Brain-Machine Interfaces

Intelligent robotics

Health Robotics

Assistive robotics

Replacing robotics (e.g. prosthesis)

Rehabilitation robotics

Neurotechnology

Physiologically connected robotics

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20201116

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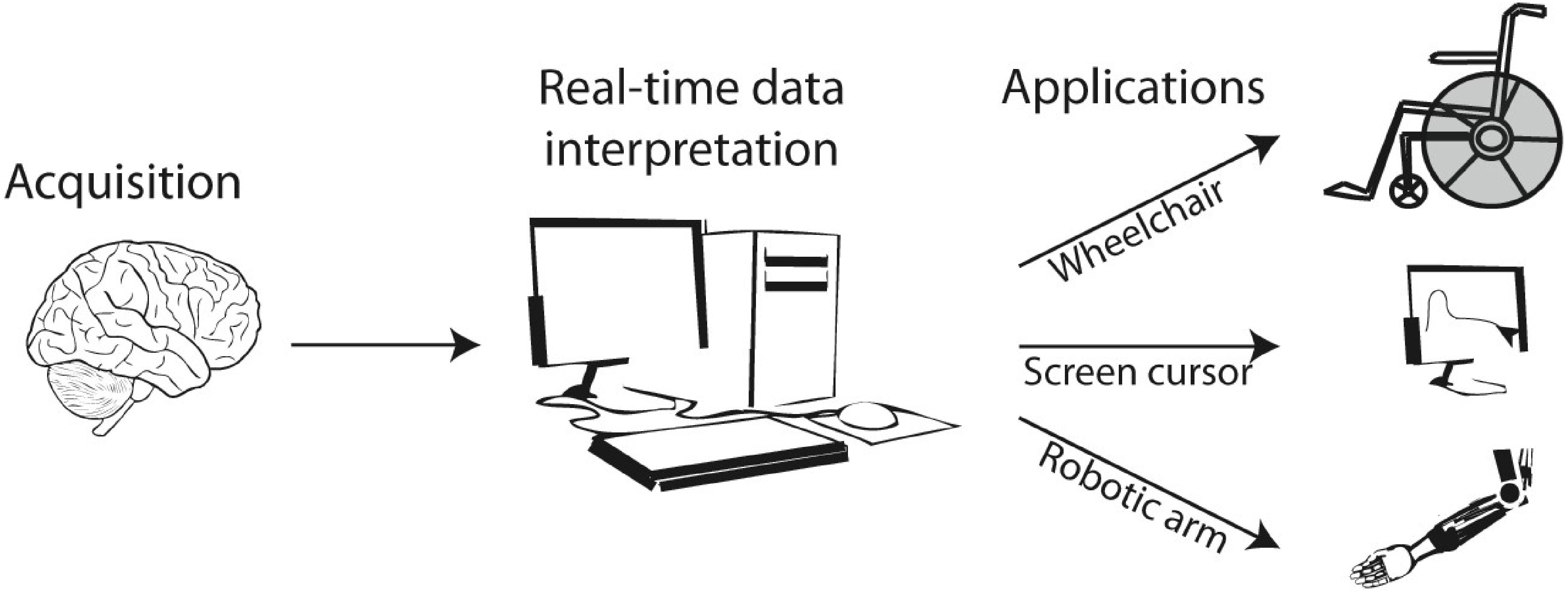
Introduction to BMIs



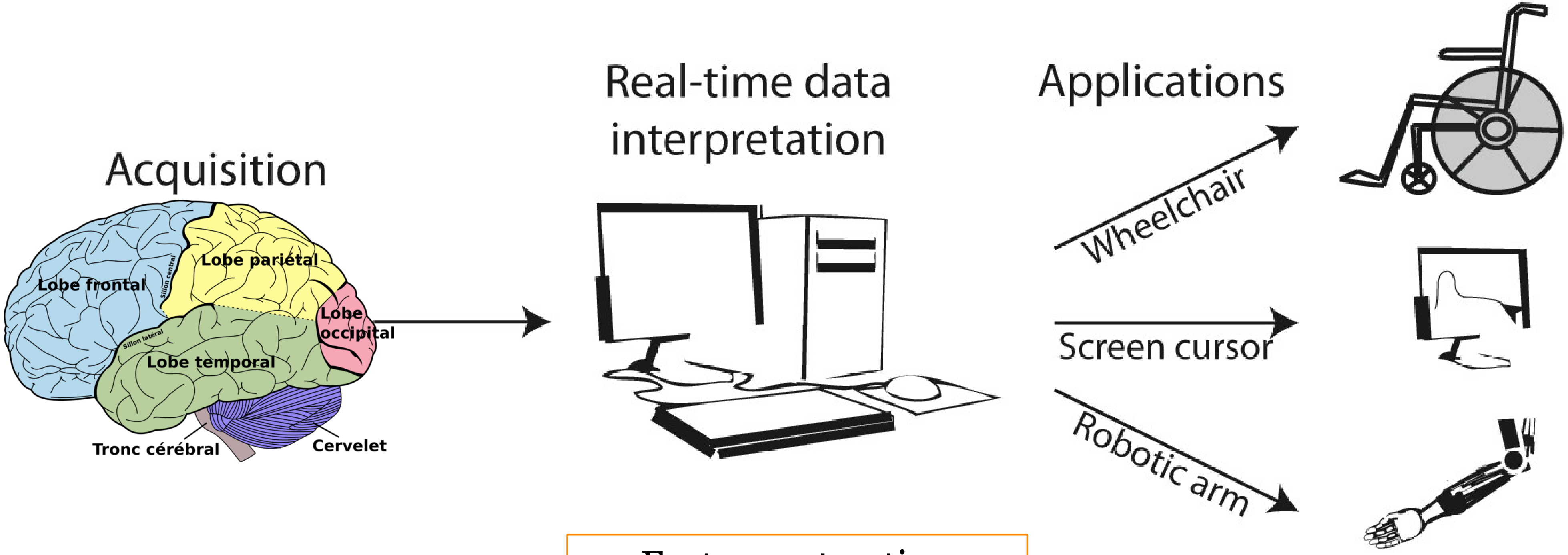
Modified from Astrand et al. (2014)

1. Real-time signal recordings
2. Protocol development

1. Pre-processing
2. Feature extraction
3. Supervised Machine Learning (or other AI algorithm)

1. Feedback/control command generation
2. End-effector/feedback execution

Introduction to BMIs



Modified from Astrand et al. (2014)

1. Real-time signal recordings
2. Protocol development
3. Pre-processing

1. Feature extraction
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3. Post-processing

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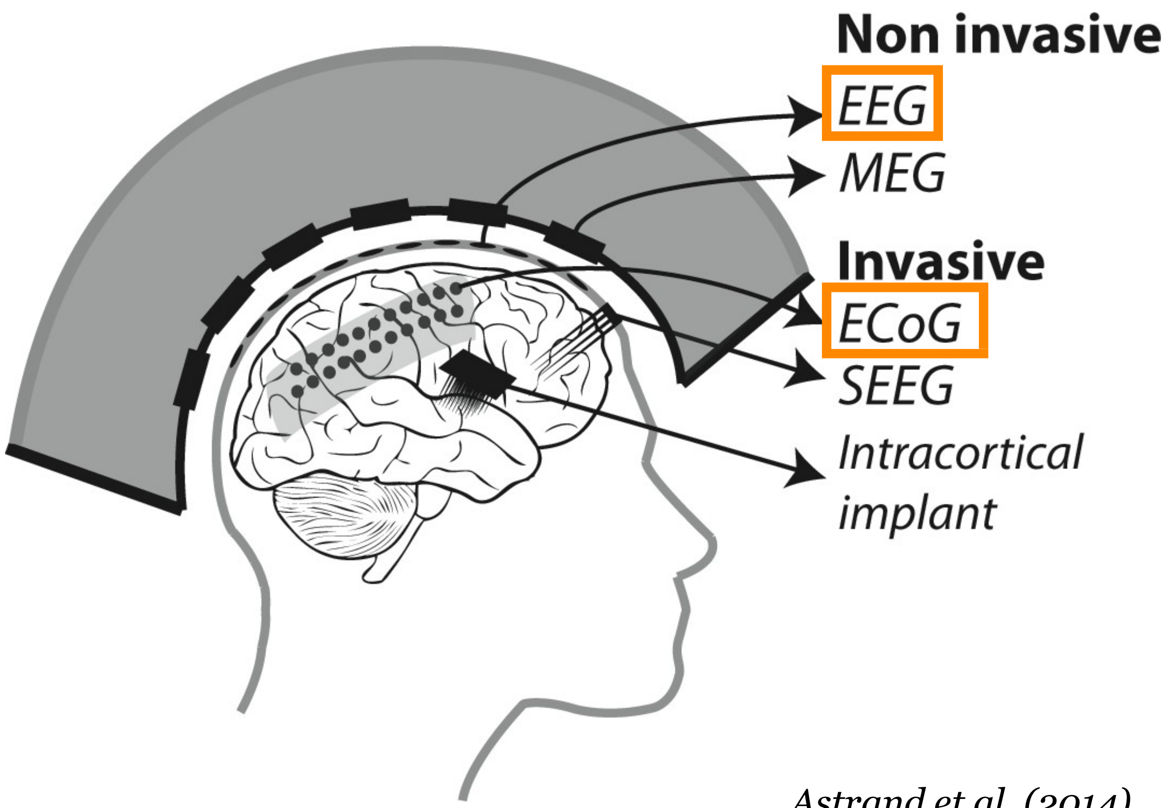
Acquisition: signal recording techniques

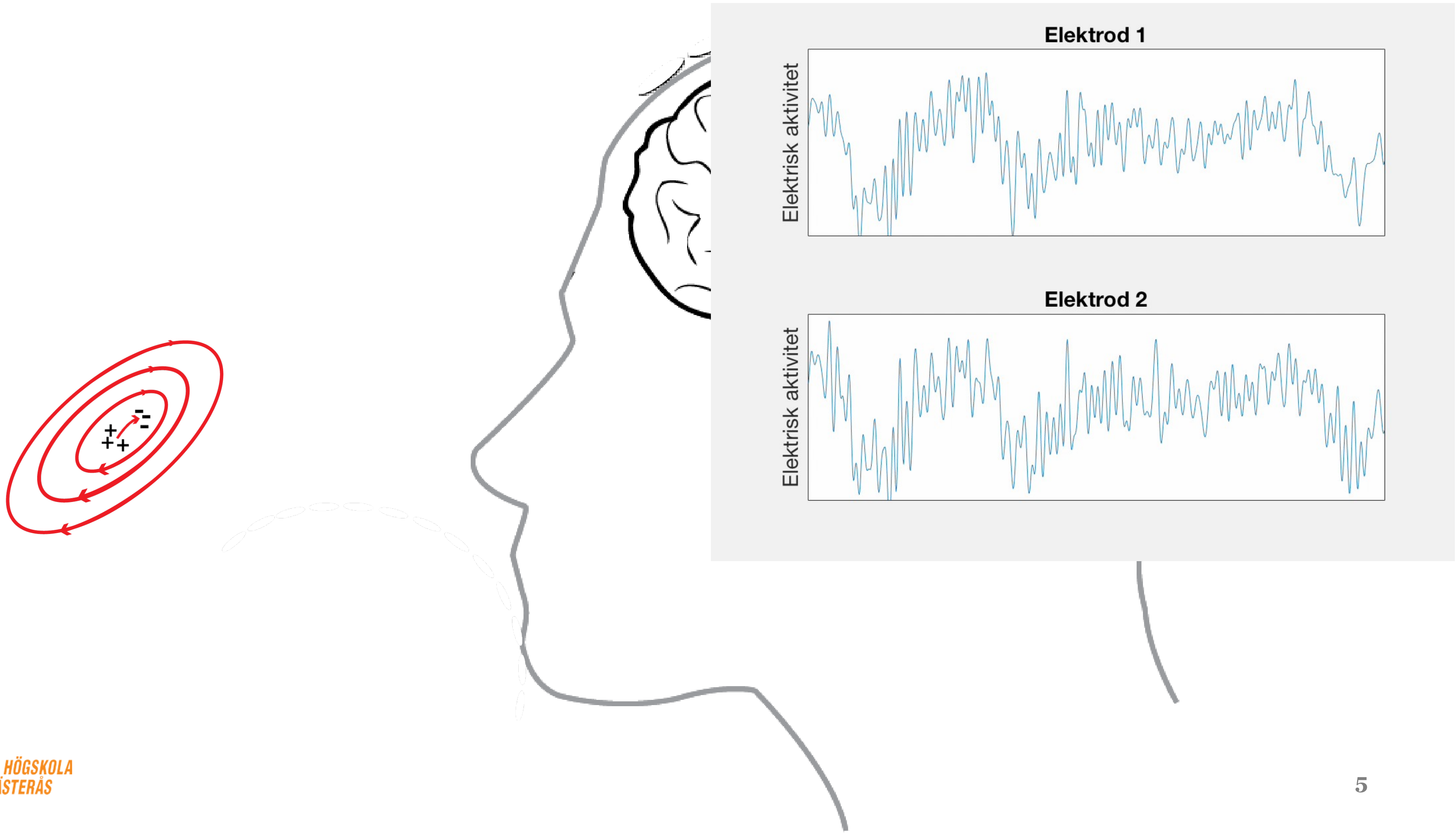


Astrand et al. (2014)

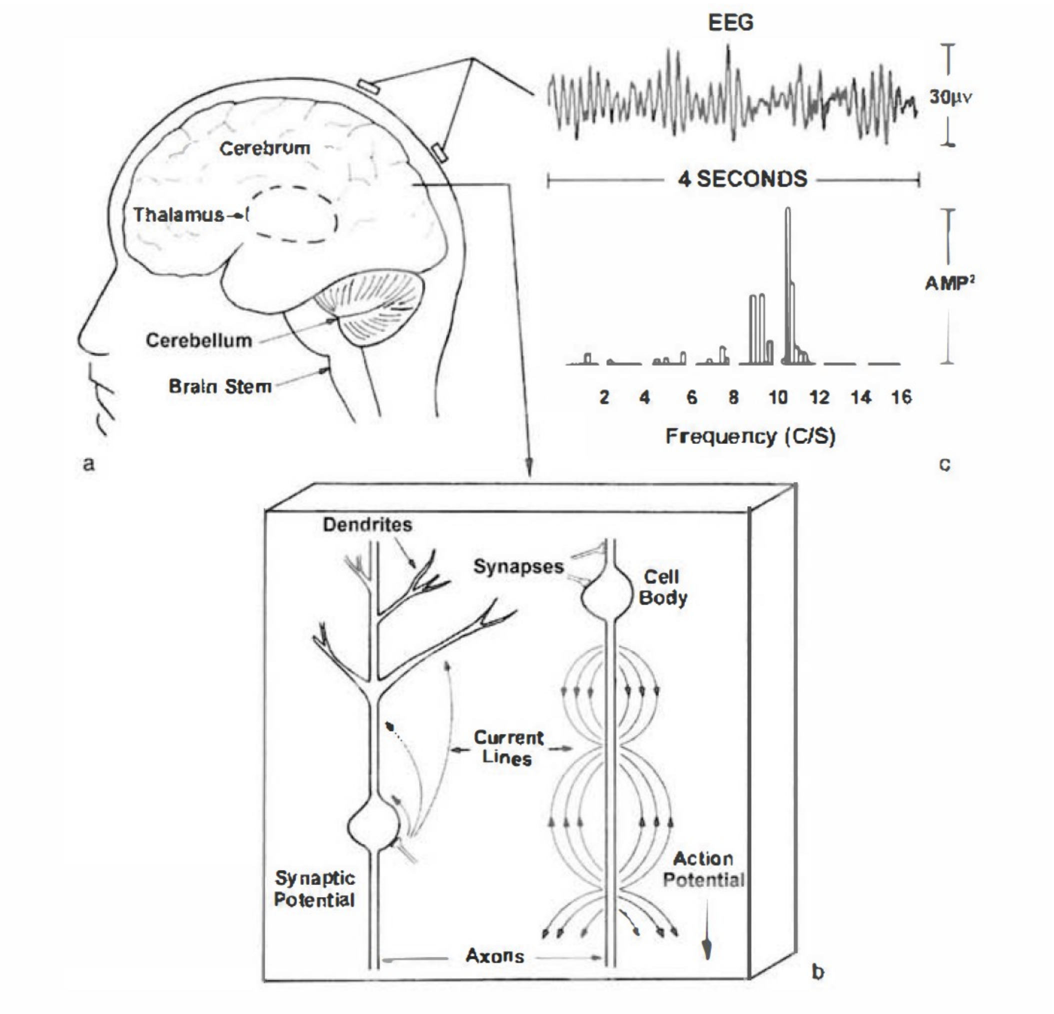
Electroencephalography (EEG):
- Non-invasive
- Portable
- Low-cost
- Low spatial resolution (due to volume conduction)

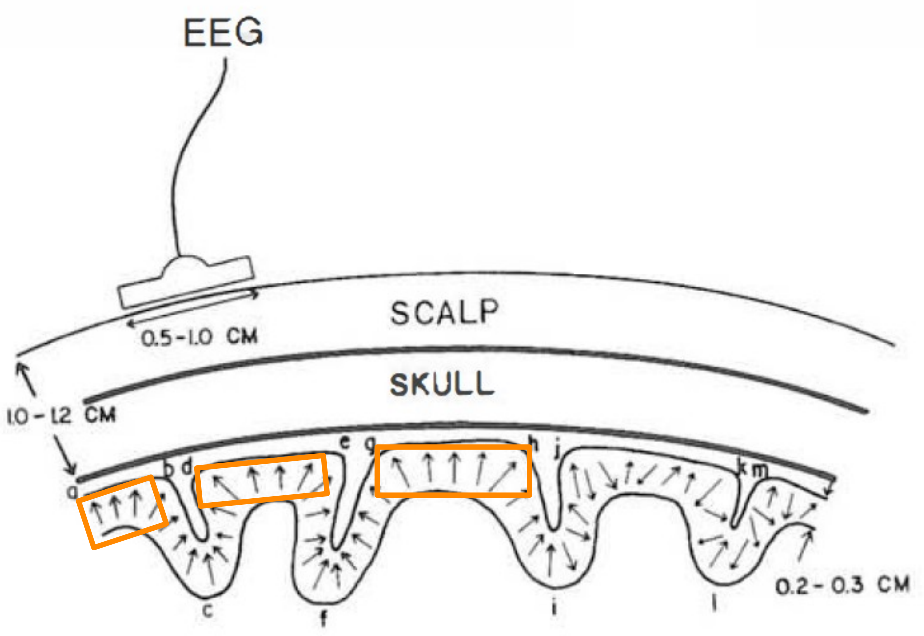
Electrocorticography (ECoG)
- Subdural (invasive) vs. epidural (semi-invasive)
- Higher spatial resolution

Acquisition: EEG signal recording



Acquisition: EEG signal recording





EEG is most sensitive to correlated pyramidal neurons/dipoles located in the cortex and oriented perpendicular to the cortical surface.

Nunez and Srinivasan (2006)

Acquisition: reference to EEG signal recording

- Modern EEG acquisition devices measure the difference of electrical potentials between each electrode placed on the head and one reference electrode
- These differences depend on both electrode locations as well as source/dipole generator configurations and locations

Where should the ideal reference electrode be placed?

Ideally, the reference electrode should contain:

- The external noise and artifacts (e.g. powerline, cords etc.)
- Physical noise generated by the subject (eye-movements, blinks, ECG etc)

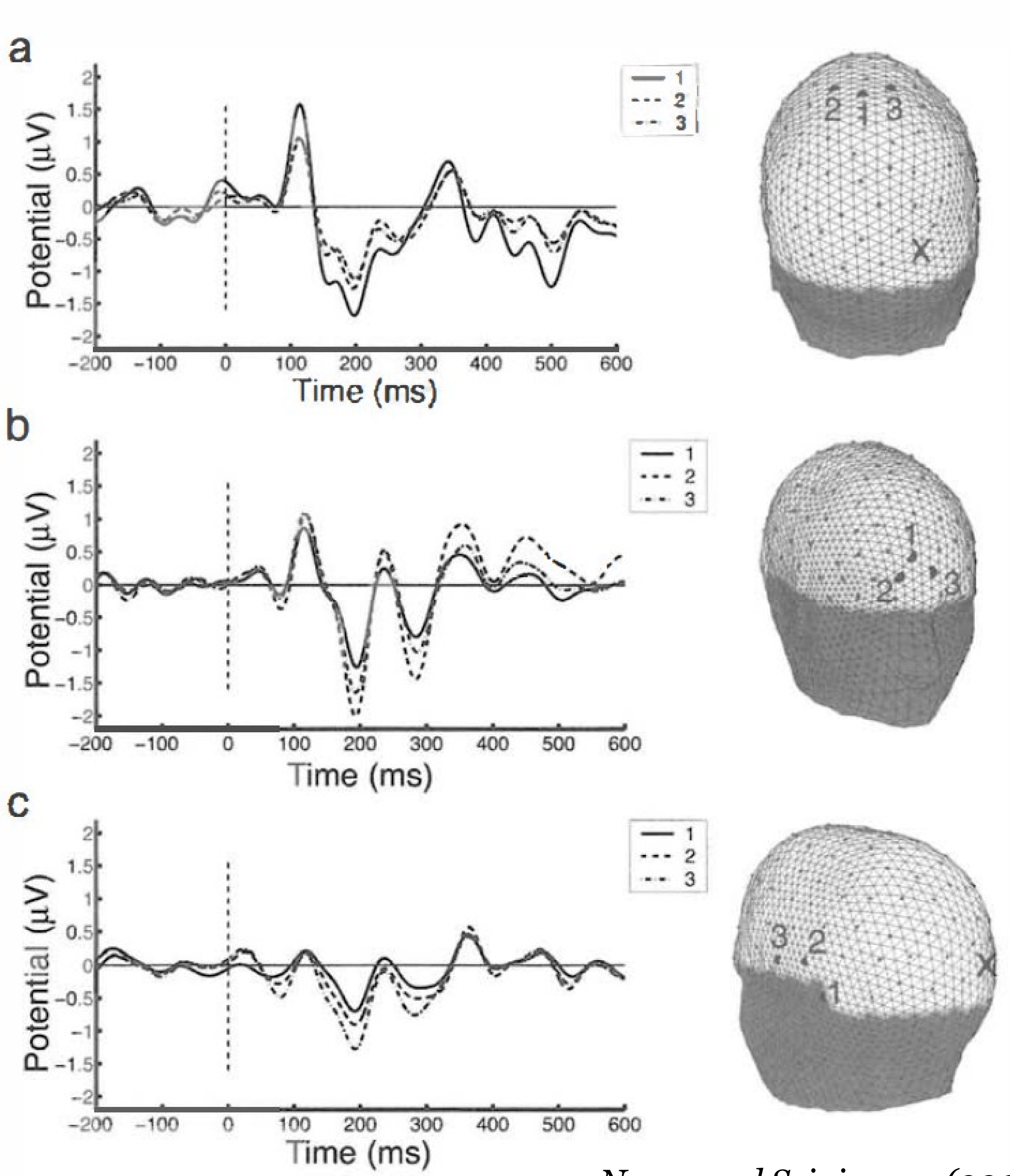
Acquisition: reference to EEG signal recording

Visually Evoked Potentials (VEP) from EEG channel O2 (denoted X) with different references (F_s = 1000Hz, bandpass filtered 0.1Hz-30Hz, 100 repetitions). Mathematical re-referencing

➔ Reference location has a substantial impact on VEP amplitude.

Common choices:

- Ear lobes
- Mastoid (linked)
- Common average
- Nose tip



Nunez and Srinivasan (2006)

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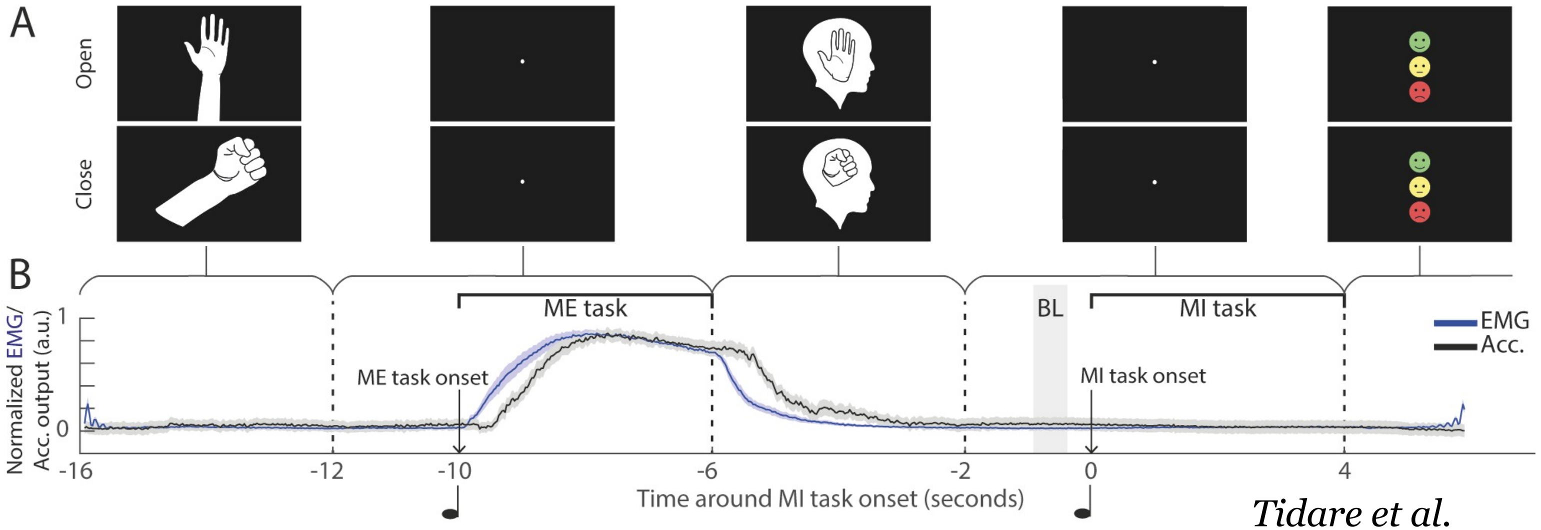
Acquisition: protocols

- Most BMI:s with the objective to control the movement of an object will depend on motor activity generated in the brain
  - Intended or imagined movements
    - Direct neural decoder
    - Remapping approach
- The **experimental protocol** is vital for:
  - obtaining clean data
  - the development of a ML model that is able to generalize



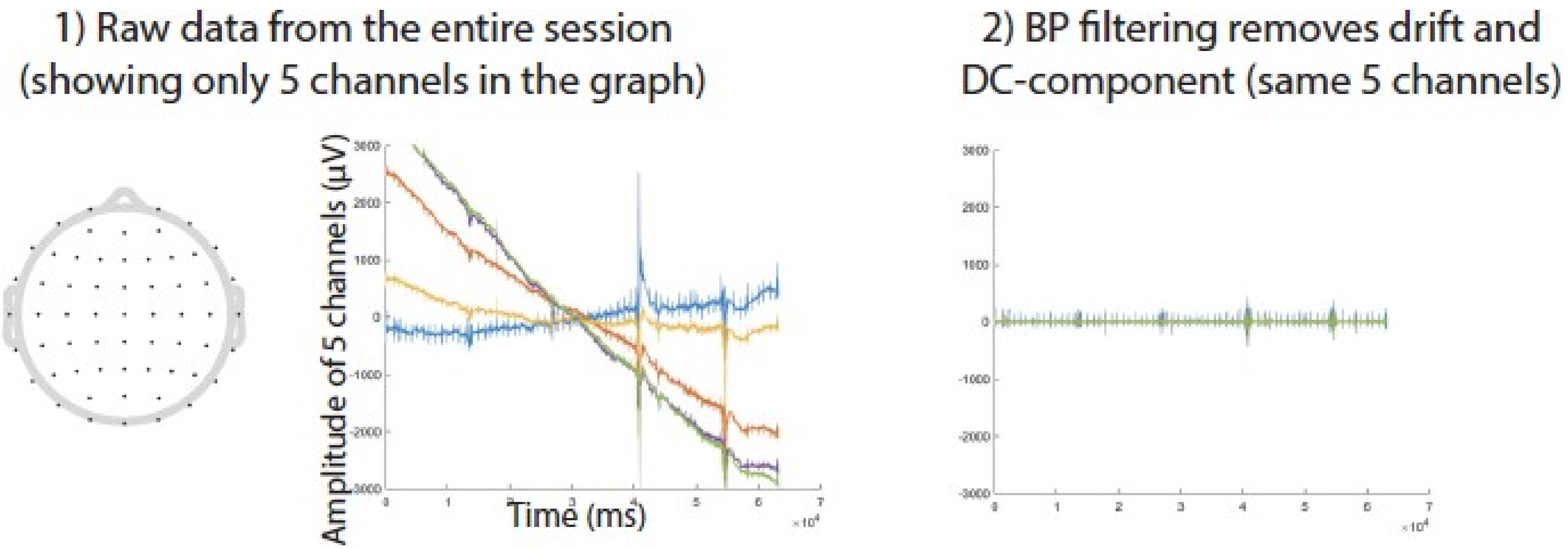
Tidare et al.

- EEG data for training ML model
- Aligned and synchronized data

Real-time data interpretation: pre-processing

Objective:

- Remove irrelevant components of the data (bandpass filtering)
  - EEG: 0.1-0.5 Hz to ~50 Hz

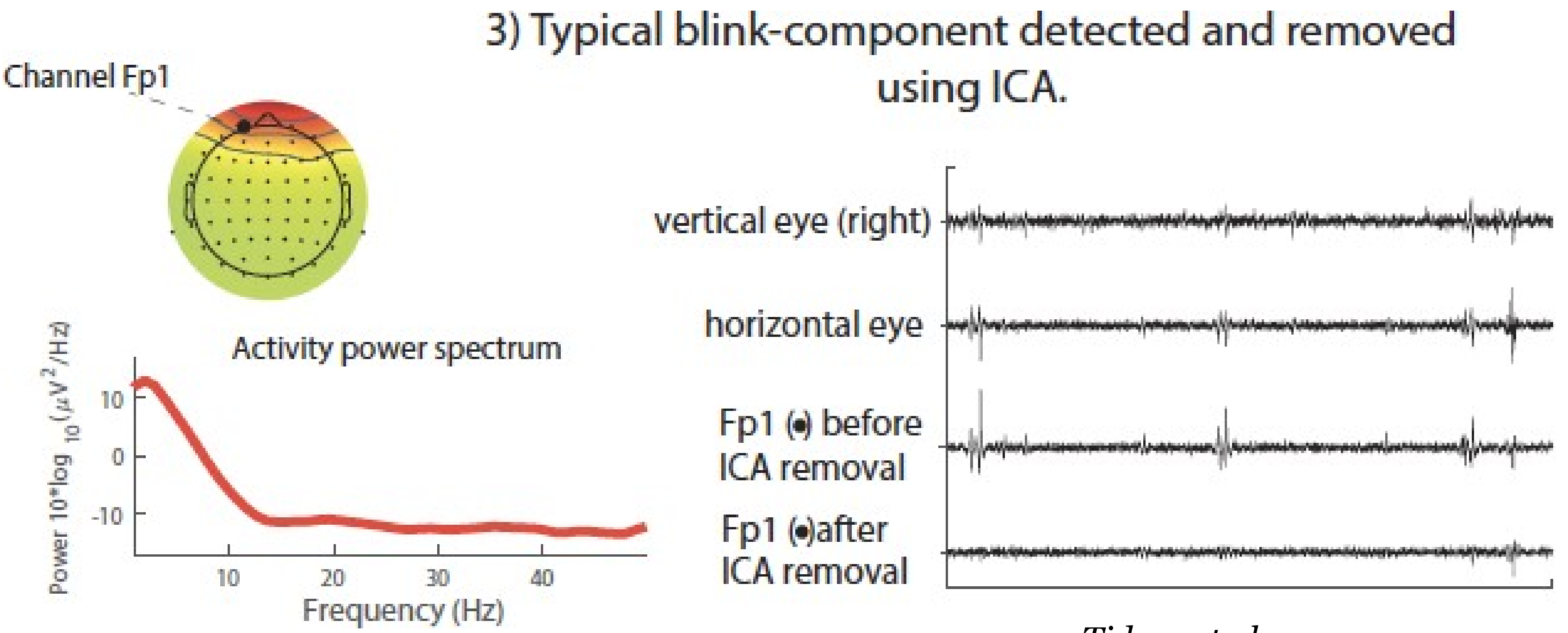


Tidare et al.

Real-time data interpretation: pre-processing

Objective:

- Noise and artifact removal (e.g. offline: ICA, online: adaptive filtering, spatial filtering)



Tidare et al.

Real-time data interpretation: feature extraction

Pre-processed raw data → Features as input to ML/AI

Most common features for ECoG and EEG:

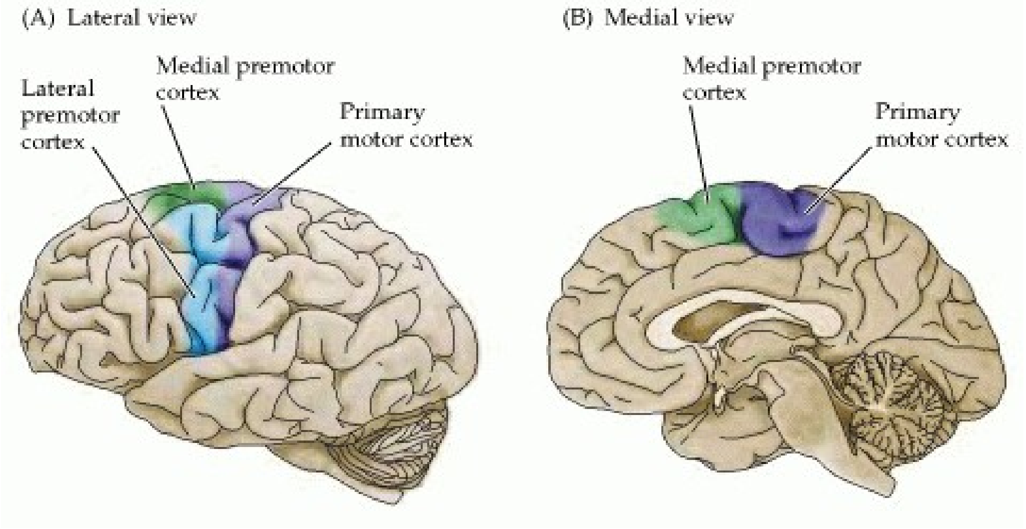
- Time-domain potentials → N channels x R repetitions
- Time-Frequency spectra →

Delta (2-4 Hz)
Theta (4-7Hz)
Alpha (8-12Hz)
Beta (18-25Hz)

- N x FB frequency bands x R
- FB = 4 or more (STFT)

Real-time data interpretation: feature extraction

Which EEG features would you expect during upper-limb motor activation?

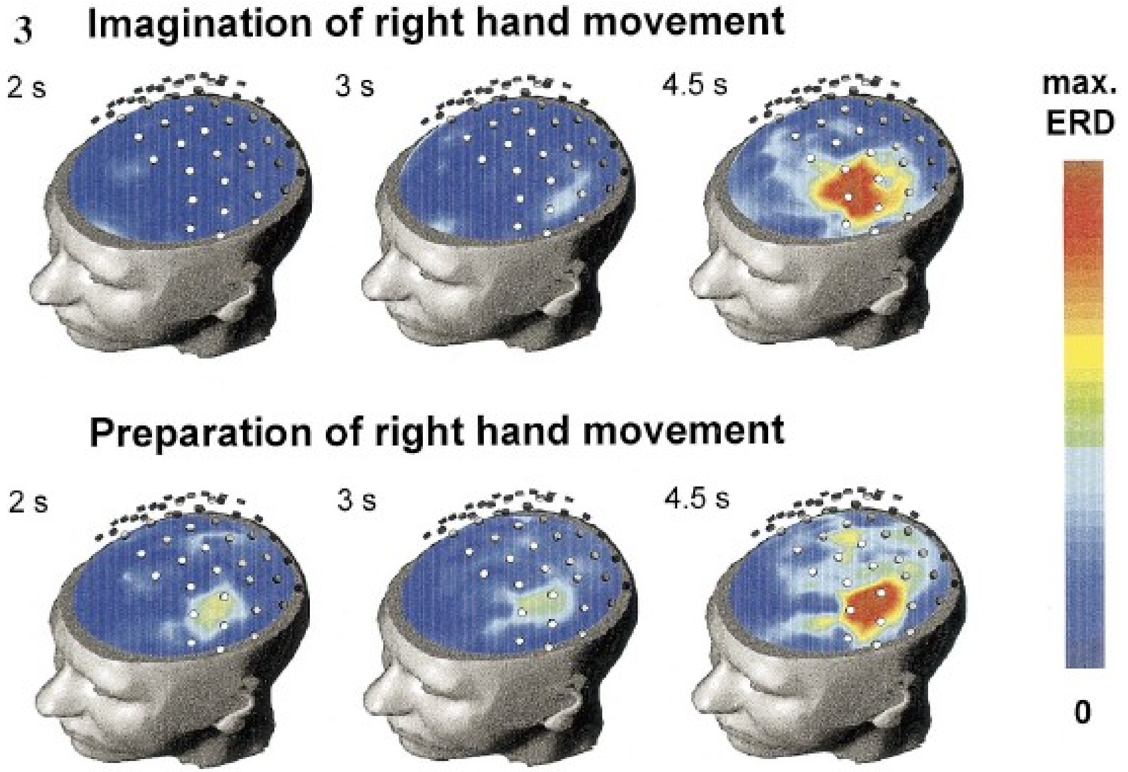


- Activity over sensorimotor cortex (central – parietal electrodes)
- Dominantly contralateral activity

- Studies show decrease in alpha and beta frequency power (Pfurtscheller & Neuper, 1997)

Real-time data interpretation: feature extraction

Which EEG features would you expect during upper-limb motor activation?



- ERD=Event-Related desynchronization, equivalent to power decrease
- 9-13 Hz frequencies
- Motor Imagery is similar to real motor preparation.
- Motor execution: bilateralization of activity

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Pfurtscheller & Neuper (1997)

Real-time data interpretation: AI

Machine Learning or AI algorithm that can extract information from brain activity:

End-point classification:

- Linear (e.g. LDA, linear regression, SVM)
- Non-linear (e.g. SVM, ANN)

Continuous movement classification:

High resolution is needed!

- e.g. Kalman filter

Important considerations:

- Important to test/validate decoder on novel data
- Generalization issues: classification accuracy is prone to decrease when going from offline to online experiments (changes in the brain activity)
- Consider adding an idle state
- Decoding algorithm must be computationally cost-efficient

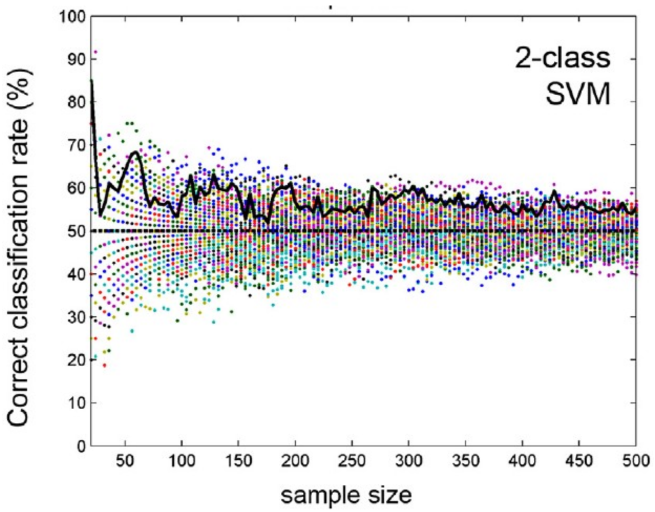
Real-time data interpretation: validation

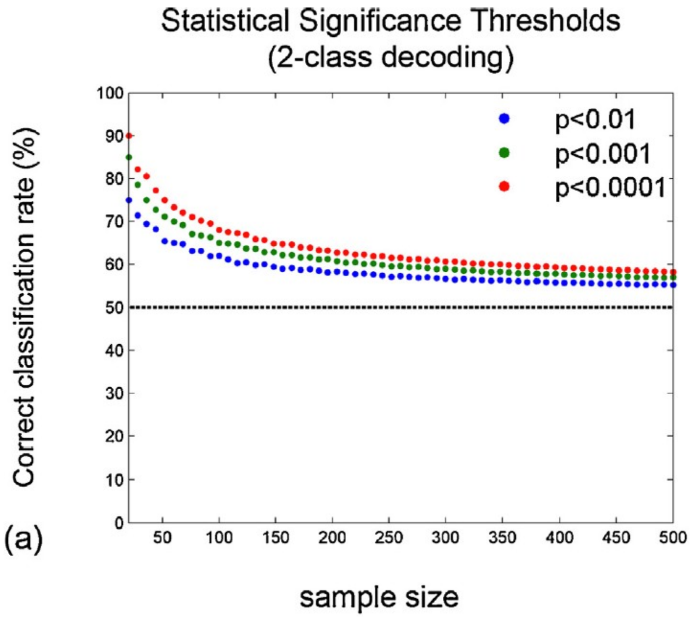
How can you be sure that the decoder performs above chance?

For a 2-class classification problem:

- Theoretical chance = 50%
- Empirical chance = ?
  - The real chance-level depends on your sample size (Combrisson and Jerbi, 2015)

Classifying random data with an SVM





Combrisson & Jerbi (2015)

Applications: asynchronous vs. synchronous BMIs

Different types of BMI:s:

- Asynchronous = operate without external cueing
- Synchronous = operate with external cueing (e.g. P300, SSVEP)

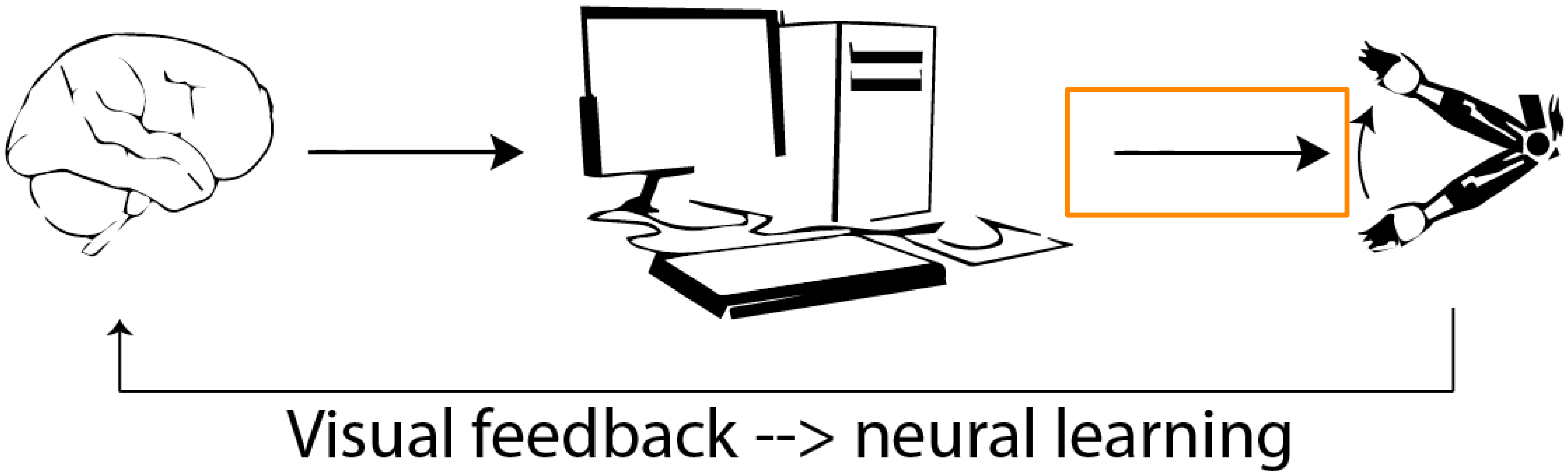
Example of SSVEP protocol

- Instruction to focus on one of the 4 circles
- Each circle flickers with a different frequency
- EEG signals over occipital and parietal electrodes show frequency components at the flickering frequency

Iscan & Nikulin (2018)

Applications: feedback/control command generation

How should the decoder output be converted into a movement command?

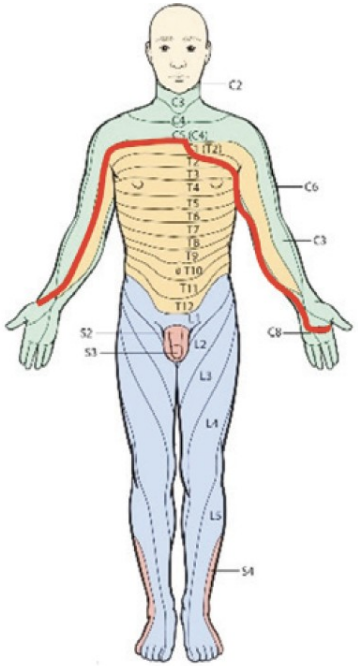


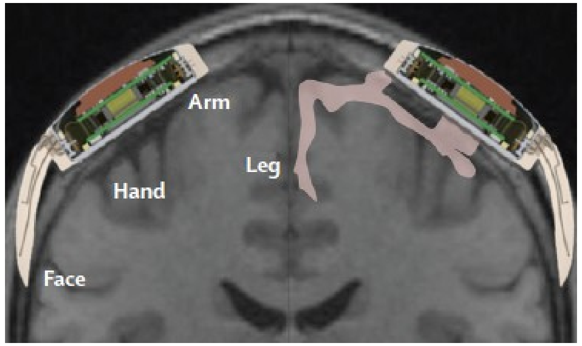
- Common: 1:1 mapping between decoder output label and movement
- Why not add more intelligence into the prothesis?

Applications: case 1

An exoskeleton controlled by an epidural wireless brain-machine interface in a tetraplegic patient: a proof-of-concept demonstration. Benabid et al., (2019)

- 1 tetraplegic patient (male, 28 years, c4-C5 spinal cord injury, little motor control of upper limbs, no motor control of lower limbs)
- Bilateral epidural ECoG (64 electrodes) over sensorimotor cortex
- Data was radio-emitted through an ultra-high frequency antenna and power supplied remotely via inductive high-frequency antenna





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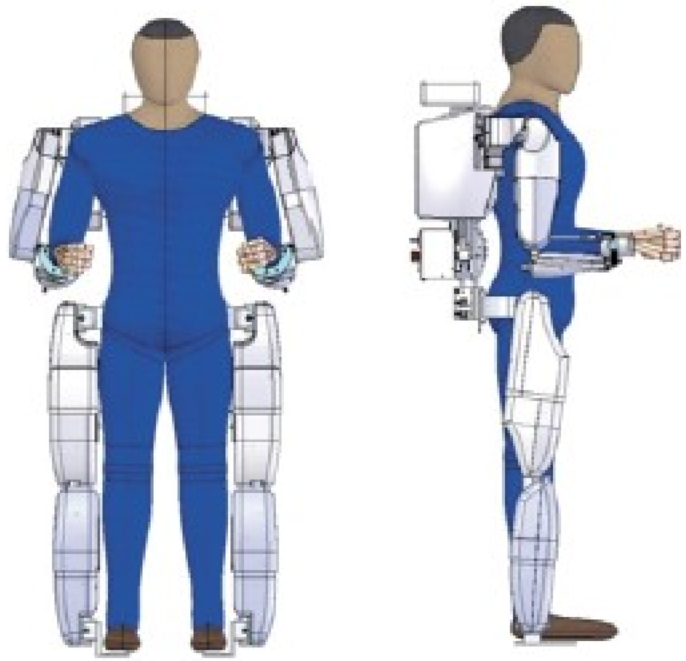
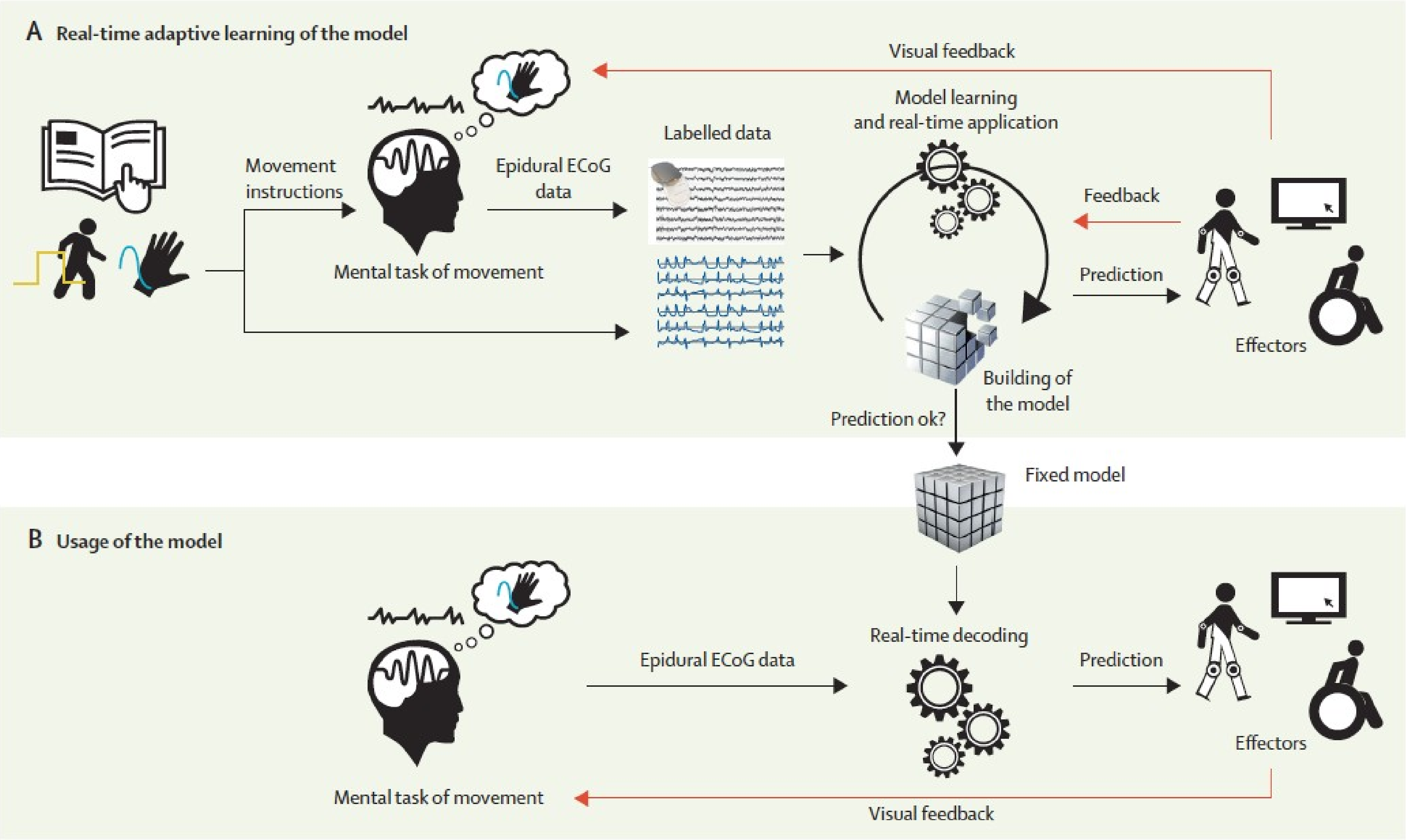
- Bilateral epidural ECoG (64 electrodes) over sensorimotor cortex
- Data was radio-emitted through an ultra-high frequency antenna and power supplied remotely via inductive high-frequency antenna
- ECoG signals from 32 electrodes at 586Hz were decoded in real time during motor imagery and translated into exoskeleton movements
- Adaptive high-resolution decoding (within 350ms)



Applications: case 1

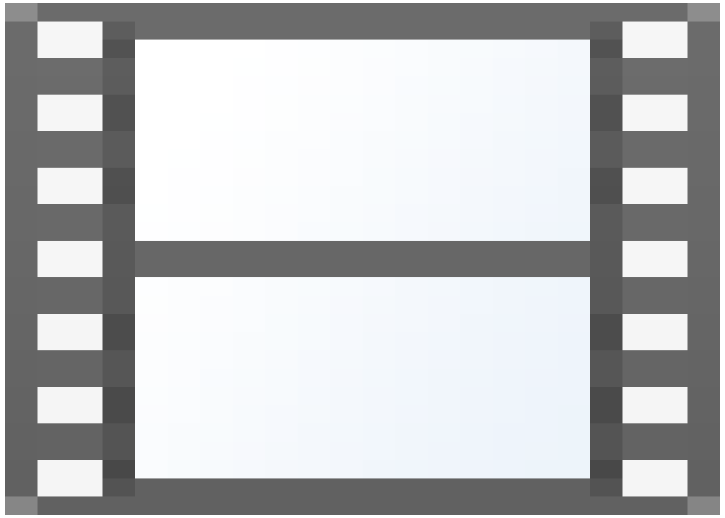
- Experiments contained 2 phases:
  1) decoder calibration/ update
  2) Use of decoder to estimate the performance

Online model training!



- A recursive, exponentially weighted, n-way, partial least squares regression algorithm with a Markov switching model (Eliseyev et al. (2017); Schaeffer & Aksenova (2016))

Applications: case 1



- First successful long-term use of wireless epidural ECoG
- Simultaneous exoskeleton control of up to 8 DoFs
- Long-term stable exoskeleton control (up to 7 weeks)

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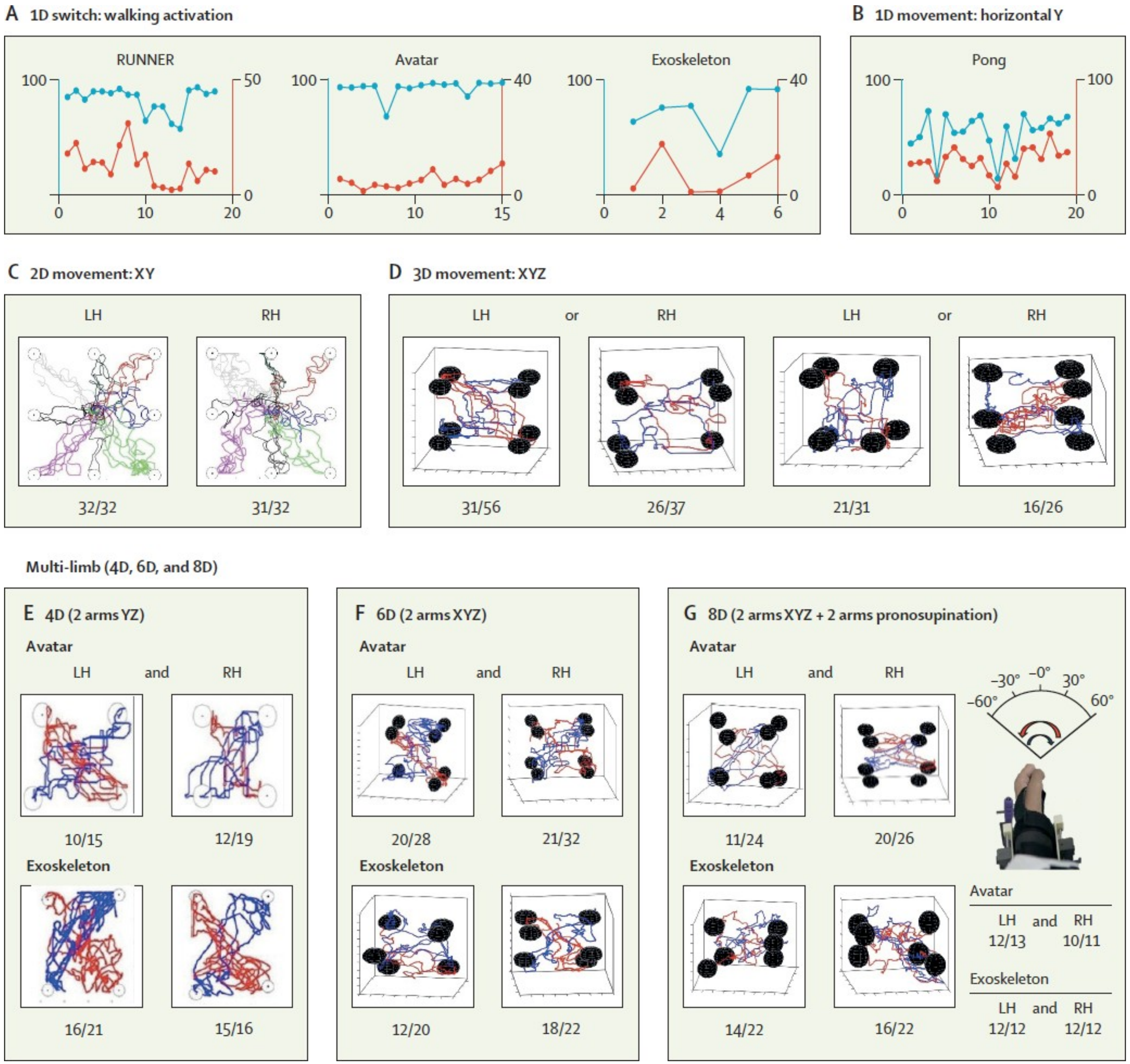


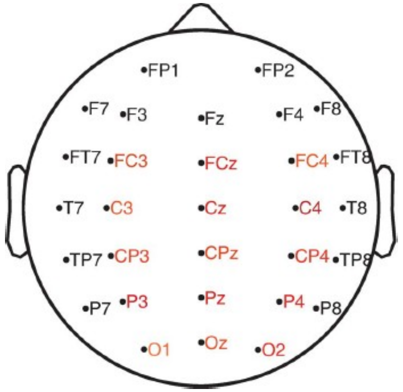
Applications: case 1

Future challenges:
- Enable data transmission from more electrodes
- Extend the duration without calibration of model
  - Online adaptation of decoding model?
- Self-balancing exoskeleton
- Decrease power consumption of exoskeleton (current: 2.5 hours)

Applications: case 2

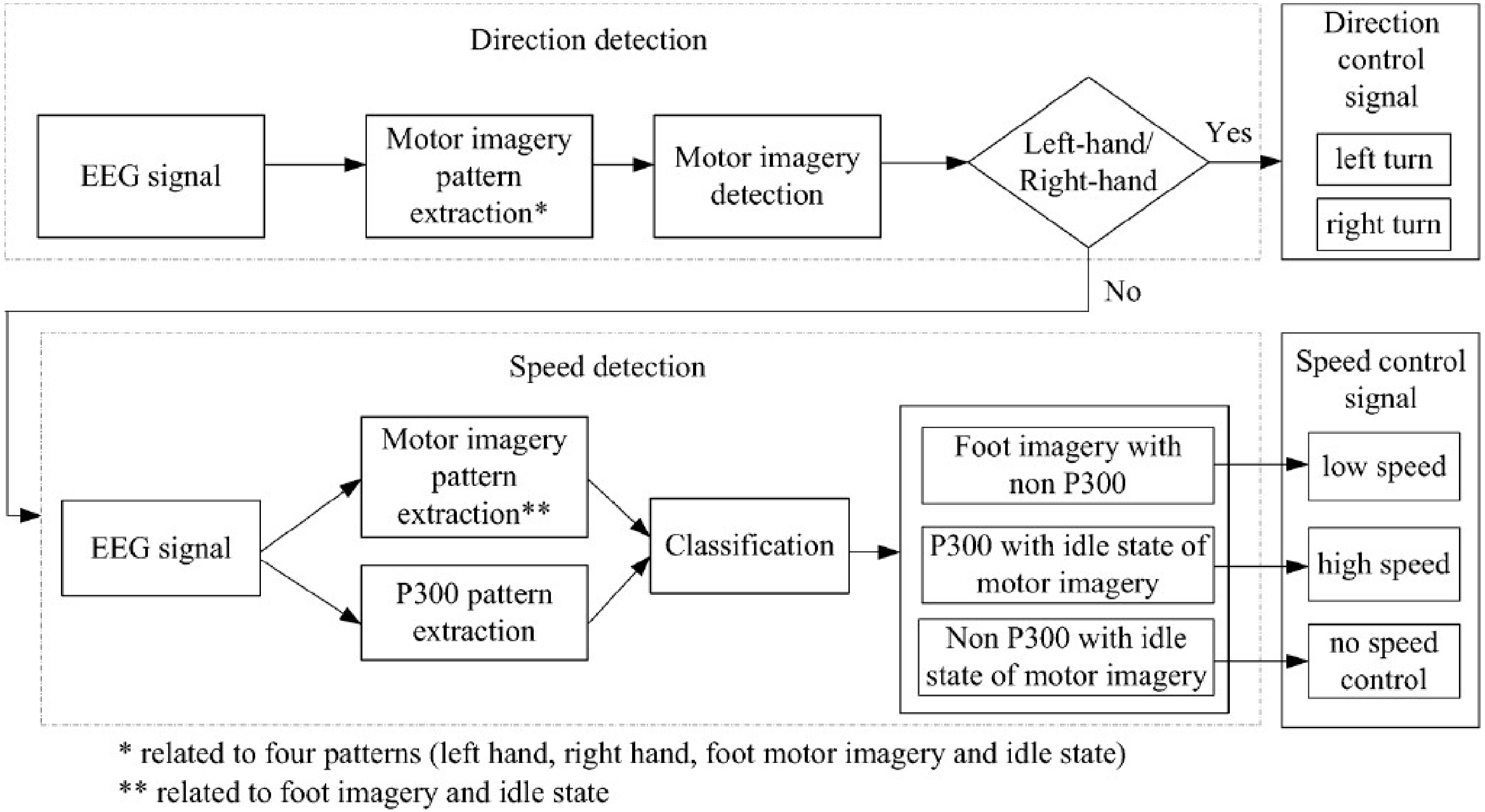
A hybrid brain computer interface to control the direction and speed of a simulated or real wheelchair. Long et al., (2012)

- 5 subjects (exp 1), 2 subjects (exp 2)
- EEG signal recordings (15 electrodes, F_s = 250Hz, bp-filtered between 0.5Hz-100Hz)
- Control commands:
  - Right/left turn: MI of right/left hand movements
  - Deceleration: MI of foot movements and ignore GUI
  - Acceleration: Attention to one of the 8 flashing buttons on a GUI and no MI



Wang et al. (2014)

Applications: case 2

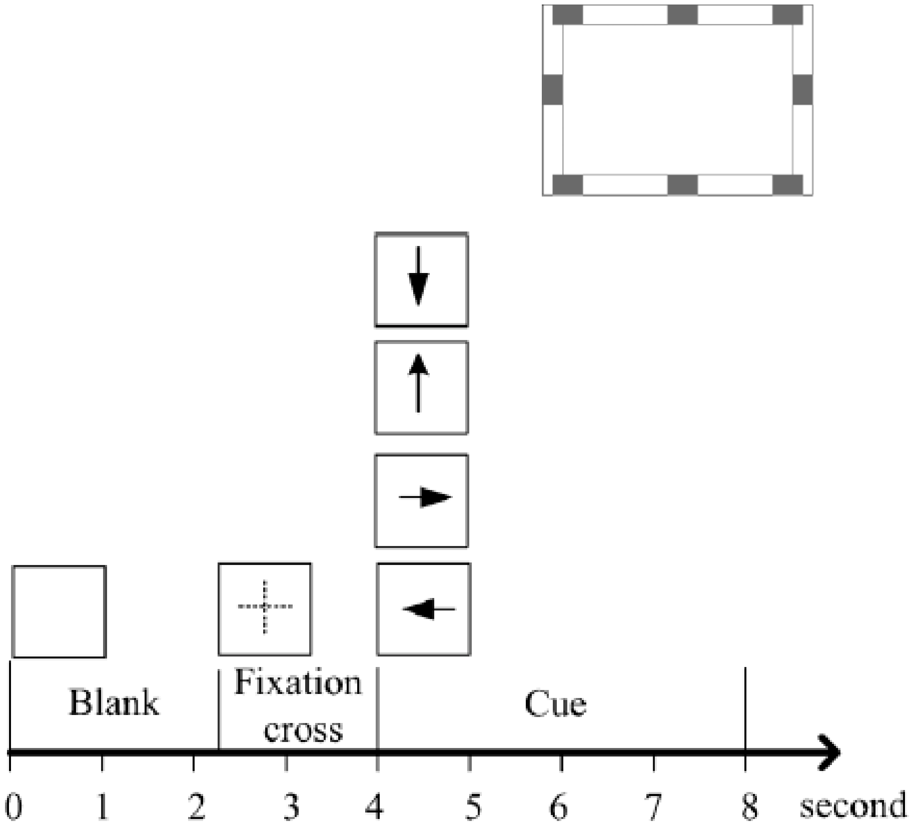


Applications: case 2

Detection of directional control signals

Classification/decoder training phase (to build a model that works in real time):

1. Obtaining a train data set with 4 classes (right/left hand MI, foot MI (up arrow), idle (down arrow))
2. Signal processing
   - Spatial filter: Common Average Reference (CAR)
   - Bandpass filter: 8-32 Hz



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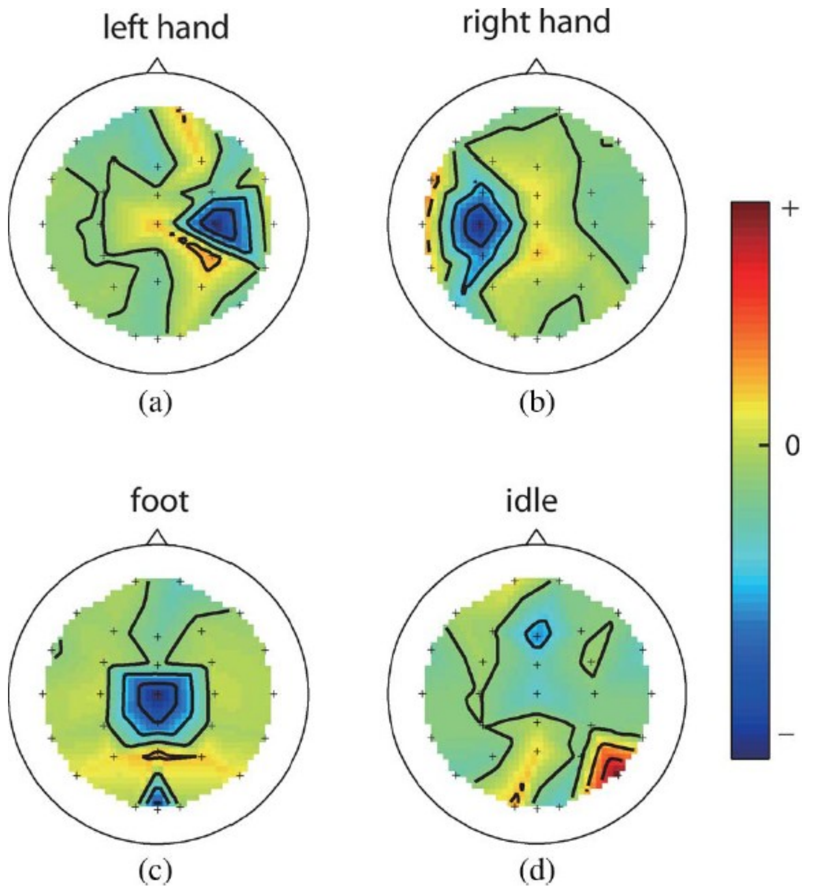
2. Signal processing
   - Spatial filter: Common Average Reference (CAR)
   - Bandpass filter: 8-32 Hz
3. Feature extraction & selection
   - Common Spatial Patterns (CSP)
4. LDA (1 vs. all) using data averaged in a 1000 ms time window with step size of 200 ms

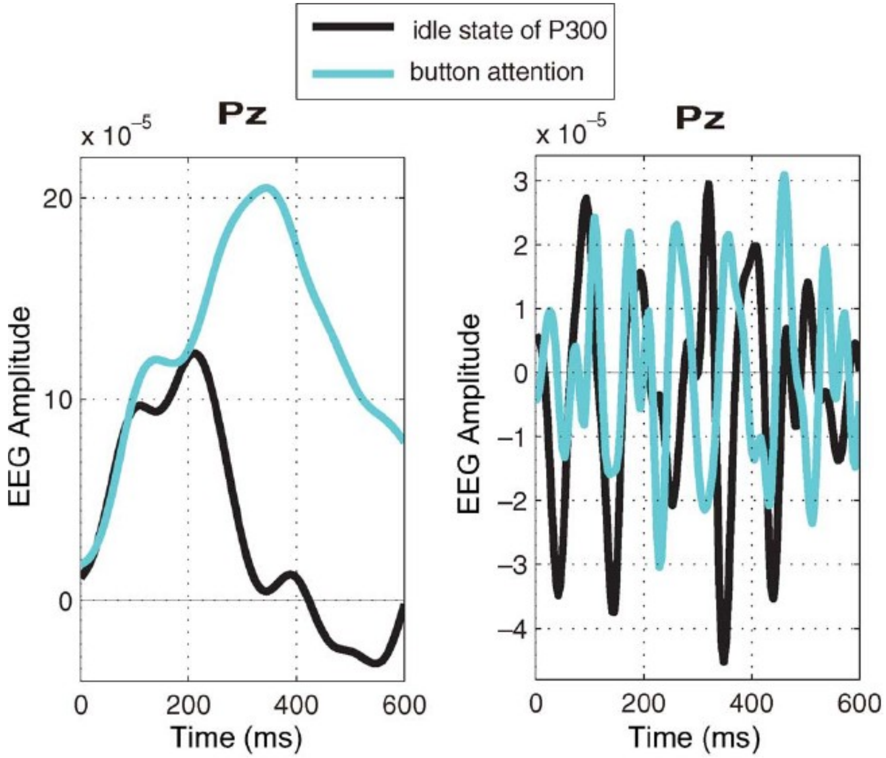
CSP weights – subject 1



Applications: case 2

Detection of speed control signals

Combining ERD/ERS of the sensorimotor rhythms and the P300 potential to detect
1) foot MI and
2) attention to a flashing button.



Procedure:
1. MI feature extraction
2. P300 feature extraction
3. 2 LDAs are trained on (1) and (2) and their scores combined to calculate 2 thresholds, $D^{\%}_{!"\#\$}$ and $D^{\&}_{!"\#\$}$
4. In the test-phase, the combined score, *D* of the test-sample data is classified as follows:

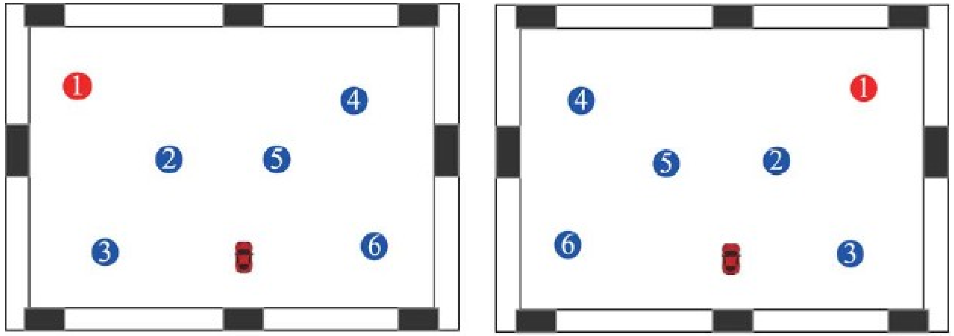
$$\hat{y} = \begin{cases} +1, & \text{if } D > D^{+}_{\text{mean}} \quad \text{Acceleration} \\ 0, & \text{if } D^{-}_{\text{mean}} \leq D \leq D^{+}_{\text{mean}} \\ -1, & \text{if } D < D^{-}_{\text{mean}}. \quad \text{Deceleration} \end{cases}$$

Applications: case 2

Validation of the brain-controlled wheelchair

- 2 phases: **1) simulated wheelchair to evaluate performance**, and 2) Real wheelchair to test the hybrid system

Simulated wheelchair virtual environment



Performance measures:

- Accuracy rate of successful navigation tasks
- Path length
- Path length optimality ratio
- Time
- Time for low speed
- Collisions

Applications: case 2

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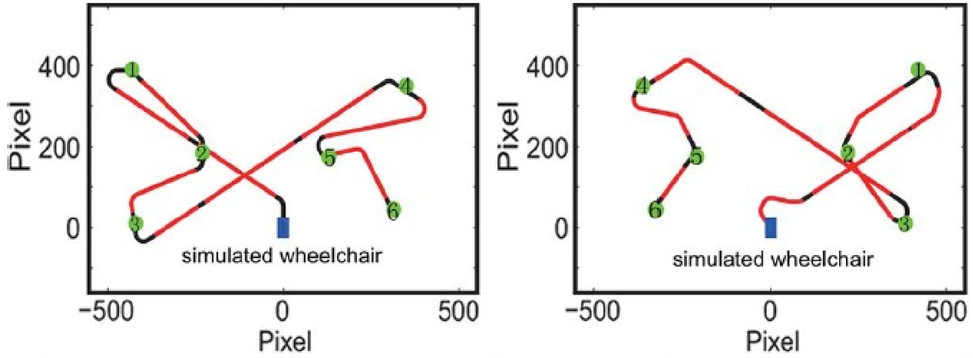


	Accuracy rate (%)	Path length (*pixel*)	Path opt. ratio	Time (*s*)	Time for low speed (s)	Collisions
S1	100±0	2837.35±66.63	1.25±0.04	82.11±1.62	22.35±1.22	0±0
S2	100±0	2761.13±51.26	1.22±0.03	80.84±1.35	23.63±1.45	0±0
S3	100±0	2919.65±76.42	1.29±0.03	88.39±1.26	30.80±1.76	0±0
S4	100±0	2856.32±73.27	1.26±0.04	85.02±1.19	27.22±1.23	0±0
S5	100±0	2842.32±54.71	1.25±0.02	85.75±1.22	29.38±1.15	0±0
mean±std	100±0	2843.46±105.41	1.25±0.05	84.42±4.63	26.67±4.18	0±0

Applications: case 2

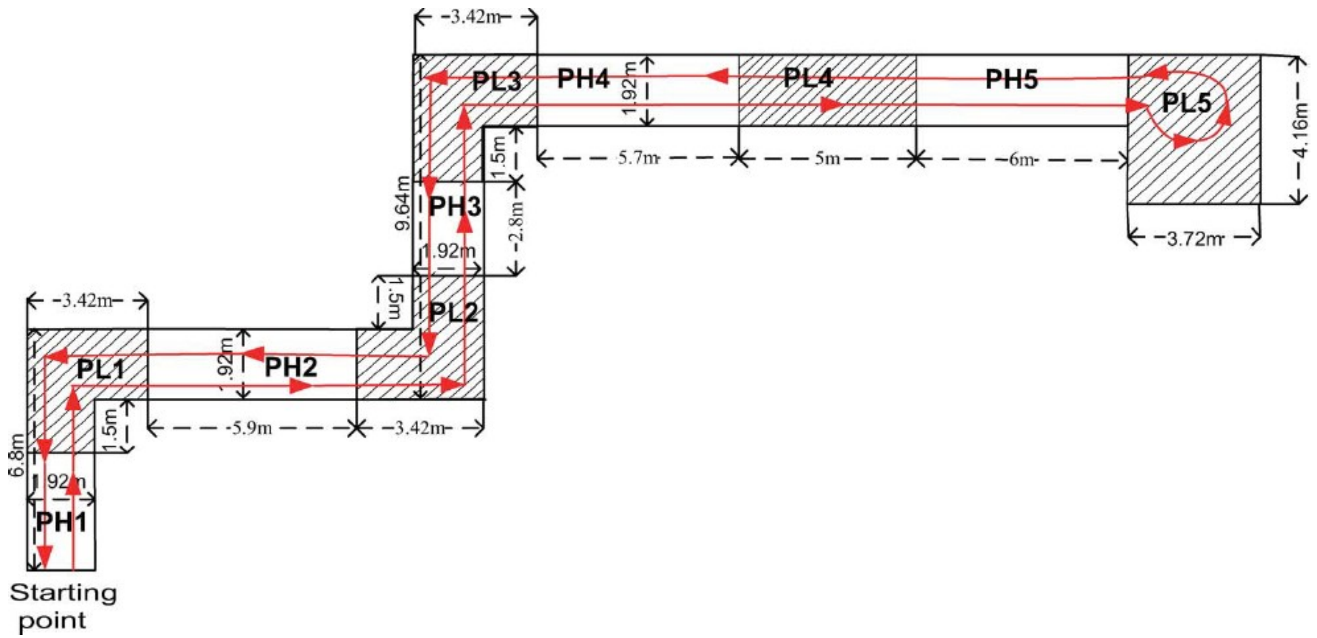
Validation of the brain-controlled wheelchair

- 2 phases: 1) simulated wheelchair to evaluate performance, and **2) Real wheelchair to test the hybrid system**

Performance measures:

- Path length
- Path length optimality ratio
- Time
- Wrong speed control time
- Collisions

Real wheelchair path



Applications: case 2

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- Time
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PERFORMANCE INDICES (AVERAGED FROM TWO SUBJECTS) OBTAINED WITH REAL WHEELCHAIR IN LOW SPEED AREAS

	Path length (m)	Path opt. ratio	Time (s)	Wrong speed control time (s)	Collisions
PL1	5.82±0.26	1.18±0.02	47.72±1.46	5.25±0.62	0±0
PL2	5.68±0.24	1.15±0.02	49.98±1.65	3.50±0.51	0±0
PL3	5.71±0.21	1.16±0.03	47.96±1.67	4.80±0.76	0±0
PL4	5.41±0.16	1.08±0.02	45.99±1.31	4.14±0.45	0±0
PL5	4.52±1.23		35.27±2.13	4.94±0.82	0±0
mean±std	5.43±2.02	1.14±0.07	45.38±5.51	4.54±1.24	0±0

TABLE IV
PERFORMANCE INDICES (AVERAGED FROM TWO SUBJECTS) OBTAINED WITH REAL WHEELCHAIR IN HIGH SPEED AREAS

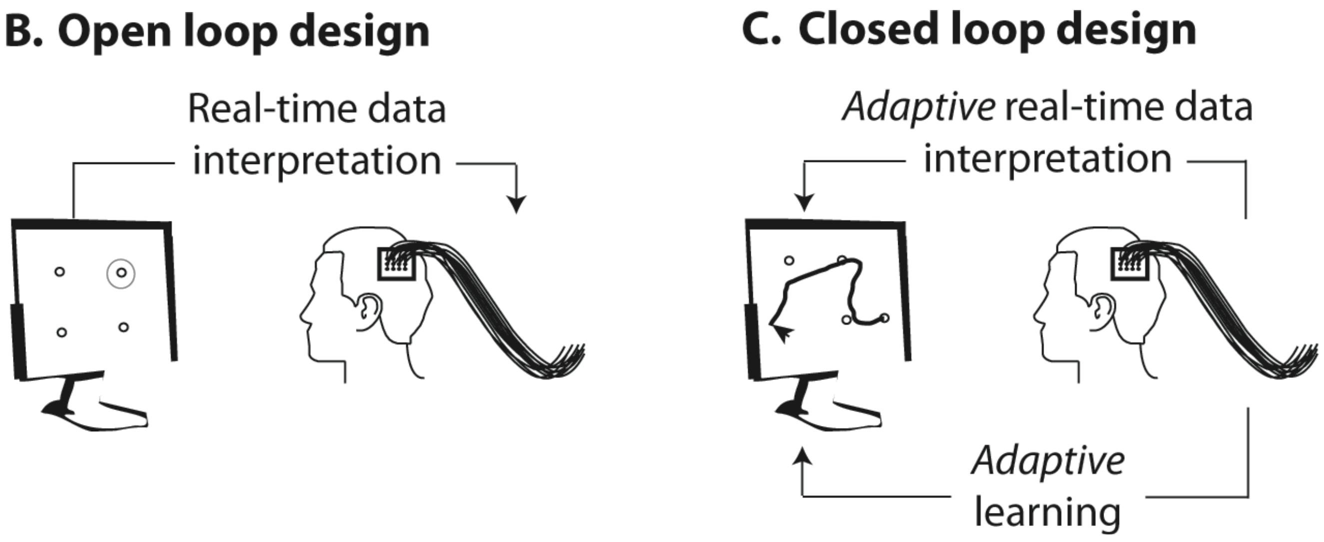
	Path length (m)	Path opt. ratio	Time (s)	Wrong speed control time (s)	Collisions
PH1	3.75±0.16	1.11±0.02	14.75±0.05	3.38±0.23	0±0
PH2	6.37±0.23	1.08±0.03	24.20±0.04	4.45±0.57	0±0
PH3	3n.14±0.13	1.12±0.01	12.46±0.06	2.99±0.38	0±0
PH4	6.27±0.18	1.10±0.02	24.24±0.06	5.01±0.52	0±0
PH5	6.54±0.15	1.09±0.02	25.07±0.07	4.91±0.64	0±0
mean±std	5.21±1.54	1.10±0.04	20.14±6.27	4.16±1.36	0±0

Applications: case 2

Future challenges?

How would you like to improve this work?

Applications: Open vs. closed-loop BMI



Modified from Astrand et al. (2014)

Open loop:
- No RT feedback to subject
- Remote monitoring applications

Closed-loop:
- RT feedback to subject
- Wide range of applications