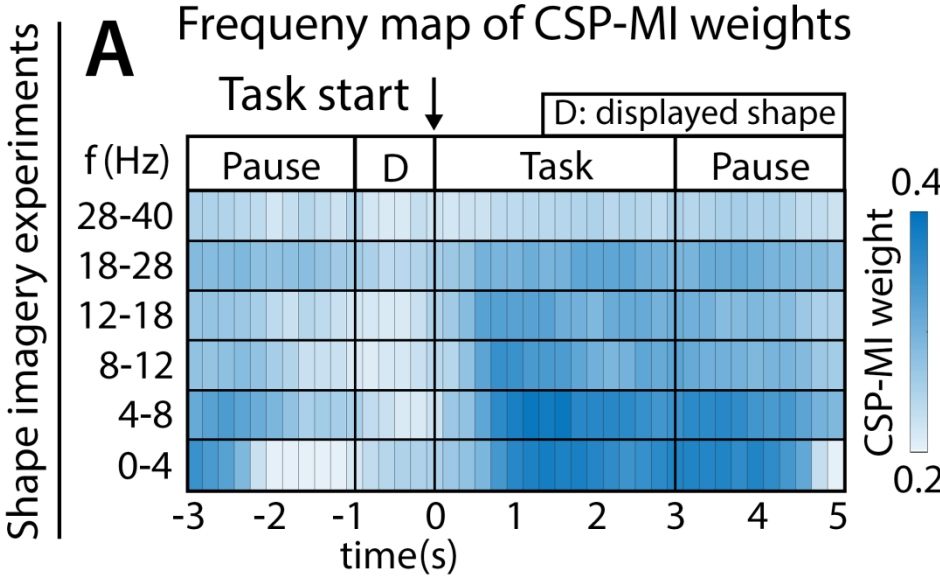
- Motor Imagery:

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

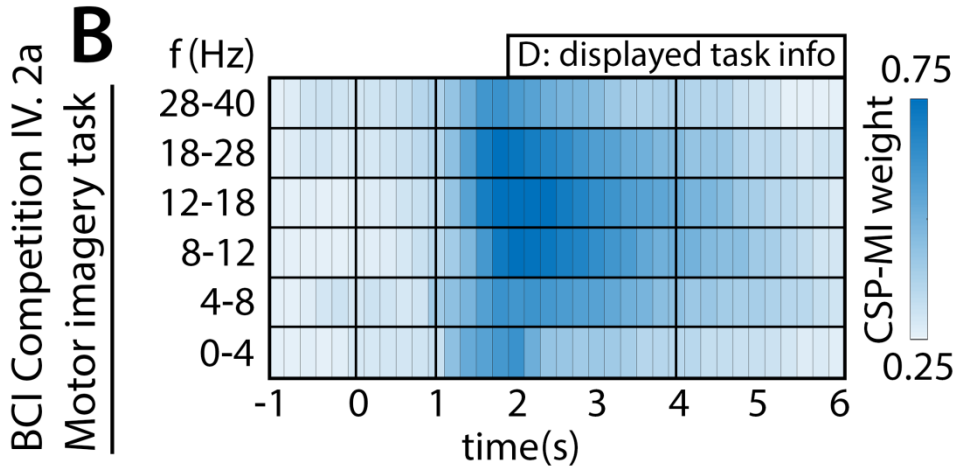


Object vs Motor Imagery

- Imaged Object:

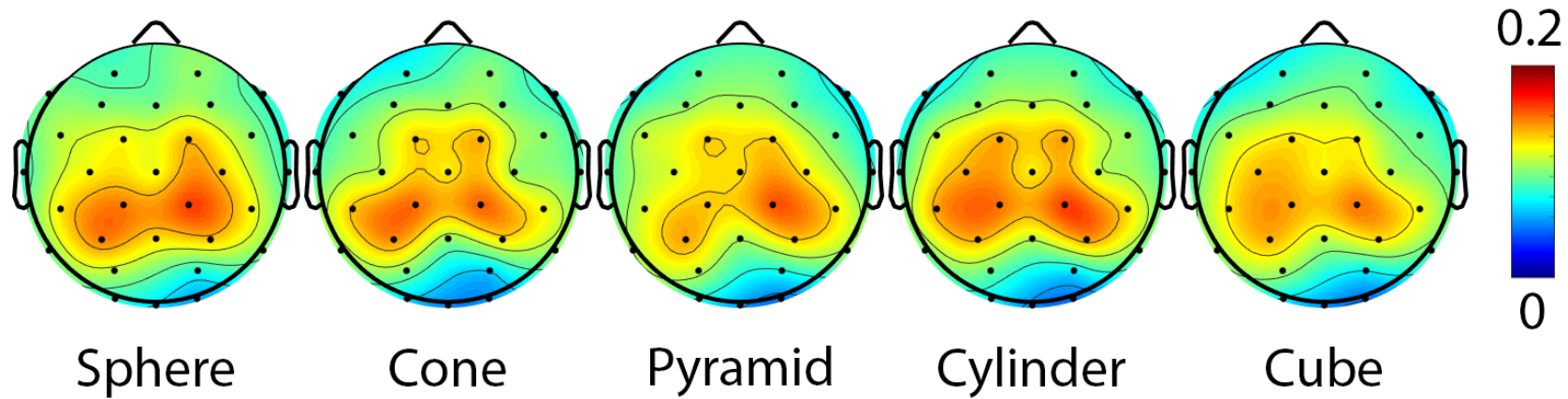


- Motor Imagery:

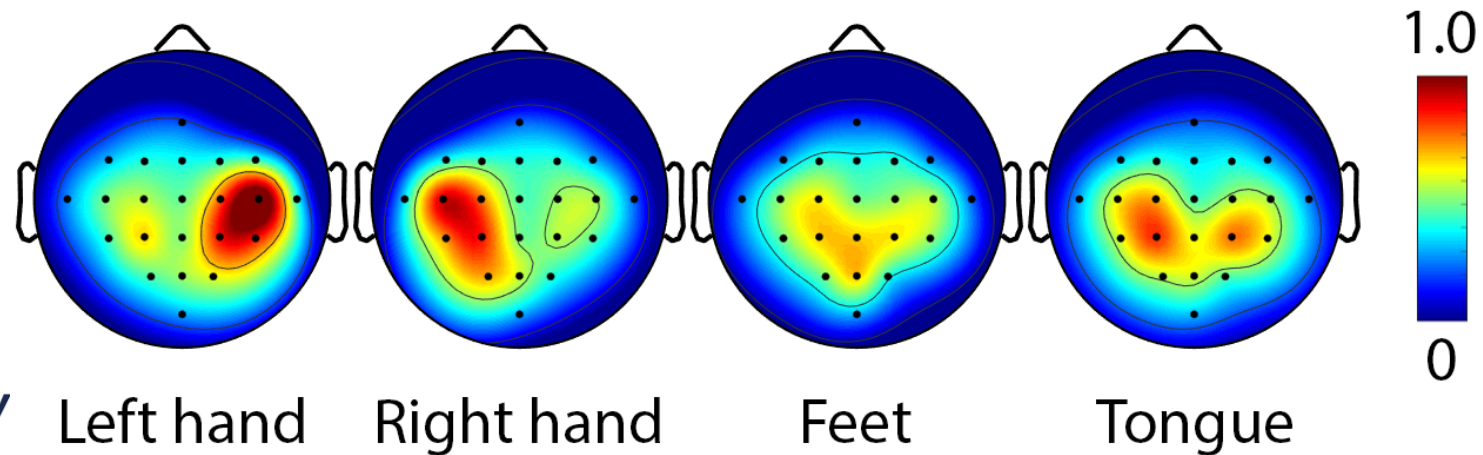


Topographical Analysis

Imaged Object:

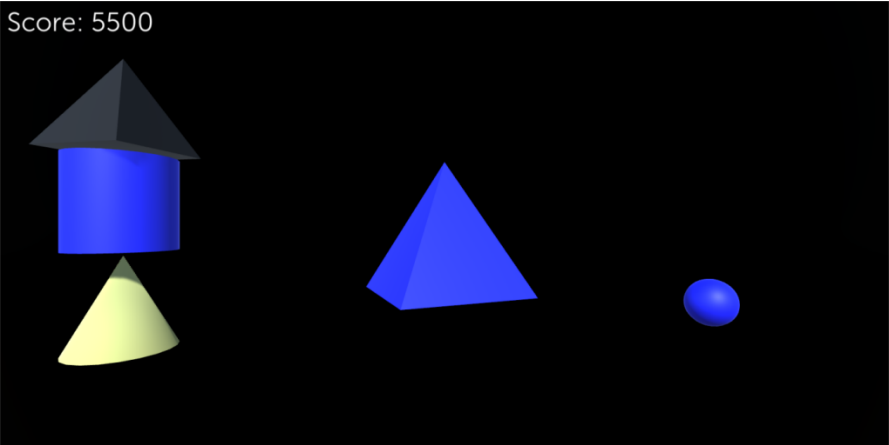


Motor Imagery:

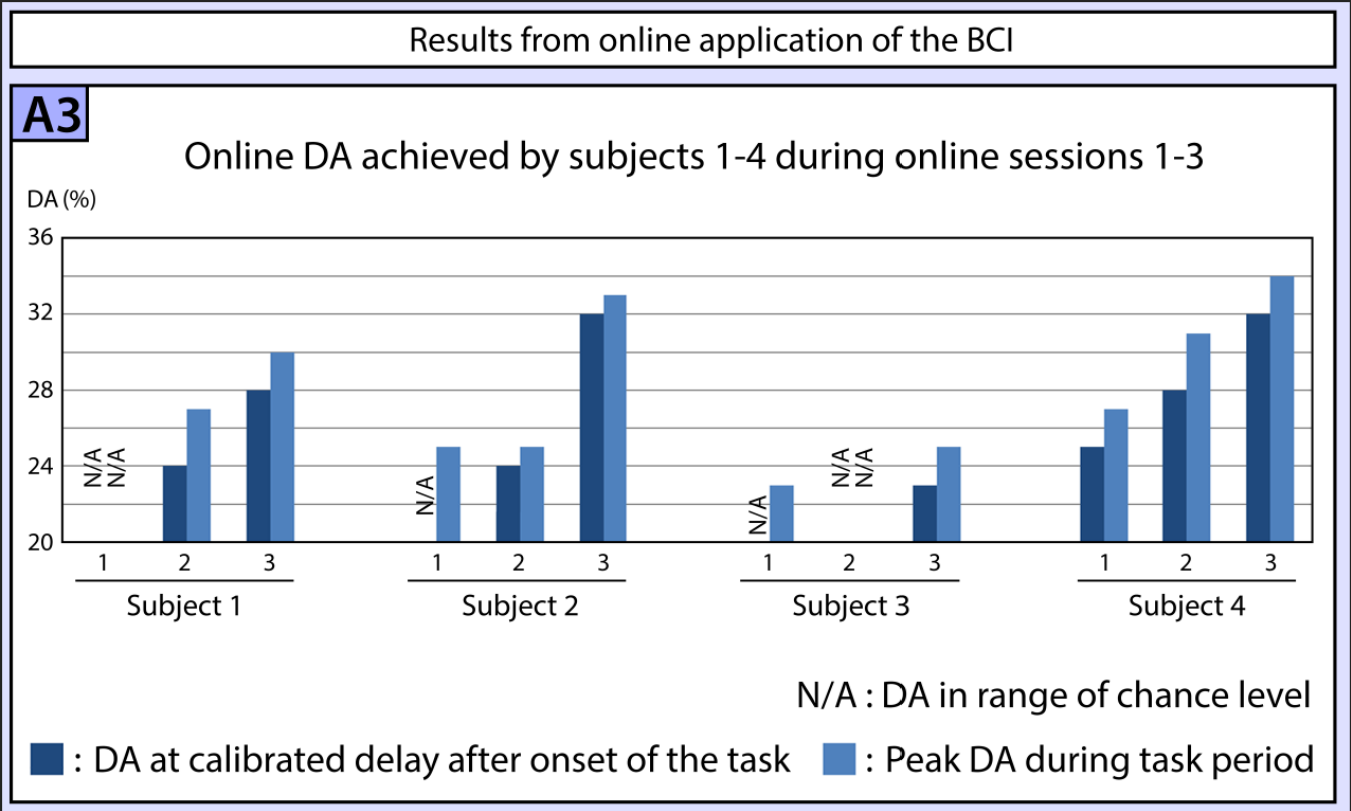
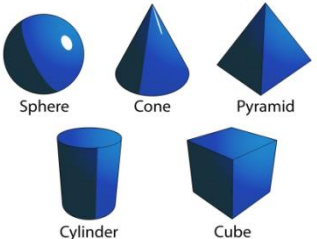


Online Decoding Accuracy

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



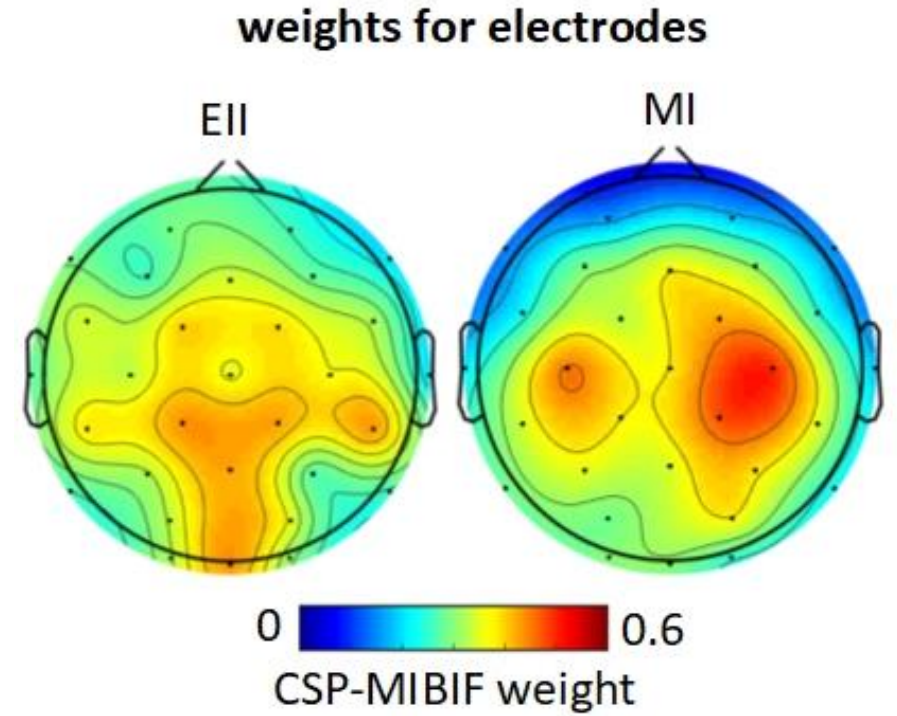
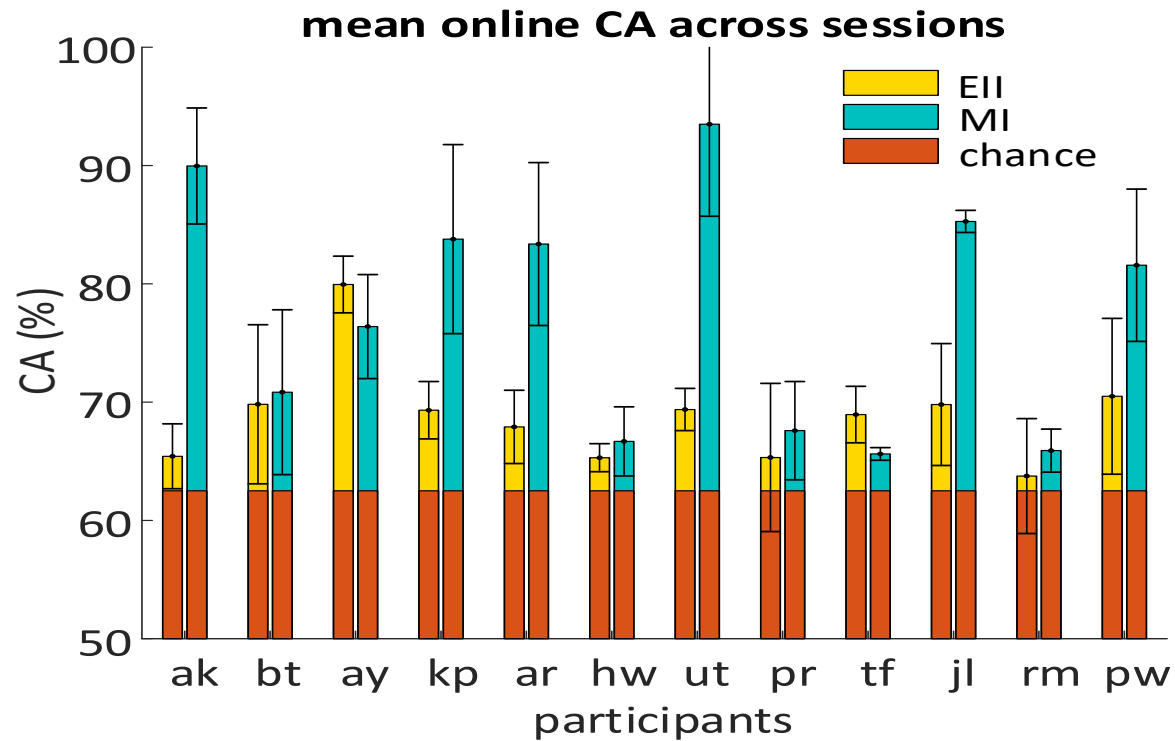
5 classes
 (20% chance level)



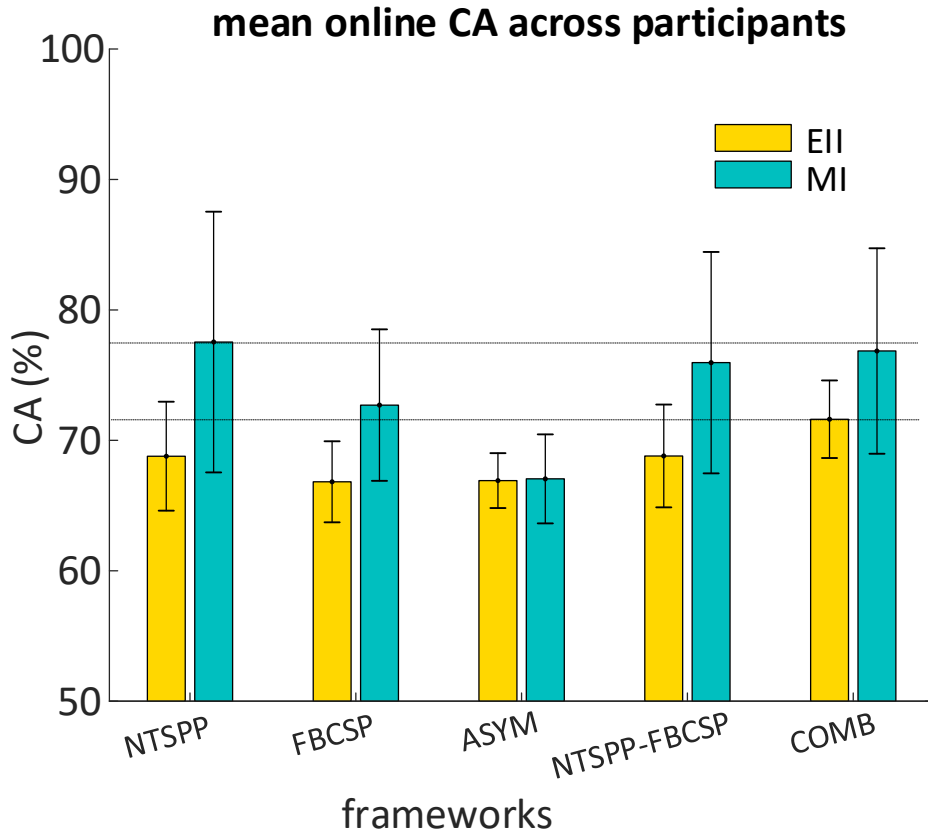
Korik, Coyle et al, (submitted)

Classifying self-induced emotions

Emotion-inducing imagery vs motor imagery



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	
Frontal-middle																
Temporal-left							*t				*g					
Central-right				*a							*b					
Parietal-left			**t				*t						**t			
Parietal-middle			*b				*a		**a		*a					
Parietal-right		*b								*t						
Occipital-left		*a		*g						*-b					*t	
Occipital-middle							*-t									
Occipital-right							*b		**t							
Occipital-right																*-t
Participants IDs	ak		bt		ay		kp		ar		tf		pw			

a = alpha, b = beta, g= gamma, t= theta band

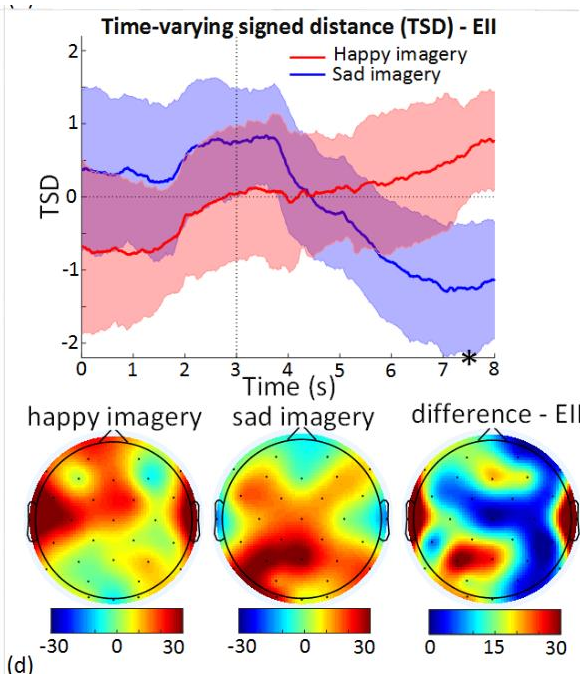
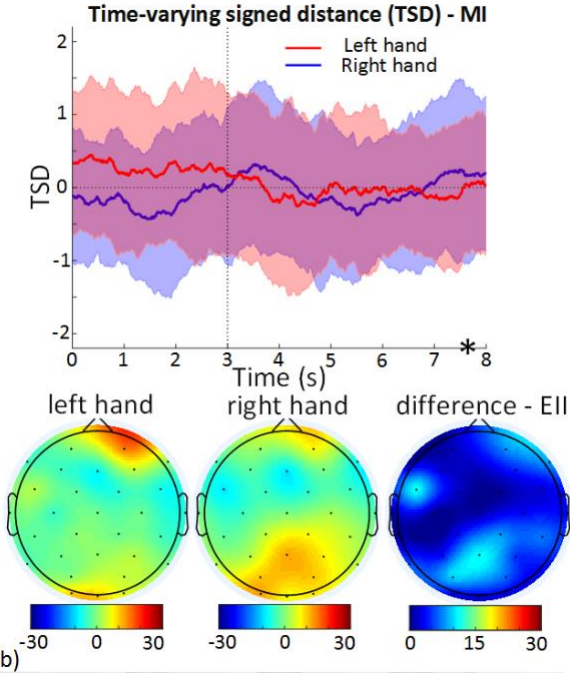
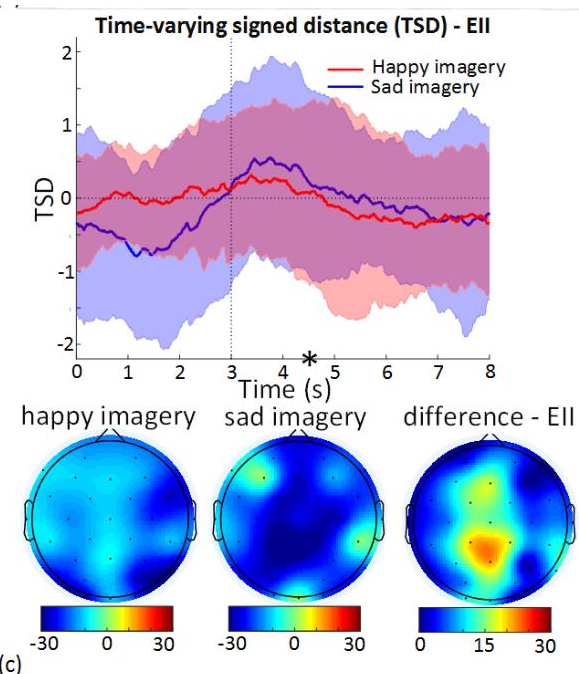
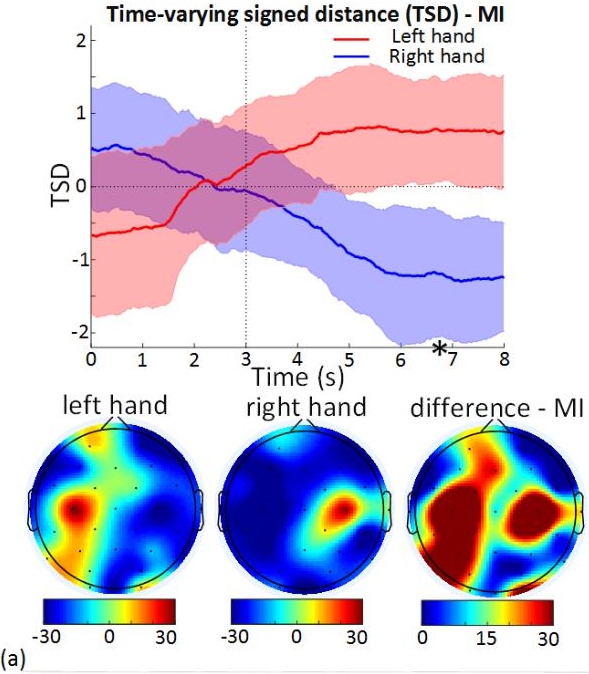
*: p < 0.05, **: p < 0.01, ***: p < 0.005

-: negative correlation

Is there a role for Emotion-inducing imagery?

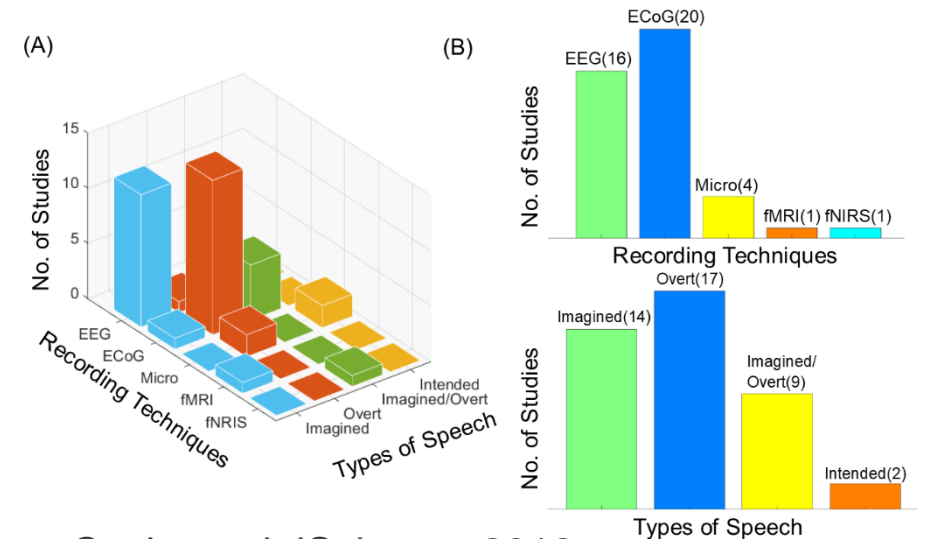
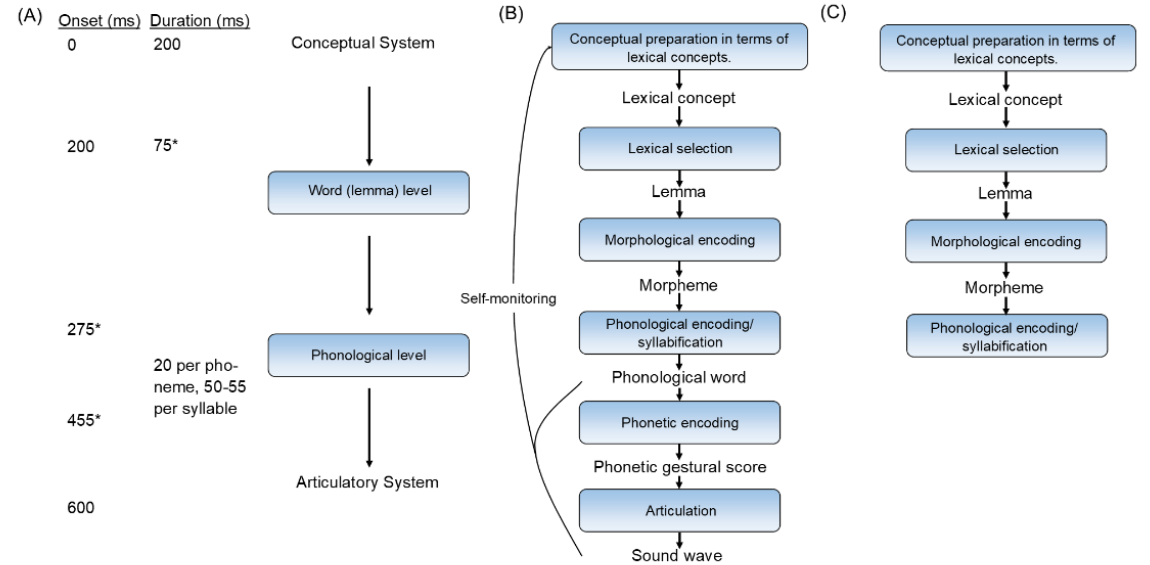
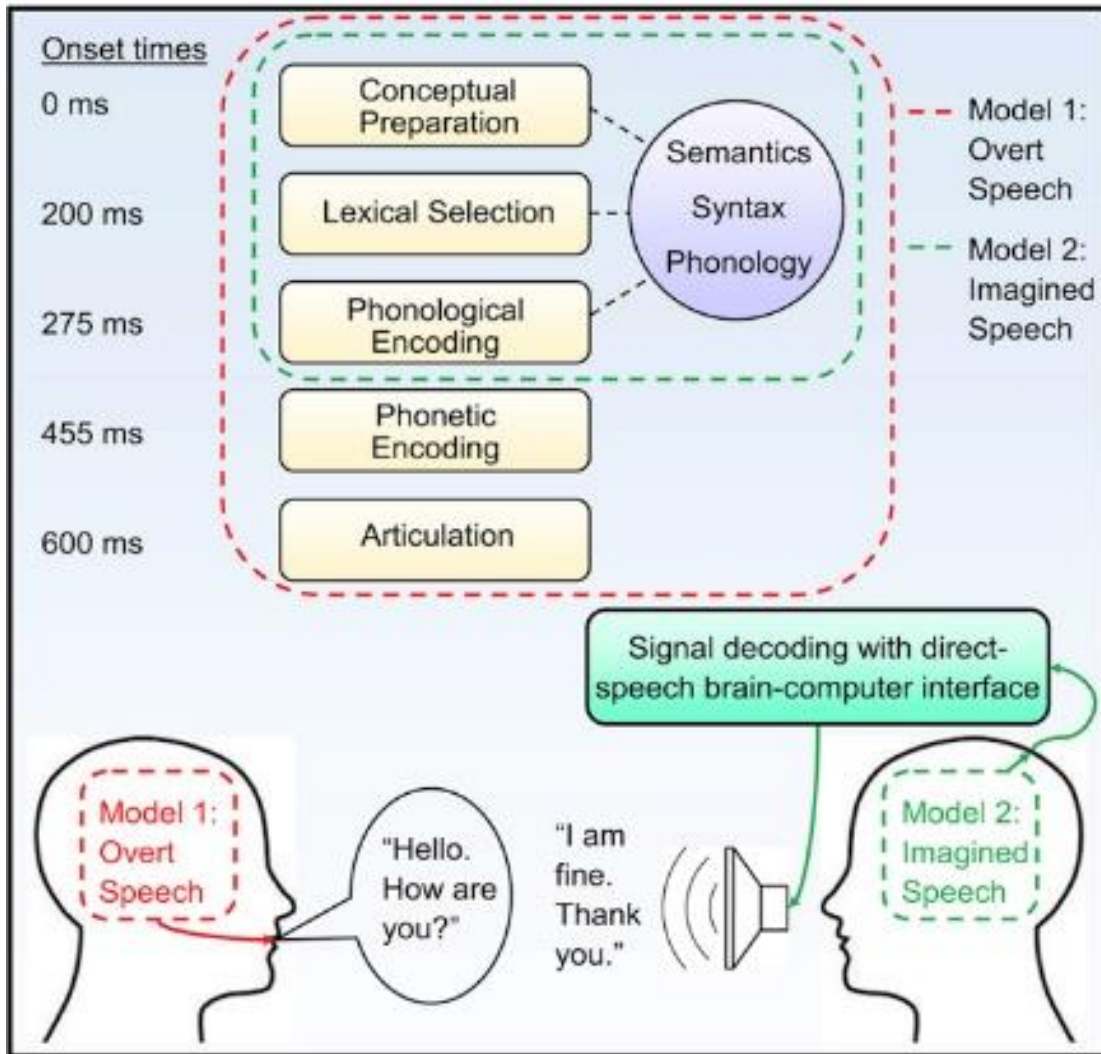
- Participant with better performance in MI

- Participant with better performance in EII



Imagined/Silent/Inner Speech for Direct-Speech BCIs

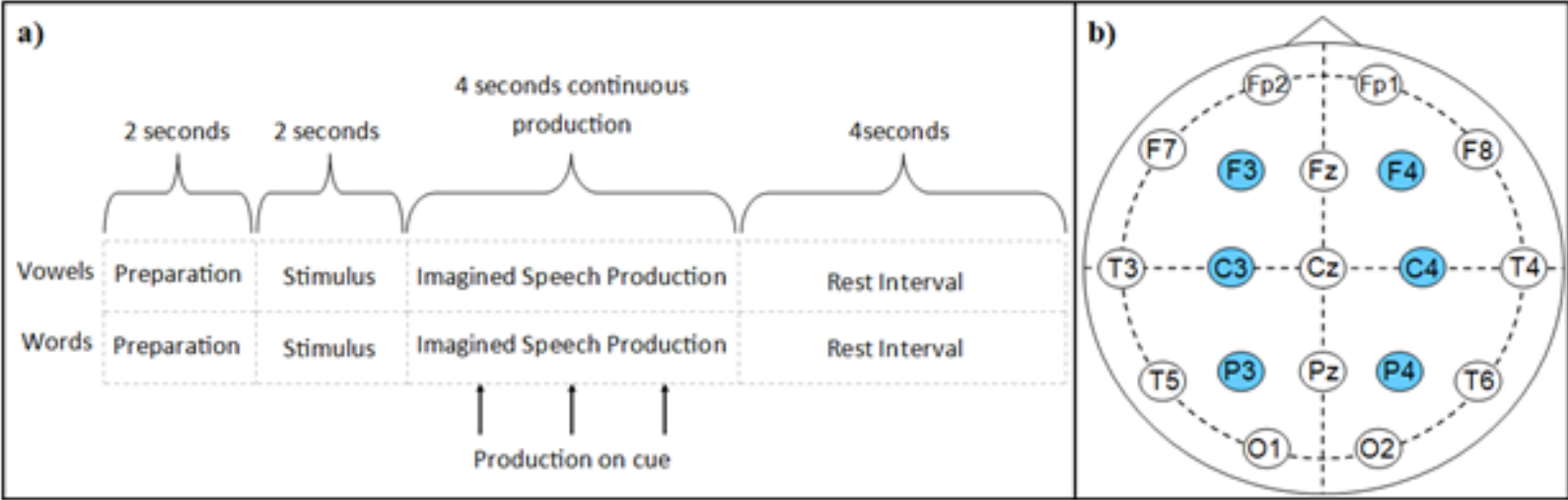
Imagined/silent speech BCI



- Cooney, Coyle et al, iScience, 2018

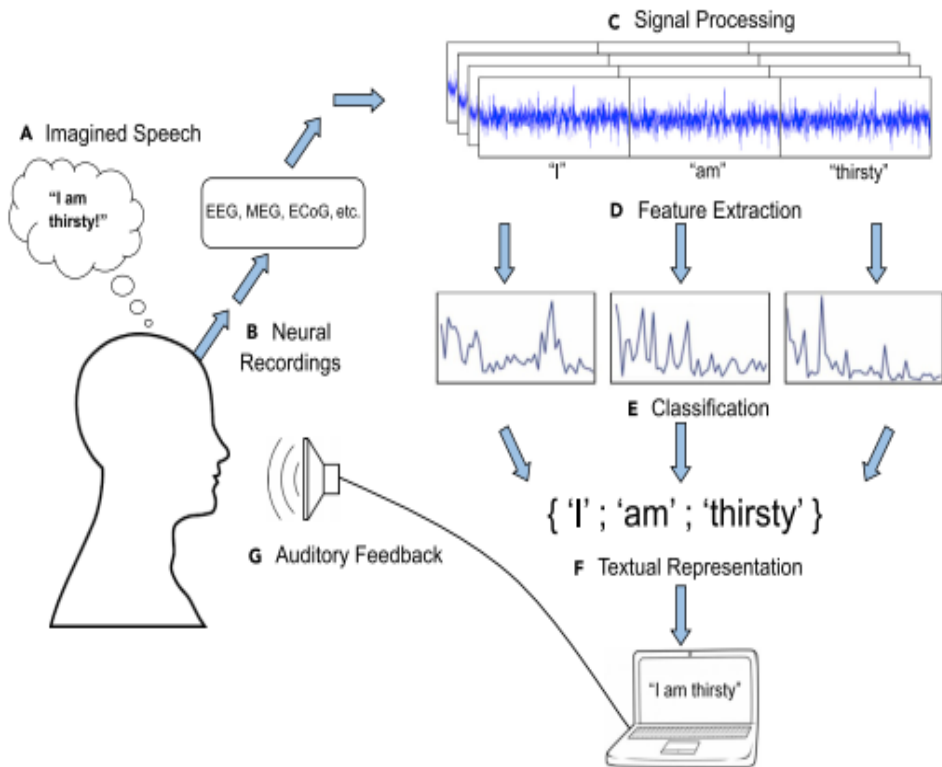
Imagined/silent speech BCI

Arriba, /a/
 Abajo, /e/
 Derecha, /i/
 Izquierda, /o/
 Adelante, /u/
 Atrás



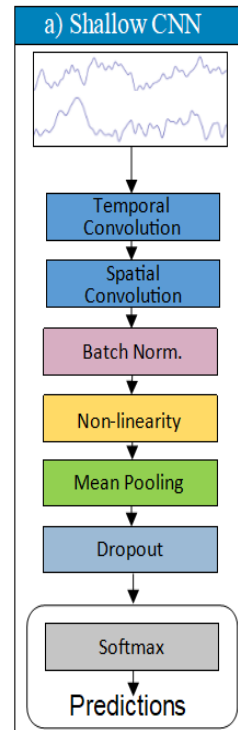
Imagined/silent speech BCI

- Machine Learning

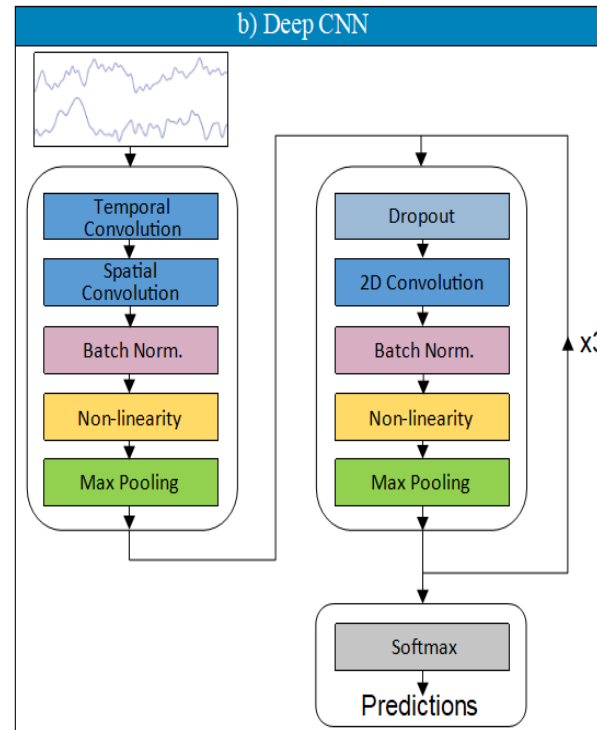


- Deep Learning

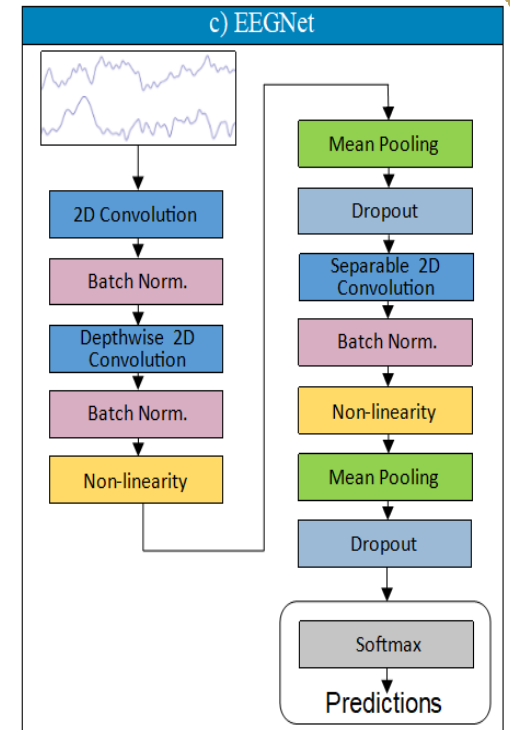
ShallowCNN



DeepCNN

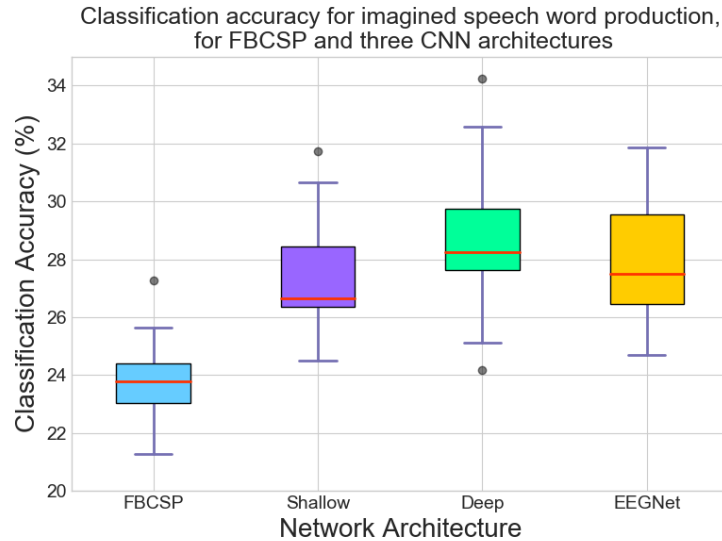


EEGNet

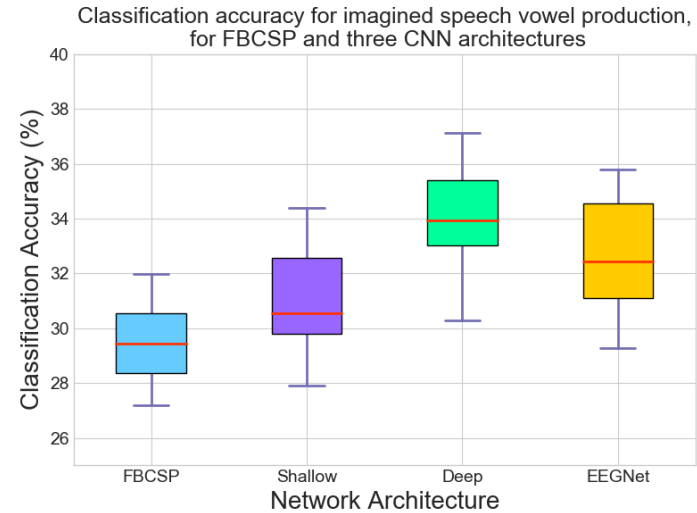


Deep learning for inner speech decoding

Arriba,
Abajo,
Derecha,
Izquierda,
Adelante,
Atrás



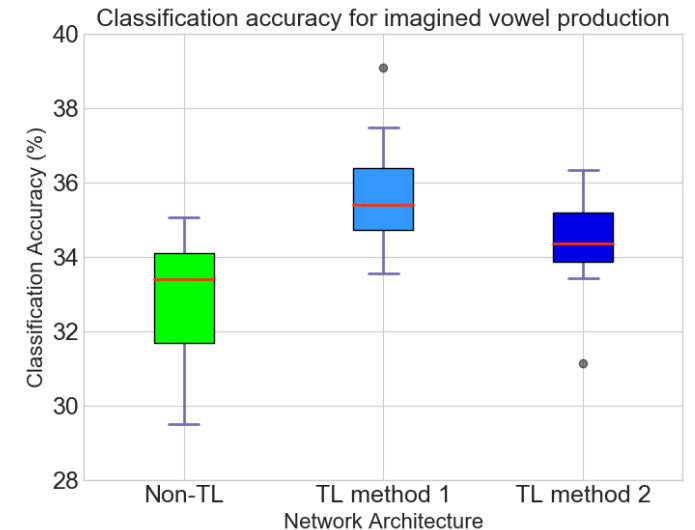
/a/
/e/
/i/
/o/
/u/



- Cooney, Coyle et al, 8th Graz BCI conf, 2019

Transfer Learning

TL1 fine tuning input layers
TL2 fine tuning output layers



- Cooney, Coyle et al, IEEE SMC, 2019 (to appear)

Hyperparameter optimization of CNNs

- relatively few studies applying any form of DL to the decoding of imagined speech from EEG
- still unclear whether or not DL methods provide consistent performance improvements over traditional ML approaches for EEG data.
- robust consideration of hyperparameter (HP) selection in EEG DL studies has been severely lacking
- almost 80% not mentioning HP searching at all
- 21% of all DL EEG studies which considered HP optimization, searching took the form of trial and error or grid-search for the majority.

Main hyperparameters

Activation function learning-rate, number of training epochs and loss function

- ELU – exponential linear unit - adds non-linearity to the network
- Square – Squaring non-linearity – simple squaring
- ReLU - Rectified Linear Units - adds non-linearity to the network
- Leaky ReLU - assigns a non-zero slope to the negative part of the function and adds sparsity to the network.

Learning-rate

- critical feature for training CNNs - too low = slow model convergence/ too high = divergence
- 0.001, 0.01, 0.1 and 1.0.

Number of epochs

- The number of iterations required for convergence of a CNN
- Optimum depends on architecture
- 20, 40, 60 and 80.

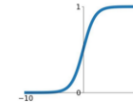
Loss functions

- NLL - negative log likelihood
- CE - cross entropy

Activation Functions

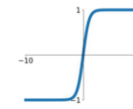
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



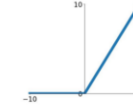
tanh

$$\tanh(x)$$



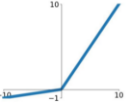
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

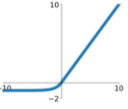


Maxout

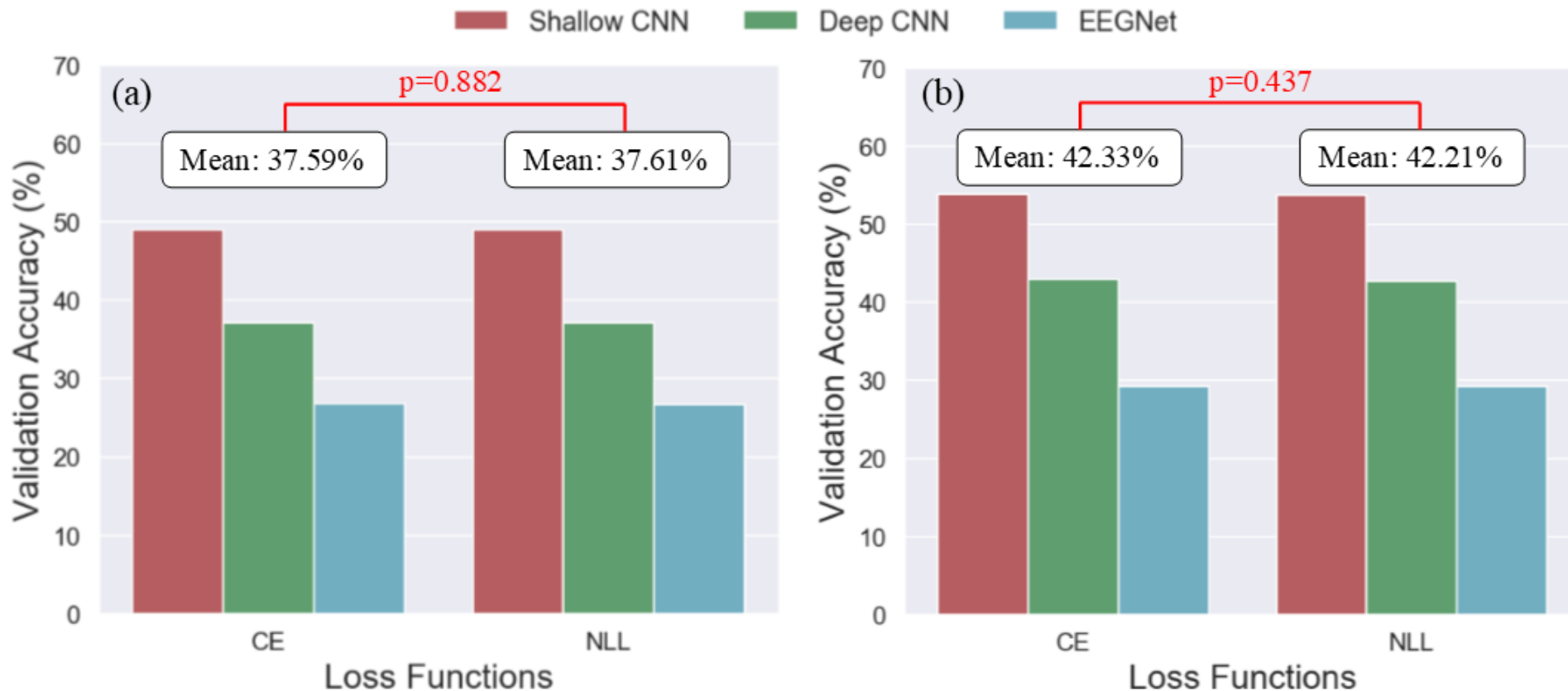
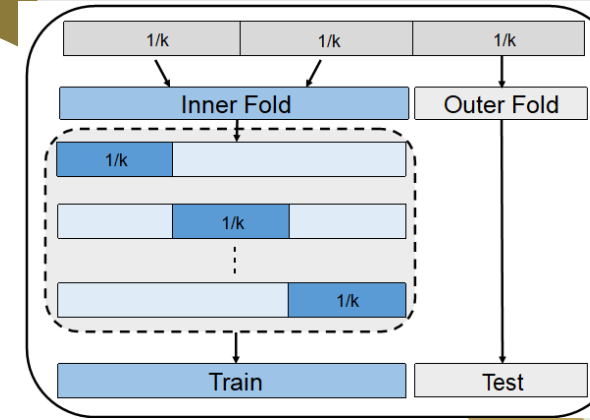
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

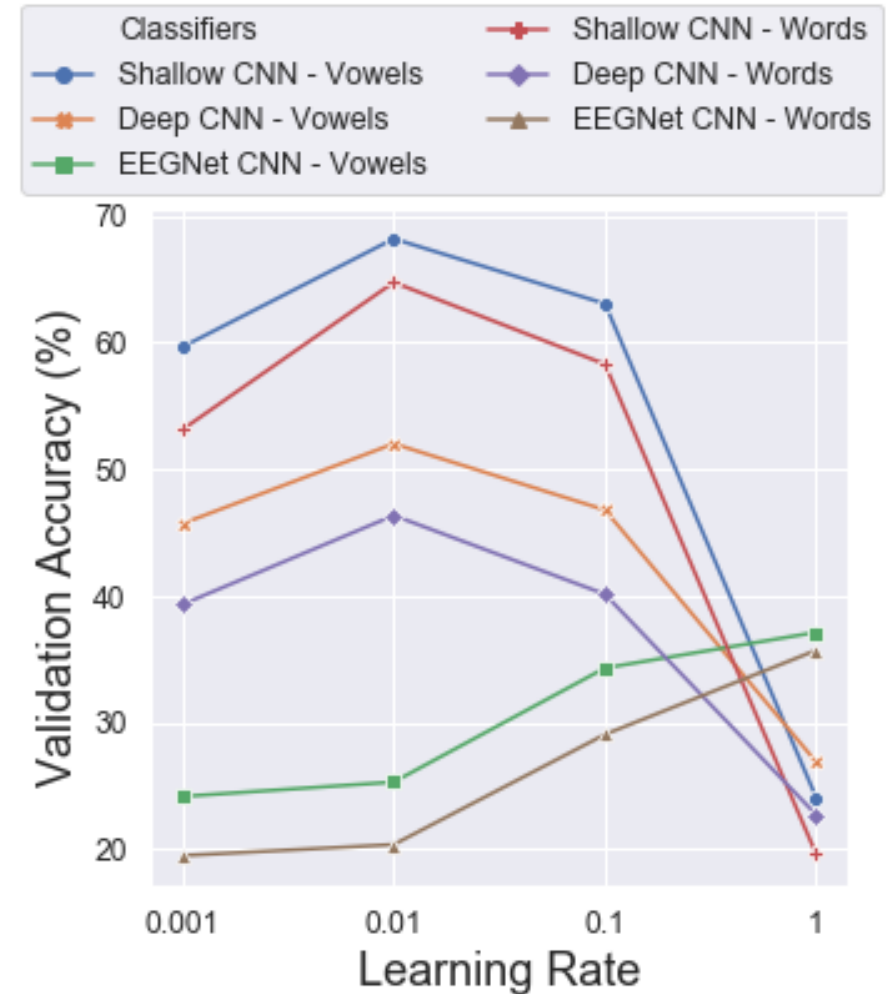
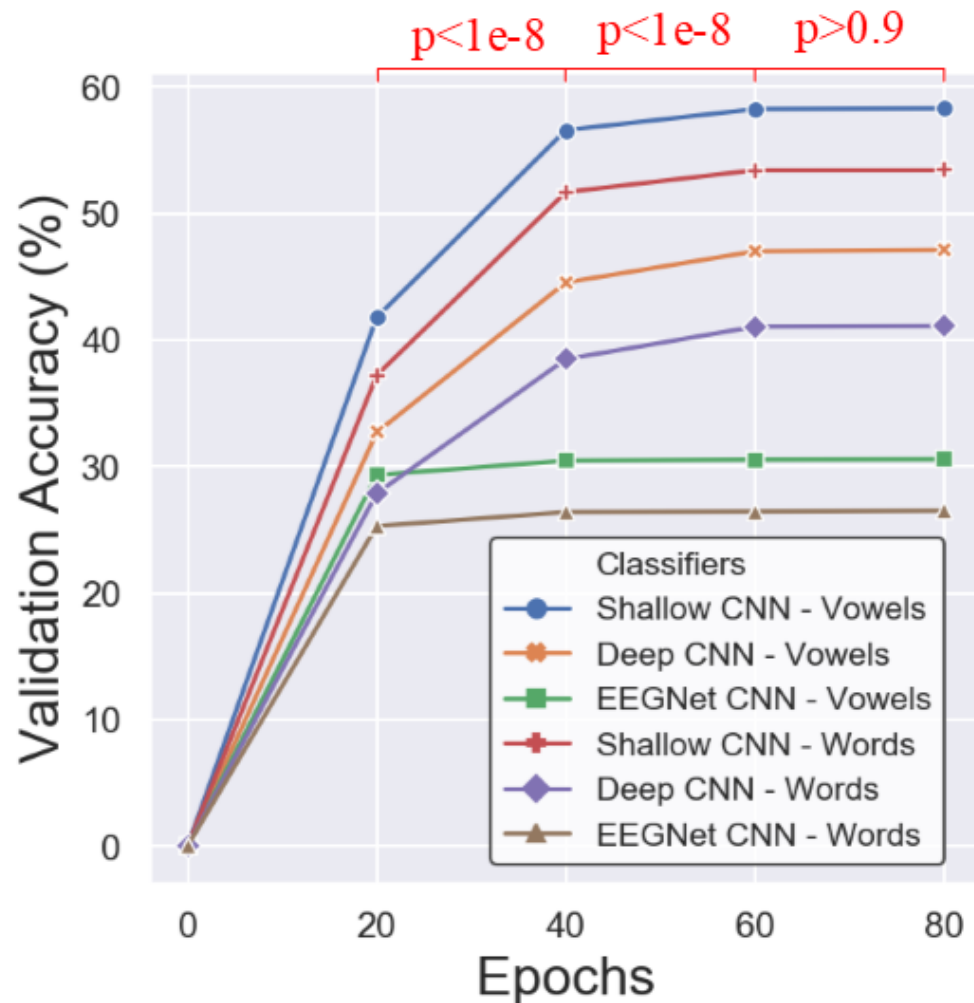
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



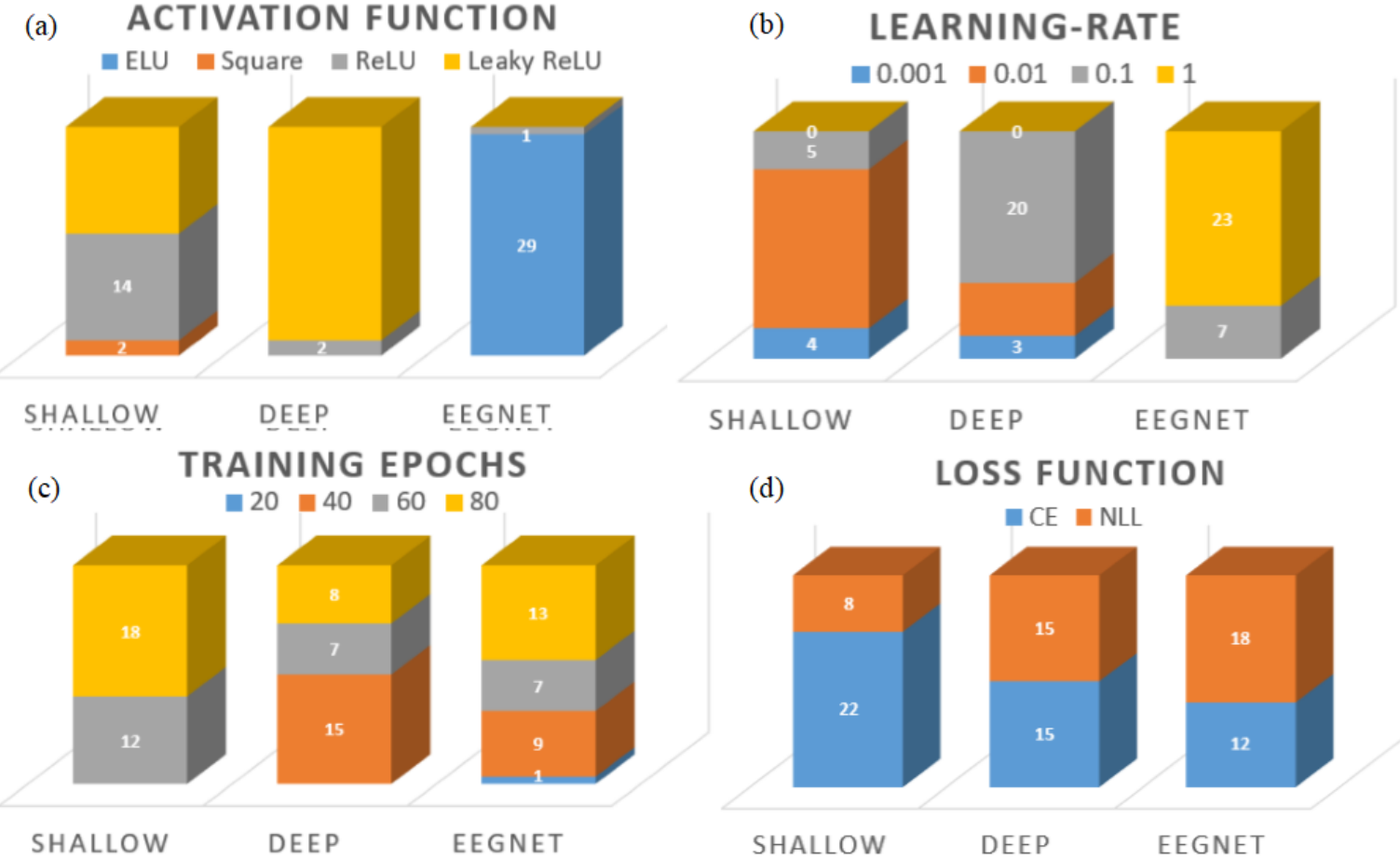
Mean inner-fold validation accuracy as a function of loss function. (a) imagined words. (b) Imagined vowels



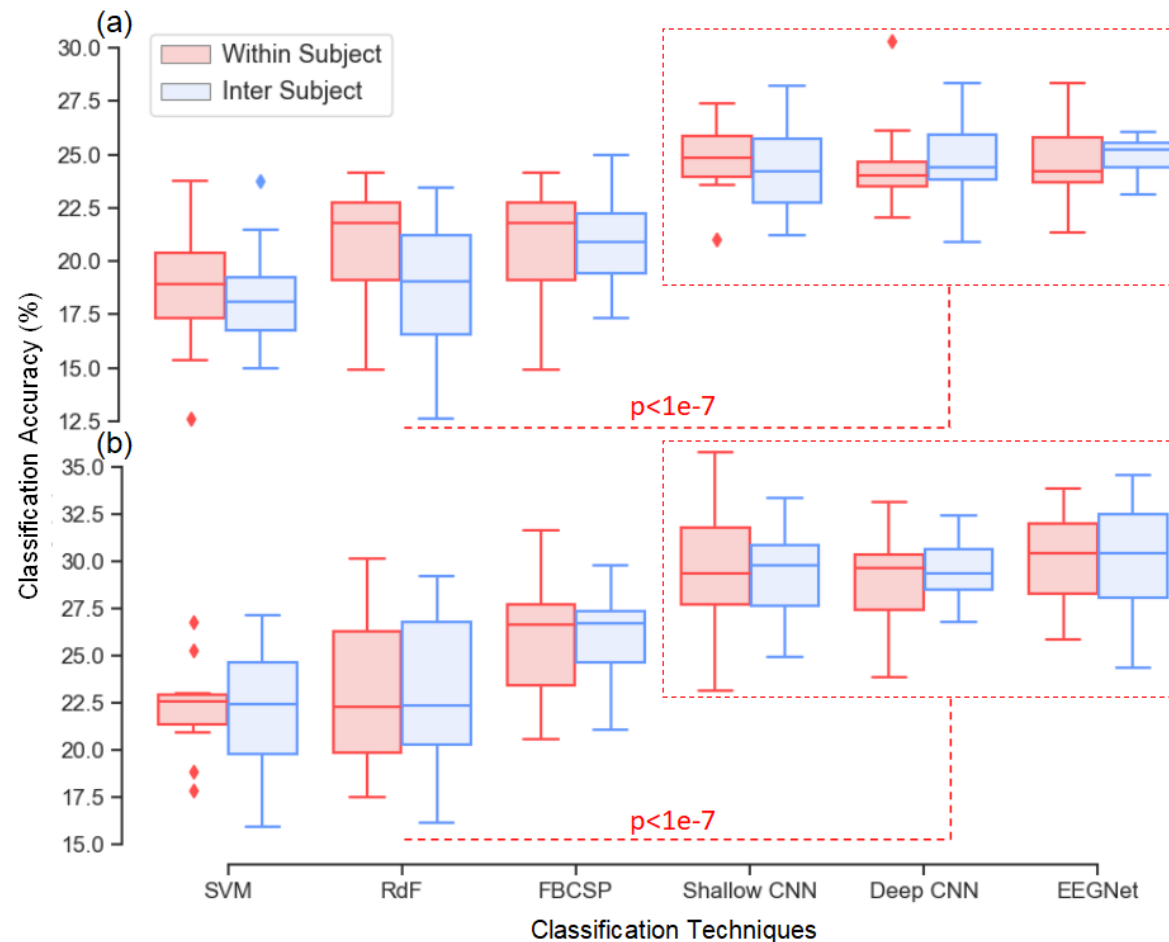
Accuracy as a function of training epochs and learning rate.



Distribution of hyperparameters selected for different CNN architectures.



Classification accuracies for (a) imagined words and (b) imagined vowels using intra- and inter-subject modes.



	Shallow CNN		Deep CNN		EEGNet	
	Words	Vowels	Words	Vowels	Words	Vowels
Activation Function	leaky	leaky	leaky	leaky	ELU	ELU
Learning Rate	0.1	0.1	0.1	0.1	1	1
Epochs	60	60	60	60	80	80
Loss	CE	NLL	CE	CE	NLL	NLL

- Cooney, Coyle et al, (submitted)

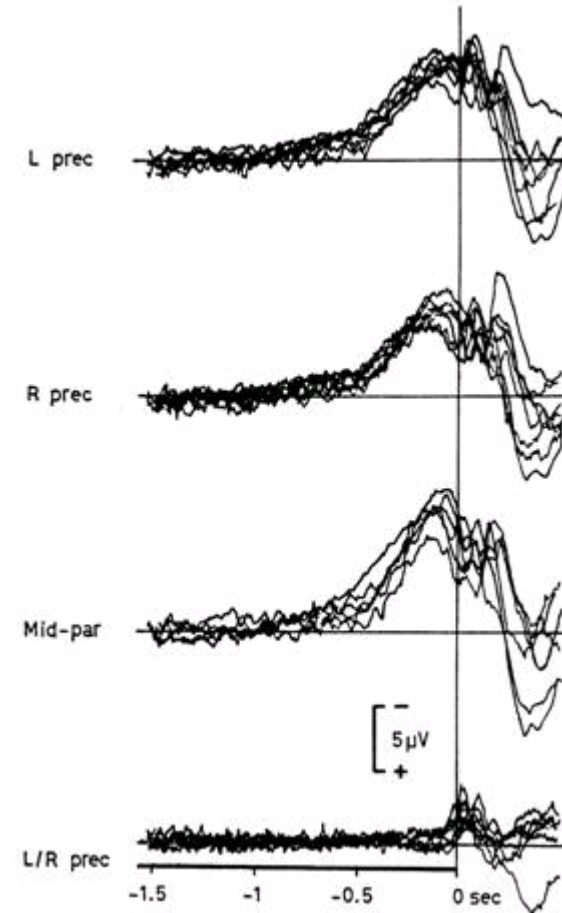
Applying CNNs

- CNNs outperform traditional machine learning for this dataset
- Model and parameter selection across subjects does not significantly impact performance
- Hyperparameters optimisation has a massive impact (learning rate and activation function)
- Different architectures require different parameters
- 6 channel dataset/single session – very limited
- Ongoing study of imagined speech - 64 channels + 8 fNIRS

Other types of BCIs

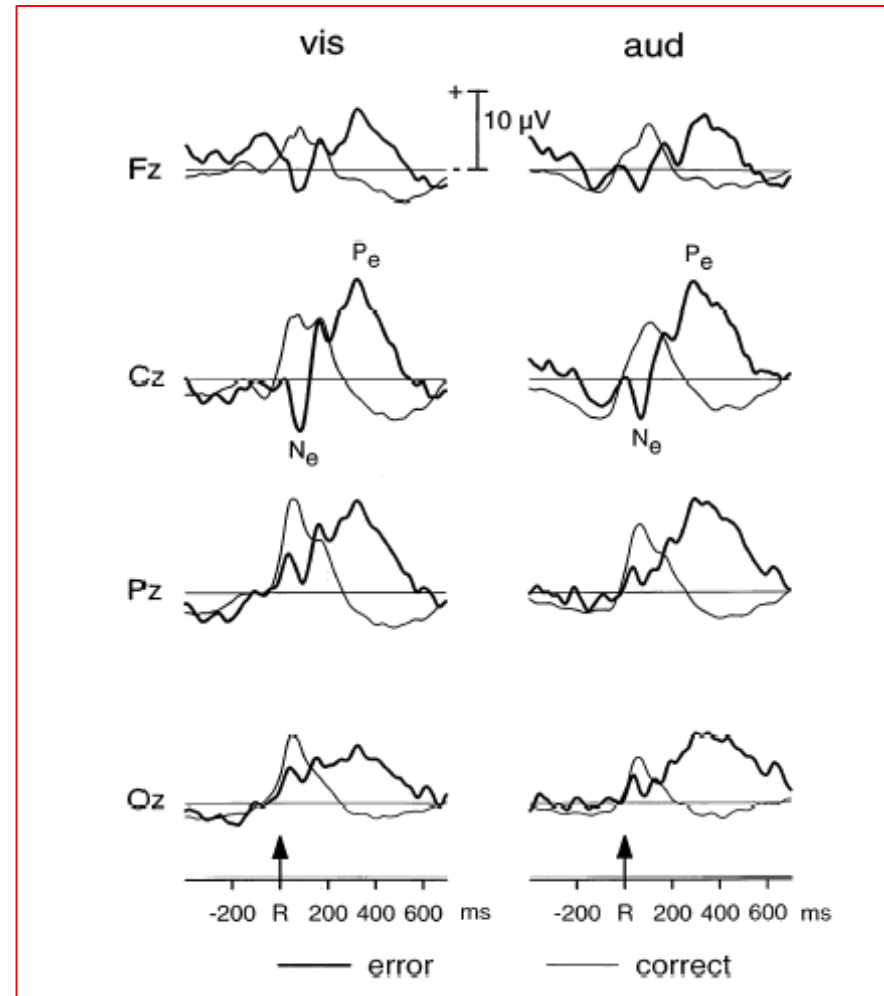
Rapid reaction

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



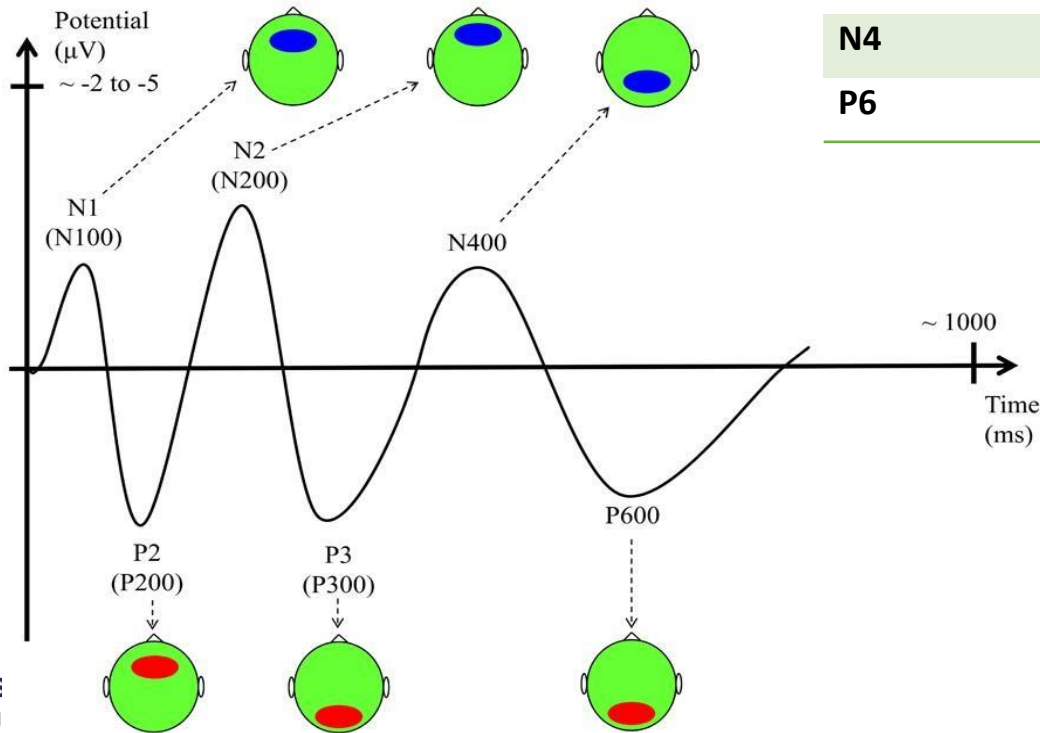
Rapid error correction

- 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.



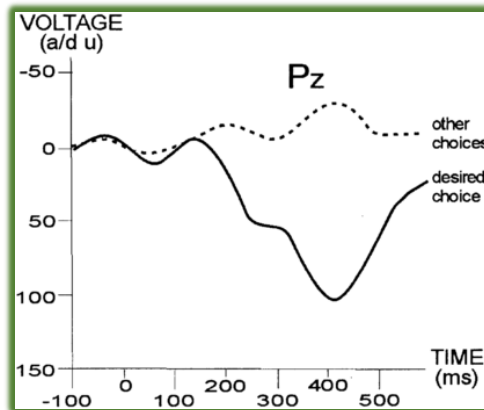
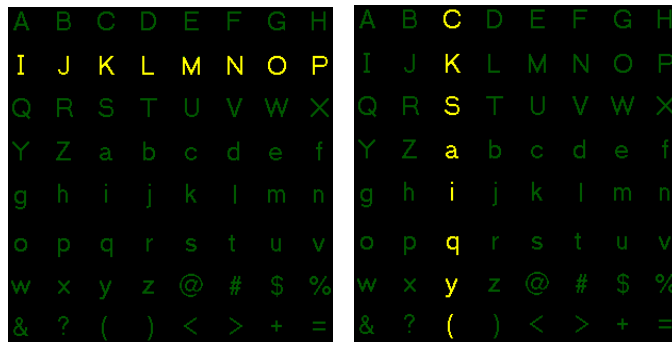
Visual evoked potentials

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

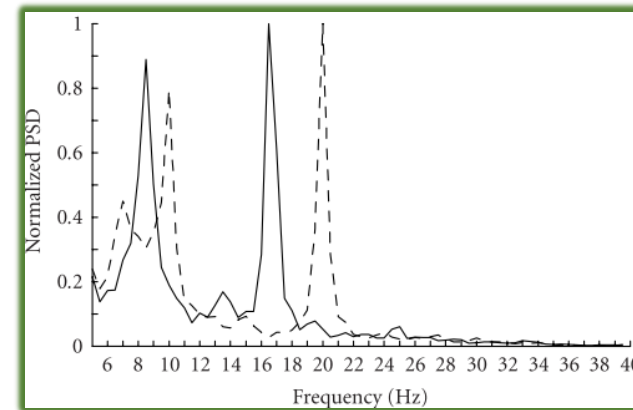


Visuals evoked potentials

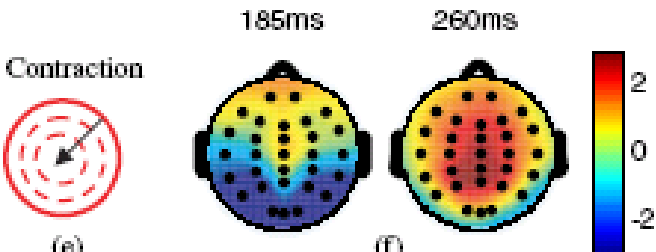
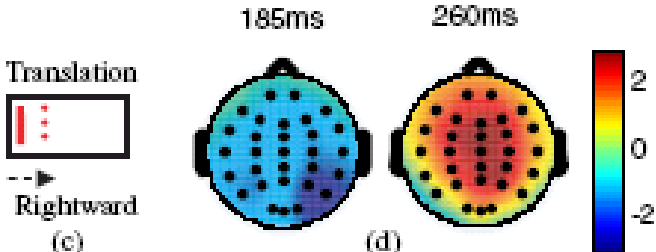
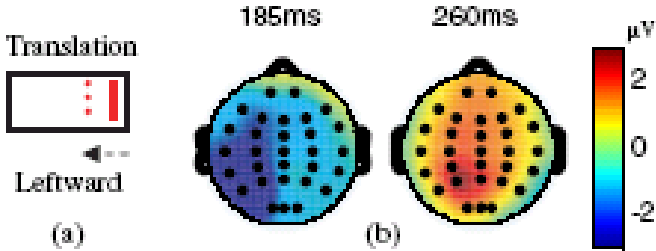
- P300 speller



- Steady-state VEP



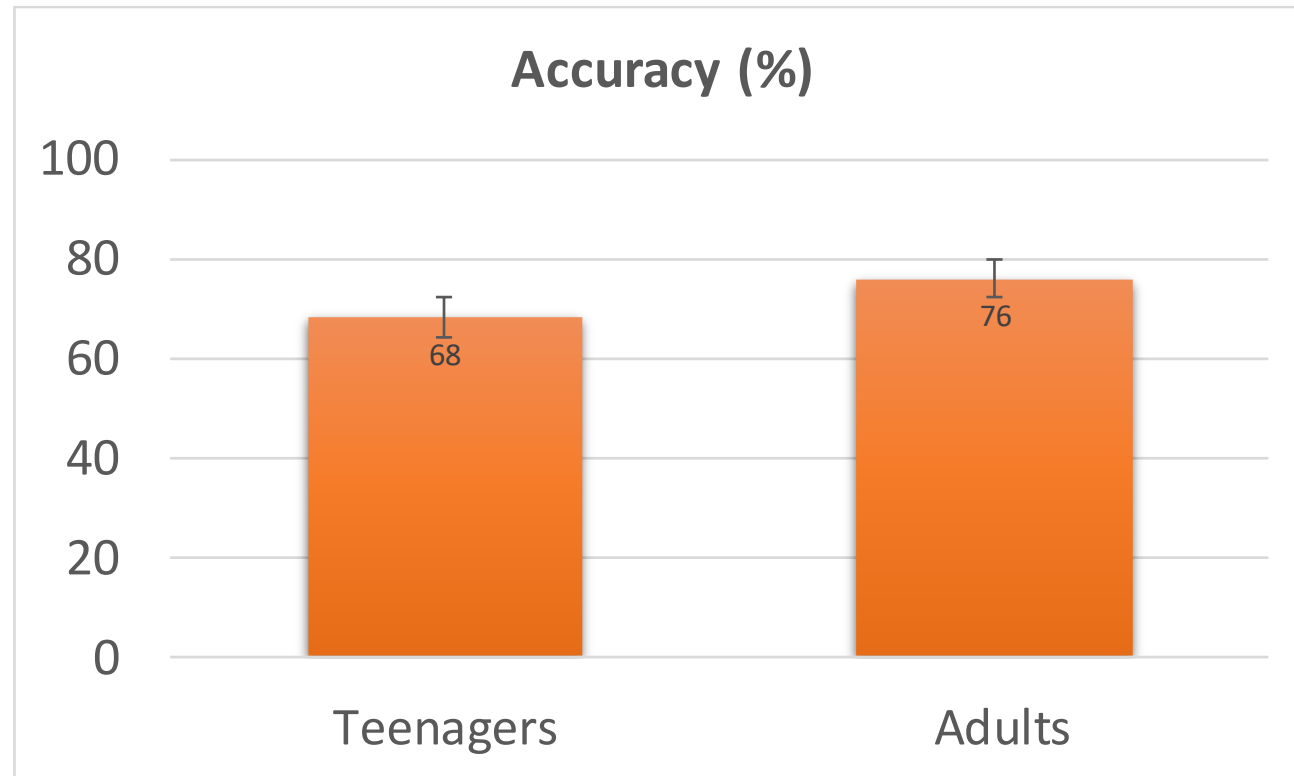
Motion onset visual evoked potentials (VEP)



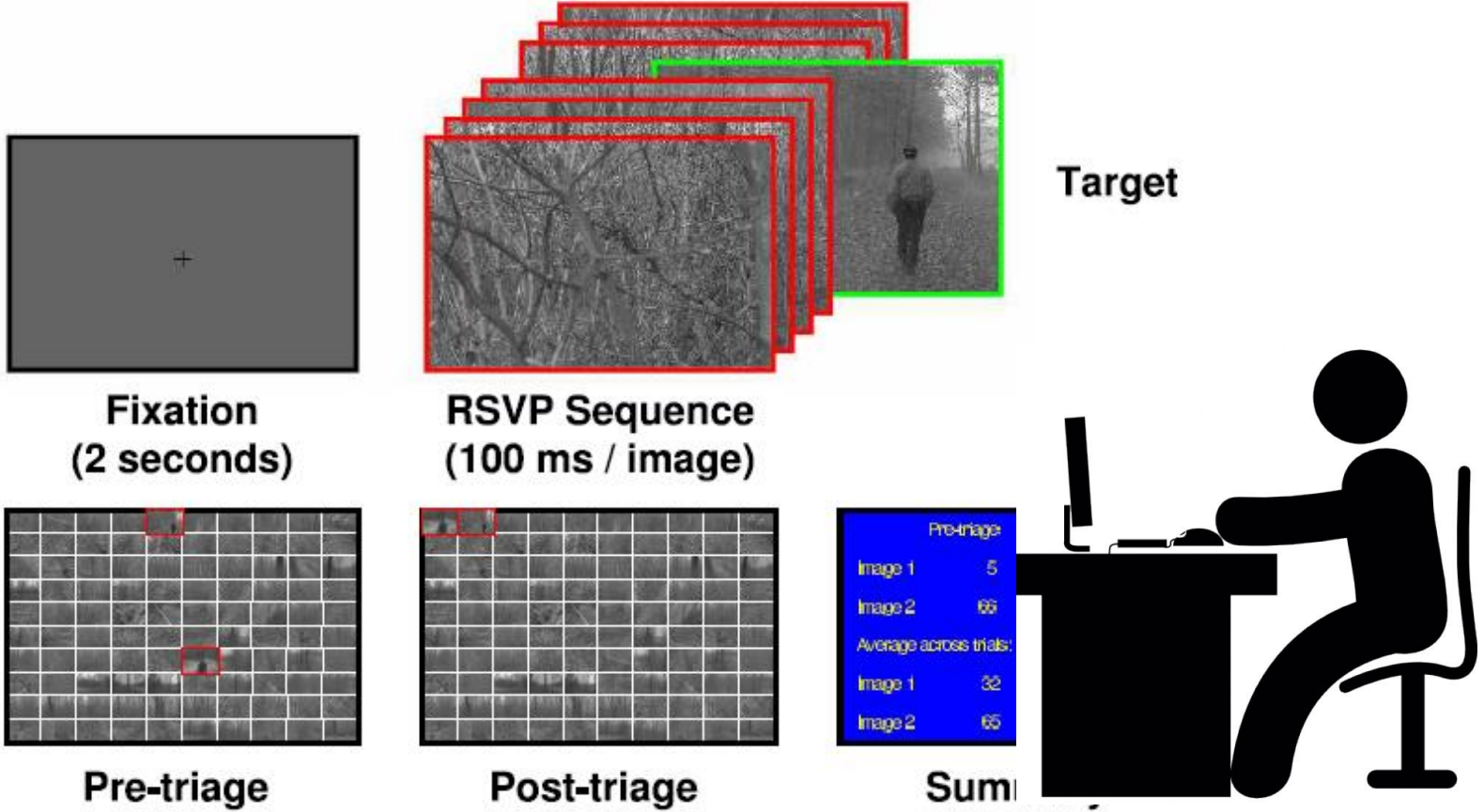
Car racing with mVEP



Adults vs Teenager



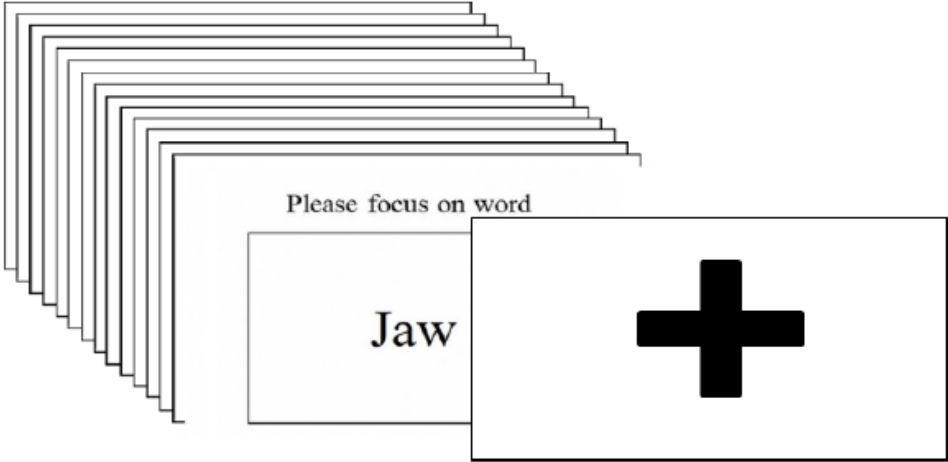
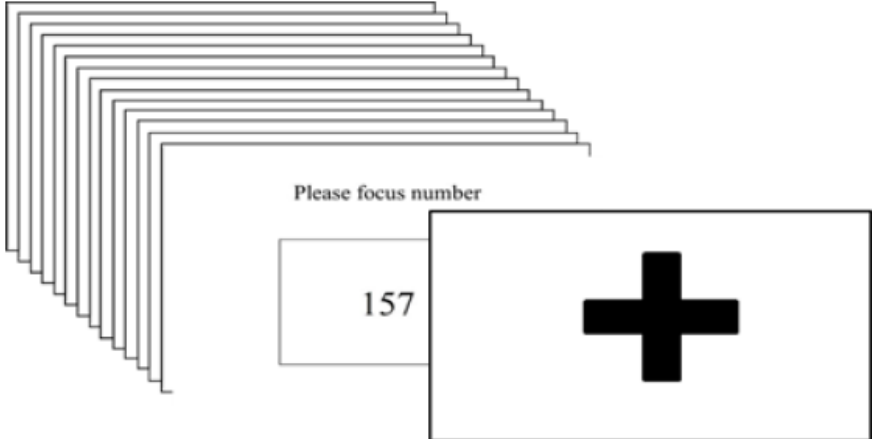
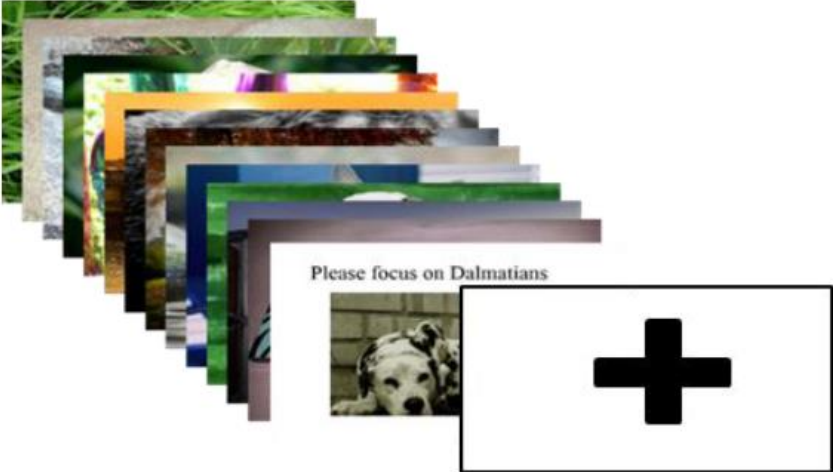
Human Machine Symbiosis



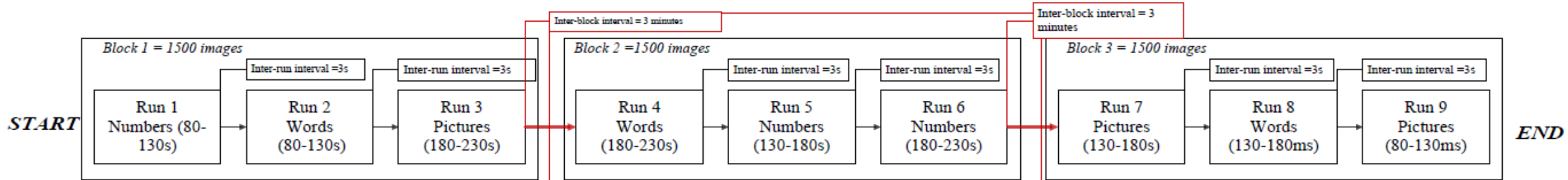
RSVP Applications

- Face recognition
- Categorization
- Surveillance – counter intelligence
- Medical image sorting – clinical diagnosis
- **Assessing human performance in decision making under uncertainty**
- **Data analytics and data labelling**
- **Human machine cooperation in sorting challenging datasets – unstructured/unlabelled**

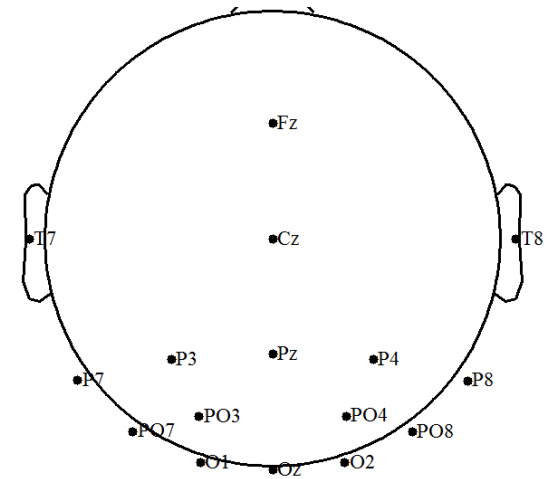
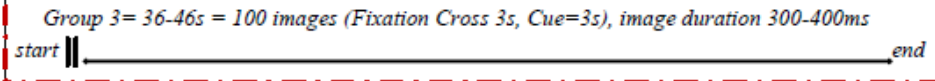
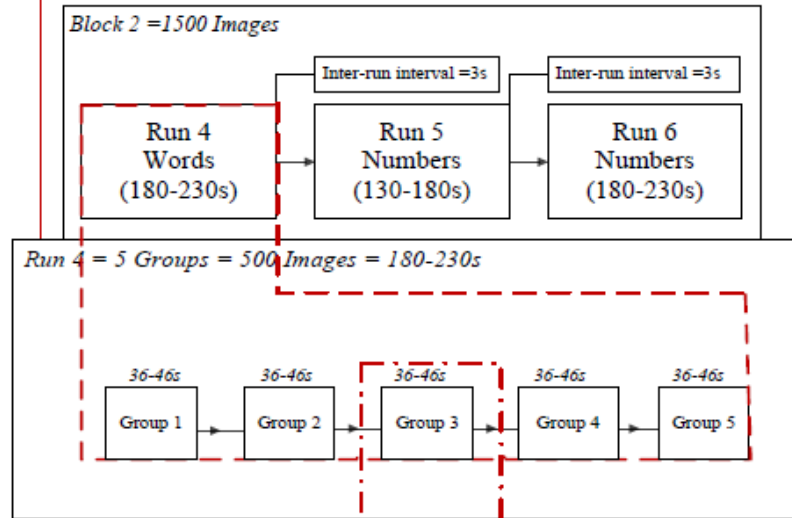
Data analytics/Image triage



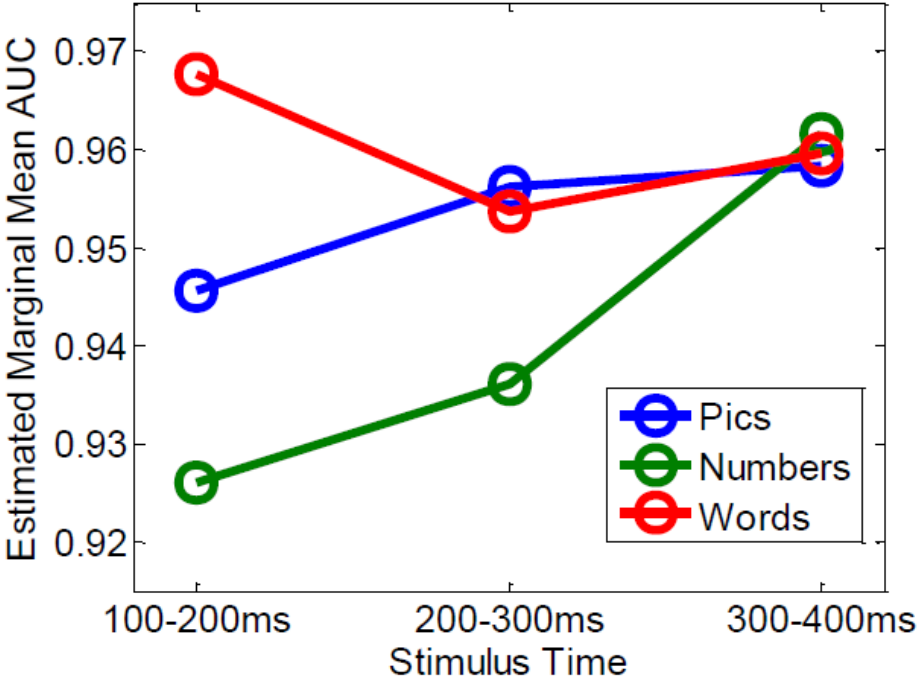
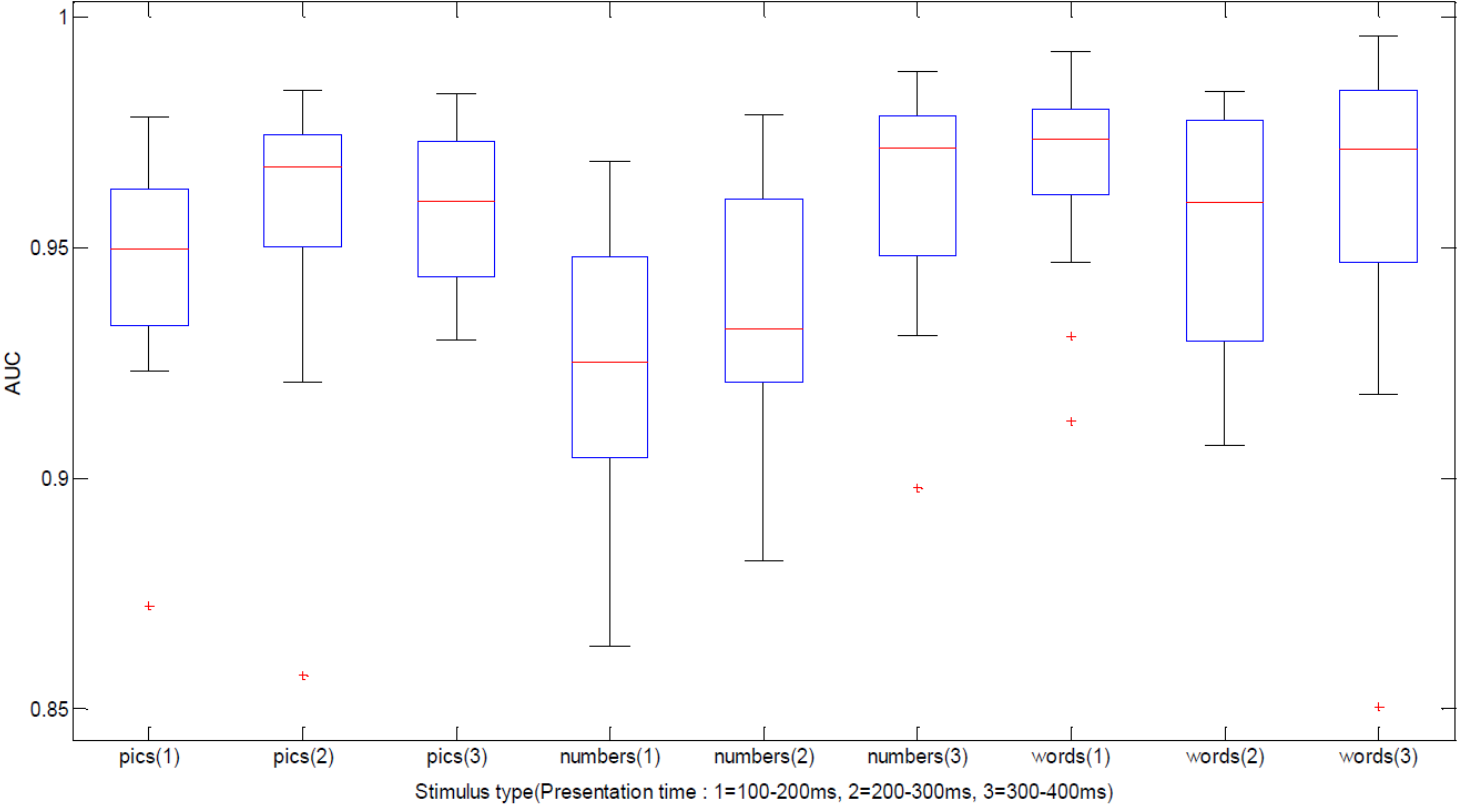
Paradigm



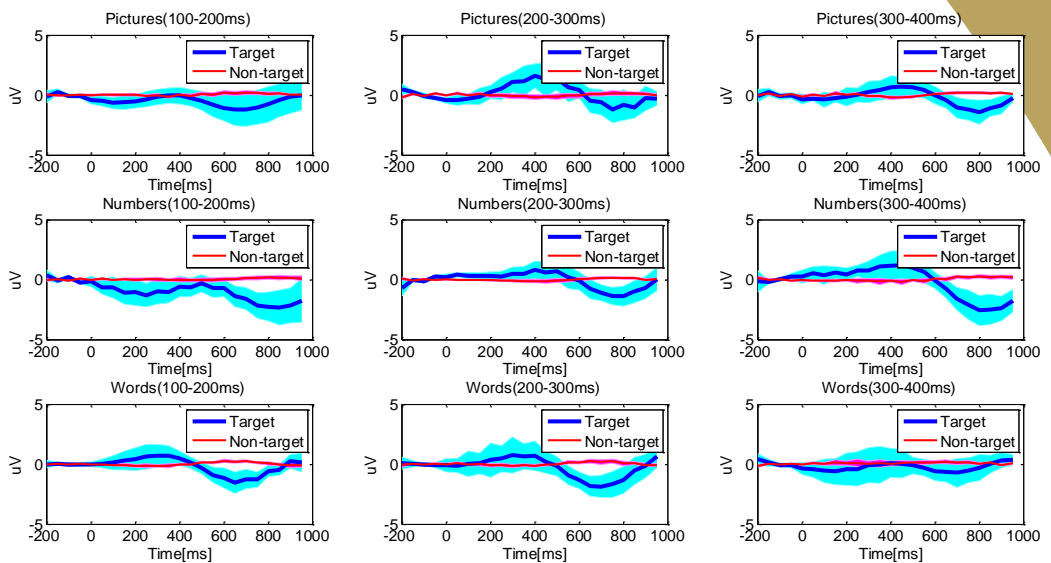
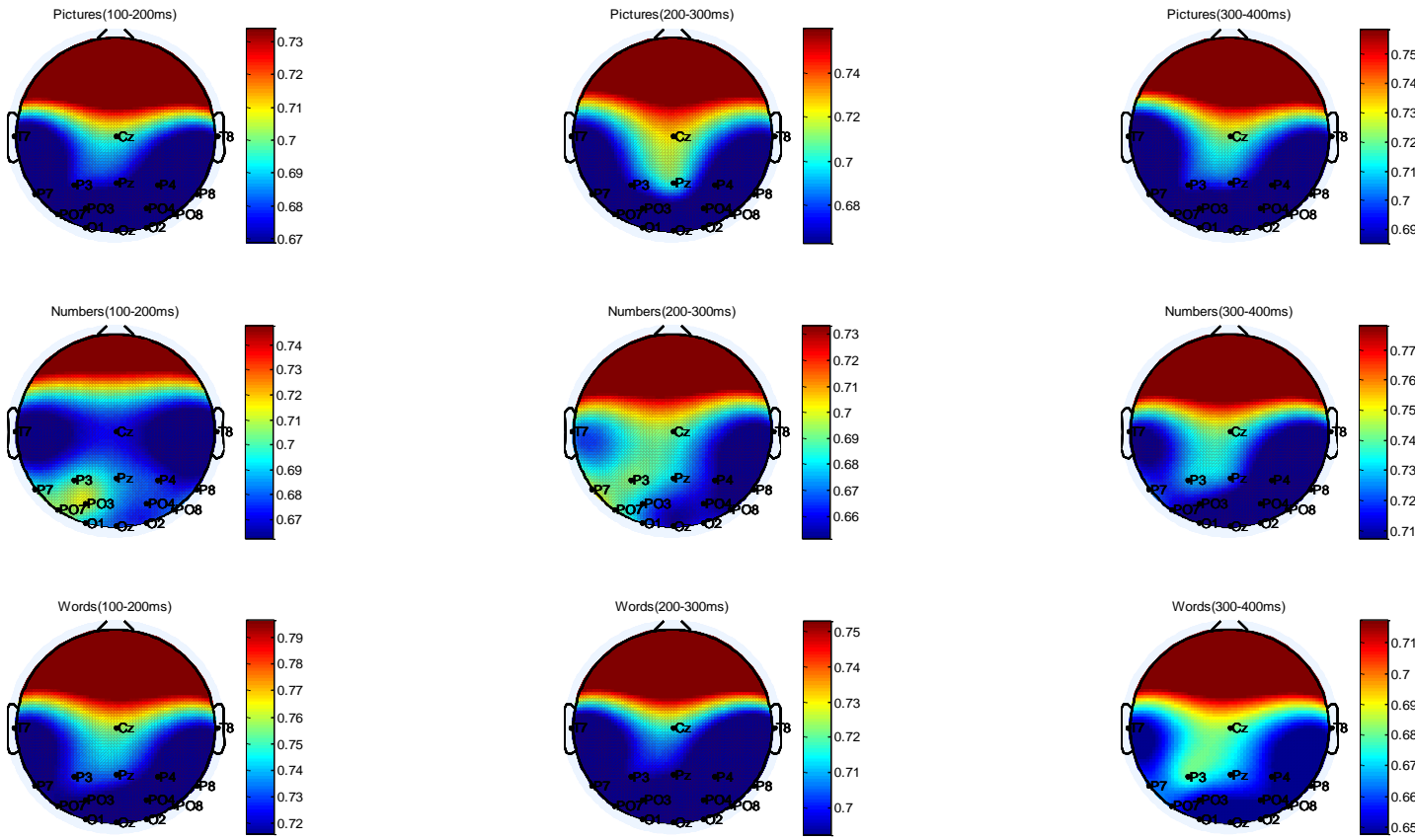
	Run1	Run 2	Run 3
Block 1	Word (300-400ms)	Picture (300-400ms)	Number (300-400ms)
Block 2	Number (100-200ms)	Word (200-300ms)	Picture (100-200ms)
Block 3	Picture (200-300ms)	Number (200-300ms)	Word (100-200ms)



Numbers are more difficult to detect at faster rates



Number are processed differently



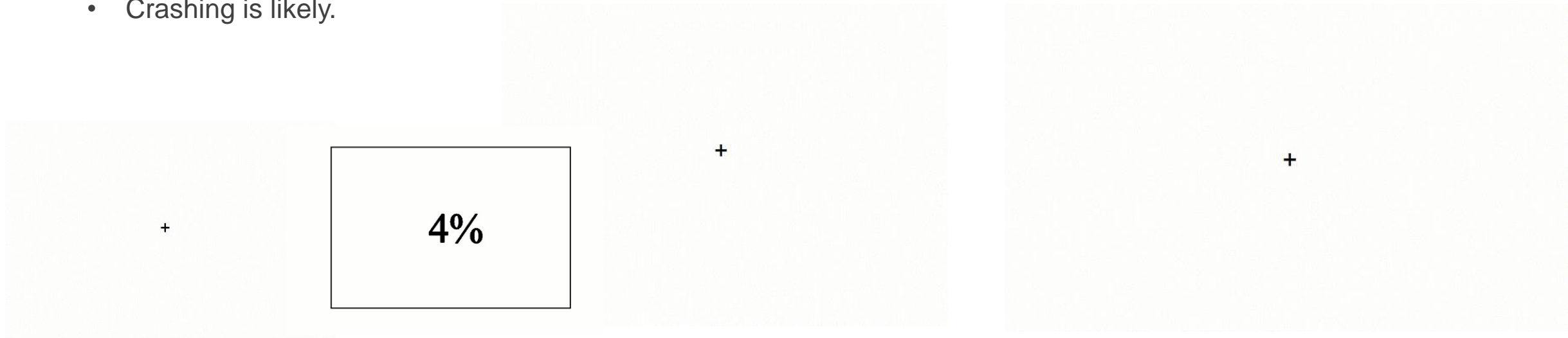
RSVP summary

- *Pictures, numbers and words* could be detected at fast presentation rates, up to 10Hz with high accuracy.
- Numbers are more challenging at faster rates
- RSVP paradigms for data analytics should bare this in mind
- First step in developing RSVP-BCI for image triage using different 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**

Uncertainty and rapid decision making

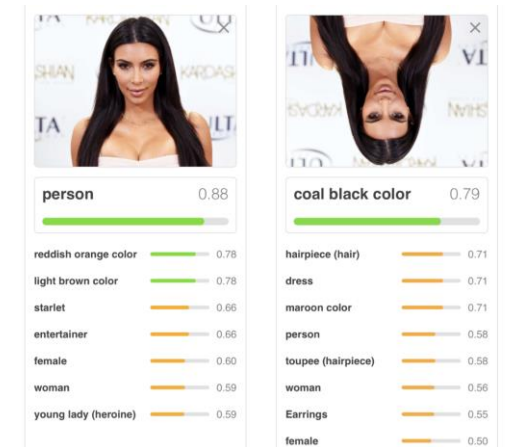
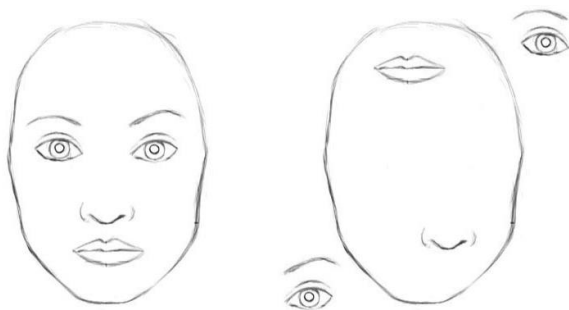
- **Quantitative indirect**
- There is a fifty-five percent chance of crashing
- **Quantitative direct**
- 55%
- **Qualitative**
- Crashing is likely.

Qualitative Statement	Associated Probability Range
highly unlikely	<10%
Unlikely	15-20%
Realistic Possibility	25-50%
Likely	55-70%
Highly likely	75-80%
Almost Certain	>90%



When deep learning fails

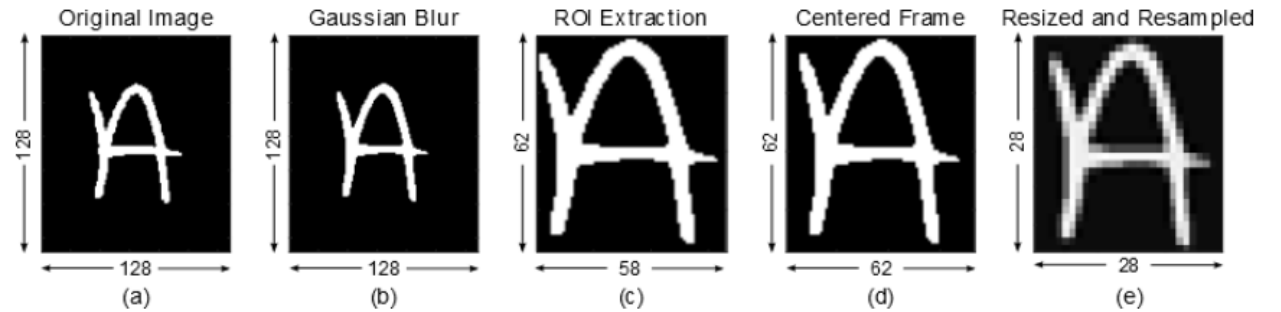
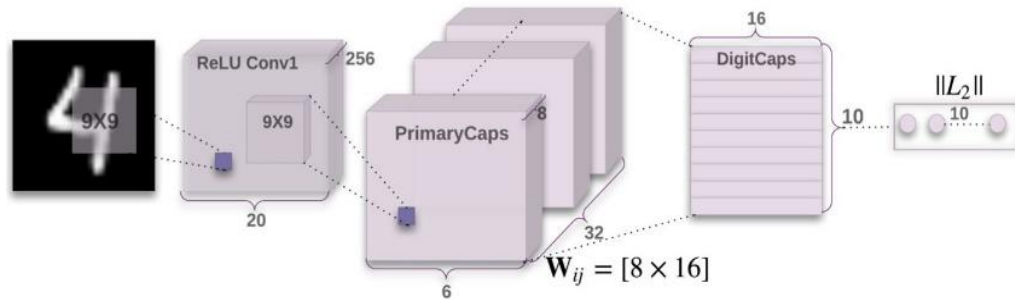
- Problem with Convolutional neural network
- CNNs does not take into account important spatial information between parts and the whole so instead of **invariance** we should be attempting **equivariance**:
- Example: Presence of eyes, mouth and nose may be identified as a face in CNNs!!



RSVP-BCI vs Capsule Neural Network

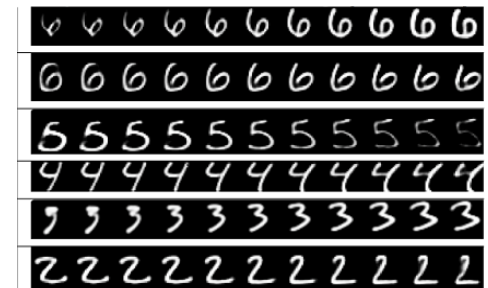
Human&Machine vs Machine

- MNIST and EMNIST image Dataset



- **Hinton:** “The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.”
- **Capsule Networks:**
 - The traditional max-pooling process is replaced by “Routing by Agreement”
 - Equivariance keeps track of where something is in the image
 - Robust to affine transformations

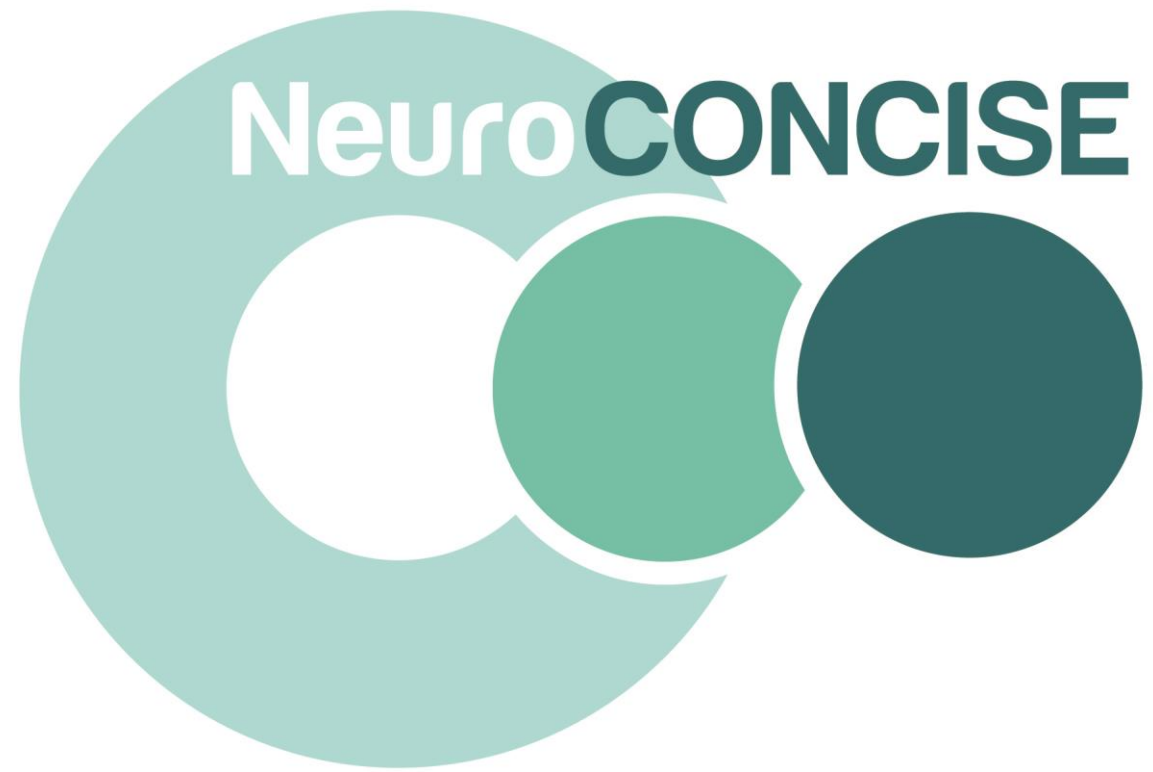
Name	Classes	No. Training	No. Testing	Validation	Total
Complete	62	697,932	116,323	No	814,255
Merge	47	697,932	116,323	No	814,255
Balanced	47	112,800	18,800	Yes	131,600
Digits	10	240,000	40,000	Yes	280,000
Letters	37	88,800	14,800	Yes	103,600
MNIST	10	60,000	10,000	Yes	70,000

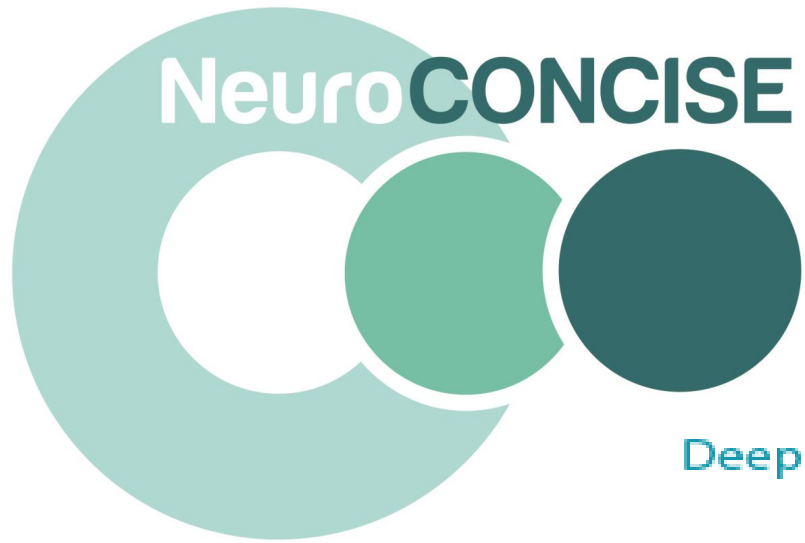


Emotions and affective states

- Fatigue
- Mood
- Stress
- Anxiety
- Joy



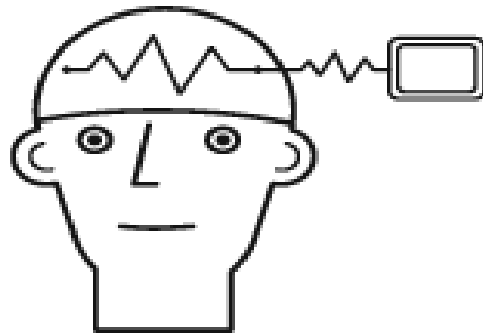
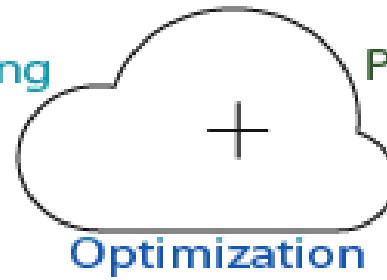




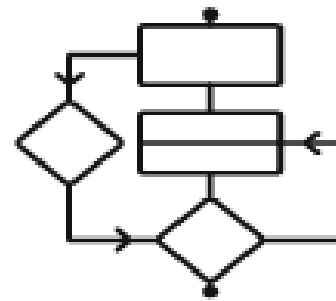
Big Brain Data Cloud

Deep learning

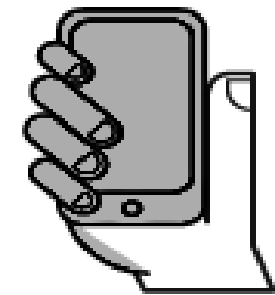
Player analytics



Hardware

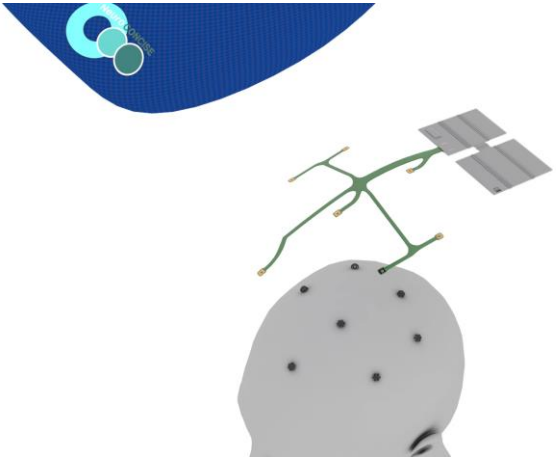


Algorithms



User App/Games

FlexEEG



FlexEEG



NeuroCONCISE - FlexEEG



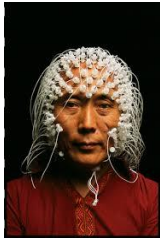
Emotiv



gTec - g.Nautilus



Neurosky - Thinkgear



Electrical Geodesics Inc



Cognionics



Ant Neuro



Enobio



OpenBCI



Interaxon Muse



EasyCap



Wearable sensing



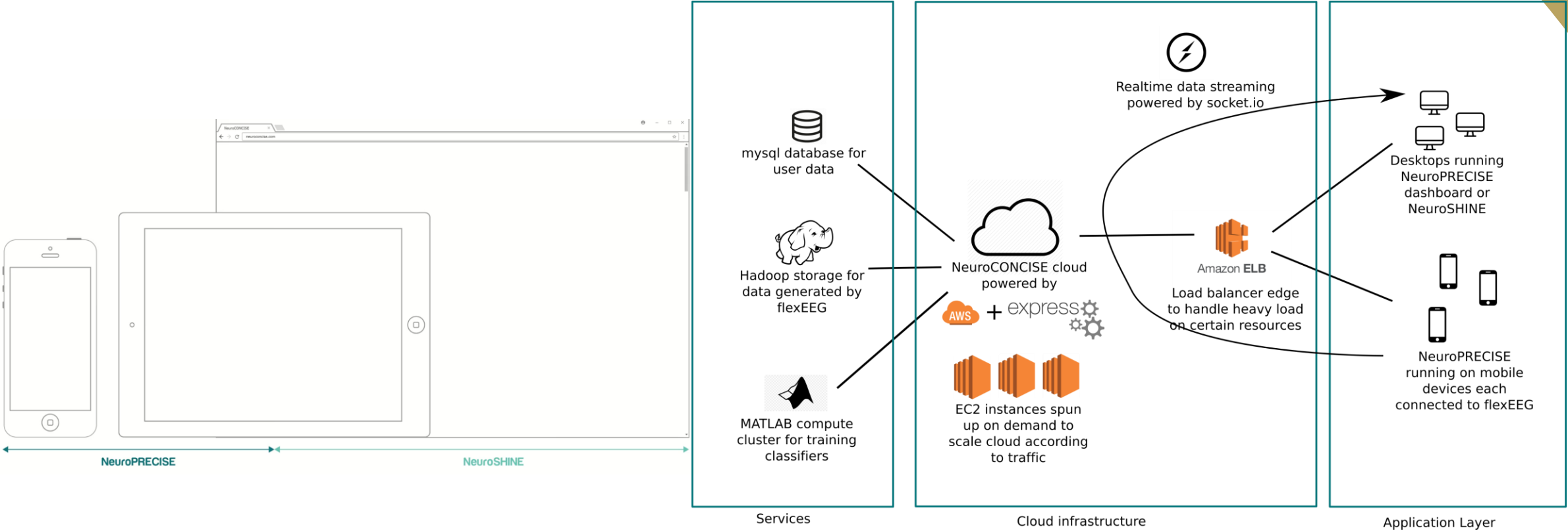
Brain Products



BrainwaveBank

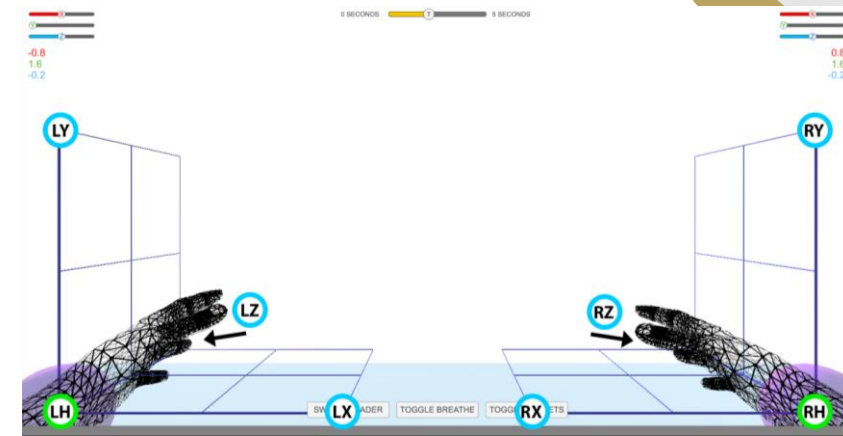
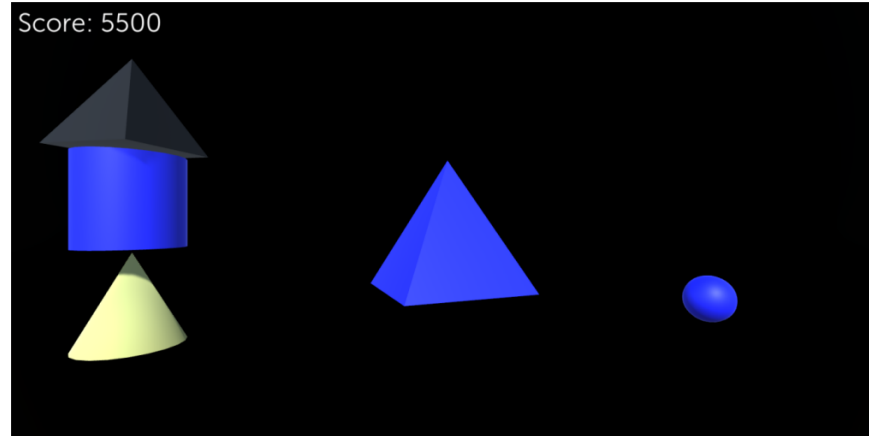


NeuroPrecise & EncepHaloCloud

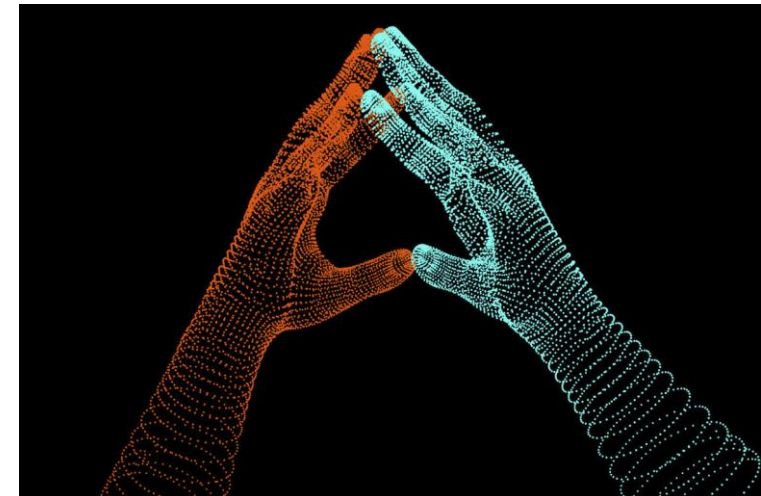


Better paradigm – Virtual/Augmented Reality and Games

2D Monitor



Augmented reality

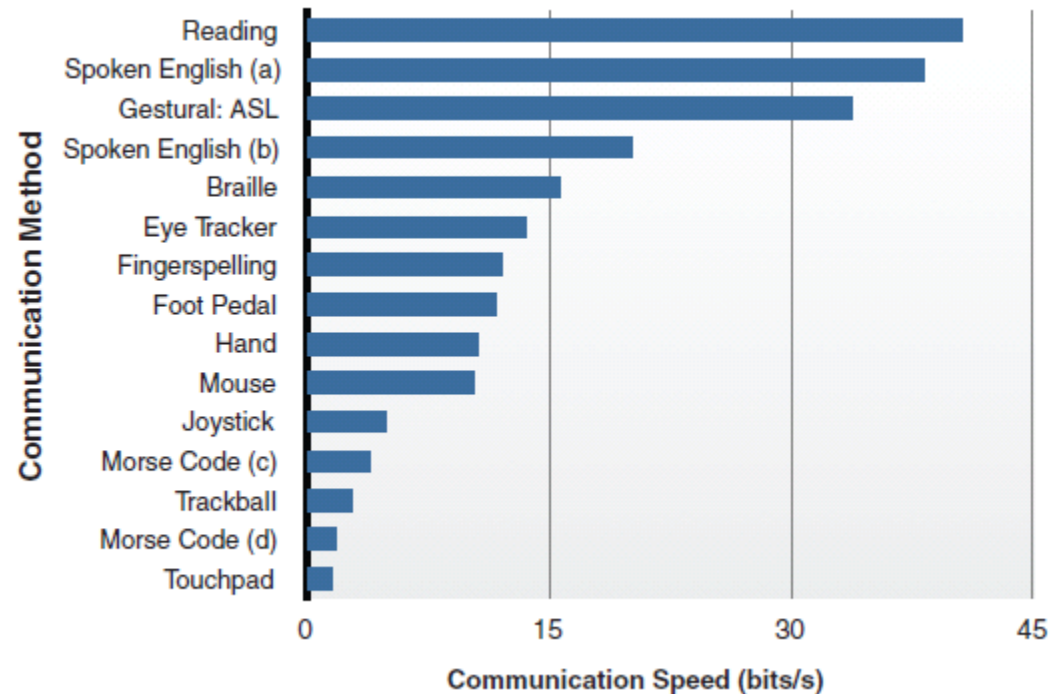


Challenges

- 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

Killer app for BCI

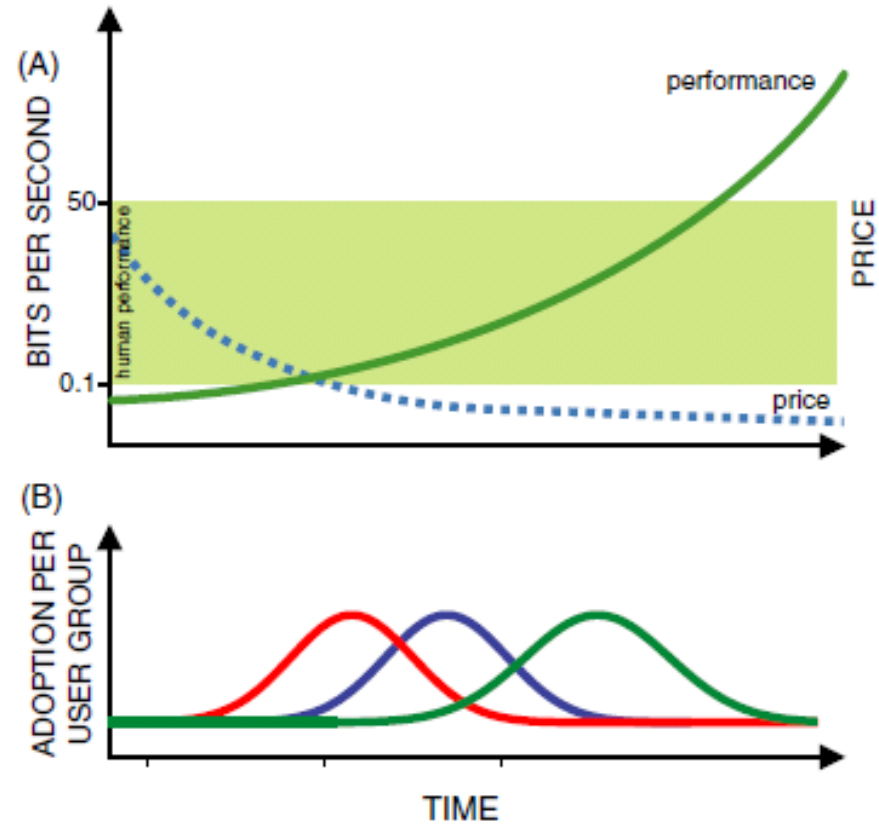
- Clinical utility is clear
- The brain twitter interface?
- First person shooter game?
- AR/VR hybrid
- Blockchain – cloud minds?
- Rapid reaction and human enhancement?



Driving forces

- 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

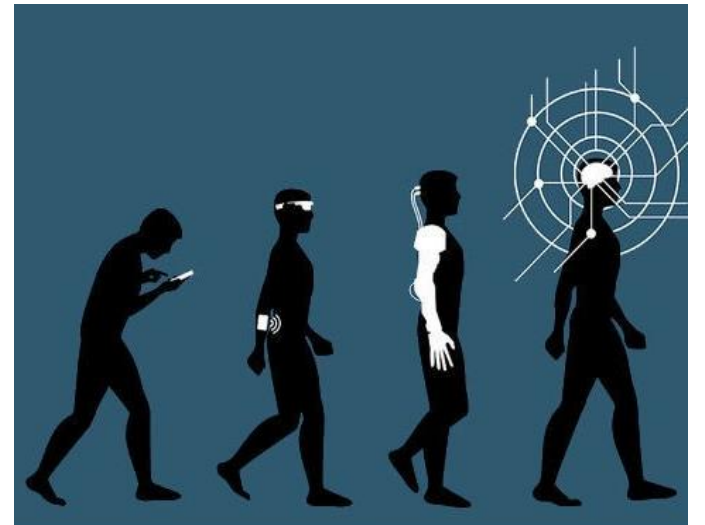
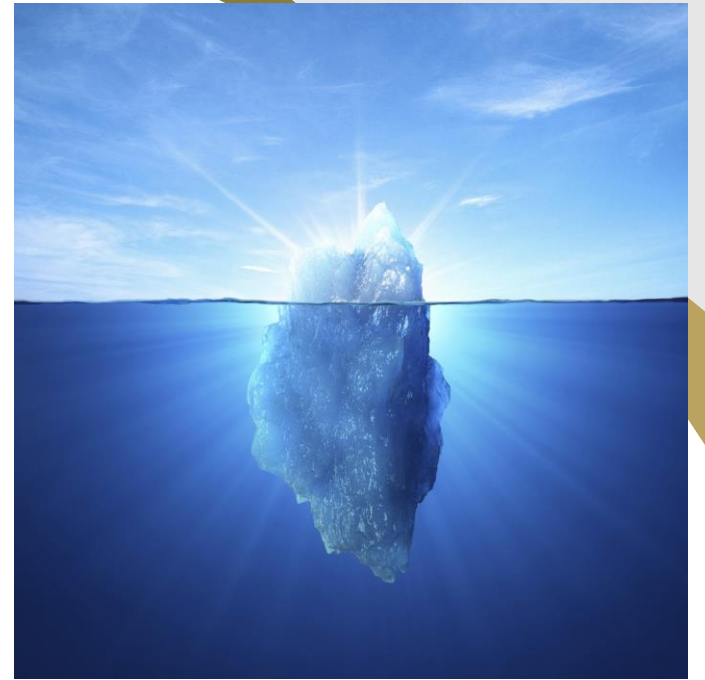
Technology diffusion



Conclusion

Management, Modelling & Collaboration

- Brain–computer interface use is a skill that user and system acquire together
- Man-machine learning dilemma requires time
- Continual adaptation and learning
- 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

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