Efficient Signal Processing Techniques towards the Development of EEG based Brain-Computer Interface (BCI)

Presented by:
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About NTU

- NTU ranked 47th in the most prestigious Quacquarelli Symonds (QS) World University Rankings 2013.
- Ranked 2nd in the world among Universities below the age of 50 by QS – 2012/2013.
- Ranked 8th in the world among Universities below the age of 50 by Times Higher Education - 2013.
- World's Biggest Engineering University with 1100 faculty members in Engineering Schools alone.

- Ranked as the 5th most-cited university with its research output ranked among the top three Universities globally in Engineering by Essential Science Indicators of Thomson Reuters.

A fast rising young University (25 years old)

Outline

- **Introduction to Brain-computer interface (BCI)**
    - *Brain: basic structure and methods for brain signal measurement.*
    - *Basic components in BCI*.

- **Electroencephalogram (EEG) based BCI**

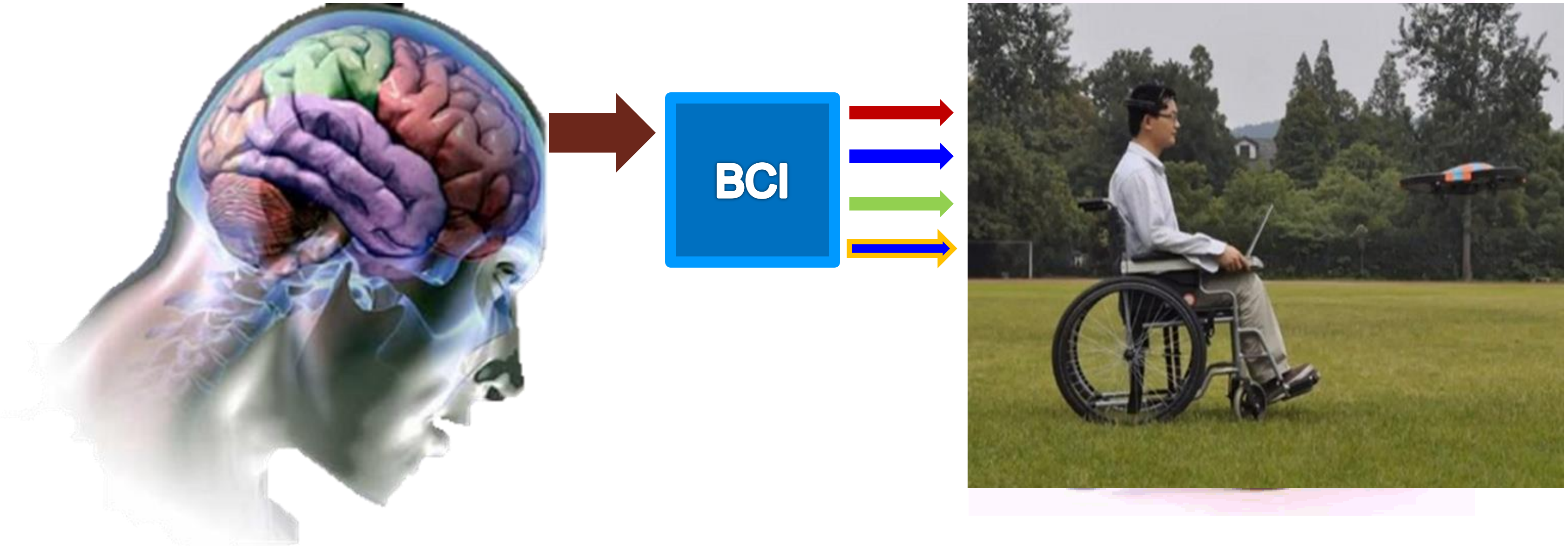
- **Challenges in EEG-based BCI**

- **Our contributions towards the development of BCI using:**
    - *EEG signals during Motor Imagery (MI)*
    - *EEG signals during execution of motor movements*
    - *Attention related EEG signals*

- **Conclusions and future work**

Brain-Computer Interface (BCI)

- Direct communication channel between brain and computer.
- Depends on brain activity and bypasses brain's normal communication pathway of nerves and muscles.
- Transforms brain activity into command signals for controlling external applications such as a neuroprosthetic device, robotic arm, computer game, wheel chair control etc.



Promising communication tool for paralyzed patients

A recent application of Invasive BCI

Paralyzed woman serves herself coffee after 15 years, using Invasive BCI controlled robotic arm.

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

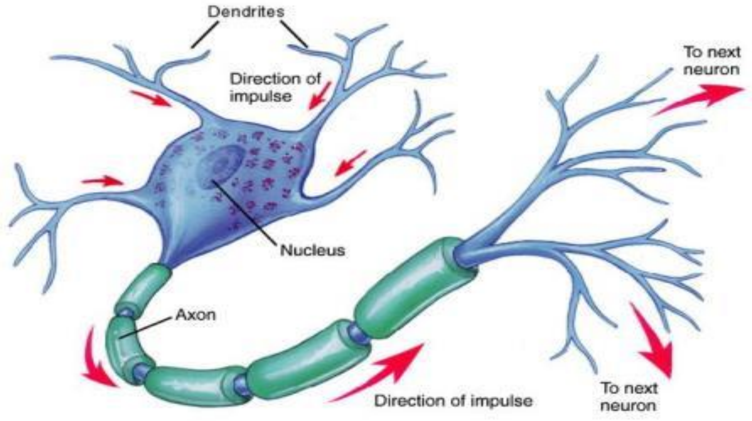
Ultimately converts mental tasks into command signals !

http://neurogadget.com/tag/braingate.

Basic Working Principles: Brain and BCI

BRAIN:

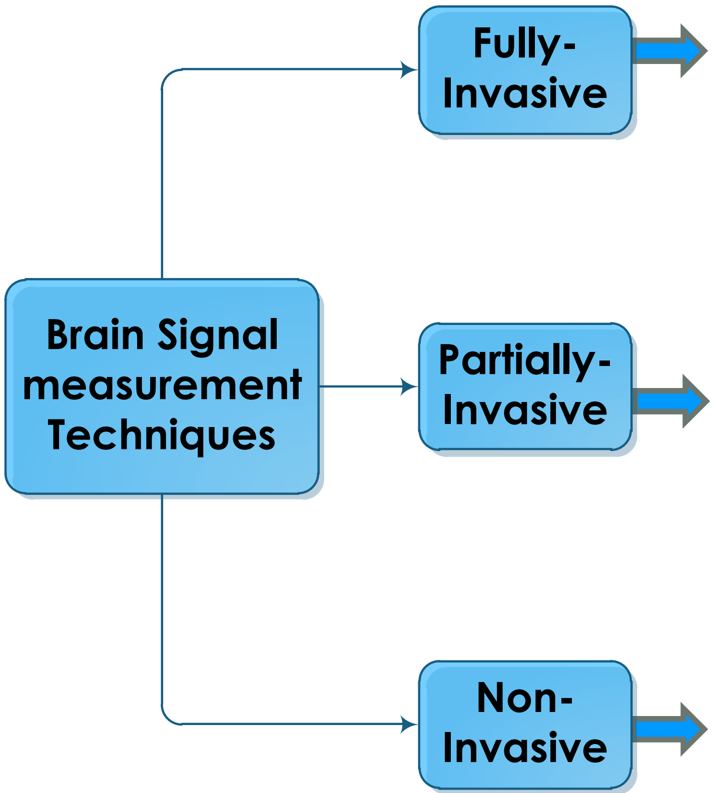
- Neurons, the basic building blocks of brain, are cells that send and receive electro-chemical signals to and from the brain and nervous system.
- Brain consists of more than hundred billion neurons, with millions of connections between them.
- Unique neural activations occur in response to specific actions, thoughts, emotions etc.
- Brain can be divided into various lobes having unique functional responsibilities.



Structure of neuron

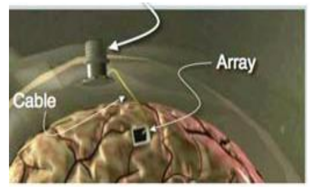
Brain parts and functions

Methods for Brain Signal measurement



Brain Signal measurement Techniques

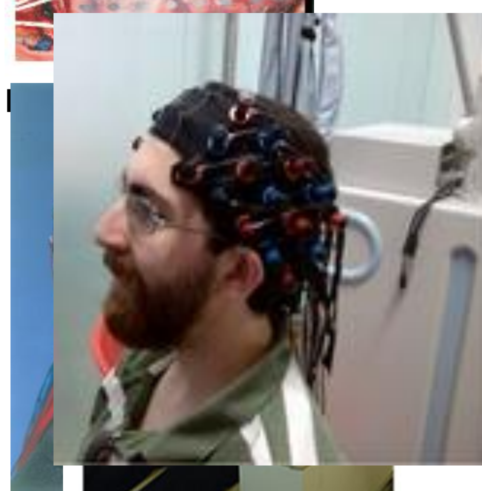
- **Fully-Invasive**
- **Partially-Invasive**
- **Non-Invasive**



Single Neuron/ MultiNeuron

Microelectrodes penetrating Cerebral Cortex

Electrode array on cortical surface



Spectroscopic method that uses the near-infrared region of the electromagnetic spectrum to measure the haemodynamic activity of brain

Mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers

Scalp

Functional Near infrared Spectroscopy (fNIRS)

Ele

Magnetoencephalogram (MEG)

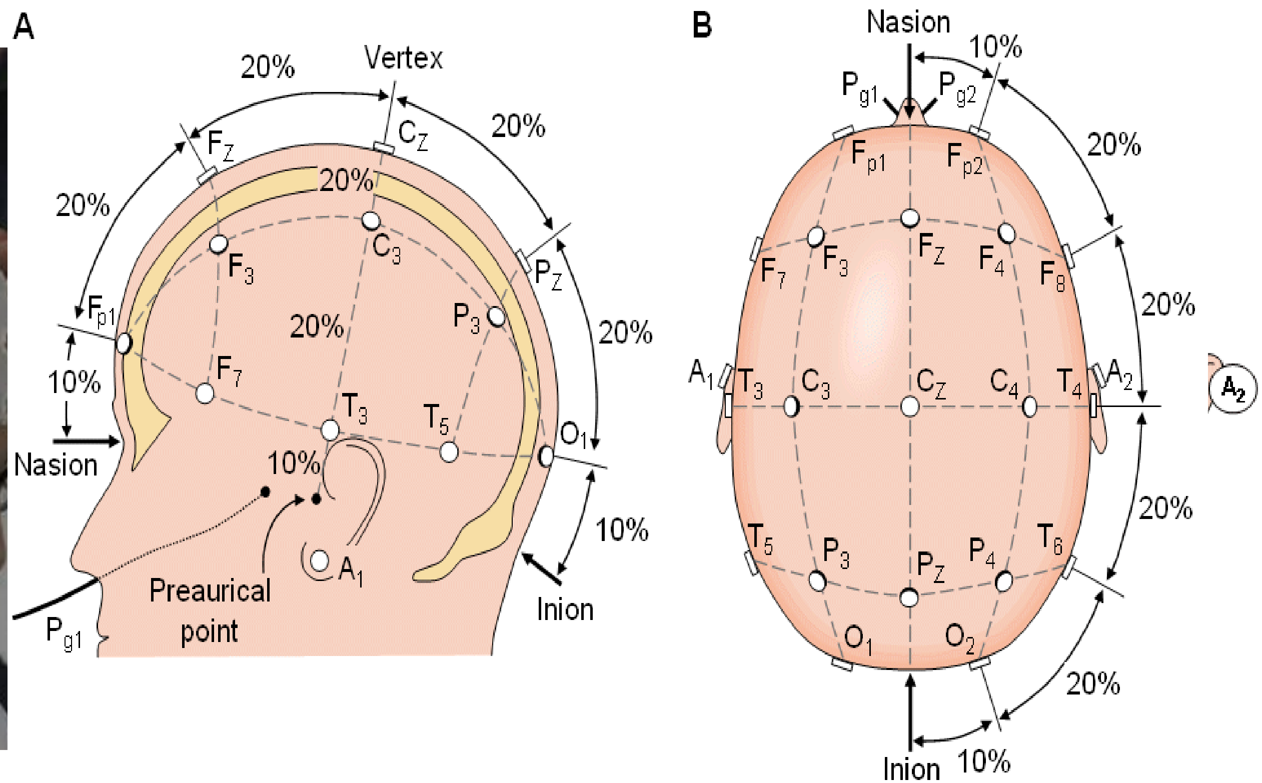
Brain activity measurements: Why EEG?

- Invasive techniques involves surgical interventions and hence risky.
- Non-invasive methods such as functional-Magnetic Resonance Imaging (fMRI) and MEG is expensive, bulky (not portable) and sensitive to subject movement.
- Non-invasive methods such as EEG and fNIRS are portable, less expensive, insensitive to movement and easy to use.
- EEG is the most economical method for measuring electrical activity of brain.
- High temporal resolution EEG signals can be obtained for various activities such as emotions, body movements, mental tasks, attention etc.

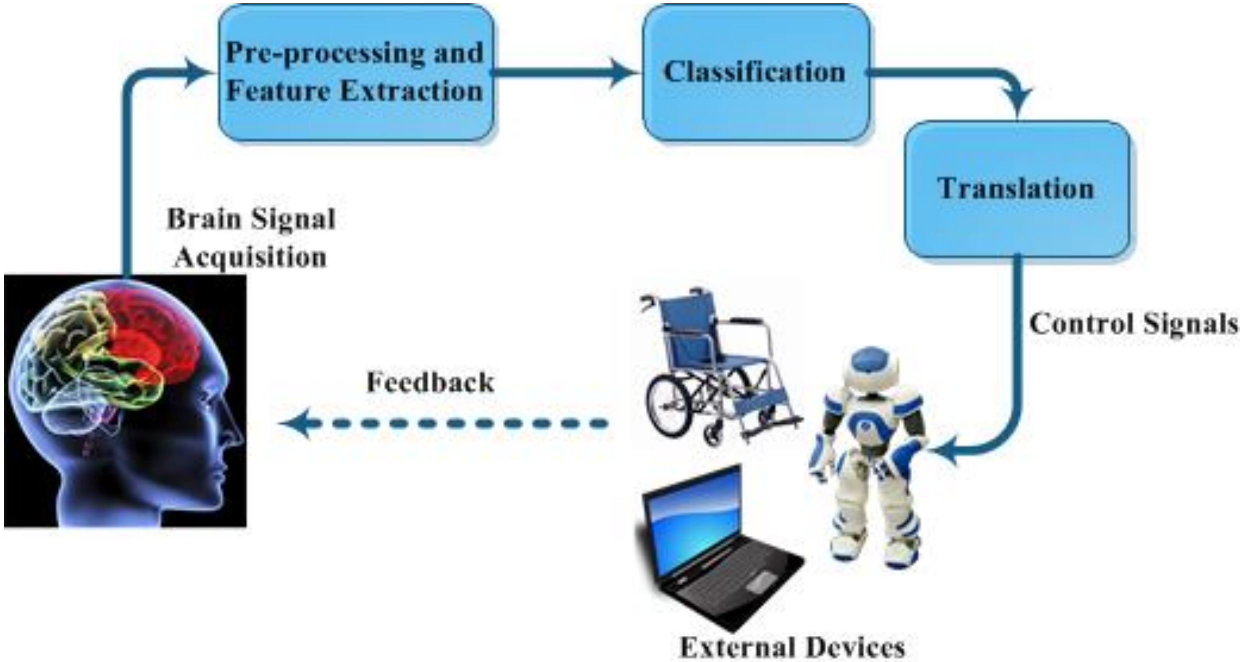
EEG measurement

- Exists inter-national standard for placing electrodes on scalp and each electrode is named according to its location.
- F: frontal, T: temporal, C: central, P: parietal and O : occipital lobes
- Left hemisphere is named with odd numbers whereas right with even numbers.
- Conductive gel is applied between scalp and electrodes to reduce the skin impedance while EEG recording.

Standard measurements from vertex, inion and nasion for international system



Block diagram of EEG based BCI



EEG-based BCI uses EEG features to command, control, actuate and communicate with the world directly by interfacing brain with peripheral devices and systems.

Basic Building blocks

- **Data Acquisition Unit**: Responsible for (i) recording EEG using electrodes, (ii) amplification and (iii) digitization of signals.
- **Signal Processing Unit**: *Consists of 2 modules*
  - Pre-processing Module: Removes the artifacts/noise from the recorded EEG signal and improve the signal to noise ratio.
  - Feature extraction Module: Extracts the hidden information from the pre-processed signals.
- **Classification Unit**: Identifies the intention of BCI user from the extracted features.
- **Translational Unit**: Translates the identified intentions into specific control signals for various BCI based applications.
- **Feedback Unit**: Feedback in BCI allows the user to self-regulate his EEG to get the desired output.

Challenges and objectives

Challenges:

- Design of less expensive, simpler and more comfortable data acquisition techniques.
- New sensors/electrodes that can provide higher SNR.
- Development of accurate and robust pre-processing and feature extraction techniques.
- Tuning robust machine learning techniques and translational algorithms.
- Design of integration and control protocols for specific applications.

Our Research focus:

Development of Signal Processing Algorithms to extract relevant features effectively and accurately for EEG-based BCI.

Relevant EEG Features

- Slow Cortical Potentials (Event-related DC shifts in EEG), P300 (Event-related potential rise (response) that occur 300 ms after a stimuli) , Visually Evoked Potentials (potential changes on occipital EEG in response to a visual stimulus) and event-related de/synchronization (ERD/ERS) etc. are widely used in BCIs.

- ERD/ERS: The naturally occuring brain rythms related to movement will undergo change during movement imagination – ERD and ERS.

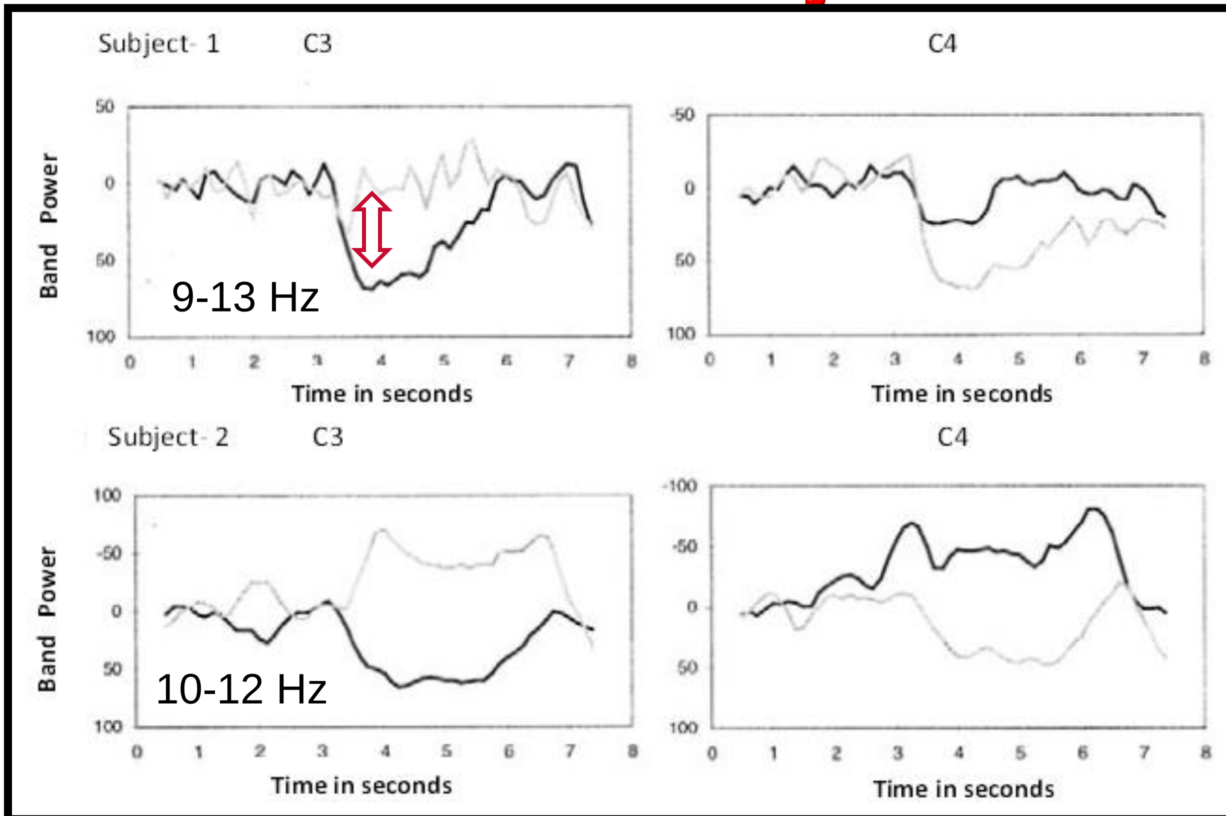
  Amplitude changes in EEG during execution, preparation or imagination of motor movements (called motor imagery (MI)), that primarily activate the motor cortex of brain.

  - **ERS**: Power increase in EEG during rest phase (neurons fire synchronously).

  - **ERD**: Power decrease in EEG, particularly contra lateral to the movement (neurons fire complex and individual patterns during motor imagery)

- **Challenges:**
- ERD/ERS are highly frequency band dependent (They can occur simultaneouly at same/different scalp locations).
- The frequency bands that best discriminate between any 2 MI tasks (discriminative frequency bands) are subject-dependent.

Time courses of ERD/ERS during MI in 2 subjects

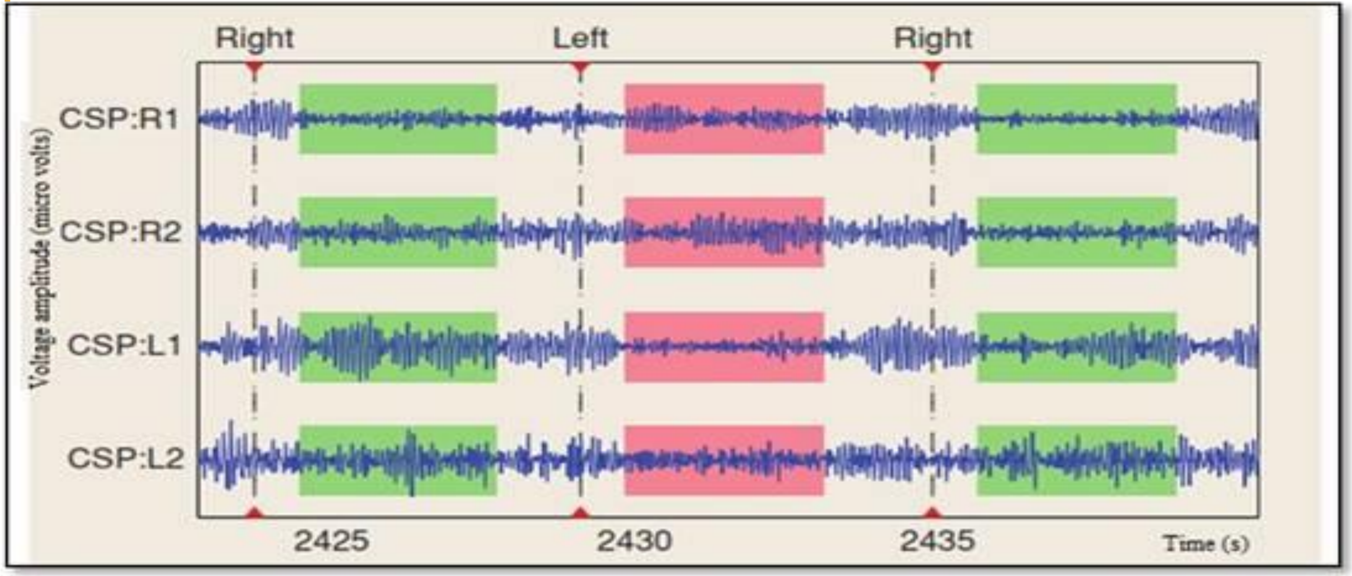


Motor imagery causes amplitude changes in EEG and they appear in subject-specific frequency bands.

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.

Extraction of MI patterns

- ***Common Spatial Pattern (CSP)*** *is a mathematical procedure for separating a multivariate signal into additive components which have max. difference in variance between two windows.*
- Application of CSP to time-varying multi-channel EEG generates a new time series, where the difference between two types of signals is maximized.



Effect of CSP transformation on EEG corresponding to Right/Left MI

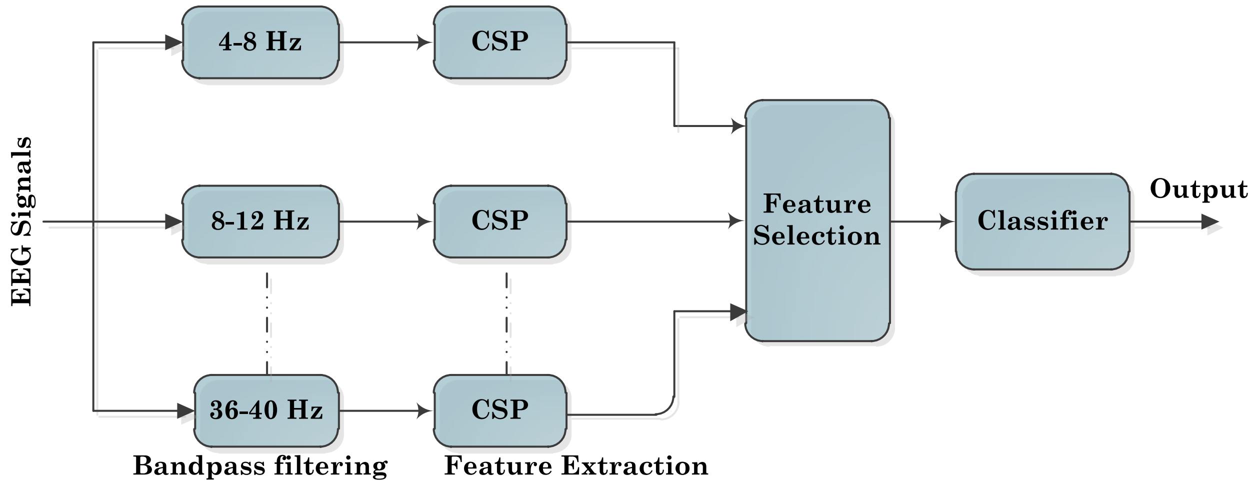
The first and last rows of CSP transformed matrix provides maximum discriminative information between classes.

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.

Our Contributions on:
Motor Imagery based BCI

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

Existing Filter Bank Common Spatial Pattern (FBCSP)



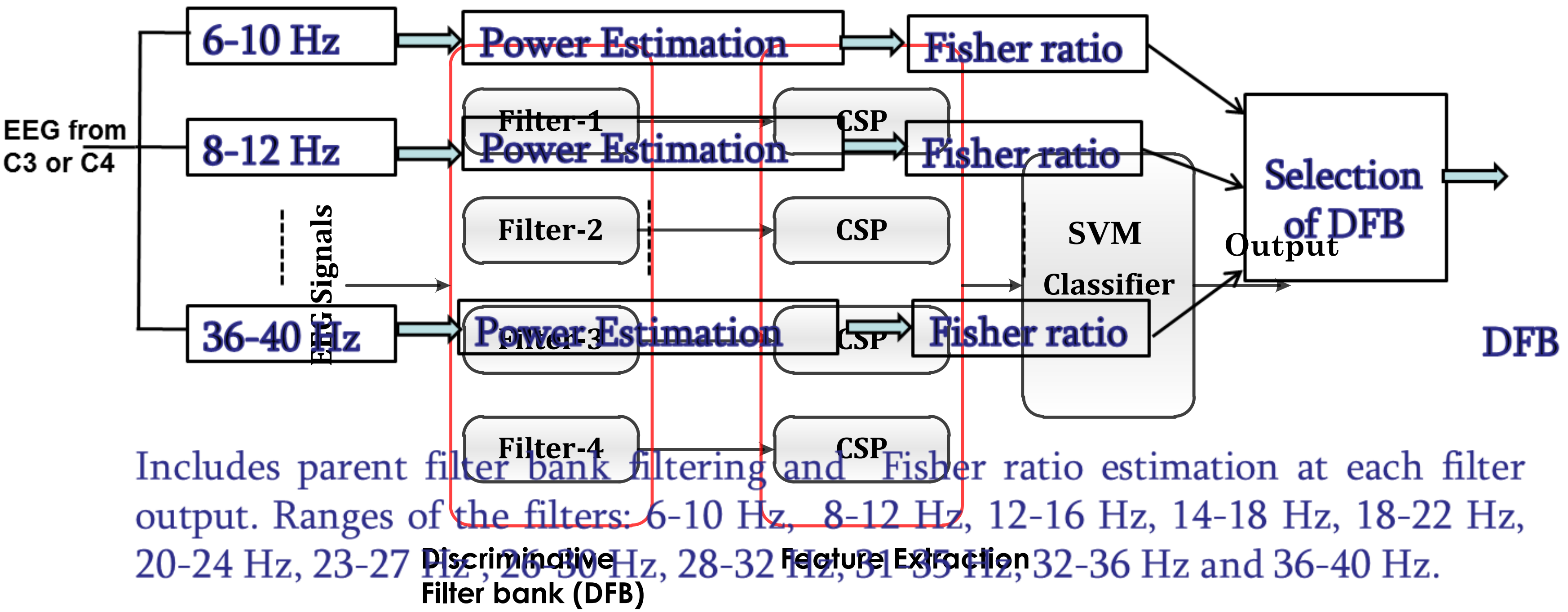
Schematic of the Existing FBCSP algorithm

(Mutual information based feature selection and SVM based classifier)

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.

Proposed 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.
- If, S_B and S_W are between-class and within-class variances of the MI signal respectively, $FR = S_B / S_W$
- **Proposed DFBCSP**



Schematic of DFBCSP algorithm

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Frequency bands selected by DFBCSP

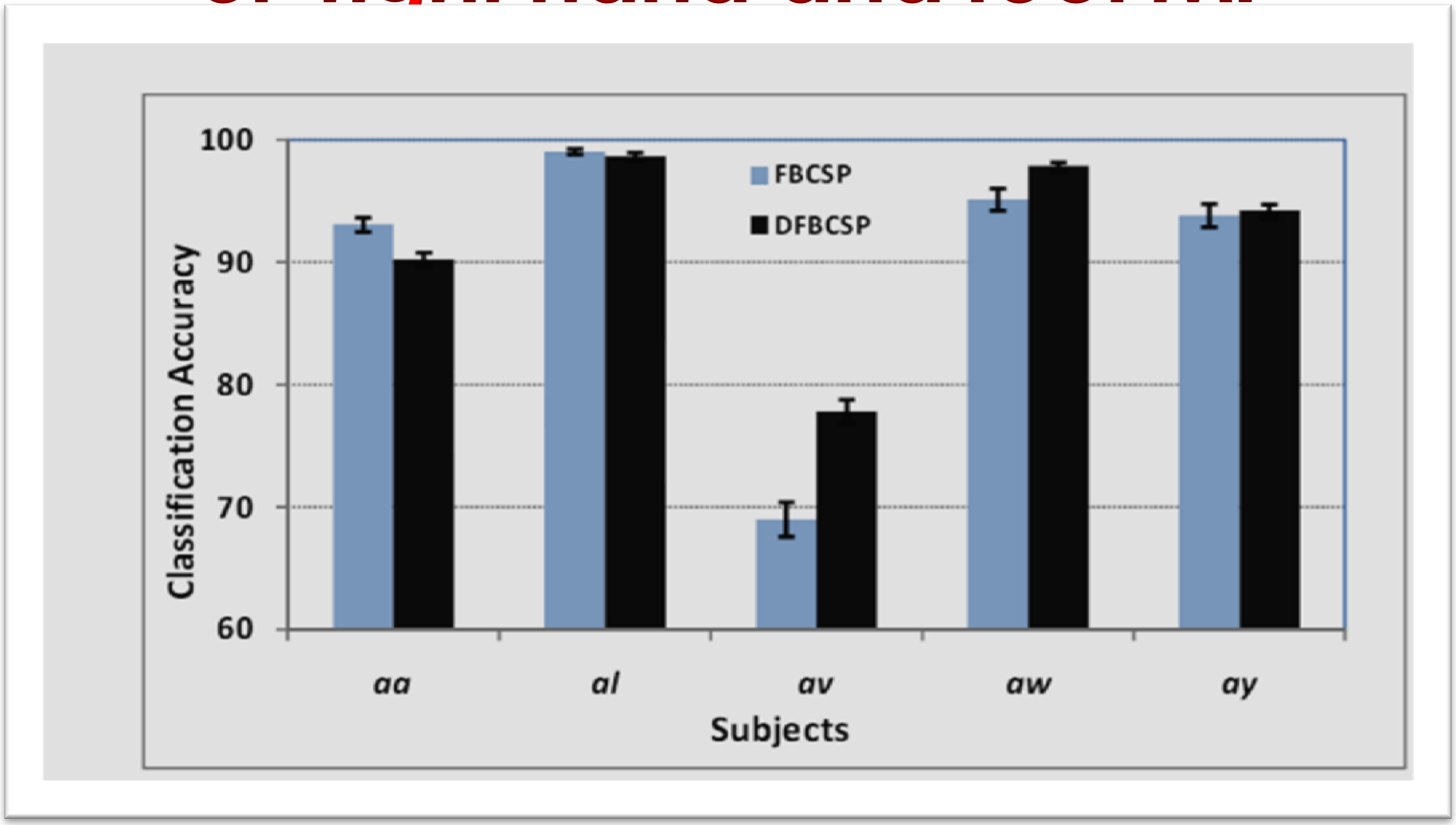
6-10Hz	8-12Hz	12-16Hz	14-18hz	18-22Hz	20-24Hz	23-27Hz	26-30Hz	28-32Hz	31-35Hz	32-36Hz	36-40Hz	
1	2	3	4	5	6	7	8	9	10	11	12	Parent FB
		1			4	2	3					‘aa’
		1	4		3	2						‘al’
	4		3	2	1							‘av’
			2	1	3						4	‘aw’
	2	4				1			3			‘ay’

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

- Exhibits Inter-subject variability

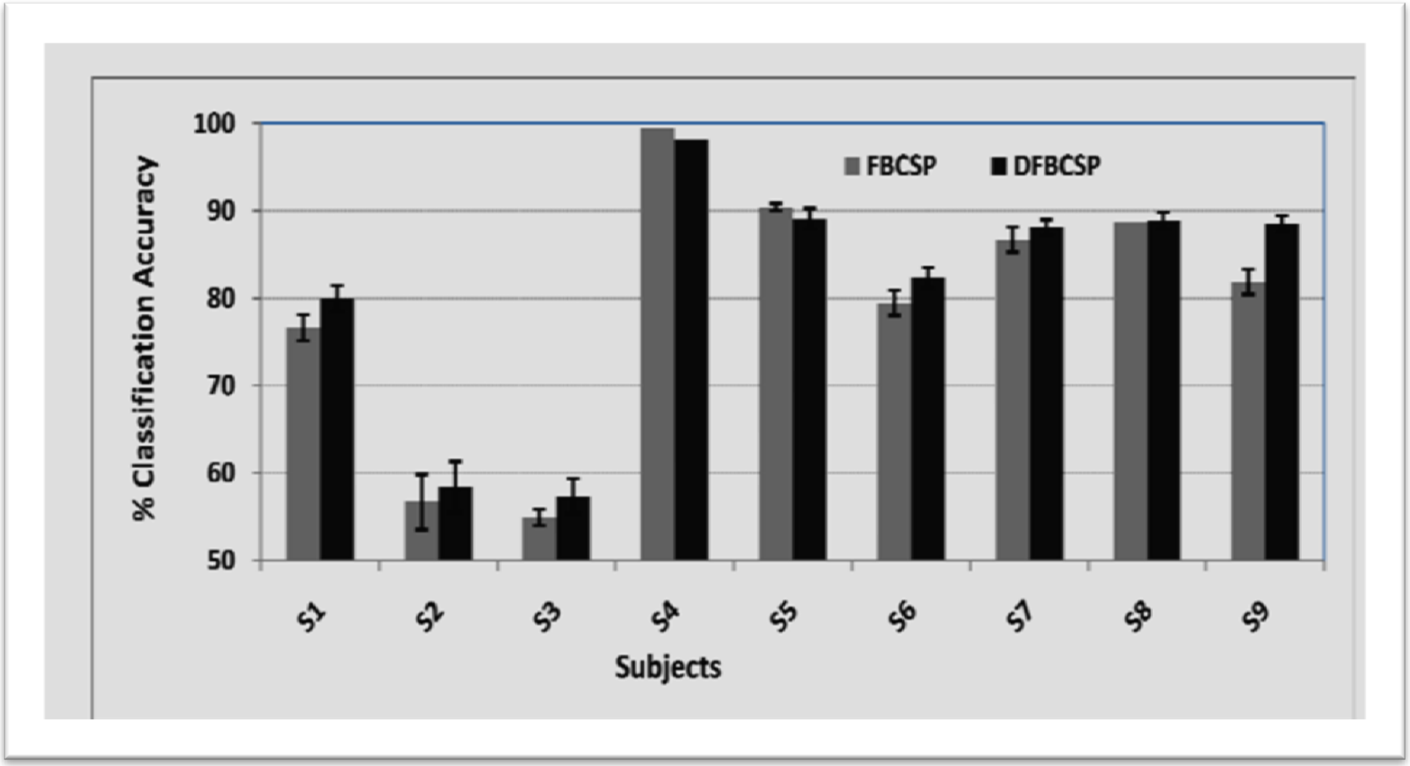
Kavitha P. Thomas, Cuntai Guan, Lau Chiew Tong, A. P. Vinod and Kai Keng Ang, “A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain-Computer Interfaces,” *IEEE Transactions on Biomedical Engineering, vol. 56, no. 11, pp. 2731-2733,* November 2009.

Comparison of classification of right hand and foot MI



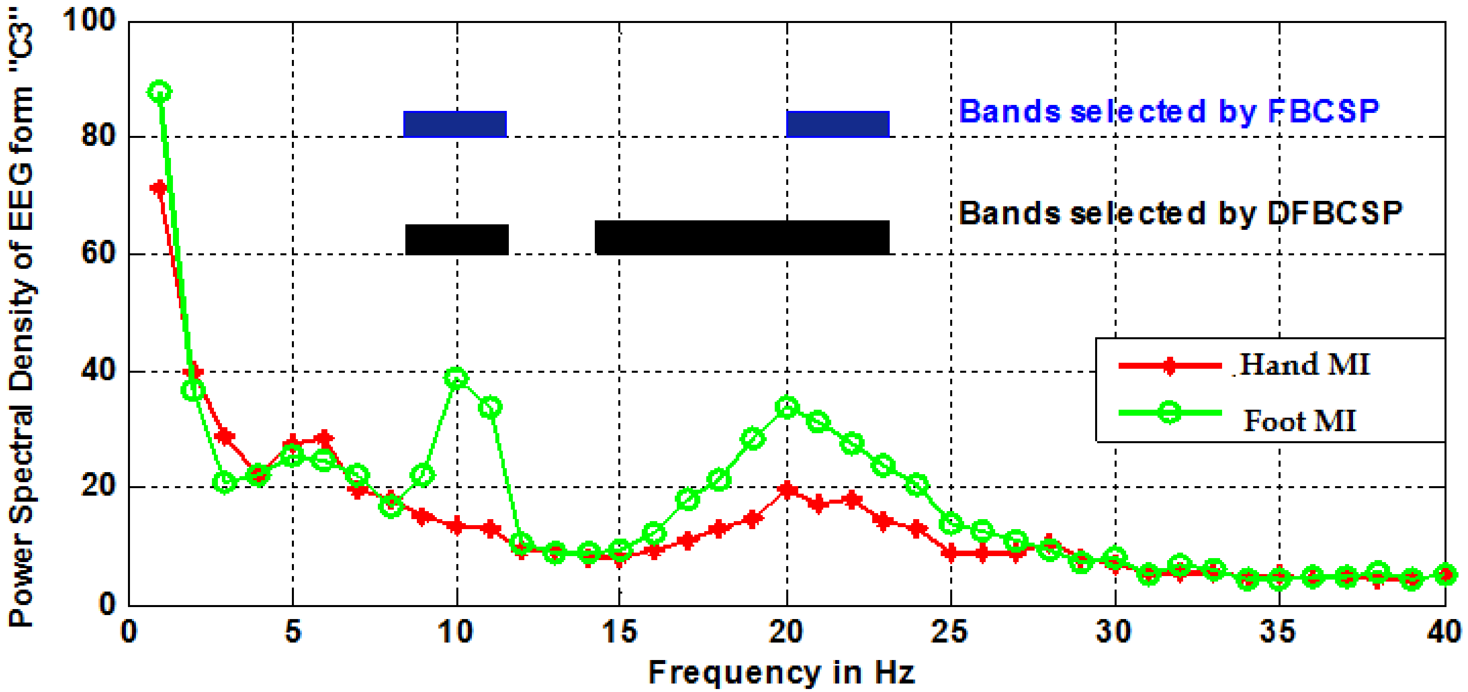
Average Accuracy by FBCSP (%): 90.01 ± 0.82
Average Accuracy by proposed DFBCSP(%): 91.75 ± 0.54

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

Power Spectral density plots of EEG

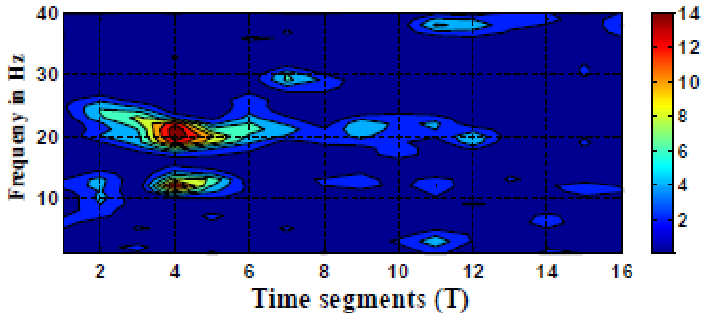


Average Power Spectral Density plots of right hand and foot trials for subject '*av*' in BCI Competition III dataset IVa.

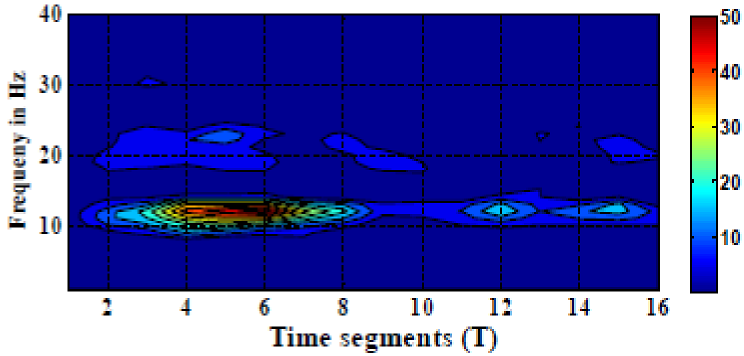
More analysis on frequency bands during MI

- Found that the selection of discriminative frequency bands highly 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 EEG which gives the Fisher values of frequency points along time domain.

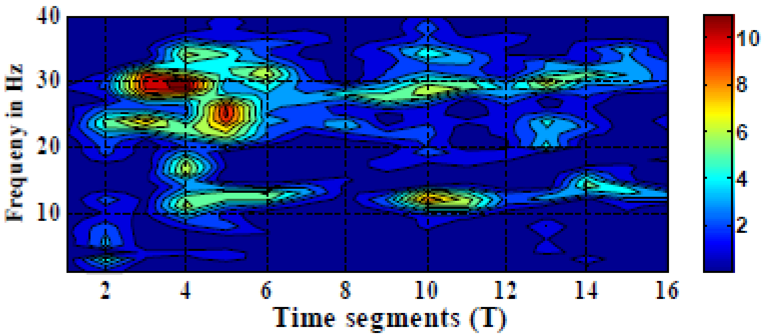
Time-Frequency Fisher pattern from channel C4 for subjects 1, 4, 5 and 9 in BCI Competition IV dataset IIb (right and left hand MI)



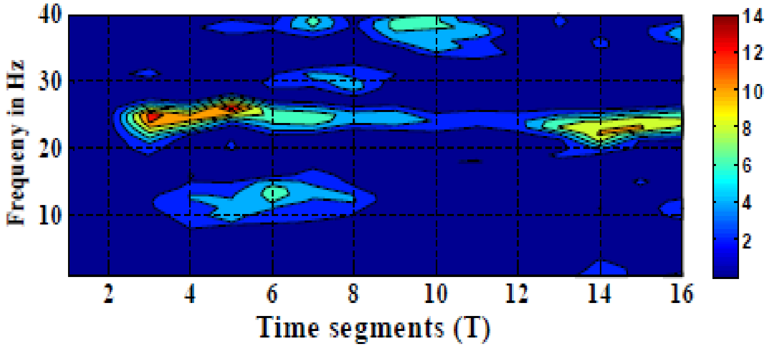
Subject-1



Subject-4

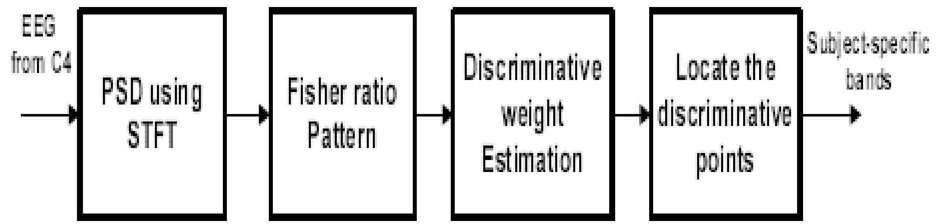


Subject-5

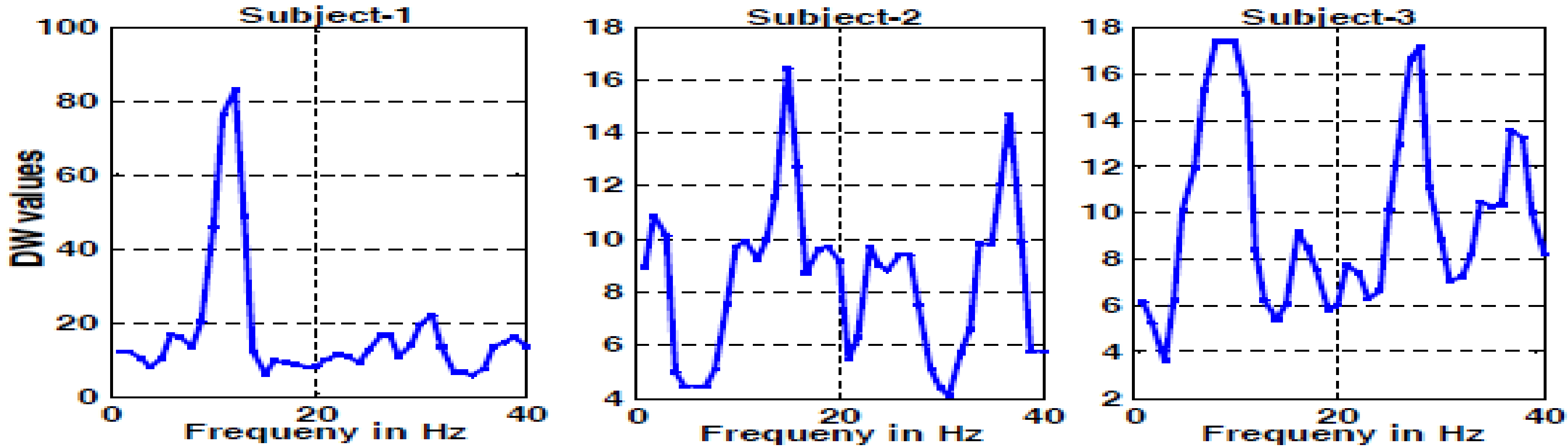


Subject-9

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.



10-14 Hz, 8-11 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)

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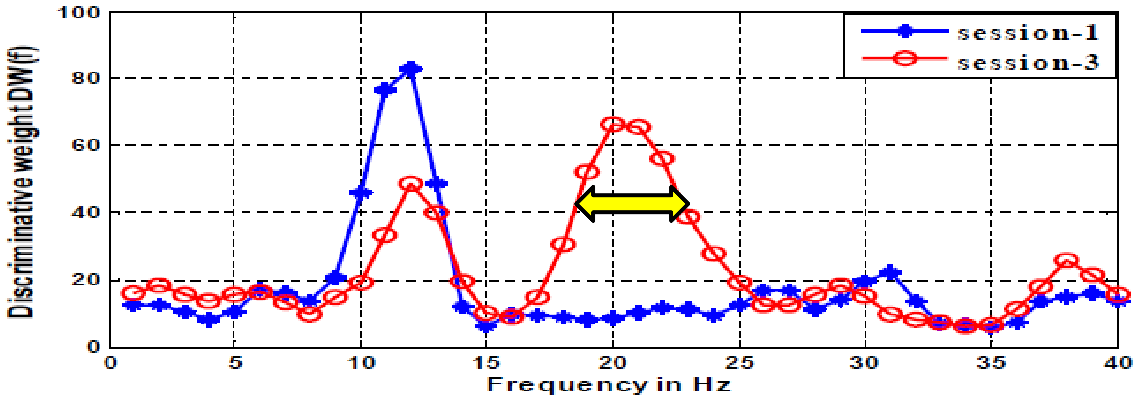
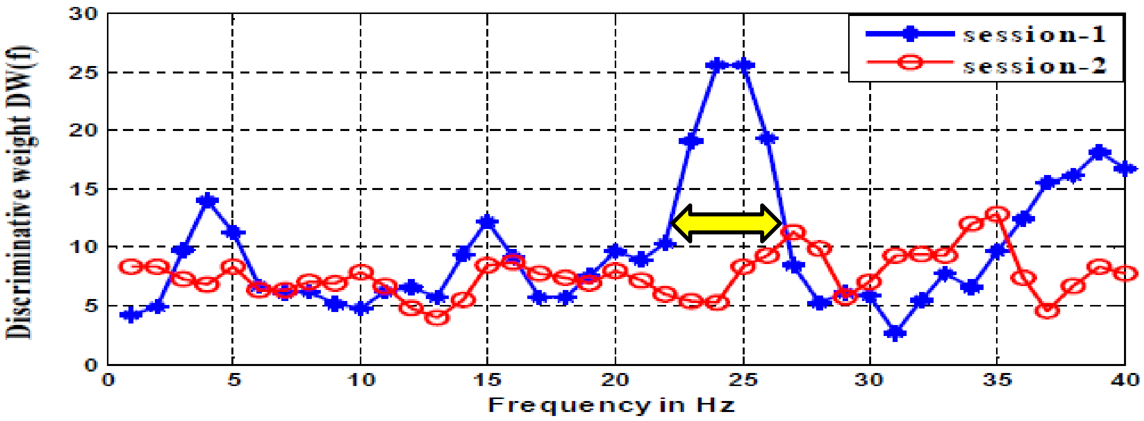
Inter-session variation of Discriminative weight (DW) values

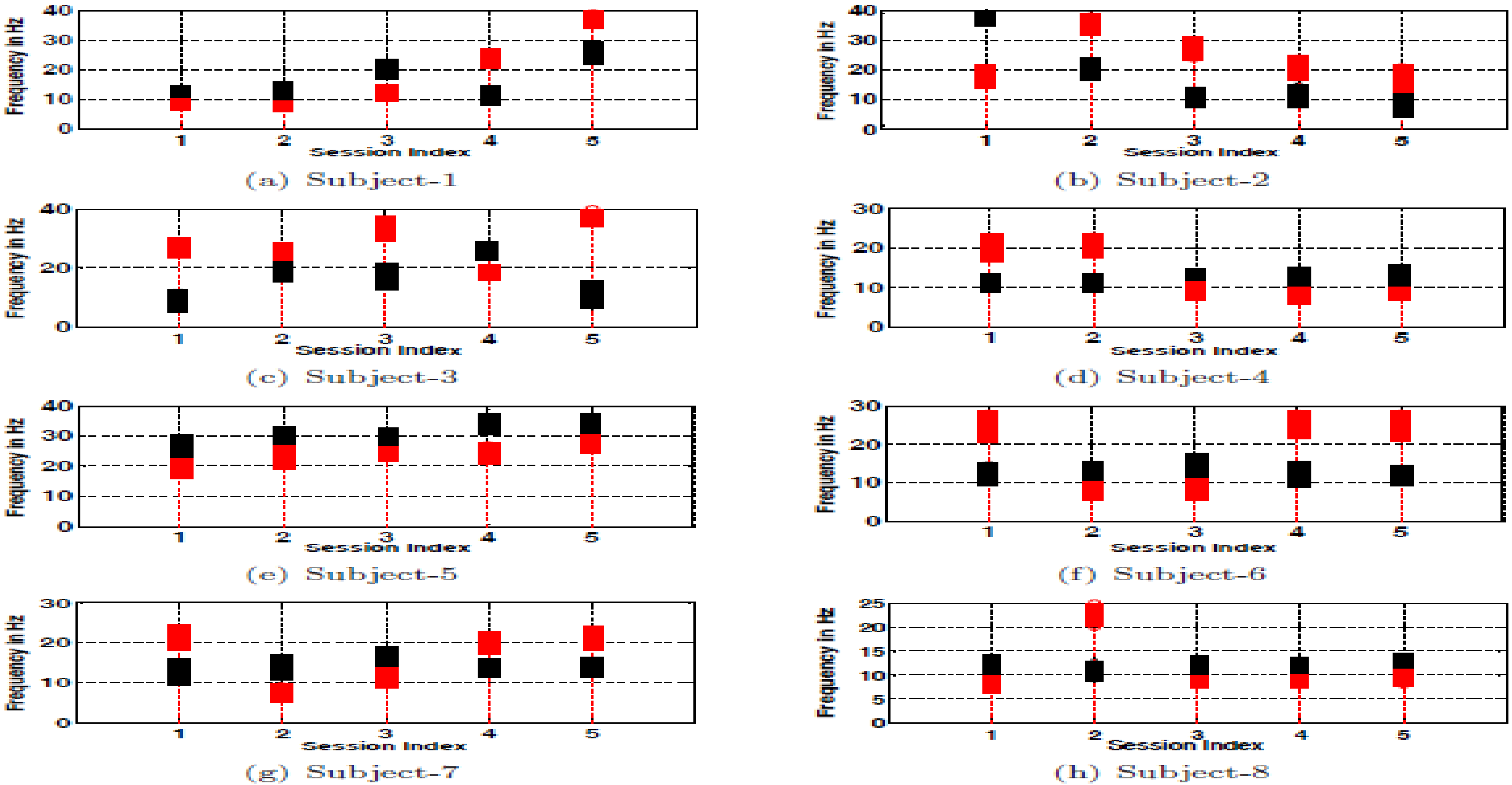


Subject-1

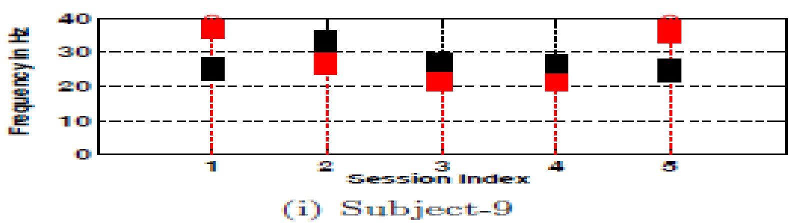


Subject-9

Variation of frequency bands over sessions



(a) Subject-1 (b) Subject-2 (c) Subject-3 (d) Subject-4 (e) Subject-5 (f) Subject-6 (g) Subject-7 (h) Subject-8



(i) Subject-9

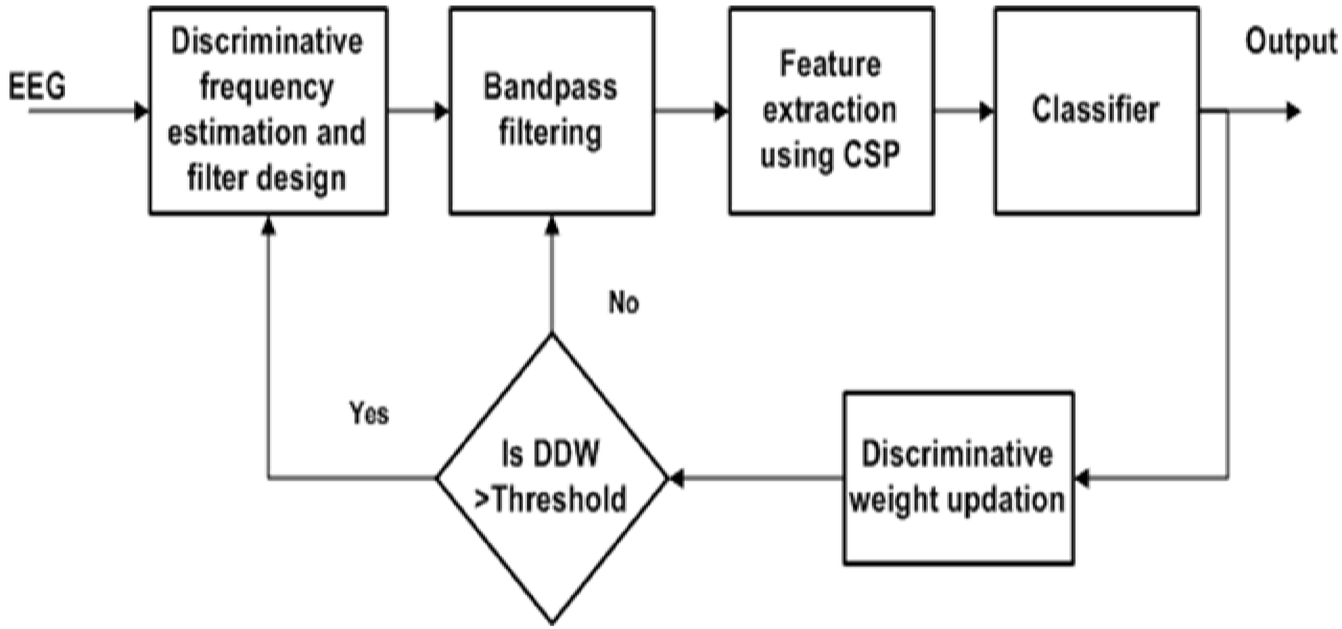
2 most discriminative frequency bands selected from DW analysis:

Black: Most discriminative Band

Red: Second most DFB

Proposed Adaptive Method for tracking the discriminative bands – To tackle Intra-Subject Variability

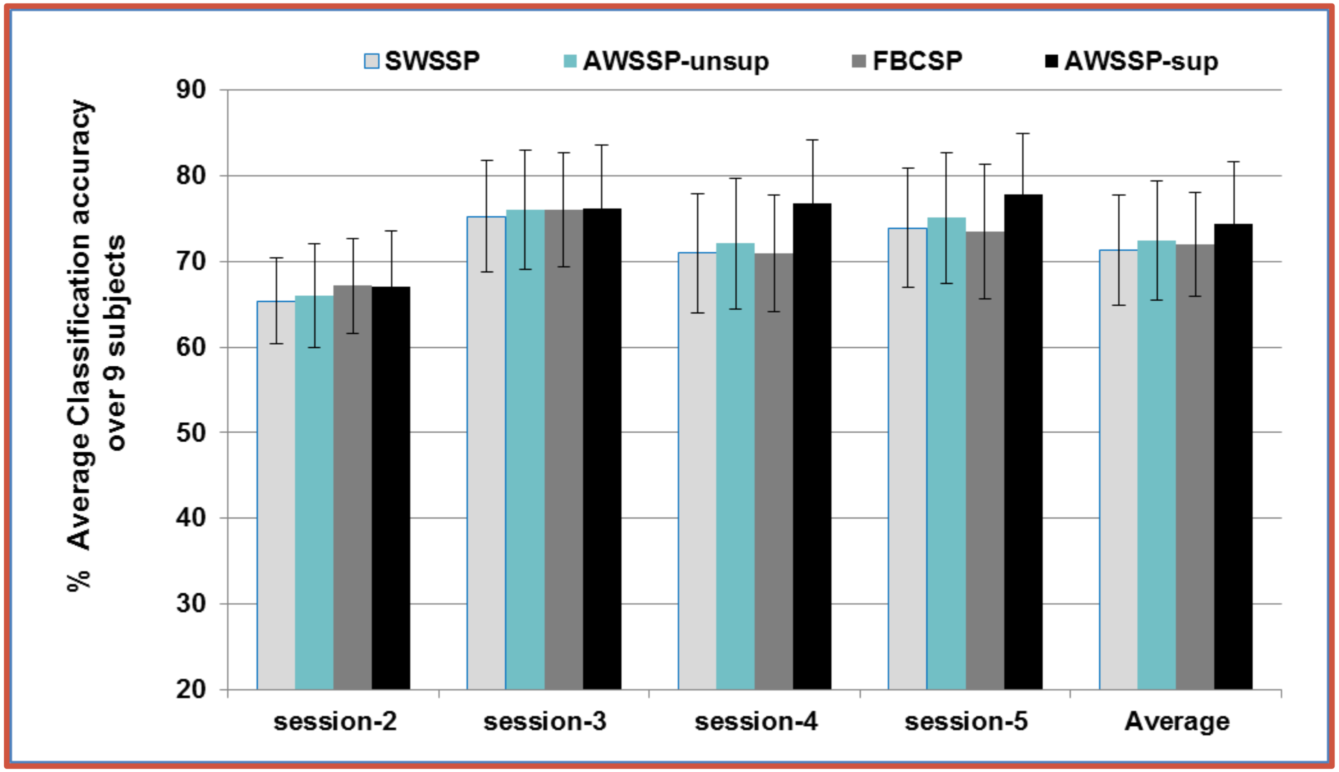
Schematic of the Adaptively weighted Spectral Spatial Pattern (AWSSP)



DDW: Deviation in Discriminative weight (DW) values

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," Accepted in Journal of Neural Engineering, February 2011.

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



SWSSP: Same filters obtained from training data (no updates).

AWSSP-unsup: Predicted class label/classifier output

AWSSP-sup: True class labels for weight updation.

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.

Classification results of online data using the proposed static and adaptive methods

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%

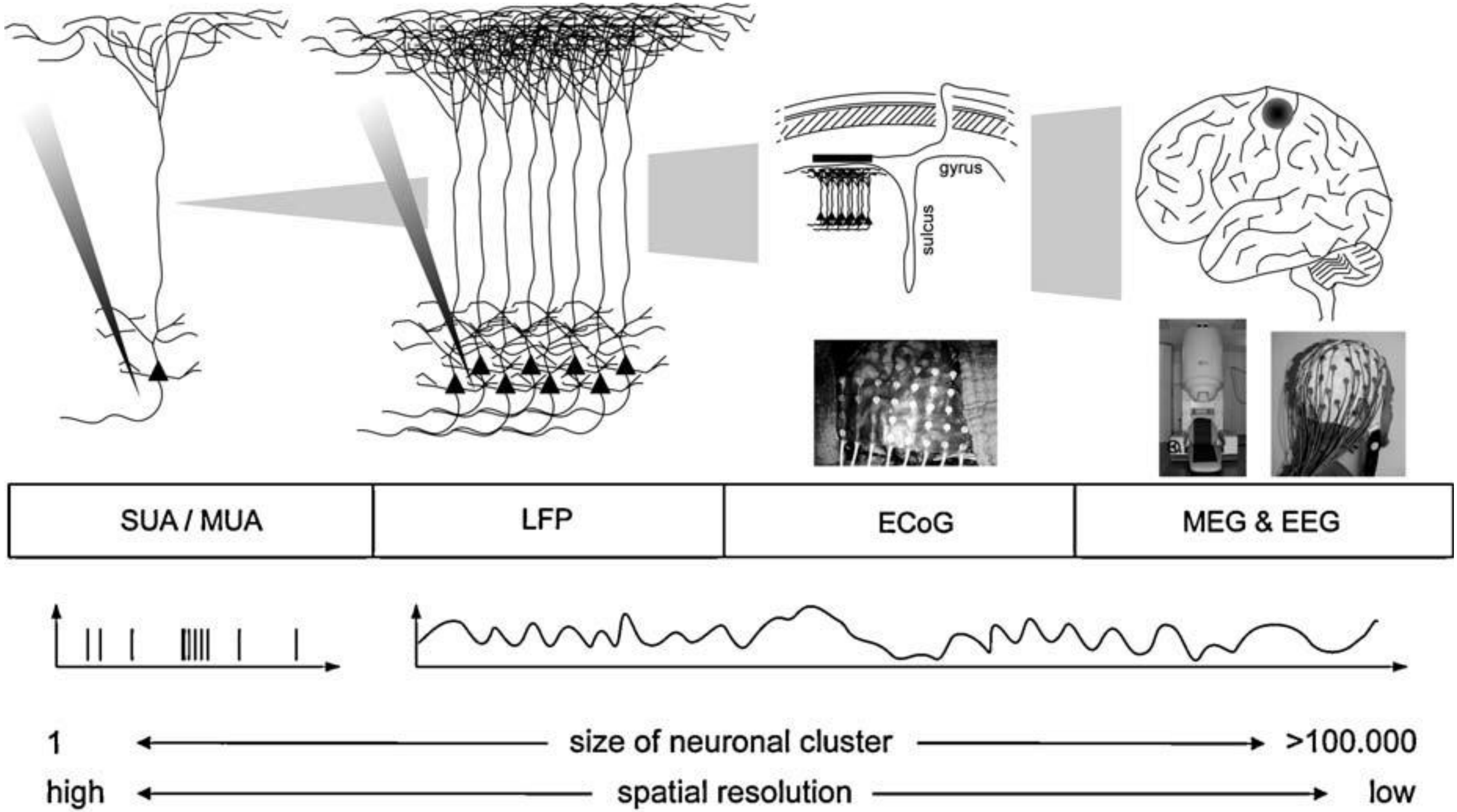
Contributions on:
Movement Execution parameters in EEG

Movement execution parameters

- Objective
  - Electrophysiological brain signals to decode various parameters of voluntary movement.
  - Movement parameters: direction, position, velocity, or acceleration.
- Why?
  - Higher degrees of freedom for output device movement.
  - Precise identification of neural patterns encoding movement or movement parameters.
- Challenge!
  - Understanding of the neural substrate for voluntary movements.
  - Non-invasive techniques do not provide sufficient signal resolution or bandwidth.

K. Jerbi, J. R. Vidal, J. Mattout, E. Maby, F. Lecaignard, T. Ossandon, C. M. Hamamé, S. S. Dalal, R. Bouet, J. P. Lachaux, R. M. Leahy, S. Baillet, L. Garnero, C. Delpuech, and O. Bertrand, "Inferring hand movement kinematics from MEG, EEG and intracranial EEG: From brain-machine interfaces to motor rehabilitation," *IRBM, vol. 32, pp. 8-18, 2011.*

Research findings



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," *J Neurosci, vol. 2, pp. 1527-37, Nov 1982.*

Mehring C, Rickert J, Vaadia E, Cardosa de Oliveira S, Aertsen A, Rotter S. Inference of hand movements from local field potentials in monkey motor cortex. Nat Neurosci 2003;6(12):1253–4.

Pistohl T, Ball T, Schulze-Bonhage A, Aertsen A, Mehring C. Prediction of arm movement trajectories from ECoG- recordings in humans. J Neurosci Methods 2008;167(1):105–14.

- Non-invasive studies in Humans using MEG/EEG
  - Successfully decoded finer details of movement such as velocity/ direction.
  - Tasks: Voluntary hand movements in different directions at different speeds.
  - Identified 3 spectral regions showing ***Movement related neural activity.***

Low frequency band (EEG/MEG: <7 Hz)	**Intermediate frequency band (EEG/MEG: 10–30 Hz)**	**Broad high-frequency band (EEG/MEG: 62–87 Hz)**
• Amplitude modulations. • Movement related potential (MRP) slow signal components.	• ERD/ERS. • Mu and beta rhythms, across motor cortex.	• Movement related amplitude increase. • Neuro-physiological meaning and mechanisms underlying this is not clear!!

Waldert S, Preissl H, Demandt E, Braun C, Birbaumer N, Aertsen A, et al. Hand movement direction decoded from MEG and EEG. J Neurosci 2008;28(4):1000–8.
Salmelin, R., Hämäläinen, M., Kajola, M., Hari, R., 1995. Functional segregation of movement-related rhythmic activity in the human brain. Neuroimage 2 (4), 237–243.

Summary

- Spectral:
  - Low-frequency components in movement parameter decoding & reconstruction
    - <7 Hz for direction decoding.
    - 2-5 Hz for speed decoding.
- Spatial:
  - Primary & Supplementary motor area.
  - Posterior parietal cortex.
- Temporal:
  - Movement intention, planning, execution, after movement.

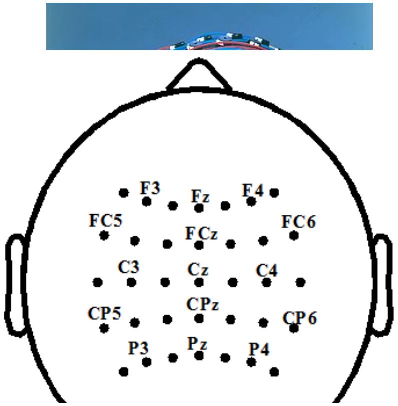
Requirements

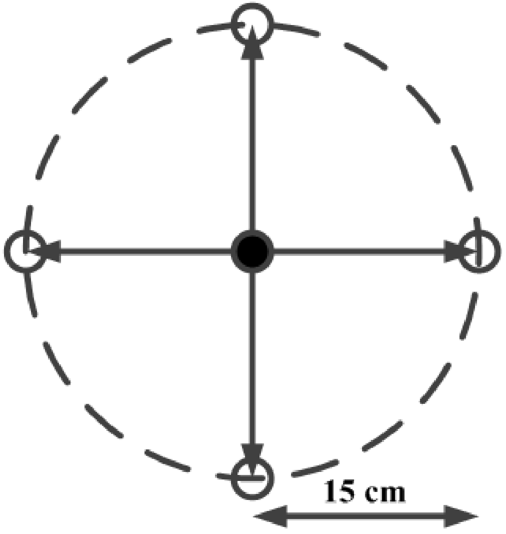
- Challenges: Why not a simple low pass filtering?
  - Extracting the precise information taking into consideration the inter trial variability.
  - Artefact removal, improve SNR.
  - Overlapping cognitive information.
- Signal Processing : Optimal information extraction from the raw data.
  - Tools:
    - ICA, PCA, CSP.
    - Kalman filter, MLR models.
    - Different parameters in time and frequency domains.
    - ***Features localized in time and space from low frequency subbands.***
  - Neural sources:
    - Movement Related Potential (MRP).
    - ERD/ERS.
    - Gamma band activity (25-40 Hz).
    - ***Low frequency EEG.***

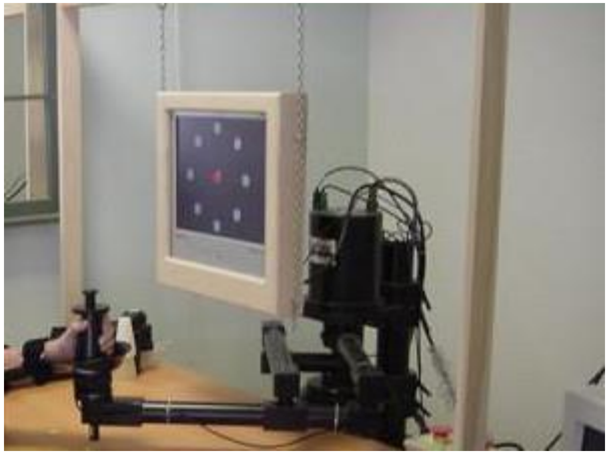
ICA - Independent Component Analysis
PCA- Principal Component Analysis
CSP – Common Spatial Pattern
MLR – Multiple Linear Regressor

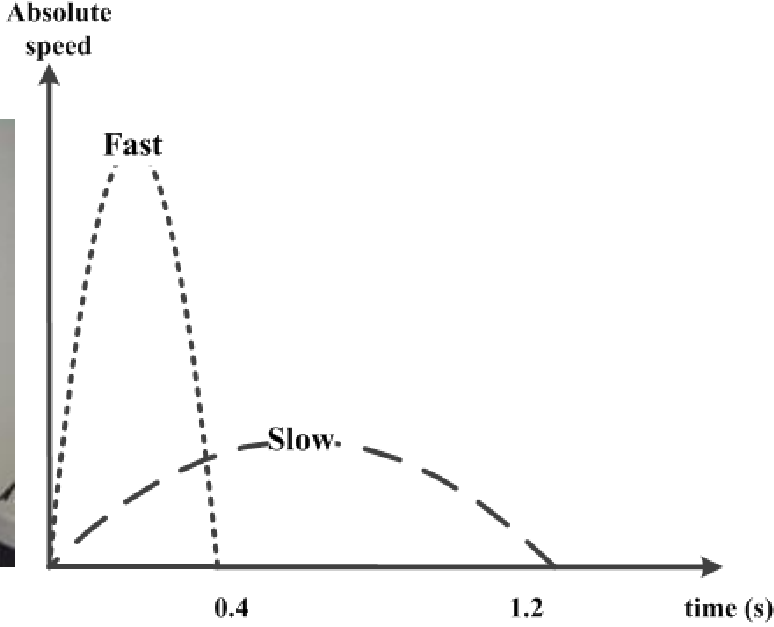
Data Acquisition

- Equipment
  - Neuroscan Synamps 128 channel EEG amplifier.
- Spatial location
  - Primary and Secondary motor areas.
- Tasks



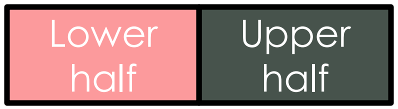


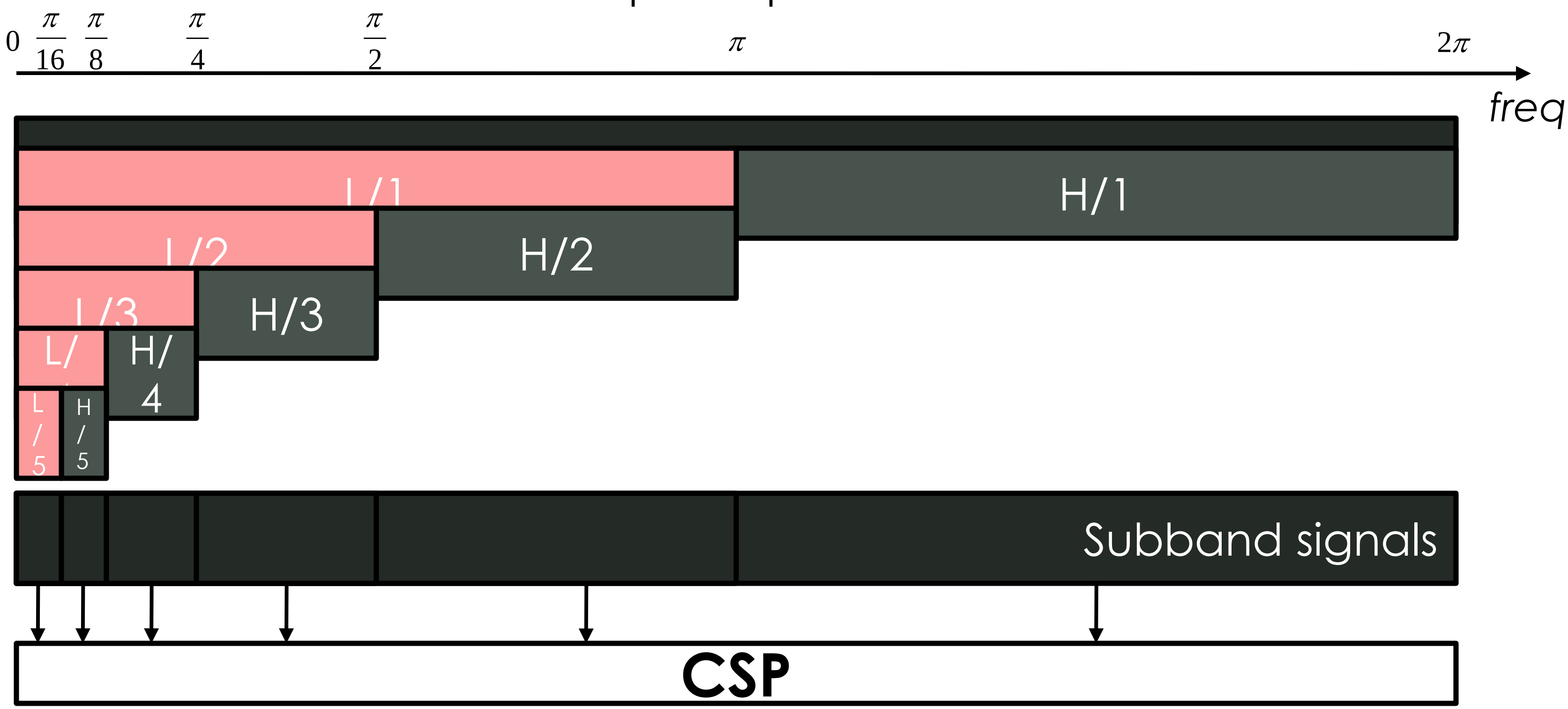




Wavelet- Common Spatial Pattern

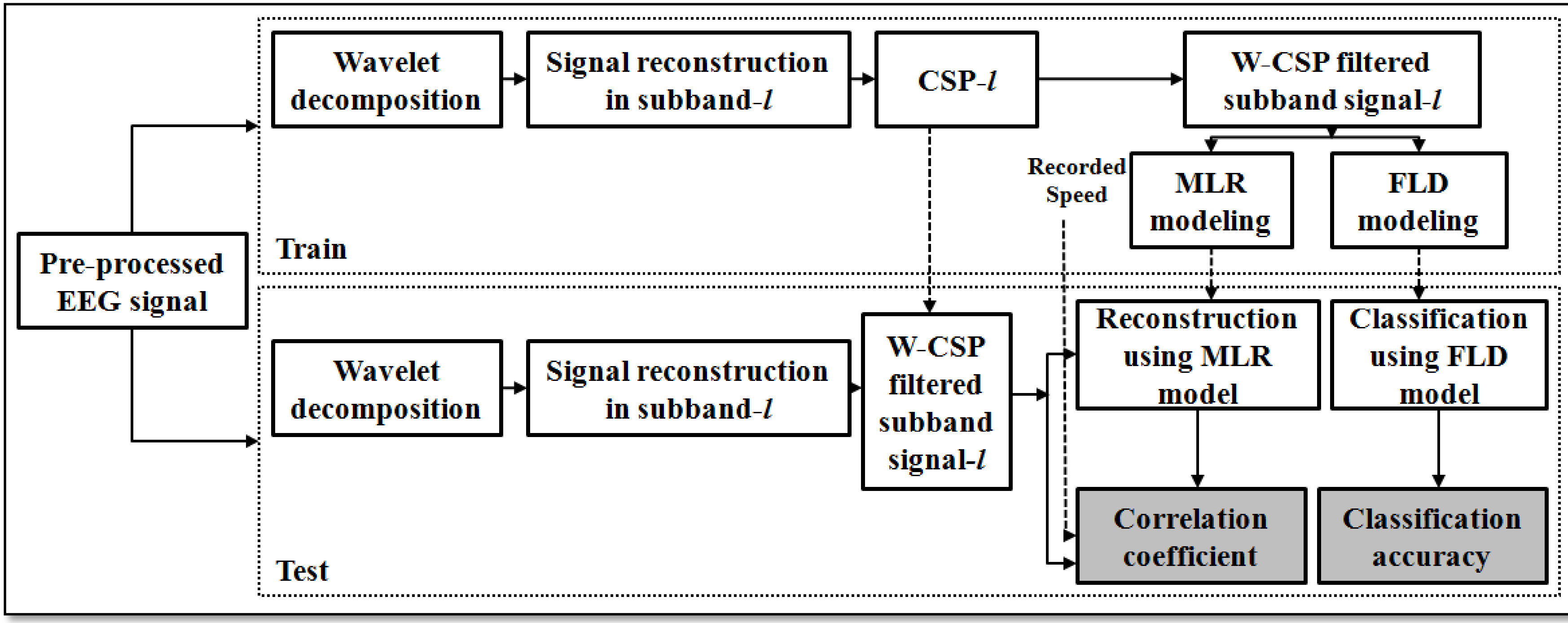
- Multi resolution Analysis by DWT
  - Octave band filtering using orthonormal wavelet bases followed by downsampling.
- CSP
  - Generates discriminative spatial patterns.





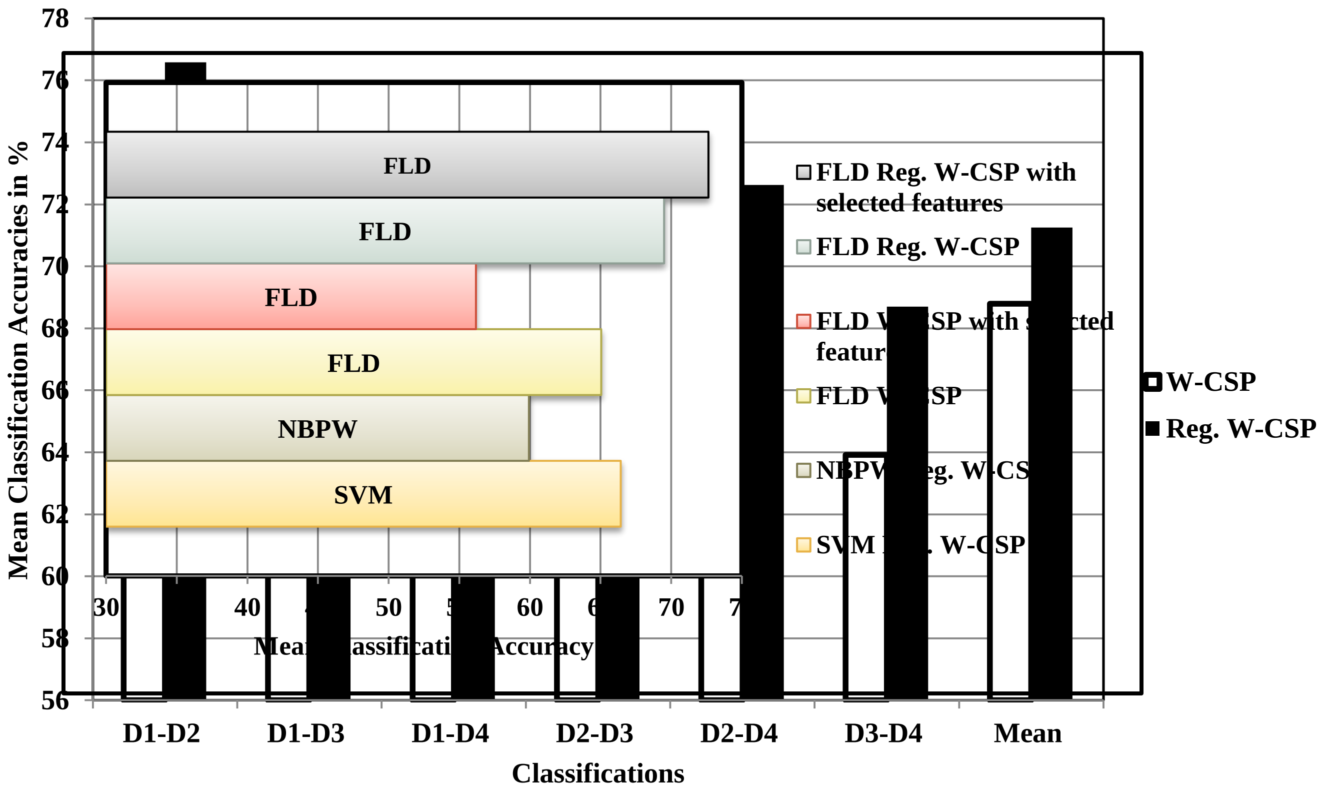
M. Vetterli, C. Herley, "Wavelets and filter banks: Theory and design," *IEEE Transactions in Signal Processing, vol. 40, no. 9, pp. 2207-2232,* Sep. 1992.
H. Ramoser, J. Muller Gerking, G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Transactions on Rehabilitation Engineering, vol. 8, pp. 441-446, Dec.* 2000.

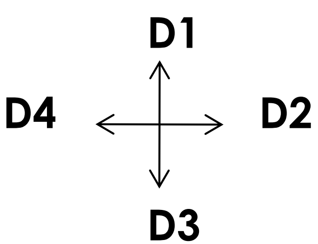
Functional block diagram – Speed Decoding



Above method is modified with regularization of CSP for direction analysis.

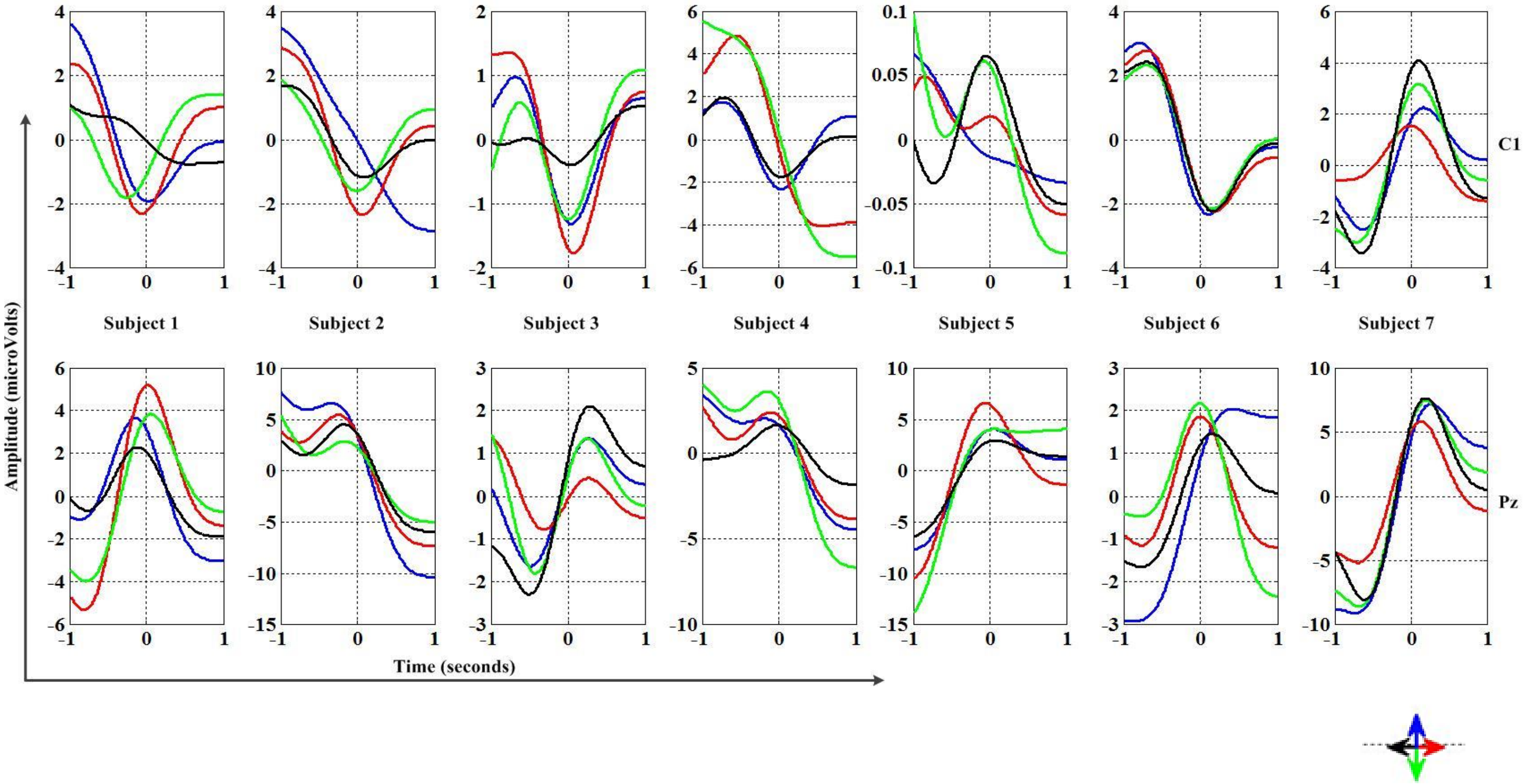
Results - Directions



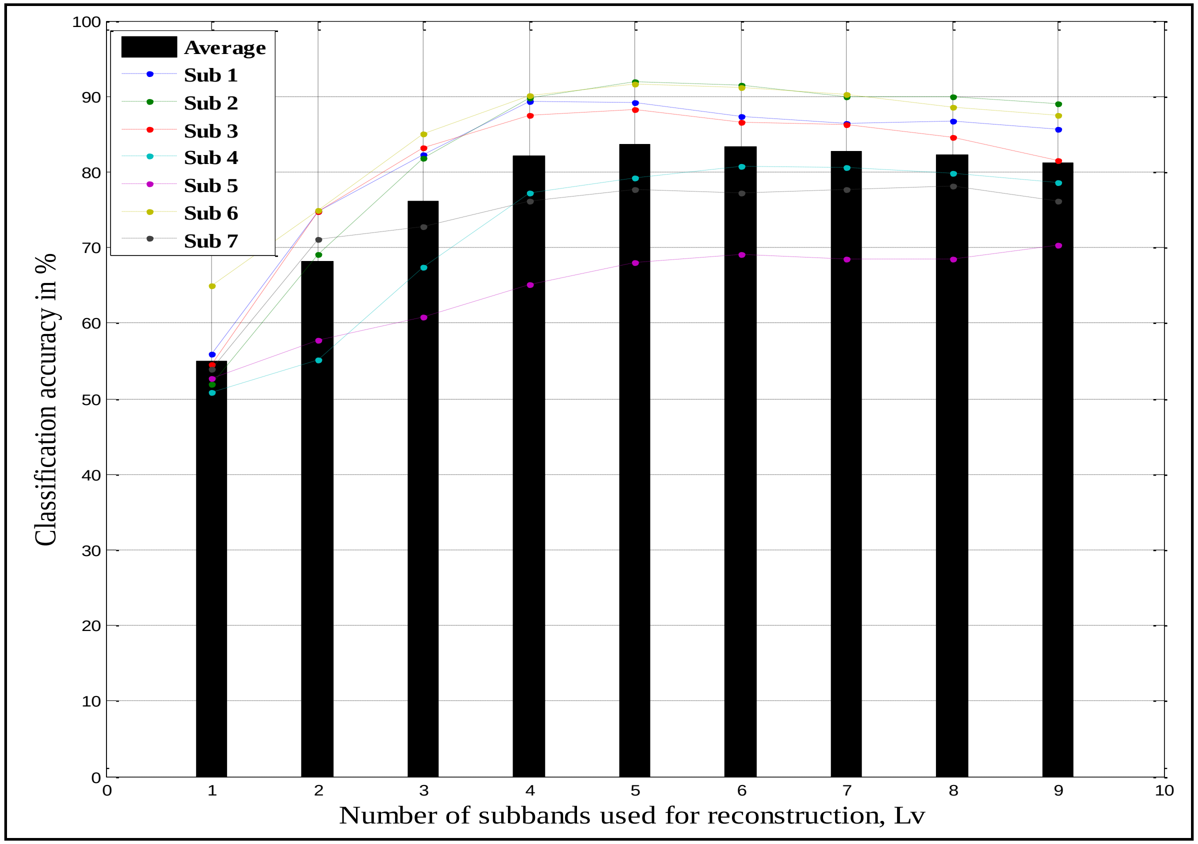


Direction dependent temporal activations

(<1 Hz range recorded from C1 and Pz)



Results - Speeds

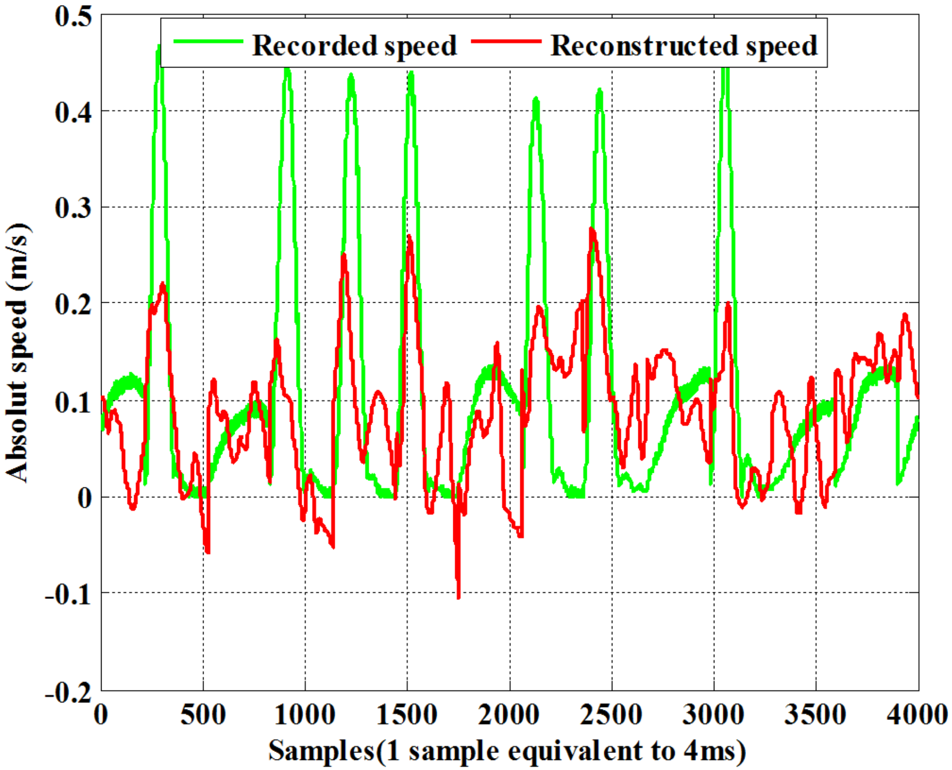


Best accuracy at 5 bands (<7 Hz): 83.7% (between fast and slow movements)

Reconstructing movement speed

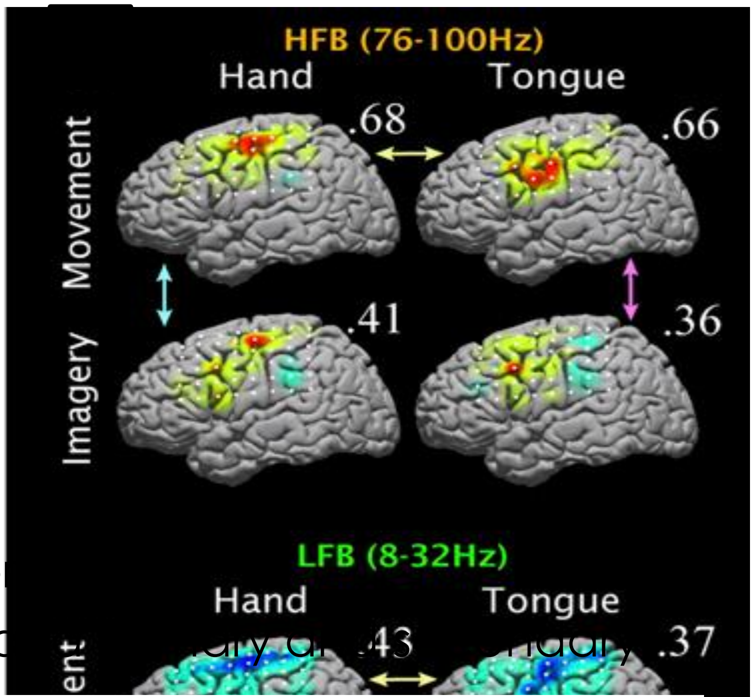
Correlation Coefficients			
	x	*y*	*abs*
M1	**0.45**	**0.31**	**0.52**
M2	**0.48**	**0.42**	**0.50**

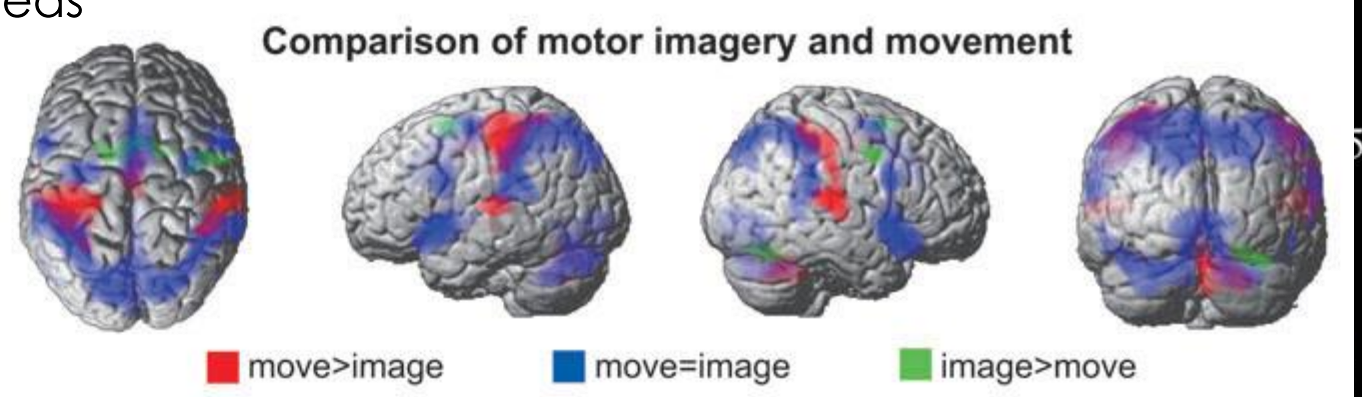
M1: MLR based on subband components.
M2: MLR based on time segments.



Moving on…..Neural correlates of movement execution & imagery

- ECoG
  - Spatial distribution of local neuronal population activity during motor imagery and actual motor movement are similar.
- fMRI: Imagery : Visual or Kinesthetic
  - Spatial overlap : Occipital and Moto
  - Primary and secondary visual areas c
    motor areas





T. Hanakawa, M. A. Dimyan, and M. Hallett, "Motor planning, imagery, and execution in the distributed motor network: a time-course study with functional MRI," *Cereb Cortex, vol. 18, pp. 2775-88, Dec 2008.*
K. J. Miller, G. Schalk, E. E. Fetz, M. den Nijs, J. G. Ojemann, and R. P. N. Rao, "Cortical activity during motor execution, motor imagery, and imagery-based online feedback," *Proceedings of the National Academy of Sciences, February 16, 2010 2010.*

Possible Future work

No study to date has reported full closed-loop decoding multidimensional imagined movement activity.

- **Goals**
  - How well motor imagery can replace the information using actual movement execution?
  - Real time systems : Subject trained models; adapted to own neural activity for movement encoding using minimum optimal information.
  - Detection of 3-D movements

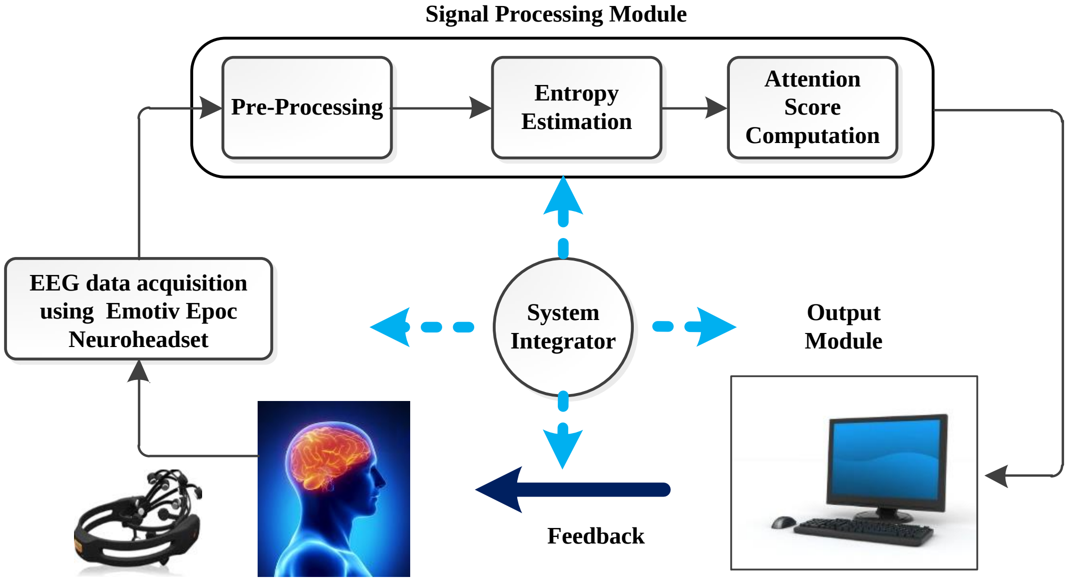
Some Applications

- Assistive technology devices (Stroke rehabilitation)
- Serious computer games
- In automotive control: Thought driven motors, Controlling acceleration/speed, Steering control.

Contributions on:
Attention related EEG

Attention detection from EEG

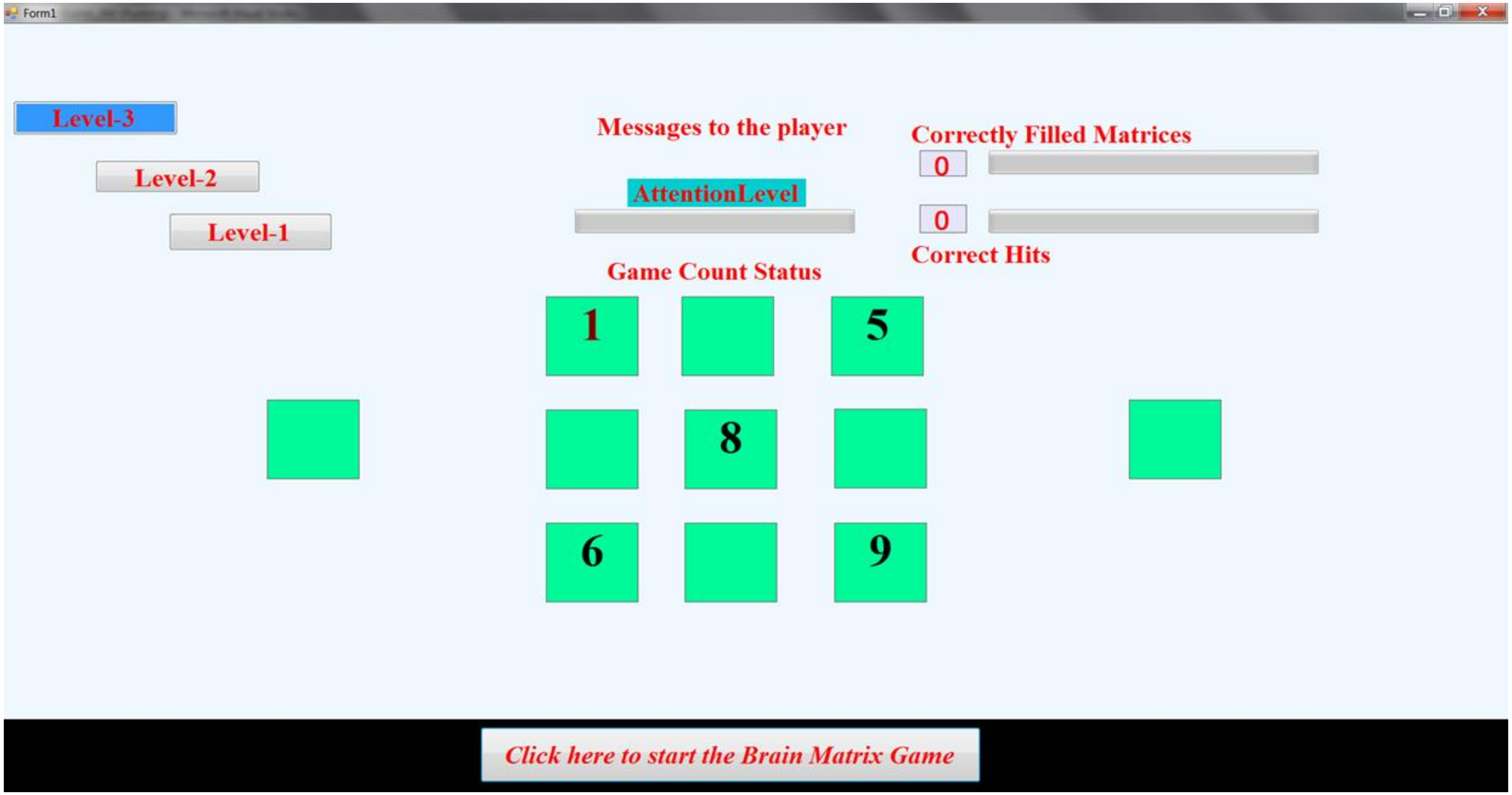
- Attention is the state of alertness
- Can be estimated using the entropy values of EEG
- Used widely in neurofeedback studies as directly related to cognition
- We have developed an attention driven computer game:



Framework of attention driven game

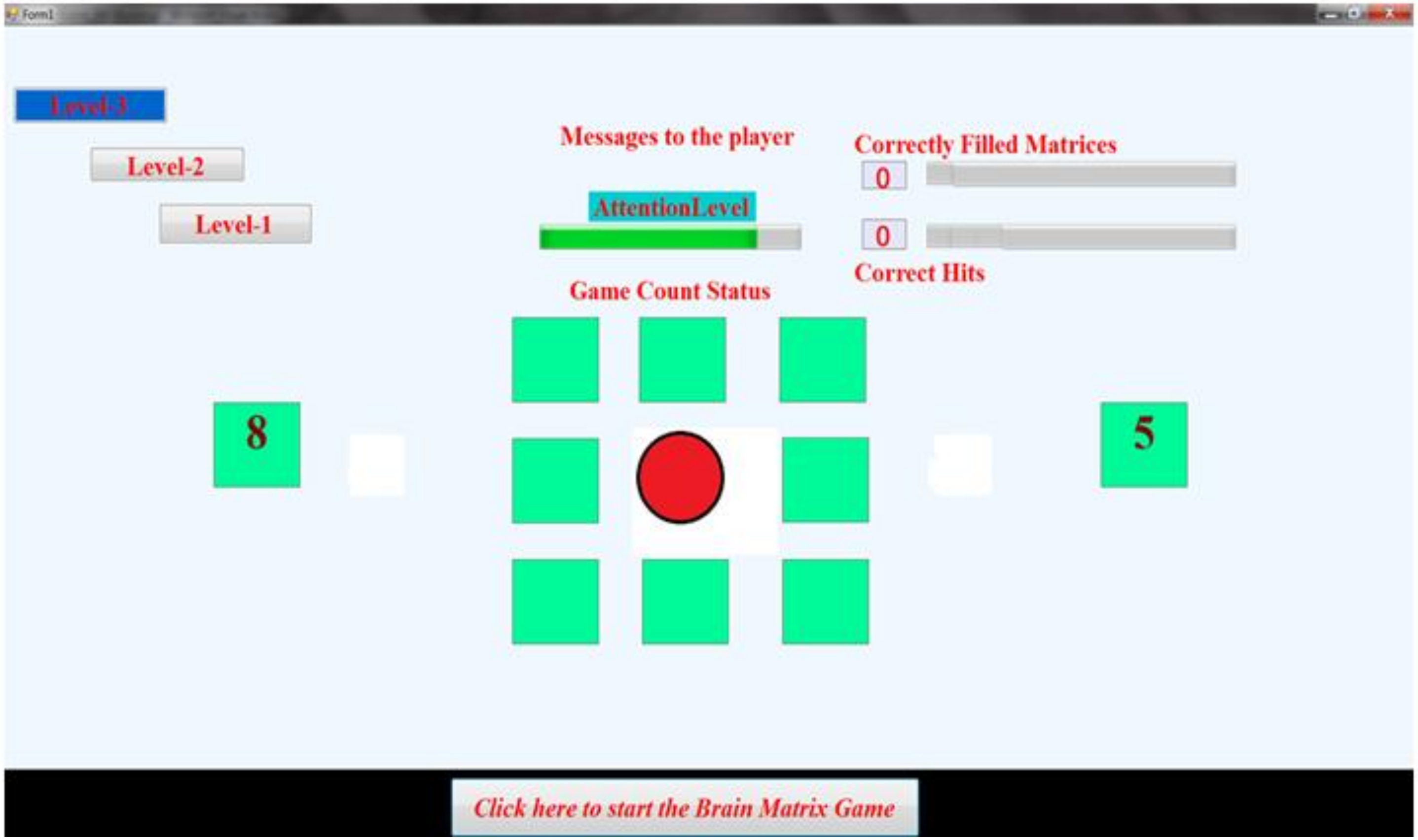
Gaming interface controlled by EEG (for ADHD Children)

Stage 1: Memorize the displayed numerals and locations



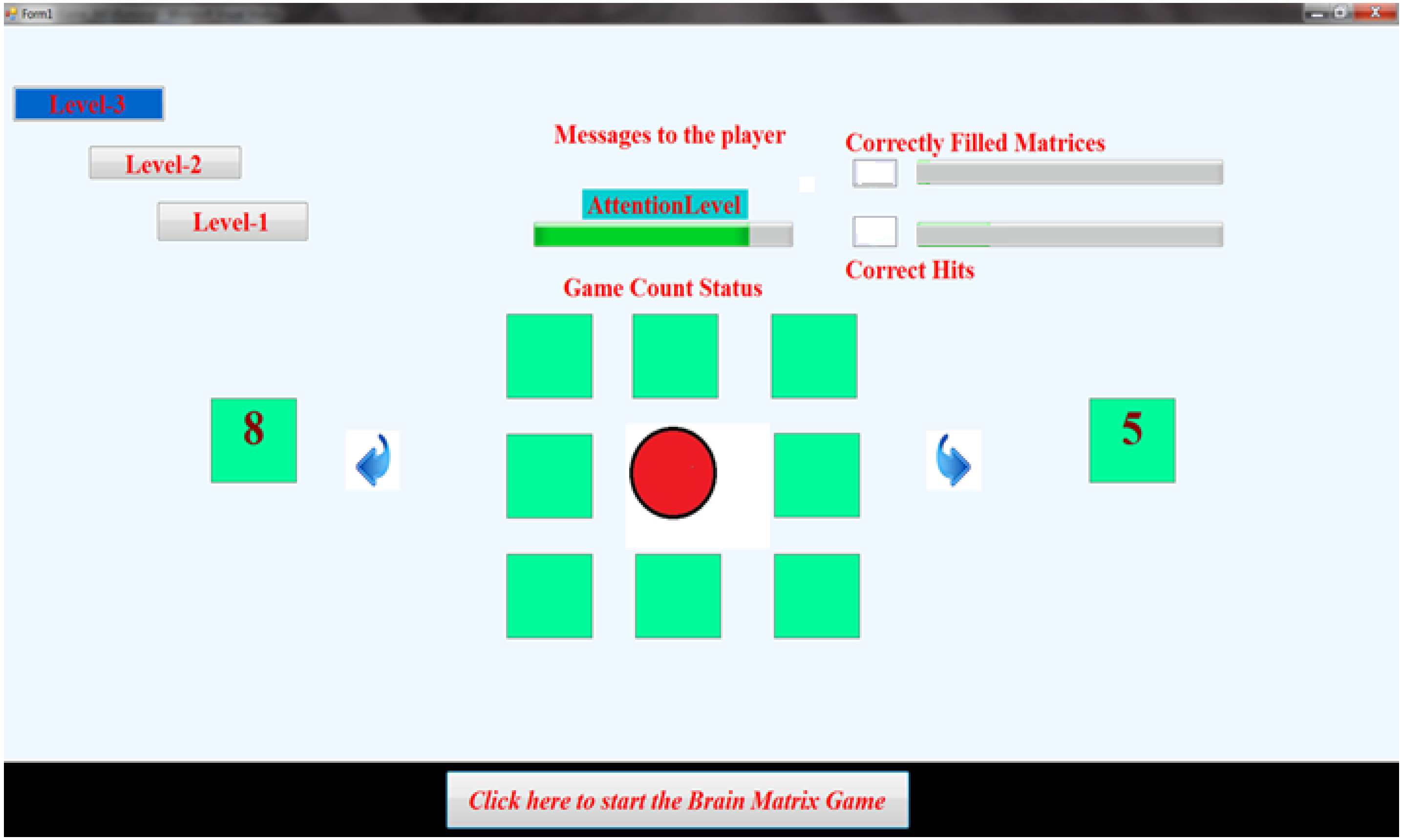
Gaming interface controlled by EEG

Stage 2: Focus on a point on interface in order to make the attention score above threshold value



Gaming interface controlled by EEG

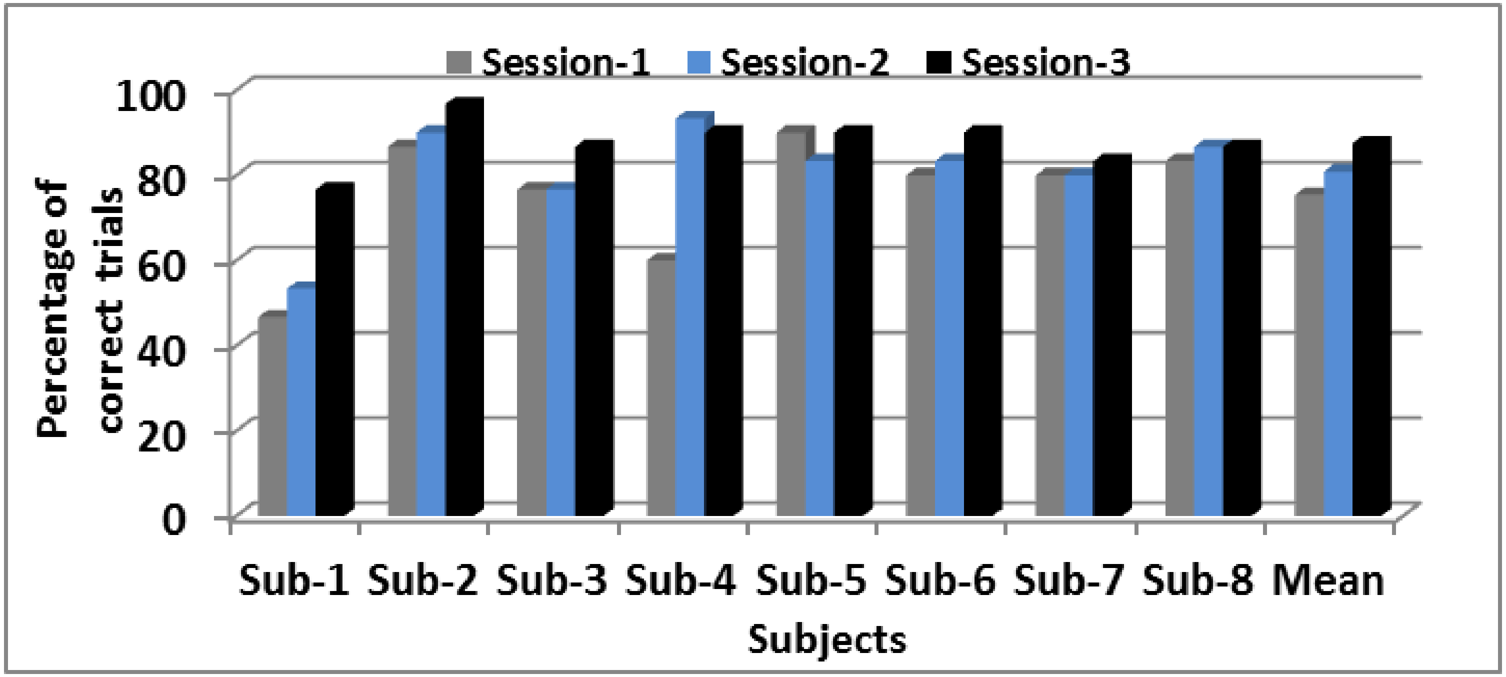
Stage 3: Display of arrows and selection of answer by keyboard



Experimental results

- **Accuracy of re-filling the matrix improves by practice.**

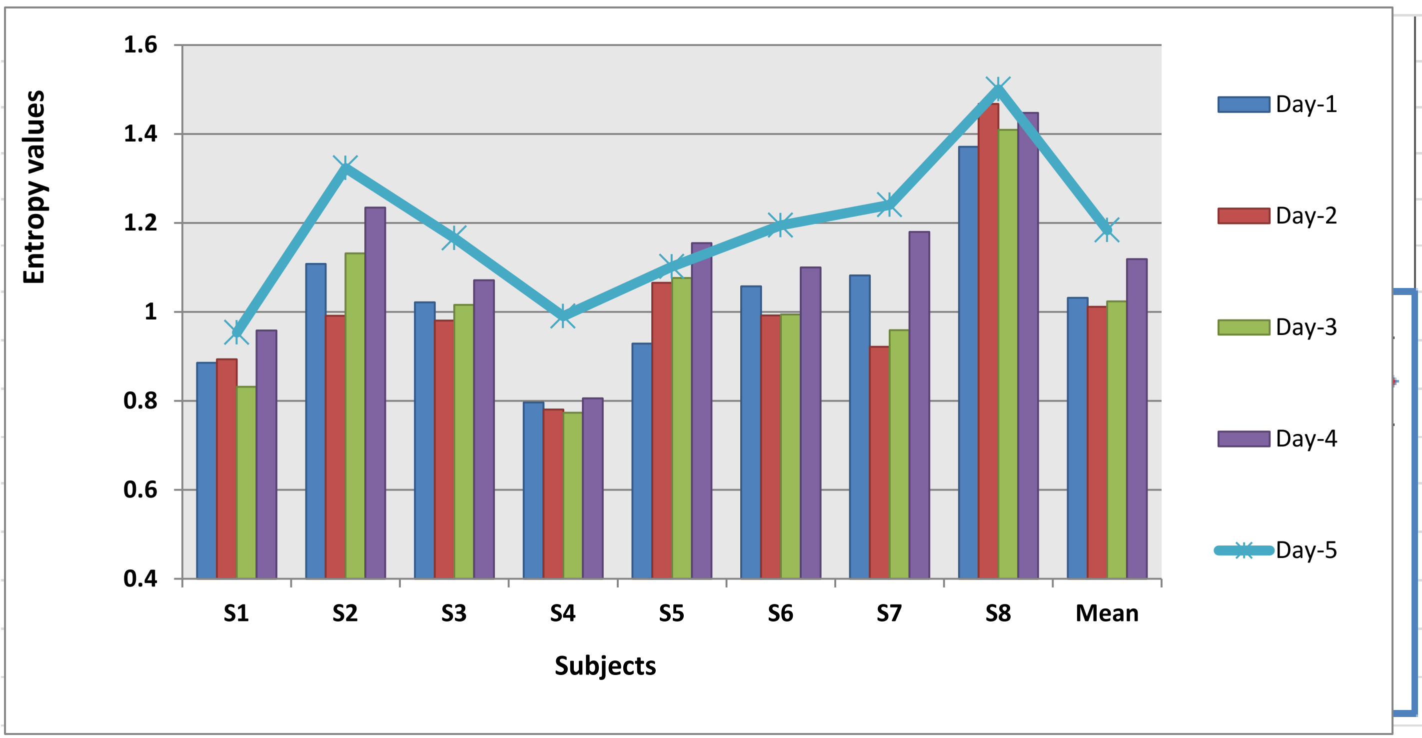
Percentage of correctly filled matrix elements in a level-3 Matrix game over 3 days (Total number of trials:30)



Percentage of Correct trials on Day-1, Day-2 and Day-3: 75, 80, 87%

Experimental results

- Neurofeedback based training enhances the threshold and attention scores also.



Variation of attention score over days.
Fixed threshold for Day-1 to Day-4.
Day-5 game is played with a higher threshold.

Variation of game points over days.
Fixed threshold for Day-1 to Day-4.
Day-5 game is played with a higher threshold.

Possible future works on attention based BCI

- Neurofeedback has been considered as an effective treatment approach for enhancing attention and cognitive skills of children with attention-deficit hyper active disorder (ADHD).
- Planning to extend our studies for developing more interactive games and use them for treating ADHD children.

Call for Papers – International Symposium on Electronic System Design (ISED 2013), 12-13 December, Singapore

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- Embedded System Design
- Emerging Technology and System Design
- Power Aware System Design
- Software System and Application Design
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THANK YOU