



BCI and Biofeedback Tools

**Engineering Techniques,
ILCB Summer School, 01-09-2022**

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Let's start with a little demo... EEG in real time



**OPENBCI
DIY
NEUROTECHNOLOGIST' S STARTER KIT**

\$ 1,499.99 USD

Split your purchase into monthly installments with [shop Pay](#) [Learn more](#)

of Channels

Up to 8 channels

Quantity

- 1 +

[Add to cart](#)

[Share](#)

Product Overview

This bundle includes a Cyton, Ultracortex, and additional electrodes & accessories for EEG, EMG, and ECG sensing. Available in 8 or 16 channels.

OPENBCI CYTON BIOSENSING BOARD (8-CHANNELS)

\$ 999.00 USD

Pay in 4 interest-free installments of \$249.75 with [shop Pay](#) [Learn more](#)

Quantity

- 1 +

[Add to cart](#)

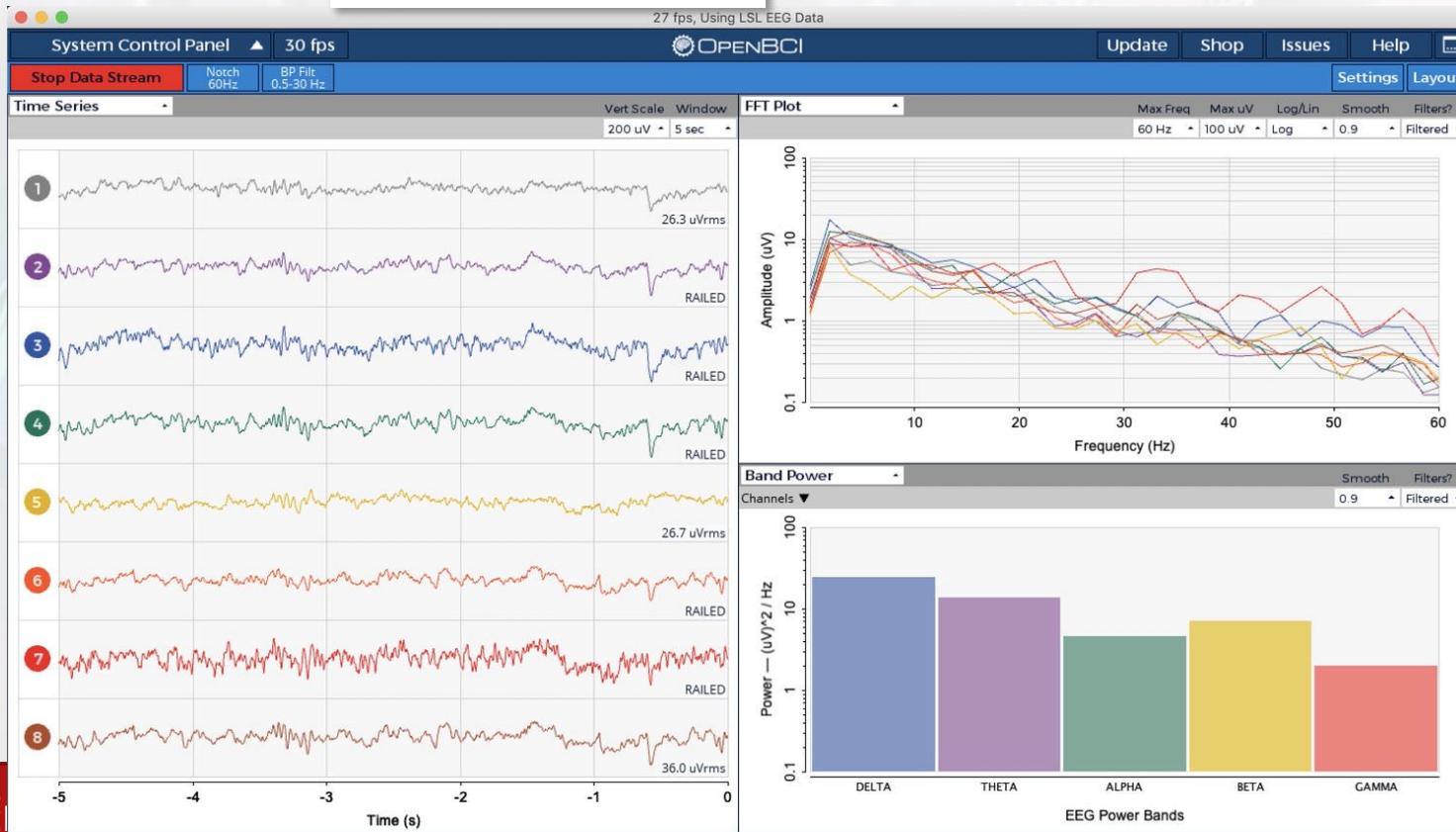
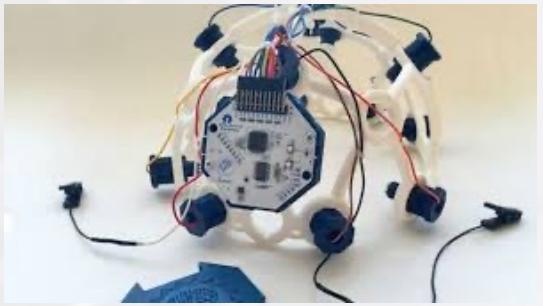
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Product Overview

The board that started it all! The Cyton allows you to gather 8-channels of scientifically-validated physiological data.

**Cyton board
8-channels
Dry electrodes
250 Hz
Ultracortex Markup IV**

OpenBCI



- Time series widget
- Frequency spectra
- Band power
- Networking: protocols to output data (Serial, LSL, OSC)

... Create your own
widget with
Processing



pySerial

Applications: SSVEP-Controlled Wheelchair





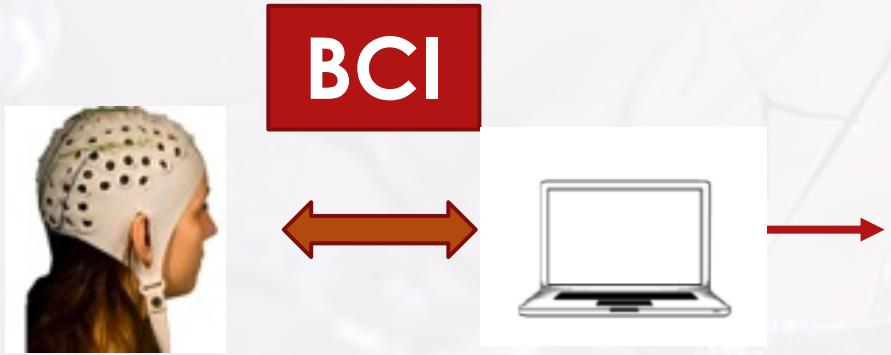
*« I have not failed, but I have found a
1000 ways not to make a light bulb »*

Thomas Edison

Overview

- Introduction to Brain-Computer Interface
- Motor-Imagery with almost live demonstration
- SSVEP-based BCI with (hopefully) live demonstration
- Discussion (yes, we expect you to talk too!)
- Concluding remarks.

Brain-Computer Interface (BCI): Introduction



**Communication
by thought**



©MindAffect



Wolpaw, 2002: tools of communication and control that allow users to interact with their environment by means of their cerebral activity alone

- To consciously act and communicate without using our muscles
- give the brain a new communication channel that is independent of conventional channels

Brain-Computer Interface (BCI): Introduction

Historical Events

* **1960s** Joe Kamiya (Pr. of psychology, Berkeley) – **1st neurofeedback paradigm**, training of participant to enter the alpha state

~~~ 1970 – development of computer sciences, simple app using neurofeedback ~~~

Some attempts by music composers to produce music in real time from brain activity

\* **1973** Pr. Jacques Vidal (computer science, Los Angeles) – **1st description of the concept of BCI** in “Towards direct brain-computer communication”

~~~ 90's - First real-time BCI designs ~~~

J. R. Wolpaw et al., 1991, “An EEG-based brain-computer interface for cursor control”

Brain-Computer Interface (BCI): Introduction

BCI Usage

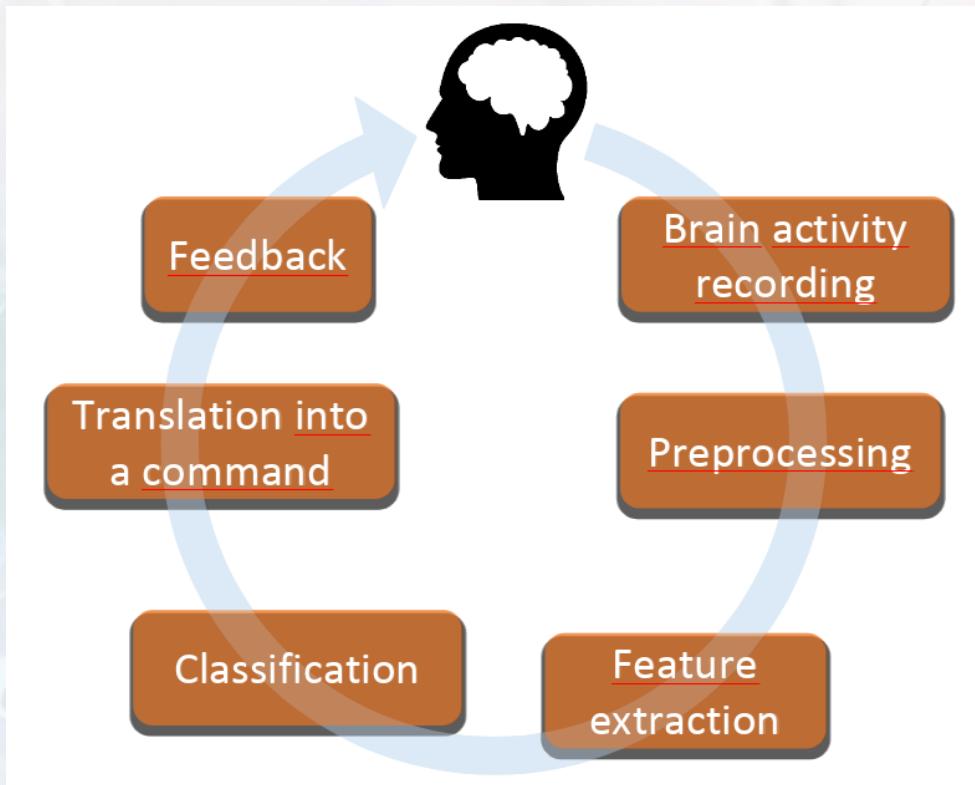
- **Replacement** of lost bodily functions
 - Communication (Speller P300, SSVEP)
 - Environment control (Prostheses)
 - Locomotion (Wheelchair)
- **Restoration** of lost brain-limb connection
 - Neuroprostheses (motor-imagery task)
- **Improvement** of impaired motor control after a stroke
 - Exercises with various feedbacks (virtual limb, robotised arm)
- **Enhancement**
 - Mental state monitoring (passive BCIs)
 - Home automation
 - Gaming and Virtual reality



Brain-Computer Interface (BCI): Introduction

BCI Architecture

- Closed loop system with usually 6 main stages



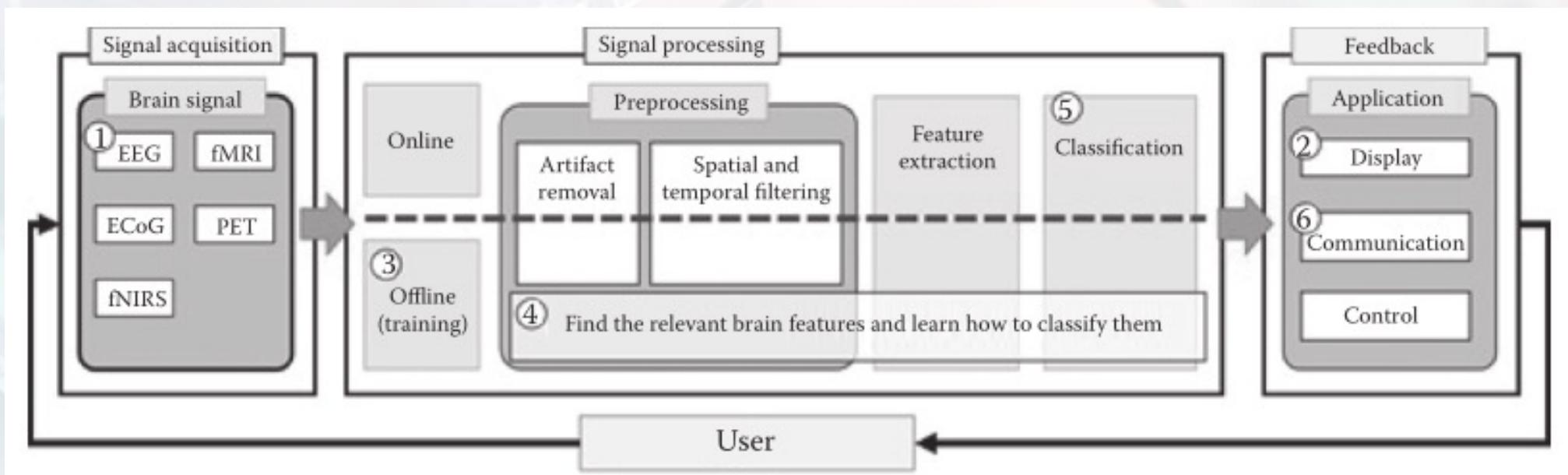
adapted from Clerc, M., Bougrain, L., & Lotte, F. (Eds.). (2016). Brain-computer Interfaces: Foundations and Methods. ISTE Limited.

Brain-Computer Interface (BCI): Introduction

BCI Architecture

Most BCIs require **two stages**:

- **offline calibration** stage: determine system's settings (costly in time)
- **online operational** stage: system recognizes brain activity patterns, translates them into application commands

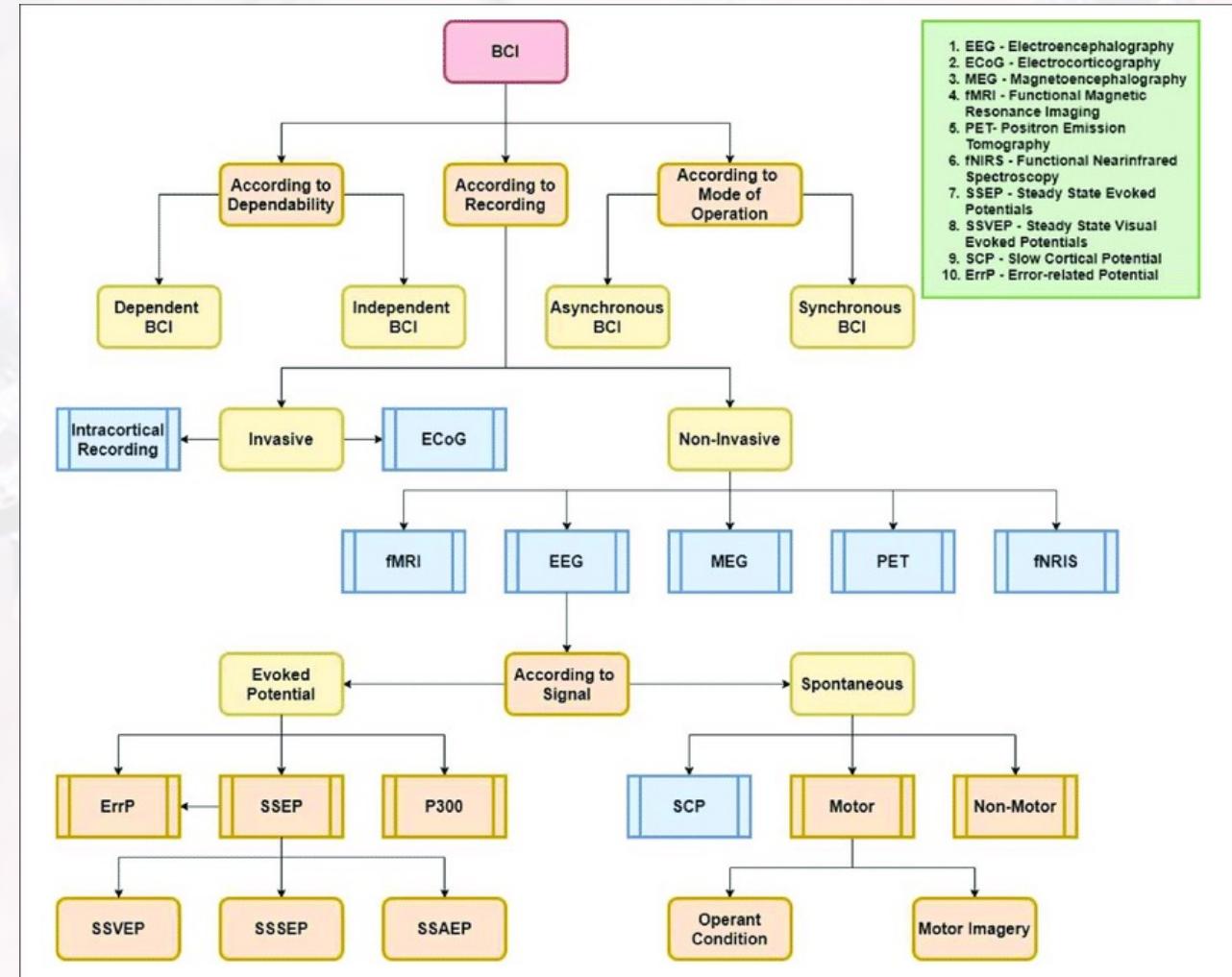


Clerc, M., Bougrain, L., & Lotte, F. (Eds.). (2016). Brain-computer Interfaces: Foundations and Methods. ISTE Limited.

Brain-Computer Interface (BCI): Introduction

BCI System Classification

- **dependent** versus **independent**
- **invasive** versus **non-invasive**
- **synchronous** versus **asynchronous**
- **active** (mental task) versus **reactive** (evoked potentials) versus **passive** (mental state, cerebral rhythms)
- Hybrid

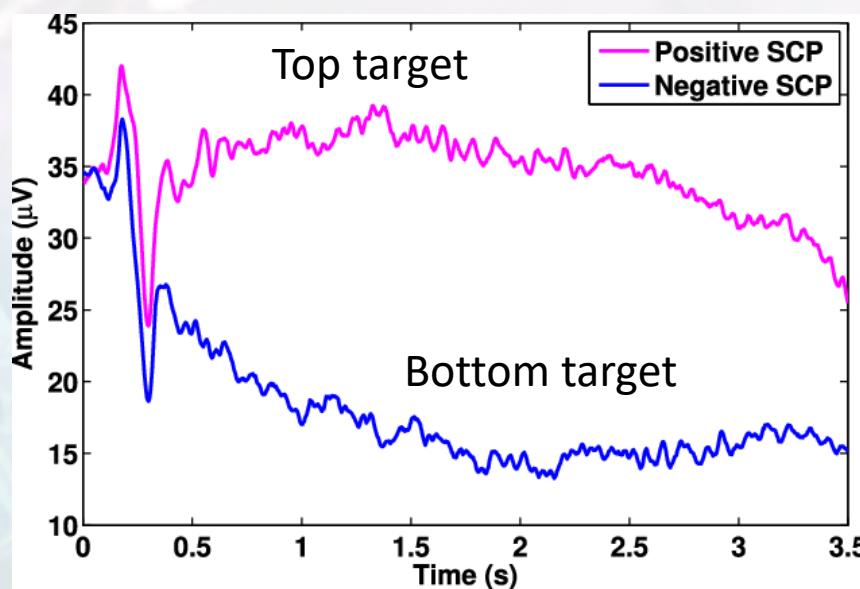


Rashid, et al. (2020)

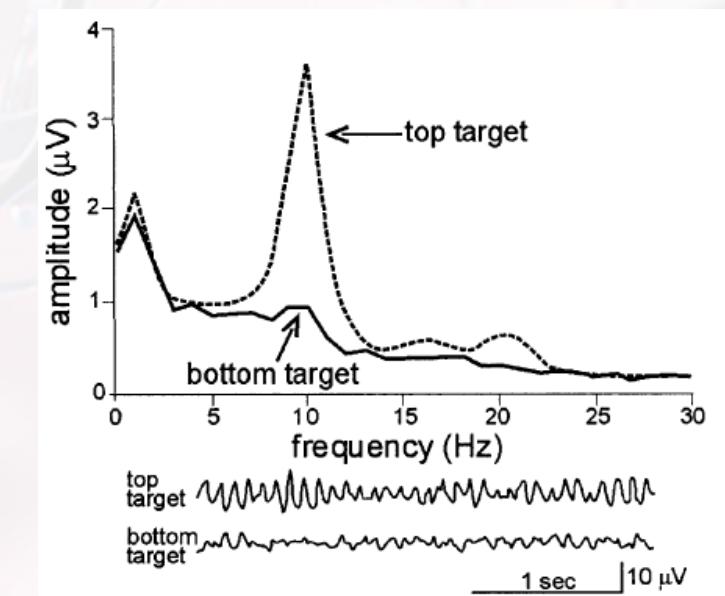
Brain-Computer Interface (BCI): Introduction

BCI Examples: Active BCIs

Slow cortical potentials



Sensorimotor rhythms (mu and beta)

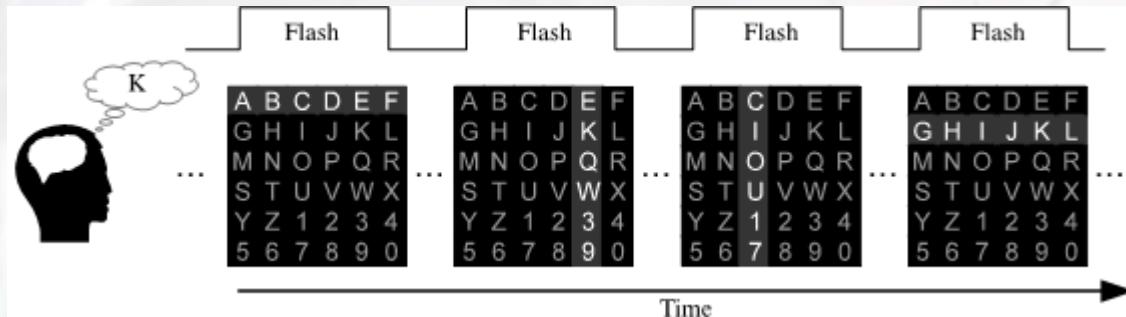


- Voluntary variations of slow cortical potentials
- Cognitive ERP: 300ms to several seconds
- Extensive training (~3 months)

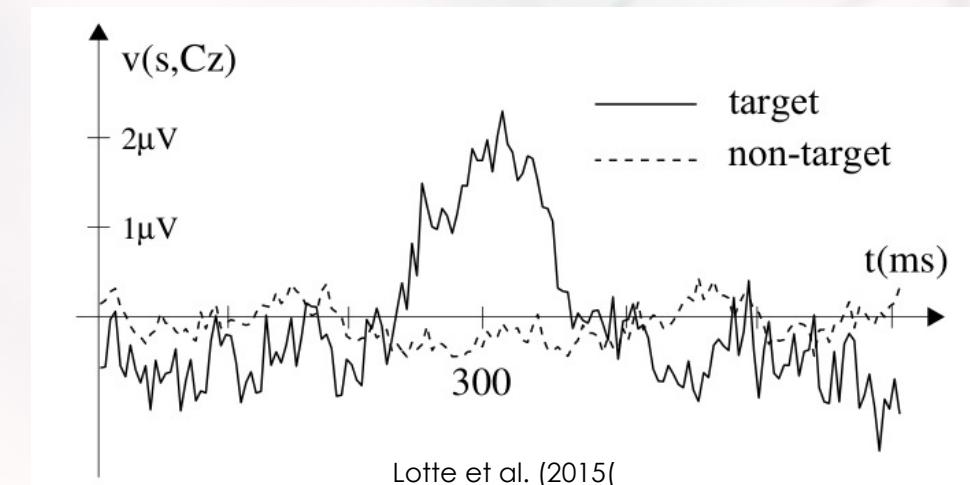
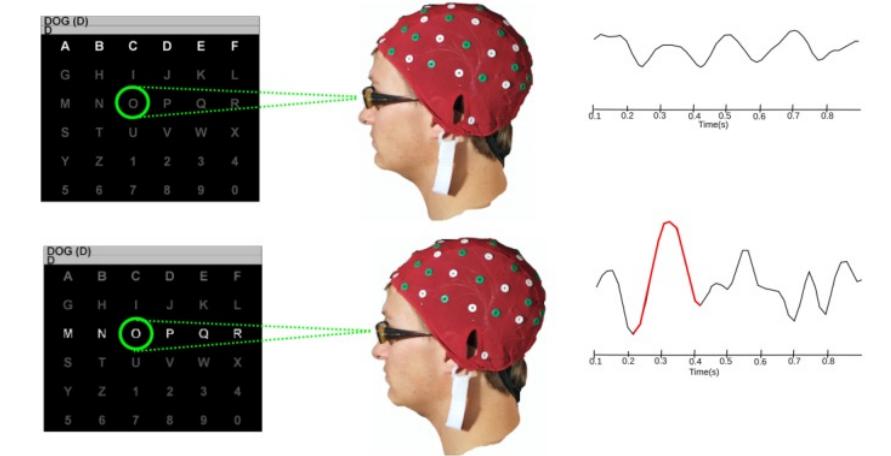
- scalp EEG recorded over sensorimotor cortex
- Users control the amplitude of a 8–12 Hz mu rhythm (or a 18–26 Hz beta rhythm)

Brain-Computer Interface (BCI): Introduction

BCI Examples: Reactive BCIs - P300 Speller



- Positive cortical potential ~300 ms after occurrence of a rare, expected event (ERP) [parietal lobe]
- little training, reliable
- but:
 - computational time (integration over several stimuli)
 - high attentional demands prevent use in complex situations (navigation, control)



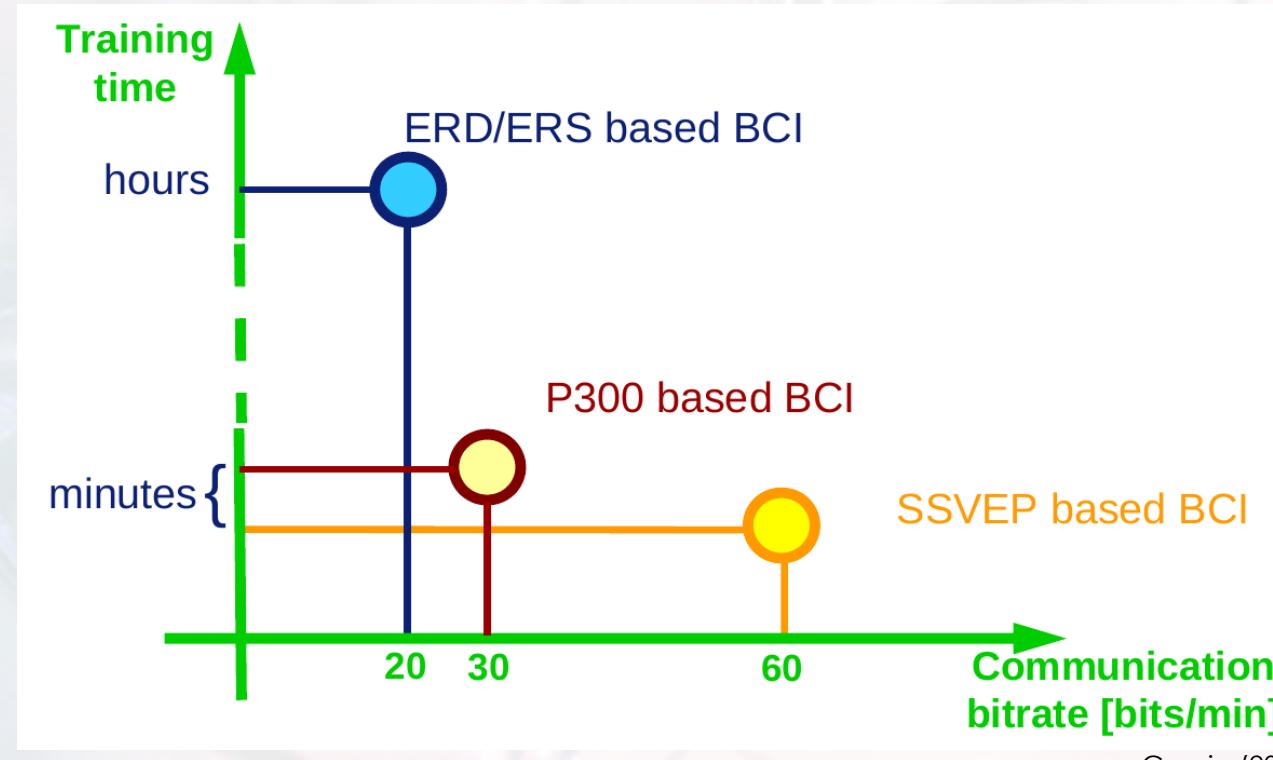
Brain-Computer Interface : P300 Speller



Brain-Computer Interface (BCI): Introduction

BCI Examples

- Mental-Imagery task -> Demo
- Evoked-Potentials (SSVEP, SSSEP, ASSEP) -> Demo



Garcia (2022)

Brain-Computer Interface (BCI): Introduction

BCI Software

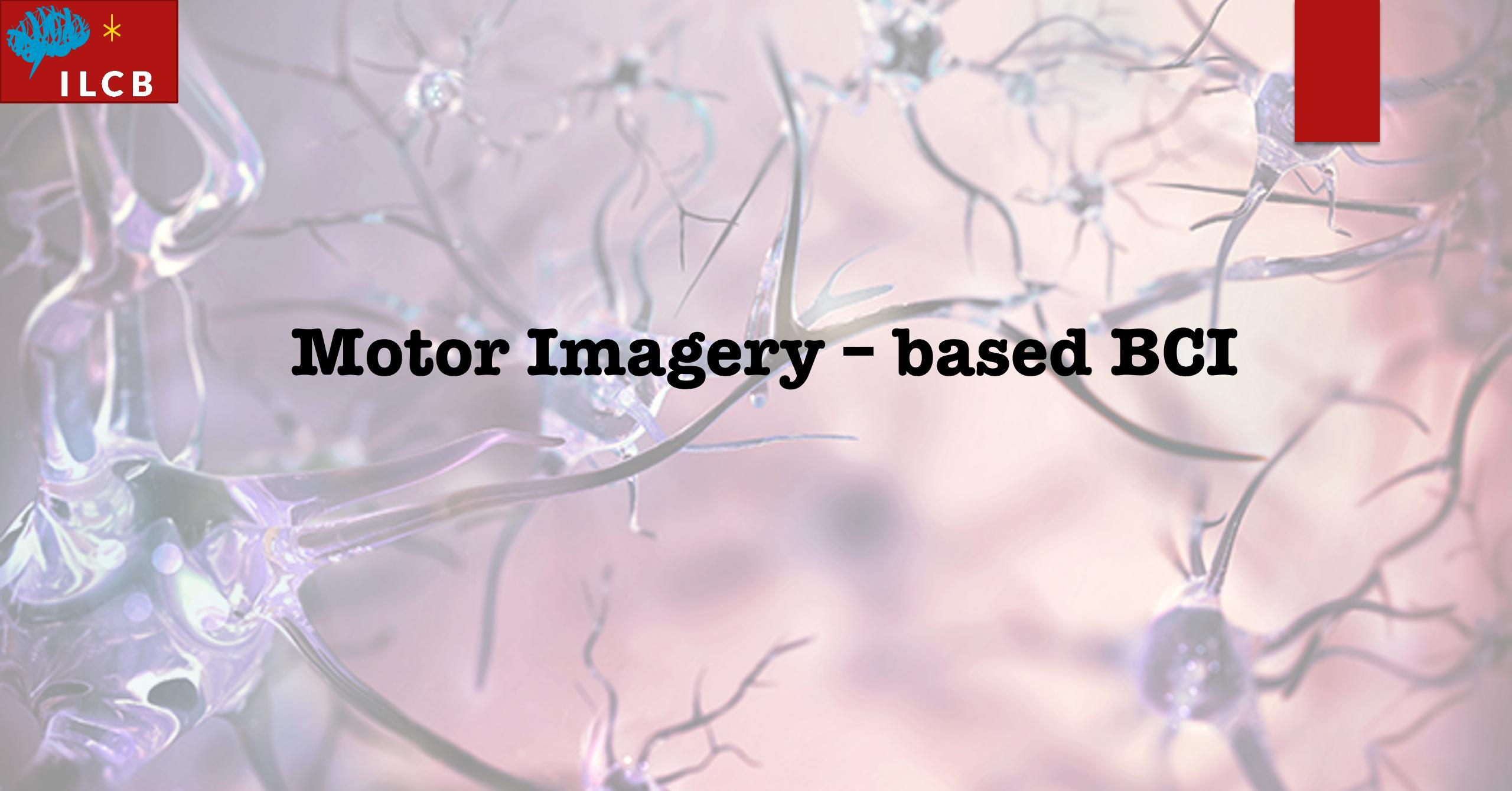
Table 1: Comparison of Software for use in BCI research

| | Primary Language | Python Bindings | BCI focused | Primary BCI Modules | Contributions within last year |
|---------------------|------------------|-----------------|-------------|---------------------|--------------------------------|
| BciPy | Python | yes | yes | yes | yes |
| BCI2000 | C++ | yes | yes | yes | no |
| OpenVibe | C++ | yes | partial | yes | yes |
| PsychoPy | Python | yes | no | no | yes |
| Psychtoolbox | Matlab | yes | no | no | yes |
| PyFF | Python | yes | no | no | no |
| BCILAB | Matlab | yes | yes | no | yes |

Table 1 Comparison of Software for use in BCI research. A breakdown of the primary programming language, python compatibility, focus on BCI, presence of all modules needed for BCI operation, and contributions within the last year. Many of these systems can operate on most modern operating systems, however maintaining compatibility with older systems is not guaranteed and acquisition devices may not provide drivers for all operating systems.

Memmott et al. (2021)

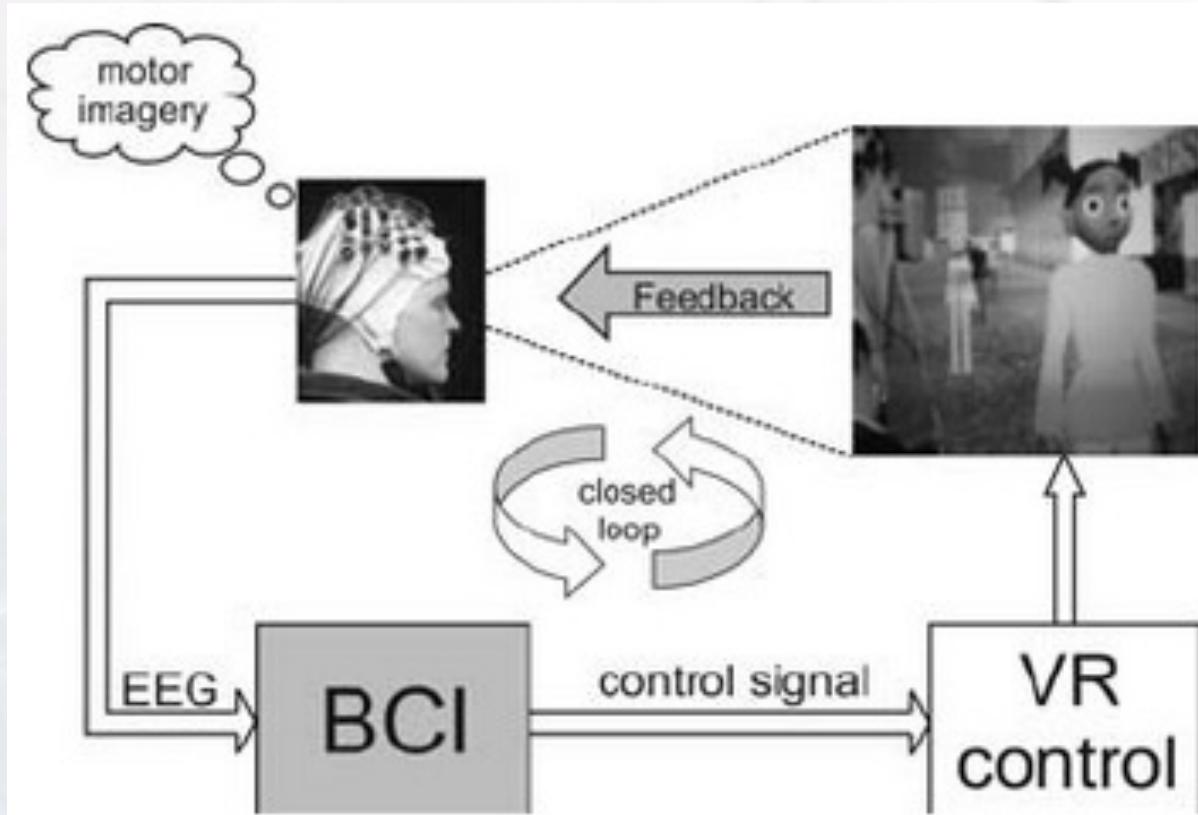
Motor Imagery - based BCI



Active BCI: Mental imagery

- ▶ Mental tasks: motor-imagery of the limb, mental calculation or navigation
- ▶ **Active BCI** that employs the user's **endogenous** brain activity in the absence of any external stimulus (*Pfurtscheller & Da Silva, 1999*)
- ▶ Initially: communication for paralyzed people (yes/no)
- ▶ Today: **neurorehabilitation** of stroke patients – MI neurofeedback effective in reestablishing motor movements immediately after a stroke
(*Mattia 2016, Pichiorri 2015*)

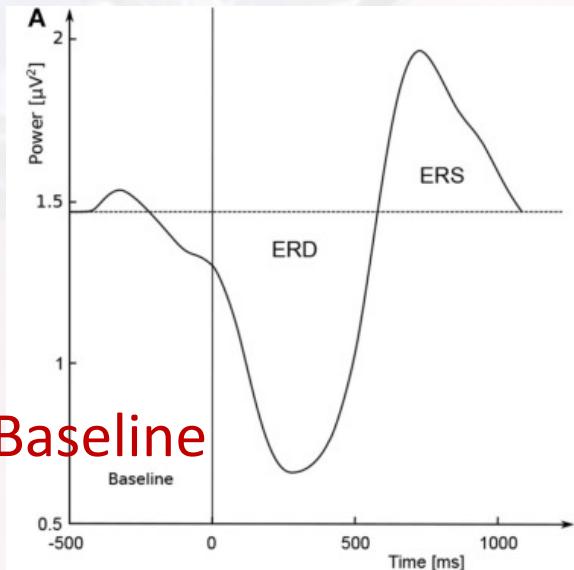
Active BCI: Mental imagery



(Pfurtscheller et al 2011)

Active BCI: Mental imagery

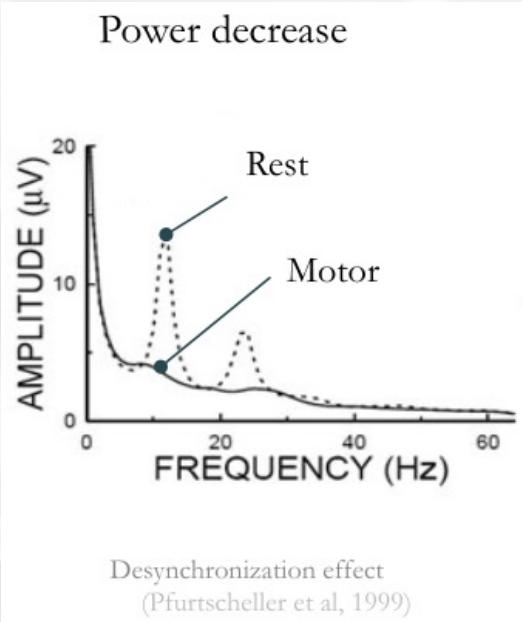
- ▶ Mental task will induce in specific cortical regions and in specific frequency bands:
 - 1°) **Event-Related Desynchronisation (ERD – while being performed)**
 - 2°) **Event-Related Synchronisation (ERS – once the user has stopped)**



$t=0$ s start of the imagery movement
(adapted from Lemm et al., 2009)

Event-Related Desync/Synchronization

- Decrease or increase in synchrony of the underlying neuronal populations reflecting cortical activation and deactivation
(Pfurtscheller & Da Silva, 1999)



Rest vs Motor



Clinical Neurophysiology

Volume 110, Issue 11, 1 November 1999, Pages 1842-1857



Invited review

Event-related EEG/MEG synchronization and desynchronization: basic principles

G. Pfurtscheller ^a✉, F.H. Lopes da Silva ^b

Neuronal networks become asynchronous during mental activity;
ERD – correlated with mental **activity**;
ERS – correlated with mental **inactivity**

Motor-imagery

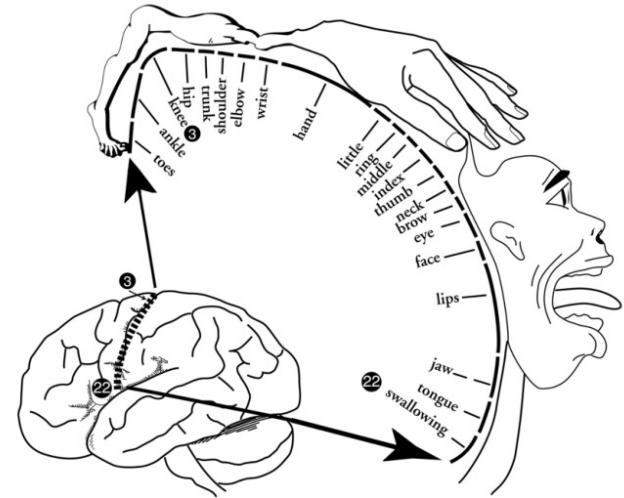
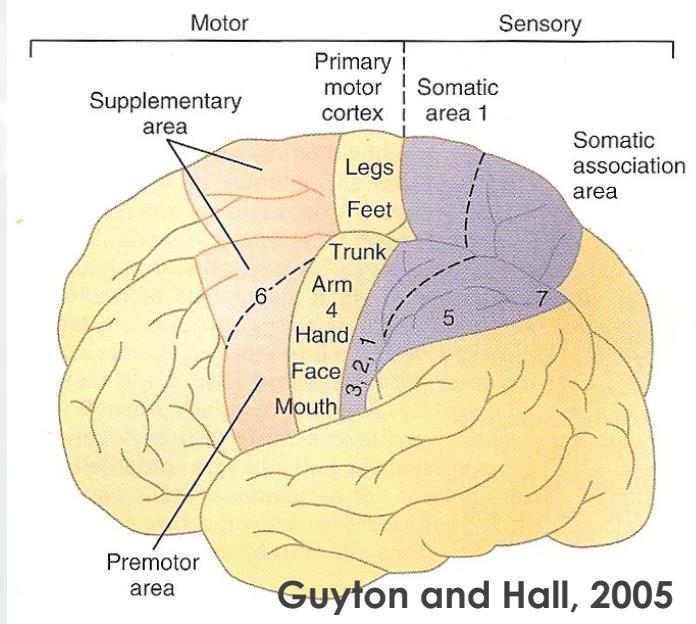


Figure 2.2: The Wilder Penfield Homunculus: the drawing of the limbs along the M1 region shows the regions responsible for generating a motor control signal to different parts of the body.[Adapted from [19]]

- ▶ The Primary Motor Cortex (PMC) is responsible for planning and executing movements
- ▶ Correspondence between the PMC areas and the various muscle groups

Motor-imagery

- ▶ Movements tasks induce changes to brain activity (ERS/ERD)

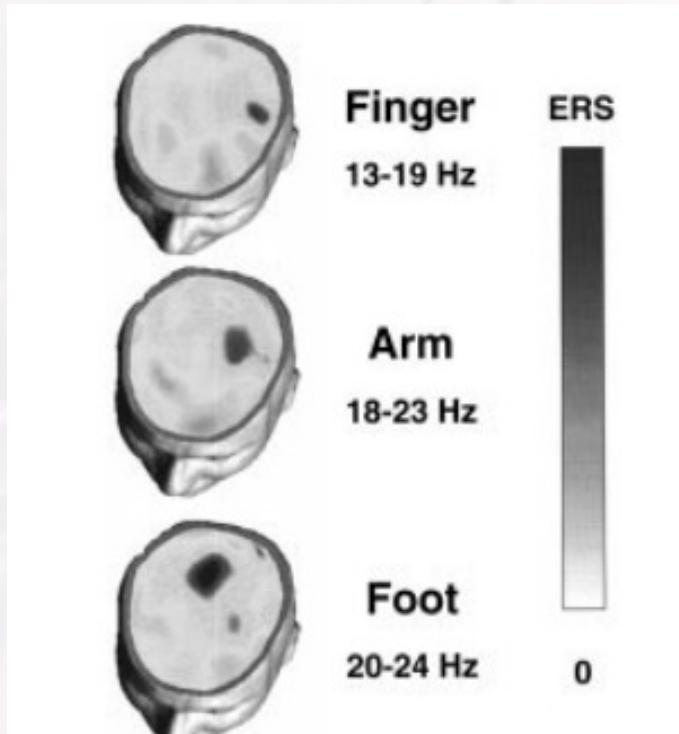
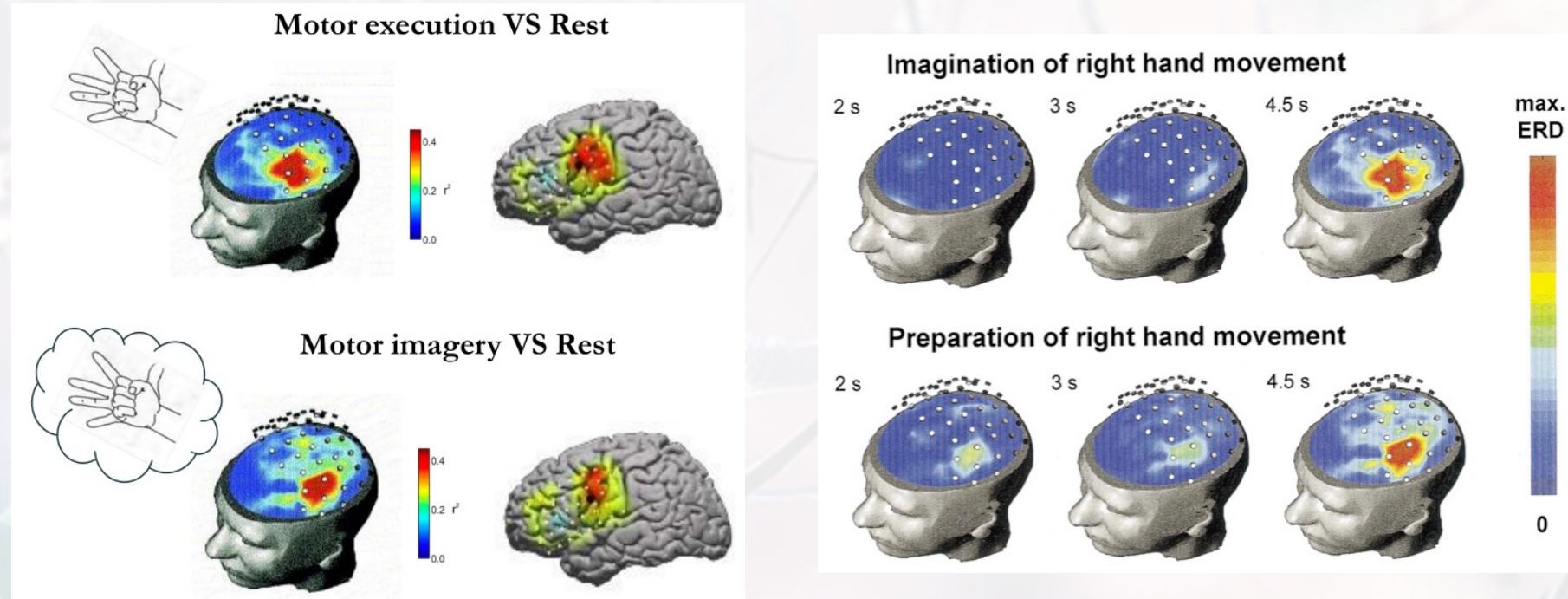


Fig. 10. Movement-specific location of the beta ERS in one subject displaying a somatotopic organization of the beta oscillations after finger, arm and foot movement. Note the different subject-specific frequency bands lowest with finger and highest with arm and foot movement, respectively. 'Black' indicates location of maximal ERS.

Pfurtscheller & Da Silva, 1999

Motor-imagery



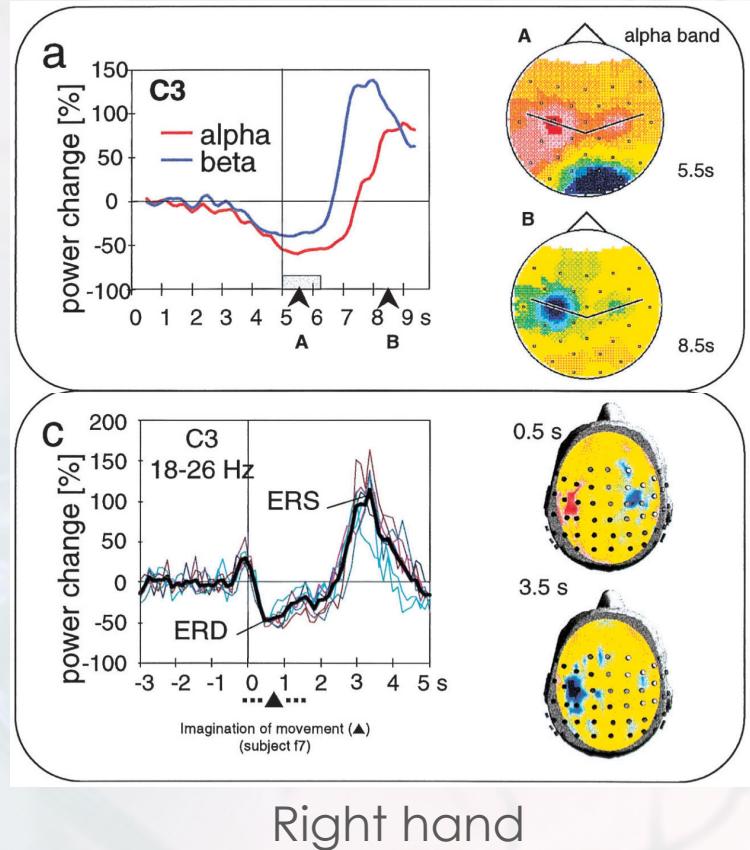
- ▶ Synchro and Desynchronisation of brain waves at motor cortex areas, whether by preparing the movement of the body or by imagining it

Motor-imagery

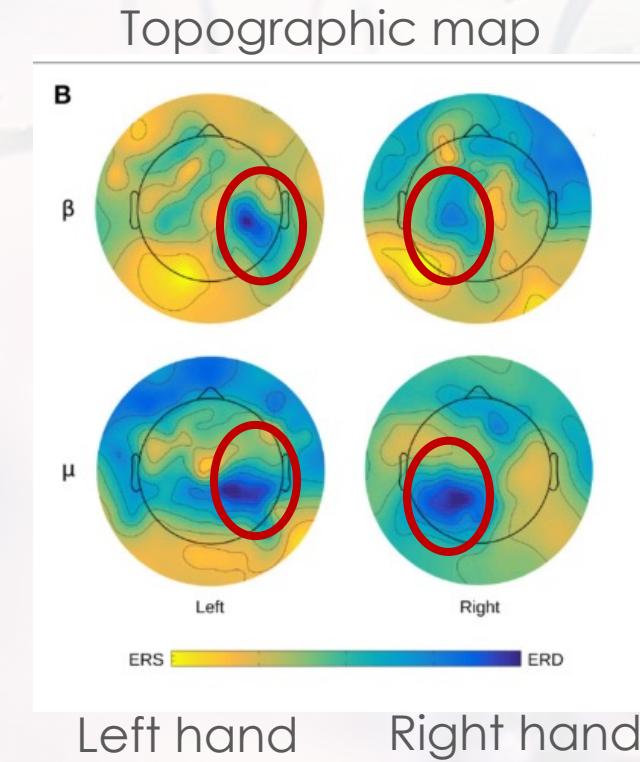
- Movements tasks induce changes to brain activity visible in the EEG

α/μ
8-12 Hz

β
18-26 Hz

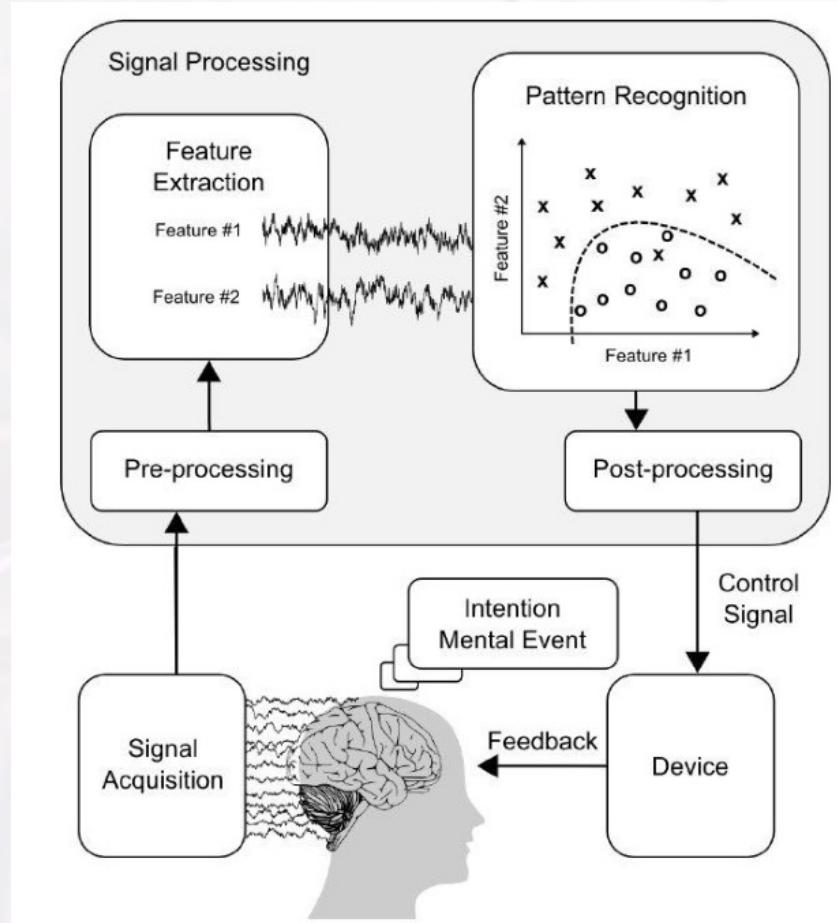


Pfurtscheller & Da Silva, 1999



► Features to be captured in BCI

Motor imagery

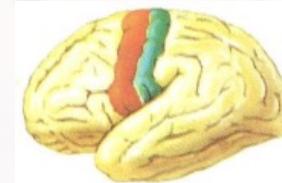


Hoffmann et al., 2006 : “A good feature extraction method should reduce the dimension of the input data as much as possible while keeping all the information necessary for classification.”

Motor imagery: Graz protocol

I- training the system

Series of MI-task (ex. Left/Right)
[feature extraction to train a classifier]



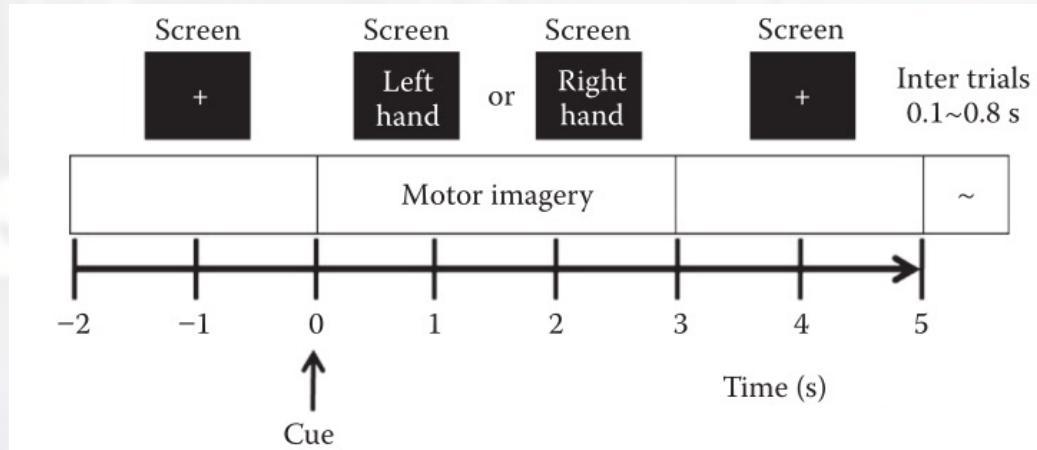
II- training the user

MI-task with feedback.
User goal: to develop effective strategies to increase system performance

Pfurtscheller & Neuper, "Motor Imagery and Direct Brain-Computer Communication", 2001

Graz protocol

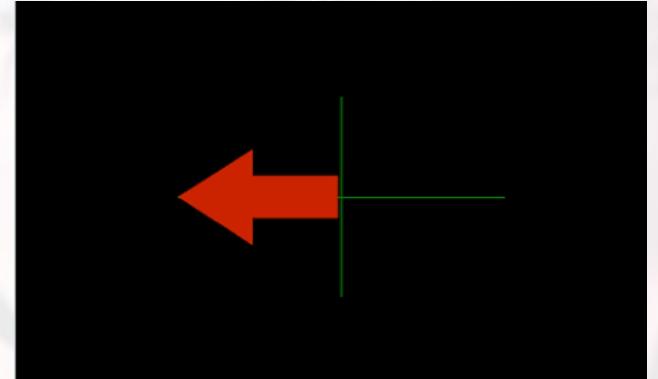
Offline



Multiple sessions, each of which multiple sequences (4-6 runs - fatigue>6)

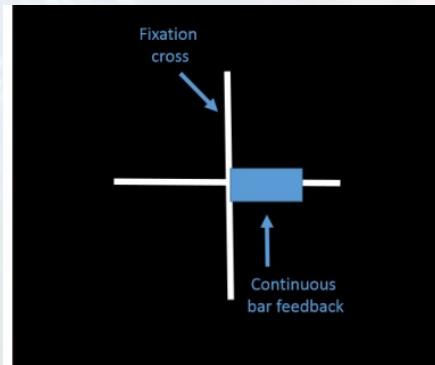
One run:

10-20 trials per class (Left/Right)
 ~ 7 min



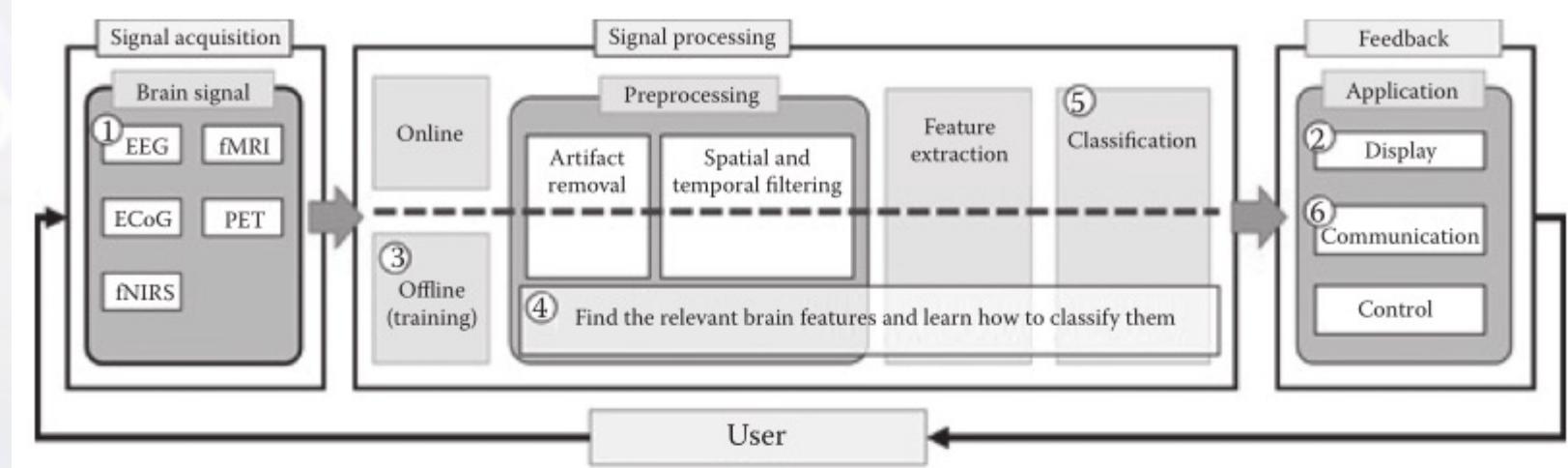
Indication of
 which MI task is
 to perform

Online



Feedback

Motor imagery



- (1) an offline calibration stage**, during which the system's settings are determined
- (2) an online operational stage**, during which the system recognizes the user's brain activity patterns and translates them into application commands

BCI research community is currently searching for solutions to help avoid the costly offline calibration stage

OpenVibe

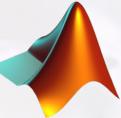


openvibe.inria.fr

An open-source software platform

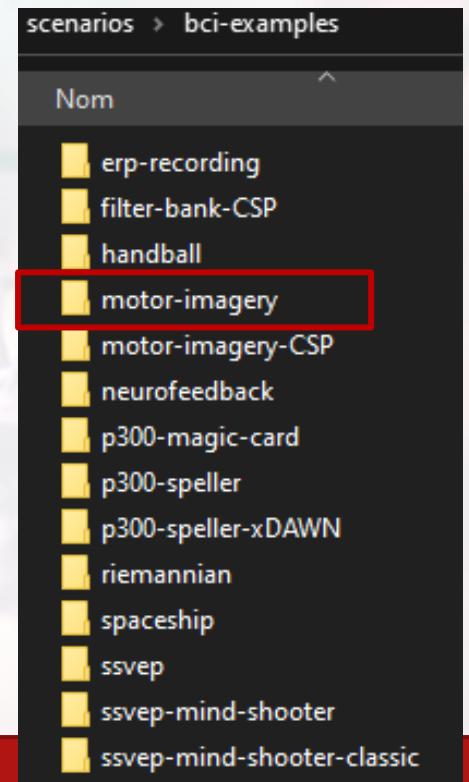
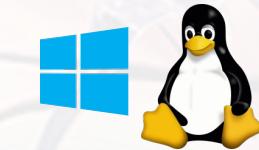
- Design, test and use BCIs
- Real-time EEG acquisition, processing and visualization
- Offline or batch analysis of large datasets

Wide EEG device compatibility (EGI, Brainamp, Biosemi,... C++ driver)

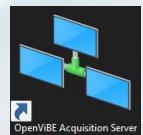
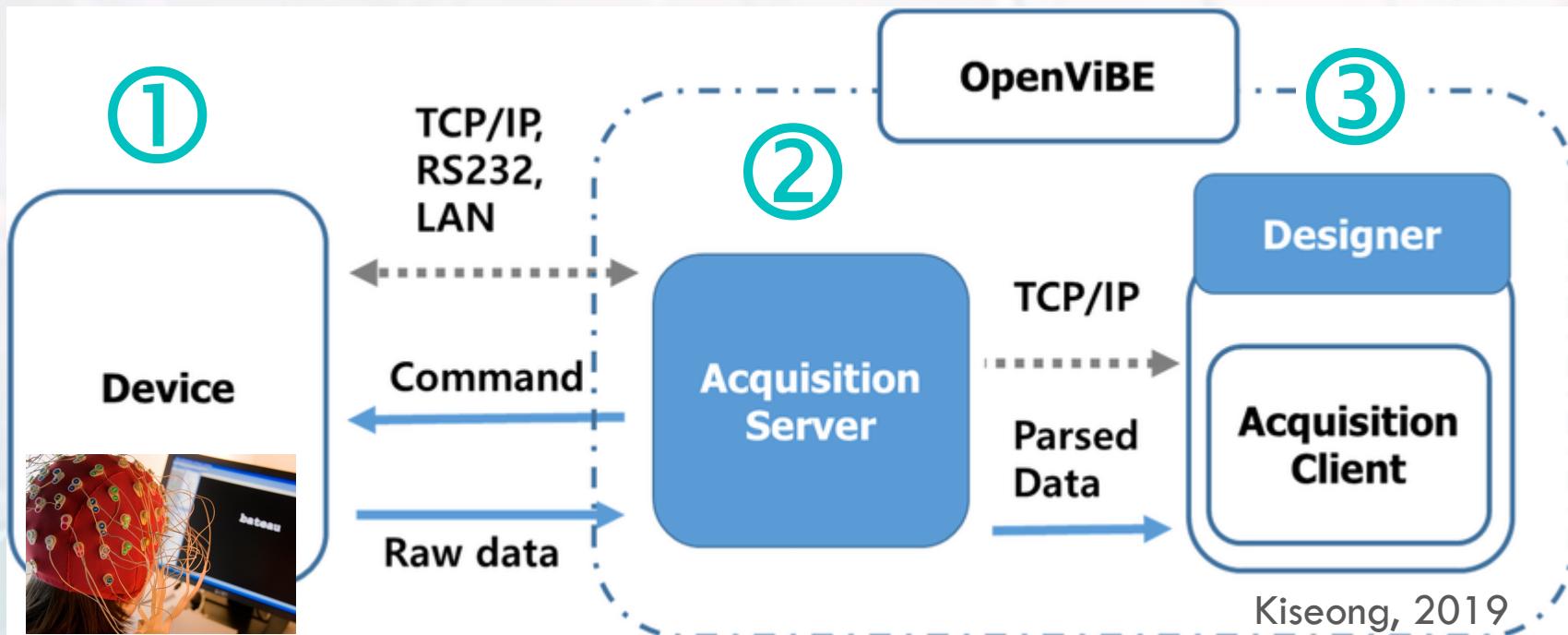
Compatibility with  & 

BCI paradigm demos available + tutorials

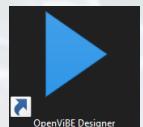
Visual programmation (GUI boxes) + own plugin development in C++



OpenVibe working flow

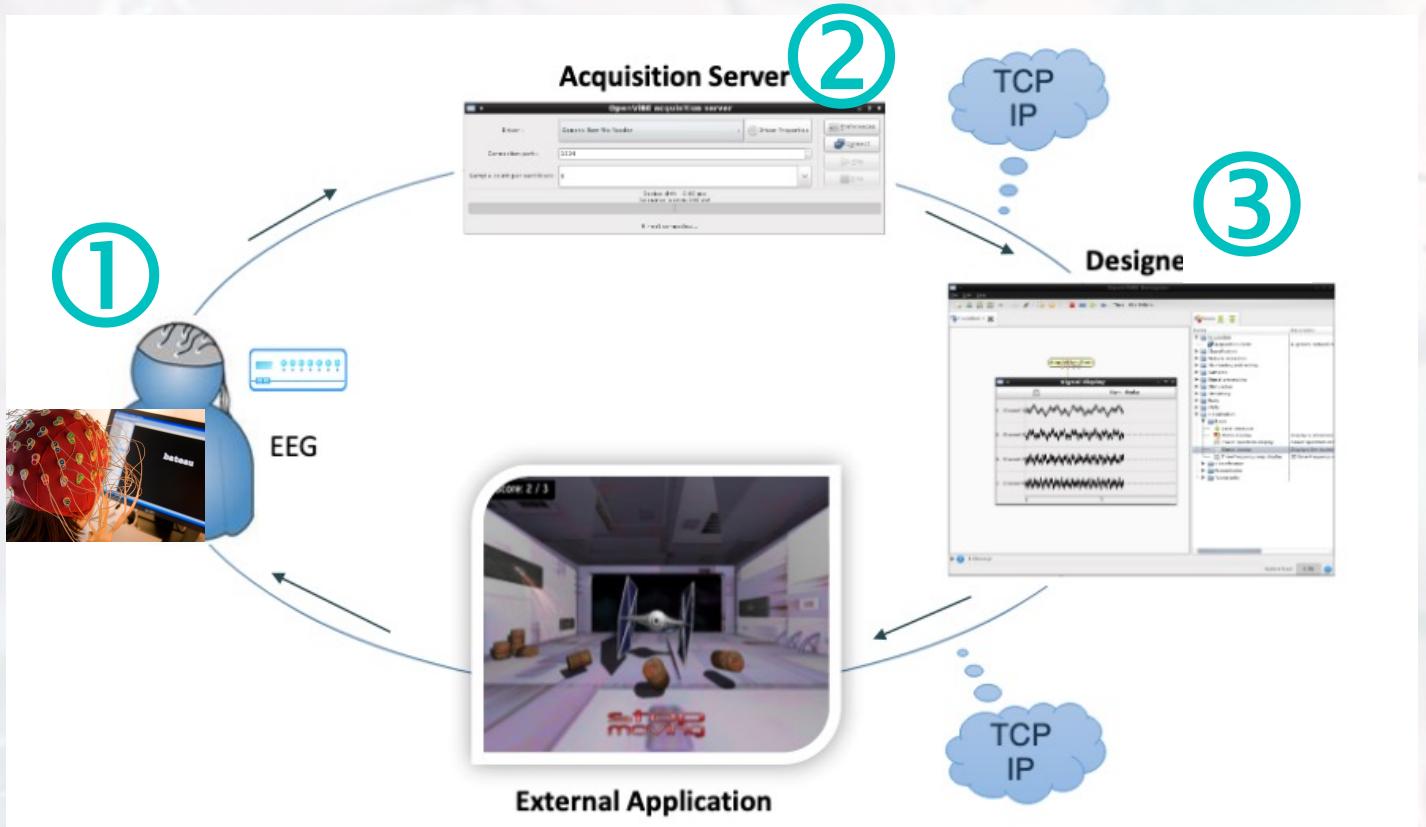


Acquisition server: Configuration to receive raw data depending on the device system

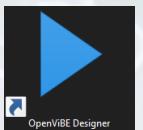


Designer: Define and Launch stimulation, online and offline data processing

OpenVibe working flow



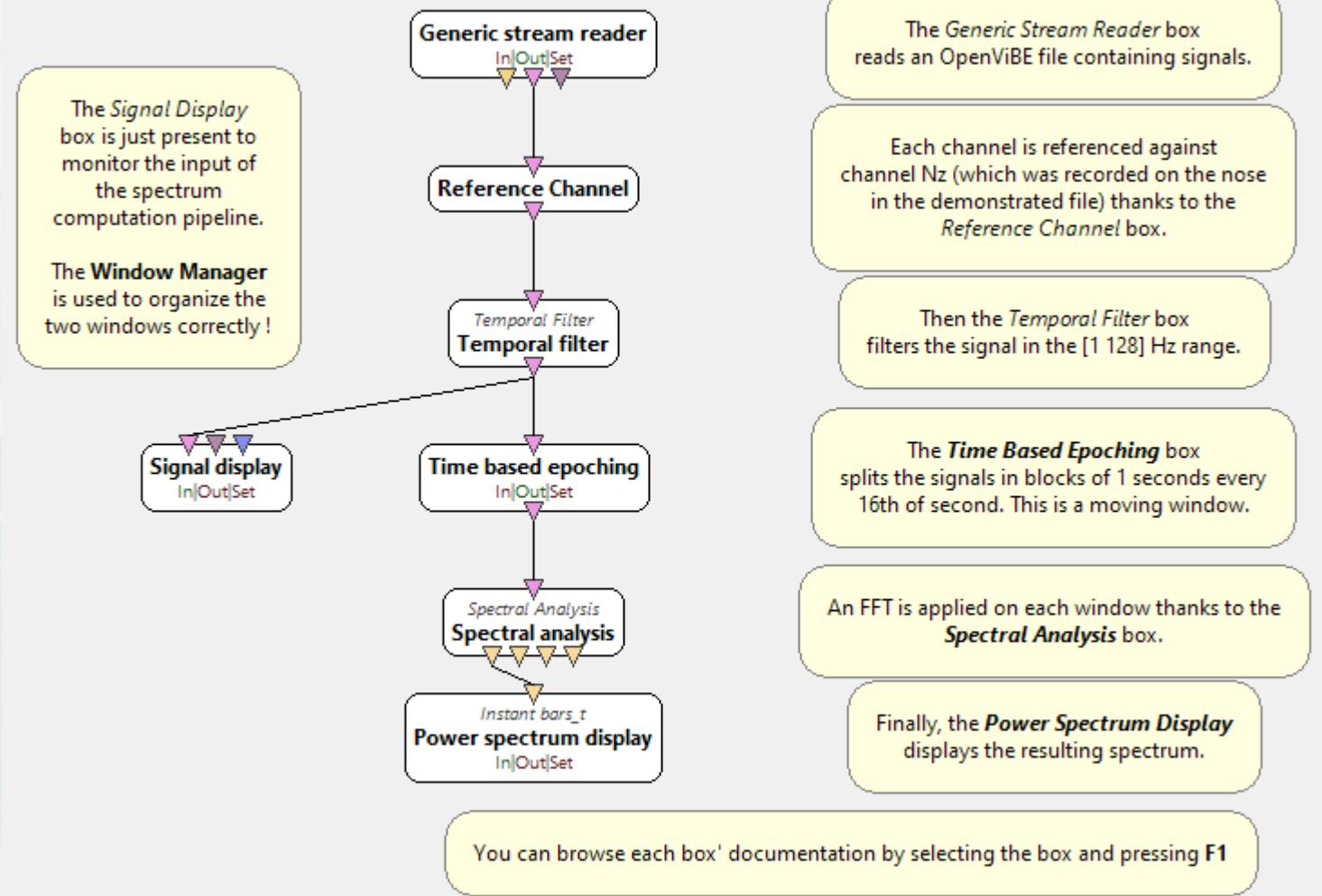
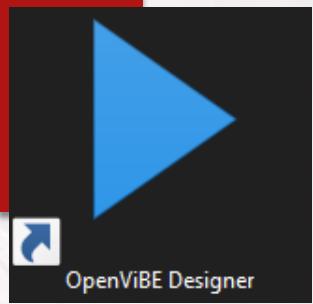
Acquisition server: Configuration to receive raw data depending on the device system



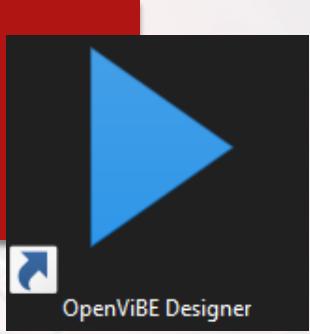
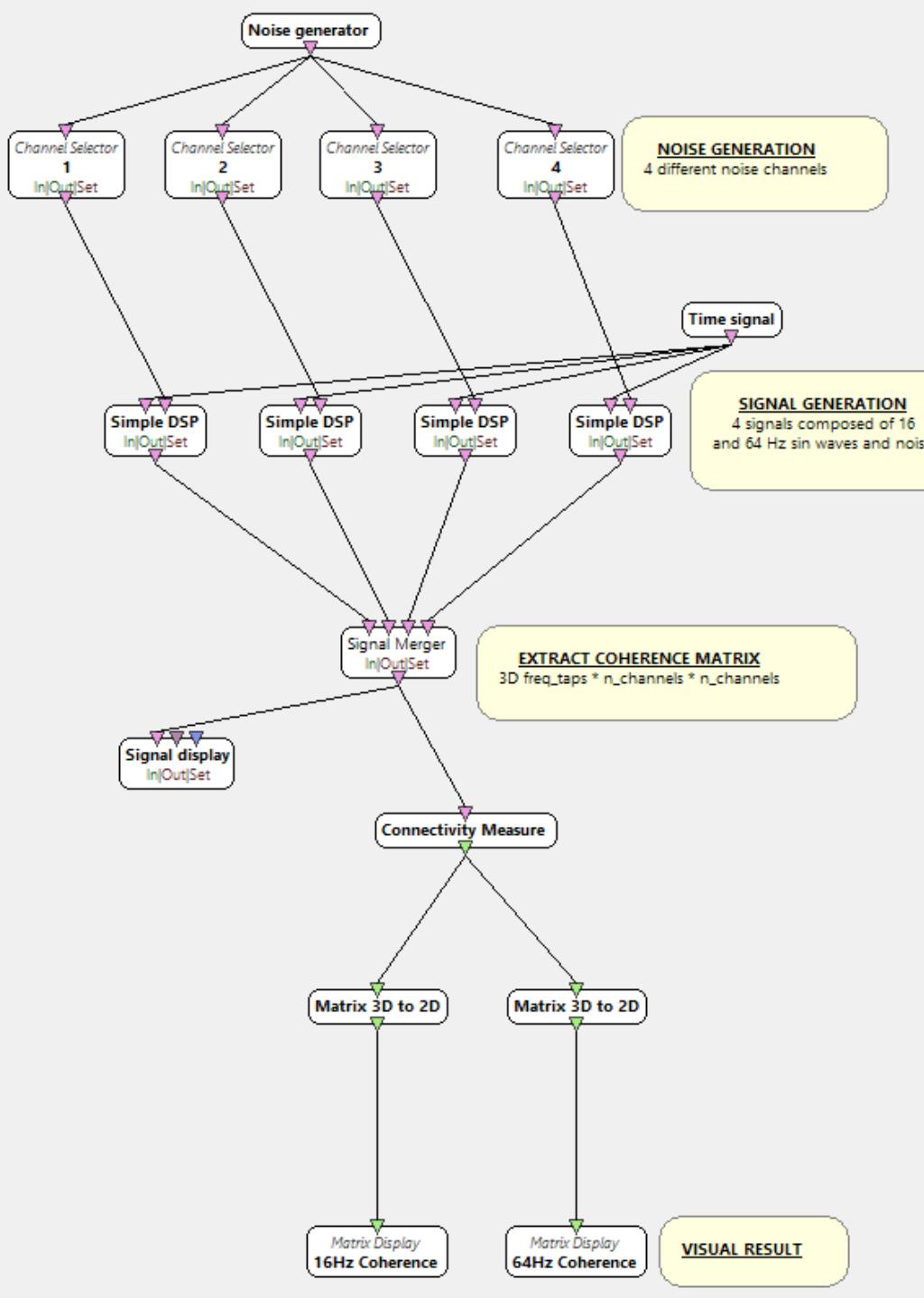
Designer: Define and Launch stimulation, online and offline data processing

Openvibe – Box tutorials

power-spectrum.xml

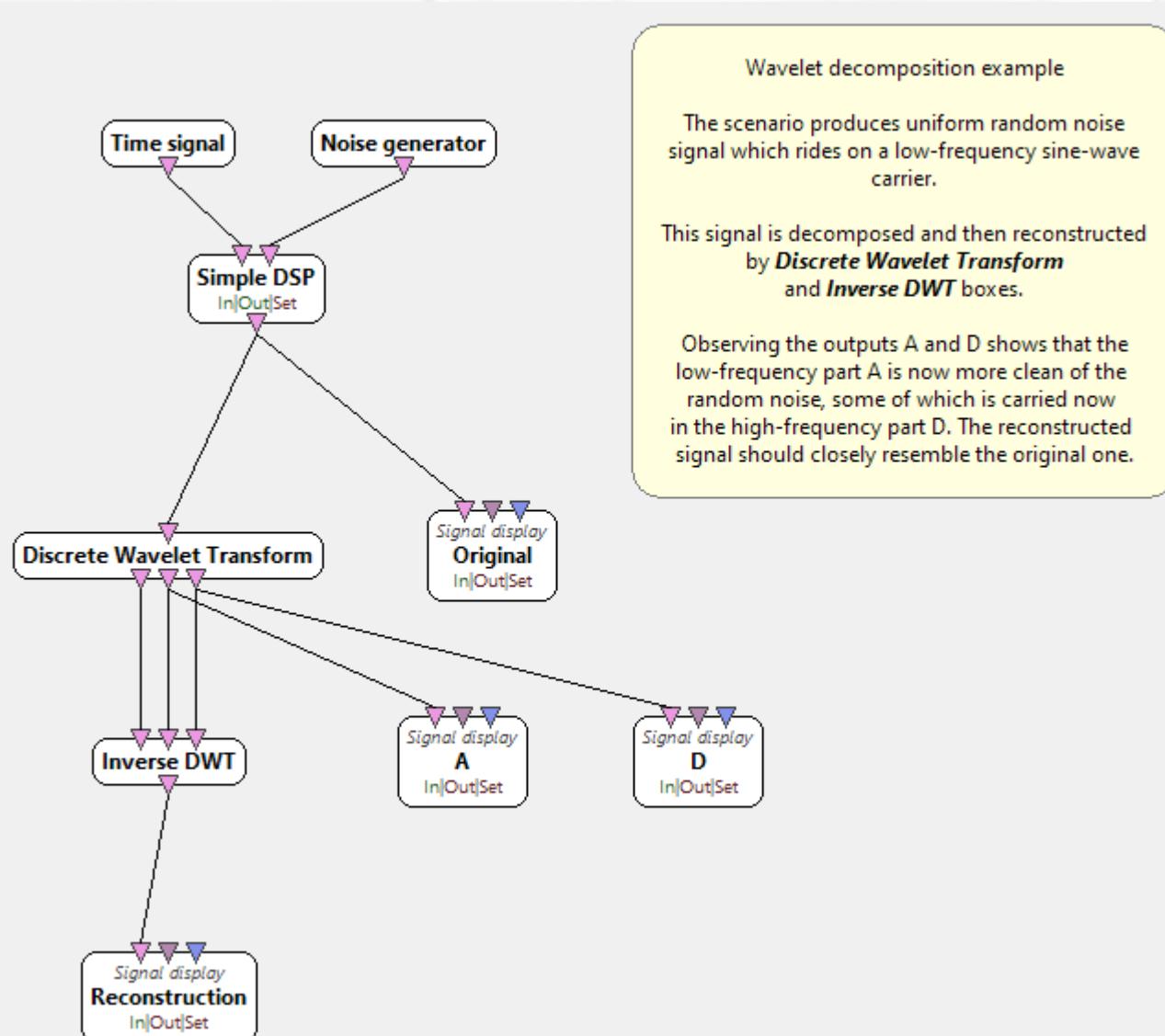
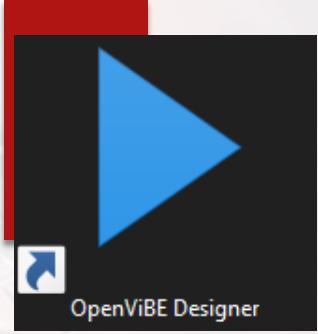


Openvibe – connectivity_measure



Openvibe – Box tutorials

wavelet-decomposition



Wavelet decomposition example

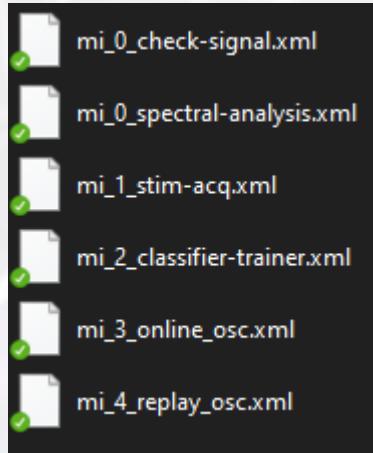
The scenario produces uniform random noise signal which rides on a low-frequency sine-wave carrier.

This signal is decomposed and then reconstructed by **Discrete Wavelet Transform** and **Inverse DWT** boxes.

Observing the outputs A and D shows that the low-frequency part A is now more clean of the random noise, some of which is carried now in the high-frequency part D. The reconstructed signal should closely resemble the original one.

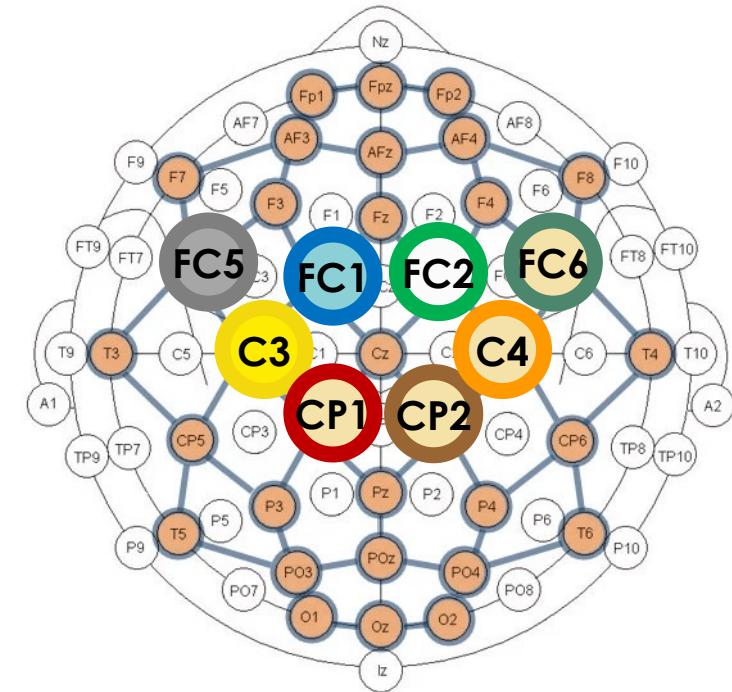
Artifact removal, PCA, Machine learning...

Openvibe: Graz protocol + OpenBCI



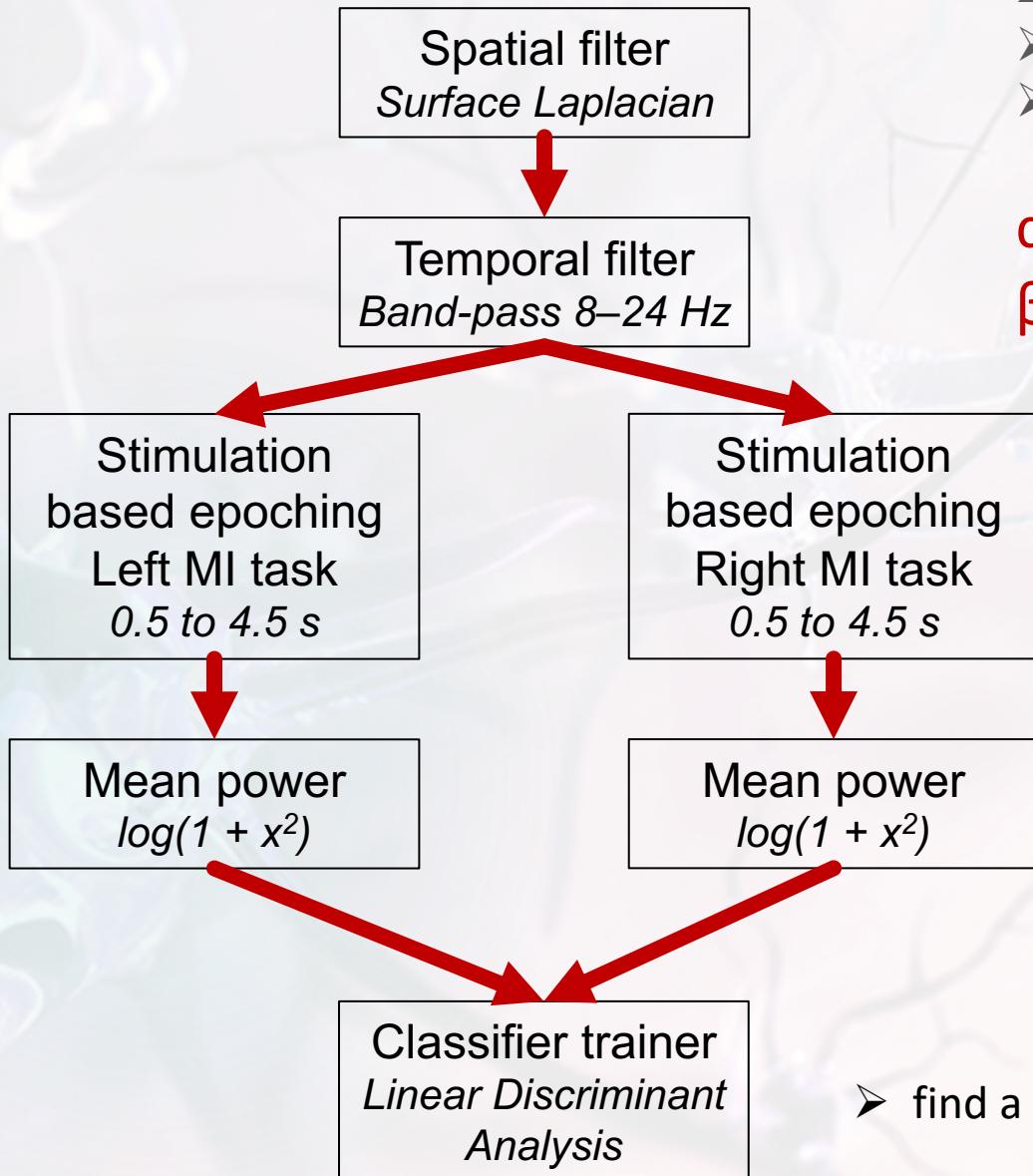
- mi_1_stim-acq: stimulation (L/R) while recording the training data set
- mi_2_classifier-trainer: classifier parameters estimate
- mi_3_online_osc: classification in real time with feedback
+ send command by OSC to a [web app](#)

Ultracortex Mark IV
Node Locations (35 total)



Based on the internationally accepted **10-20 System** for electrode placement in the context of EEG research

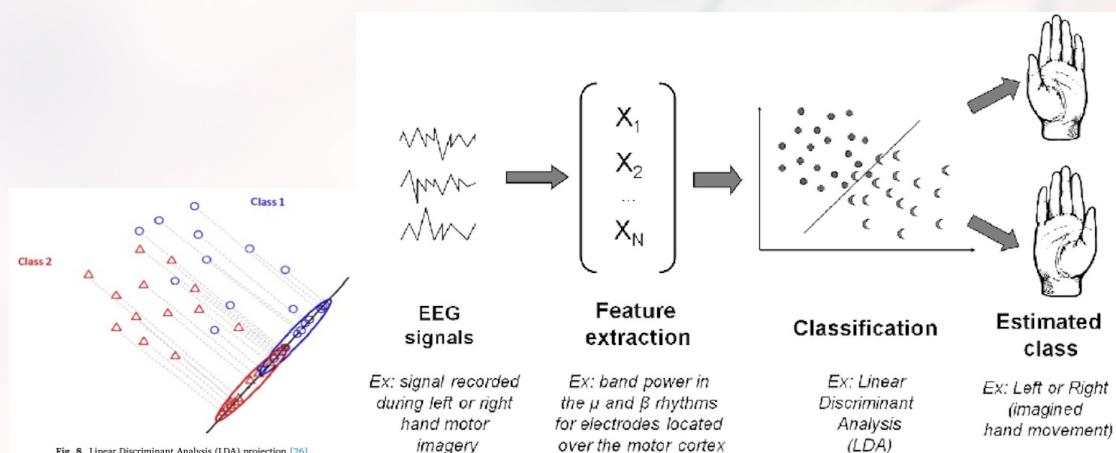
Motor imagery: data processing pipeline



2 output channels:

- **Left side:** 3*C3 – (FC5 + FC1 + CP1)
- **Right side:** 3*C4 – (FC6 + FC2 + CP2)

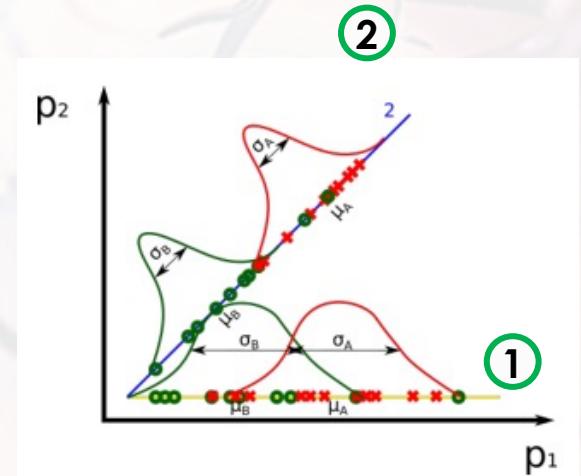
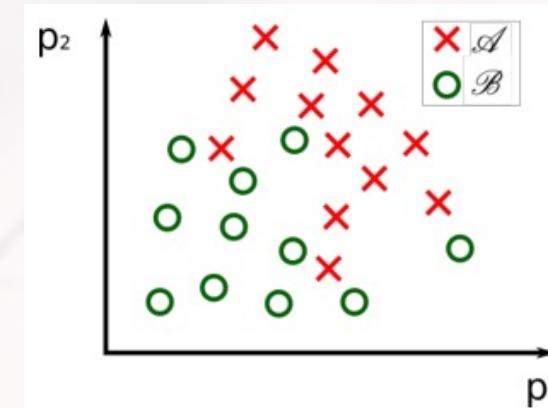
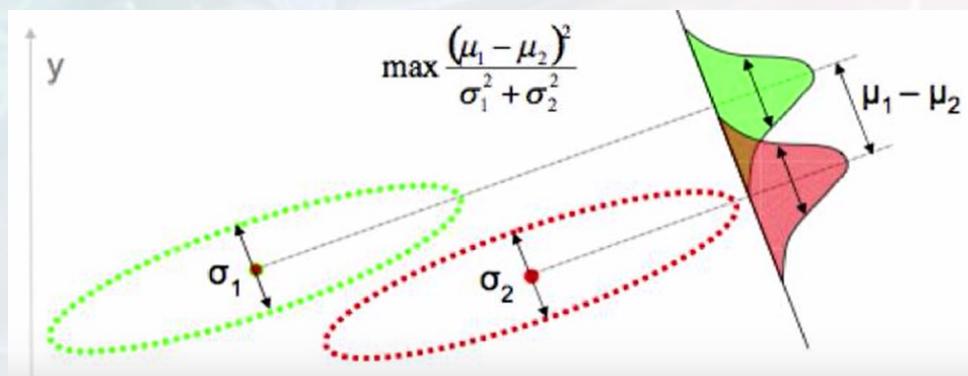
α/μ : 8-12 Hz
 β : 18-26 Hz



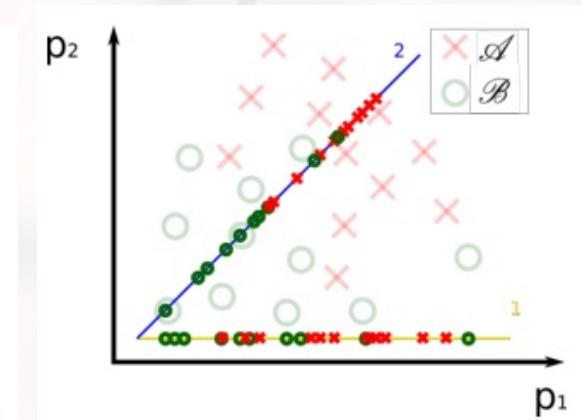
- find a linear discrimination of the two features

Linear discriminant Analysis

- Find the projector line that gives:
 - maximum separation between means of projected classes
 - minimum variance within each projected class
- Solution: eigenvectors based on between-class and within-class covariance matrices



Example - Projector 2: best discriminant



Openvibe: Graz protocol + OpenBCI

- Multiple sessions with Franziska
- Low classification accuracy by imagining the movement (60% with the Left class being better discriminated)

```
Cross-validation test accuracy is 55.836040% (sigma = 5.424622%)  
    Cls vs cls      1      2  
    Target 1: 58.5 41.5 %, 1020 examples  
    Target 2: 46.9 53.1 %, 1020 examples  
Training set accuracy is 60.441176% (optimistic)  
    Cls vs cls      1      2  
    Target 1: 63.4 36.6 %, 1020 examples  
    Target 2: 42.5 57.5 %, 1020 examples
```

- By actually doing the movement: good accuracy (92%!) – classification based on the mu-beta features is very reliable

```
Classifier trainer> Cross-validation test accuracy is 92.354288% (sigma = 7.365529%)  
Classifier trainer>    Cls vs cls      1      2  
Classifier trainer>    Target 1: 97.1 2.9 %, 1020 examples  
Classifier trainer>    Target 2: 12.4 87.6 %, 1020 examples  
Classifier trainer> Training set accuracy is 92.156863% (optimistic)  
Classifier trainer>    Cls vs cls      1      2  
Classifier trainer>    Target 1: 96.9 3.1 %, 1020 examples  
Classifier trainer>    Target 2: 12.5 87.5 %, 1020 examples
```

Motor imagery

- ▶ Co-adaptation user/machine - substantial training to find the correct imagination strategy that leads to the most distinct ERD/ERS
- ▶ Currently it can only be used with a maximum of 3 or 4 different MI tasks to ensure maximal performances (classification accuracy)

■ BCIs improvement

« Illiterate users »

Most current systems do not properly establish this mutual understanding

- 10 to 30 % of users unable to control a BCI: “BCI illiteracy” or “BCI deficiency” phenomenon
- MI-BCI : even for not “illeterate”, performance rather low
 - 75% of classification accuracy for 2 class MI-BCIs
 - 20% reach 80 to 100%
- 2 main factors
 - (1) Signal processing (Stage I) – many studies over the last years
 - (2) The user-training role: mostly neglected – inefficient training protocol (instructions, training tasks, feedback and training environment)
- Controlling an BCI requires acquisition of specific skills = to generate stable and distinct brain activity patterns while performing the tasks
- Understand how the human learn and how to adapt training process

■ BCIs improvement

BCI

Summary guidelines for designing more effective training protocols (C. Jeunet)

Training task

Progression (increasing difficulty), adaptative user-specific

Self-paced and asynchronous sessions

Preparatory training tasks (meditation)

Feedback

Visual with emotional connotations (smileys) – tactile is promising (channel much less saturated in interactive situations) / increase the quantity and quality of information (topography of cerebral activity...)

Training environment

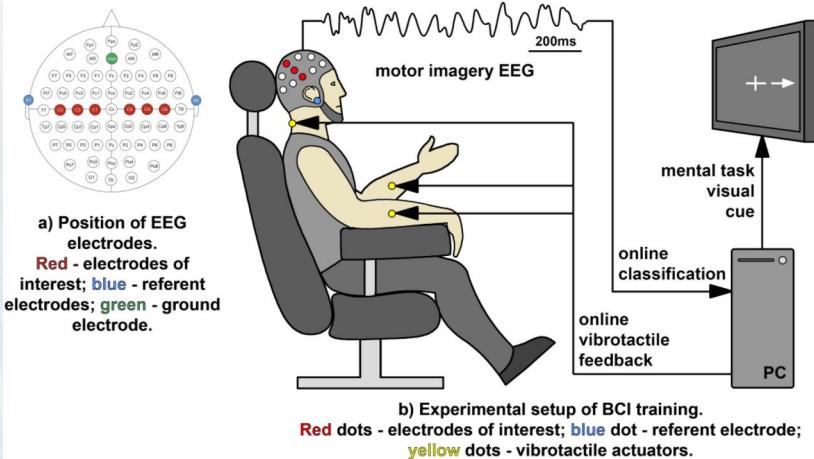
Improvement of user motivation & experience: gamified protocols (ex. ball-basket paradigm, spaceship that must avoid asteroids)

Integration of virtual reality. Ex “Use the force” – allows users to levitate a spaceship by imagining moving their feet

MI-based BCIs improvement

Continuous Tactile Feedback for Motor-Imagery based Brain-Computer Interaction in a Multitasking Context

Camille Jeunet, Chi Vi, Daniel Spelmezan, Bernard N'Kaoua, Fabien Lotte,
Sriram Subramanian



"Vibrotactile feedback during MI training induced significant enhancement of ERD activity only for non-dominant, left hand over contralateral motor cortex area measured in C4 electrode"

New Results

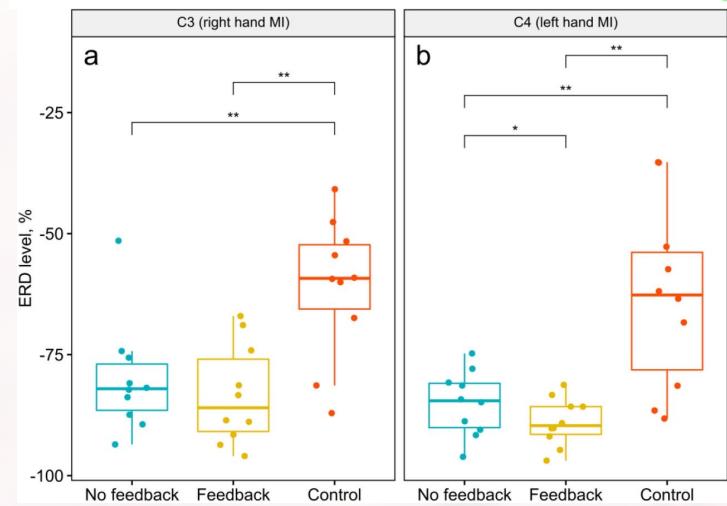
 [Follow this preprint](#)

A BCI-based vibrotactile neurofeedback training improves motor cortical excitability during motor imagery

N. Grigorev, A. Savosenkov, M. Lukoyanov, A. Udroatina, N. Shusharina, A. Kaplan, A. Hramov, V. Kazantsev, S. Gordleeva

doi: <https://doi.org/10.1101/2021.02.28.433220> 

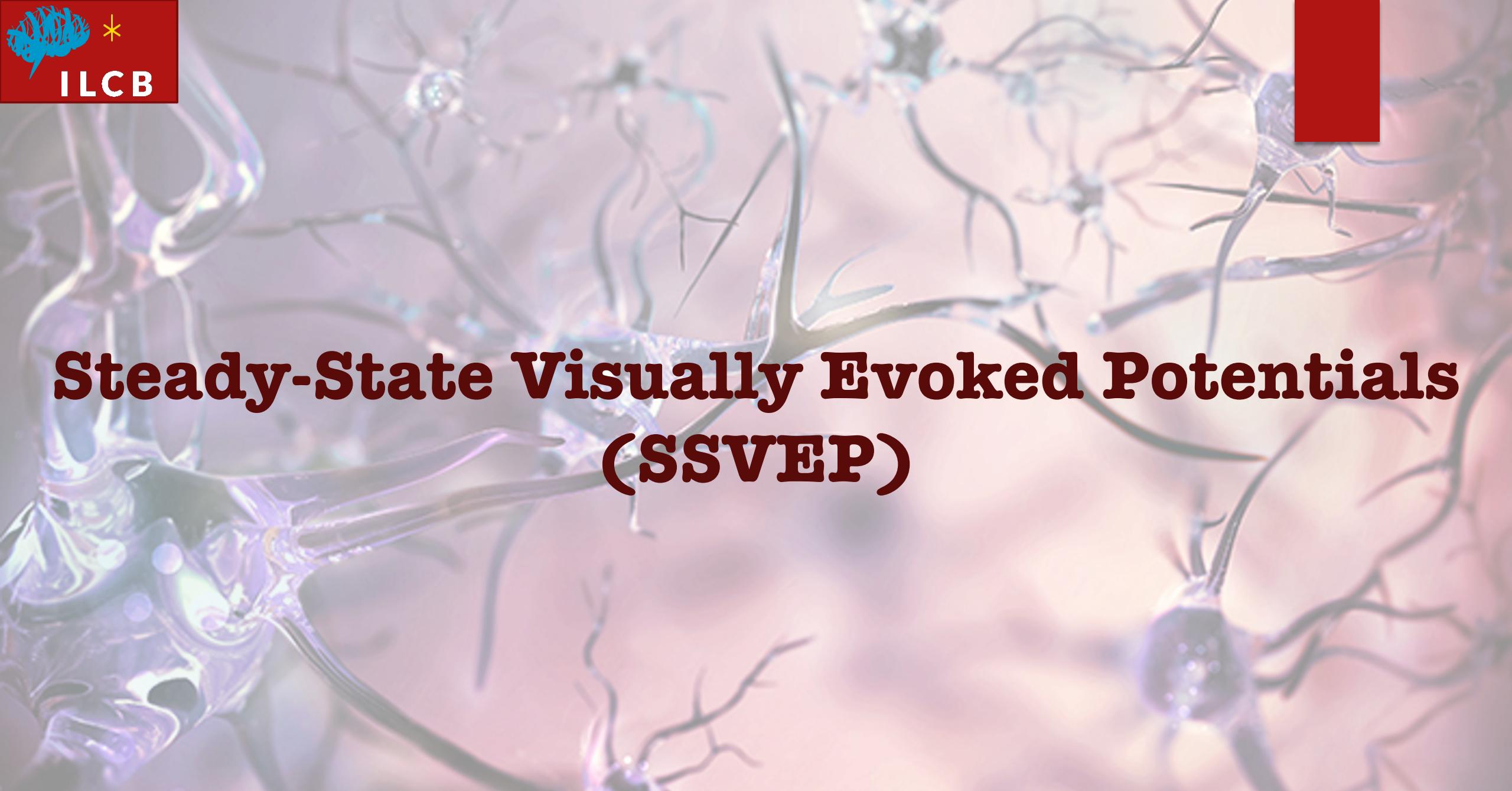
Now published in *IEEE Transactions on Neural Systems and Rehabilitation Engineering* doi: [10.1109/tnsre.2021.3102304](https://doi.org/10.1109/tnsre.2021.3102304) 





ILCB

Steady-State Visually Evoked Potentials (SSVEP)



Evoked Potentials Brain Computer Interface

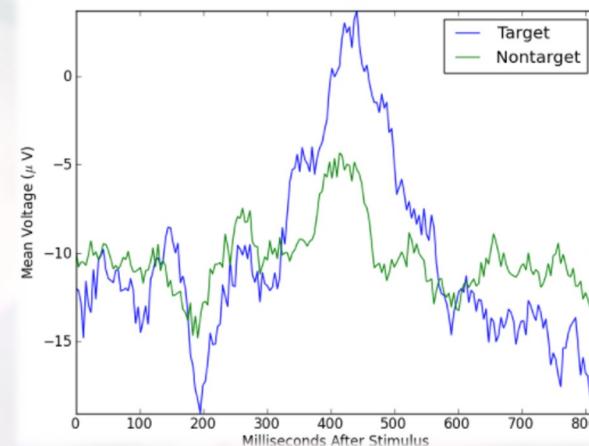
Evoked potentials: electrical potentials elicited when a stimulus is presented. They can be...

- **Visual:** visually evoked potentials (**VEP**) & steady-state evoked potentials (**SSVEP**)
- **Auditory:** auditory steady-state response (**ASSR**)
- **Haptic:** steady-state somatosensory evoked potentials (**SSSEP**)

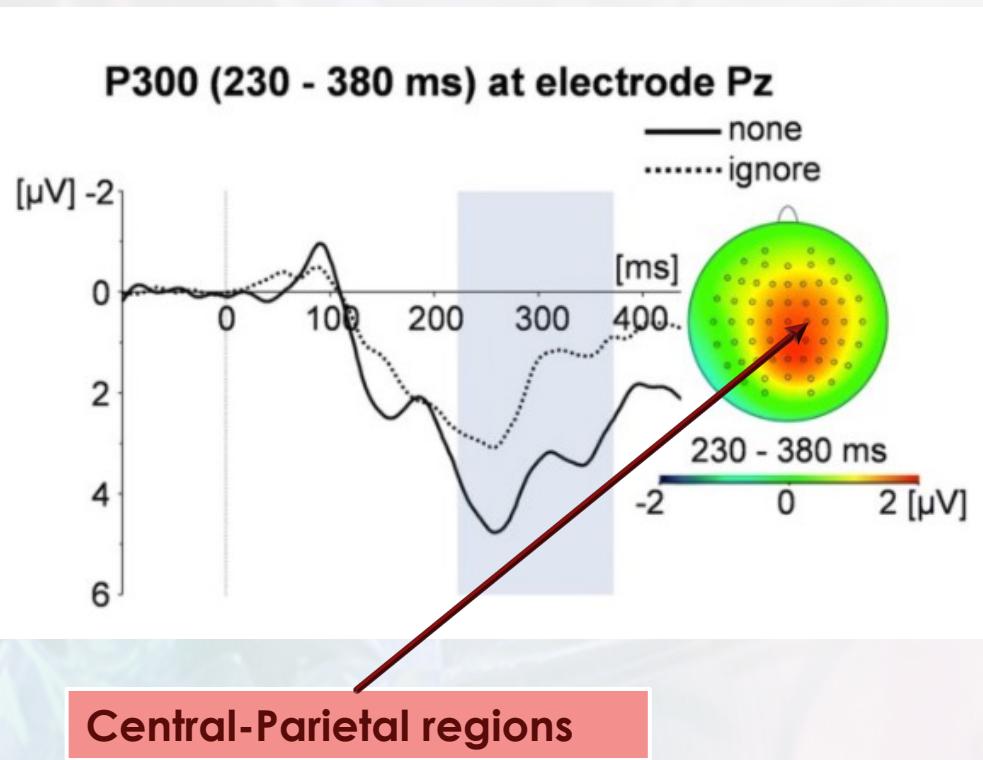
Event-Related Potential (ERP) based BCI:

- Electrophysiological response triggered by a specific event or stimulation.
- Response is time delayed in relation to the event → ERP Latency
- Response has a direction or polarity → positive or negative

P300 : Positive deflection that (generally) peaks 300ms after event onset.

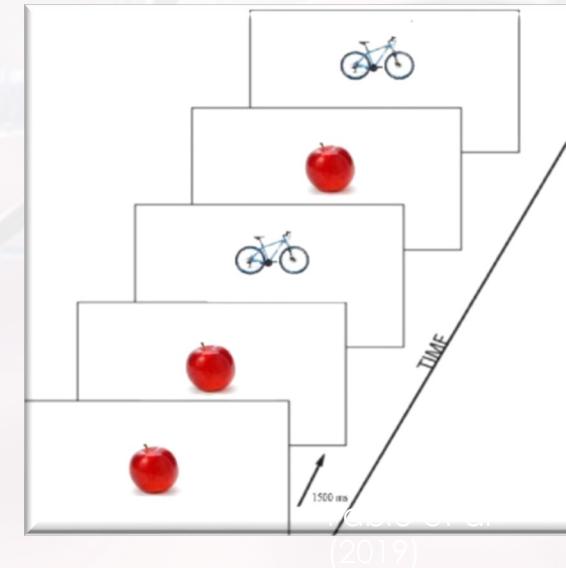


Evoked Potentials Brain Computer Interface



- Linked to attentional and memory processes
- Usually generated by the **oddball paradigm**.

Visual oddball

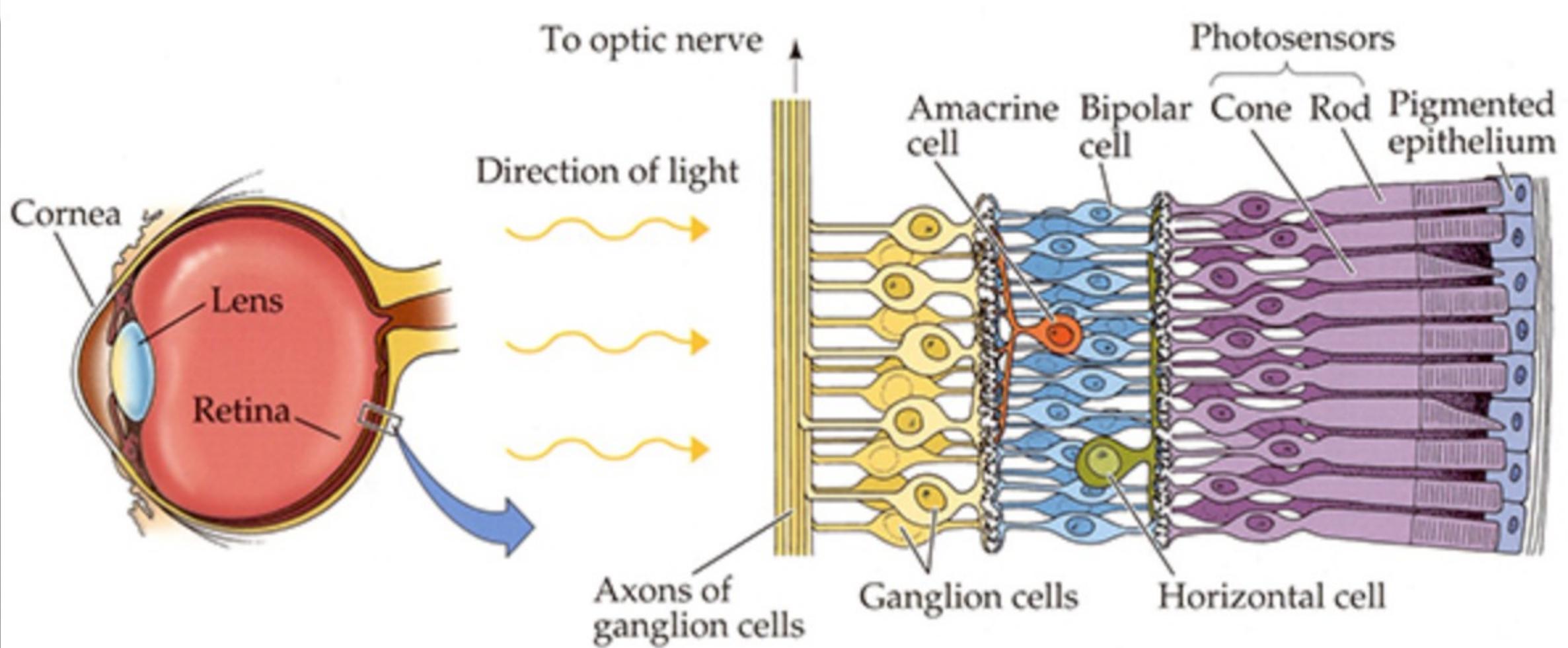


Auditory oddball



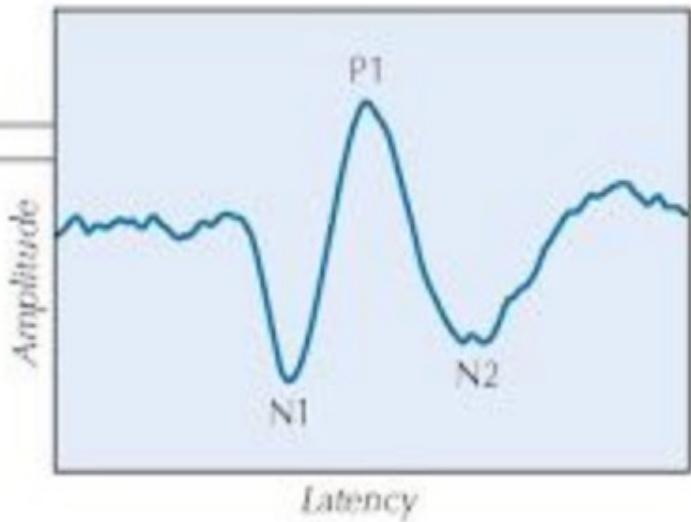
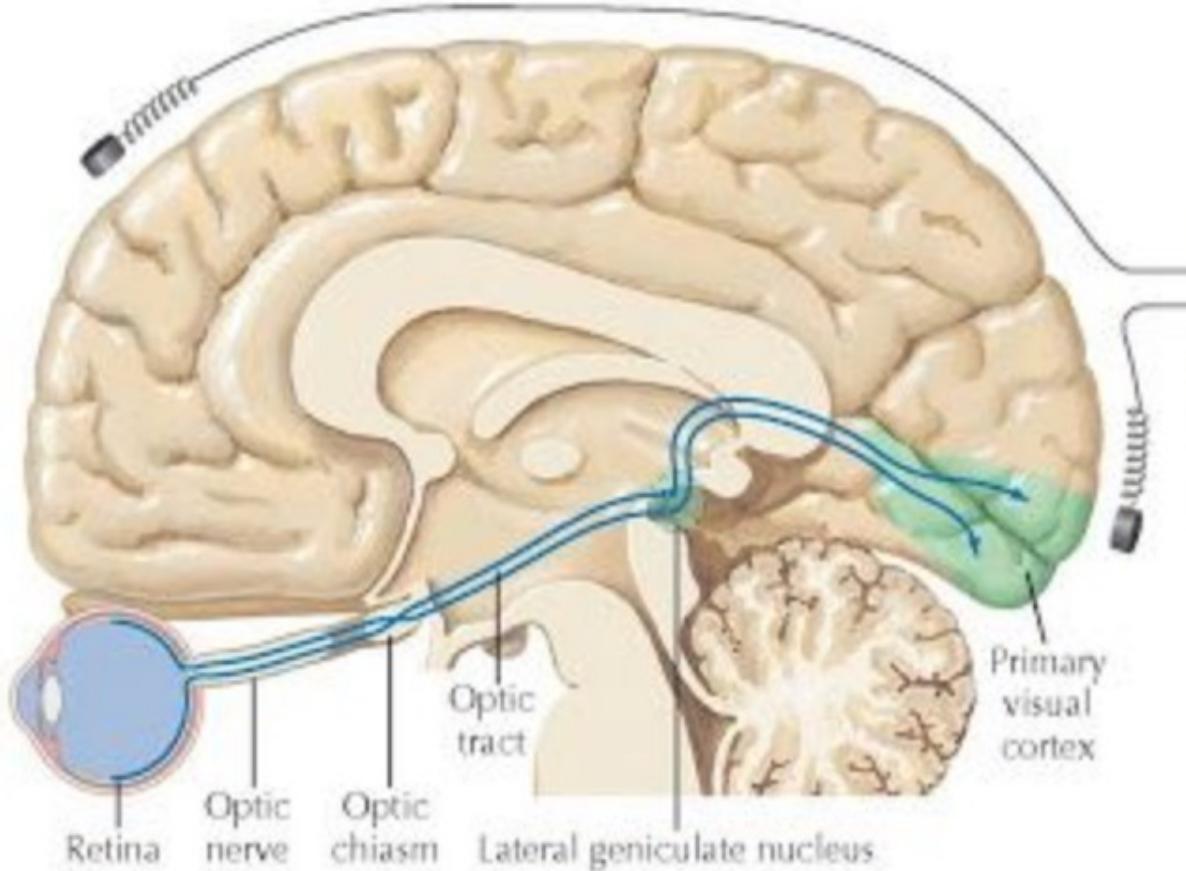
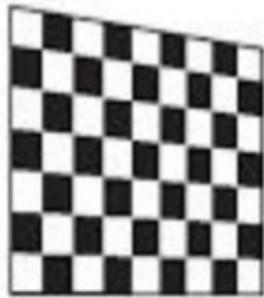
P300 component widely used in BCI applications as it is relatively easy to generate.

Visually-Evoked Potentials (VEPs)



Visually-Evoked Potentials (VEPs)

Alternating
checkerboard
pattern displayed



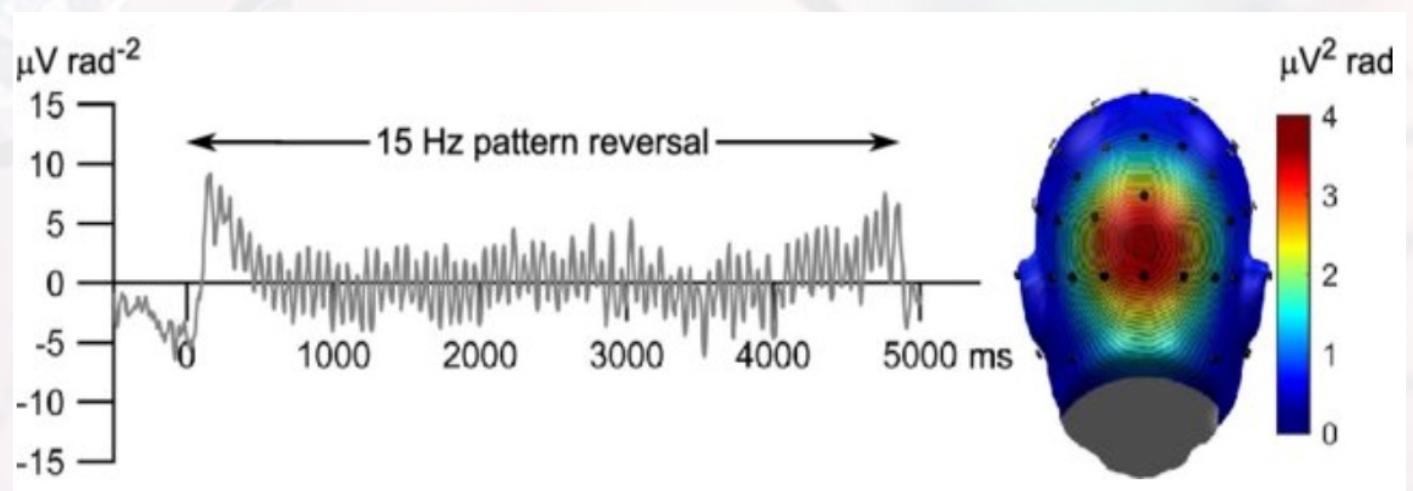
Steady-state Visually Evoked Potential (SSVEP)

SSVEPs are generated when a user focuses attention on a visual flicker at a certain frequency from 6Hz to 75Hz.

The continuous visual stimulation **evokes** a synchronised steady-state brain activity, whose frequency spectrum depends on the flicker frequency of the visual stimulus.

A **resonance phenomenon**.

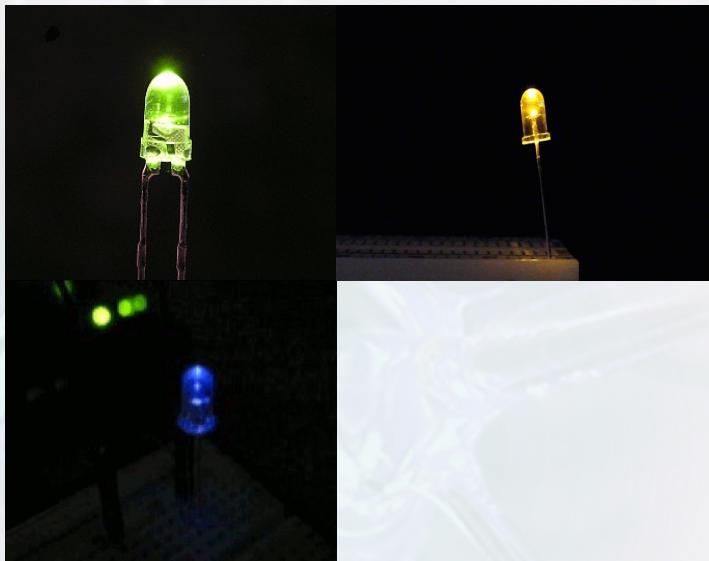
Time & phase-locked to the driving stimulus.



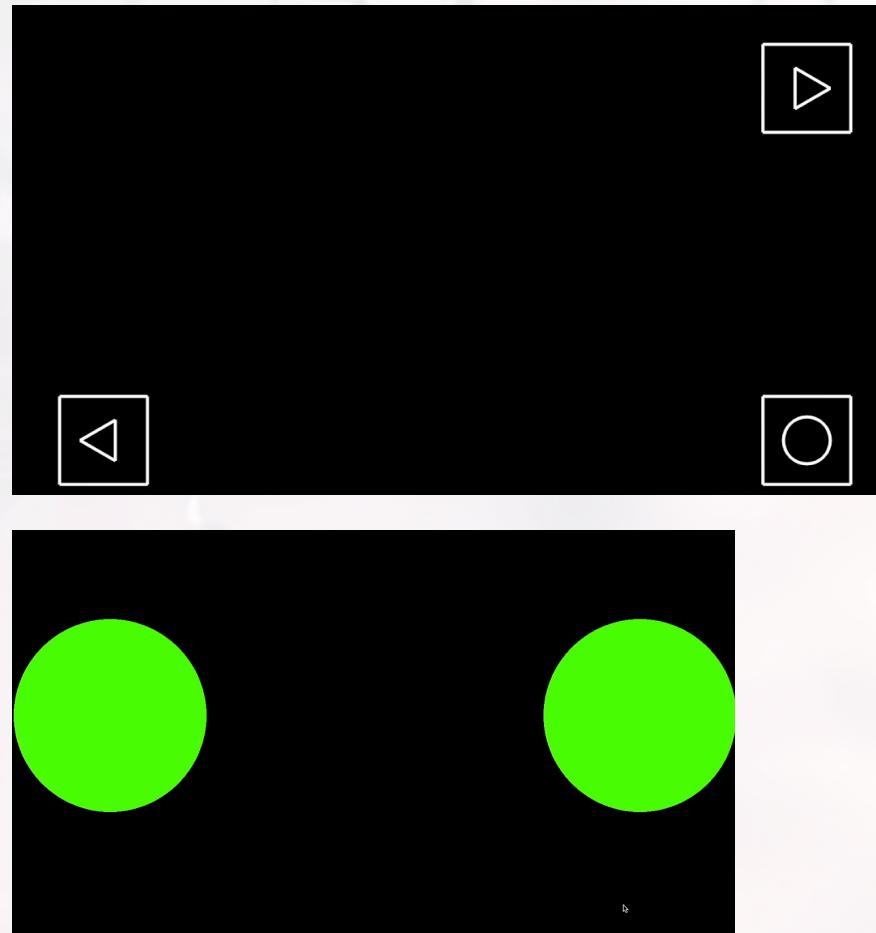
Antov, M.I., Plog, E., Bierwirth, P. et al. Visuocortical tuning to a threat-related feature persists after extinction and consolidation of conditioned fear. *Sci Rep* **10**, 3926 (2020)

SSVEP: Repetitive Visual Stimuli (RVS)

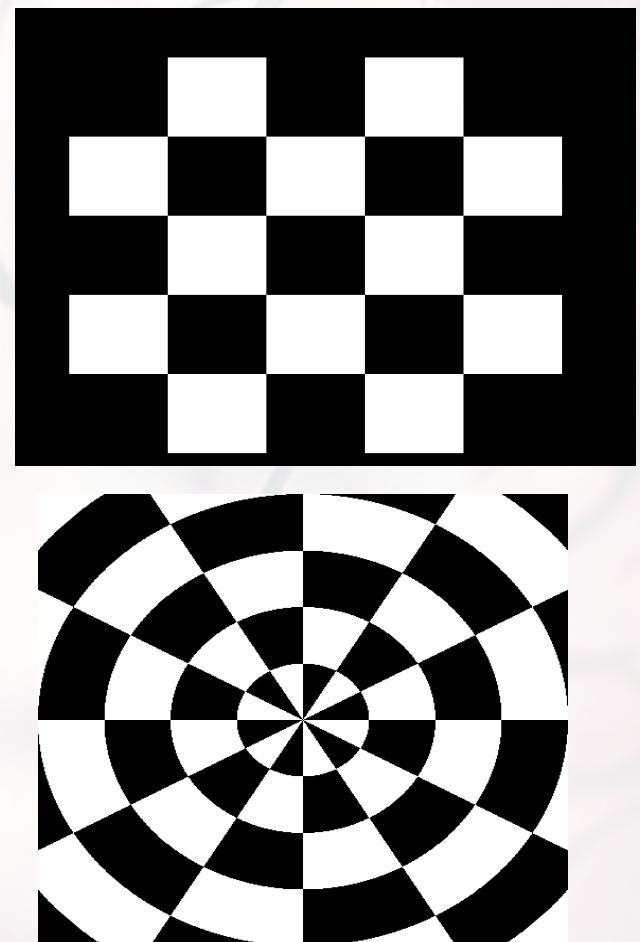
Light stimuli i.e. LEDs



Single Graphics Stimuli

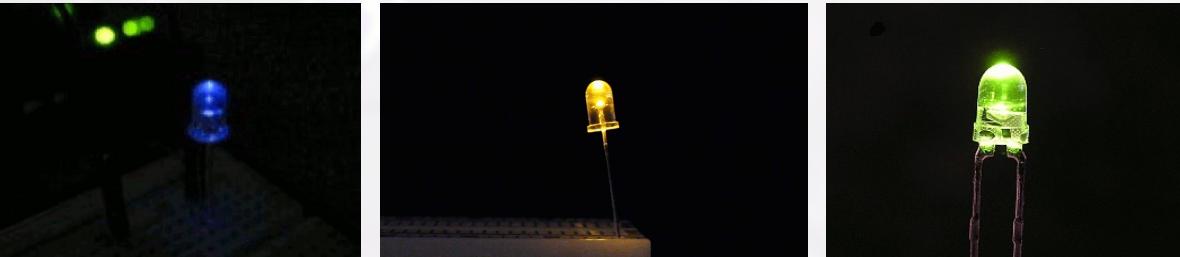


Pattern Reversal



SSVEP: Repetitive visual stimuli (RVS) Types

Light stimuli i.e. LEDs



Modulation depth to quantify the strength of the stimulus

$$\frac{(l_{max}-l_{min})}{(l_{max}+l_{min})}$$

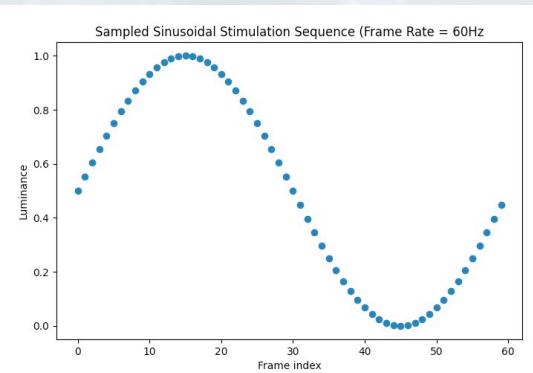
where l is the *luminance* (measure of intensity)

Single Graphics Stimuli:

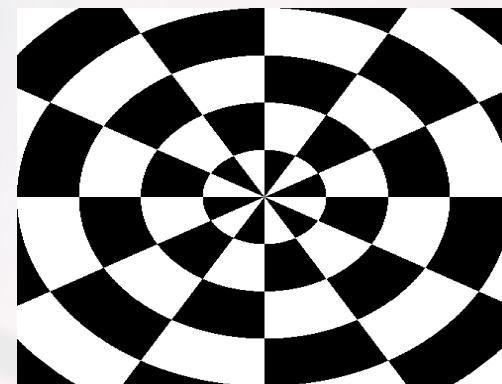
$$s(f, i) = \frac{1}{2} \{1 + \sin[2\pi f(i/\text{Refresh rate})]\}$$

Sampled sinusoidal stimulation.

- Stimulation frequency as the number of full cycles per second.
- The colour contrast.



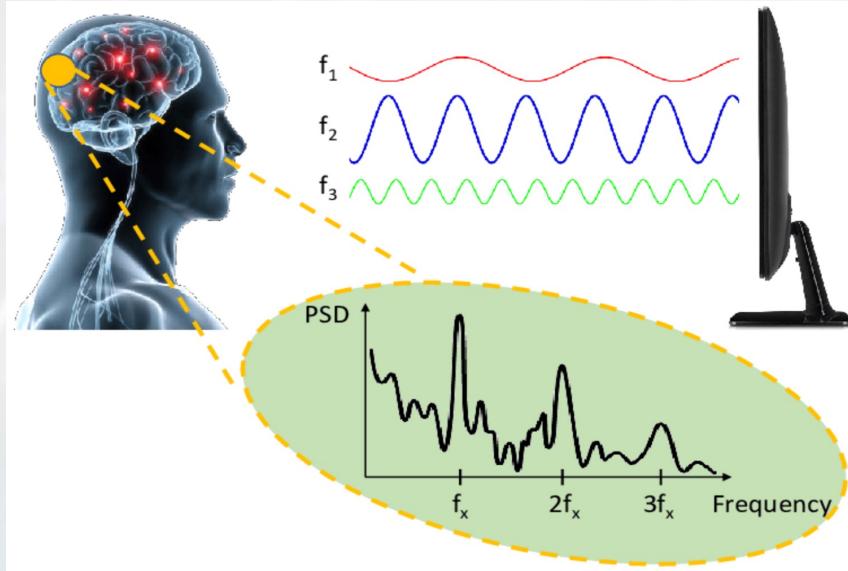
Pattern Reversal :



Oscillatory alternation of two patterns. Patterns are alternated at a certain number of alternations per second.

- Number of reversals per second
- Subtended visual angle of each tile.
- The pattern contrast.

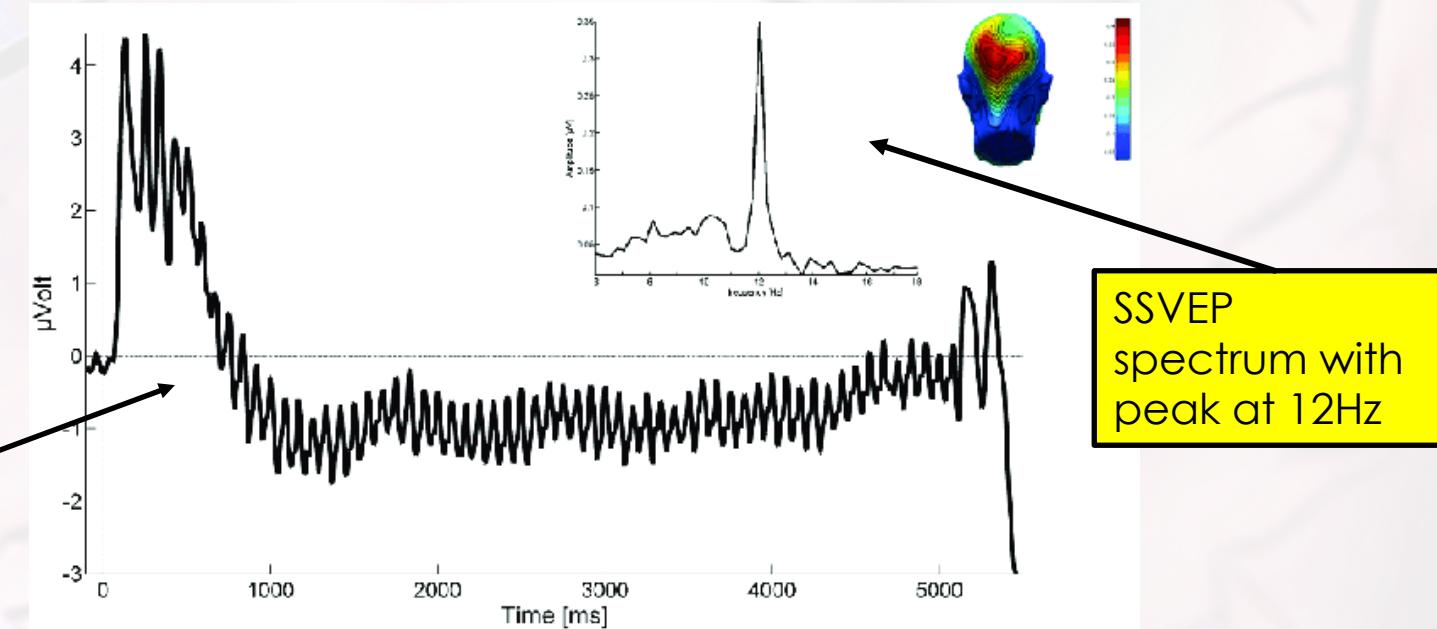
Steady-state Visually Evoked Potential (SSVEP)



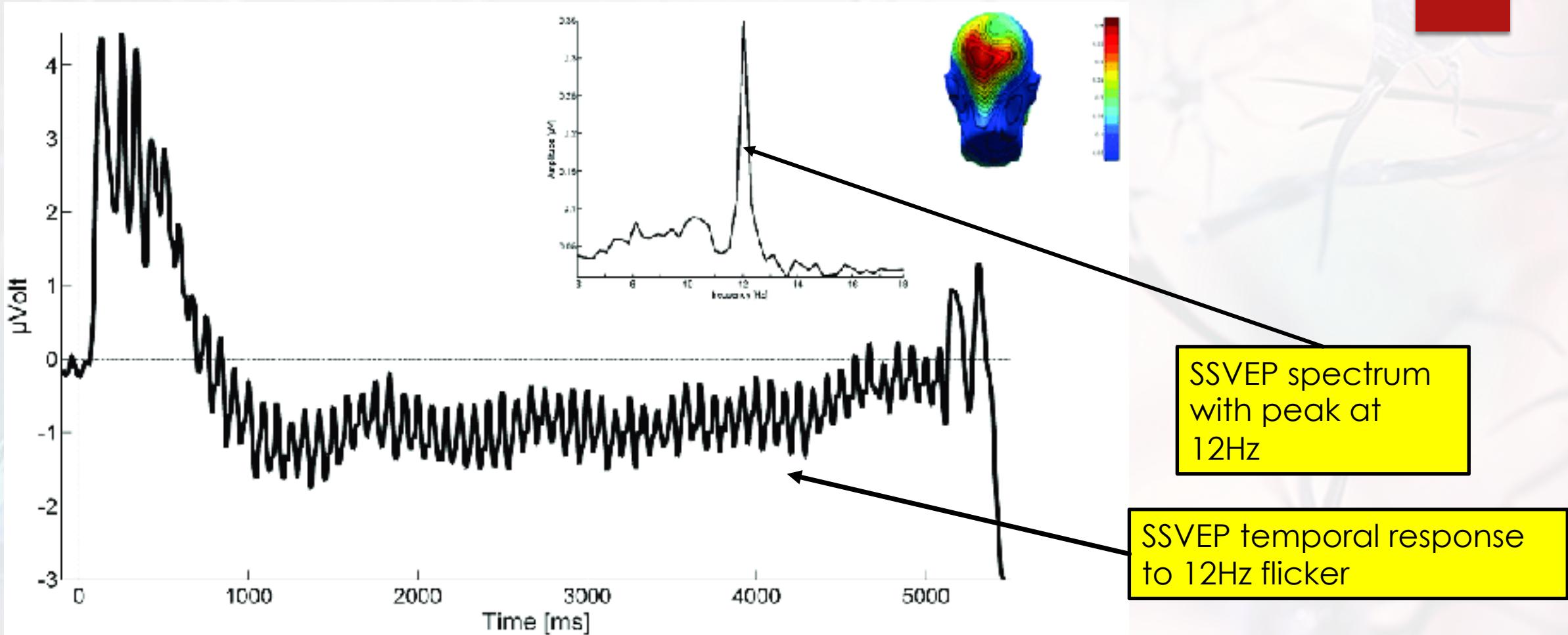
SSVEPs are generated over the occipital region when the retina of the eye is excited with visual stimulus that flickers at fixed frequencies exceeding 4Hz.

Activity in the occipital region of the brain entrains to the rhythmic flickering of the visual stimulus.

Evoked SSVEP is in phase with the flickering visual stimulus.



Steady-state Visually Evoked Potential (SSVEP)



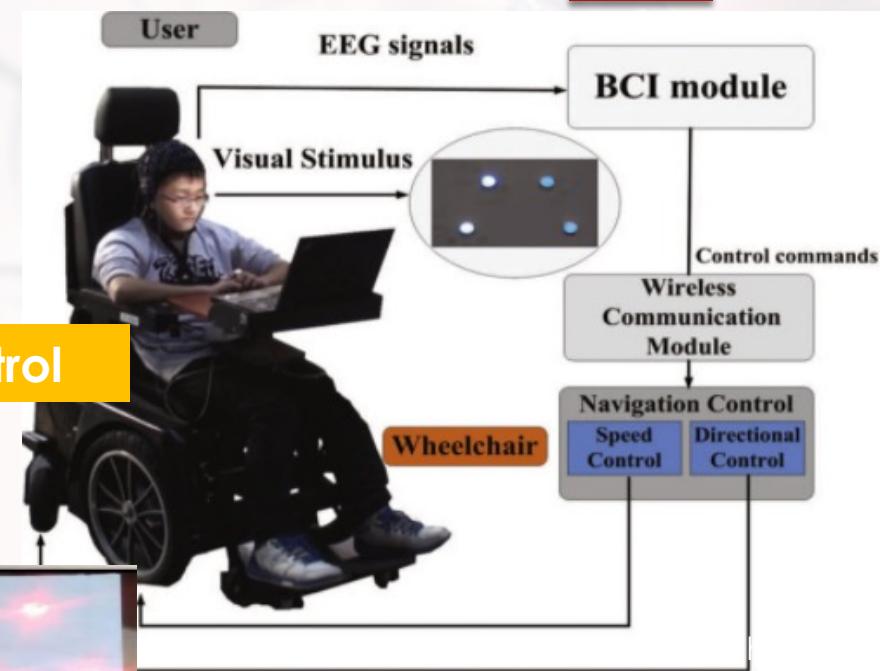
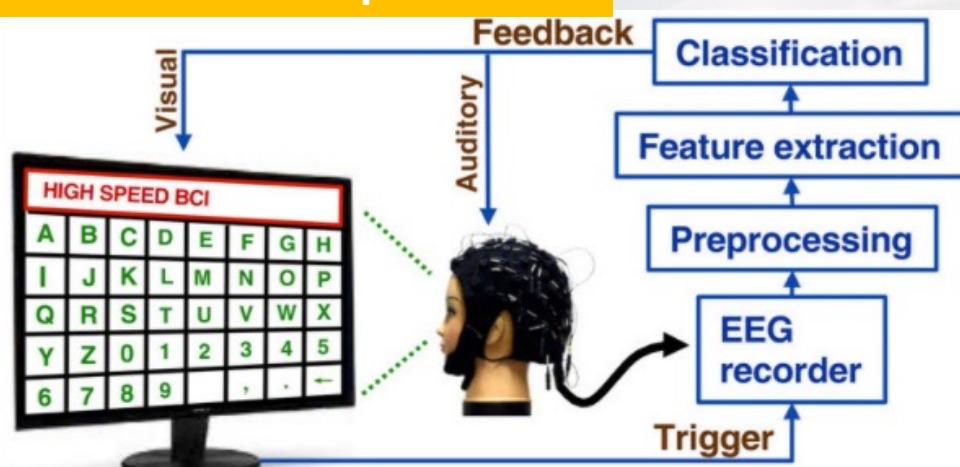
The frequency of the stimulus repetition and its harmonics can be detected in the spectrum of the SSVEP.

SSVEP-Based Brain-Computer Interface

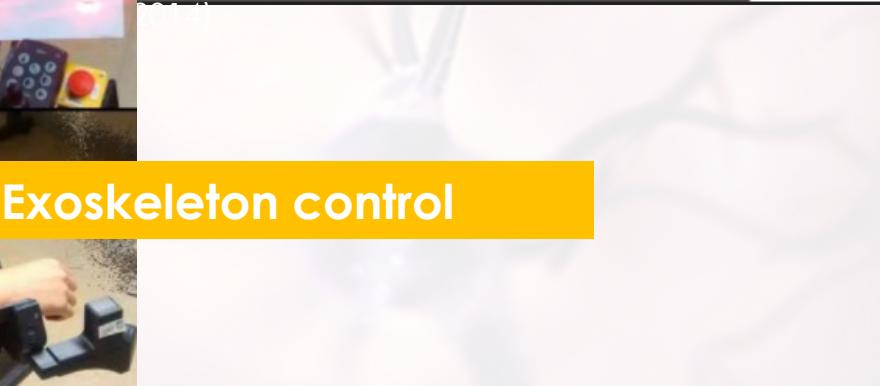
SSVEPs are very popular in the field of BCI due to their:

- Reliability (high accuracy).
- High information transfer rate.
- The protocol is relatively easy to set up.
- It requires little to no training.
- SSVEPs are robust to artifacts.

SSVEP-based Speller



Wheelchair control

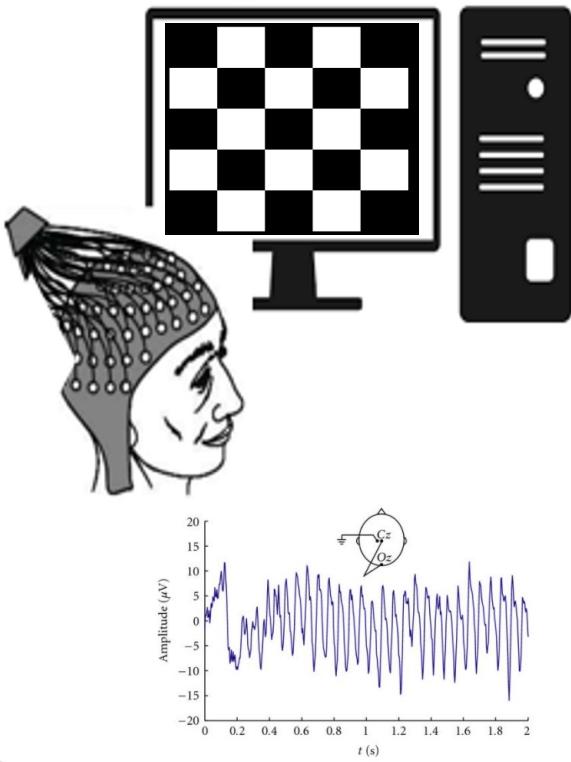


Exoskeleton control

SSVEP: OVERVIEW OF SSVEP-BASED BCI PIPELINE

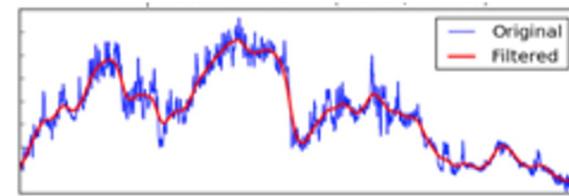
1

Data Acquisition



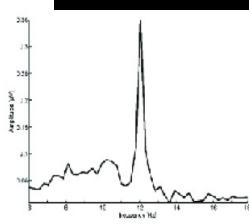
2

Preprocessing



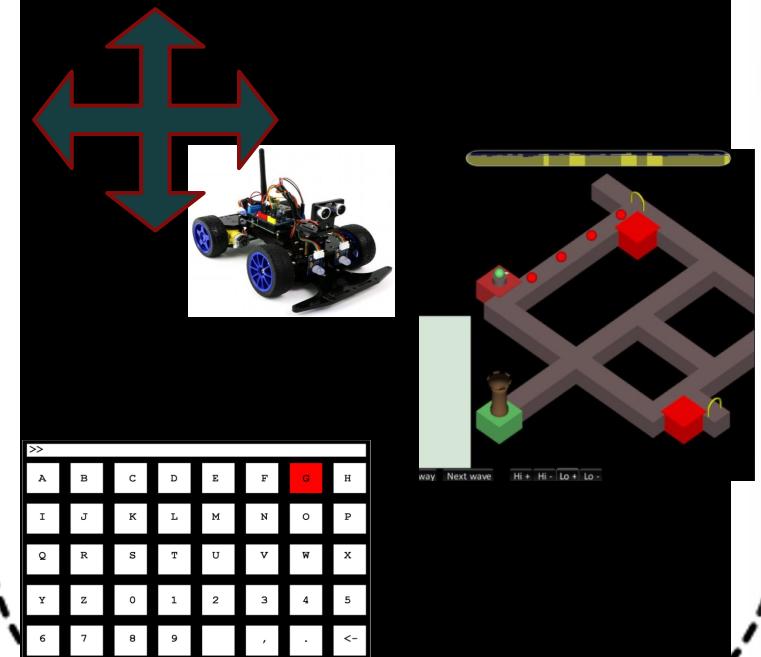
Calculate SSVEP peak frequency

Canonical Correlation Analysis

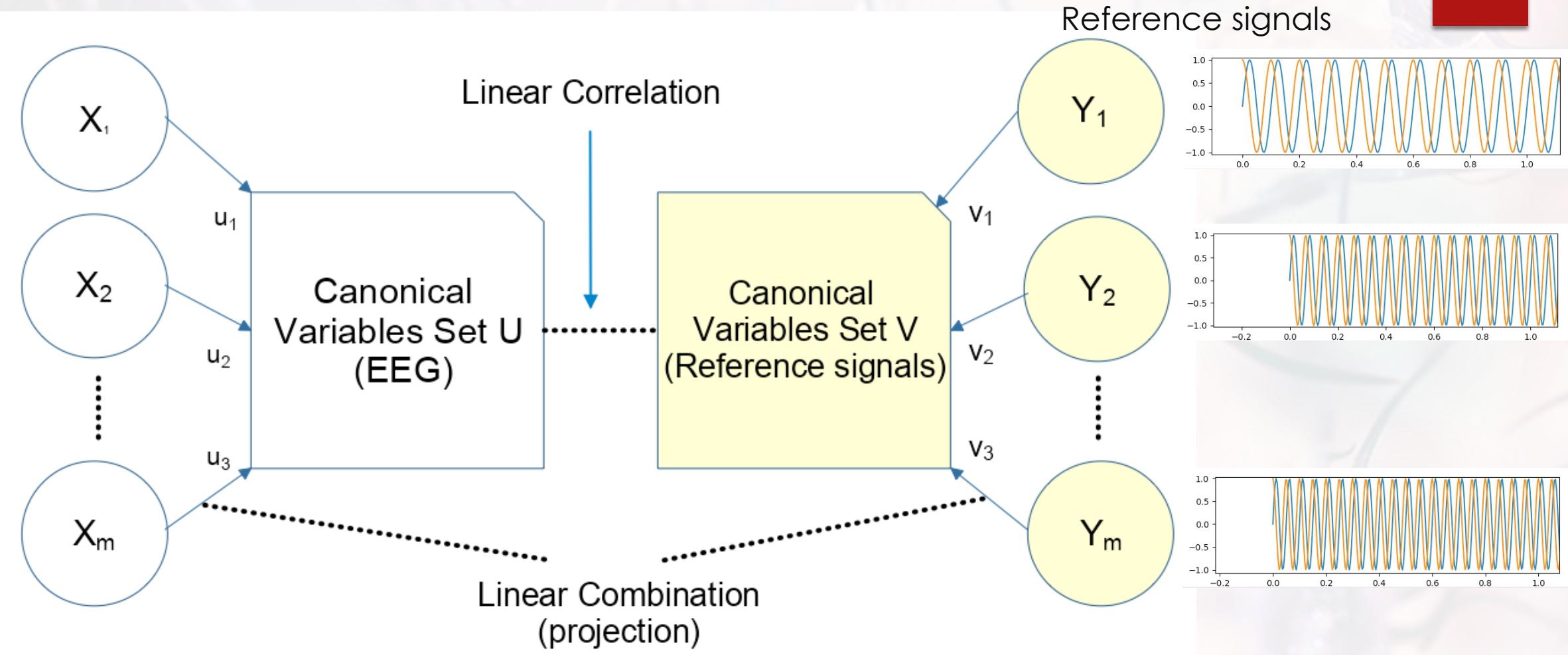


3

Translate into Commands



SSVEP DETECTION: CANONICAL CORRELATION ANALYSIS



Spatial filtering method that finds the linear combination of two datasets that maximizes the linear correlation.

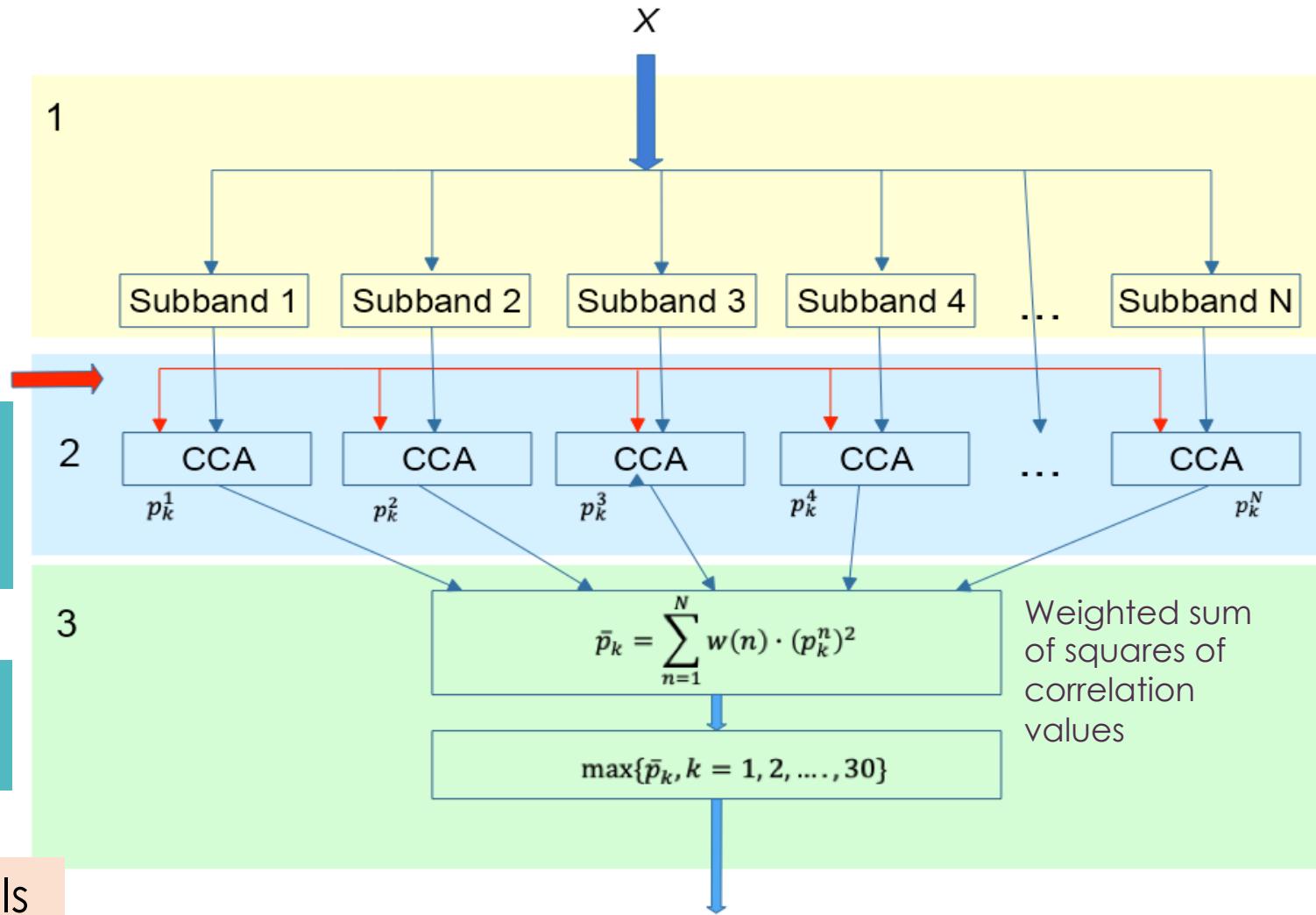
SSVEP Detection: Filter-bank CCA

Sub-band decomposition

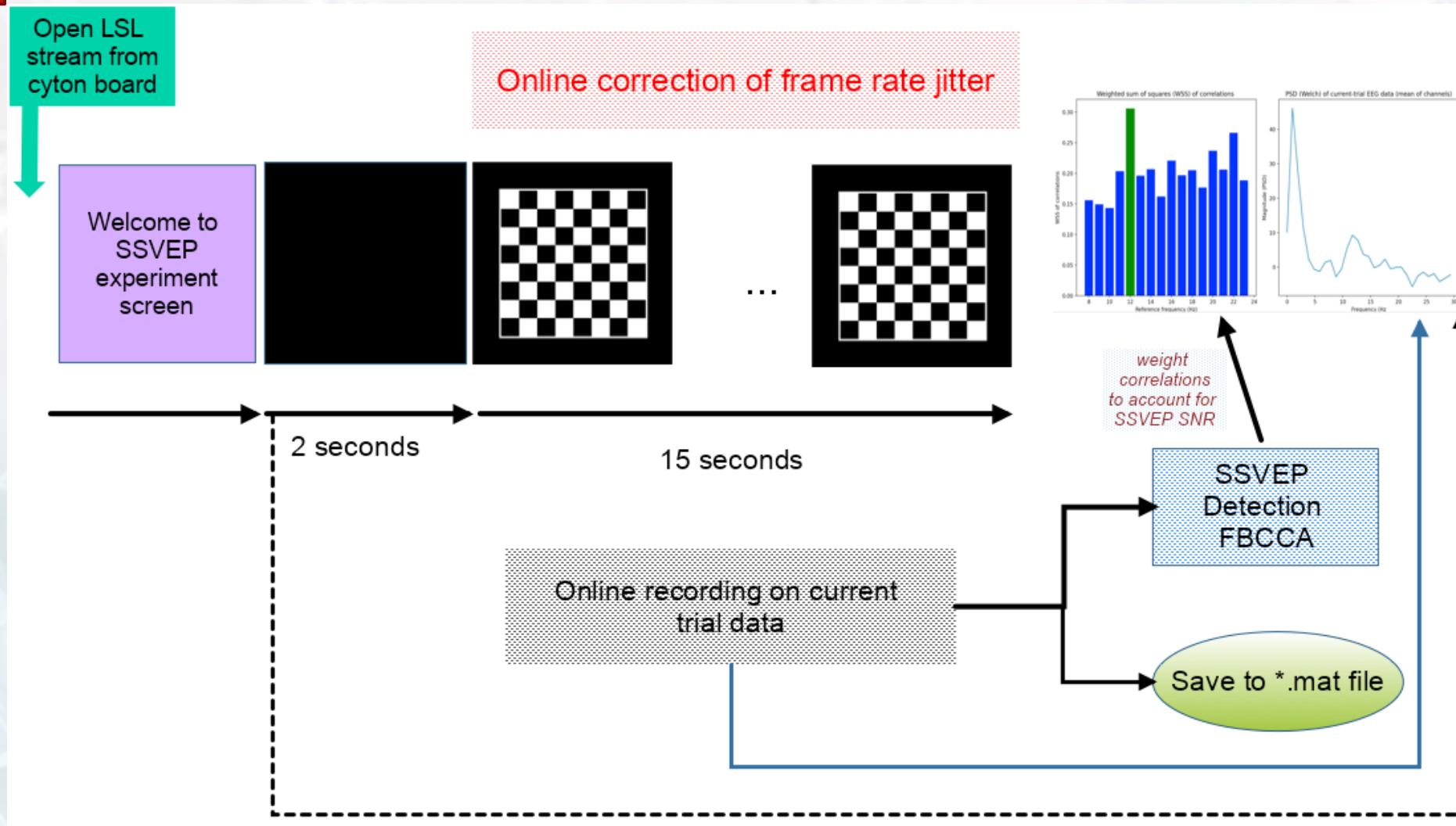
Y_{fk}
Canonical Correlation Analysis (CCA)

Identification of target frequency

Y_{fk} = reference signals



Simple SSVEP-Based BCI



Terminal - geringswald@Q: ~/tools/OpenBCI_GUI

File Edit View Terminal Tabs Help

IPython: home

```
openBCI_GUI: [DEFAULT]: D
[ERROR]: Fai
OpenBCI_GUI: -----
ControlPanel
-----
ControlPanel [WARN]: Foun
Success: Hos
Successfully [DEFAULT]: A
initButtonPr
OpenBCI_GUI: -----
|| -----
OpenBCI_GUI: Sending conf
OpenBCI_GUI: "Arial" is n
InitSettings
SessionSetti [SUCCESS]: S
[DEFAULT]: o
OpenBCI_GUI: -08-28_14-48
OpenBCI_GUI: 28_14-48-21/
Brainflow st [DEFAULT]: D
WARNING: Los
[DEFAULT]: o
Brainflow st [DEFAULT]: D
SHUTDOWN HOO
openBCI_GUI: [DEFAULT]: D
X11Util.Disp g (open in c
X11Util: Ope
X11Util: Open[0]: NamedX11Display[:0.0, 0x7f936c0012c0, refCount 1, unCloseable false]
X11Util: Open[1]: NamedX11Display[:0.0, 0x7f936c019d20, refCount 1, unCloseable false]
geringswald@Q: ~/tools/OpenBCI_GUI$
```

Terminal - geringswald@Q: ~/projects/CREx/summer_school/2022/cours_bci/SummerSchool_2022_BCI/BCI_SSVEP-main

File Edit View Terminal Tabs Help

```
geringswald@Q: ~/projects/CREx/summer_school/2022/cours_bci/SummerSc... x geringswald@Q: ~/projects/CREx/summer_school/2022/cours_bci/SummerSc... x
```

geringswald@Q: ~/projects/CREx/summer_school/2022/cours_bci/SummerSchool_2022_BCI/BCI_SSVEP-main\$

Sci/BCI_SSVEP-main/record_data.py - Mousep

utilsSSVEP.py Untitled 7

```
ip.argmax(scores)]) + "Hz")
```

installation_notes Videos

| Type | Date Modified |
|---------------------|-------------------------------|
| Folder | Fri 26 Aug 2022 20:01:21 CEST |
| Folder | Fri 26 Aug 2022 19:56:19 CEST |
| Folder | Mon 01 Aug 2022 12:44:22 CEST |
| Folder | Mon 01 Aug 2022 11:19:31 CEST |
| Folder | Mon 01 Aug 2022 10:49:19 CEST |
| Folder | Mon 01 Aug 2022 03:10:01 CEST |
| Folder | Fri 29 Jul 2022 14:37:28 CEST |
| Folder | Fri 29 Jul 2022 12:11:35 CEST |
| Folder | Thu 28 Jul 2022 18:57:59 CEST |
| Folder | Thu 28 Jul 2022 18:50:57 CEST |
| Folder | Thu 28 Jul 2022 18:31:11 CEST |
| Folder | Thu 28 Jul 2022 18:25:06 CEST |
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| Folder | Thu 28 Jul 2022 12:29:32 CEST |
| Folder | Thu 28 Jul 2022 12:16:10 CEST |
| plain text document | Sun 28 Aug 2022 15:32:28 CEST |
| MPEG-4 video | Sun 28 Aug 2022 15:31:03 CEST |

graphical object
ind. (b) In pattern
ted at a specified

Filetype: Python UTF-8 Line: 325 Column: 31 Selection: 2 OVR

Navigate to Dining Room, turn on the Lamp, and return to the Living Room. The accuracy of the commands is R-R-R-R-D-R-R-D-U-L-L-L-L.

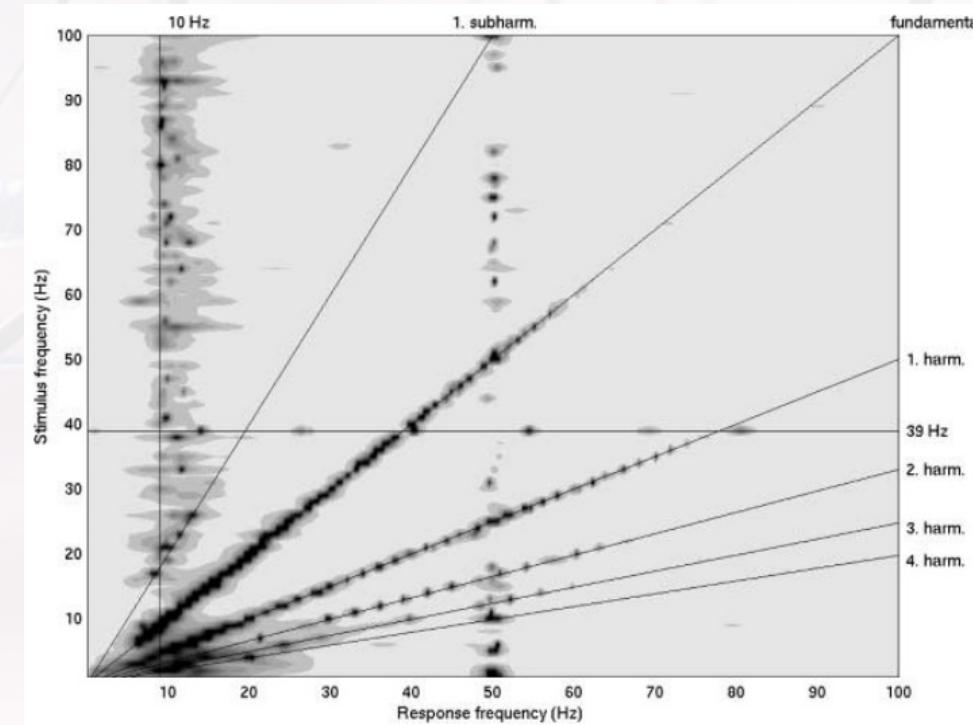
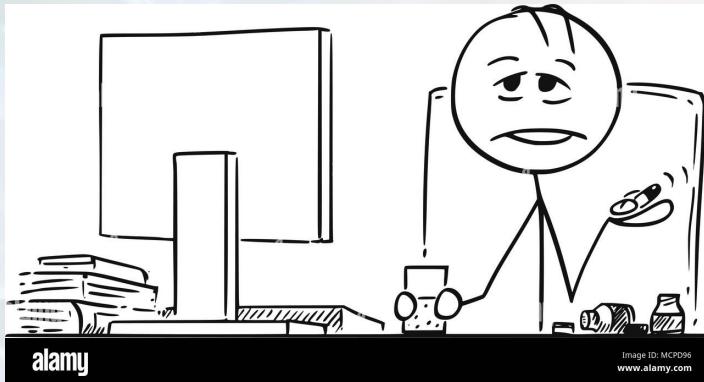
accuracies of

Page 24 of 24 7,490 words, 46,487 characters Default Page Style

110% 120%

Steady-state Visually Evoked Potential (SSVEP) Discussion

- What are limiting factors of the SSVEP-BCI?
 - Stimulus presentation
 - Hardware
 - User
 - Feature Selection (EEG Signal)
 - Frequency



Herrmann
(2001)

Q. Is SSVEP-based BCI « dependent » or « independent » BCI ...Why?

A. It is dependent.

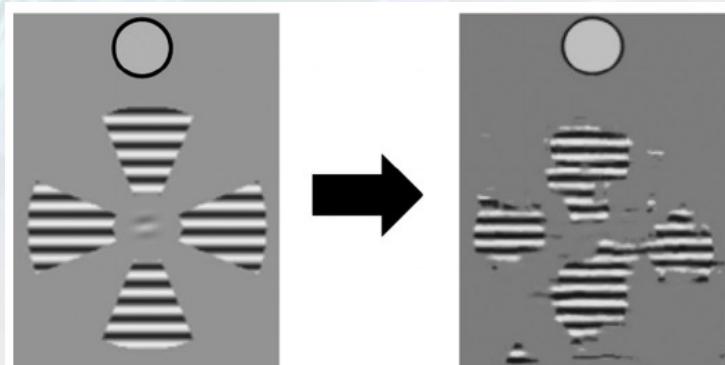
The participant uses their eye muscles to focus on the target stimulus gaze control.

Steady-state Visually Evoked Potential (SSVEP) Discussion

- SSVEP-BCIs: visual stimuli
 - the human visual field
 - the role of eye movements
 - dependent versus independent BCI
 - covert versus overt attention



Marmor & Marmor
(2010)



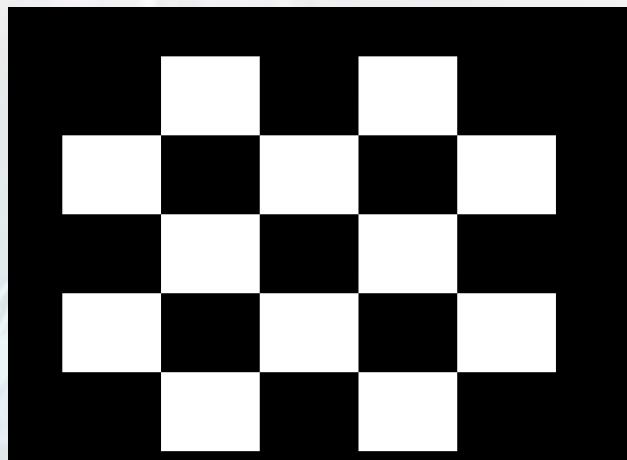
Rosenholtz et al. (2019)



Rosenholtz et al. (2012)

Steady-state Visually Evoked Potential (SSVEP) Discussion

- SSVEP-BCIs: visual stimuli
 - adapted stimuli (scaling according to eccentricity)
 - spatially overlapping stimuli



vs

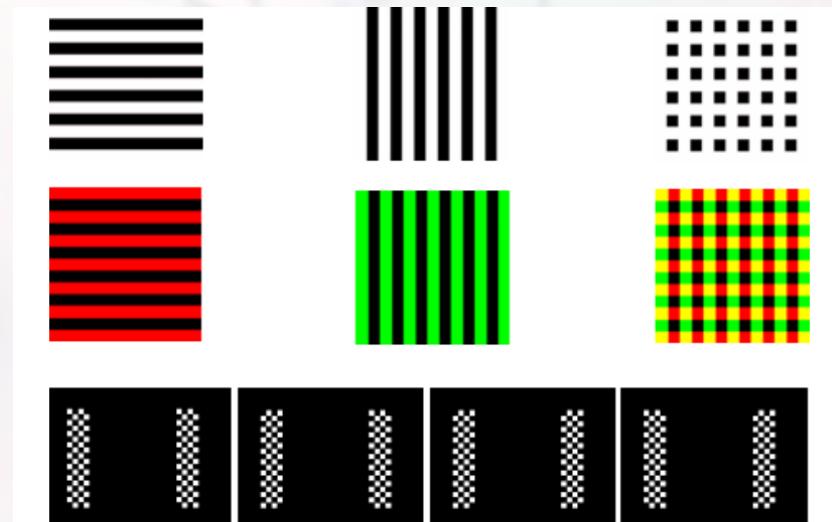
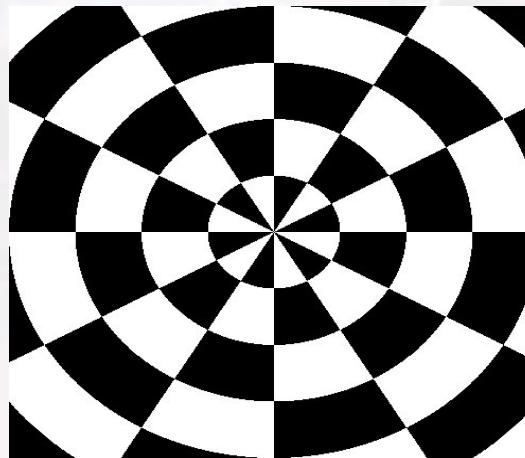


Figure 1.

The top row presents the three images used in the BW linebox condition, and the middle row contains three images used in the color linebox condition. The four images used in the BW checkerbox condition are on the bottom row.

Allison et al. (2008)



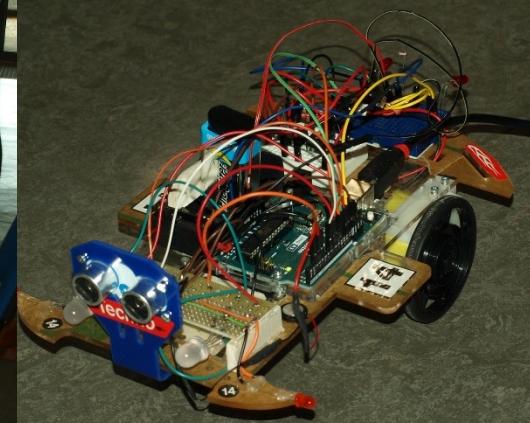
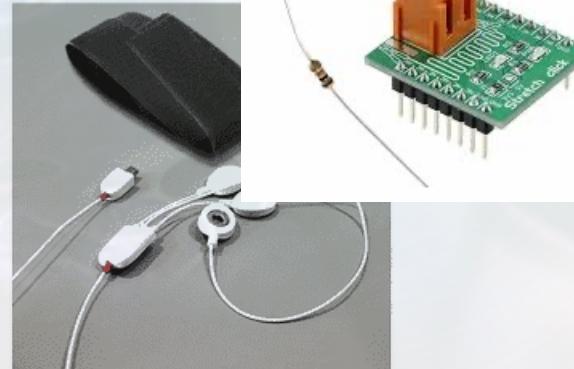
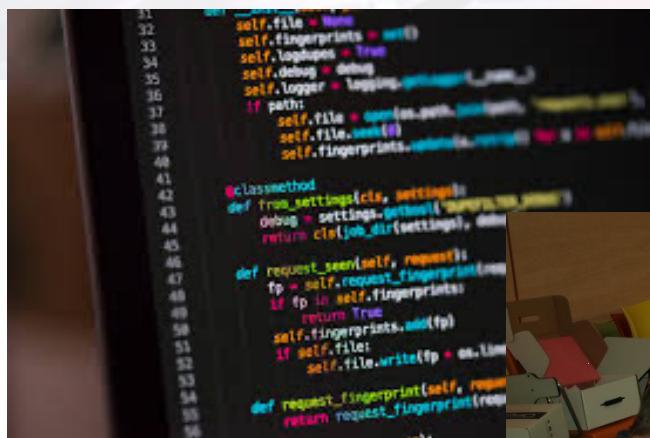
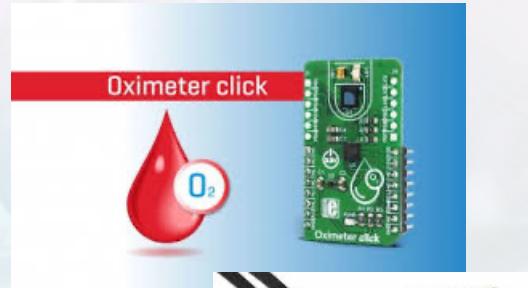
CONCLUSION

Brain-Computer Interface (BCI): Conclusion

BCI

- Designing a BCI is a complex and difficult task that requires knowledge of several disciplines (computer science, electrical engineering, signal processing, neuroscience, psychology)
- Many ongoing challenges
 - Illiteracy (using an interactive, co-learning approach)
 - Long-term use of BCIs: health implications or change in brain functionality?
 - Ethical standards: liability in case of accidents, appropriate use of bio-signal data, privacy (marketing, political agendas) #
- Open community (software, hardware)

For more of this fun...UE Ingénierie Cognitive

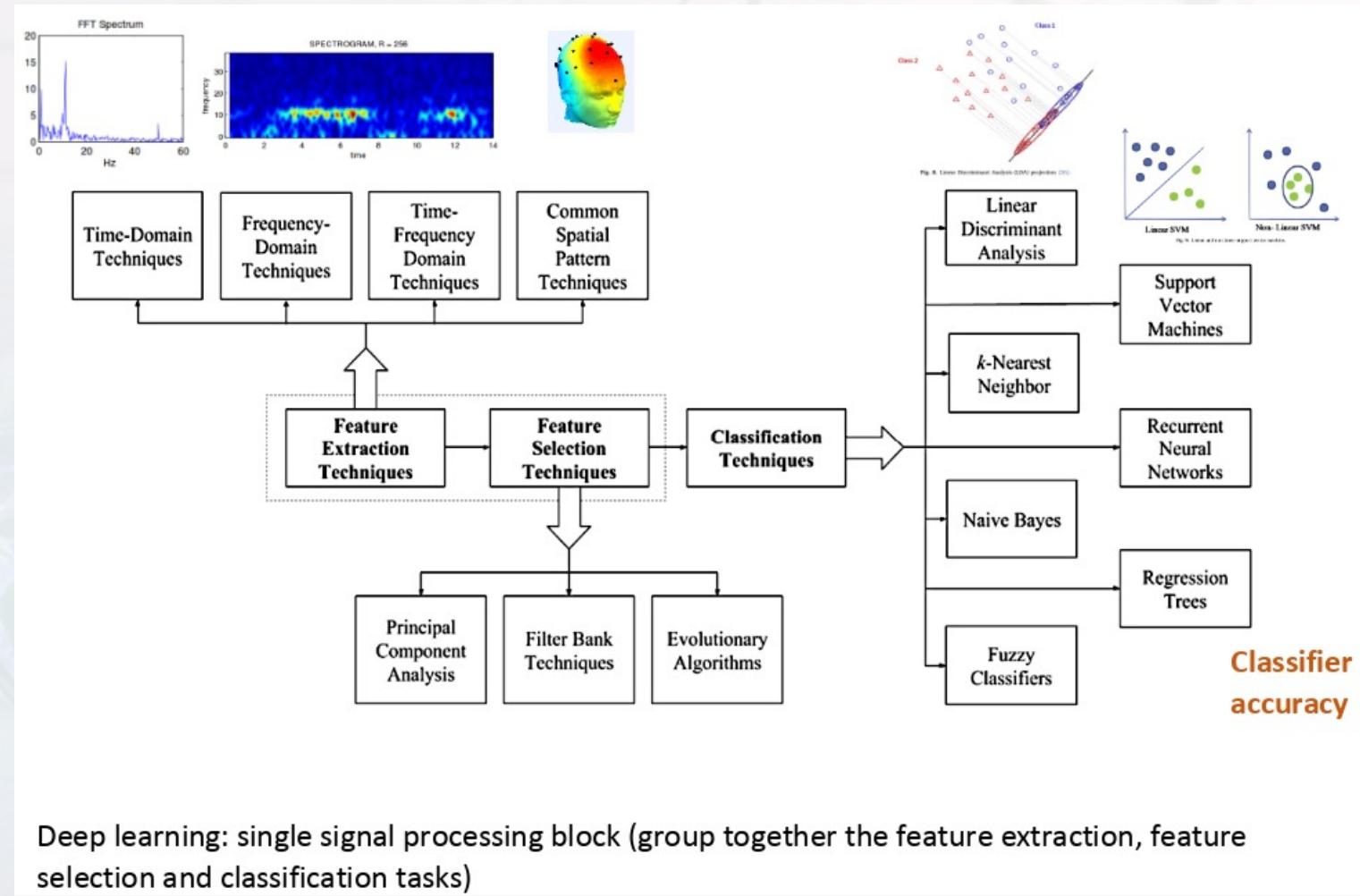




**Thank you for your attention in
this...
Brains-CREx Interface!**

Brain-Computer Interface (BCI): Introduction

BCI architecture: Signal Processing



adapted from Padfield et al.
(2019)