ROBUST BCI ALGORITHMS FOR MOTOR IMAGERY CLASSIFICATION AND UPPER LIMB KINEMATICS DECODING

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Overview

- Brain Computer Interface (BCI) Applications
- Relevant EEG Features used in BCI
- Motor Imagery BCI Classification
- BCI for Motor Control & Decoding Movement Kinematics
- Future Directions on Movement Kinematics study
- Summary

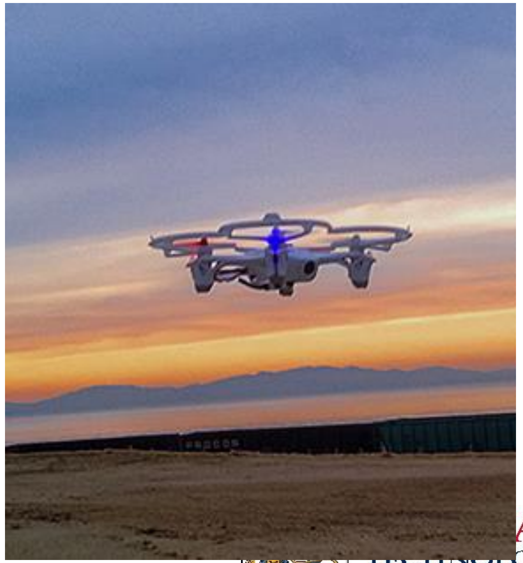
BCI Applications

- Based on the user activity (motor, cognition, perception etc.)
  - Clinical applications – In rehabilitation of neuromuscular disorders, attention, memory and learning disabilities
  - Communication devices – Speller devices, keyboard controls etc.
  - Cognitive Training & Entertainment applications – Military personal training, Virtual reality navigation and multimedia game control.

- Significance of Motor Control BCI
  - Main objective of BCI – To provide basic communication and control capabilities for people with motor disabilities (paralyzed, or 'locked in')
  - Neuro rehabilitation, Neuro motor prostheses, Neuro robotics
  - Develop new neuronal interconnections, acquiring new functions and compensating for motor impairment using neuroenhancement strategies

BCI Applications – Motor Control

- Clinical
- Robotics
- Performance Training
- Entertainment
- Virtual Reality



Relevant EEG features used in BCI

- **Slow Cortical Potentials:** +ve/-ve EEG polarizations generated at cerebral cortex that lasts from 300 ms to few seconds. Negative SCPs are associated with movement (cortex activity).

P300: A positive deflection in EEG voltage (at central & parietal regions of cortex) that occurs 300 ms after infrequent visual/auditory stimulus.

- Used in BCI Spellers, Wheel chair navigation, Home automation control etc.

- **Steady State Visually Evoked Potential (SSVEP)**: Evoked potential (at visual region of cortex) in response to visual stimulus.

  - Frequency-coded brain response modulated by the frequency of periodic visual stimuli > 6 Hz. SSVEP Amplitude increases with the frequency of 2nd and 3rd harmonic of visual stimulus (flickering image).

  - High SNR, High information transfer rate and needs minimal user training.

  - Robot control, game control etc.

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Relevant EEG Features for Motor Control

- **Sensory Motor Rhythm (SMR) based BCIs**
  - Oscillations recorded over the sensorimotor areas
- **Neurophysiology**
  - Mu (10-12 Hz) and Beta (13-30 Hz) bands activations in response to preparation, execution and imagination of movement
- **Neural features used in SMR-BCI:**

- Amplitude changes in EEG during execution, preparation or motor imagery (MI) that primarily activate the motor cortex of brain.
  - **ERD**: Power decrease in EEG, particularly contra lateral to the movement
  - **ERS**: Power increase in EEG.

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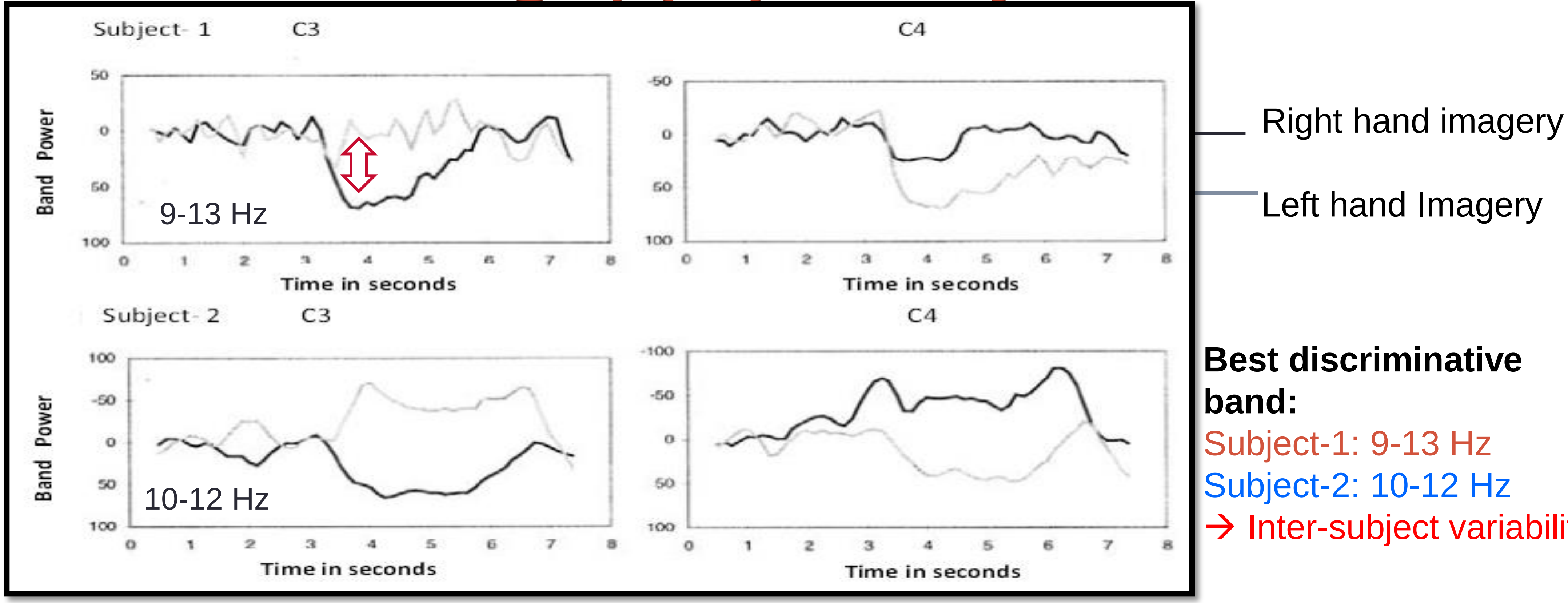
Motor-Imagery BCI

- Motor imagery based BCI translates motor intentions into control signals.
- The discriminative EEG frequency bands are subject-dependent which introduces a high Inter-Subject Variability in motor imagery based BCIs.
- Moreover, the discriminative frequency bands for each subject vary over time – causes Intra-Subject Variability.
- The subject-specific frequency bands for discriminating ERD/ERS has a significant role in the feature extraction and hence in the classification accuracy of a motor imagery based BCI.

Time courses of ERD/ERS during Motor Imagery (MI) in 2 subjects



Best discriminative band:
Subject-1: 9-13 Hz
Subject-2: 10-12 Hz
→ Inter-subject variability

ERD visible for Right-hand MI on C3

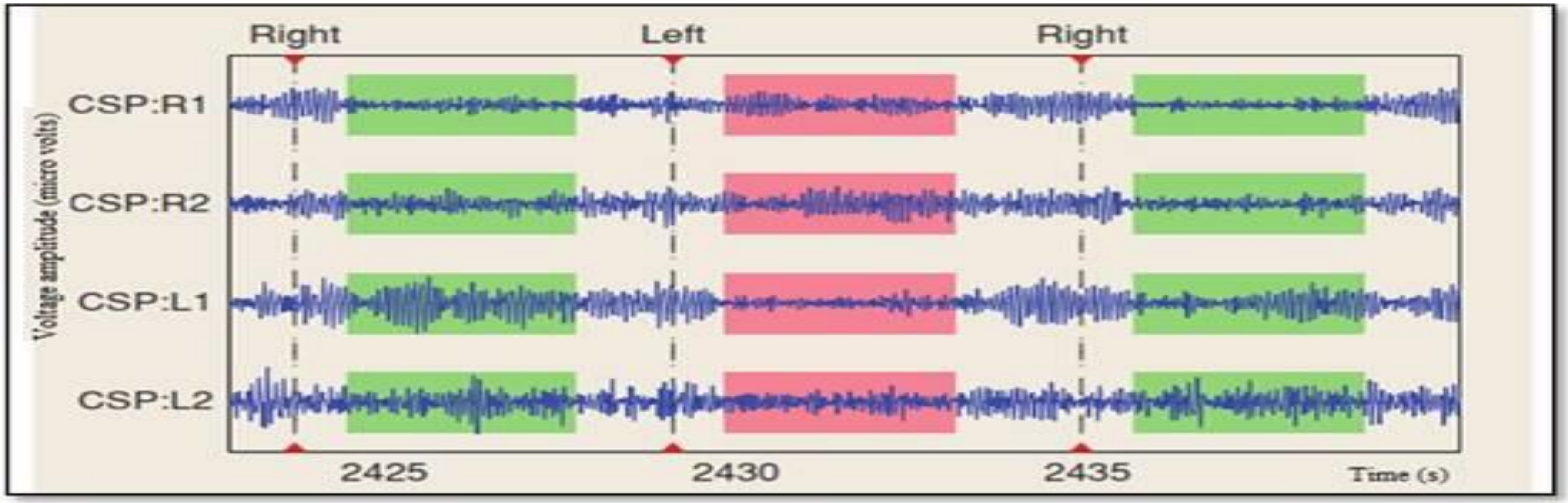
Motor imagery causes amplitude changes in EEG and they appear in subject-specific frequency bands.

ERD visible for Left-hand MI on C4

G. Pfurtscheller, C. Neuper, A. Schlogl and Klaus Lugger, "Separability of EEG Signals recorded During Right and Left Motor Imagery using Adaptive Autoregressive Parameters," *IEEE Transactions on Rehabilitation Engineering, vol. 6, pp. 316-325,* September 1998.

How do we extract MI patterns?

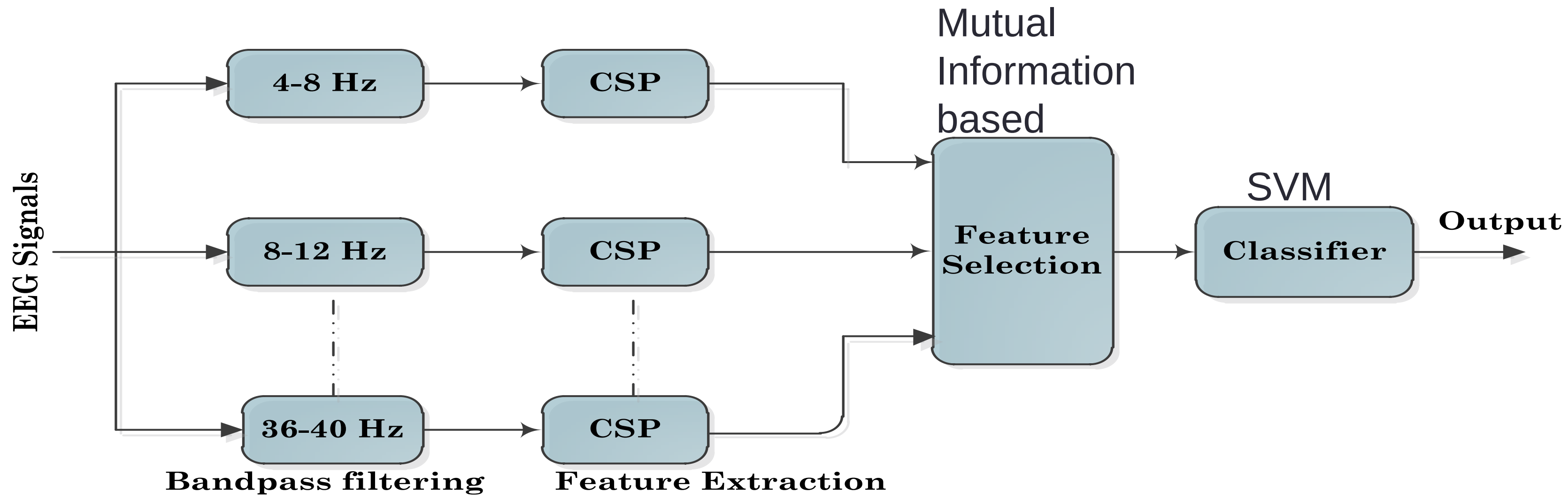
- ***Common Spatial Pattern (CSP)*** *is one of the most efficient methods for MI based BCIs (Muller-Gerking et. Al., 1999)*.
- A transformation technique to convert time-varying EEG to a new time series, where the difference between two types of signals is maximized.
- CSP transformed matrix: First ***m*** rows gives higher variance for one class MI and last ***m*** rows will be having relatively higher variance for second class MI.
- **For Right MI:** Low variance in R1 and R2 & High variance in L1 and L2.
- **For Left MI:** Low variance in L1 and L2 & High variance in R1 and R2.
- Logarithmic Sum of the variance of segment forms the feature.



Effect of CSP transformation on EEG signals during left/right hand MI (Pink-Left MI; Green-Right MI)

Selection of subject-specific discriminative bands is significant in Common Spatial Pattern (CSP) operation of MI.

Filter Bank Common Spatial Pattern (FBCSP), winner of BCI competition IV, 2008.



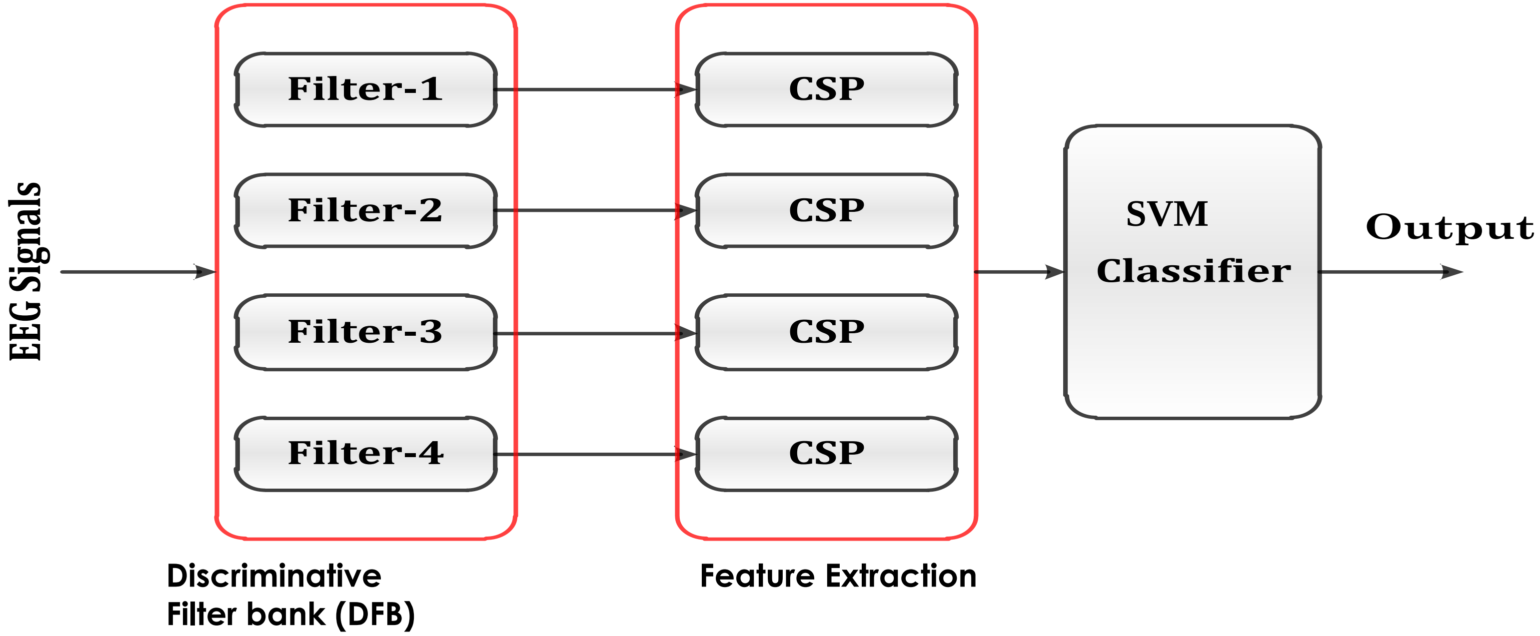
Schematic of the Existing FBCSP algorithm

Kai Keng Ang,, Z. Y. Chin, H Zhang and Cuntai Guan, "Filter bank common spatial patterns (FBCSP) in Brain-Computer Interface", International Joint Conference on on Neural Networks, pp. 2390-2397, June 2008.

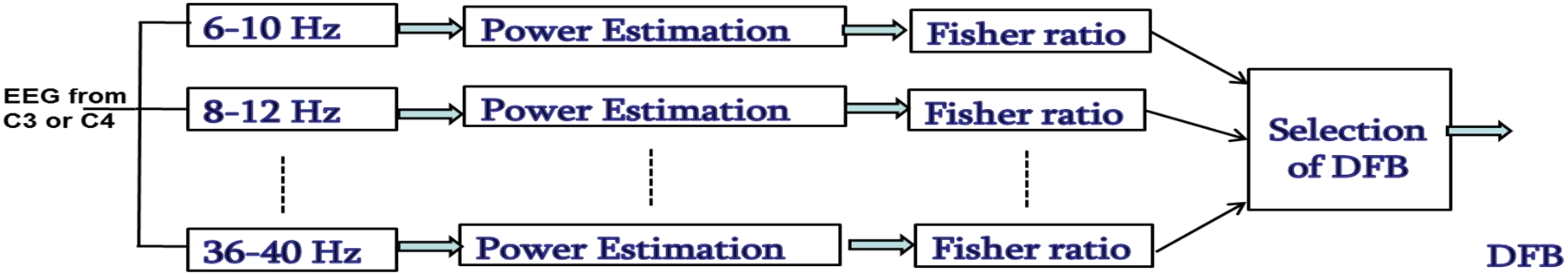
Discriminative Filter bank Common Spatial Pattern (DFBCSP)

- **Proposed a discriminative filter bank selection method:** Selects 4 filters from a set of 12 filters (parent filter bank) based on a Fisher ratio (FR) criterion → Higher FR means higher discrimination between MI types.
- If, S_B and S_W are between-class and within-class variances of the MI signal respectively,
- **Proposed DFBCSP**

$$FR = S_B / S_W$$



Discriminative Filter bank Common Spatial Pattern (Cntd.)



Includes parent filter bank filtering and Fisher ratio estimation at each filter output. Ranges of the filters: 6-10 Hz, 8-12 Hz, 12-16 Hz, 14-18 Hz, 18-22 Hz, 20-24 Hz, 23-27 Hz , 26-30 Hz, 28-32 Hz, 31-35 Hz, 32-36 Hz and 36-40 Hz.

Schematic of DFBCSP algorithm

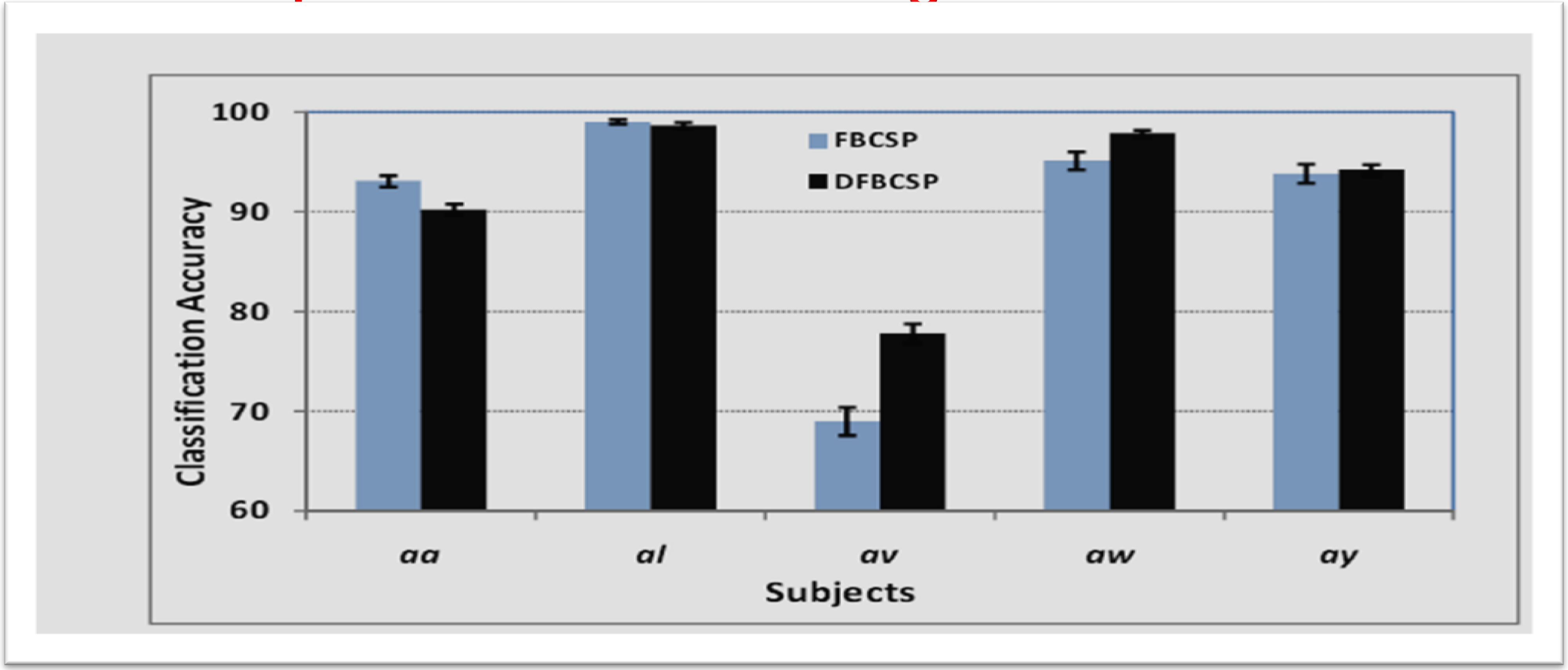
Frequency bands selected by DFBCSP

6-10Hz	8-12Hz	12-16Hz	14-18hz	18-22Hz	20-24Hz	23-27Hz	26-30Hz	28-32Hz	31-35Hz	32-36Hz	36-40Hz	
1	2	3	4	5	6	7	8	9	10	11	12	**Parent FB**
		1			4	2	3					***'aa'***
		1	4		3	2						***'al'***
	4		3	2	1							***'av'***
			2	1	3						4	***'aw'***
	2	4				1			3			***'ay'***

DFB selected in the DFBCSP algorithm for 5 subjects in BCI Competition III dataset IVa (Right hand and foot MI)

Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong, A. P. Vinod and Kai Keng Ang, "A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain-Computer Interfaces," *IEEE Transactions on Biomedical Engineering, vol. 56, no. 11, pp. 2731-2733,* November 2009.

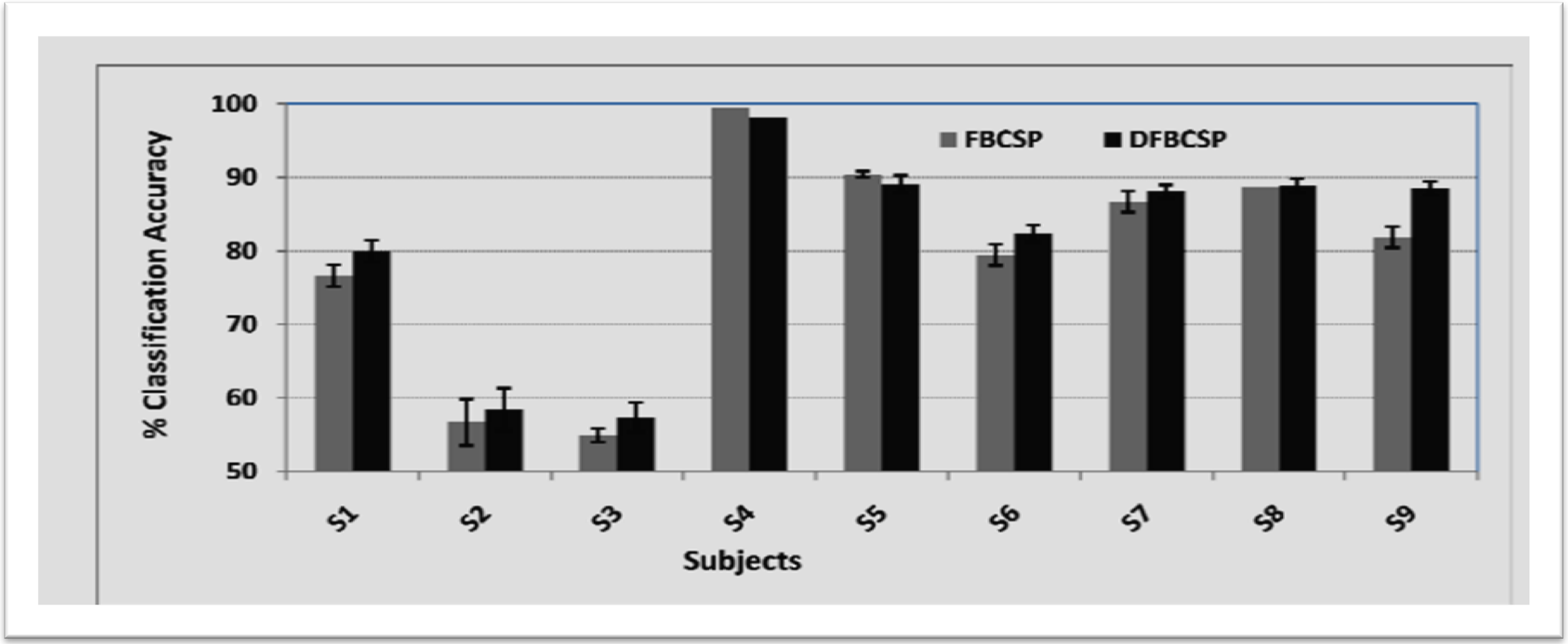
Comparison of classification of right hand and foot MI



Average Accuracy by FBCSP (%): 90.01 ± 0.82
Average Accuracy by proposed DFBCSP(%): 91.75 ± 0.54

Subject-specific discriminative frequency bands is a key factor in accurately determining the tasks. Proposed DFBCSP gives better results than existing FBCSP.

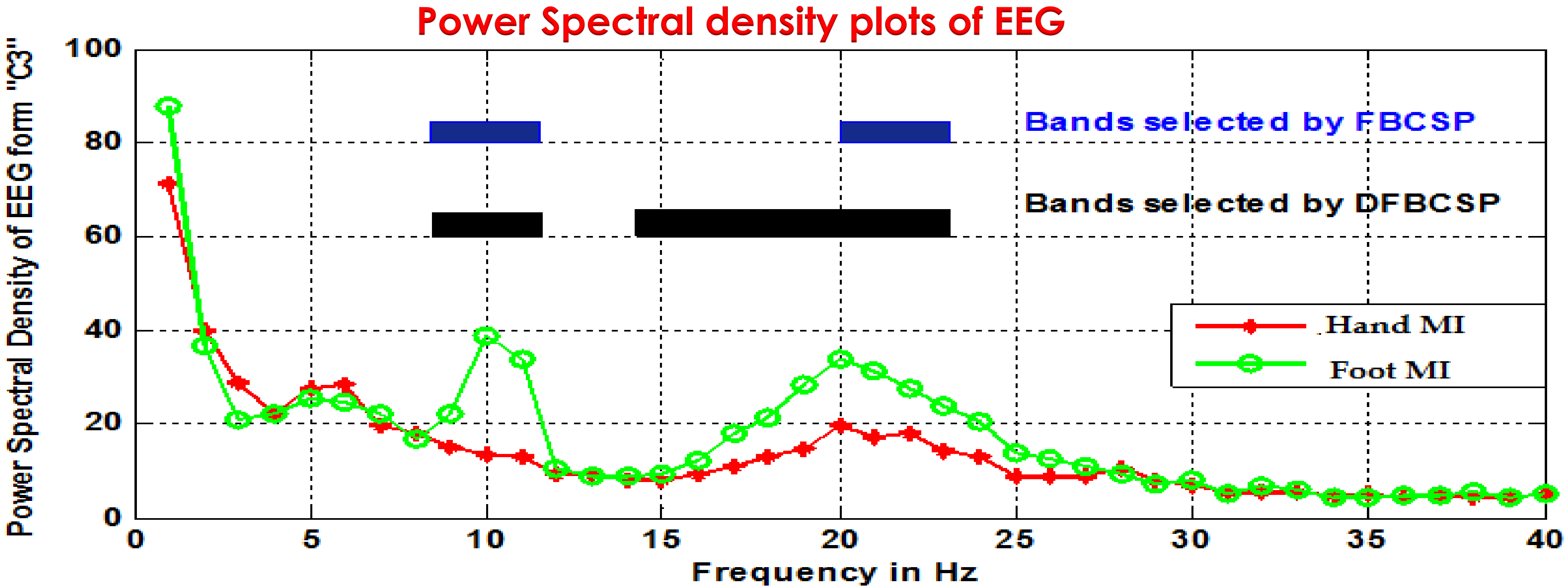
Comparison of classification of right hand and left hand MI



Average Accuracy by FBCSP (%): 79.44±1.15
Average Accuracy by proposed DFBCSP(%): 81.07±1.26

DFBCSP has low computational complexity because CSP operation is done only for the selected 4 bands.

Why DFBCSP outperforms FBCSP?



Average Power Spectral Density plots of right hand and foot trials for subject '*av*' in BCI Competition III dataset IVa.

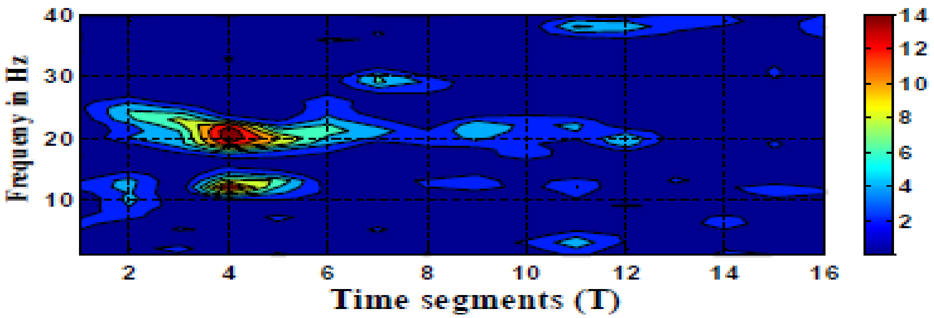
FBCSP selects the features from channels 9-12 Hz and 20-23 Hz.
DFBCSP extracts from 9-12 and 14-23 incorporating more discriminative spectral information.

More analysis on frequency bands during MI

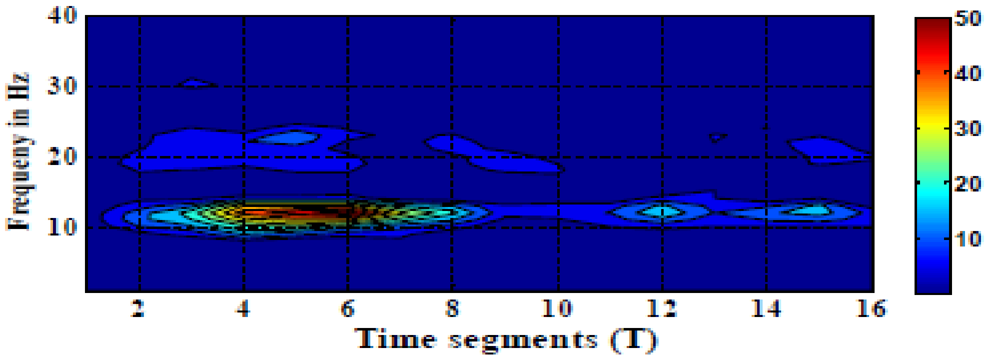
- Found that the selection of discriminative frequency bands affects the classification accuracy of MI patterns.
- DFBCSP requires multiband filtering to select the subject-specific DFB.

- In order to avoid this multi-band filtering, another method of time-frequency Fisher ratio patterns is proposed.
- Involves the computation Power spectral density (PSD) using STFT of right hand and left hand MI EEG which gives the Fisher values of frequency points along time domain.

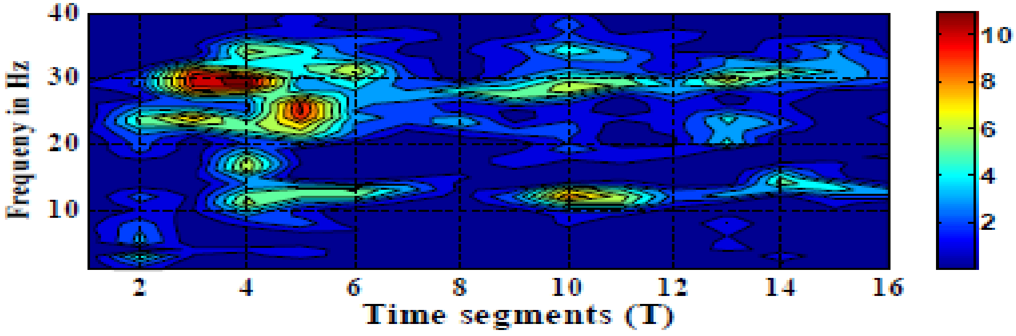
Time-Frequency Fisher pattern from channel C4 for subjects 1, 4, 5 and 9 in BCI Competition IV dataset IIb (right and left hand MI)



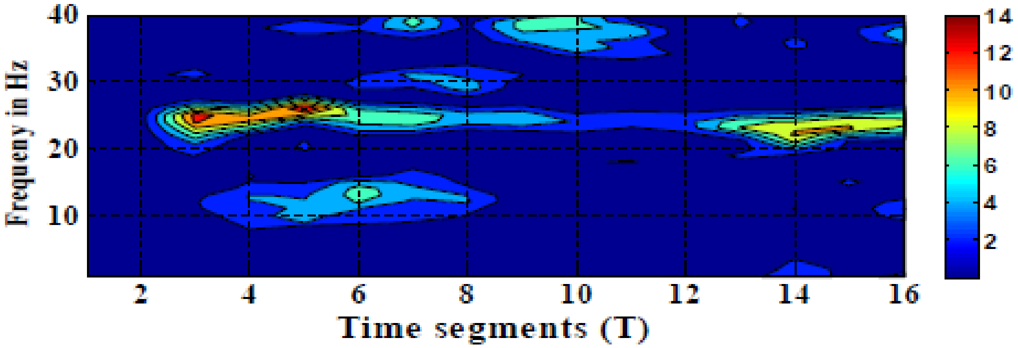
Subject-1



Subject-4

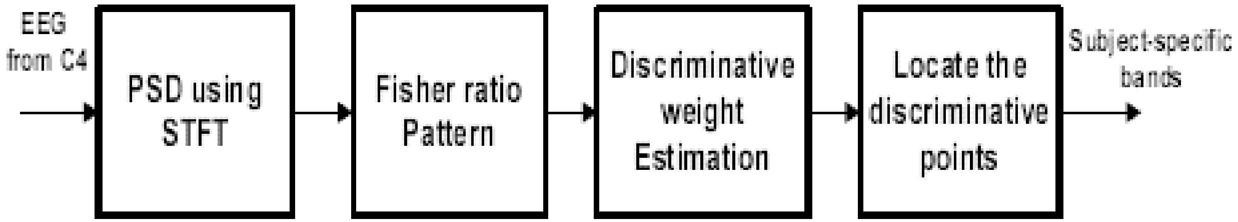


Subject-5

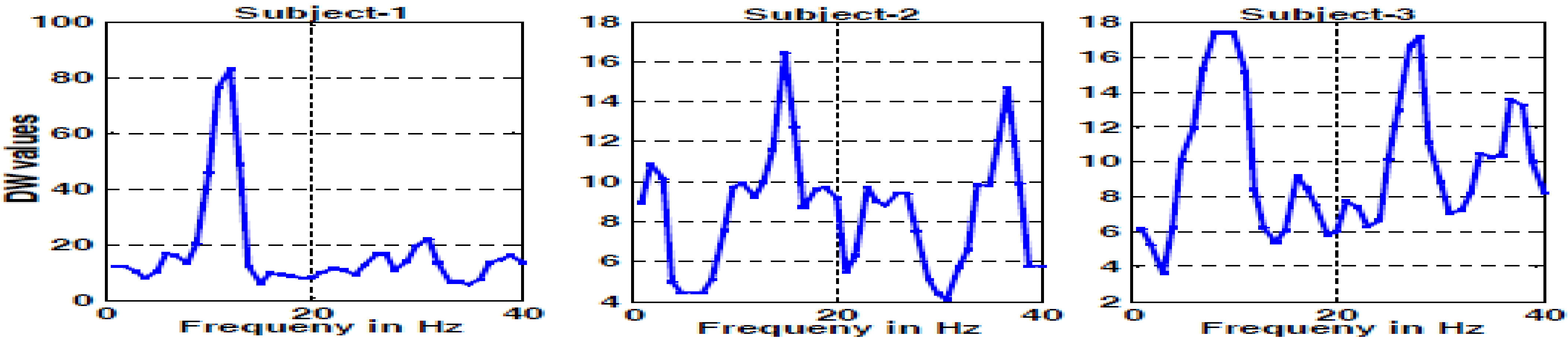


Subject-9

Discriminative band selection from Fisher ratio pattern



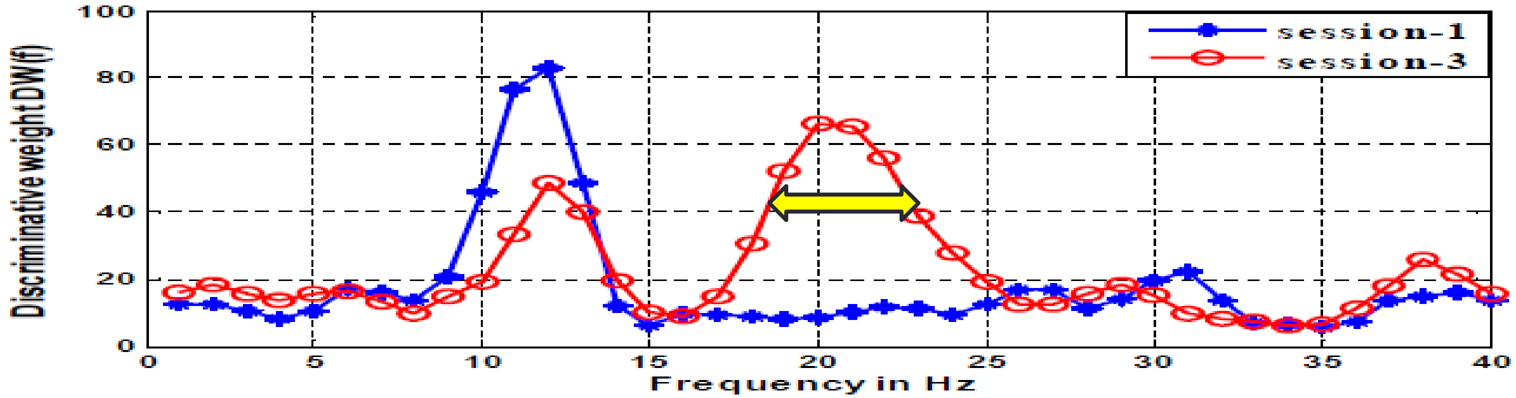
Discriminative Weight (**DW**) values: Sum of the Fisher values for each frequency component along the time domain in FR pattern.



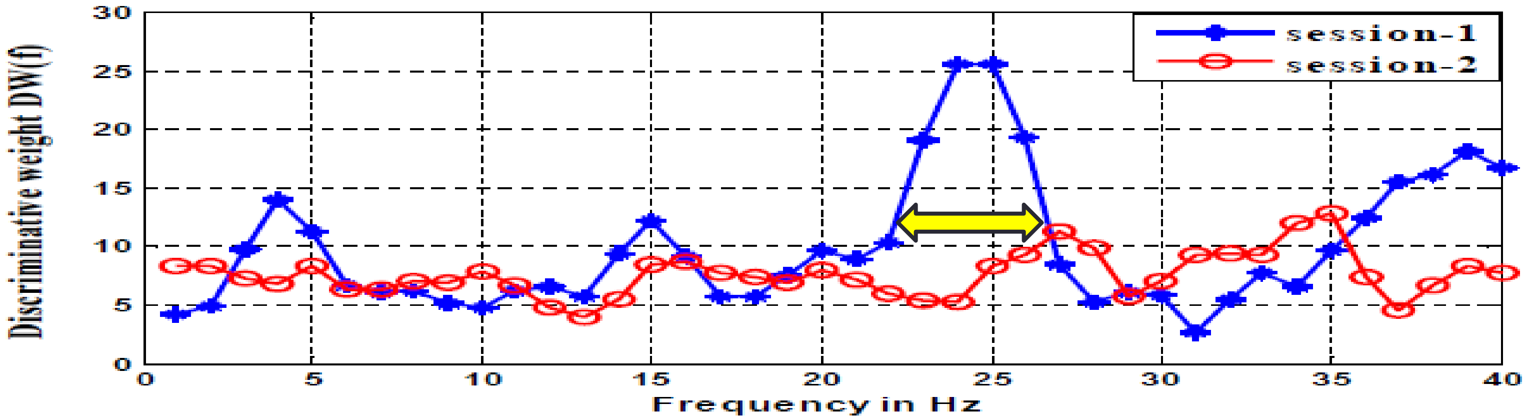
8-11 Hz, 30-34 Hz **11-17 Hz, 34-39 Hz** **7-12 Hz, 25-30 Hz**

DW values and estimated bands in 3 subjects in BCI Competition IV Dataset IIb (right and left hand MI)

Inter-session variation of Discriminative weight (DW) values



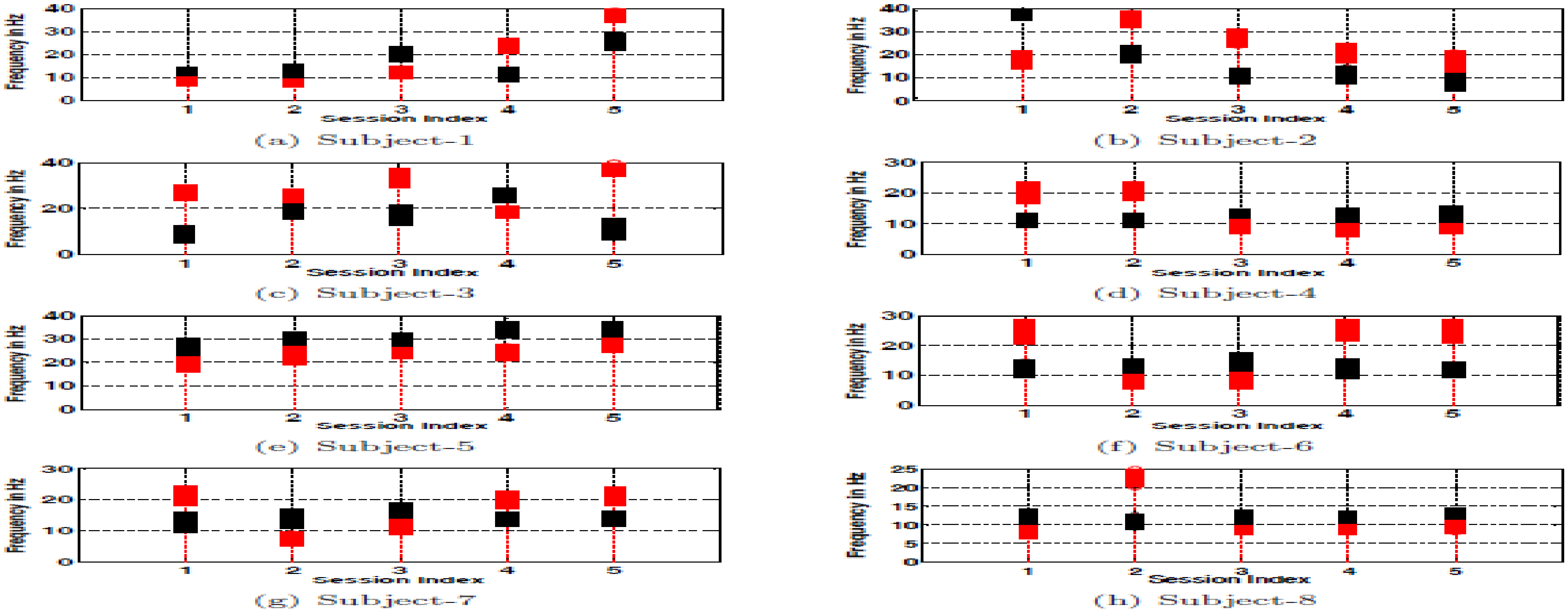
Subject-1

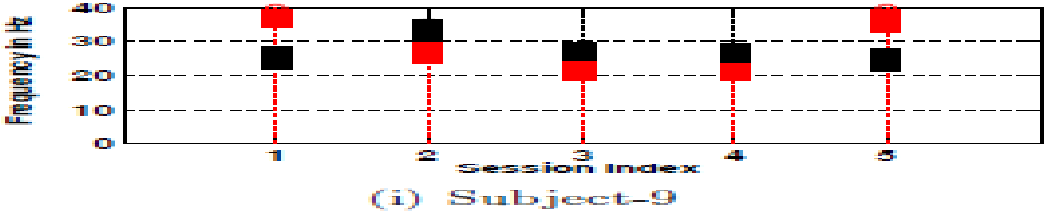


Subject-9

Exhibits Intra-Subject Variability.

Variation of most discriminative frequency bands over sessions





Black: Most discriminative Band

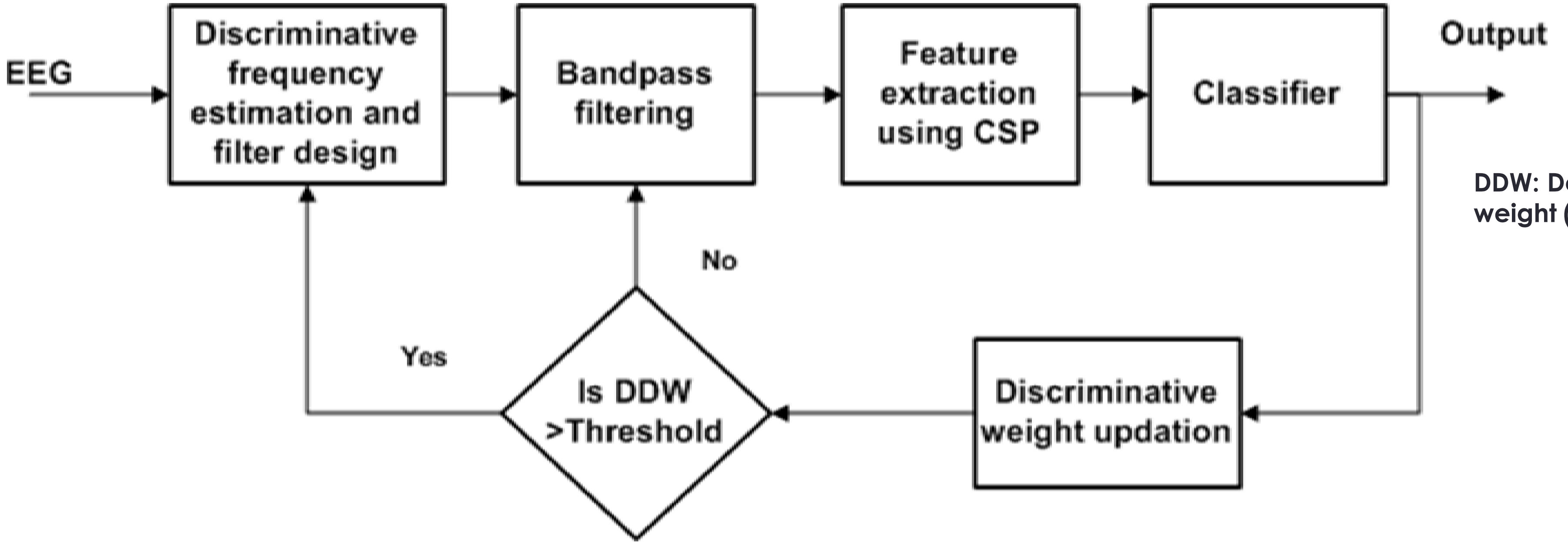
Red: Second most DFB

Exhibits variation between subjects and within subjects.

Proposed Adaptive Method for tracking the discriminative bands

To track the intra-subject variability of DW values and frequency bands

Schematic of the Adaptively weighted Spectral Spatial Pattern (AWSSP)

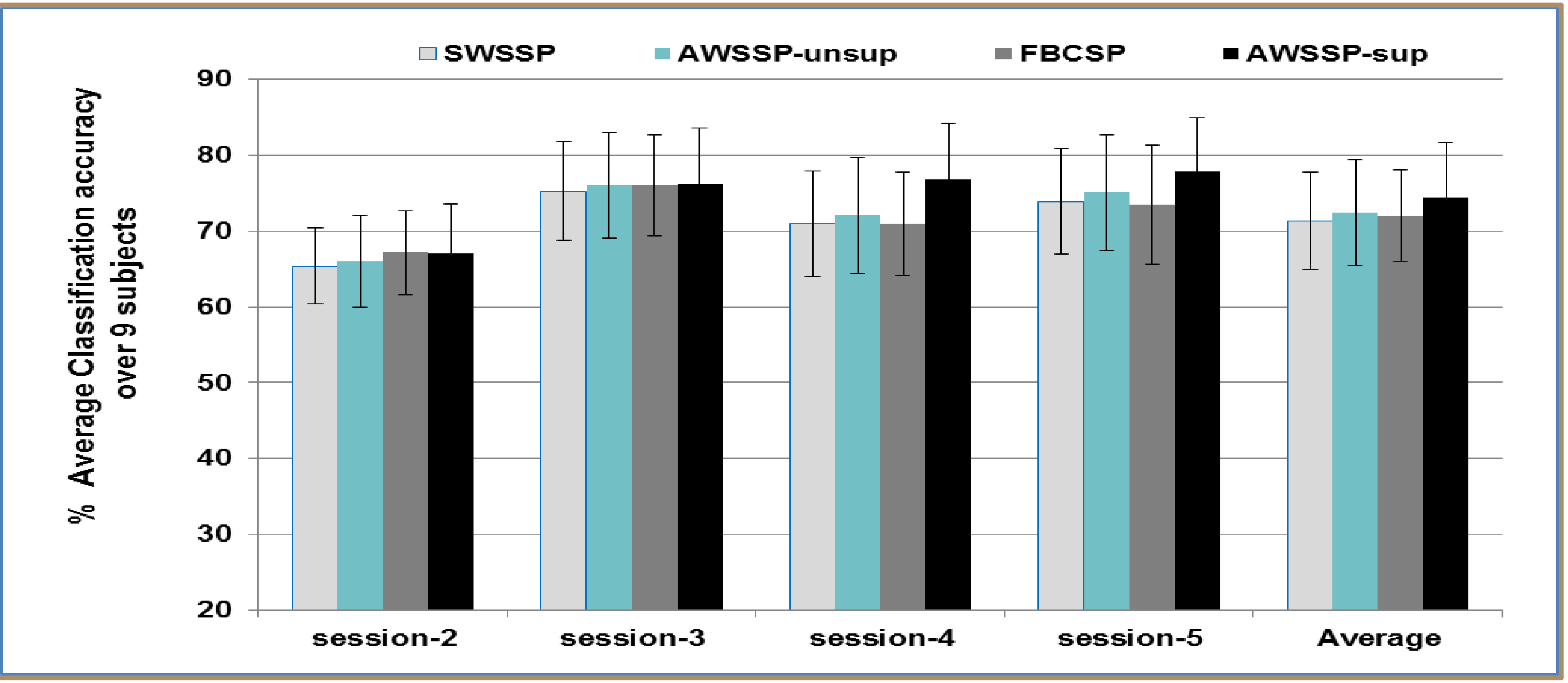


DDW: Deviation in Discriminative weight (DW) values

- Start with the frequency bands calibrated from the training data.
- For test signal, the DWs of frequency components are continuously computed.
- If DDW values is greater than a pre-defined threshold (30%), the frequency bands are updated. The classifier is also re-trained.

Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong, A. P. Vinod and Kai Keng Ang, "Adaptive tracking of discriminative frequency components in EEG for a robust Brain- Computer Interface," Journal of Neural Engineering, June 2011.

Classification results for 5 sessions of 9 subjects in BCI Competition IV dataset IIb



Classification Accuracies of BCI Competition IV Dataset IIb (**9 subjects in 5 sessions**) using FBCSP* and proposed Static/Adaptively Weighted Spectral Spatial Pattern (SW/AWSSP) Methods.

Static WSSP: Use the same set of filters as obtained from training data, no updates.

Awssp unsup: Uses the predicted class label or the classifier output .

Awssp: Uses the true class labels for weight updation.

Classification performance of Awssp sup is better than all the methods presented here.

Classification results of <u>online data</u> using the proposed static and adaptive methods

Performed online experiments for 3 subjects, 2 types of MI left and right hand MI

In session-1 and session-2, two sets of EEG trials were recorded which were processed using static and adaptive schemes.

Session	Session-1		Session-2	
Subject	Static	Adaptive	Static	Adaptive
SG	85.83%	92.50%	84.51%	87.50%
SM	84.17%	87.50%	81.66%	88.33%
SS	79.17%	86.67%	74.17%	82.50%
Average	83.05%	88.90%	80.11%	86.11%

Desirable Features of Motor Control

- Motor control requirements
  - Need for continuous control
  - Need for higher dimensional output – higher degrees of freedom of movement

- Most BCI systems have limited by number of control commands
  - Discrete classification of executed or imagined (hand, foot, tongue) movements

BCI for Movement Kinematics

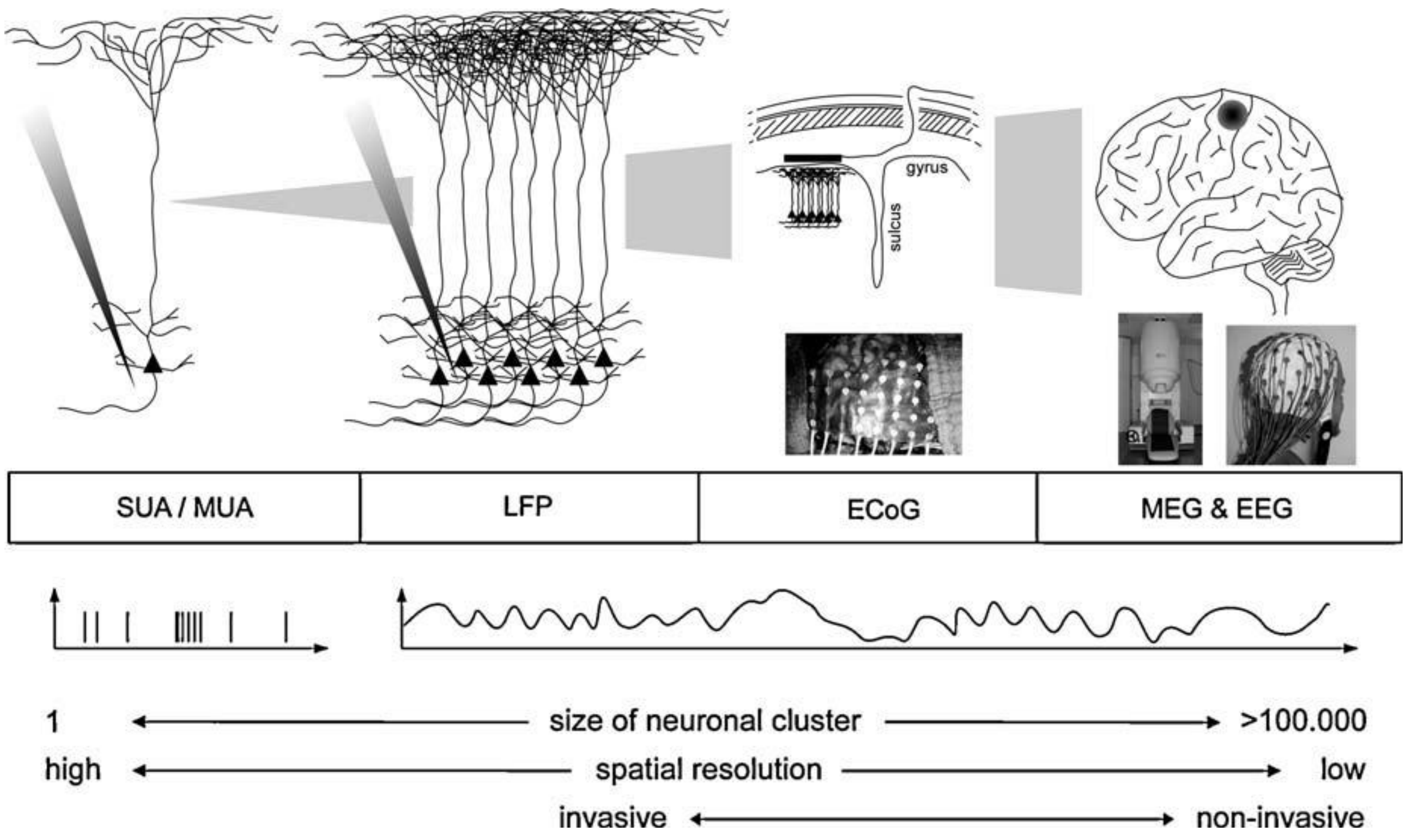
- Movement Kinematics
  - Description of movement; Quantifying properties of movement
  - Trajectory, Position, Acceleration, Speed, Force etc.

- Goals of BCI
  - To identify neural correlates of movement kinematics
  - To decode movement kinematics from recorded brain activity
  - To provide real-time, continuous motor control to an interfaced device

Neurophysiology – Movement Kinematics

- **BCI-Movement decoding studies**
  - Modalities
    - Invasive and Non-invasive BCI studies
  - Mode of motor control
    - Discrete: Centre-out movement experiments
      - Movement parameter classification, Direction tuning etc.
    - Continuous: Target tracking experiments
      - Decoding trajectory, speed etc.

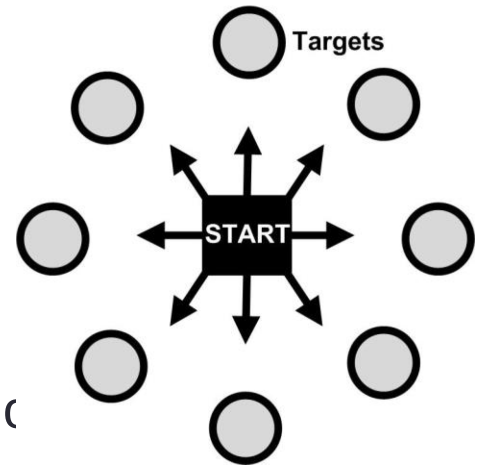
Brief overview of BCI modalities used in movement kinematics research



SUA/MUA: Single/Multi Unit Activity
LFP: Localized Field Potential
ECoG: Electrocorticography
MEG: Magnetoencephalography
EEG: Electroencephalography [1]

1. S. Waldert, T. Pistohl, C. Braun, T. Ball, A. Aertsen, and C. Mehring, "A review on directional information in neural signals for brain-machine interfaces," *Journal of Physiology-Paris,* vol. 103, pp. 244-254, 2009.

Invasive – BCI Studies: Center-out movements

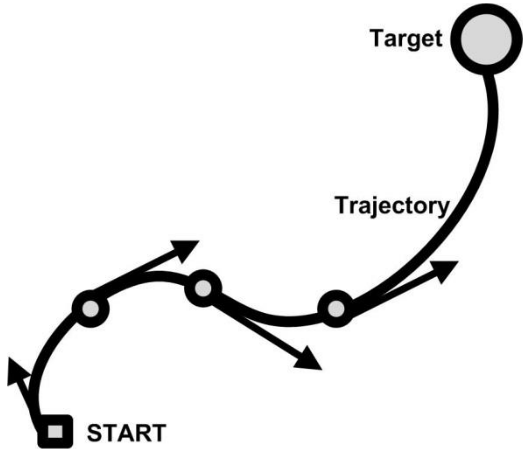


- **Primate Studies:**
- **SUA/MUA**: Studied activity of single cells in the monkey motor cortex and identified directional tuning (cosine) of neurons [1]
- **SUA/MUA**: Population of motor cortical neurons determine uniquely the direction of movements in three-dimensional space [2]
- **SUA/MUA**: Movement prediction algorithms and visual feedback of brain-controlled trajectories [3]
- **LFP**: Modulation of signal components in the time and frequency domains and application of LFP amplitude spectra to decode movement direction [4]
- **Human Study:**
- **ECoG**: T-F analysis for finding the relation between Spectral amplitude modulations and cortical functional anatomy for arm movement direction [5]

1. P. Georgopoulos, J. F. Kalaska, R. Caminiti, and J. T. Massey, "On the relations between the direction of two-dimensional arm movements and cell discharge in primate motor cortex," *The Journal of Neuroscience,* vol. 2, pp. 1527-1537, 1982.
2. A. P. Georgopoulos, R. E. Kettner, and A. B. Schwartz, "Primate motor cortex and free arm movements to visual targets in three-dimensional space. II. Coding of the direction of movement by a neuronal population," *The Journal of Neuroscience,* vol. 8, pp. 2928-2937, 1988.
3. D. M. Taylor, S. I. H. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science,* vol. 296, pp. 1829-1832, 2002.
4. J. Rickert, S. C. de Oliveira, E. Vaadia, A. Aertsen, S. Rotter, and C. Mehring, "Encoding of movement direction in different frequency ranges of motor cortical local field potentials," *The Journal of Neuroscience,* vol. 25, pp. 8815-8824, 2005.
5. T. Ball, A. Schulze-Bonhage, A. Aertsen, C. Mehring, "Differential representation of arm movement direction in relation to cortical anatomy and function," *Journal of Neural Engineering,* vol. 6(016006), 2009.

Invasive-BCI Studies – Trajectory decoding

- **SUA/MUA**: Kalman filter to decode movement trajectory from multi-cell recordings in monkey's motor cortex [1]
  - **LFP**: Reconstruction of arm movement target and velocity from multi channel LFPs in monkey's motor cortex [2]



- **ECoG**: Continuous trajectories of 2D hand position approximately predicted using data from hand/arm motor cortex using Kalman filters [3]
- **ECoG:** Local motor potential feature derived from ECoG to decode movement trajectory [4]

1. W. Wu, M. Black, Y. Gao, E. Bienenstock, M. Serruya, and J. Donoghue, "Inferring hand motion from multi-cell recordings in motor cortex using a Kalman filter," in *SAB'02-workshop on motor control in humans and robots: On the interplay of real brains and artificial devices*, 2002, pp. 66-73.
2. C. Mehring, J. Rickert, E. Vaadia, S. C. de Oliveira, A. Aertsen, and S. Rotter, "Inference of hand movements from local field potentials in monkey motor cortex," *Nature neuroscience,* vol. 6, pp. 1253-1254, 2003.
3. T. Pistohl, T. Ball, A. Schulze-Bonhage, A. Aertsen, and C. Mehring, "Prediction of arm movement trajectories from ECoG-recordings in humans," *Journal of neuroscience methods,* vol. 167, pp. 105-114, 2008.
4. G. Schalk, J. Kubanek, K. Miller, N. Anderson, E. Leuthardt, J. Ojemann, D. Limbrick, D. Moran, L. Gerhardt, and J. Wolpaw, "Decoding two-dimensional movement trajectories using electrocorticographic signals in humans," *Journal of Neural Engineering,* vol. 4, p. 264, 2007.

Neuromotor Prostheses – 1

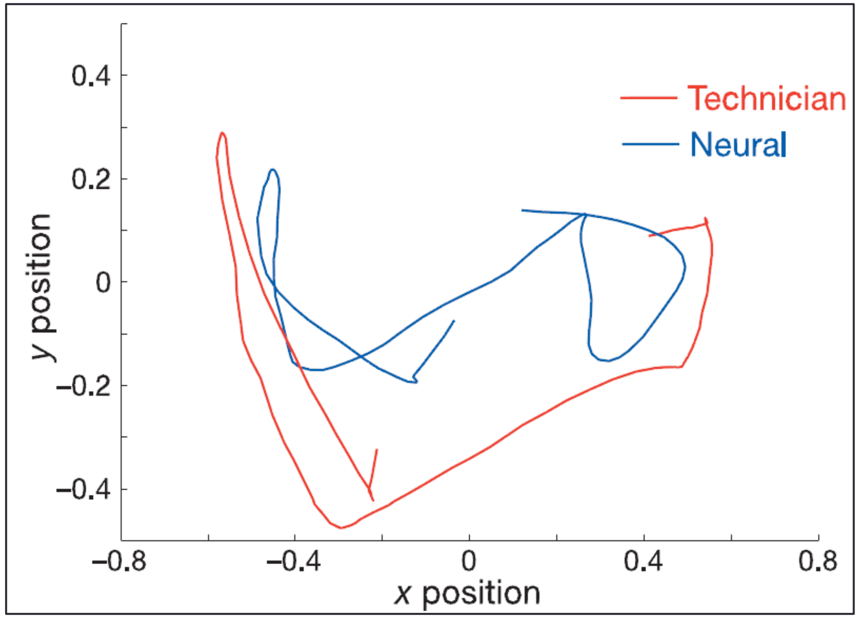
- Neural Interface Systems (Invasive) [1]
- **Aim:** Replace or restore lost motor functions in paralyzed humans
  - Routing movement-related signals from the brain, around damaged parts of the nervous system, to external effectors
  - Intention-driven neuronal activity converted into control signal
- **Cursor control** by a Tetraplegic human

- 25 yr old male sustained a knife wound that transected spinal cord between C3-C4, resulting in complete tetraplegia
  - 96-microelectrode array implanted in primary motor cortex
  - Intended hand motion modulates cortical spiking patterns
  - Linear filtering algorithm to model relation between intended movement and neuronal firing.

1. L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn, and J. P. Donoghue, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature,* vol. 442, pp. 164-171, 2006.

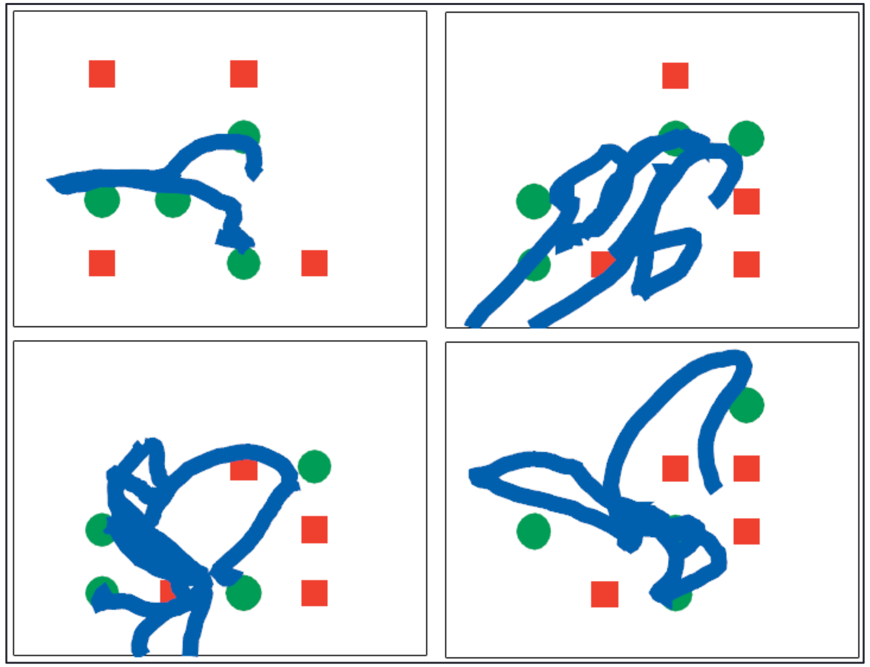
Neuromotor Prostheses – 1 (Cntd.)

In a target tracking task



x coordinate $r^2 = 0.56 \pm 0.18$
y coordinate $r^2 = 0.45 \pm 0.15$

In a target acquisition/obstacle avoidance task



Green circle: Target
Red square: Obstacle
Blue: Decoded trajectory

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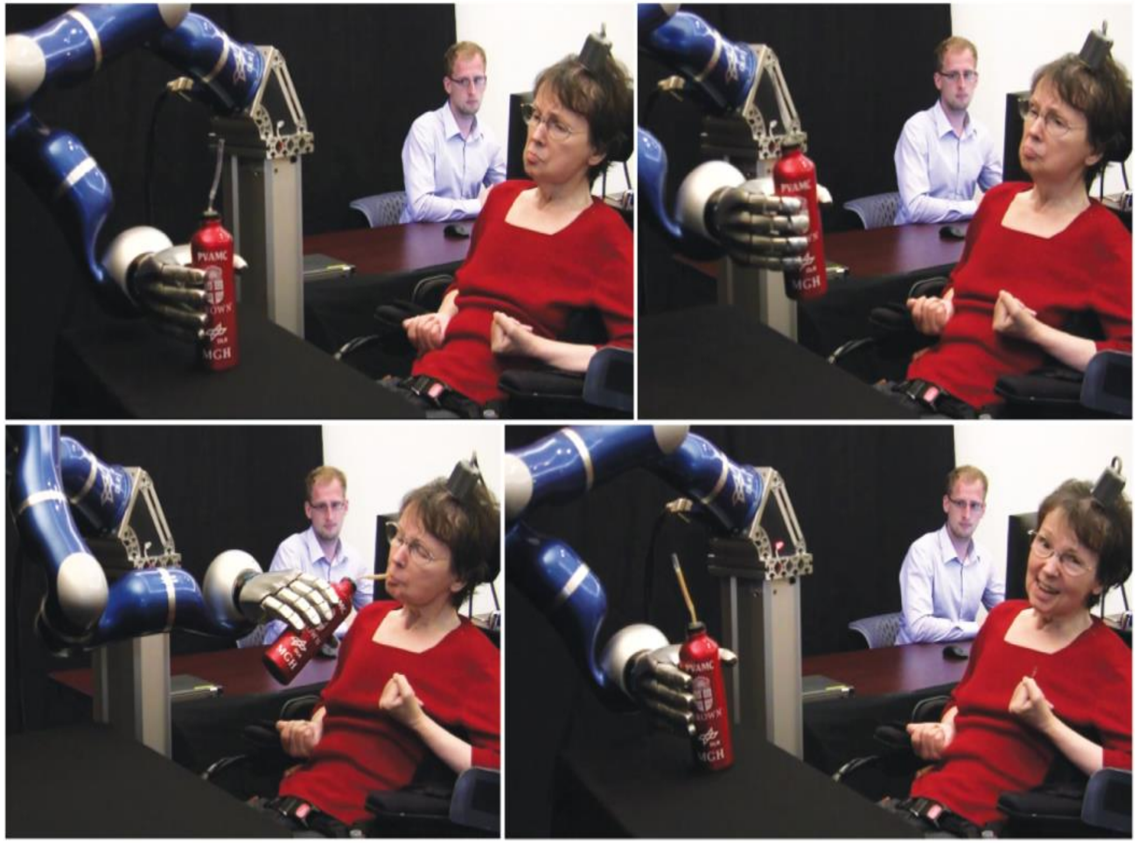
Neuromotor Prostheses – 2

- **Goal:** Recreate useful **multidimensional control of complex devices** directly from a small sample of neural signals from people with tetraplegia [1]
- Robotic arm control to perform three-dimensional reach and grasp movements (motor imagery)
- 96-channel microelectrode array implanted in the dominant MI hand area
- Kalman filtering algorithm to decode.



Study performed in Institute for Brain Science at Brown University in Rhode Island (2012).

1. L. R. Hochberg, D. Bacher, B. Jarosiewicz, N. Y. Masse, J. D. Simeral, J. Vogel, S. Haddadin, J. Liu, S. S. Cash, and P. van der Smagt, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature,* vol. 485, pp. 372-375, 2012.

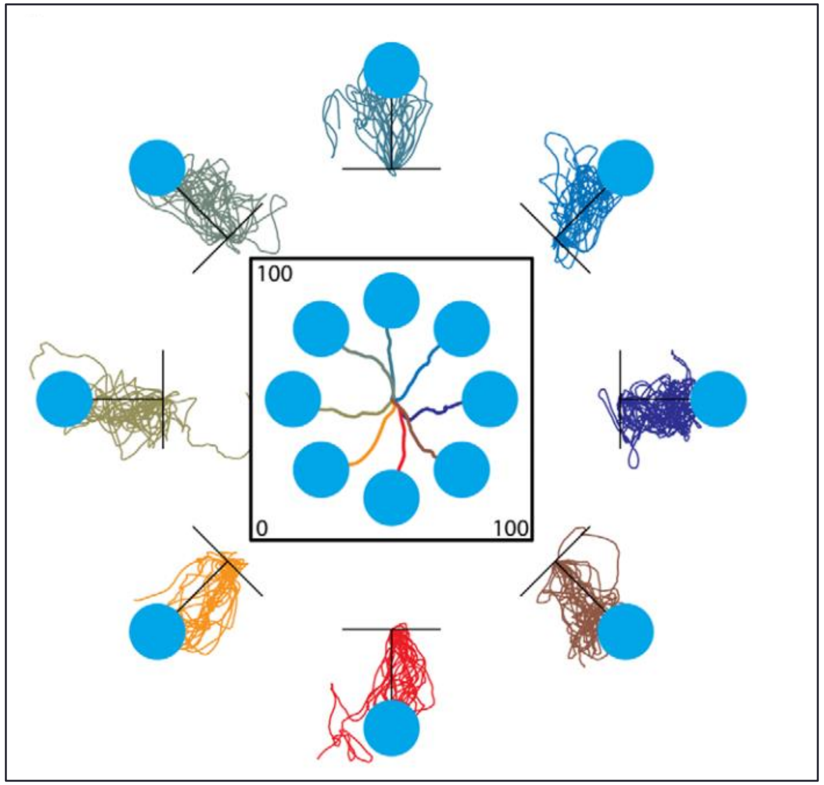
Neuromotor Prostheses – 3

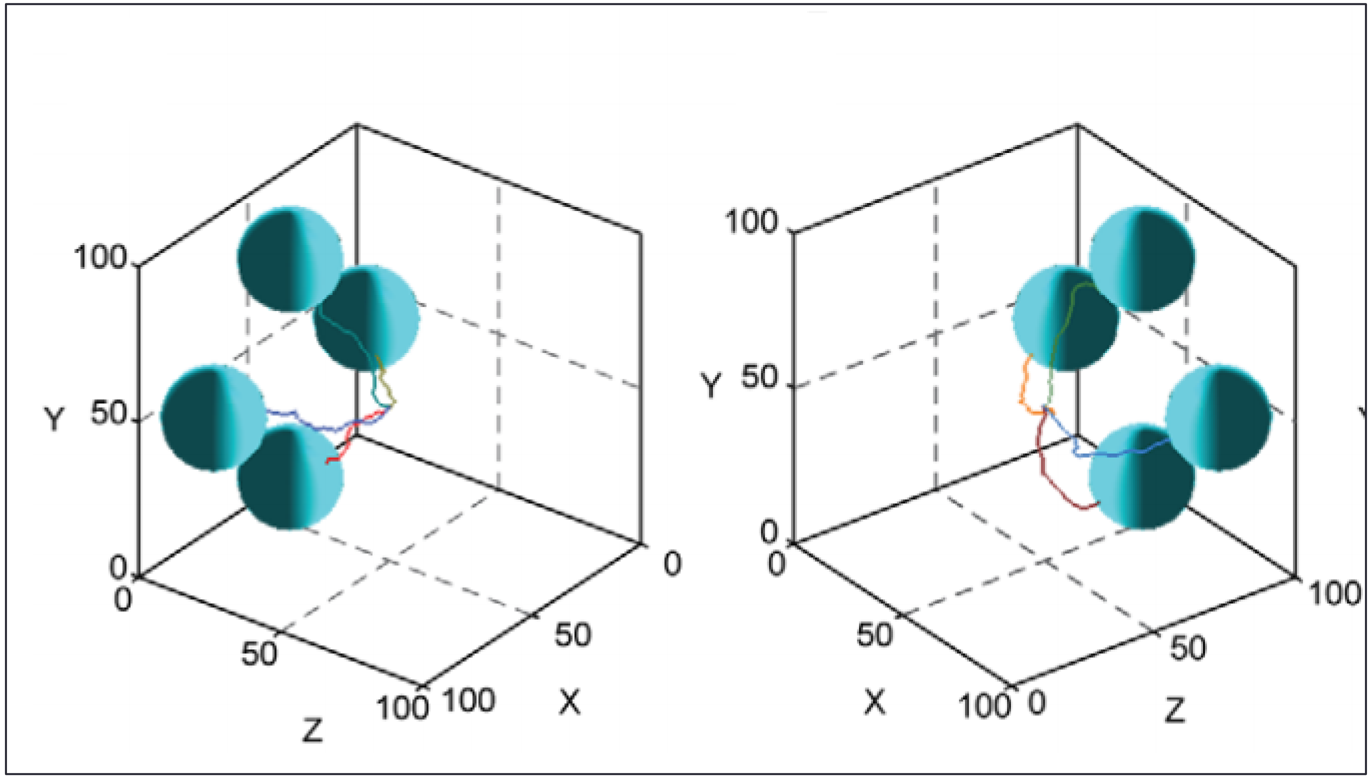
- ECoG BCI system in an individual with tetraplegia caused by C4 level spinal cord injury [1]
- High-density 32-electrode grid over the left sensorimotor cortex
- Voluntarily activate the sensorimotor cortex using **attempted movement**
- Users trained to control 2D and 3D cursor movement
- Power of 10 Hz wide frequency band from one channel used as neural feature and optimal linear estimator (OLE) algorithm used for decoding.

1. W. Wang, J. L. Collinger, A. D. Degenhart, E. C. Tyler-Kabara, A. B. Schwartz, D. W. Moran, D. J. Weber, B. Wodlinger, R. K. Vinjamuri, and R. C. Ashmore, "An electrocorticographic brain interface in an individual with tetraplegia," *PLoS ONE,* vol. 8, p. e55344, 2013.

Neuromotor Prostheses – 3 (Cntd.)

Trial-averaged trajectory estimated using proposed method in 2D and 3D.





- Robust control of 2D cursor movement

- Robust control of 3D cursor movement

After excessive training, final success rate of 80% for 3D cursor control achieved.

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Non-invasive BCI Studies

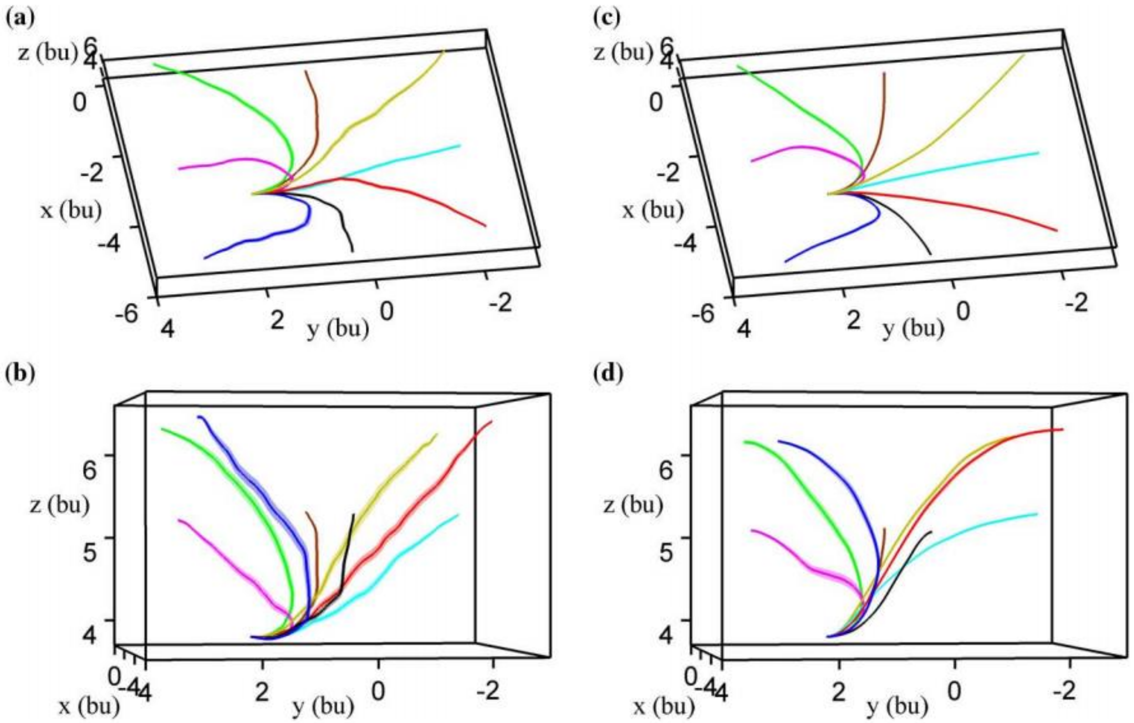
- MEG
  - Single-trial classification (4-class) of hand movement direction – band powers in linear discriminant classifier [1]
  - Intended movement direction (4-class) decoded from planning period – sensor space decoding analysis [2]
  - Decoding hand position and velocity – regression method [3]

- EEG
  - Single-trial classification (4-class) of hand movement direction – band powers in linear discriminant classifier [1]
  - Decoding target location during a planned reach – meta classifier based on multiple features [4]
  - Reconstruction of 3D hand movement and identified contribution of scalp areas– regression method [5]
  - Decoding hand movement velocities during a two-dimensional drawing task – Kalman filter [6]

1. S. Waldert, H. Preissl, E. Demandt, C. Braun, N. Birbaumer, A. Aertsen, and C. Mehring, "Hand movement direction decoded from MEG and EEG," *The Journal of Neuroscience,* vol. 28, pp. 1000-1008, 2008.
2. W. Wang, G. P. Sudre, Y. Xu, R. E. Kass, J. L. Collinger, A. D. Degenhart, A. I. Bagic, and D. J. Weber, "Decoding and cortical source localization for intended movement direction with MEG," *Journal of Neurophysiology,* vol. 104, pp. 2451-2461, 2010.
3. T. J. Bradberry, J. L. Contreras-Vidal, and F. Rong, "Decoding hand and cursor kinematics from magnetoencephalographic signals during tool use," in *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* pp. 530, *2008.*
4. P. S. Hammon, S. Makeig, H. Poizner, E. Todorov, and V. R. De Sa, "Predicting reaching targets from human EEG," *Signal Processing Magazine, IEEE,* vol. 25, pp. 69-77, 2008.
5. T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals," *The Journal of Neuroscience,* vol. 30, pp. 3432-3437, 2010.
6. J. Lv and Y. Li, "Decoding hand movement velocities from EEG signals during a continuous drawing task," in *Fuzzy Systems and Knowledge Discovery (FSKD), 2010 Seventh International Conference on*, 2010, pp. 2186-2189.

3D Virtual Helicopter Control

- Controlled flight of a virtual helicopter in 3D space using EEG [1]
- Imagined left, right, both hand movement and rest for commands – Go right, left, up and Stop respectively
- Features – Autoregressive spectral amplitude from multiple sensors and frequency bins
- Discrete commands used for goal-directed navigation
- Not exactly decoding of continuous MI.

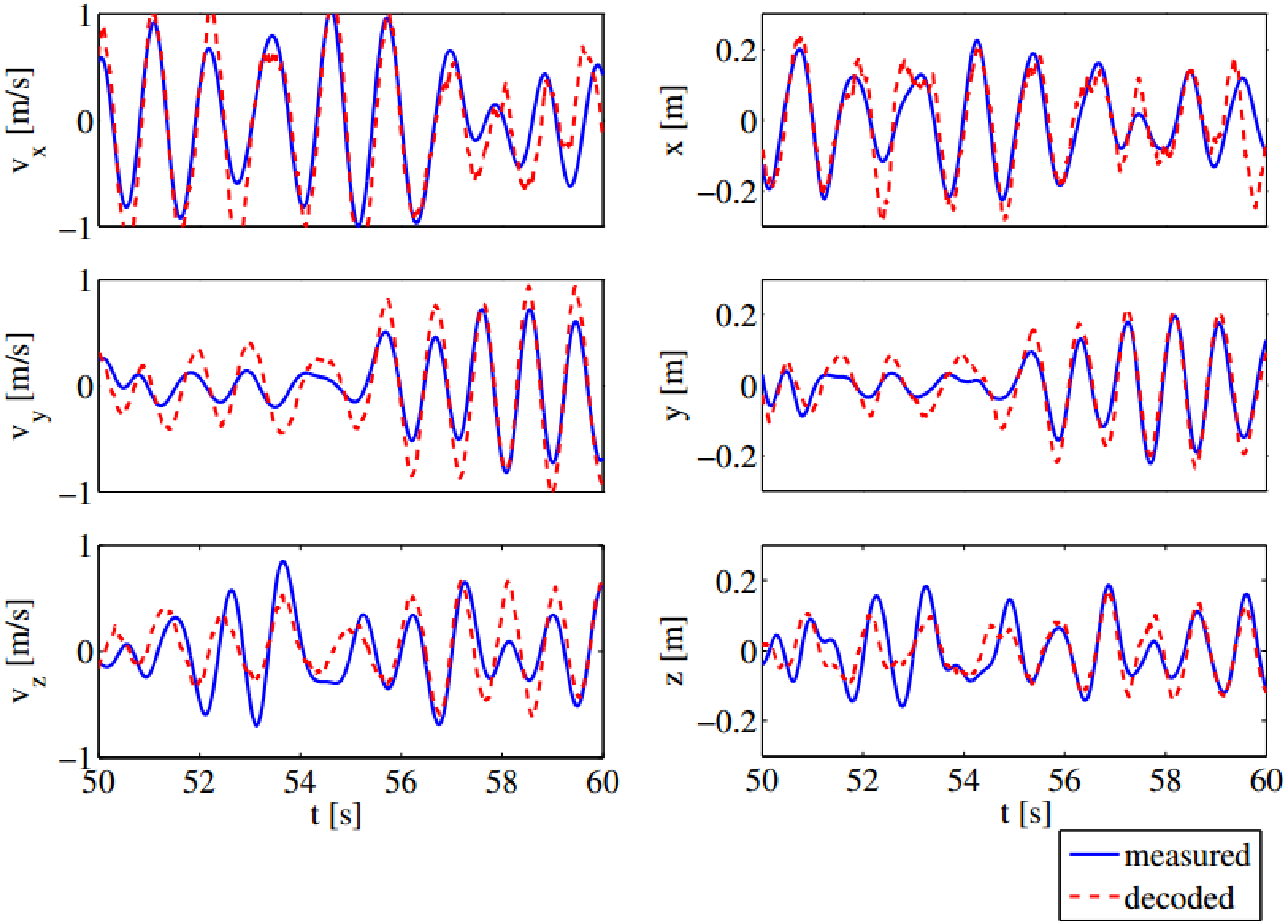


- (a,b) – BCI paths; (c,d) – Cursor paths
- ~0.99 correlation between the two paths
- bu indicates virtual reality system units

1. A. S. Royer, A. J. Doud, M. L. Rose, and B. He, "EEG control of a virtual helicopter in 3-dimensional space using intelligent control strategies," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 18, pp. 581-589, 2010.

3D Arm Movement Decoding

- Continuous and self-chosen movement trajectory decoding using EEG [1]
- Multiple linear regressor models to reconstruct instantaneous velocity and position.
- High correlation (0.7) .



1. P. Ofner and G. Muller-Putz, "Decoding of velocities and positions of 3D arm movement from EEG," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 2012, pp. 6406-6409.

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Neural Correlates of Movement Kinematics

- Why is it important?
  - Maximizes the probability of correct brain state identification at the BCI output
  - Improves efficacy of rehabilitation strategies by targeting exact neural substrates
- Information of interest
  - Directional tuning of neural/scalp-recorded signals
  - **Signal amplitude spectra**
  - Cortical/scalp activation patterns

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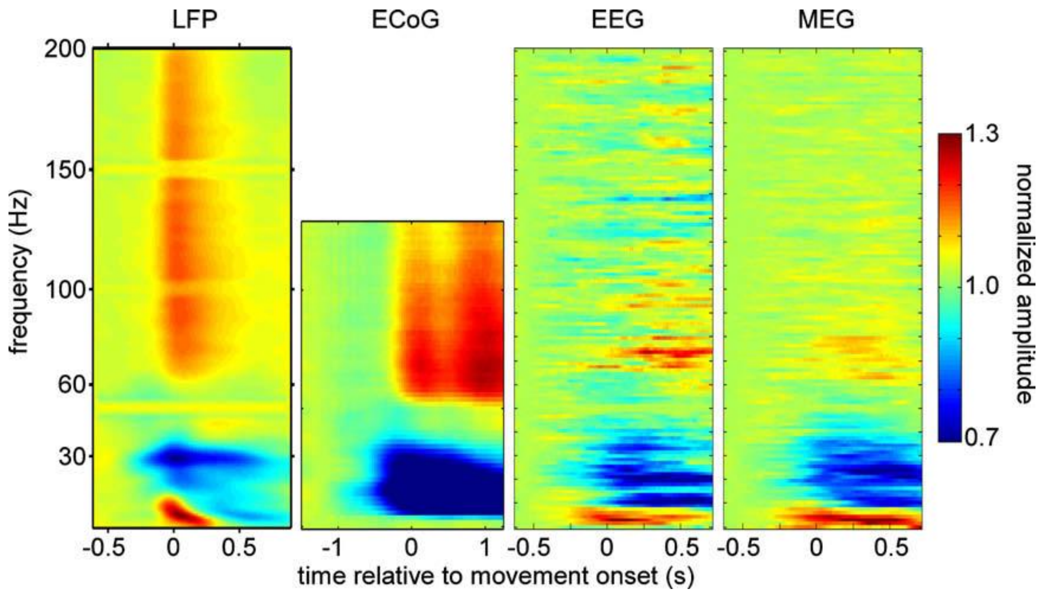
Signal amplitude spectra

- Low frequency band [1]
  - (LFP: <13 Hz, ECoG: <2 Hz, EEG/MEG: <7 Hz)
  - **Low-pass Filtered EEG is found to be highly relevant for decoding of movement direction**



Activation during center-out hand movements

- Intermediate frequency band
  - (LFP: 16–42 Hz, ECoG: 6–30 Hz, EEG/MEG: 10–30 Hz)
  - SMR rhythms that accompany any movement activity
- High-frequency band
  - (LFP: 63–200 Hz, ECoG: 34–128 Hz, EEG/MEG: 62–87 Hz)

1. S. Waldert, T. Pistohl, C. Braun, T. Ball, A. Aertsen, and C. Mehring, "A review on directional information in neural signals for brain-machine interfaces," *Journal of Physiology-Paris,* vol. 103, pp. 244-254, 2009.

Challenges – Movement Kinematics Decoding

- Movement parameters encoded in neuronal firing are not accessible due to the low signal resolution of EEG
  - Efficient signal processing strategies to extract optimal information

- Challenges in non-invasive SMR-BCI
  - Understanding neurophysiology – Lack of generic and consistent information regarding correlates of movement parameter in EEG
  - BCI experiment design and restricting artifacts: Eye movement and muscle activation restrictions; tracking MI parameters difficult.
  - Impact of decoding error in the BCI system: Inter-relation between direction, speed and force.

Research Objectives

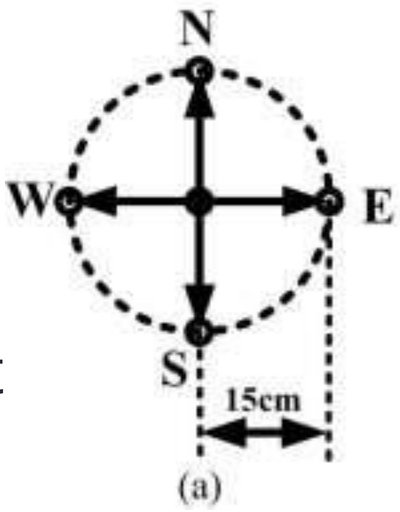
- SMR-BCI systems with higher degrees of freedom and defined control command set

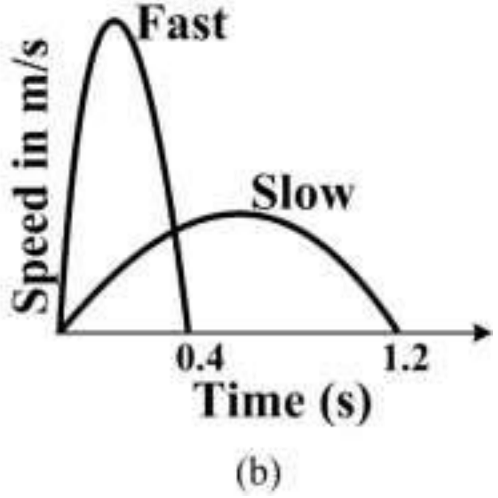
- Development of an EEG-BCI system to,

  - Investigate neurophysiology underlying hand movement kinematics – position, speed, direction
  - Extract optimal and informative neural correlates of movement kinematics
  - Construct classifiers/decoders that can reconstruct movement trajectory using these features

Our Experiment

- Seven subjects – Healthy males, Right-handed
- Location – Brain Computer Interface Laboratory of Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore
- Experiment and Data collection
  - Right hand 2D center-out hand movement task in horizontal plane
  - Defined tasks – (a) 4 orthogonal directions (b) 2 different speeds





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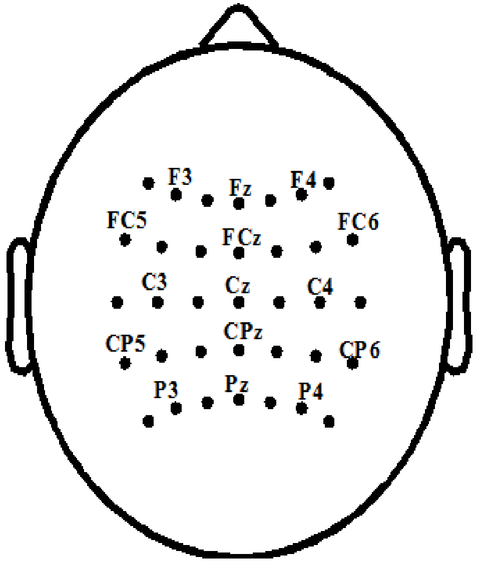
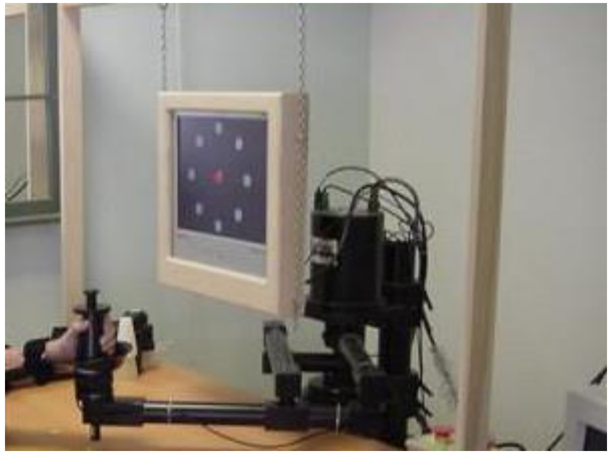
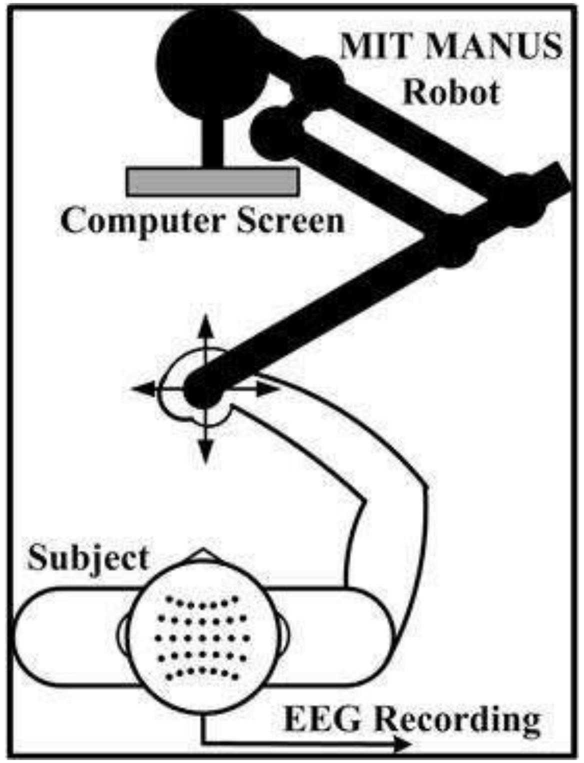
Experiment (Cntd.)



- Equipment
  - Brain data recording – Neuroscan SynAmps 128 channel EEG Amplifier
    - Sampling rate: 250 Hz
  - Movement parameter recording – MIT MANUS Robot
    - Sampling rate: 250 Hz
- Experiment set-up





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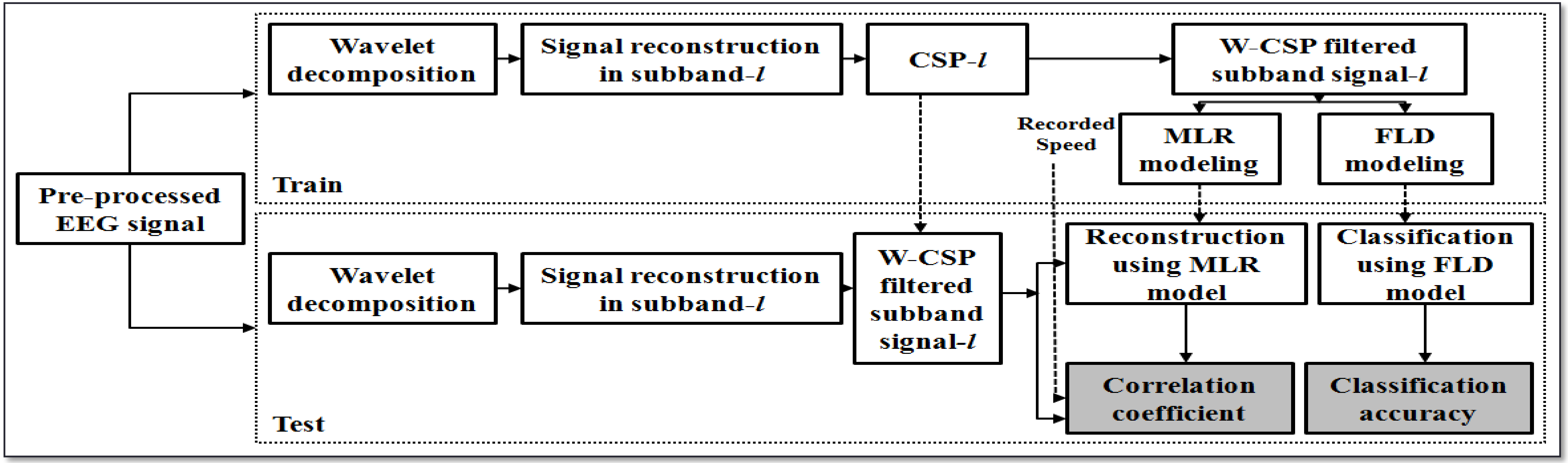
Functional block diagram – Hand Movement Speed Decoding from EEG



MLR: Linear fitting strategy that models dependent variable as a linear combination of a set of independent predictors

FLD: Calculates transformation that maximizes between class scatter and reduces within class scatter

Above schematic with slight modification (Regularization of CSP) is used for direction analysis.

Data Processing Units

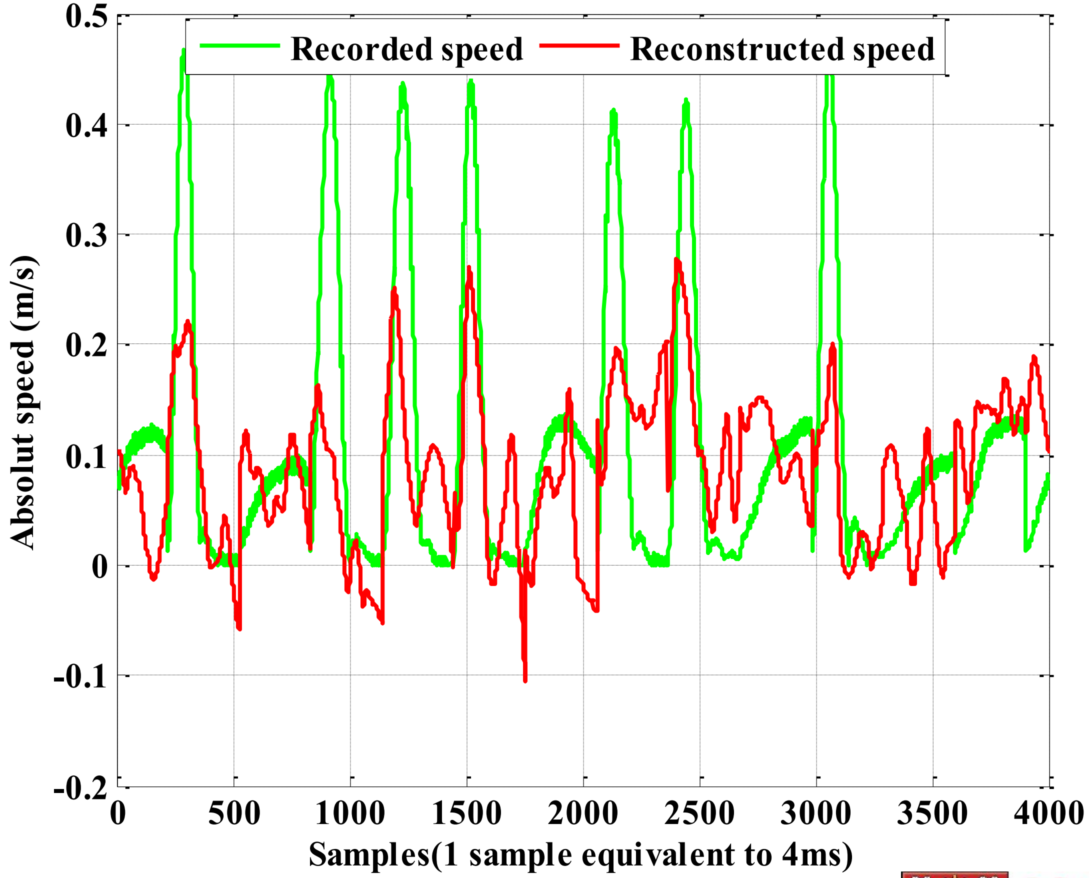
- Movement Parameter (MP) Signal Processing – Speed and Position 2D coordinates
  - Pre-processing: Low pass filter at 1 Hz
- EEG signal processing
  - Signal lower cut-off frequency: 0.05 Hz
  - Pre-processing

Artefact	Background noises	Power line frequency	Eye movement artefact	Muscle movement artefact
Technique	Low pass filtered at 96 Hz	Notch filtered at 50 Hz	ICA filtering that removes components correlated with recorded EOG [1]	Spatial filtering using Laplacian to remove diffused EMG activity [2]

1. T P Jung, S Makeig, C Humphries, T W Lee and M J McKeown, “Removing electroencephalographic artifacts by blind source separation,” *Psychophysiology*, vol. 37, pp. 163-78, 2000.
2. D J McFarland, L M McCane, S V David and J R Wolpaw, 1997 Spatial filter selection for EEG-based communication,” *Electroencephalography Clinical Neurophysiology*, vol. 103(3), pp. 386-94, 1997

Movement Parameter – Speed

- Reconstruction speed profile – Correlation values
  - x-coordinate: 0.48
  - y-coordinate: 0.42
  - absolute: 0.50



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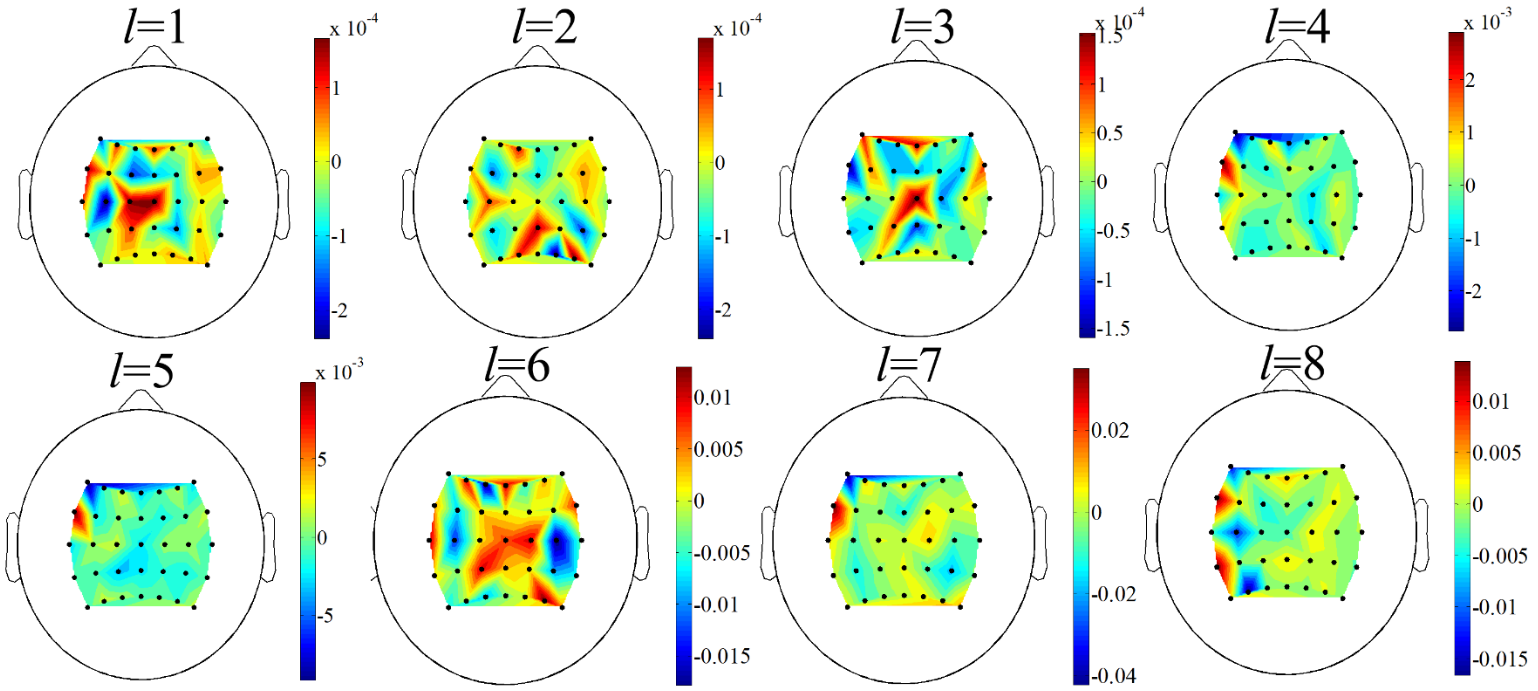
Movement Parameter – Speed

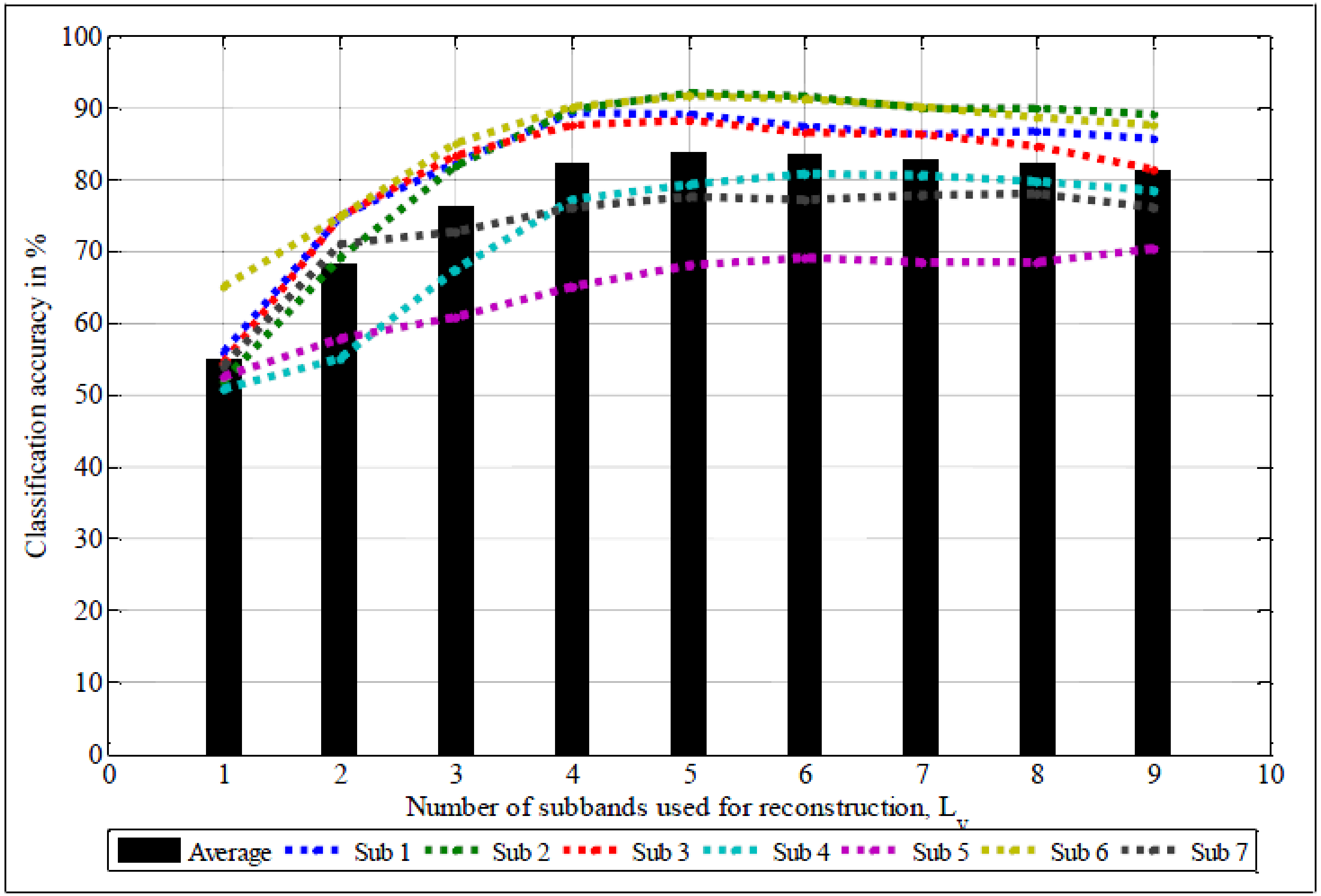


- Regressor coefficient values in various subbands (*l*)
- Note the higher values in lower subbands (*l=1, 2, 3*), especially in the contralateral motor region

Movement Parameter – Speed

- Fast v/s Slow classification accuracy: 83.71 ± 8.98 %

- Highest accuracy reported when number of subband used is 5 (0.05-6 Hz)



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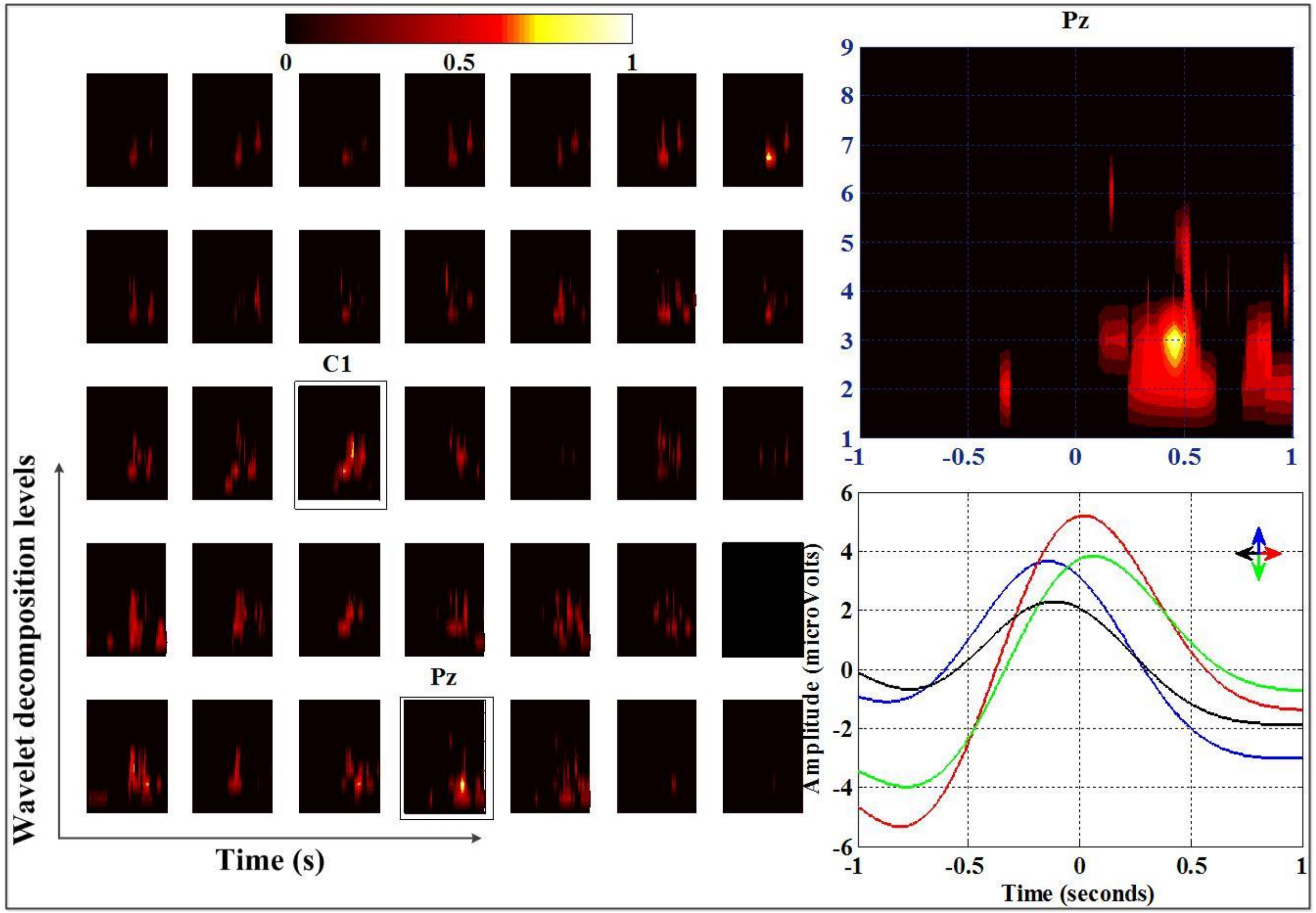
Movement Parameter – Direction

- **Contribution of each T-F bin in direction decoding**
- Contralateral and Parietal region
- Low frequency (0.05-6 Hz) band
- Temporal amplitude modulations



- **Direction dependent SNR plots** indicate information rich time-frequency areas of EEG channels

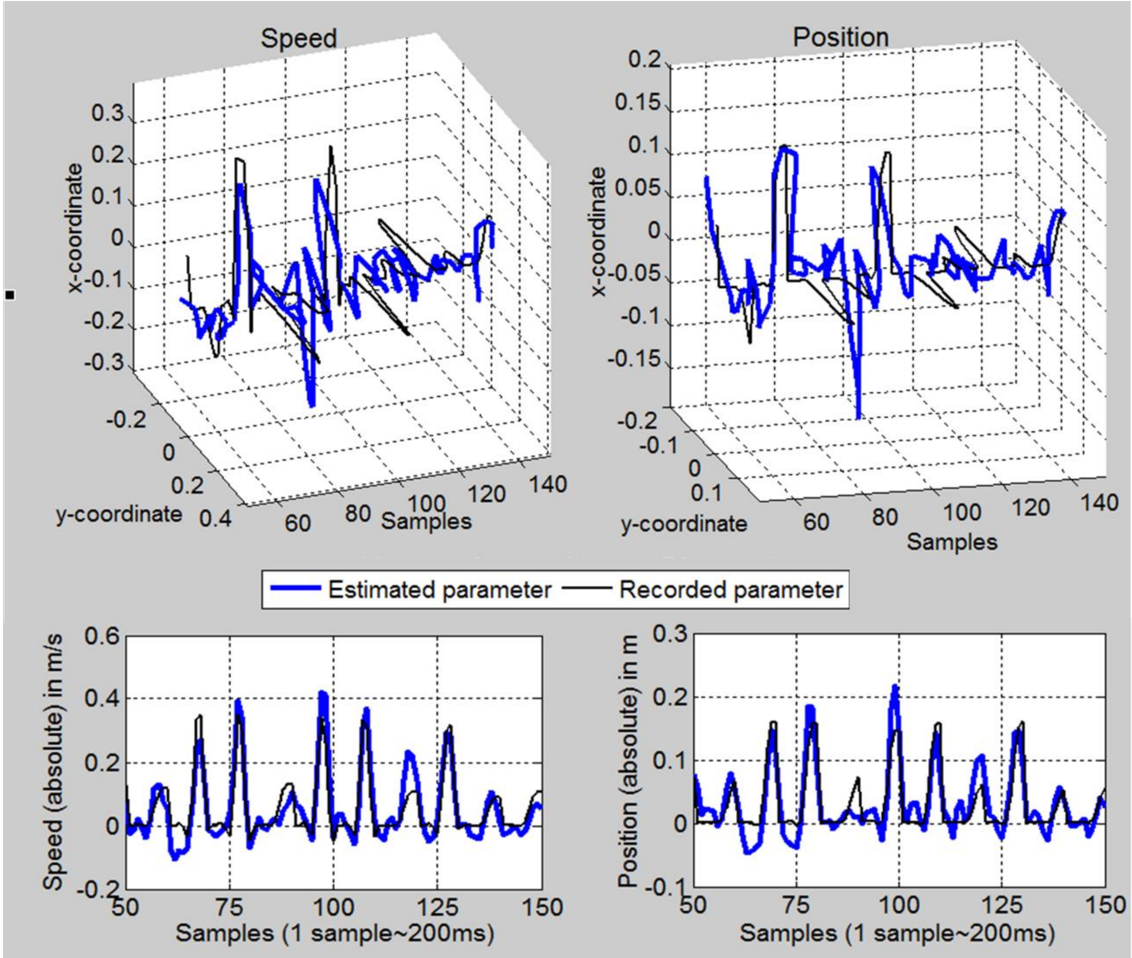
Movement Parameter – Direction

- **4-class classification**
  - CSP is regularized to reduce over-training of spatial filter
  - Mutual information based feature selection
  - 80.24 ± 9.41 % accuracy significantly higher than existing methods is achieved

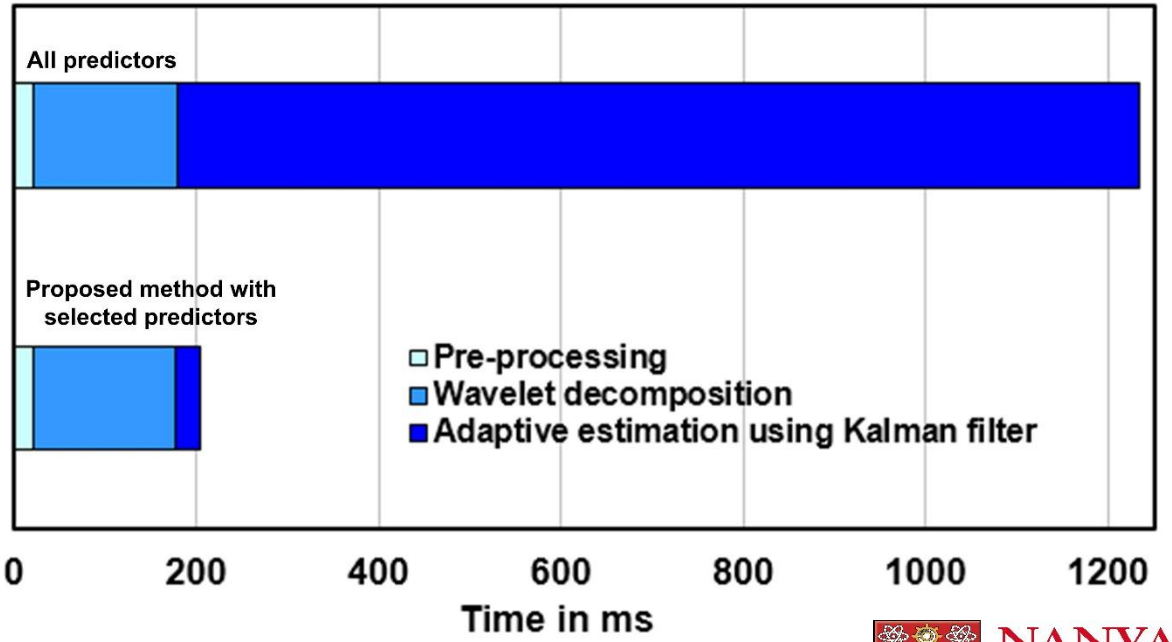
Movement Trajectory

- Multichannel time-frequency localized EEG variables used to create reconstructor model
  - Predictor and channel selection incorporated to optimize information
    - Channel selection using ranking based on Correlation or Mutual Information
    - Predictor selection – Backward subset selection
  - MLR and Kalman filters used for reconstruction

Movement Trajectory



- Adaptive estimation using Kalman filters and selected predictors
  - Average correlation value: 0.57 ± 0.04
  - **83.3% speed-up → real-time application feasibility**



Future directions in Movement Kinematics Study

- Limitations of methods reported in existing literature [1]
  - Use of linear methods limits the spectral region explored
- Reconstructing imagined trajectory – Challenges in experiment design
  - To ensure active involvement of user to imagine movement and prevent visual tracking
- Asynchronous and real-time generic BCI systems
  - Asynchronous and instantaneous motor control to interfaced devices
  - Lack of generic subject-independent BCI system with zero-training sessions

1. J. M. Antelis, L. Montesano, A. Ramos-Murguialday, N. Birbaumer, and J. Minguez, "On the usage of linear regression models to reconstruct limb kinematics from low frequency EEG signals," *PLoS ONE,* vol. 8, p. e61976, 2013.

Summary

- BCI Applications
- Relevant EEG Features in BCI
- Motor-Imagery BCI – Robust Algorithms to Tackle Inter-Subject and Intra-Subject Variability
- BCI for motor control
  - Significance and specific applications
  - Key aspects of motor control BCIs
- Research on Movement Kinematics
  - Neurophysiology and research findings
  - Research highlights
  - Future directions in Movement Kinematics Study

Thank You!

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