Non-invasive Brain-Computer Interfaces: Enhancing Applicability using Computational Intelligence and Technological Advances

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Presentation outline

- State-of-the-art non-stationary BCI
- R&D challenges
- CI approaches to handling challenges
- EEG-based post-stroke neuro-rehabilitation
- MEG-based Post-stroke neuro-rehabilitation
- Conclusions and further R&D challenges

Background

- Brain-computer Interface - a direct communication pathway between a human brain and a computer.
- Mainly useful for patients suffering from motor impairments: world-wide about 20M annual stroke sufferers; approx. 40k SCI patients in UK alone.
- A broad range of promising applications such as alternative augmentative communication (AAC) systems for environmental control, tele-robotics & mobility, and neuro-rehabilitation systems involving prosthetics and/or orthotics/exoskeletons.
- However because of <u>high brain signal non-stationarity</u> and other <u>practical issues</u>, BCI systems have found limited practical use.

Types of BCI

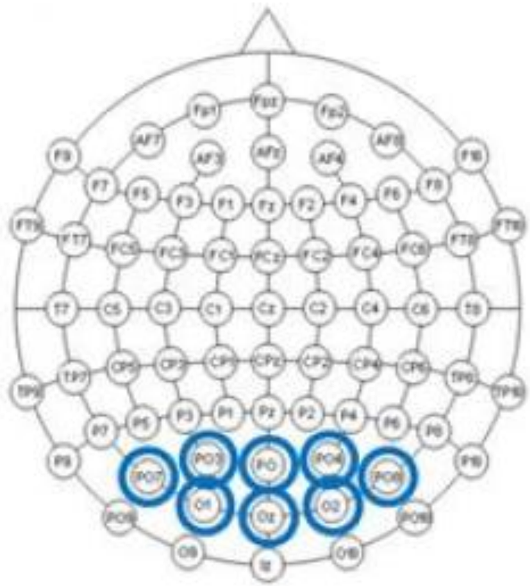
- Invasive techniques
  - Using micro-electrodes or electro-corticogram (ECoG).
  - Electrodes are implanted directly onto a patient’s brain.
  - Need for surgery; may cause scar, and materials issues.
  - Ethical issues; risk of infection.

Photo Courtesy:
University of Utah
Department of Neurosurgery

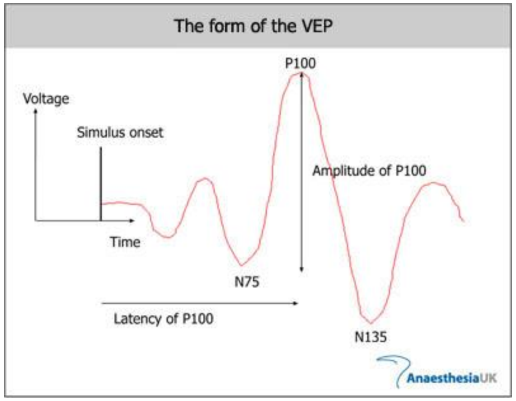
- Noninvasive techniques
  - Using EEG, MEG, NIRS, and/or fMRI.
  - External sensors for availing brain signals.
  - Susceptible to noise.
  - Most widely used is EEG being easy to use, low cost & portable.

Non-invasive BCI Categorisation based on Mental Tasks

- Visually Evoked Potential (VEP): SSVEP most common
- P300
- Sensorimotor activity



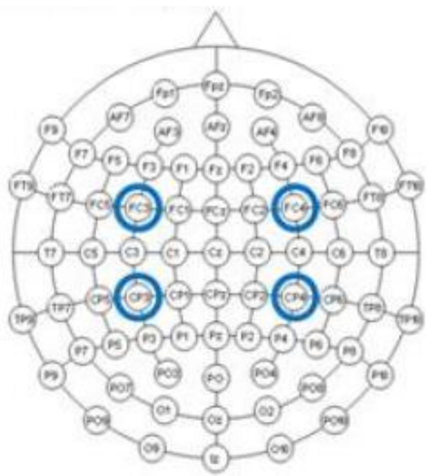
Top View of the brain
Electrode placement



Potential changes of the occipital EEG under stimulation of light

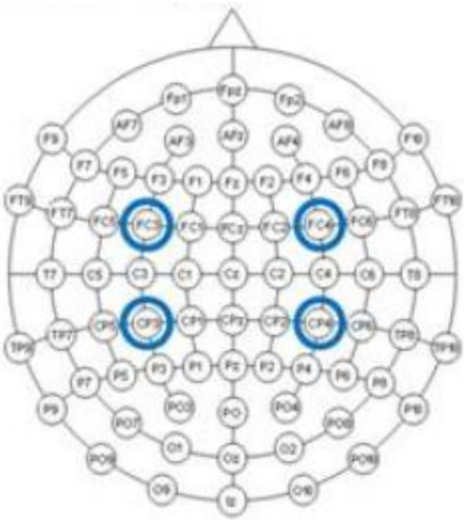
Non-invasive BCI Categorisation….

- Sensorimotor
    - Sensorimotor rhythm (SMR) (e.g., mu rhythm) gets modulated when a person imagines to move (i.e. motor imagery by a healthy person), intends to move (e.g., by a disable person), or actually moves his/her right and/or left hand, tongue, or foot.

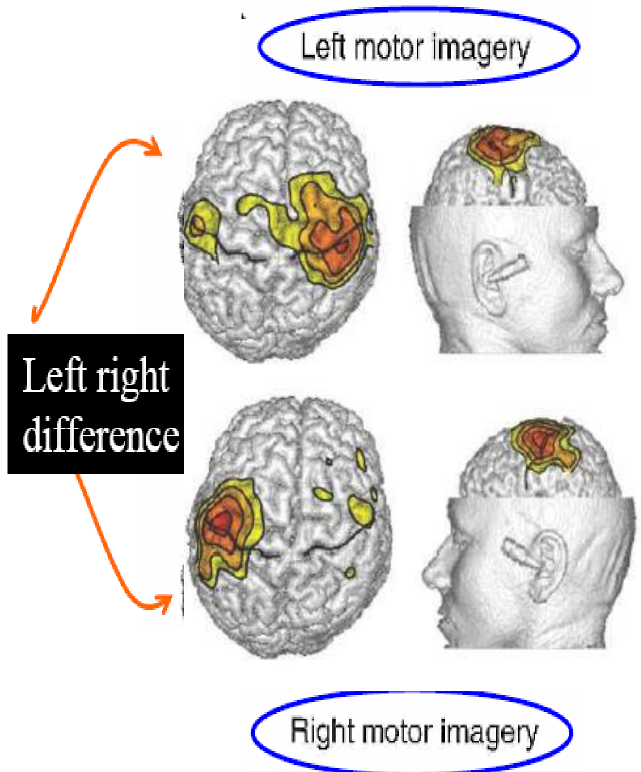


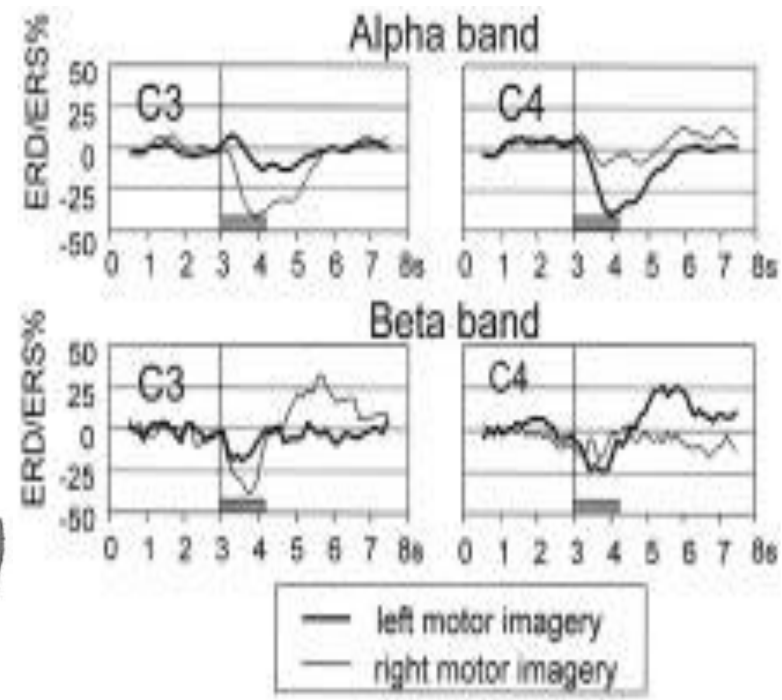
If we can **decode** the information from brain to <u>display human thinking</u>, we can design a very intuitive and natural communication channel.

SMR/Motor Imagery based BCI



Electrode placement

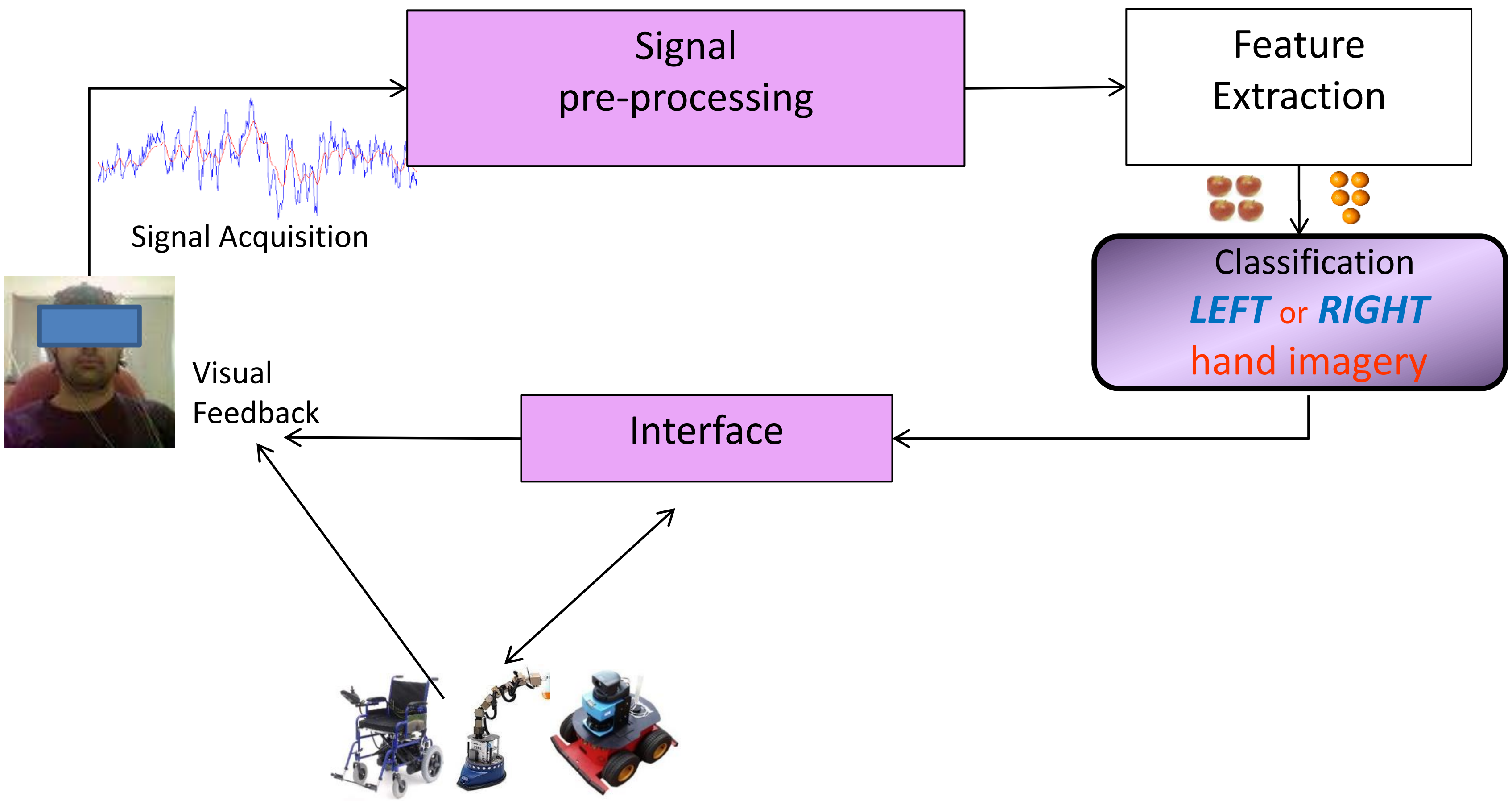




Pfurscheller 2002

Event Related Synchronization / Desynchronization

Operational Block Diagram of a BCI



Critical Performance Limiting Factors

Human Factors:

Brain signals change due to mood, fatigue, attention, motivation, medications, sensory stimuli, circadian rhythms, progression of disease, and amount of practice.

Head movements and eye blinking may cause artefacts.

Machine Factors:

Electromagnetic (EM) noise may affect recordings.

For EEGs, impedance changes due to sweating, drying gel, electrode placement variation, surface metal degradation, and lead wear.

Issues arising

- Presence of superfluous noise, redundant and unwanted information.

- Significant differences between the data samples extracted from training session and the samples extracted during online operation.

- Need for identifying user-specific parameters (frequency bands, channels, time point of maximum separability, and detection thresholds).

- There are people who are not very good at MI and can be categorised as having BCI aphasia. Accuracy in many cases may be in the range 60-75% .

Laboratory facilities

BCI Laboratory

- In an EMF screened room, a state-of-the-art BCI experimental setup: g.tec 64 channel g.BSamp system.
- 8/16 EEG/EMG/ECG channel mobile units; several sets of head-gear (or cap) along with passive and active wet EEG electrodes as well as dry electrodes.
- Bio-signal acquisition and processing system and eye tracker.

Spatial Computing and Neurotechnology Innovation Hub (SCAN i-hub)

- A state-of-the-art driving/flight simulator, 64 channel neurotechnology devices allowing measurement of EEG and near infrared spectroscopy (NIRS) simultaneously, augmented/virtual reality headsets, and virtual reality treadmills/walkers allowing movement within virtual environments.
- Enables the study of people's interaction with next generation technologies for fundamental research, offering industry a hub to understand SCAN and how their customers respond to new products/services and enables the development of impactful technologies emerging from the multidisciplinary R&D at the ISRC.

Laboratory facilities…

- **NI Functional Brain Mapping facility**

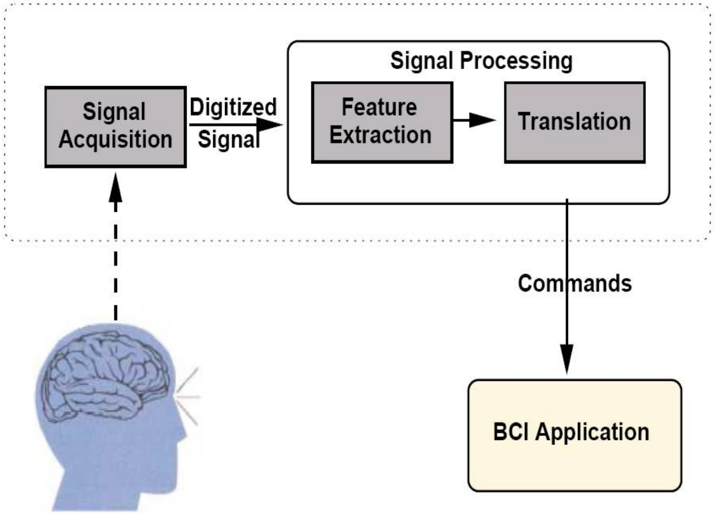
- A joint investment of £5.3M from Invest Northern Ireland (INI) and UU equipped with the latest whole head 306 channels Elekta Neuromag MEG TRIUX system. First MEG on island of Ireland, about 200 worldwide.
- Magneto-encephalography (MEG) records magnetic field induced by brain activities across the whole scalp while maintaining much higher spatial and temporal resolution.
- Research focus:
  - Improved understanding of dynamics of human brain signal processing;
  - Neurological disorders, stroke, Alzheimer's disease, and epilepsy.
- Outputs:
  - More effective diagnostic tools for early diagnosis;
  - More effective prevention or intervention measures;
  - Collaborative development of Biomarkers;
  - Enhanced software tools for more automated medical image analysis.

Some R&D works addressing challenges

- Rapid selection of user-specific parameters and intelligent pre-processing [e.g. data analytics for optimal channel selection (*Roy et al. (2020), J Neural Eng*); signal pre-processing using SOFNN or recurrent Quantum NN (Gandhi et al. (2013), *IEEE T NN & Learning Sys*)]
- Optimal methods for feature extraction [e.g. PSD (*Herman et al. (2008), IEEE T Neural Sys Rehab Eng.*) & bi-spectrum (Shahid & Prasad (2011), *J Neural Eng*)];
- Adaptable and robust classifier design and transfer learning [e.g. Interval Type-2 Fuzzy Logic (Herman et al. (2017), *IEEE T Fuzzy Sys*); Riemannian geometry based tangent space (Gaur et al. (2019), IJNS), Deep learning (Roy et al. (2020), Frontiers in Neuroscience].
- Multi-modal BCI through multi-sensor integration combining EMG, ECG, and/or eye-tracker [e.g., EEG-EMG Correlation based feature (*Choudhury et al. (2019), J Neuroscience Methods*)]
- Appropriate user interface (visual and auditory) development for neurofeedback and accomplishing tasks such as text entry, web-page access, wheelchair/mobile robot control, and stroke rehabilitation & related game playing [e.g., Auditory NFB *(McCreadie et al. (2014) IEEE T Neural Sys Rehab Eng.)]*

Integration of BCI and robotic exoskeleton : A way forward for neuro-rehabilitation

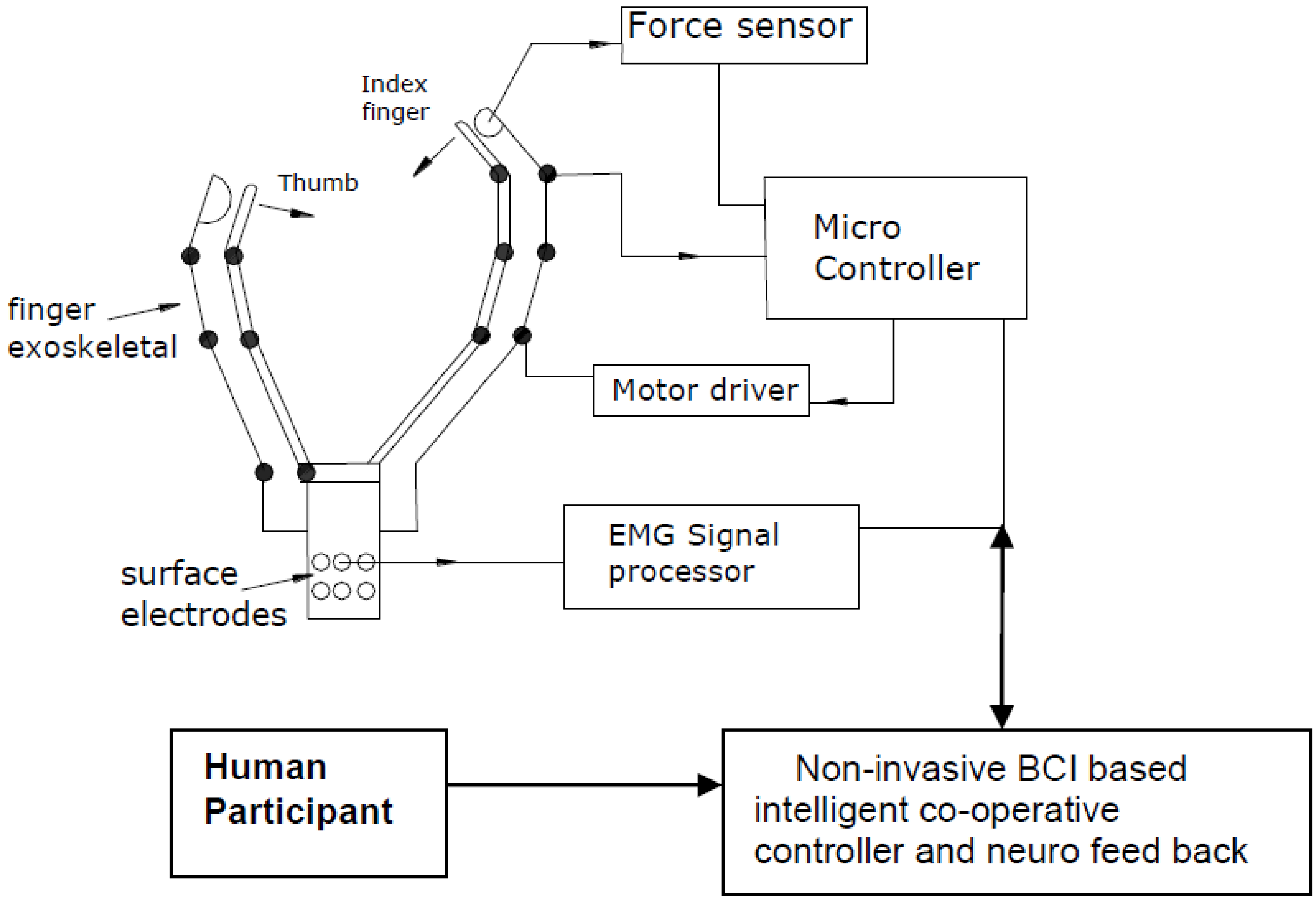
- Robots administer repetitive exercises but may not be sufficiently engaging for neuroplasticity to occur due to:
  - lack of interactive and engaging user interface.



- A symbiotic fusion of BCI and robot can facilitate:
  - Engaging and natural user interface;
  - Capturing of patient's attention while allowing intense repetition of therapeutic task, causing neuroplasticity;
  - Reliable quantification of patient's performance and recovery process;
  - Applicability to wide range of motor impairments.

MIT-MANUS (Krebs et al., 2004)

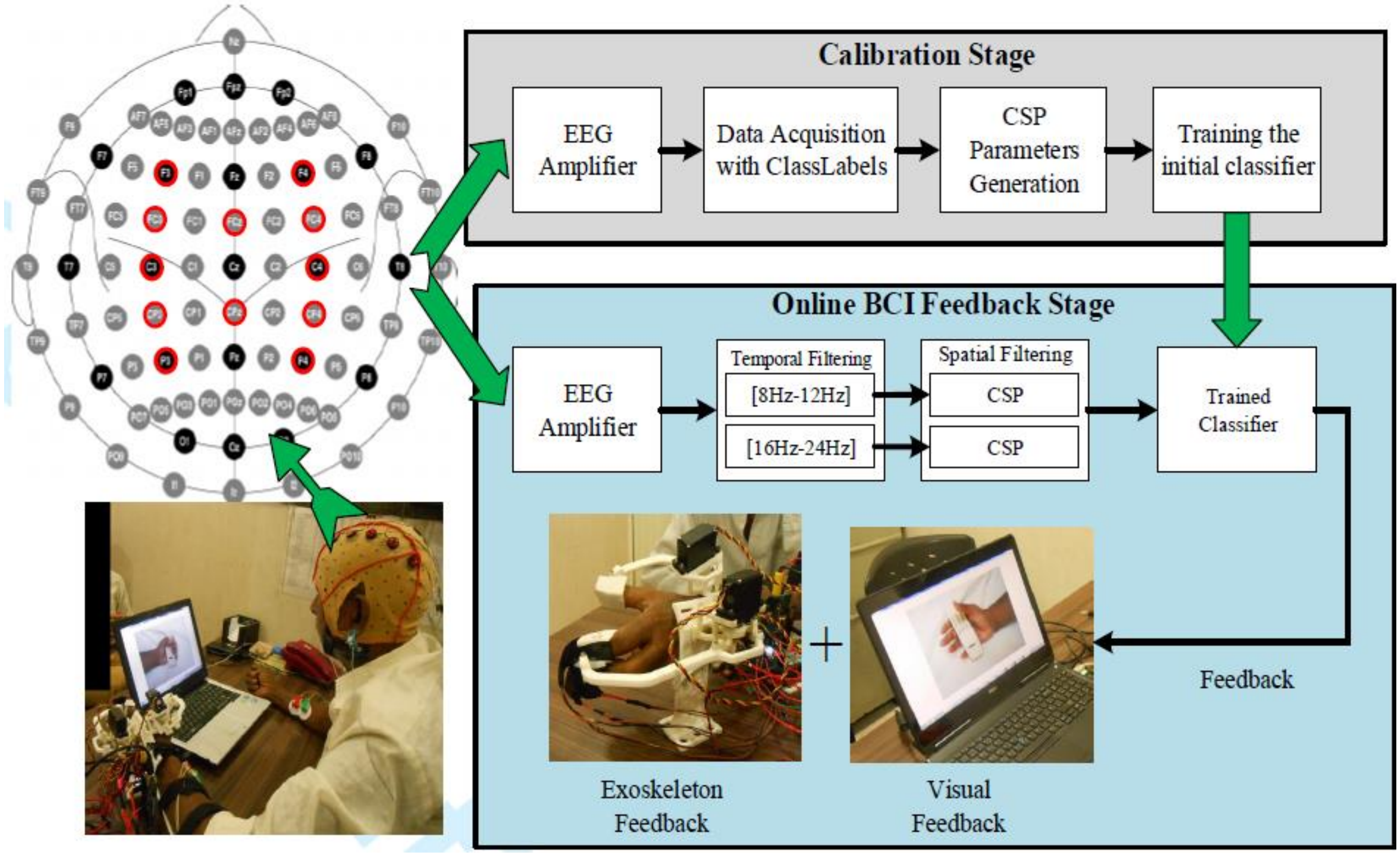
Layout of BCI Operated Hand Exoskeleton



Ulster-IIT Kanpur India UKIERI Phase-2 Project (UKIERI DST-2013-14/126)

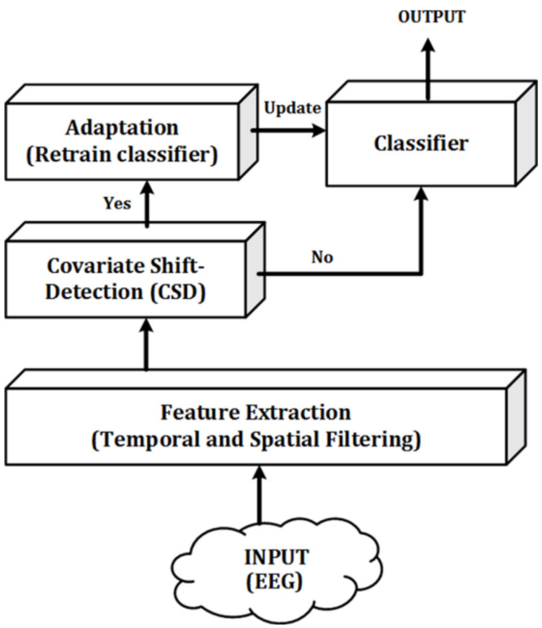
Completed RTD:

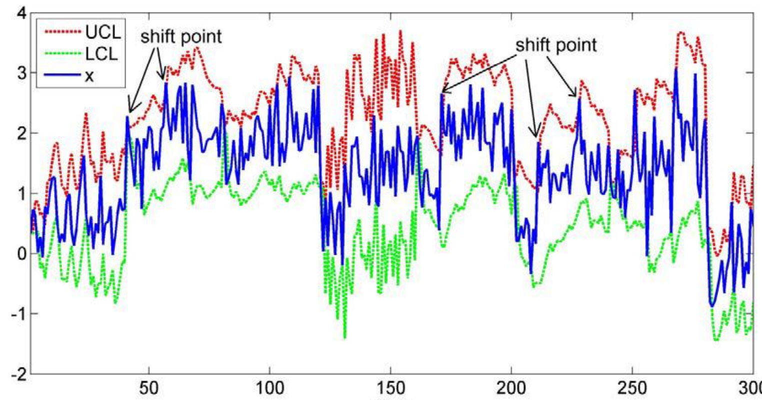
Integrating EEG-based BCI and Exoskeleton

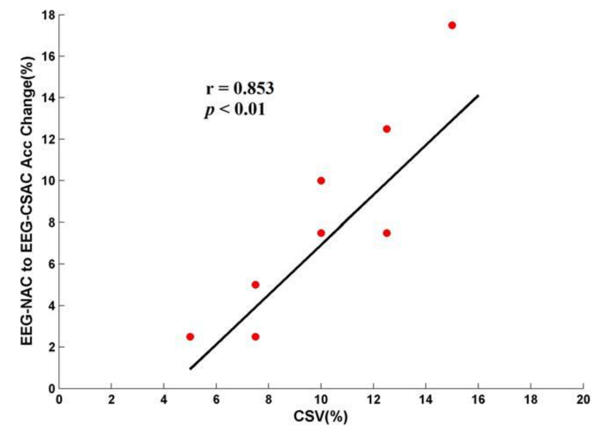


- **Features**: CSP; Cortico-muscular coherence (CMC) / EEG-EMG band-limited power time-courses (CBPT) Correlation;
- **Feature Classifier**: SVM

Just-in-time Adaptive Classifier for accounting intra-session non-stationarity







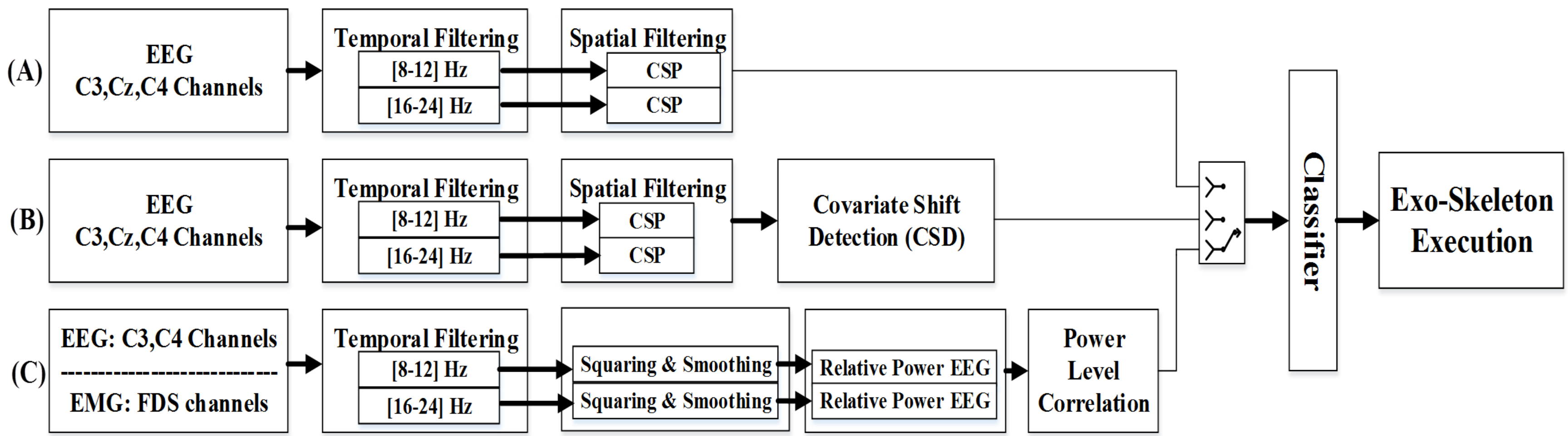
Group	Subject	CSV in (%)	EEG-NAC to EEG-CSAC change(%)
Healthy	S01	7.50	2.50
	S02	5.00	2.50
	S03	7.50	2.50
	S04	7.50	5.00
	S05	7.50	2.50
	S06	12.50	7.50
	S07	12.50	7.50
	S08	12.50	12.50
	S09	15.00	17.50
	S10	5.00	2.50
Patients	S01	7.5	2.50
	S02	7.50	5.00
	S03	10.00	7.50
	S04	12.50	7.50
	S05	7.50	2.50
	S06	7.50	5.00
	S07	12.50	7.50
	S08	7.50	2.50
	S9	10.00	10.00
	S10	7.50	5.00

- Strong linear correlation between CSV rate and non adaptive classifier (EEG-NAC) to covariate shift (CS) triggered adaptive classifier (EEG-CSAC) accuracy improvement; CS detection using EWMA modelling.
- Adaptation in **<u>only small % of trials (CSV);</u>** Adaptation using continual learning **<u>(CL) in all trials is not</u>** <u>required</u>.

[*Chowdhury et al. (2018), IEEE T Cognitive & Developmental Systems*]

Completed RTD…

Cortico-Muscular-Coupling based BCI

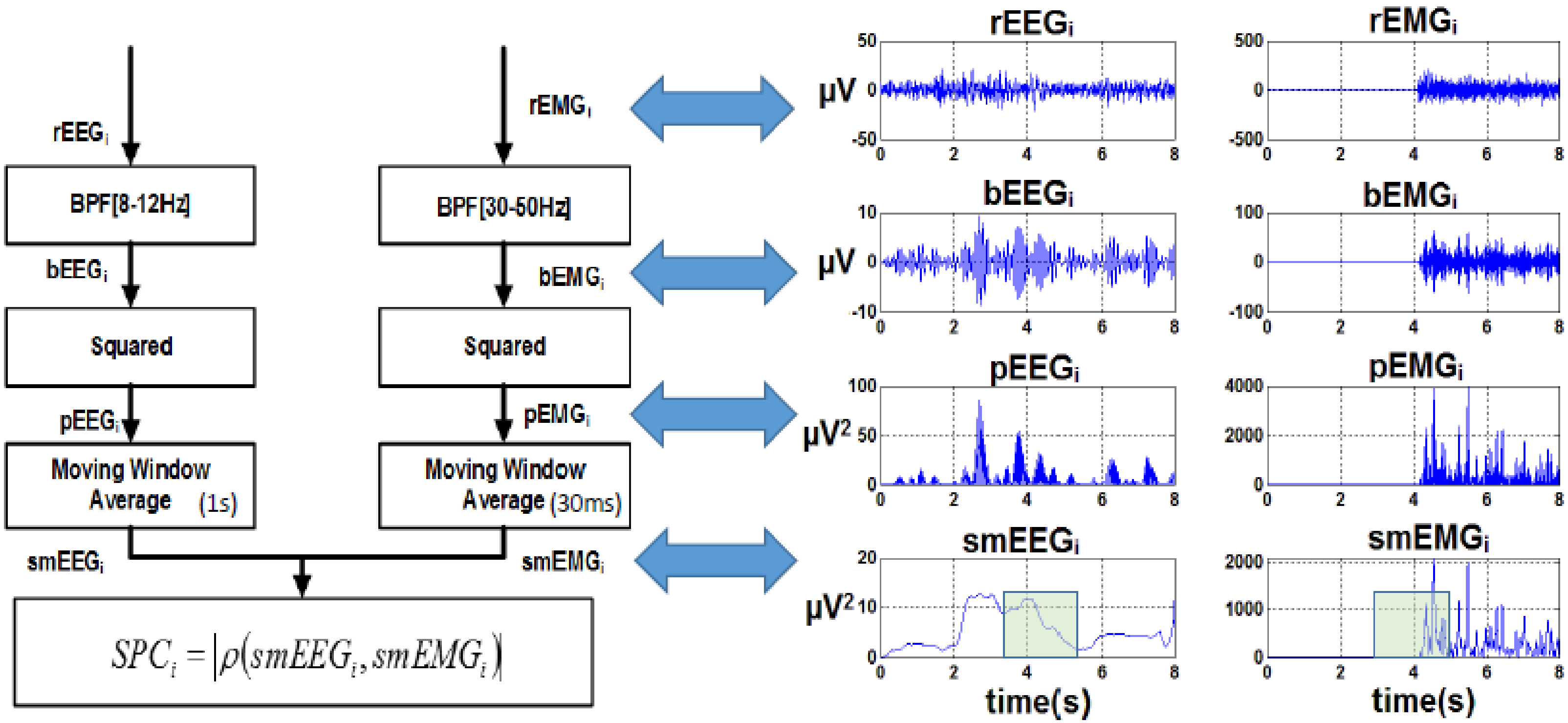


(A) EEG based Non-Adaptive BCI, (B) EEG based Adaptive BCI (EEG-ALC) and (C) EEG-EMG band-limited power time-courses (CBPT) correlation based BCI

[Chowdhury et al. (2019), *Journal of Neuroscience Methods*]

Completed RTD…

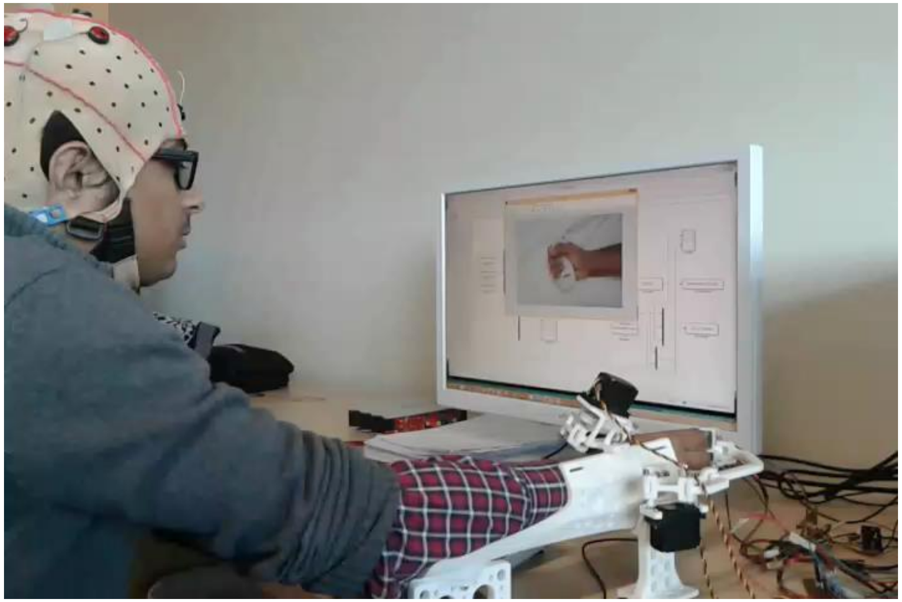
Cortico-Muscular-Coupling…

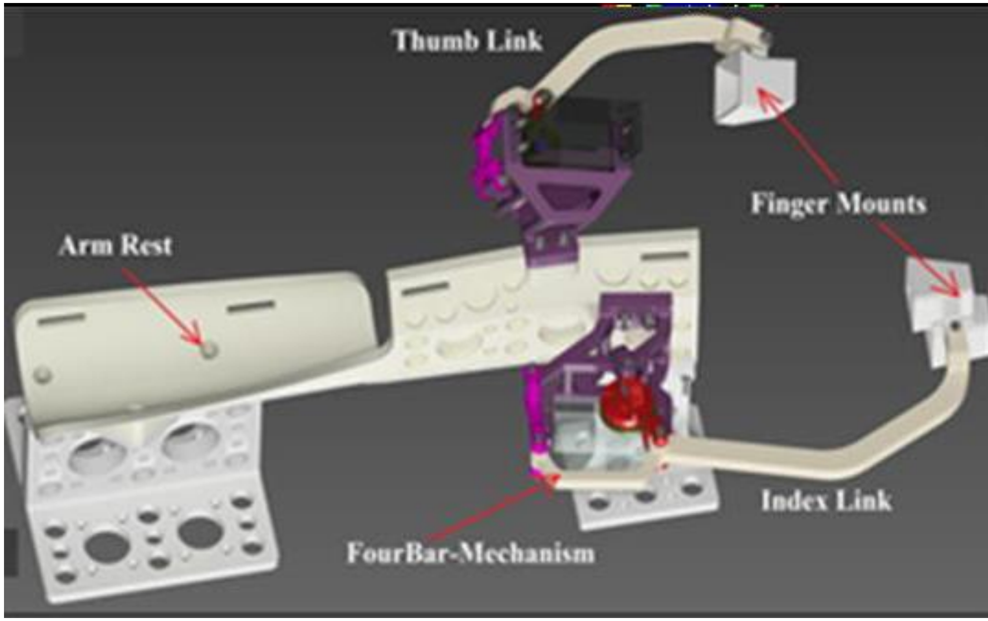


EMG signal from the flexor-digitorum-superficialis (FDS) muscle

Completed RTD…

A Participant using the Neuro-rehabilitation System





[*Chowdhury et al. (2018), IEEE T Cognitive and Developmental Systems*]

Completed RTD...

Pilot Clinical Trial

- **Participant Selection Criteria**
  - Stroke patients with partial or full finger motion disability.
  - Time since stroke not less than 6 months.
  - MMSE score more than 21/30.

- **Experimental Protocol** [Prasad et al., 2010]
  - Assist-as-needed Physical Practice (30 min).
  - BCI based Mental Practice (30 min).
  - 2/3 therapy sessions per week; Six week long.
  - Four stroke (ischemic) (1 male, 3 females, mean time after stoke:23(4.6) months, MMSE score:28.34(±1.25)).
  - Recovery outcome measures:
    - Action Research Arm Test (ARAT) (1-57): Pinch(18),Grip(12),Grasp(18),Gross movement(9).
    - Grip Strength.

Completed RTD…

Pilot Clinical Trial…

Demographics of the Patients

Sub id	**Age (years)**	**gender**	**Imp aired side**	**Domin ant Side**	**Time Since Stroke (months)**	**Minimental State Test Score**
P01	61	F	R	R	22	30/30
P02	56	M	L	R	28	30/30
P03	69	F	R	R	24	30/30
P04	59	F	L	R	19	30/30

Completed RTD…

Pilot Clinical Trial…

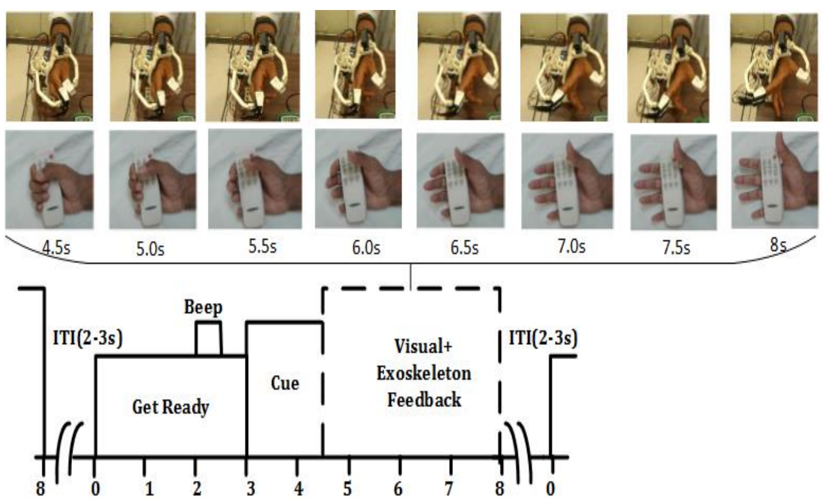
- **Physical Practice (PP):**
  - Repetitive finger flexion and extension exercise in assist-as-needed mode for 30 min
  - Strategy implemented by a force threshold based switching between active non-assist and passive assistance mode.
  - Participants applied finger-tip force is converted into exoskeleton motion using an impedance model if force is above a certain threshold level (active non-assist mode).
  - Switches to passive assistance mode providing full assistance when the applied force is below the threshold.
  - The difficulty level of the PP is adjusted by updating the impedance parameters according to the average force generation ability.

Completed RTD…

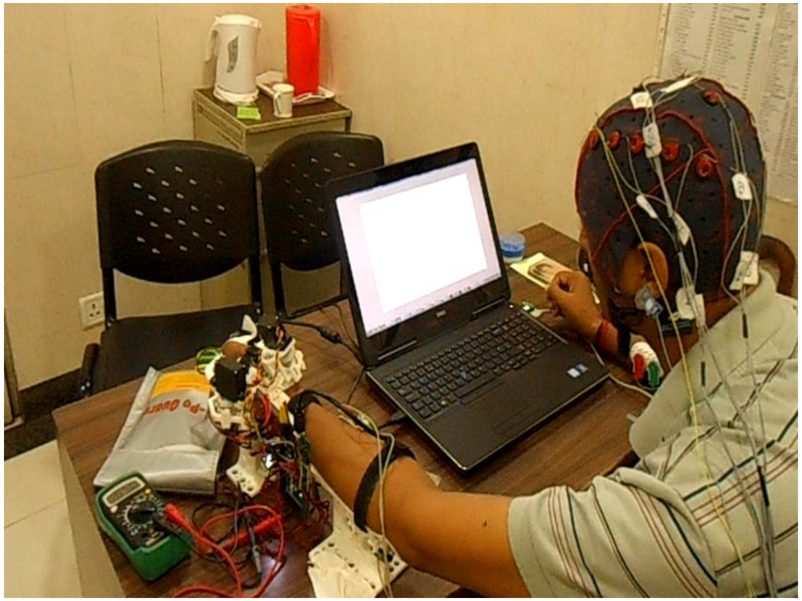
Pilot Clinical Trial…

➢ Mental Practice

- **BCI system** 16 channel EEG/EMG g.USBamp system from g.tec



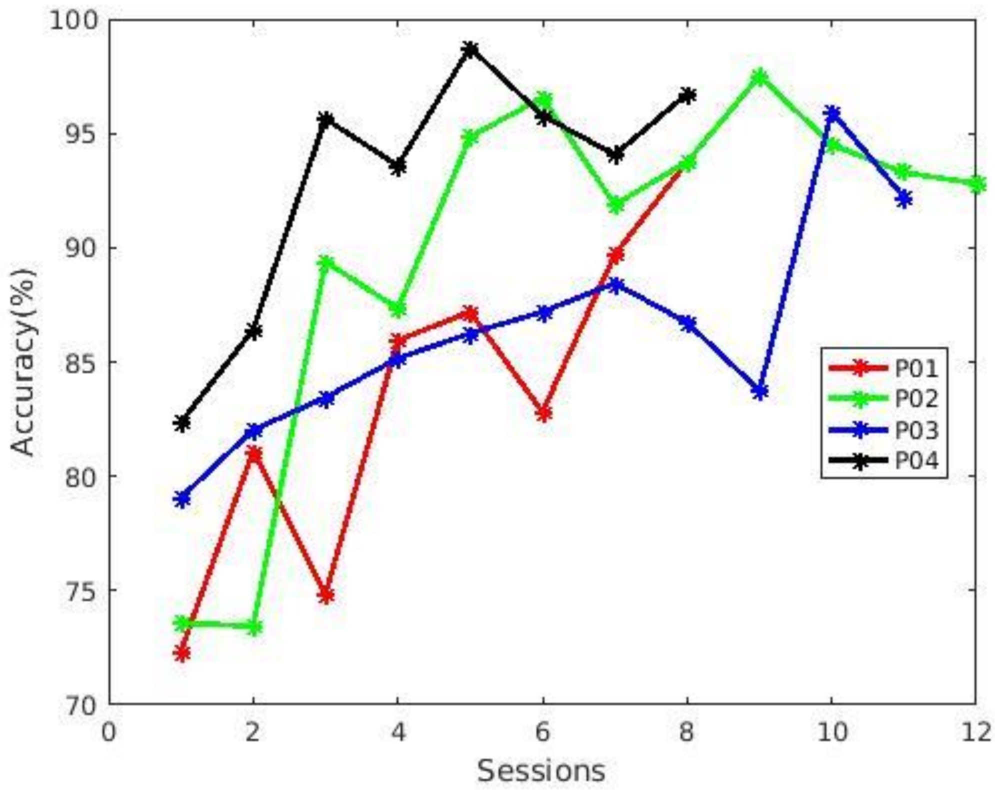
Visual neurofeedback along with paradigm timing diagram.



A Patient undergoing the trial

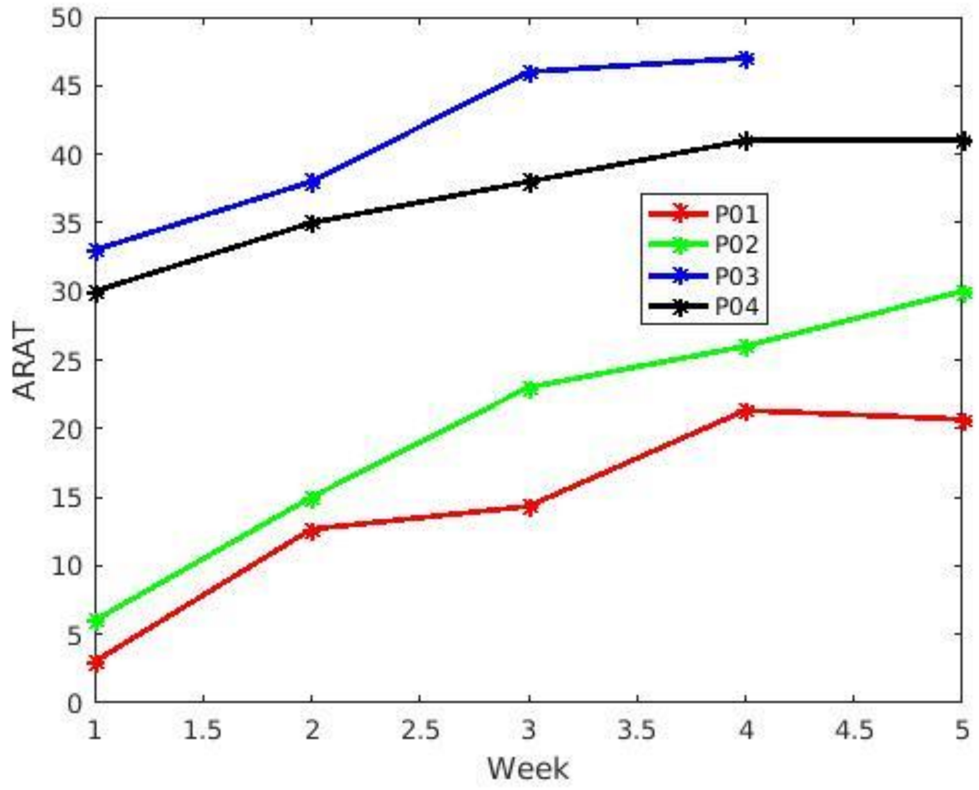
Completed RTD…

Change in BCI Classification Accuracy



Completed RTD…

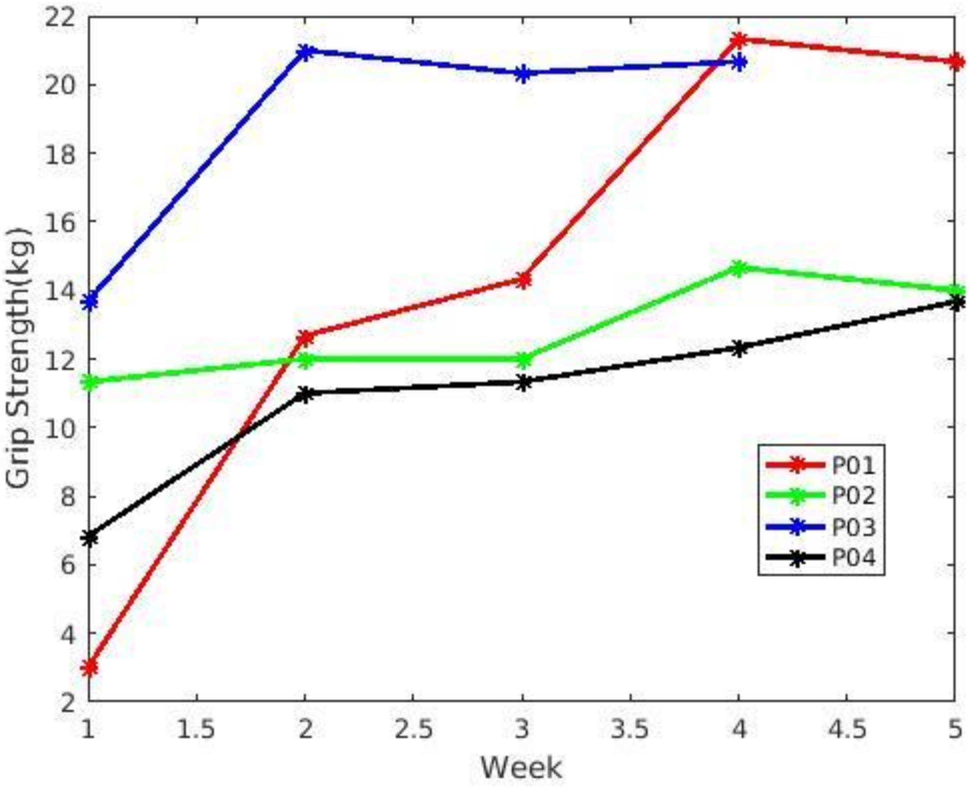
Clinical Outcome Measure: Action Research Arm Test (ARAT)



All the participants achieved Minimal Clinically Important Difference (MCID) in their ARAT.

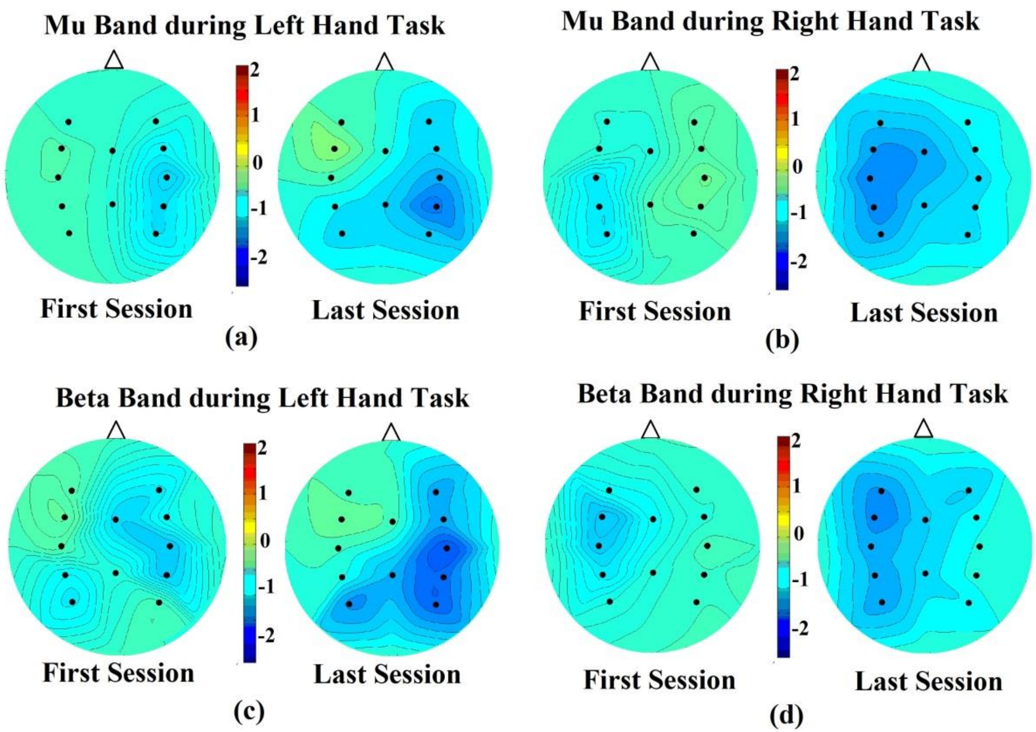
Completed RTD…

Clinical Outcome Measure: Grip Strength



Completed RTD…

Scalp Topoplots for ERD/ERS Changes

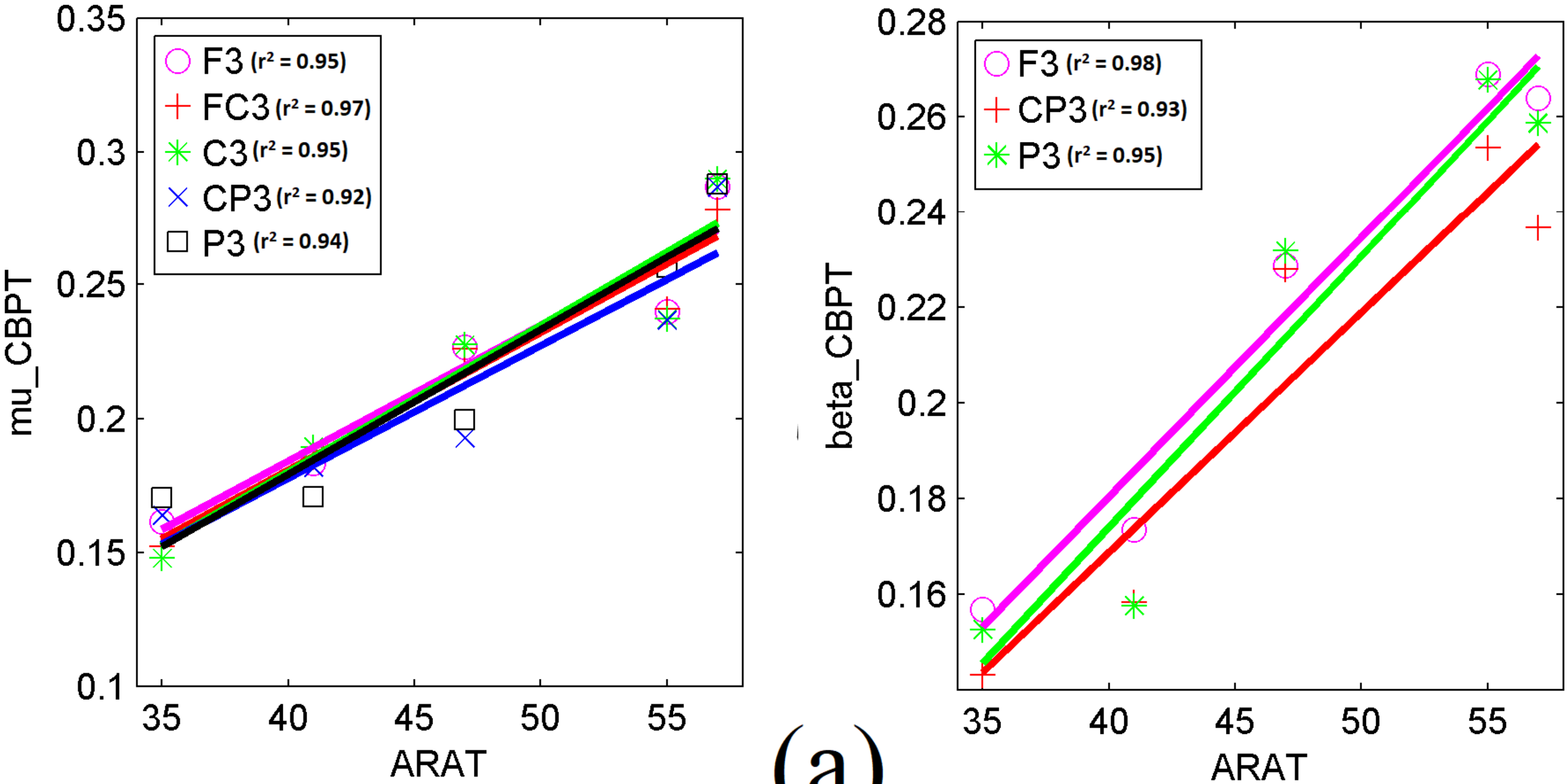


$$ERD/ERS_b^{ch} = \frac{E_{task}^b}{E_{ref}^b}$$

- Both mu and beta band ERD increased from first to the last session
- Significant pre vs post ERD changes in EEG :
  Mu band Left Task: CP4; Mu band Right Task: C3, CP3
  Beta band Left Task: C4; Beta band Right Task: F3 and FC3

[*Chowdhury et al. (2019), IEEE Journal of Biomedical and Health Informatics*]

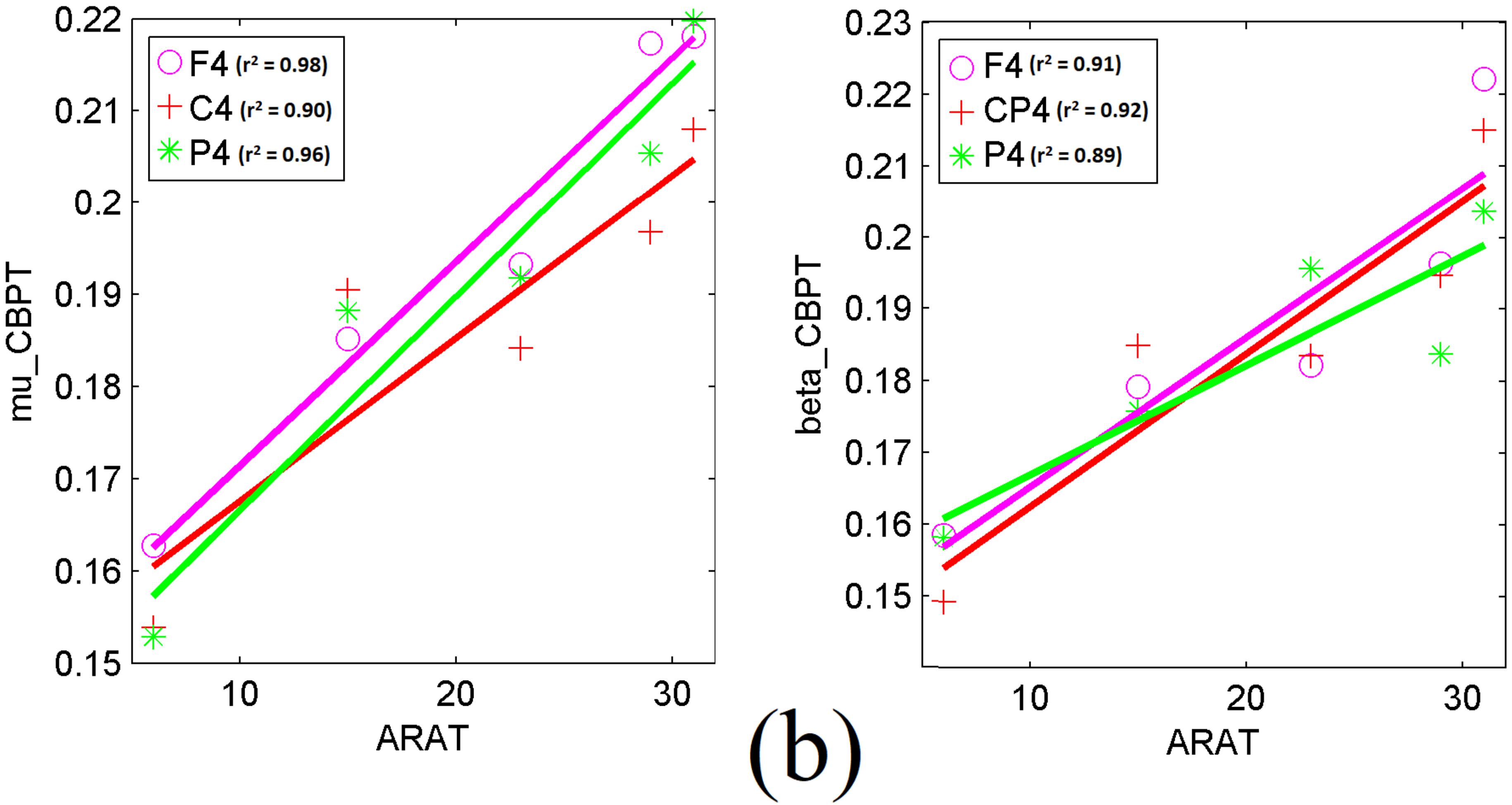
CBPT changes with motor recovery



(a)

[*Chowdhury et al. (2020), IEEE Access*]

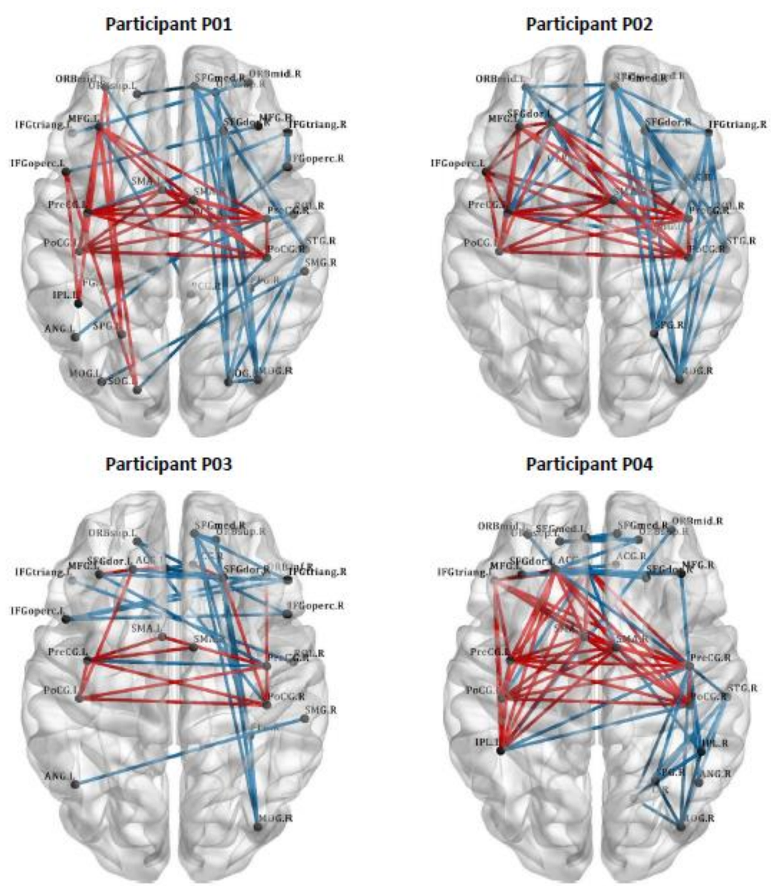
CBPT changes with motor recovery



[*Chowdhury et al. (2020), IEEE Access*]

Completed RTD…

Resting State beta band connectivity change in MEG – A Neuroplasticity Analysis



Left -> Ipsilesional hemisphere

- Functional connectivity (FC) clusters correlated positively (Red) and negatively (Blue) with the hand functional recovery index for all four participants in beta-low frequency band (15-26 Hz).
- The intra-hemispherical FC values in M1, S1, and SMA within both ipsilesional and contralesional hemispheres increase with UL functional recovery.
- The ipsilesional hemisphere possesses larger number of positively correlated clusters.
- The inter-hemispherical FC analysis showed a stable pattern of positively correlated connections within the motor cortical regions whereas the inter-hemispheric negative cluster is variable across the participants.

[Rathee et al., IEEET Neural Systems & Rehabilitation Eng., 2019]

Advancing MEG-based BCI Supported Neurorehabilitation

-MEG Issues:

- Highest spatiotemporal resolution (204 gradiometer & 102 magnetometer channels, Triux, Elekta, recorded at 1k Hz) of all neuroimaging modalities.
- Sensors in a dedicated helmet rather than physically placed on subjects' scalps resulting in significant signal attenuation.
- Low decoding accuracy, despite using large number of channels.
- For MEG-based BCI no channel selection methodology has been reported.

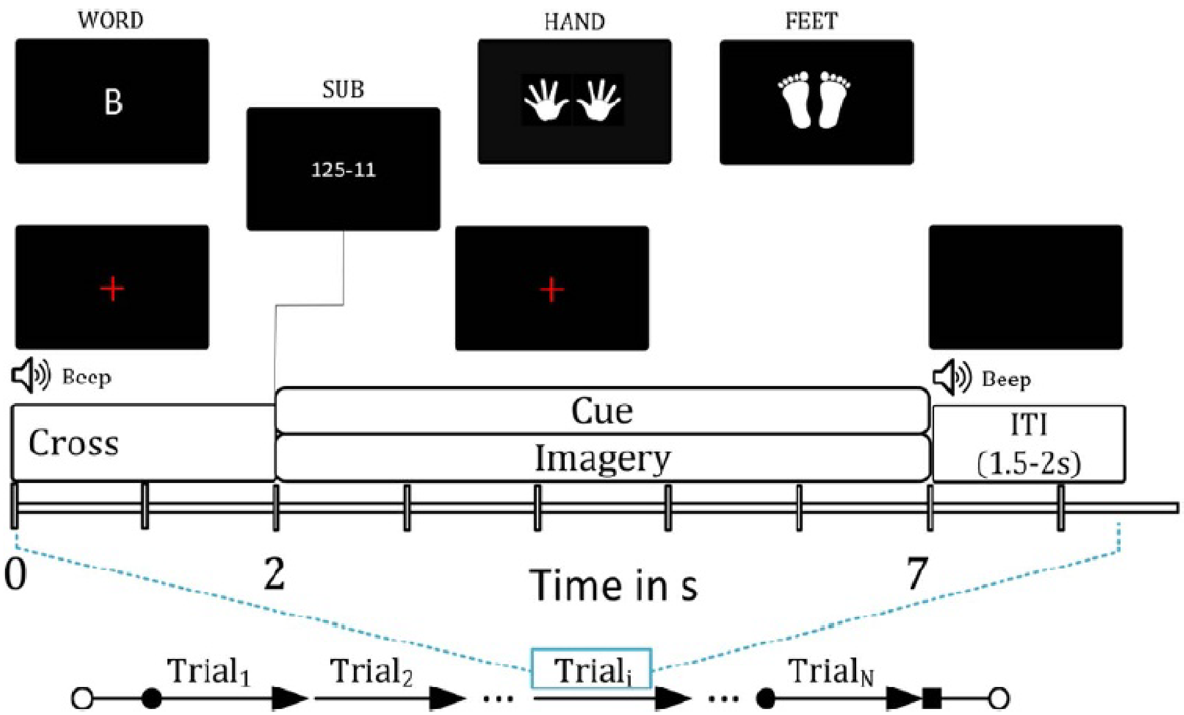
  - UKIERI phase-3 project: Advancing MEG-based Brain-Computer Interface Supported Upper Limb Post-Stroke Rehabilitation (DST UKIERI 2016 -17 -128, PI, £145k, 2017 –21).

Channel Selection Procedure using CI

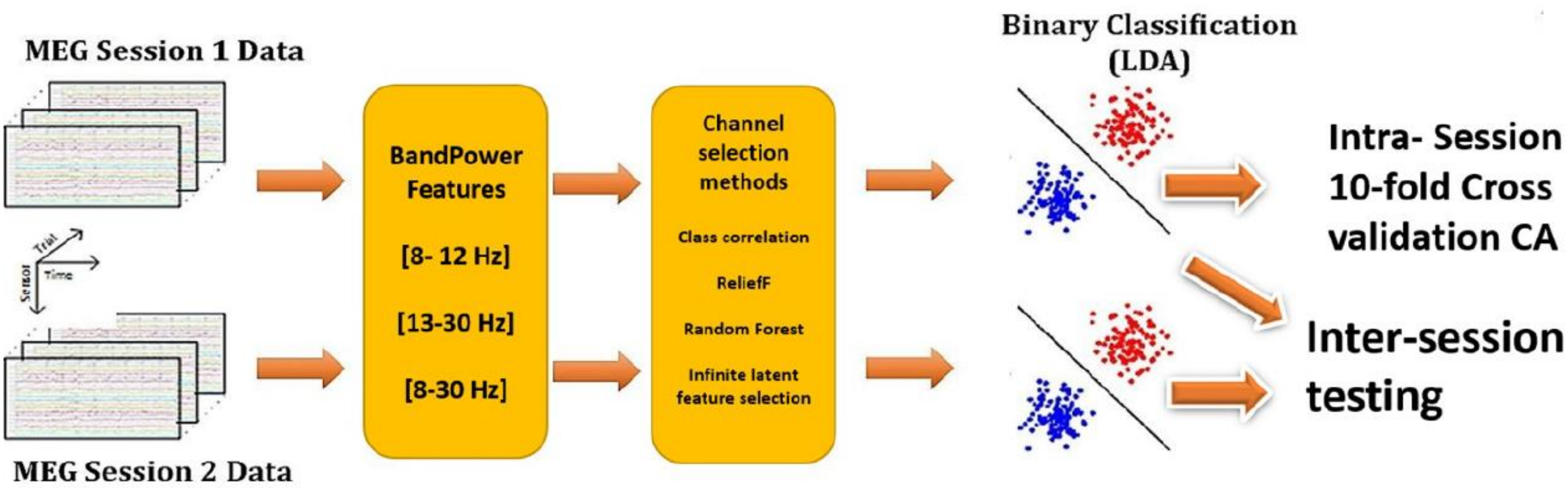
- Timing paradigm design for data recording;
- MEG data recorded for two sessions from 15 healthy participants performing mixed imagery tasks pairs;
- Channel selection methods *Class-Correlation*, *ReliefF*, *Random Forest*, and *Infinite Latent Feature Selection* were applied across six binary tasks in three different frequency bands;
- Features: Bandpower and common spatial pattern (CSP)
- Feature classification using Linear Discriminant Analysis (LDA) classifier.

Roy, Rathee, Chowdhury, McCreadie, & Prasad (2020). Assessing impact of channel selection on decoding of motor and cognitive imagery from MEG data. *Journal of Neural Engineering*, *17*(5).

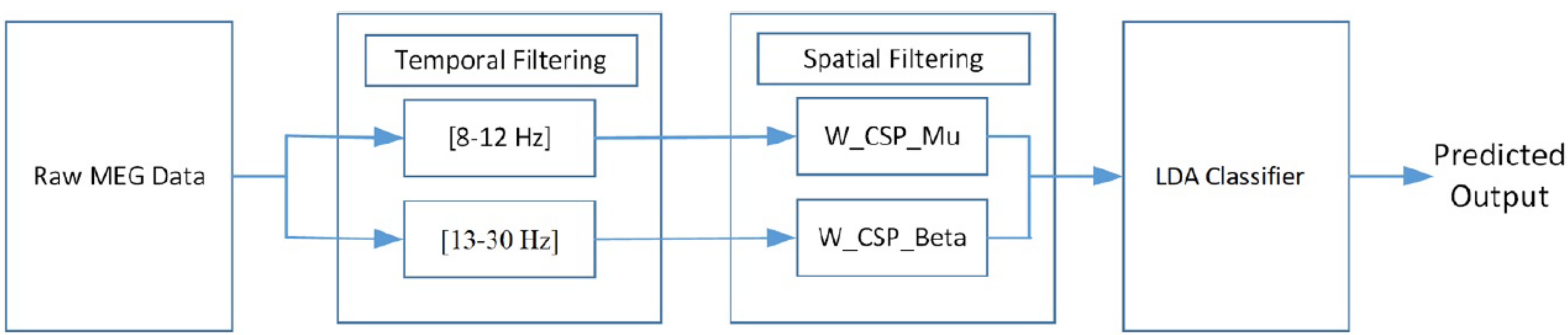
Timing diagram of MEG-based BCI paradigm



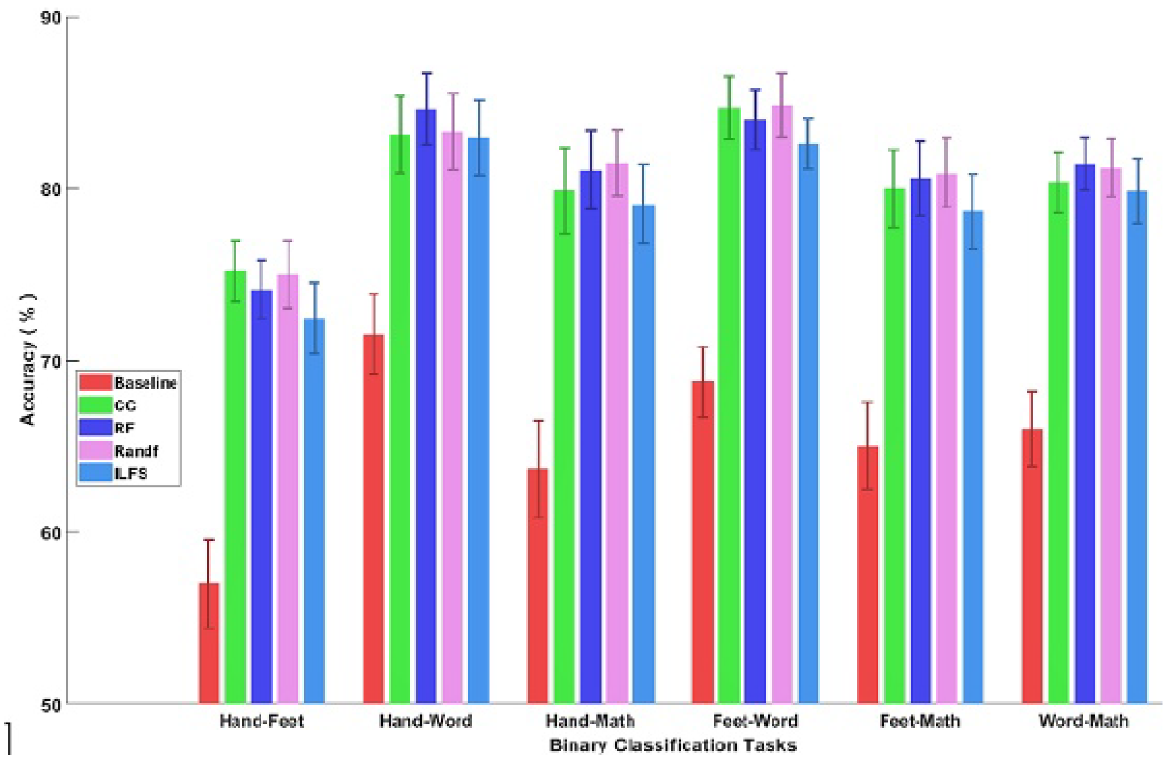
Schematic diagram of signal processing pipeline using bandpower feature



The data processing pipeline using CSP

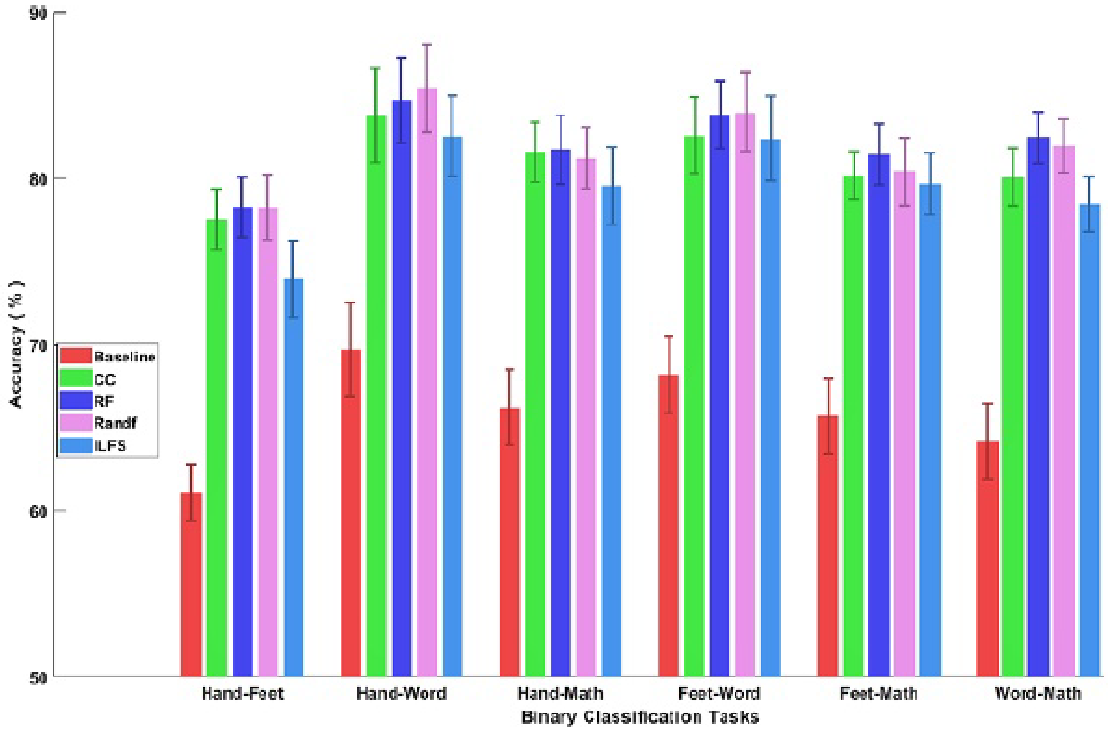


Mean classification accuracies (CAs) for α band (8-12 Hz) for session-1 using 10-fold cross-validation.

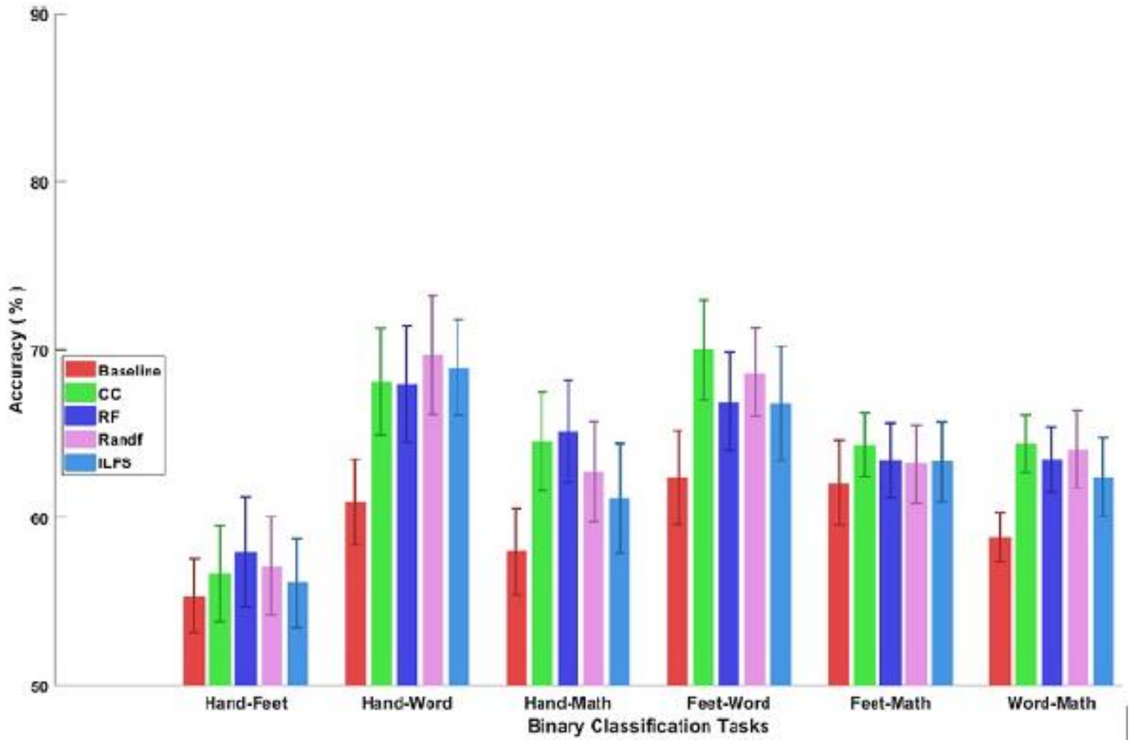


- RandF provided a statistically significant improvement over ILFS in H-F, H-M, W-M, F-W and W-M task pairs ($p < 0.05$).
- Overall mean CA across subjects using RandF is 81.11% (±6.02), ILFS is 79.30% (±6.51), CC is 81.72% (±6.25), and RF is 81.14% (±6.22) for session 1 whereas baseline was 65.32% (±8.09).

Mean CAs for the α band (8-12 Hz) for session-2 using 10-fold cross-validation



Mean classification accuracies (CAs) for α band for a classifier trained on session-1 data and tested on session-2 data

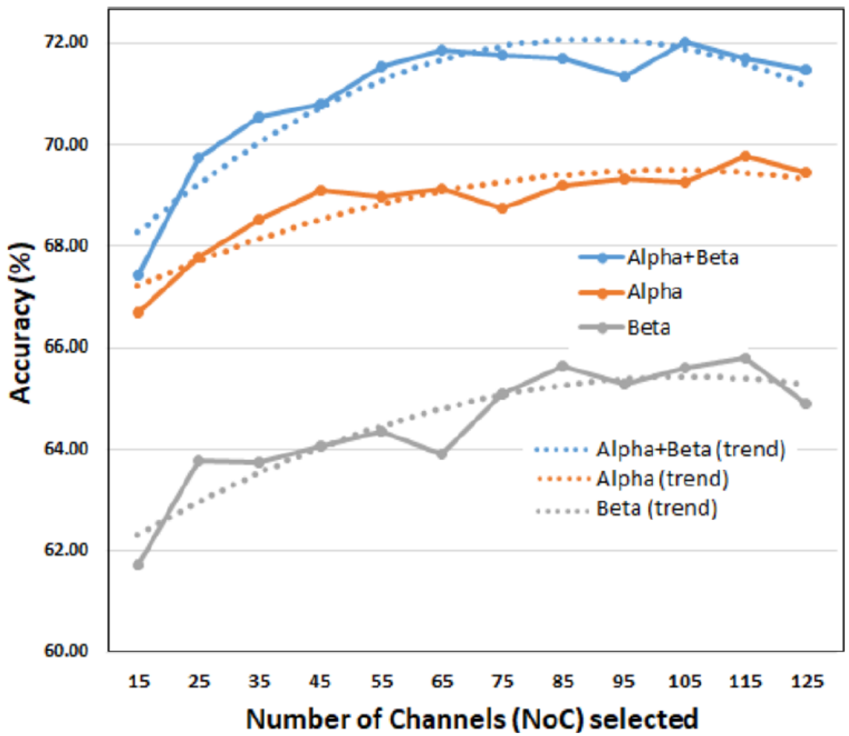


- H-W group provided higher accuracy than the MI (H-F) group.

Number of channels contributing to maximum accuracy using RandF method in α+β band using bandpower feature

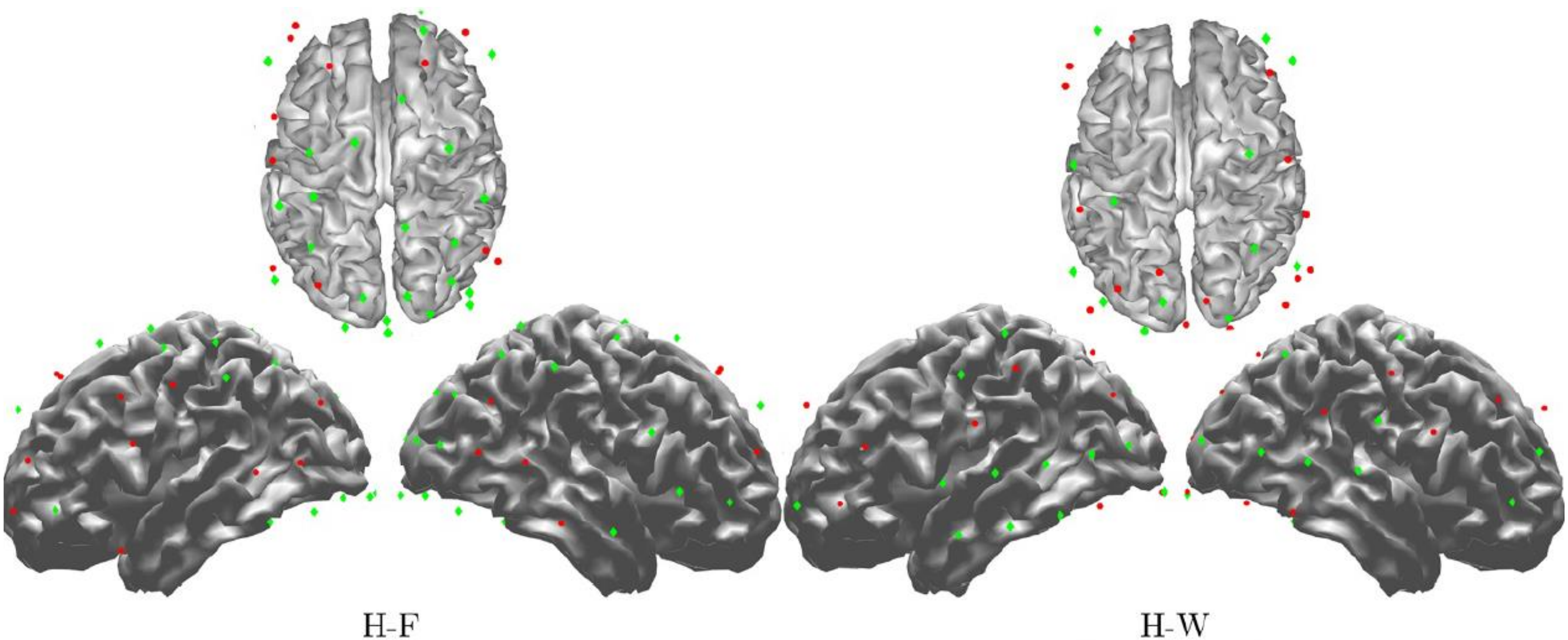
	Hand vs Foot		Hand vs Word		Hand vs Math		Feet vs Word		Feet vs Math		Math vs Word	
Participants	S01	S02	S01	S02	S01	S02	S01	S02	S01	S02	S01	S02
P01	7	7	14	5	16	5	9	7	14	19	11	12
P02	13	11	14	4	23	12	15	12	6	15	9	9
P03	10	8	10	13	10	12	9	9	8	8	14	13
P04	14	11	5	13	8	14	14	16	17	1	12	10
P05	9	9	14	9	7	21	5	6	8	6	16	9
P06	14	6	24	15	11	15	18	17	14	9	18	6
P07	16	6	19	11	14	10	11	10	6	9	14	6
P08	13	12	13	14	9	14	13	10	8	12	10	21
P09	22	12	18	9	13	13	16	9	13	2	13	9
P10	4	13	9	16	10	12	15	18	10	16	18	6
P11	16	11	9	12	14	14	19	18	14	7	12	14
P12	9	19	2	12	3	7	17	12	7	12	9	6
P13	13	11	16	7	10	13	10	11	3	8	5	4
P14	7	5	12	8	15	14	10	5	6	20	7	2
P15	11	18	16	8	9	11	16	18	8	13	11	11
Mean	**11.87**	**10.6**	**13**	**10.4**	**11.47**	**12.47**	**13.13**	**11.87**	**9.47**	**10.47**	**11.93**	**9.2**

Mean transfer-session accuracy with the channels selected using CSP in all the three bands



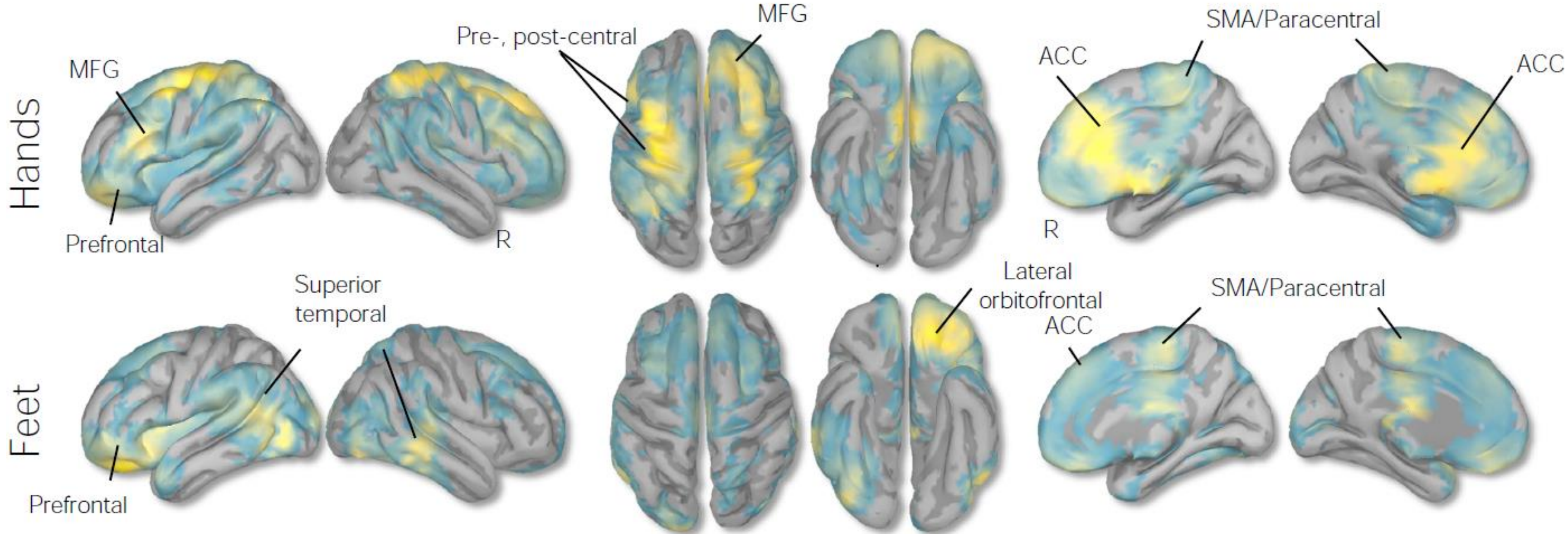
If we feed the CSP with a larger NoC it can optimize the CSP projection matrix very well which could lead to higher discriminability between the two classes.

Plot of channels common for minimum of three participants' imagery tasks for 8–30 Hz



• represents channels in session 01 & ♦ represents channel in session 2.

Group source analysis of task-imagery BCI experiment



Activation maps corresponding to Hands and Feet motor imagery tasks measured by the DICS beamformer source analysis in a frequency range of beta (17-25Hz) from 14 participants. t -maps are thresholded at a whole-cortex corrected $p < 0.05$.

[Youssofzadeh, et al. (2023). Human Brain Mapping]

Main Findings of MEG-based BCI Performance Analysis

- Channel selection improved intra-session BCI CA significantly but inter-session CA improvement is marginal.
- The optimal channel number varied not only in each session but also for each participant.
- Reducing the NoC helps to decrease the computational cost and maintain numerical stability in cases of low trial numbers.
- For all combinations, the mixed imagery task pairs (H-W, H-M, F-W & F-M) provided higher separability as compared to the H-F and W-M task pairs in α band.
- Findings support that the suppression of alpha band power around 10 Hz is a stronger marker for movement planning, execution and imagery than beta band.
- It resulted into substantial channel reduction, from 204 channels to:
  - a range of 1–25 channels using bandpower as a feature and
  - 15-105 channels using common spatial pattern (CSP) features.

- Roy, Rathee, Chowdhury, McCreadie, & Prasad (2020). Assessing impact of channel selection on decoding of motor and cognitive imagery from MEG data. *Journal of Neural Engineering*, *17*(5).

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Conclusion

- *Neurorehabilitation system* integrating BCI and a hand exoskeleton.
- *BCI* - neurofeedback of motor imagery practice enhances rehab effectiveness and patient focus.
- *BCI* – brain activations in EEG/MEG trigger hand exoskeleton to provide active rehab exercises.
- *Exoskeleton* - proprioceptive neurofeedback enhances BCI effectiveness for focused mental practice of rehab tasks.
- *Completed Pilot trial* - demonstrated enhanced effectiveness through a six week clinical trial on four hemiplegic stroke patients; functional recovery gain in terms of GS and ARAT scores and other transformative change in stroke participants.
- Significantly enhanced decoding accuracy obtained on MEG-based BCI using computational intelligence techniques for channel selection.
- Trials are on-going on the Neurorehabilitation System using MEG-based BCI controlled exoskeleton.

Further Research

- Enhanced multi-modal, distributed and bidirectional BCI design as multiple brain areas are involved in processing any perception-action [Youssofzadeh et al., 2016].

- Extensive randomised controlled trial on people with impairments to ascertain the advantages gained from using the BCI in conjunction with the hand exoskeleton and develop a robust prognosis method.

- Developing a self-adapting home-operable system monitored and controlled through a mobile NeuroRehab app.

- For wider research community participation, MEG BCI data is made available in:
  - D. Rathee, H. Raza, S. Roy, G. Prasad, “A magnetoencephalography dataset for motor and cognitive imagery-based brain-computer interface,” **Scientific Data-Nature**, vol. 8, no. 1, p. 120, 12, 2021.

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