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# An introduction to Brain Computer Interface

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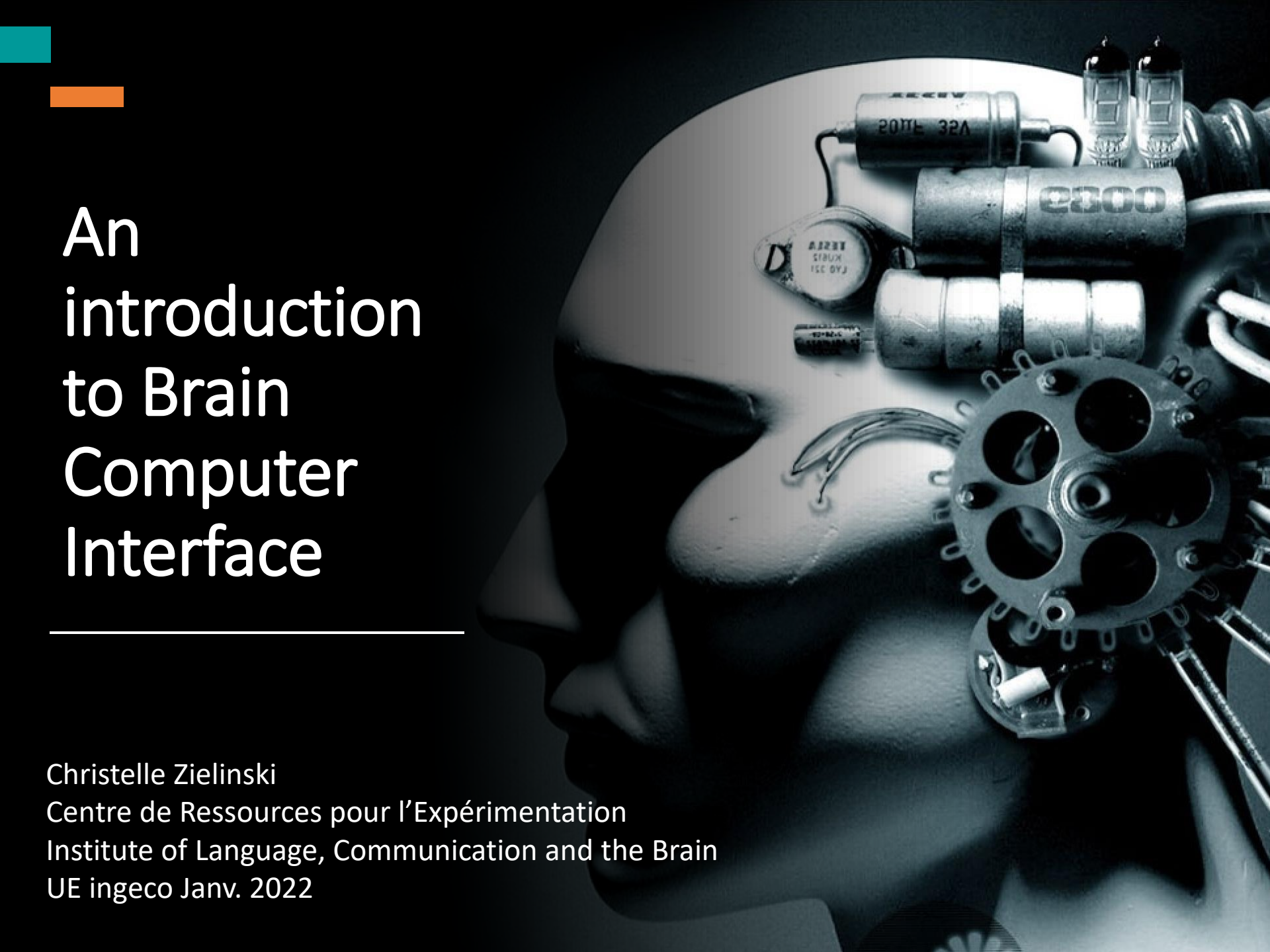
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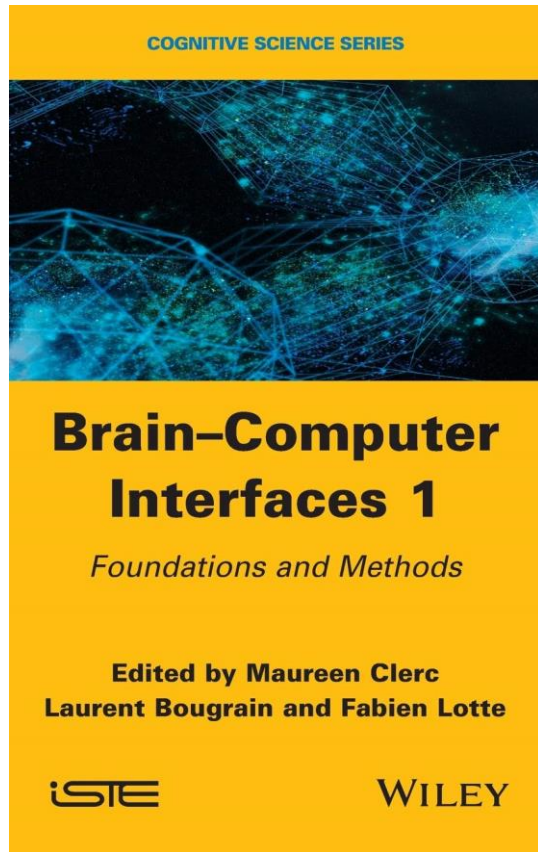


# An introduction to Brain Computer Interface

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UE ingeco Janv. 2022

# An introduction to Brain Computer Interface



## Understanding & Improving Mental-Imagery Based Brain-Computer Interface (Mi-Bci) User-Training : towards A New Generation Of Reliable, Efficient & Accessible Brain- Computer Interfaces

Camille Jeunet

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sensors



Review

## EEG-Based Brain-Computer Interfaces Using Motor-Imagery: Techniques and Challenges

Natasha Padfield <sup>1</sup>, Jaime Zabalza <sup>1</sup>, Huimin Zhao <sup>2,3,\*</sup>, Valentin Masero <sup>4</sup> and Jinchang Ren <sup>1,5,\*</sup>

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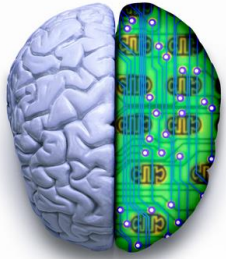
<sup>5</sup> School of Electrical and Power Engineering, Taiyuan University of Technology, Taiyuan 030024, China

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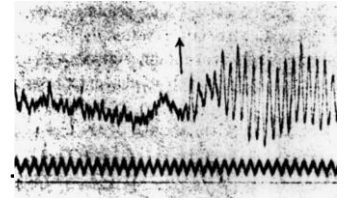
# Brain Computer Interface



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

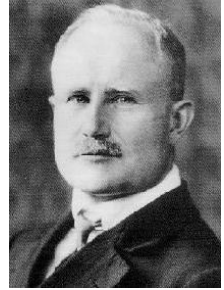
- To consciously act and communicate without using our muscles
- Target population has been people with motor disabilities and preserved cognitive functions (assistive devices)
- Recent years: rehabilitation of motor or even cognitive functions for patients after CNS injury, brain state monitoring for healthy subjects, and new tools for studying human brain functions

# Historical events



\* **1875** Richard Caton (UK medical Dr), the pioneer in electrophysiology: the brain produces electrical activity (electrodes in dog's brain)

\* **1924** Hans Berger (German psychiatrist and neurologist), the father of the EEG – 1st human EEG, alpha wave description, alteration during epileptic seizures



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

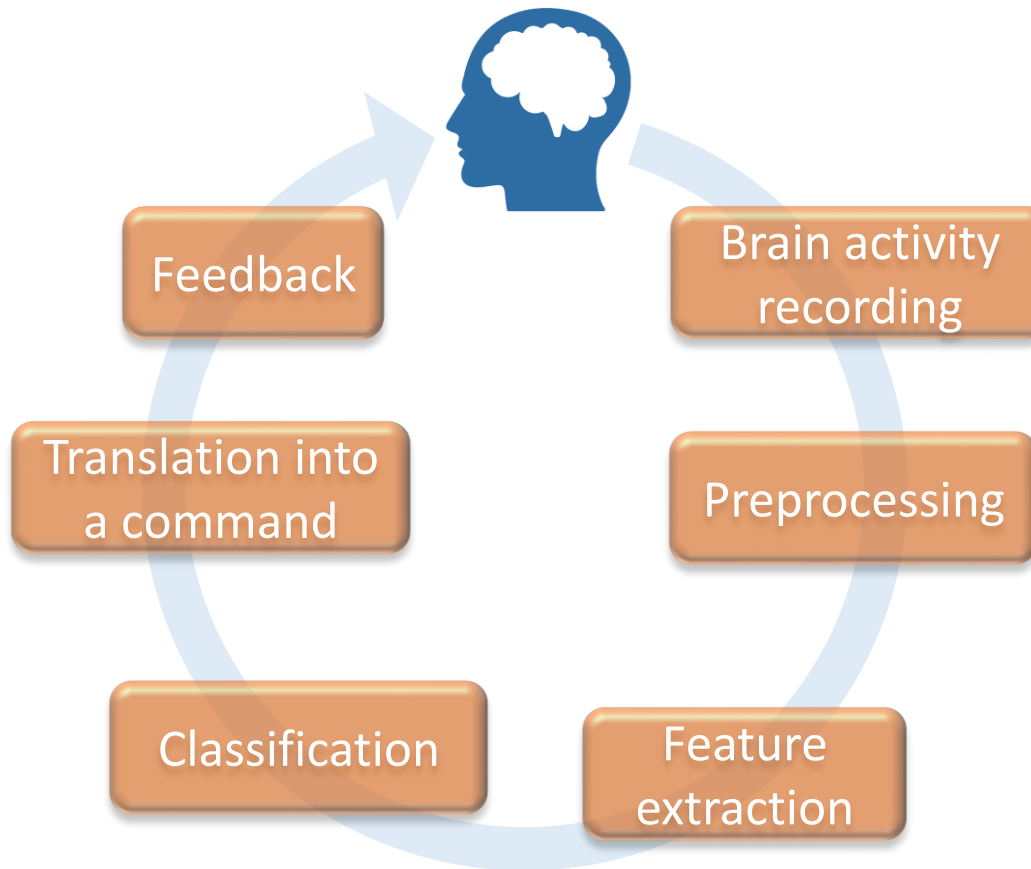
~~~ 1970 – development of computer sciences, simple app using neurofeedback ~~~

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

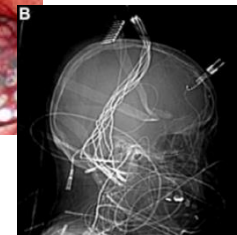
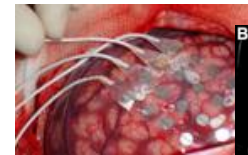
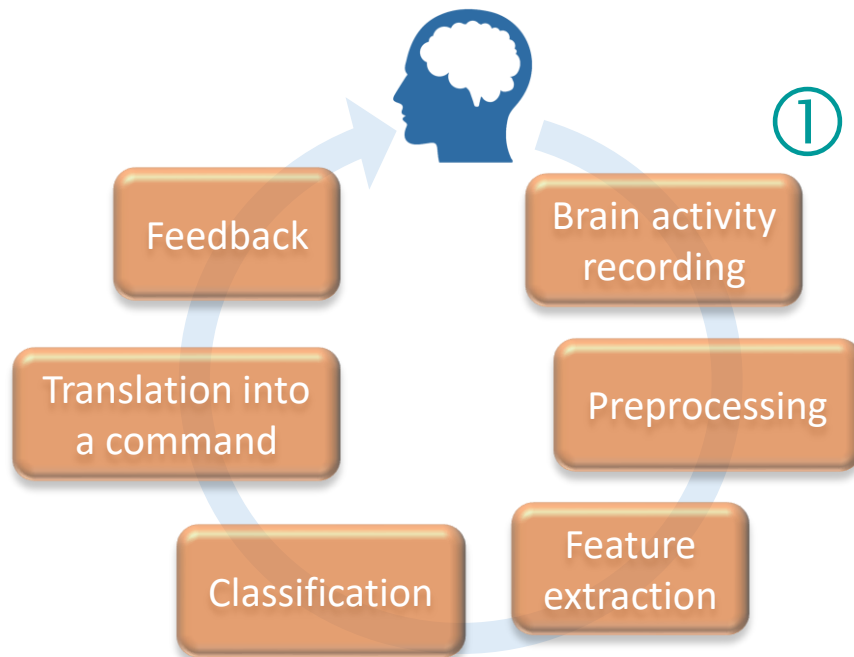
\* **1973** Pr. Jacques Vidal (computer science, Los Angeles) – 1st description of the concept of BCI in “Towards direct brain-computer communication”

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

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



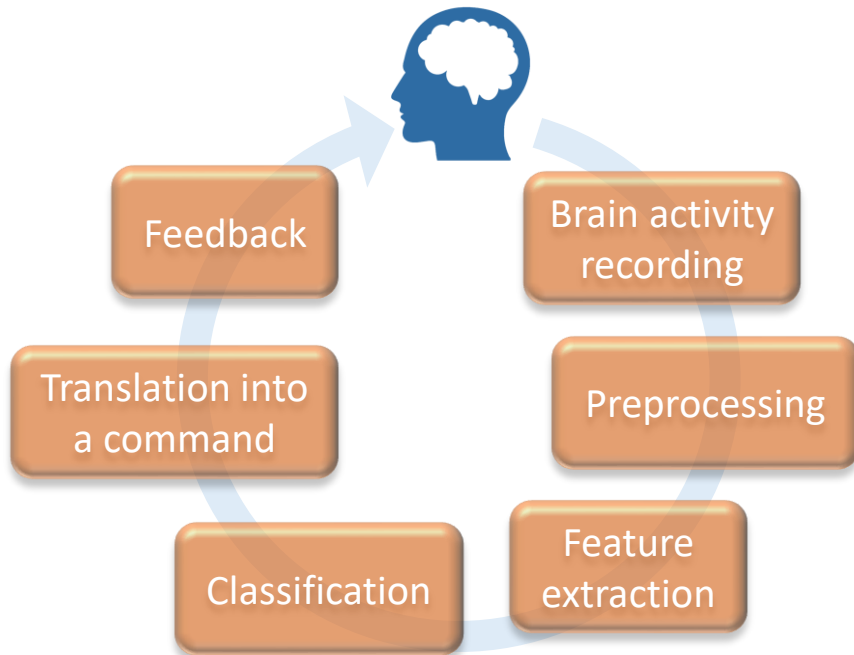
Closed loop systems usually composed of 6 main stages



Acquisition of raw data that reflect the user's brain activity

EEG widely used:

- ✓ non-invasive, high time resolution, potential for mobility, low cost
- ✗ processing challenges: non-stationary, external noise, signal artefacts



2

Figures 8 to 11 depict four examples for artifacts in EEG devices:

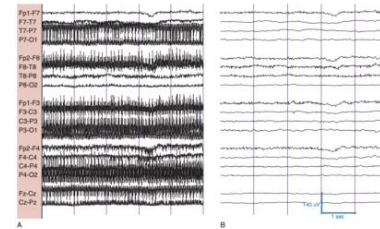


Fig. 8: 60Hz power line artifacts without (A) and with (B) an applied filter (from Marcuse et al., 2016, p. 34).

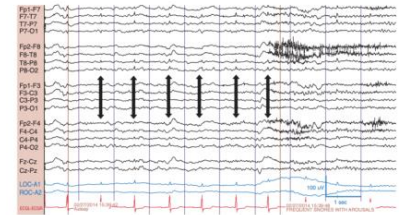


Fig. 9: The arrows indicate ECG (electrocardiography - heart muscle) artifacts (from Marcuse et al., 2016, p. 20).

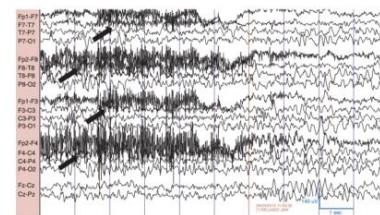


Fig. 10: Marked by the arrows are jaw muscle artifacts (from Marcuse et al., 2016, p. 27).

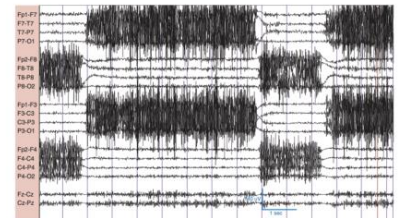
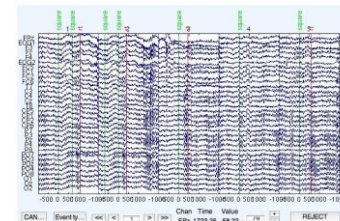
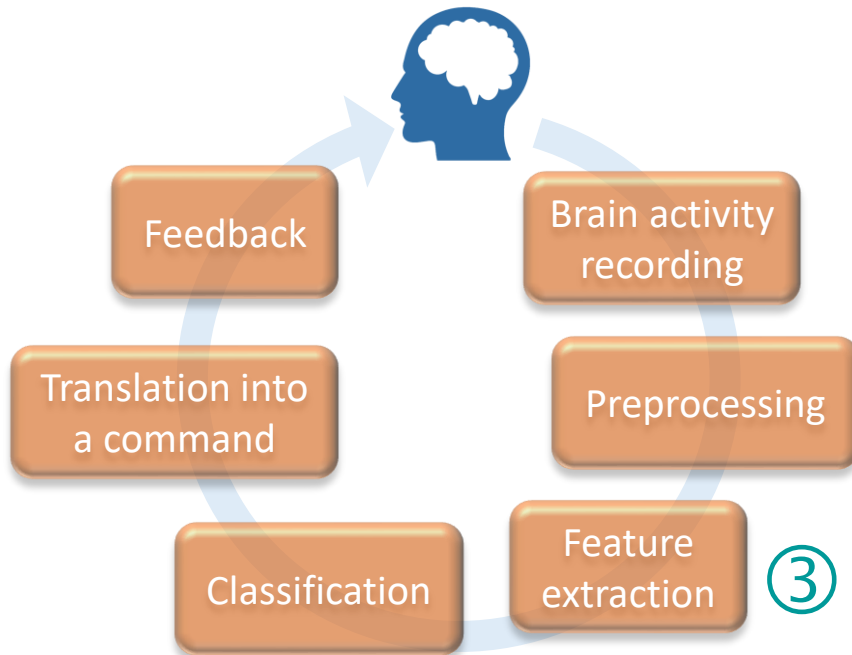


Fig. 11: These highly disruptive artifacts were produced by alternating tooth grinding (from Marcuse et al., 2016, p. 28).

Cleaning up and reducing noise from raw data to extract the relevant information





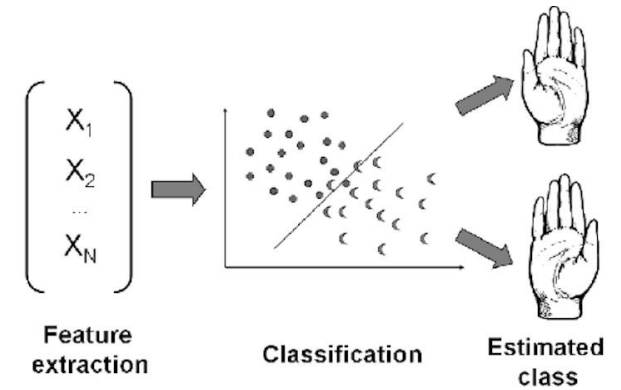
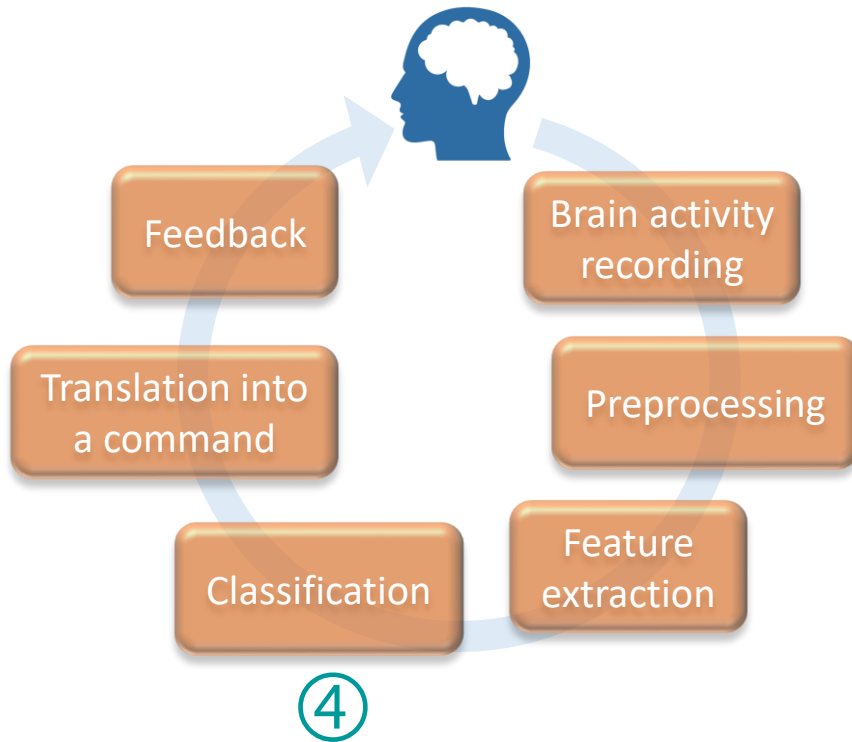
$$\begin{pmatrix} X_1 \\ X_2 \\ \dots \\ X_N \end{pmatrix}$$

Ex. Band power in the mu and beta rhythms in C3 and C4

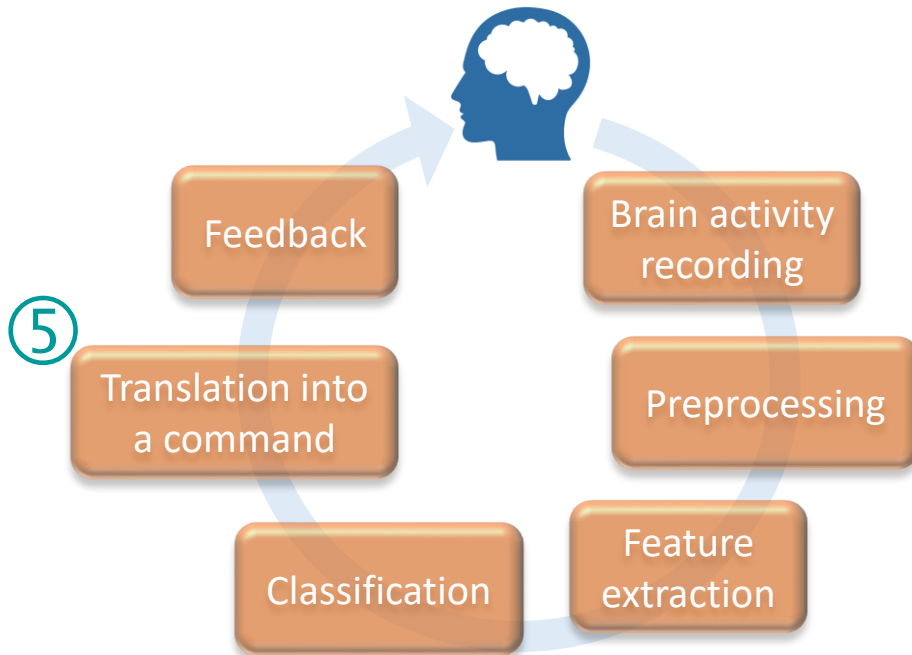
Extraction of discriminative and non-redundant information from the EEG to form a set of features on which classification can be carried out

Certain patterns of brain signals that can be categorized into task-specific brain state (ex. right hand movement)

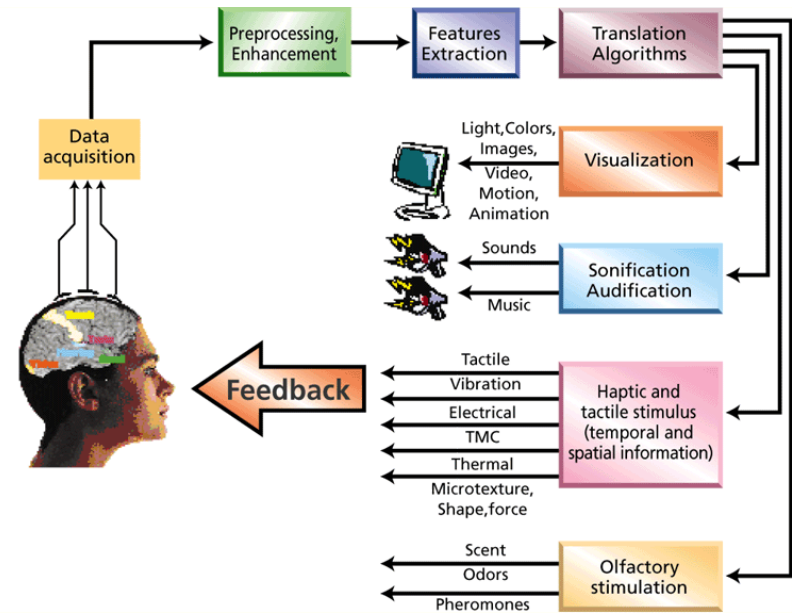
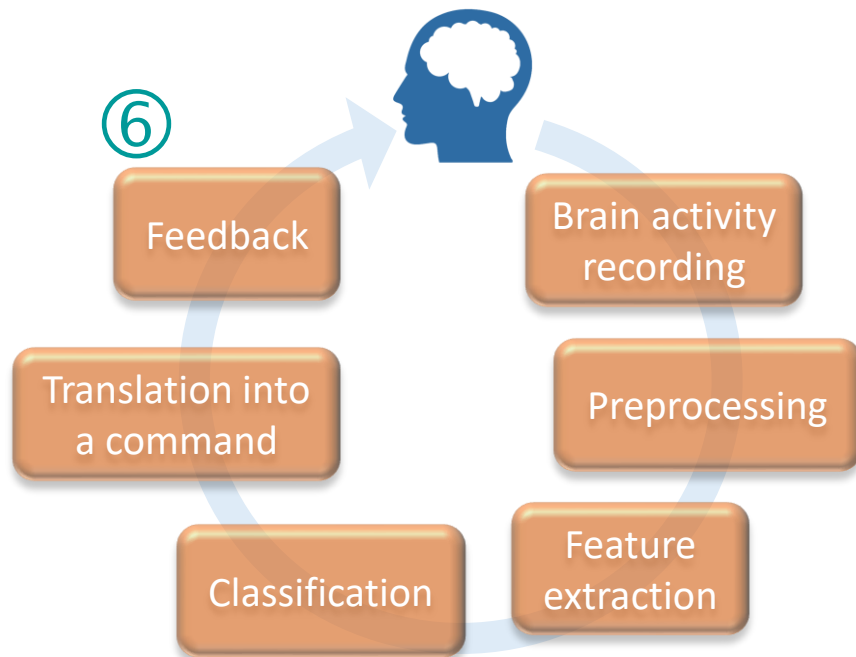
The feature extraction method depends on the type of mental task



Associates a class to a set of features – machine learning



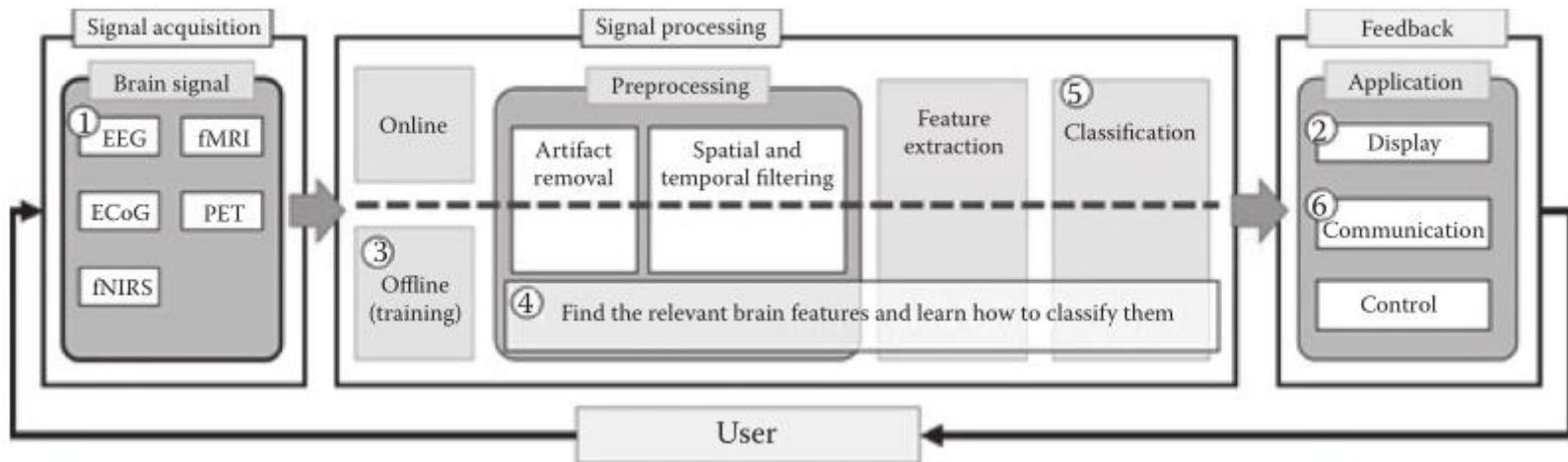
Associates a command with the identified brain activity pattern / intention  
Software / Hardware



The brain activity pattern that have been recognized → user

Helps the user to learn to modulate brain activity to improve the control of the BCI

# Offline/Online steps

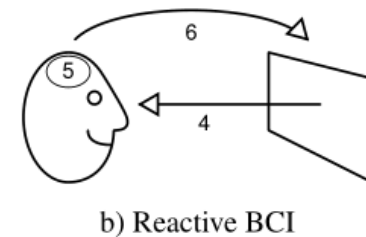
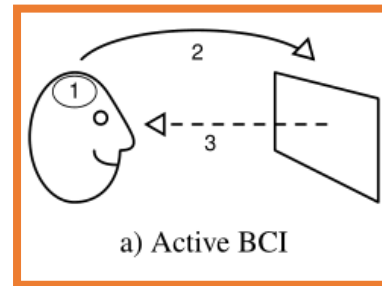


**(1) an offline calibration stage**, during which the system's settings are determined

**(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*

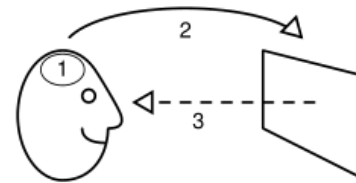
## Active / Reactive / Passive



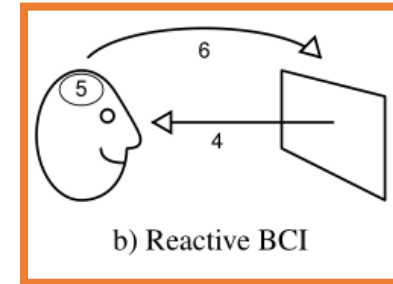
### Active

- user actively employed by performing mental task to control the system (endogen origin) (ex. imagine hand movement)
- 2 main paradigms: Slow Cortical Potential based BCIs (SCP-BCI) and Mental-Imagery based BCIs (MI-BCI)

## Active / Reactive / Passive



a) Active BCI



b) Reactive BCI

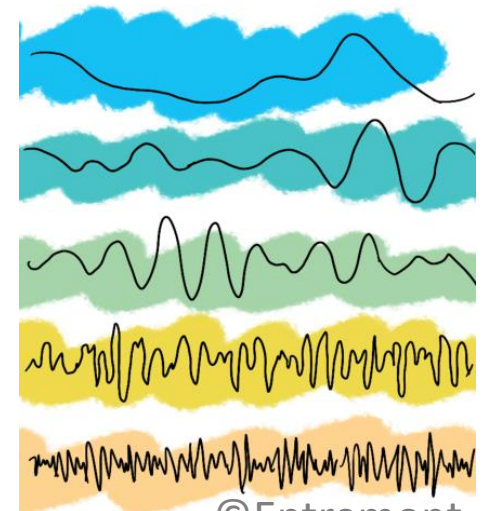
## Reactive

- employs the user's brain reactions to given stimuli (exogen origin)
- Visual, auditory or sensory stimulation
- ERP-based (P300) and Steady-State Visually Evoked potentials (SSVEPs)

## Active / Reactive / Passive

### Passive

- passively analyses the user's mental state in real time
- ex. their cognitive (workload), emotional (frustration) or motivational states, which can also be combined with other physiological and behavioral data
- an application/the environment can be adapted to the user's state (ex. user not motivated for an exercise, exercise can be modified)
- Cerebral rhythms...





# BCIs properties

Active / Reactive / Passive

Synchronous / asynchronous

user can only control a BCI at specific times / at any time

Dependent / independent

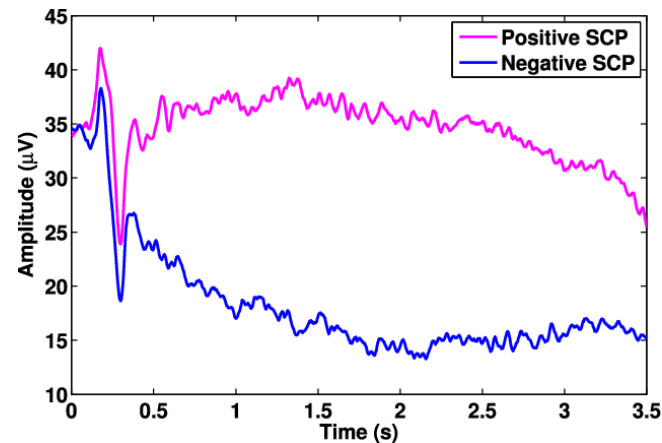
depends on motor control (ex. user has to move his eyes to observe a stimuli) / without any movement at all

Invasive / non-invasive

Hybrid

combination of BCIs (ex. MI task + brain responses to stimuli SSVEP, to release the cognitive load); BCI + non-cerebral commands (muscular signals) or other interaction mechanisms (mouse)

## Slow Cortical Potential



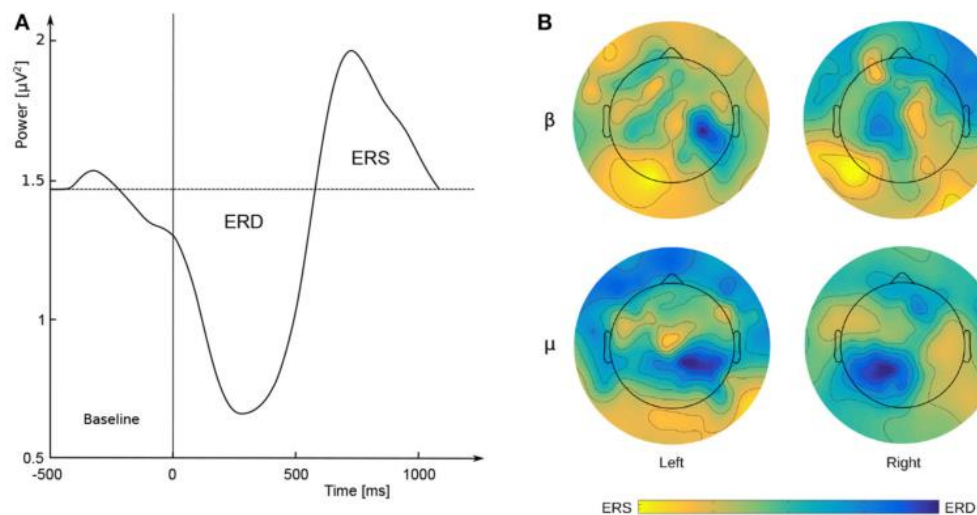
Top target

Bottom target

- Voluntary variations of slow cortical potentials
- Cognitive ERP triggered from 300ms to several s after an internal or external event (expected) occurs - **internal**: people can train to modulate the SCP (positively or negatively with respect to the baseline) in a self-paced way
- Extensive training (~3 months) to learn to control SCPs
- First SCP-BCI enabling to control a spelling device: “A spelling device for the paralysed”, Birbaumer et al., 1999

## Mental-imagery task

- Mental tasks: motor-imagery of the limb, mental calculation or navigation
- Induce in specific cortical regions:
  - 1°) Event-Related Desynchronisation (ERD – while being performed)
  - 2°) Event-Related Synchronisation (ERS – once the user has stopped)



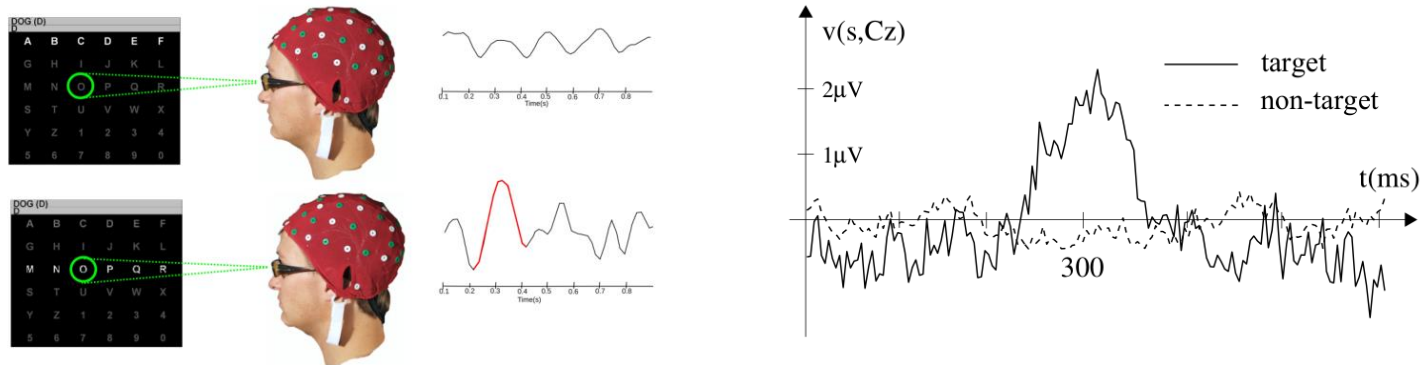
Ex. ERD/ERS during motor imagery tasks (Left/Right hand movements)

## Mental-imagery task

- ERD/ERS
  - can “be considered to be due to a decrease or an increase in synchrony of the underlying neuronal populations” (Pfurstcheller et al)
  - suggested to reflect cortical activation and deactivation
- Rather natural and intuitive to use, since their users “just” have to imagine a specific task to send control commands
- Enable asynchronous control and do not require valuable attentional resources // reactive BCI
- Co-adaptation user / machine - substantial training to find the correct imagination strategy that leads to the most distinct ERD/ERS
- Can currently only be used with a maximum of 3 or 4 different MI tasks to ensure maximal performances (recognition accuracy)

## P300

- Landmark technologies
- Positive cortical potential around 300 ms after the occurrence of a rare and relevant event which is expected by the user (ERP) [parietal lobe]

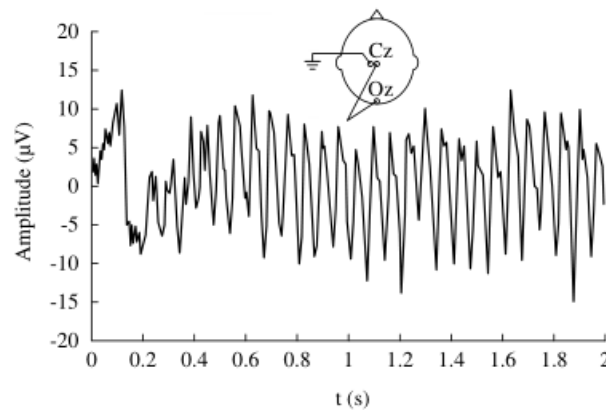


- No much user-training requiring and very reliable
- Results need to be integrated over several stimuli: computational time
- Considerable attentional resources, preventing use in interactive situation that requires high levels of attention (such as navigation and control)

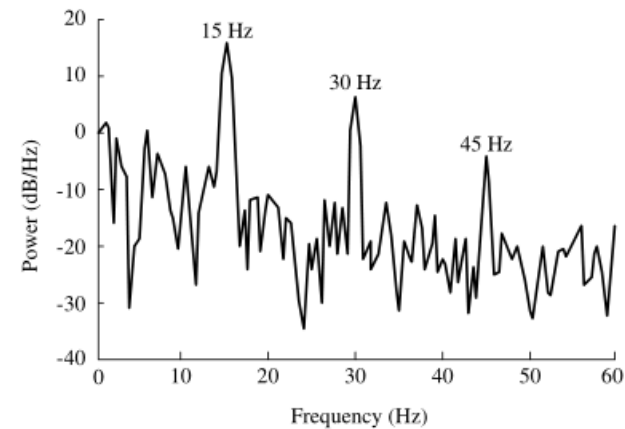
# Markers examples / Reactive BCI

## SSVEP / SSSEP / ASSEP

- Looking at (or paying attention to) a **flashing stimulus** at a frequency  $f$  produces potential variations in the occipital lobe at a close frequency  $f$  (over-representation of the fovea)
- Detectable by a frequency analysis (Fourier) amplitude/phase.



a)

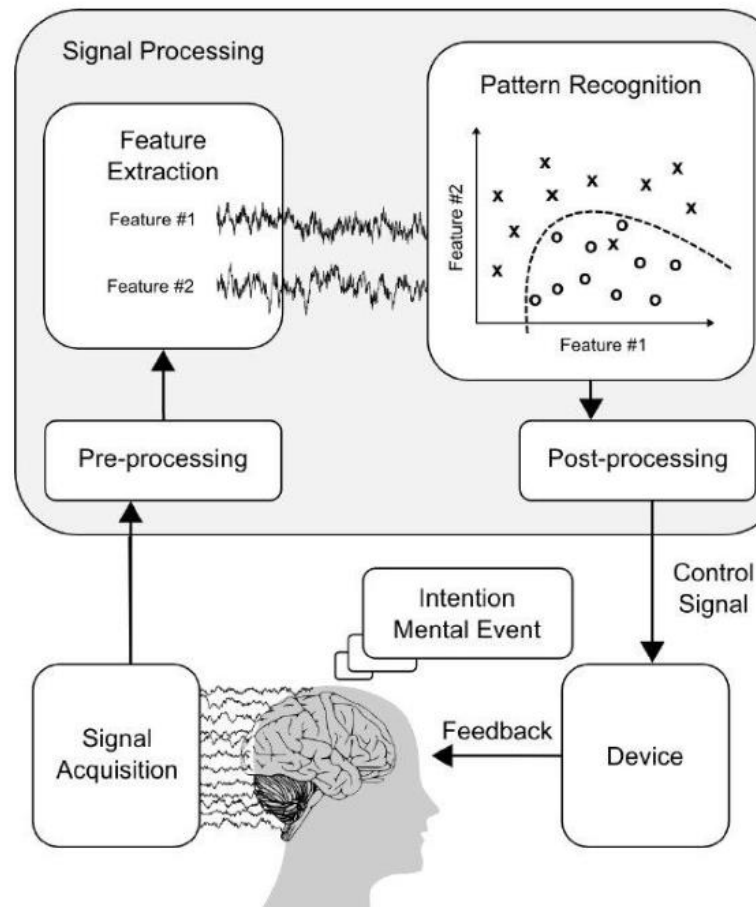


b)

## SSVEP / SSSEP / ASSEP

- Stimulation frequencies between 3 and 40 Hz :
  - < 3 Hz insufficient for a steady-state; brain responses = a succession of unitary responses
  - > 40 Hz, the SSVEP's amplitude becomes too small to be detected from surface EEG signals.
- Easy to extract with basic processing of EEG signals
- Characteristics relatively independent of the subject, with the condition of specifically selecting electrode positions providing maximum amplitude
- Little affected by muscular artifacts such as blinking and facial muscles' EMG

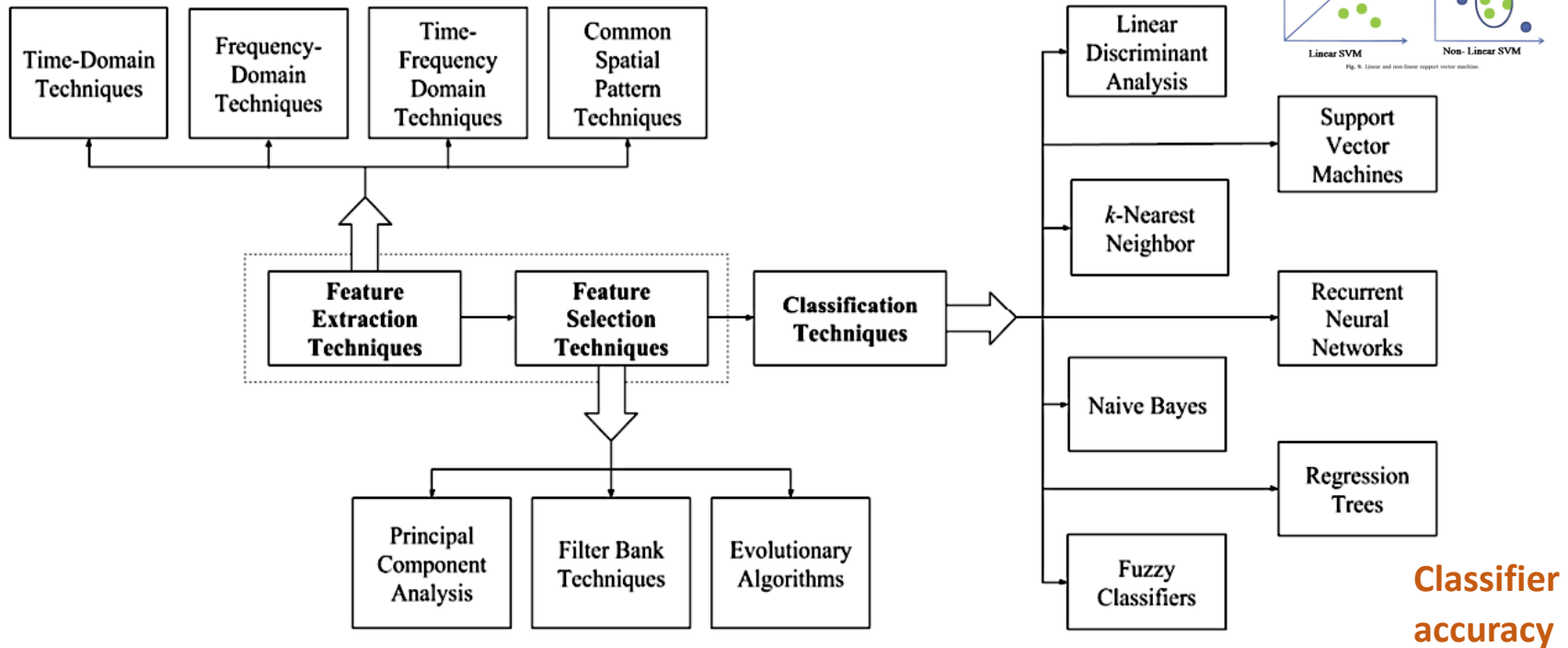
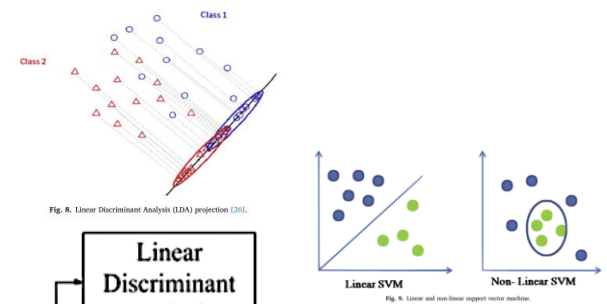
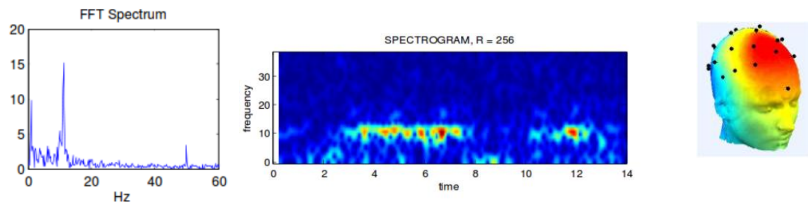
## Feature extraction (based on specific markers) and Classification



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.”



# Signal processing



Deep learning: single signal processing block (group together the feature extraction, feature selection and classification tasks)

## A wide variety of the different pipeline structures

**Table 2.** A comparison of the different combinations BCI structures used in the literature, including features extracted, feature selection approach if used and classification method.

| Paper   | Feature Extraction Method <sup>1</sup>              | Feature Selection Method <sup>2</sup>                            | Classification Method <sup>3</sup>                                 | Classification Accuracy <sup>7</sup>  |
|---|---|--|--|---|
| Rodríguez-Bermúdez & García-Laencina, 2012 [26] | AAR modelling, PSD                                  | LARS/LOO-Press Criterion   | LDA with regularization  | 62.2% (AAR), 69.4% (PSD)  |
| Kevric & Subasi, 2017 [11]                      | Empirical mode decomposition, DWT, WPD <sup>4</sup> | Kaiser criterion   | <i>k</i> -NN   | 92.8% (WPD) <sup>6</sup>  |
| Zhou et al., 2018 [28]                          | Envelope analysis with DWT & Hilbert transform      | None   | RNN LSTM classifier  | 91.43%  |
| Kumar et al., 2017 [47]                         | CSP & CSSP <sup>5</sup>                             | None, FBCSP, DFBCSP, SFBCSP, SBLFB, DFBCSP-MI <sup>4</sup>       | SVM  | Classification accuracy was not quoted.   |
| Yu et al., 2014 [65]                            | CSP   | PCA  | SVM  | 76.34%  |
| Baig et al., 2017 [3]                           | CSP   | PSO, simulated annealing, ABC optimization, ACO, DE <sup>4</sup> | LDA, SVM, <i>k</i> -NN, naive Bayes, regression trees <sup>4</sup> | 90.4% (PSO), 87.44% (simulated annealing), 94.48% (ABC optimization), 84.54% (ACO), 95% DE <sup>8</sup> |

# Graz motor imagery protocol

## I- training the system

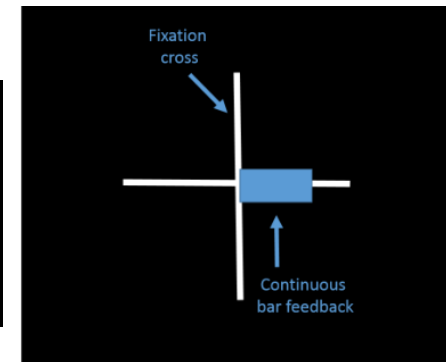
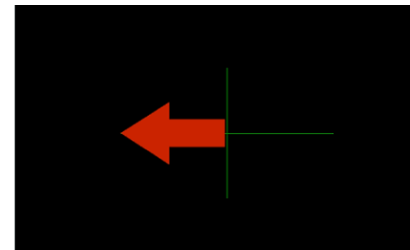
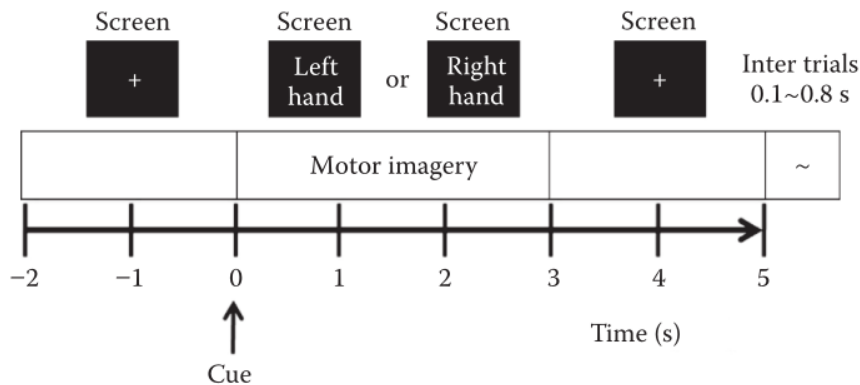
Series of MI-task (ex. Left/Right)  
[feature extraction to train a classifier]



## II- training the user

MI-task with feedback.

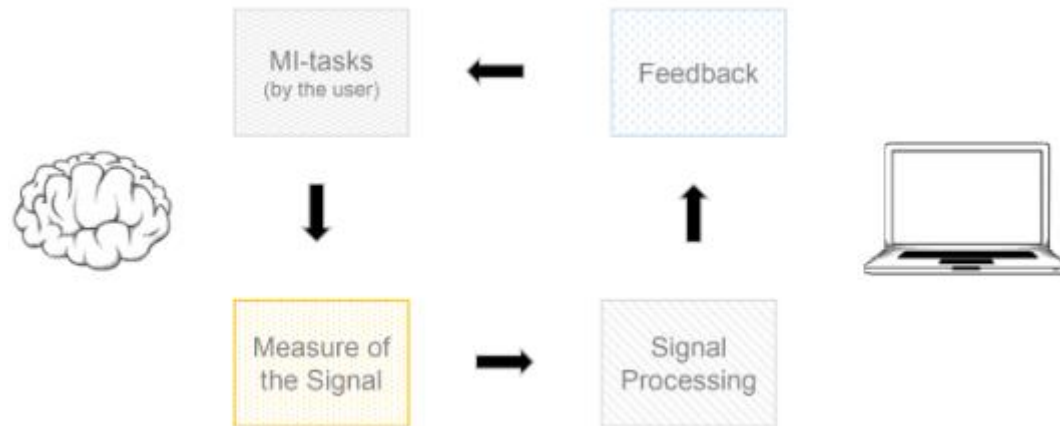
User goal: to develop effective strategies to increase system performance



- Multiple sessions, each of which multiple sequences (4-6 runs - fatigue > 6)
- One run:
  - 10-20 trials per class (MI-task)
  - 1 run lasting approx. 7 min

# User's brain and computer learning

Make the two components « understand each other »



**Stage I** : the computer attempts to understand the command sent by the user, generally by extracting relevant information followed by classification (**signal processing, machine learning**)

**Stage II** : the user's turn to attempt to understand the meaning of the **feedback** generated by the computer, which indicates how the computer understood the command that is received

## « 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 humain learn and how to adapt training process

## 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

## Replacement

Can be a last resort for patients that have lost bodily functions

Communication (Speller visual or auditory spellers P300, SSVEP)

Environment control (Prosthesis)

Locomotion (Wheelchair)

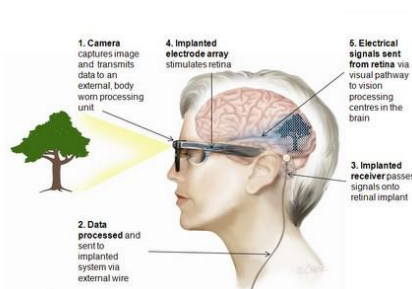
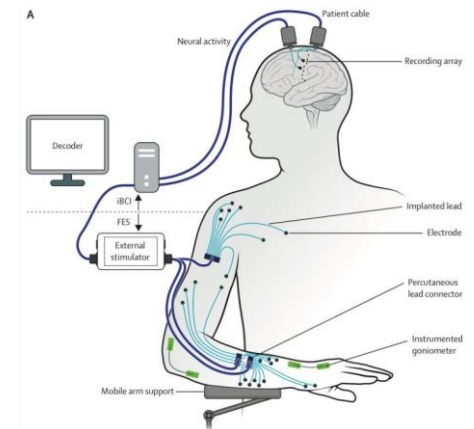


## Restoration

Connection brain – limb that have been destroyed

### Neuroprosthesis

- motor-imagery task
- challenge: no tactile or proprioceptive feedback
- current efforts: adding stimulations in the somatosensory cortex or the skin to obtain the complete action-perception loop



Australian Bionic Eye



Bill Kochevar raising his arm for the first time in years (from Boseley, 2017)



## Improvement

Rehabilitation after a stroke (impaired motor control)

- BCI as a bridge in the action-loop
- Exercises with various feedbacks (gauge, virtual limb, robotised arm, or even functional electrical stimulation of the real limb)
- Neural plasticity
- Therapist can visualize patient's brain activity when performing attempted movement



## Enhancement

Mental state monitoring (passive BCIs)

More-or-less reliably in EEG signals: mental workload (pressure on the user cognitive resources, e.g. working memory), attention and, though less accurately, emotions (communication and personal development)

- Detection in the vigilance levels, loss in attention (car driver, air traffic controller) - auditive / visual notification
- Adaptation of application to improve user experience (ex. exercises as a function of attention / frustration)

## Enhancement

Home automation



©Neurable

## Gaming and Virtual reality

- Select objects by paying attention to them (P300/SSVEP responses)
- Navigation in Virtual Environments VE (left/right/foot MI, or SSVEP on flickering control buttons overlaid to the game)
- Limited number of commands (1 to 3): BCI as a complementary input device of game pad, to trigger some actions
- alphaWoW (alpha World of Warcraft) game: avatar can turn from a brutal bear into a fragile elf depending on the player's relaxation level (alpha band)

Some examples: <https://www.mindaffect.nl/labs/>

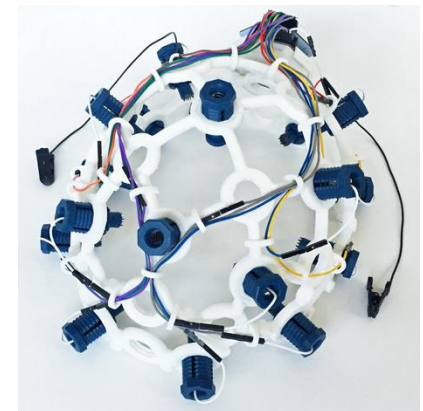
- Illiteracy (using an interactive, co-learning approach)
- Long-term use of BCIs requires repeated use of particular neural pathways -> possible health implications or change in brain functionality ?

*Ex. long-term use of BCI-external actuators has led to restructuring of the brain's map of the body, with actuators perceived as an extension to the body*

- Ethical standards
  - establish liability in case of accidents using controlled apparatus
  - deal with the appropriate use of bio-signal data
  - privacy (influence on a user's mood – exploit user emotions / marketing or political agendas)

# Concluding remarks

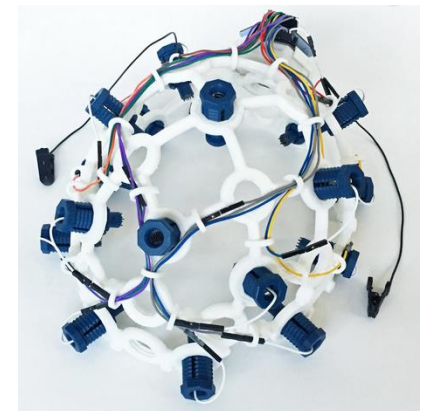
- ➔ Designing a BCI is a complex and difficult task that requires knowledge of several disciplines (computer science, electrical engineering, signal processing, neuroscience, psychology)
- ➔ Many ongoing challenges
- ➔ Open community (software, hardware)
- ➔ Many projects for patients and healthy people



« Meet Milo, the brain controlled wheelchair »

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Are you ready?