Brain Computer Interfaces

Principles, Algorithms and Tools

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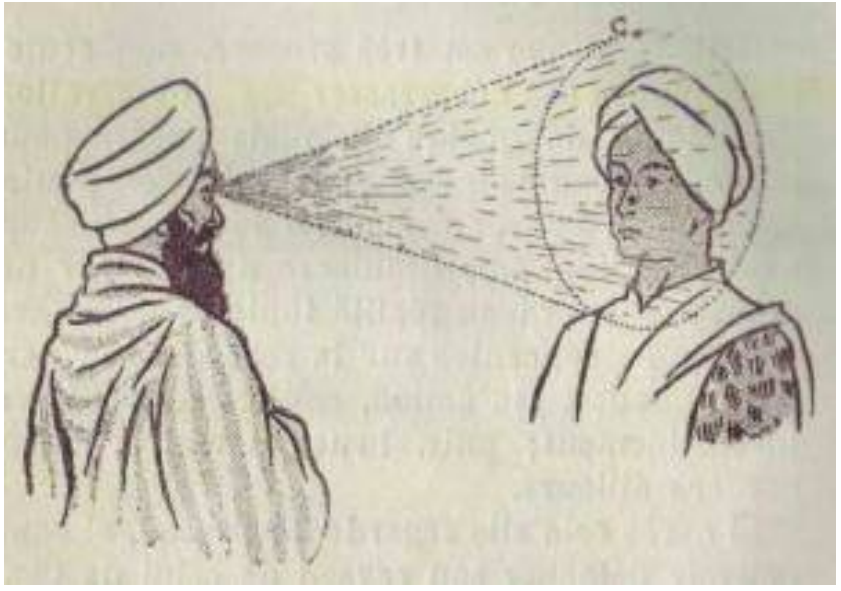
Advanced Course in Computational Neuroscience

December 2023

Agenda

- A very brief historical perspective.
- What are Brain Computer Interfaces (BCI).
- Main principles.
- Study of some classical paradigms:
  - P300 speller.
  - Beta rebound.
  - Visually Evoked Potentials.
- Future directions.
- Ethical issues.

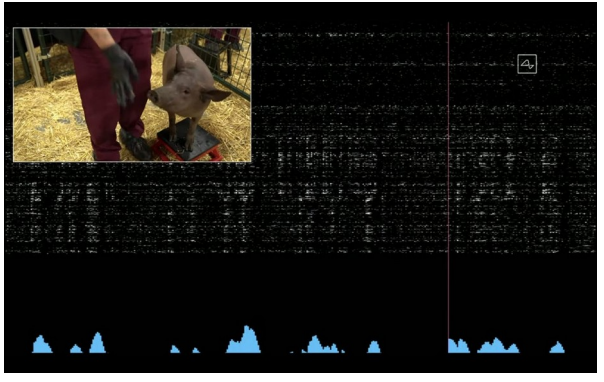
An old fantasy of humanity...



Magnetic encirclement
Hindu magnetic treaty ©ISI-CNV



e-Mote fake advertisement – 2011.
BBC real test in 2015.



NEURALINK

27/08/2020

Game changers...

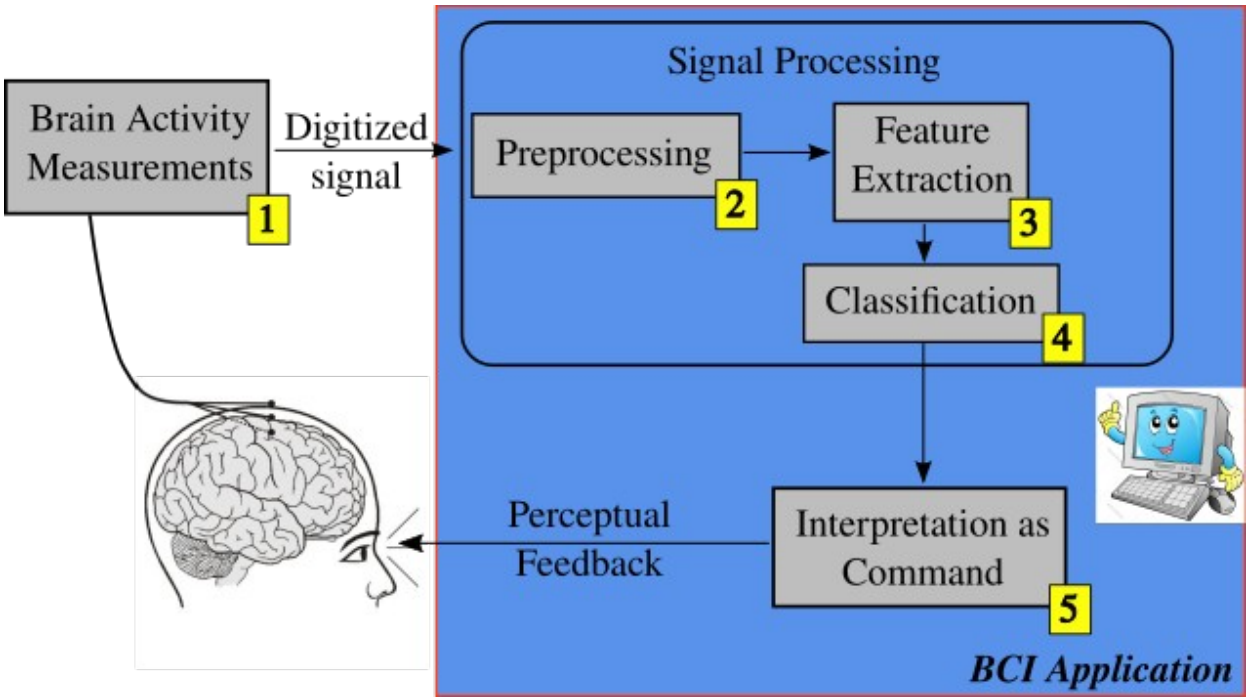
- Explosion of the techniques to measure the brain activity:
  EEG (1929), ECoG (early 1950s), MEG (1972), fMRI (1990), Optical Tomography (1993), …
  → Cognitive sciences: understanding of some brain processes.

- EEG biofeedback (1960-1970):
  - Voluntary control of brain rythms (α , μ , θ).
  - Reduction of ictal activity.
  - 1973:

TOWARD DIRECT BRAIN-COMPUTER COMMUNICATION

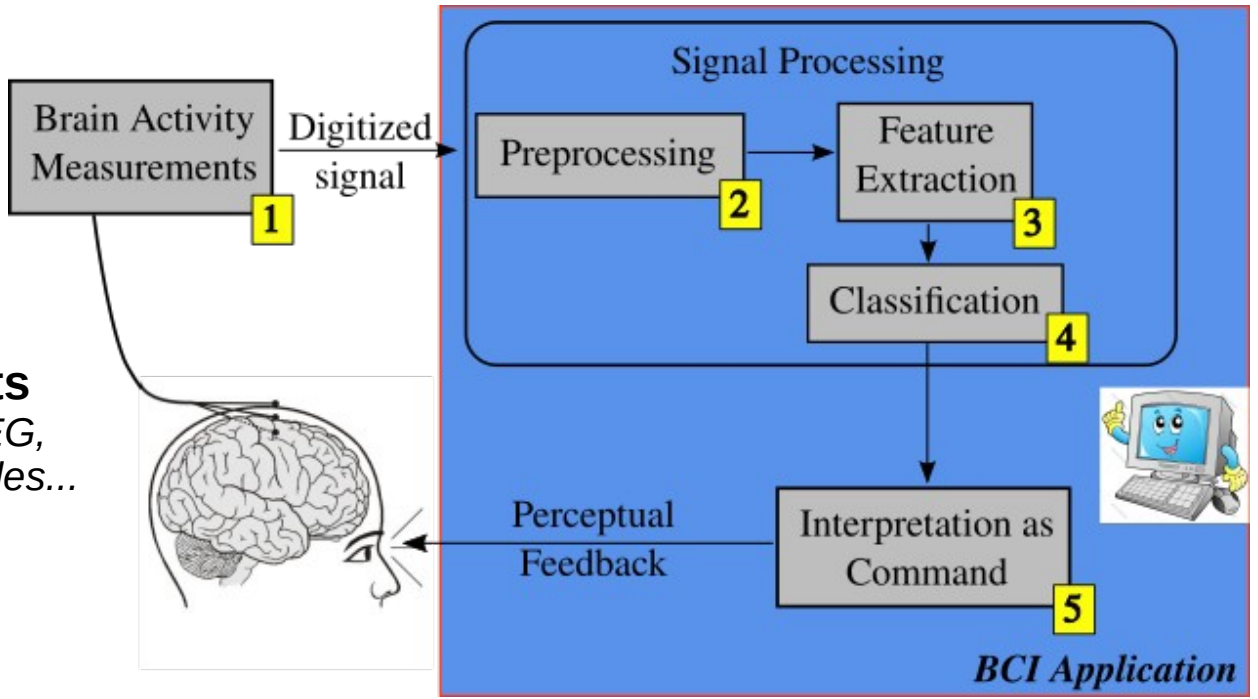
JACQUES J. VIDAL[1]
Brain Research Institute,
University of California, Los Angeles, California

BCI: main principles



A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: main principles

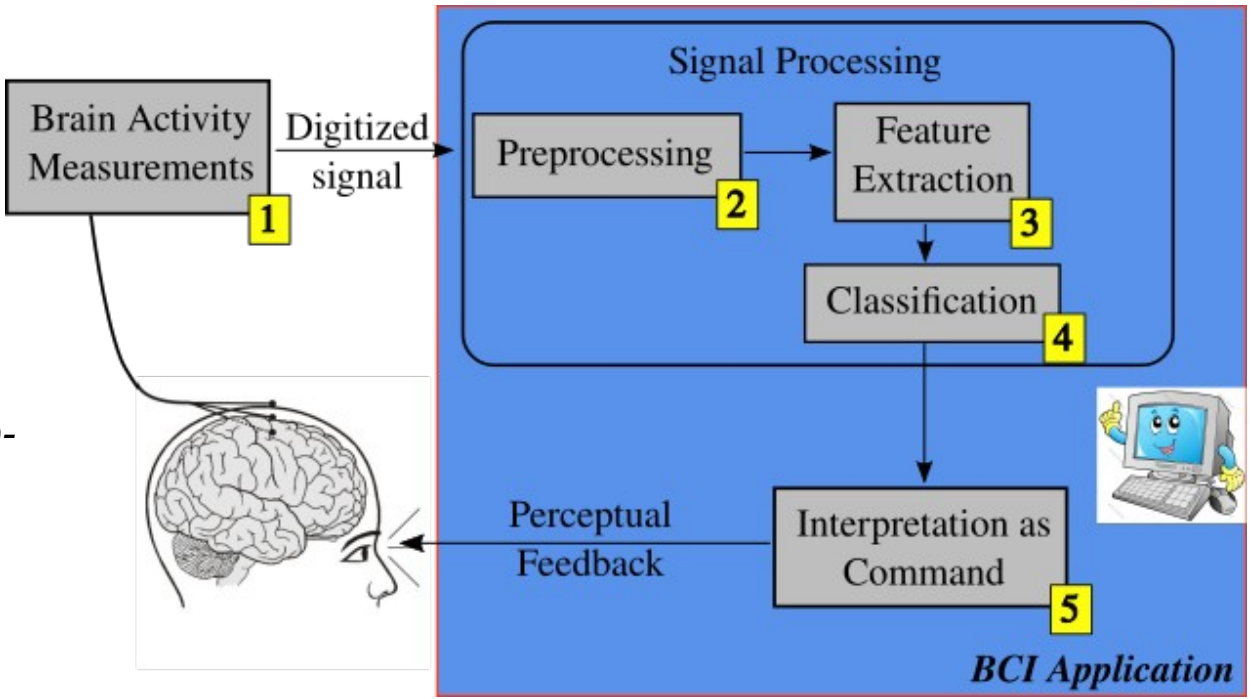


1 Brain Activity Measurements

Any non destructive type: ***EEG***, *MEG, fMRI, ECoG, intra-cerebral electrodes...*

A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: main principles

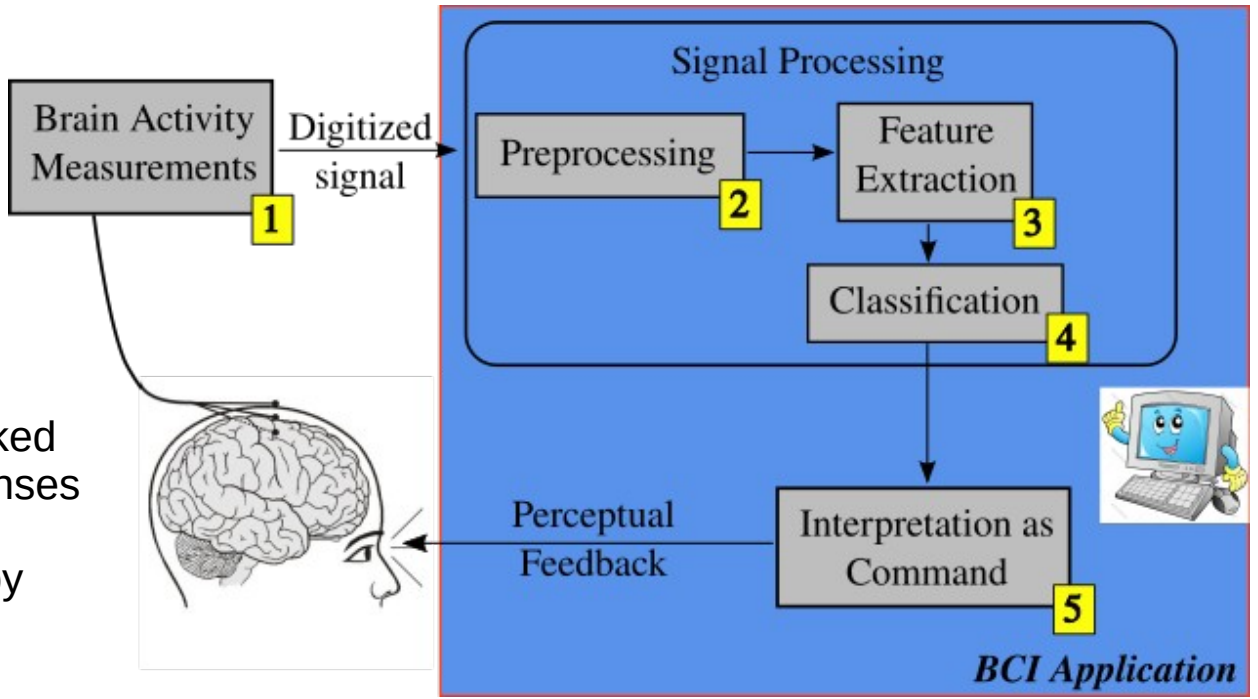


2 Preprocessing

Basic stuff: *channel selection,sub-sampling, filtering, ...*

A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: main principles

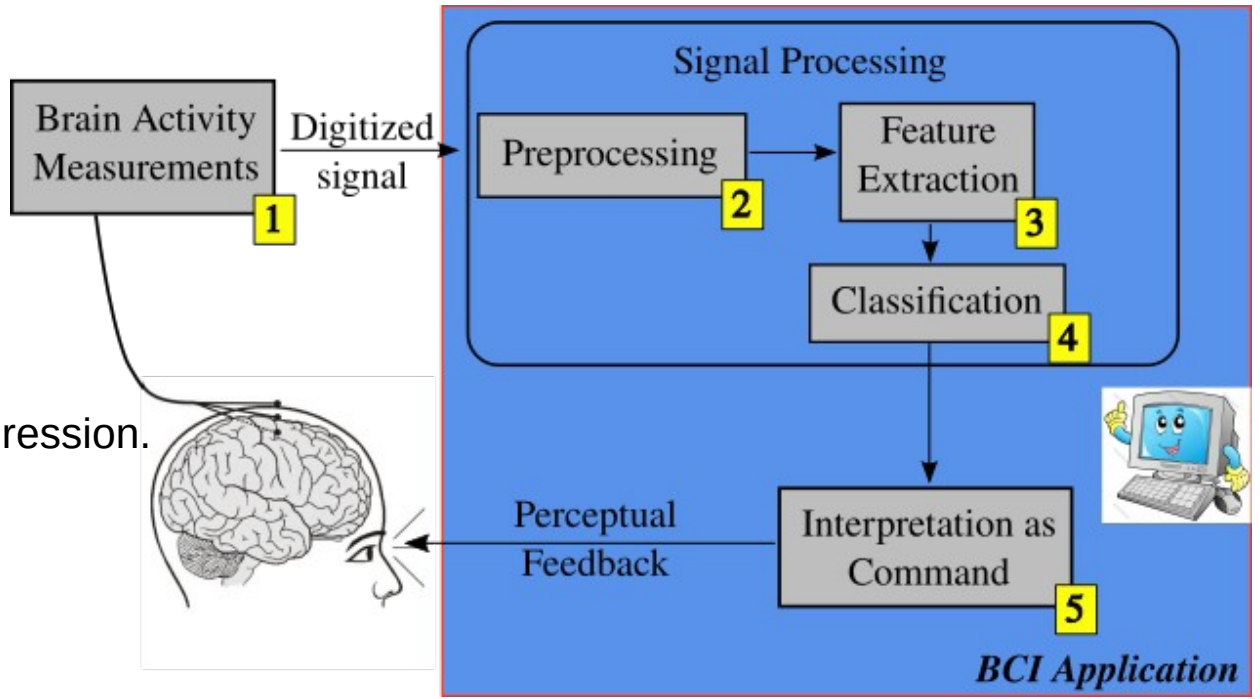


3 Feature Extraction

- Obtain a vector of numbers linked to neurological states or responses used by the system.
- User controlled or modulated by attention.

A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: main principles

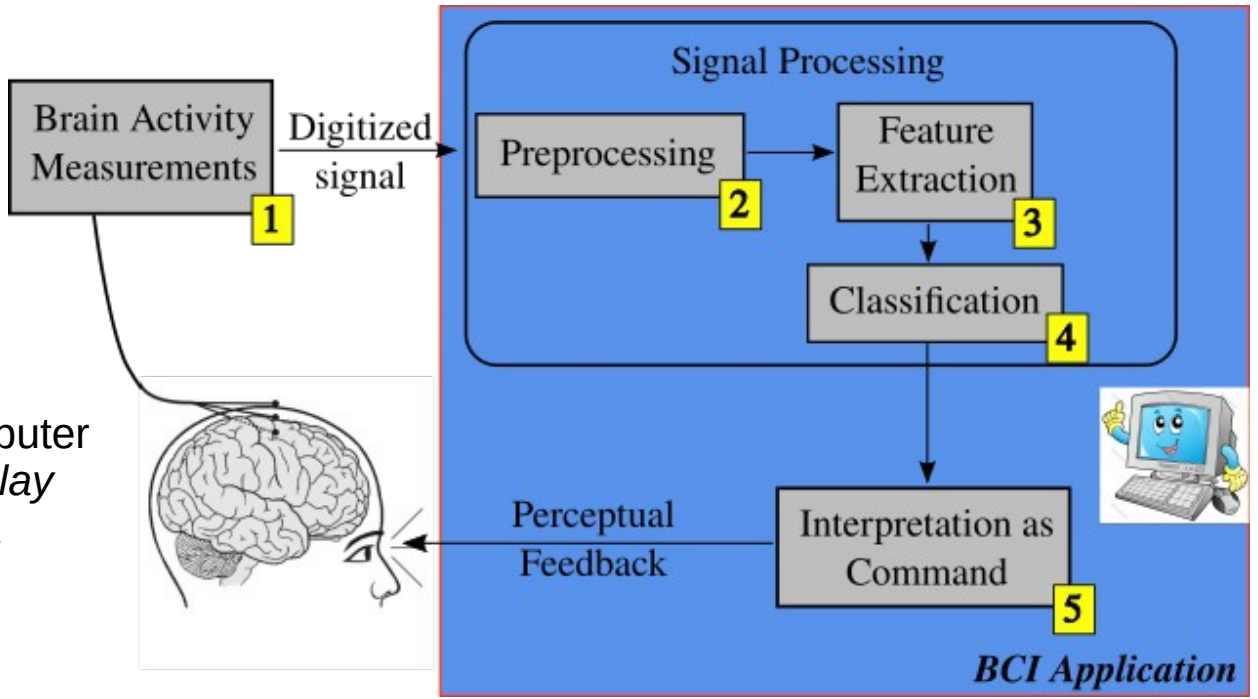


4 Classification

- Detection / Classification / Regression.
- Needs to be learnt.
- Training and testing phases.
- ***Online*** / Offline.

A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: main principles

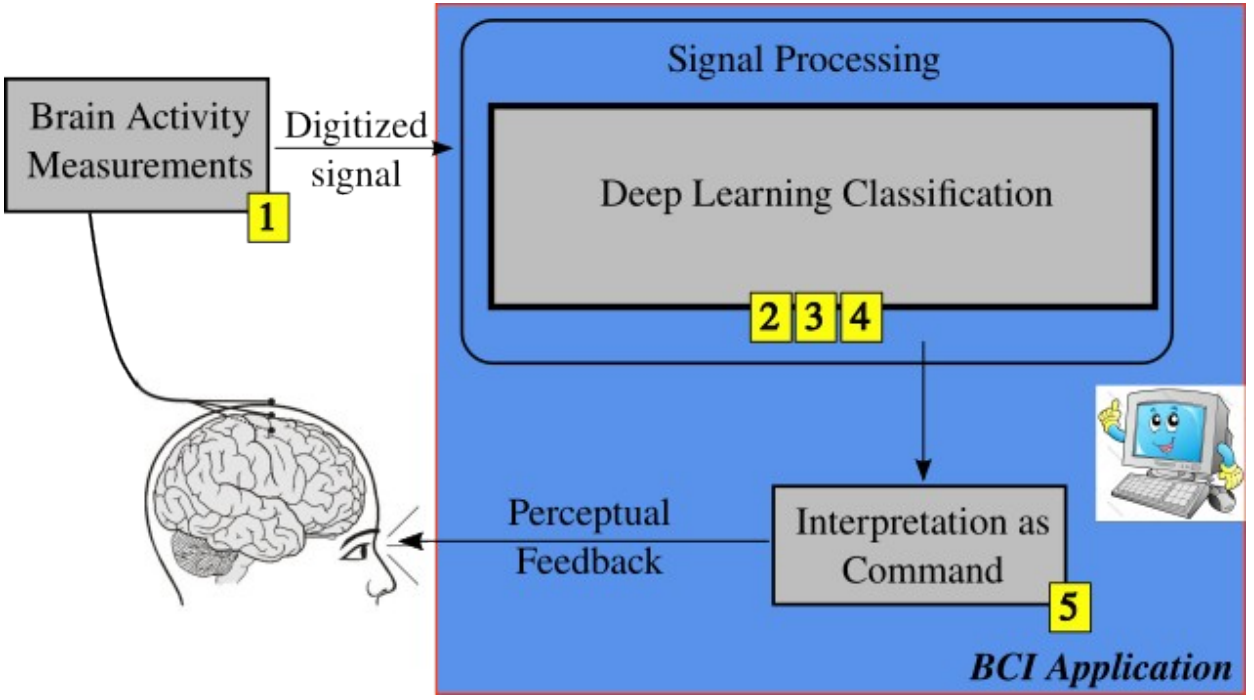


5 Interpretation as Command

The goal of the system. Any computer controlled action is possible: *display an image, play a sound, control a robot or an appliance, push an interface button, ...*

A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: Deep Learning variant



A closed loop system between a subject (brain) and a computer (at least in principle…)

BCI: a multidisciplinary field

- Cognitive Brain Science.
- Signal Processing / Real time processing.
- Statistics: learning/classification.
- Human Computer Interaction / Ergonomy.
- Human learning.
- ….

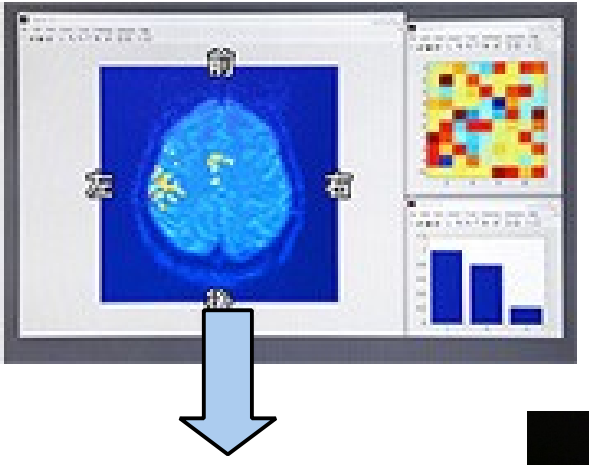
→ A very rich domain.

Example: *Roc-Paper-Scisors*

HRI (Honda) and ATR, May 2006.



Chi-Fou-Mi in fMRI



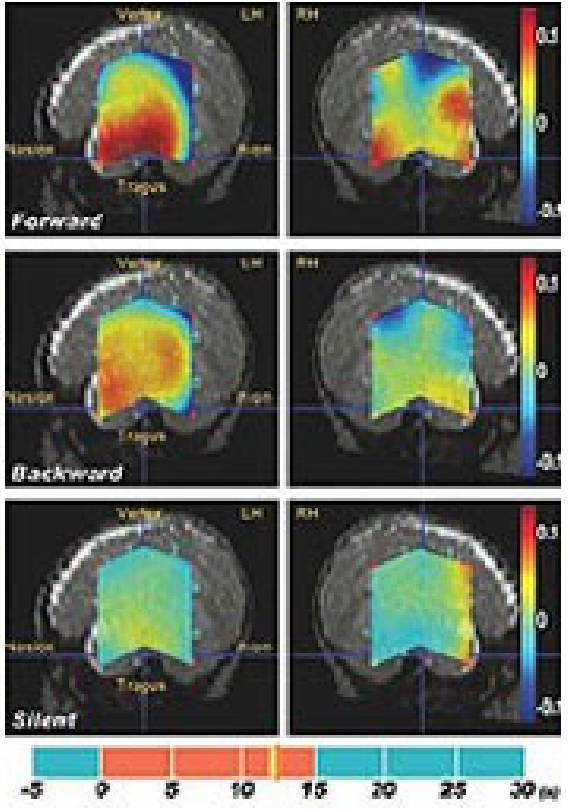
Robotic hand.



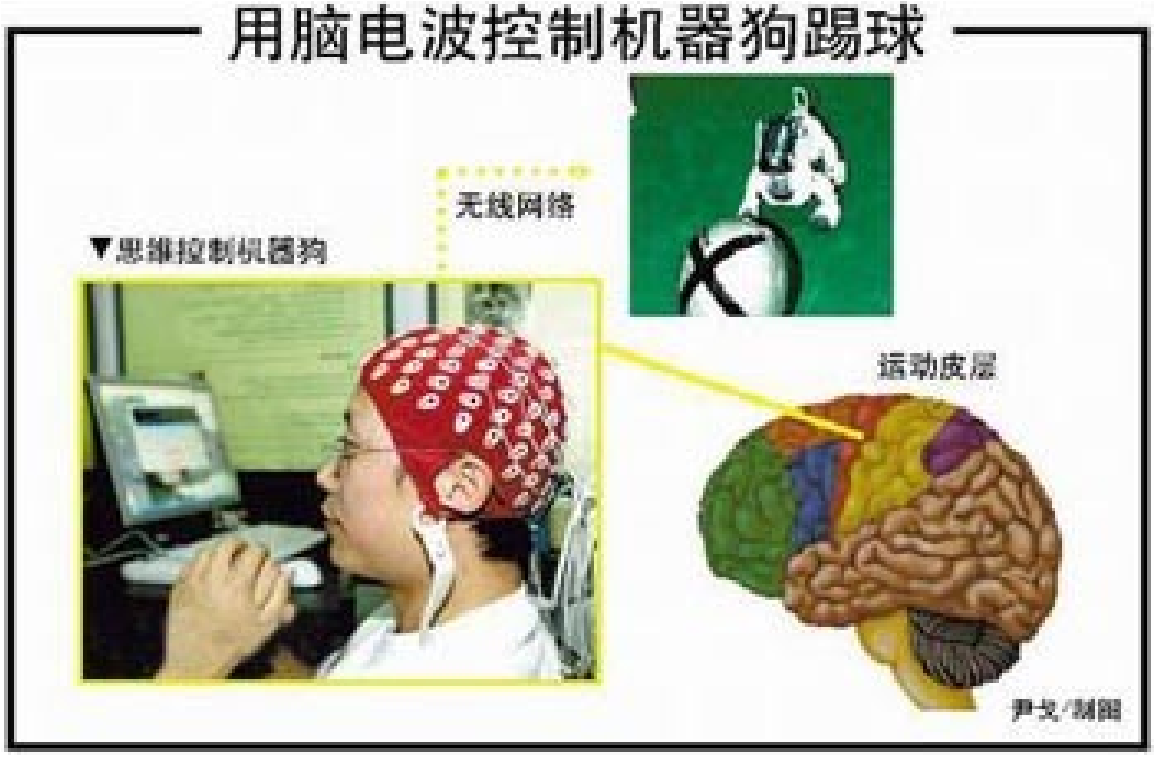
Example: *On-Off Command*

Hitachi 2007 fNIRS
Start/Stop an electrical train.



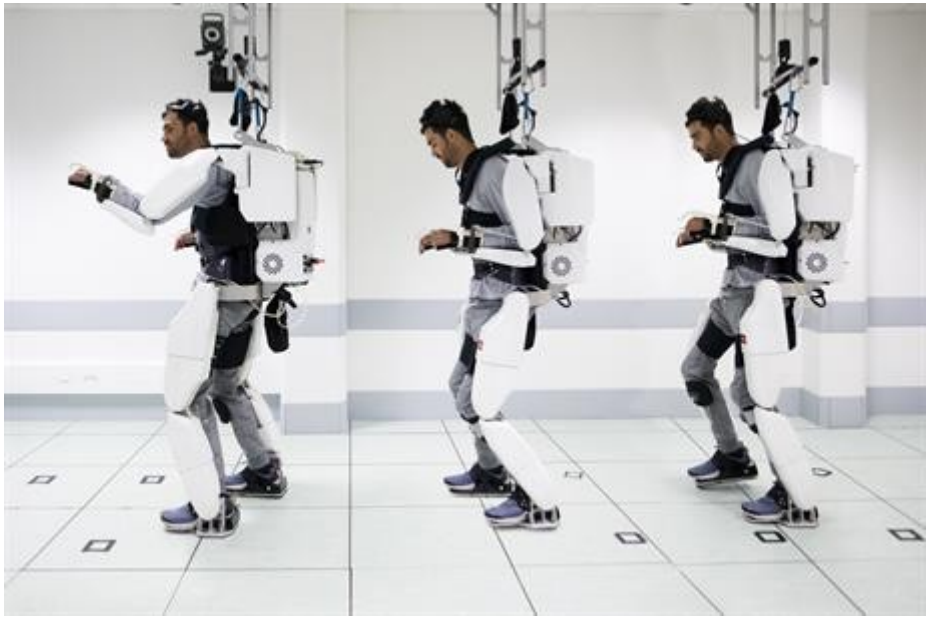


Example: *Robotic dogs playing football*



EEG based
Qinghua University
June 2006
Source: **People's Daily online**.

Example: Exo-squelton





Clinatec (CEA, CHU Grenoble Alpes), 2019.

Semi-invasive implant.

Tetraplegic patient.



Example: Spinal chord stimulation



Gert-Jan walks again with a walker. • © FABRICE COFFRINI / AFP

CEA / EPFL /

Lausane Hospital, 2023.

Semi-invasive implant.

Paraplegic patient.
Spinal chord stimulation.



Example: Spinal chord stimulation



YouTube link

CEA / EPFL /

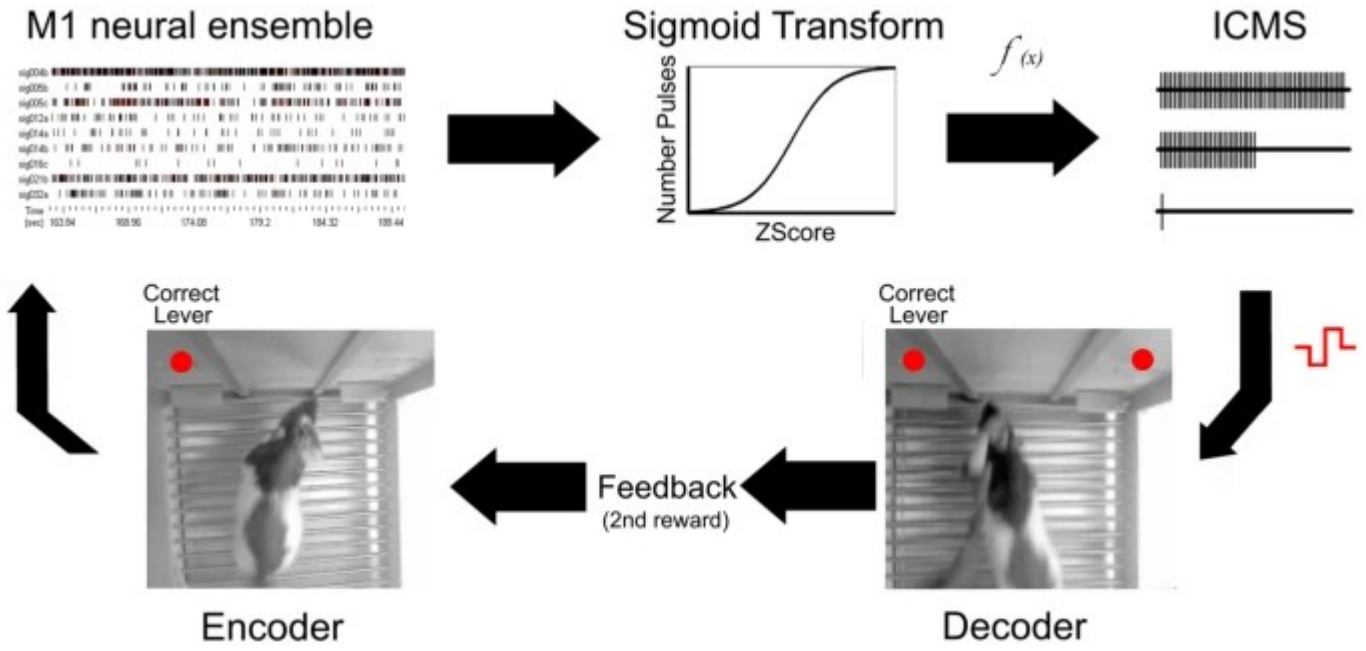
Lausane Hospital, 2023.

Semi-invasive implant.

Paraplegic patient.
Spinal chord stimulation.



Example: Network BCI



Brain-to-Brain transfer. Worked between US and Brazil !!!

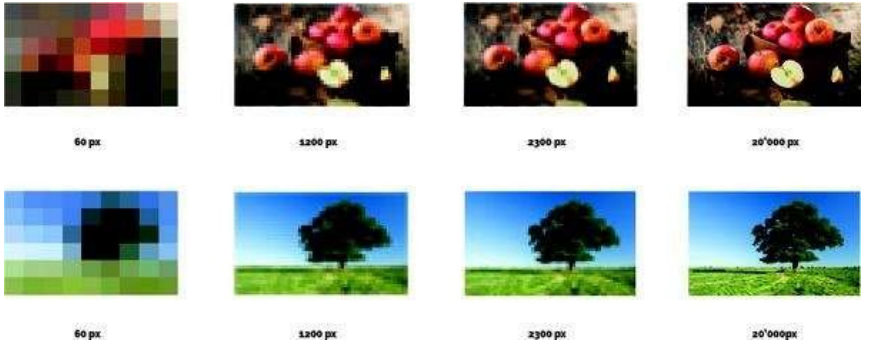
A Brain-to-Brain Interface for Real-Time Sharing of Sensorimotor Information, Duke University, Nicolelis Lab, 2013.

Peripheral CNS implants...

Neuroprosthetics:

- Cochlear implants.
- Visual implants.
- Pain relief.
- Blader control implants.
- ...







EPFL retinal implant (2018).

BCI: main characteristics

- Invasive / **Non invasive.**
- Evoked or spontaneous.
- Synchronous/Asynchronous (self-paced) protocols.
- Visual, auditory, sensory, motor (real, imaginary or intentional), purely voluntary, mental states, high level.
- Practical difficulties:
  - SNR
  - Variability:
    - For a same subject: intra / inter-session.
    - Inter-subjects.
  - Real time.

Phenomenons

- **VEP: Visual Evoked Potentials.**

  Often Steady State SSVEP, but also CVEP.
- SCP: Slow Cortical Potentials.
- **ERP: Event Related Potential, often P300.**
- **ERD/S: Event Related (De)Synchronisation.**
- MRP/LRP: Movement/Lateralized Readiness Potential.
- Self Controlled Brain Rhythms Modulation: α waves...
- ERN: Error Related Negativity.
- VHFO: Very High Frequency Oscillations.

Cerebral rythms

- Delta (< 4 Hz): Deep sleep.
- Theta (4-7 Hz): Drowsiness.
- Alpha (8-16 Hz): State of diffuse awakeness.
- Mu (10-14 Hz): Motor rhythm.
- Beta (15-30 Hz): Normal activity state.
- Gamma (40 Hz): Perceptive link / Cognitive integration.

Main challenges...

- Reliability and Limited communication capability.
- Real time processing.
- Training time and Human adaptation.
- Non invasive systems:
  - Noise, noise, noise…
  - Spatial resolution

  } → Detectability / Accuracy / Speed.
- Invasive systems:
  - Brain coverage / Number of electrodes.
  - Tissue scars around electrodes.
  - Costs (not only €, human).

  } → Stability in time / High specificity.

Main challenges...



Technological

- **Tedious Calibration**
  - Search for features.
  - Inter-subject + intra-session variability.

Neurophysiological

- **Low information tranfert rate**
  - Somewhat artificial applications.

Ergonomy

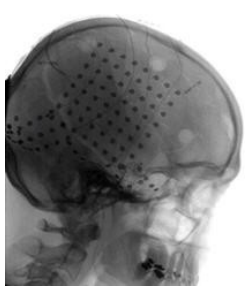
- **Human learning needed for BCI** use
  - Often time consuming.
  - Fails for a fraction of the subjects
    (in particular for some sub-population like locked-in).

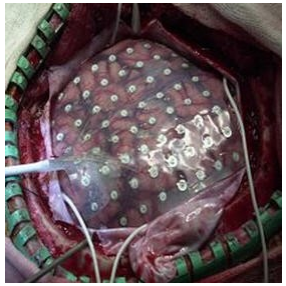
Main Characteristics (1)

Invasive

Subdural or intracortical electrodes.

- ✔ More focal than scalp electrodes.
- ✔ Less artifacted signal.
- ✗ Lower spatial coverage.
- ✗ Invasive, costly.





EcoG grid, photo by G. Schalk (Wadsworth center), K. Miller and J. Ojemann (U. of Washington).

Non invasive

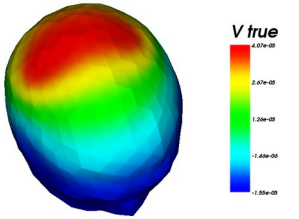
Scalp sensors (EEG, MEG, …).

- ✔ Non invasize, cheap (EEG).
- ✔ High spatial coverage.
- ✗ Blurred spatial information.
- ✗ Artifacts.



EMOTIV EPOC

OpenEEG
openeeg.sourceforge.net
EEG for the rest of us!



Main Characteristics (2)

Online

✔Feedback.
✔“Real BCI”.
✗ Need for real time process
✗ Less sophisticated method

Offline

✔More sophisticated algorithms.
✔Proof of concept.
✔Easier and more tools available.
✗ “False BCI”.
✗ No subject feedback.

Main Characteristics (3)

Asynchronous (Self paced)

The subject decides when...

- ✔ Friendlier for the subject.
- ✔ Less tiring.
- ✗ More difficult for the computer.
- ✗ Higher demand on the signal processing.
- ✗ More training.
- ✗ Need for paradigms creating strong signals.

Synchronous (Clocked)

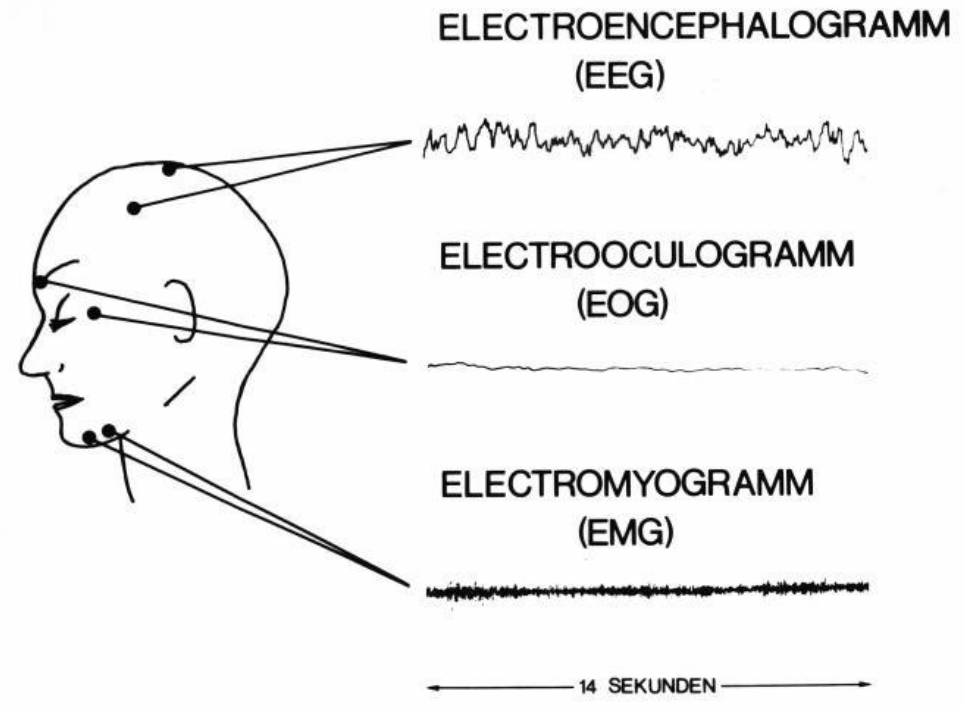
The computer decides when...

- ✔ Simpler for the signal processing.
  The computer knows when to look.
- ✔ Ability to do multiple trials.
  Reduction of signal to noise ratio,
  More paradigms can be used.
- ✔ Less training.
- ✗ Less comfortable for the subject.
  User concentration, effort.
- ✗ Non stoppable by the user.

Artifacts

- Main drawback of scalp vs intra EEG.
  - EMG, EOG.
  - Patients with motor control problem.

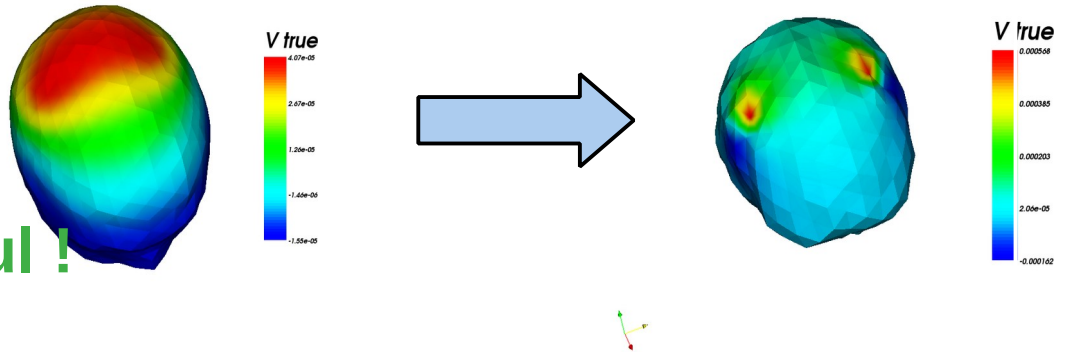
- Artifact processing.
  - Rejection or not.
  - Suppression.
  - To be done in real time.



Feature extraction

- Spatial signal improvement:
  - Laplacian.
  - Cortical mapping.
  - Source localization.

  Unclear if really useful !

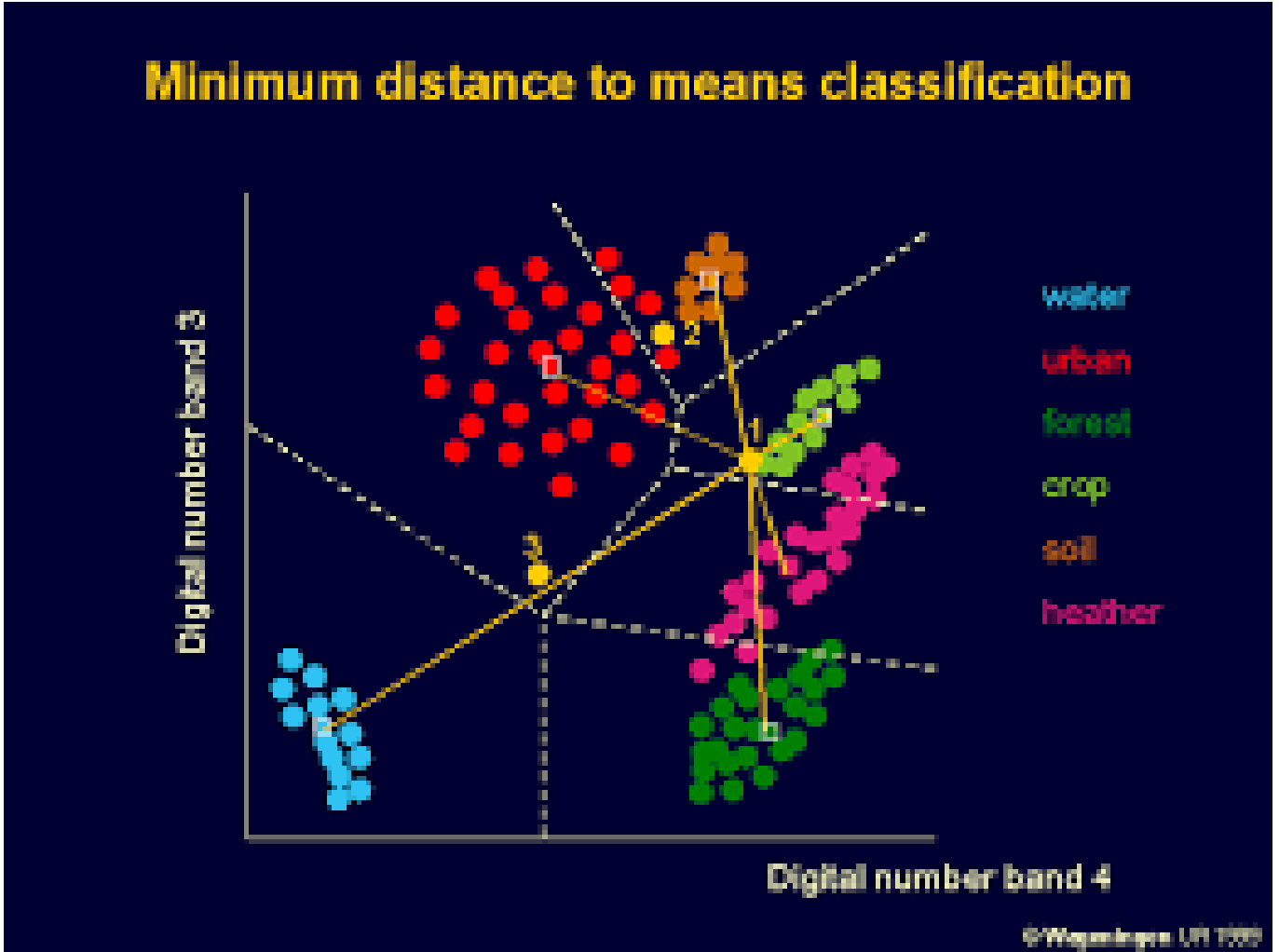


- Temporal analysis:
  - Filtering.
  - Time-frequency maps (wavelets, STFT).
  - Phase analysis.
  - ERD/ERS.
  - ICA / PCA.

Classification

- Nearest Neighbors / MDM.
- Linear (Fischer) / Quadratic Discriminant Analysis (LDA/QDA).
- Common Spatial Patterns (CSP). Max variance.
- Support Vector Machine (SVM).
- Self Organizing Maps..
- HMM, Temporal Hidden Markov Trees.
- Decision trees, Voting.
- Perceptron / Neural Networks / Deep Learning.
- ...

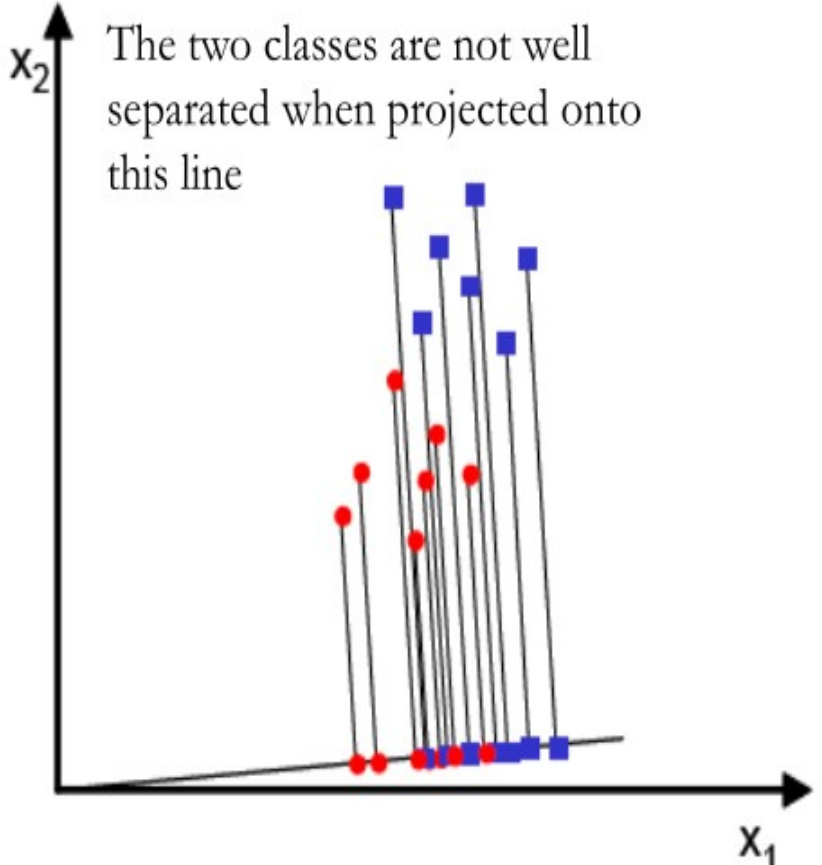
Classification Basics: MDM

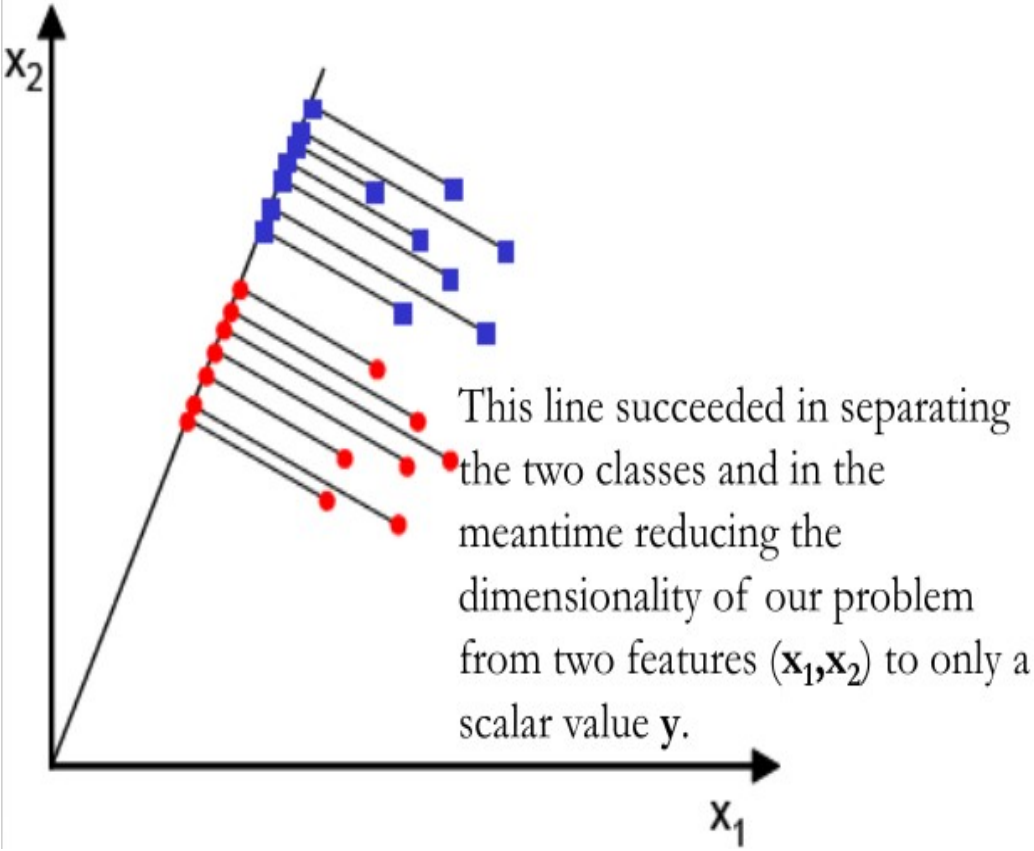


Classification Basics: LDA

Find a projection / projections that best separates the classes.

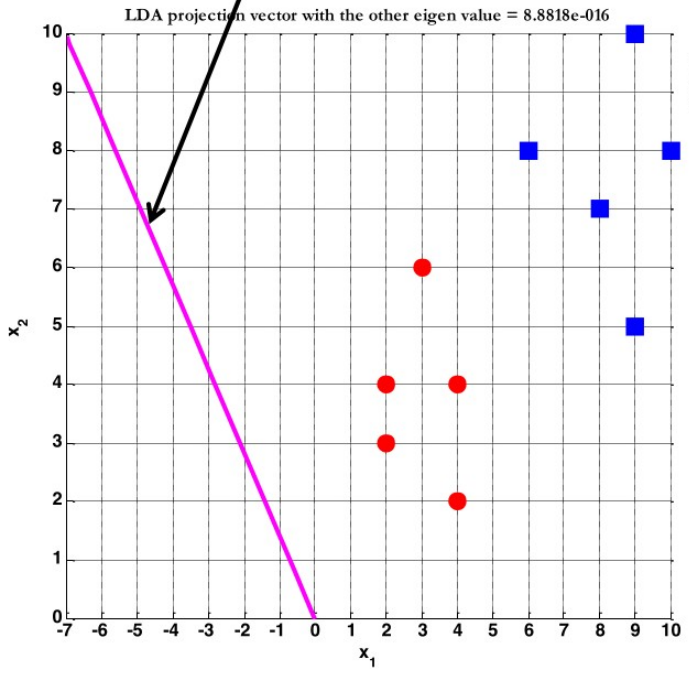
Solved as an eigenvector problem that maximizes the distance between classes normalized by the total within variance.

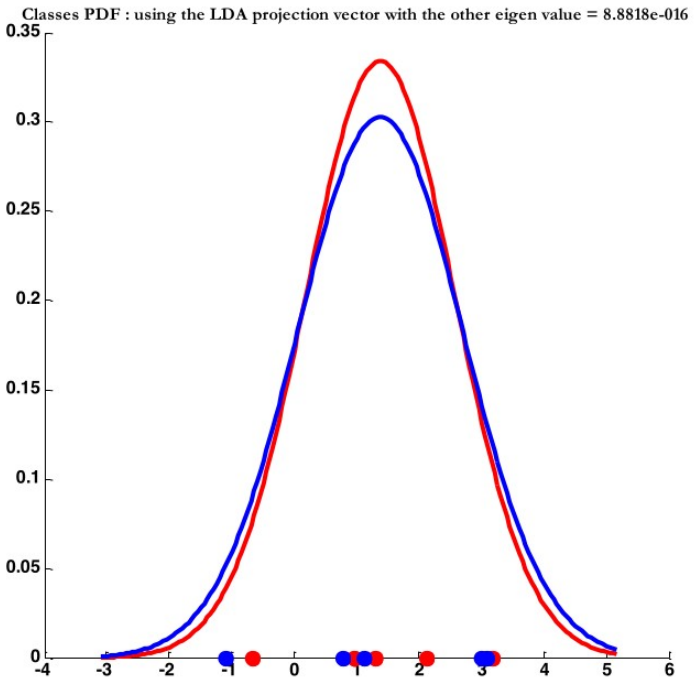




Classification Basics: LDA

The projection vector corresponding to the **smallest** eigen value



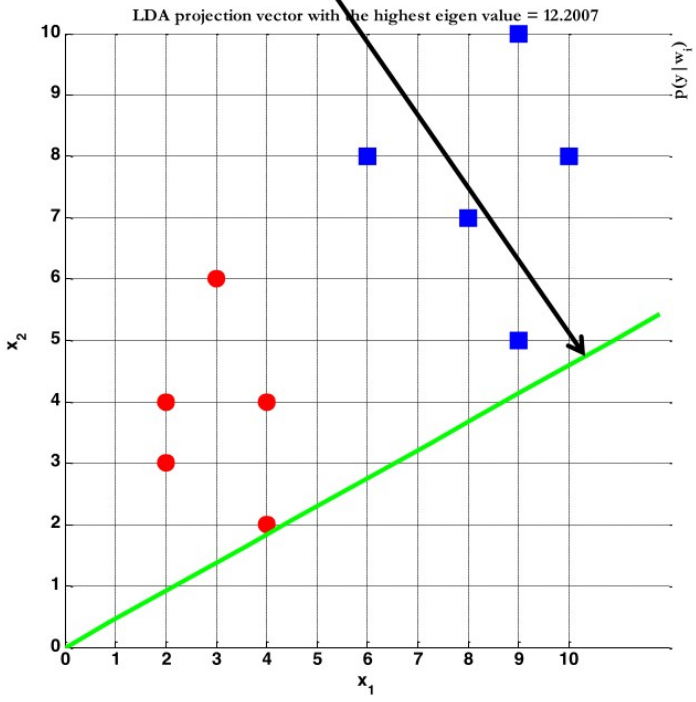


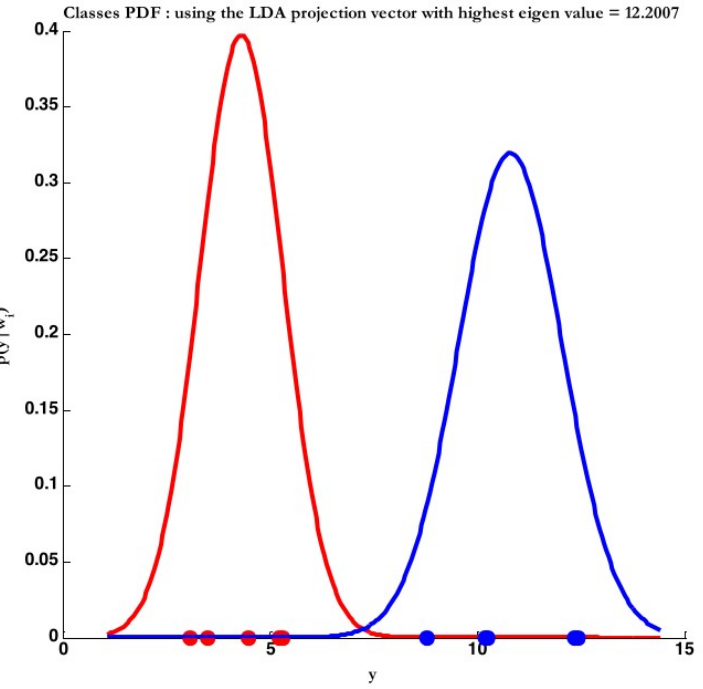
Using this vector leads to **bad separability** between the two classes

Linear Discriminant Analysis (LDA)

Two classes - Example

The projection vector corresponding to the **highest** eigen value

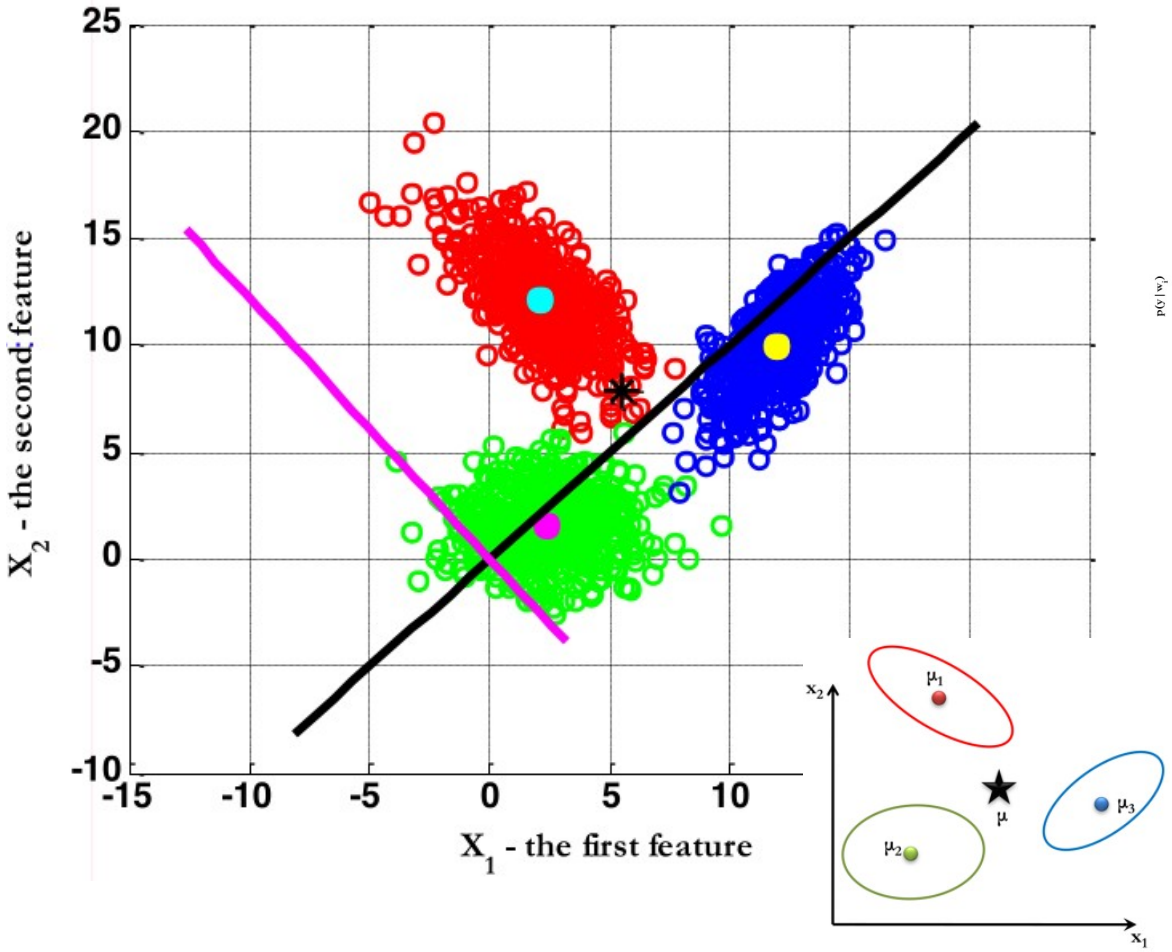


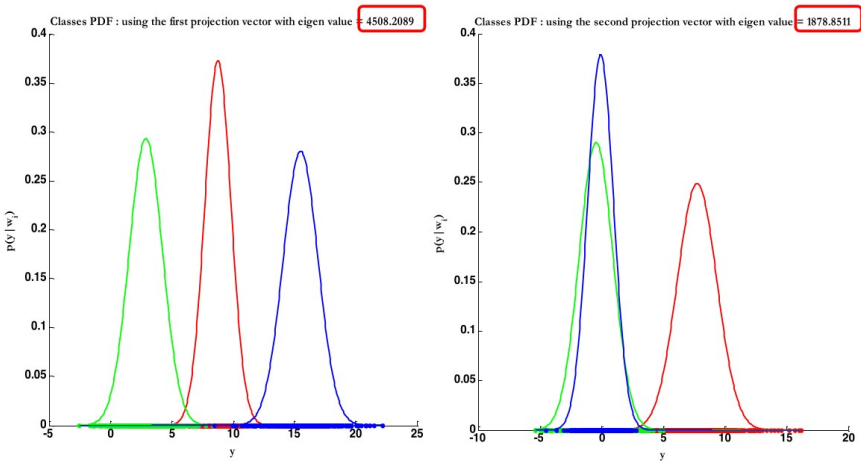


Using this vector leads to **good separability** between the two classes

Linear Discriminant Analysis (LDA)

C classes





The projection vector with the highest eigenvalue provides higher discrimination power between classes.

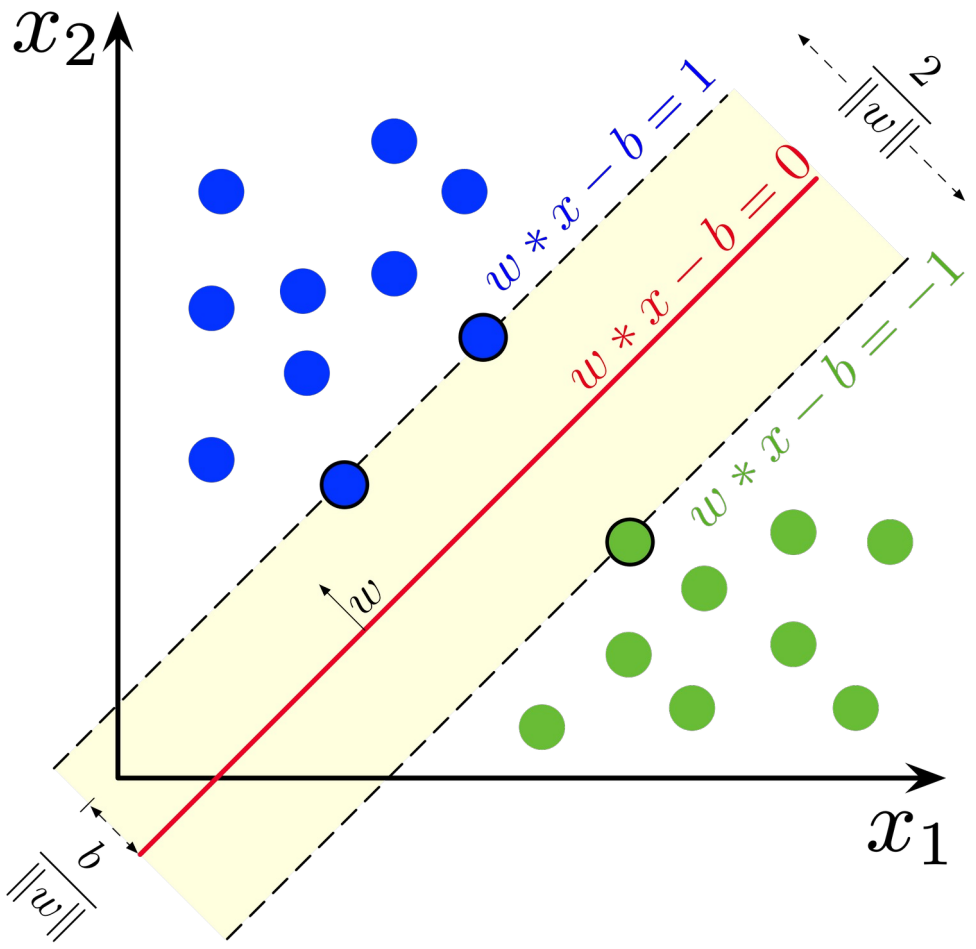
LDA vs CSP

- CSP (Common Spatial Pattern) is very similar to LDA and tries to find a projection that maximizes the ratio of class variances. Solved with a generalized eigenvalue problem.
- LDA separates data that have different means.
  CSP ignores means.
- CSP is good for example in separating signal from noise when both distributions have zero mean. LDA fails while CSP finds a projection that makes the variance of the signal components as large as possible w.r.t. noise so that the signal stands out.

Support Vector Machine (SVM)

Vapnik 1992

- Hard margin.
- Soft margin.



Riemannian approaches

For data that live on non linear spaces.
Geodesics.

Compute Riemannian means.

Two main classification options:

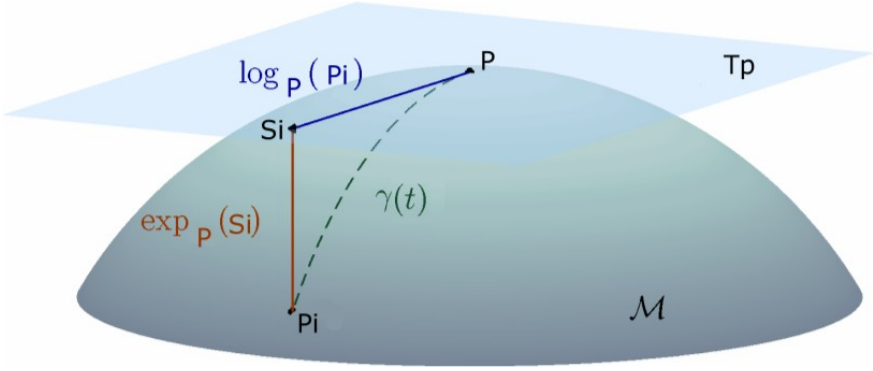
- Distance to the mean.
- Project all points on a tangent plane.
  → In that plane, apply MDM, LDA, SVM, ...

Example of SPD matrices.
(Covariance matrices)

$$\delta_R(\mathbf{P}_1, \mathbf{P}_2) = \left\| \log\left(\mathbf{P}_1^{-\frac{1}{2}} \mathbf{P}_2 \mathbf{P}_1^{-\frac{1}{2}}\right) \right\|_F = \left[\sum_{i=1}^{n} \log^2 \lambda_i\right]^{1/2}$$

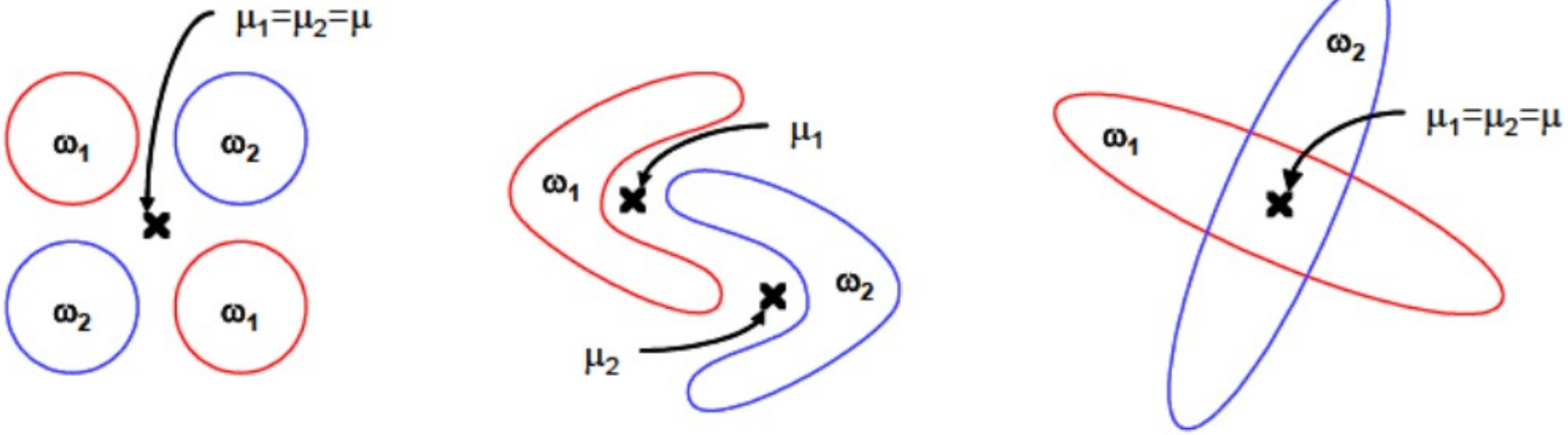
$$\mathrm{Exp}_{\mathbf{P}}(\mathbf{S}_i) = \mathbf{P}^{1/2} \mathrm{Exp}\left(\mathbf{P}^{-1/2} \mathbf{S}_i \mathbf{P}^{-1/2}\right) \mathbf{P}^{1/2}$$

$$\log_{\mathbf{P}}(\mathbf{P}_i) = \mathbf{P}^{1/2} \log\left(\mathbf{P}^{-1/2} \mathbf{P}_i \mathbf{P}^{-1/2}\right) \mathbf{P}^{1/2}$$



Barachant, Bonnet, Congedo, 2010.

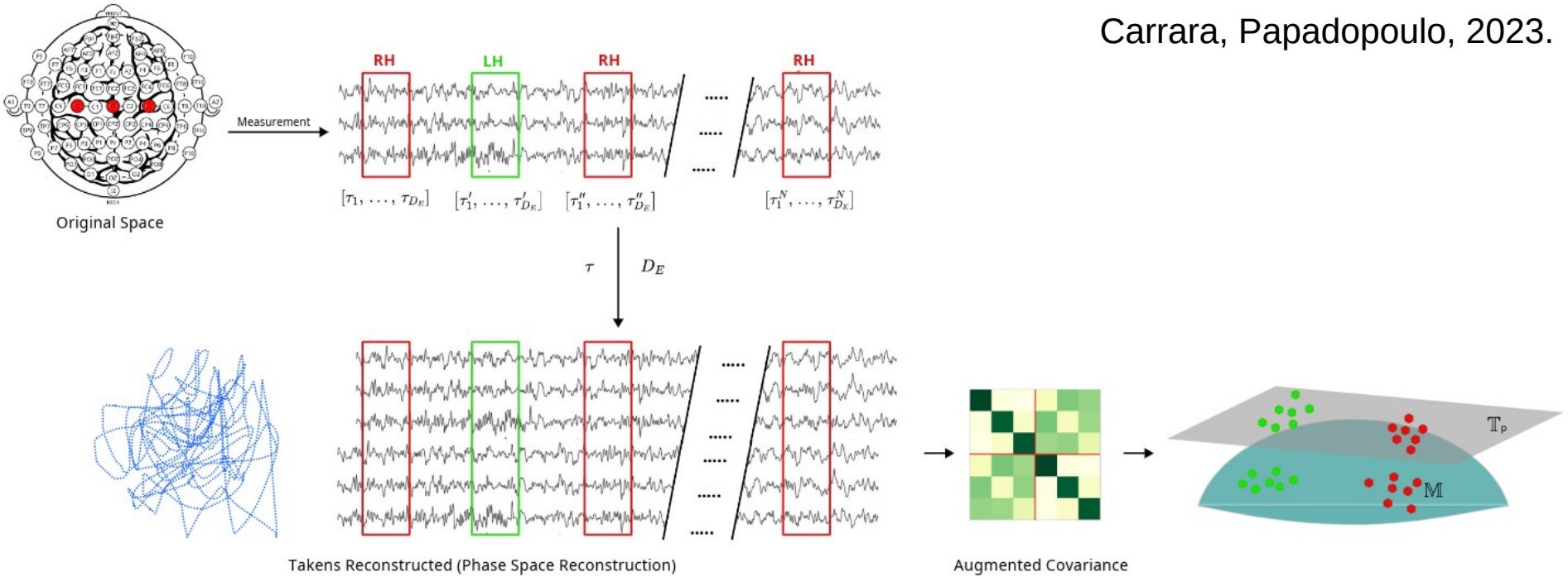
Limitations of linear methods



- Use high dimensional embeddings.
- Alternatively, non-linear methods.
- Deep learning latent spaces are such embeddings (auto-encoders).
- Augmented methods / Dynamical systems.

Augmented Covariance Methods

Carrara, Papadopoulo, 2023.



Original Space

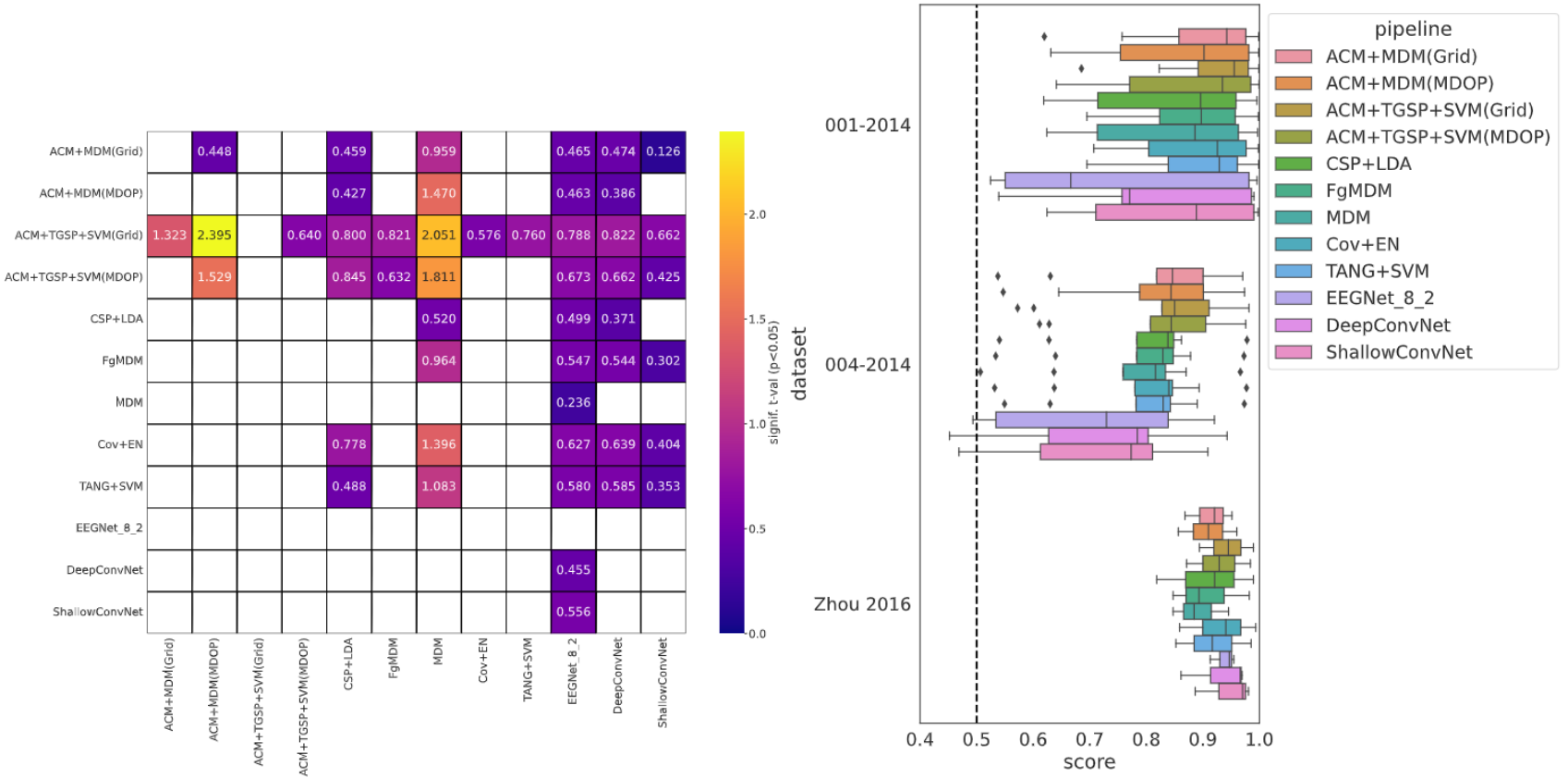
Takens Reconstructed (Phase Space Reconstruction)

Augmented Covariance

Linked to dynamical systems: Takens delay embedding theorem, Koopman's theory.
Linked to auto-regressive models: Yule-Walker equations.

Use of more sophisticated spatio-temporal patterns.

Augmented Covariance Methods



Carrara, Papadopoulo, 2023.

Deep Learning Classification

- Really trendy nowadays…
- Many proposals: EEGNet, DeepConvNet, SPDNet, ShallowConvNet, …

- Often promising, but also often not much better than classical methods:
  - Probably related to the size of training dataset.
  - But also on the difficulty of the signal (poor SNR).

- In rapid development...
- Helped a lot by the generalization of data sharing.

Feedback

- Important for subject implication.
- Visual or auditory.
- Embodiement (robot, orthesis, neuroprosthesis).
- “Bidirectional” BCIs with neurostimulation.

- Ergonomy.
- Human learning theory.

Applications

- Severe neuromuscular deficiencies:
    - Amyotrophic lateral sclerosis.
    - Brain stem vascular accidents (strokes).
    - Spinal chord injury.

  ➔ Neurorehabilitation, man-machine interface.
- Post-amputation treatment:

  ➔ Proprioception, phantom pains.

  ➔ Prosthesis control.
- Control of attention: Neurofeedback.
- Gaming.

Tools

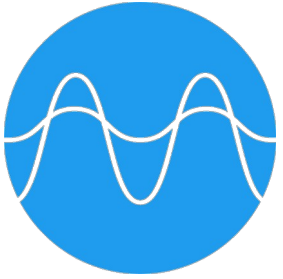
- Software

All learning and deep learning frameworks.









Timeflux

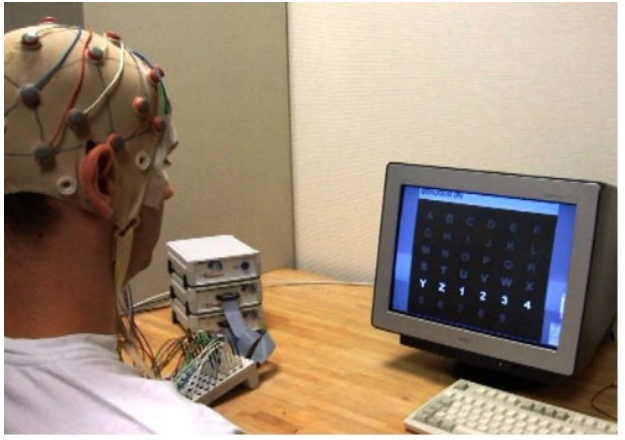
- Open hardware



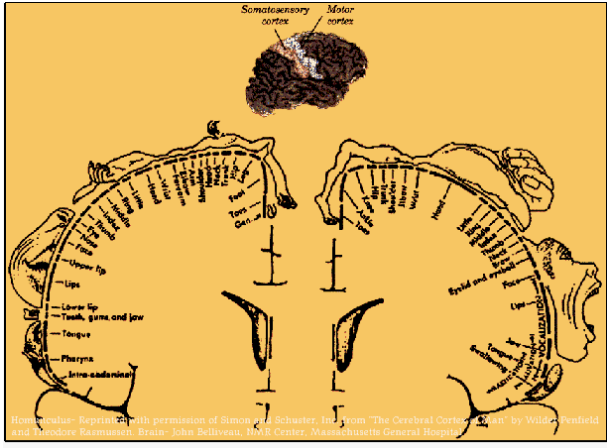




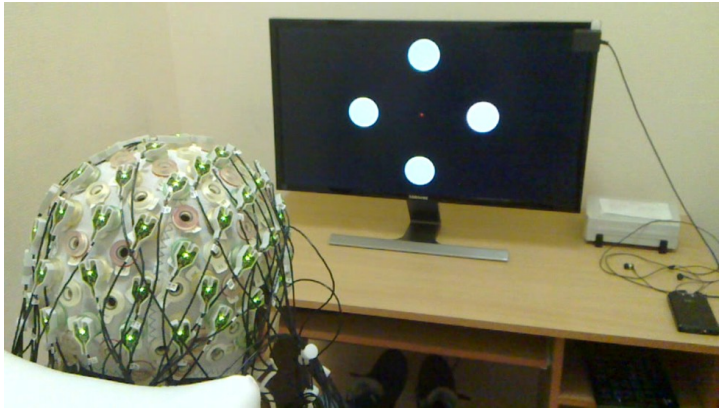
Typical paradigms



P300 speller keyboard



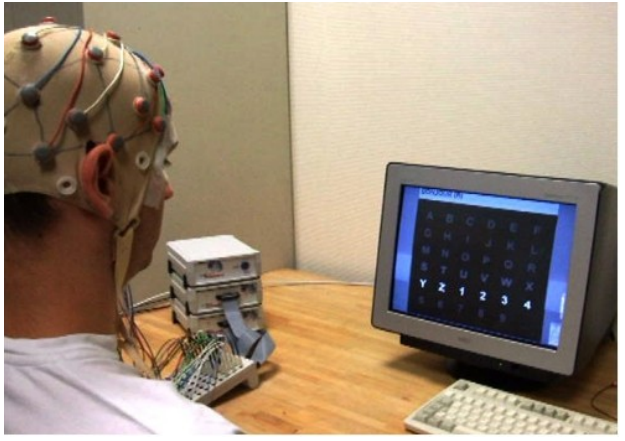
Motor imagination



Visually Evoked Potential

P300 wave based paradigms

P300 speller



A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

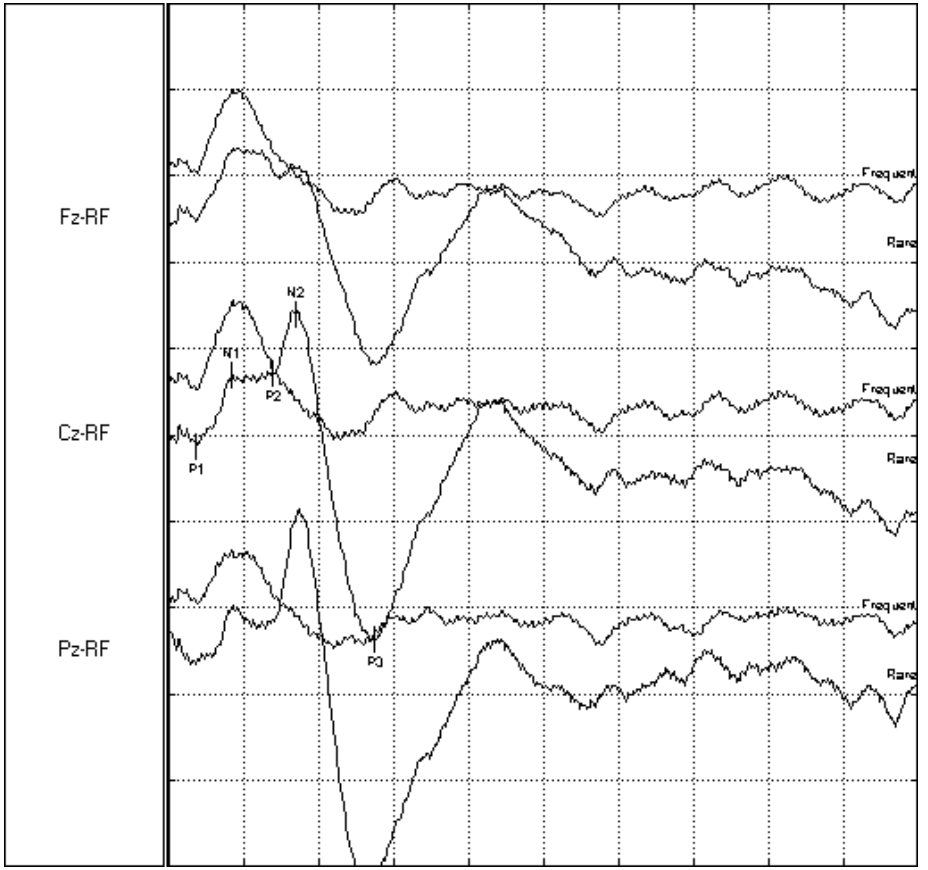
A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

- P300 wave linked to the **perception of a rare but expected event.**
- Can be visual or auditive.
- Random presentation of stimuli in groups.
- **Subject's attention** focused on an item of his/her choice.

P300 waves

Synchronous protocol: pace imposed by the system.

P300 / Non P300 waves

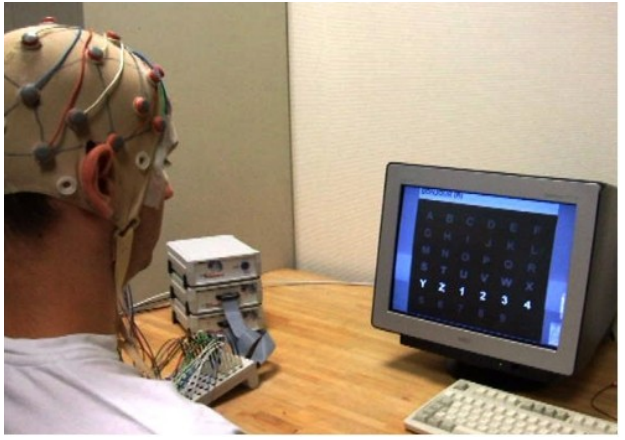


P300 speller Demo



YouTube link

P300 speller

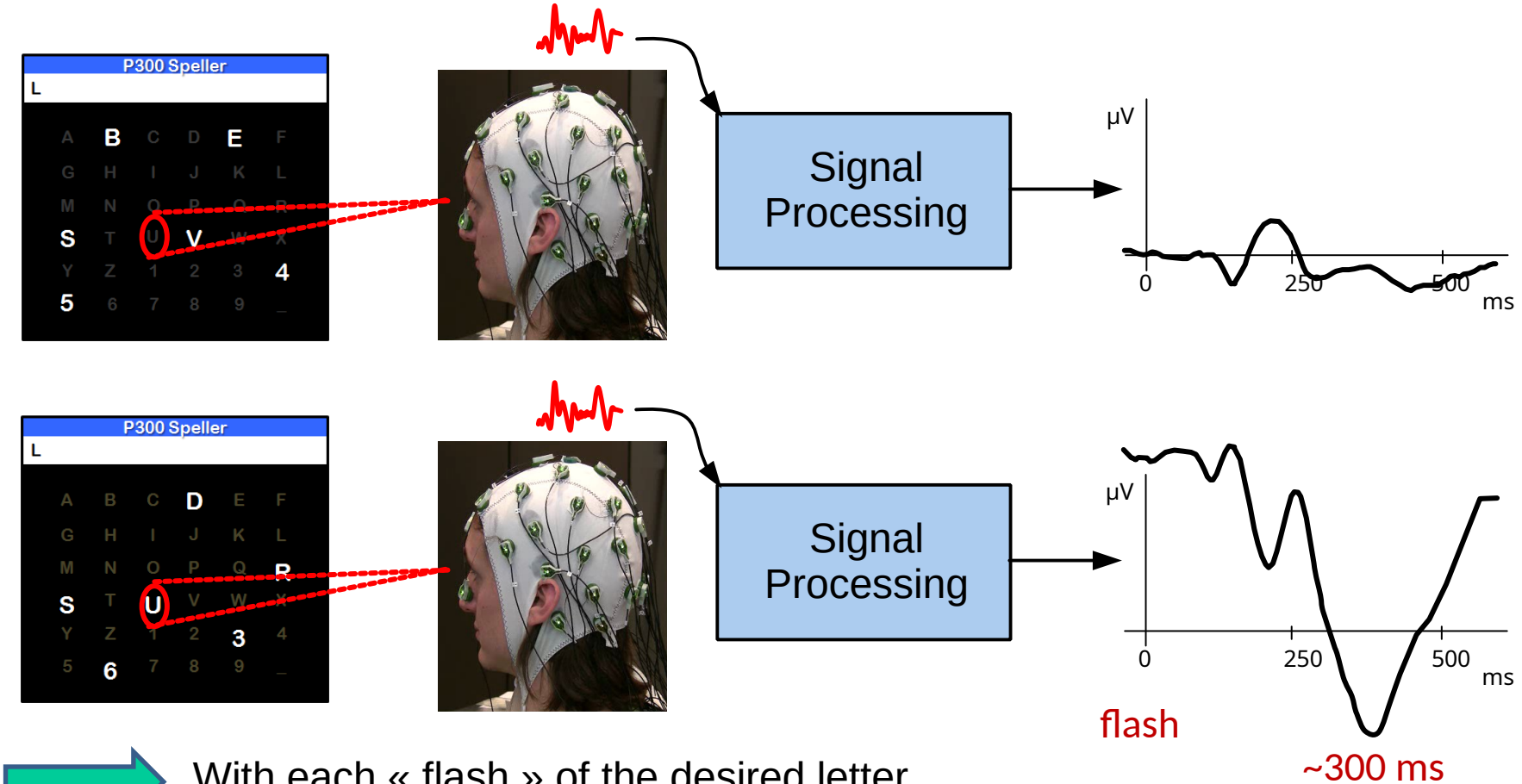


A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	_

- P300 wave linked to the **perception of a rare but expected event.**
- Visual P300 paradigm.
- Random flashes of letters in groups.
- **Subject's attention** focused on a letter of his/her choice.
- Classification of EEG → intersection of groups (e.g. lines / columns).
- Single letter intersection between two groups.

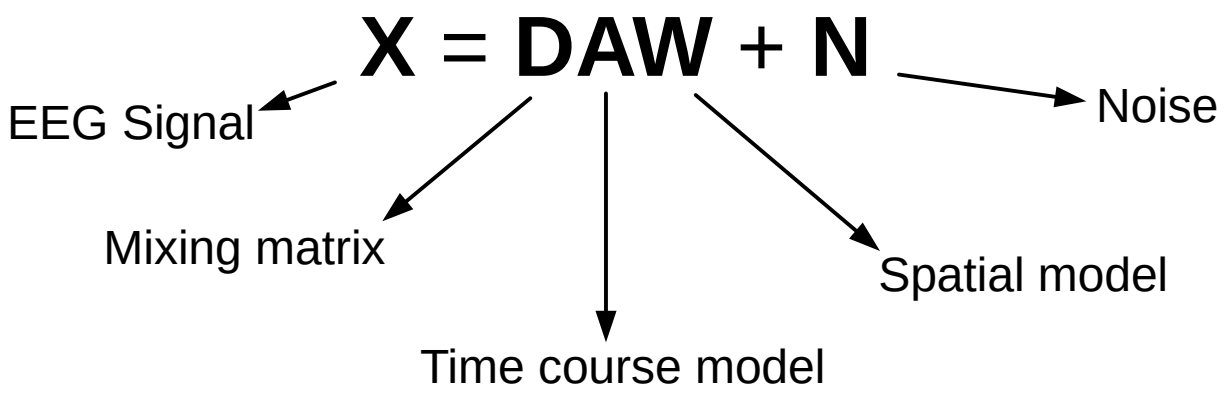
P300 speller: Principle



With each « flash » of the desired letter,
the interface should detect a P300 signal.

P300: Classification scheme

XDAWN algorithm (Rivet etal, 2009):



Classification

$\hat{\mathbf{S}} = \mathbf{X}\mathbf{W}^T + \mathbf{N}\mathbf{W}^T$

$\hat{\mathbf{S}}$ is then compared to $\mathbf{A}_t$ or $\mathbf{A}_{nt}$.

Training

$\mathbf{X} = \mathbf{D}_t\mathbf{A}_t\mathbf{W} + \mathbf{D}_{nt}\mathbf{A}_{nt}\mathbf{W} + \mathbf{N}$

- $\mathbf{D}_t$, $\mathbf{D}_{nt}$ → Given by the computer clock (Toeplitz matrices).
- $\mathbf{A}_t$, $\mathbf{A}_{nt}$,$\mathbf{W}$ → Computed from calibration data.

P300: Applications

The P300 speller principle can be used in all cases involving commands based on multiple choices, not requiring a too fast choice:

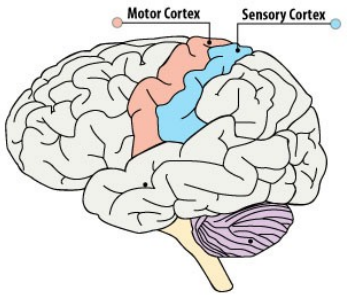
- Keyboards.
- Games.
- Environmental control (with pictograms).
- …

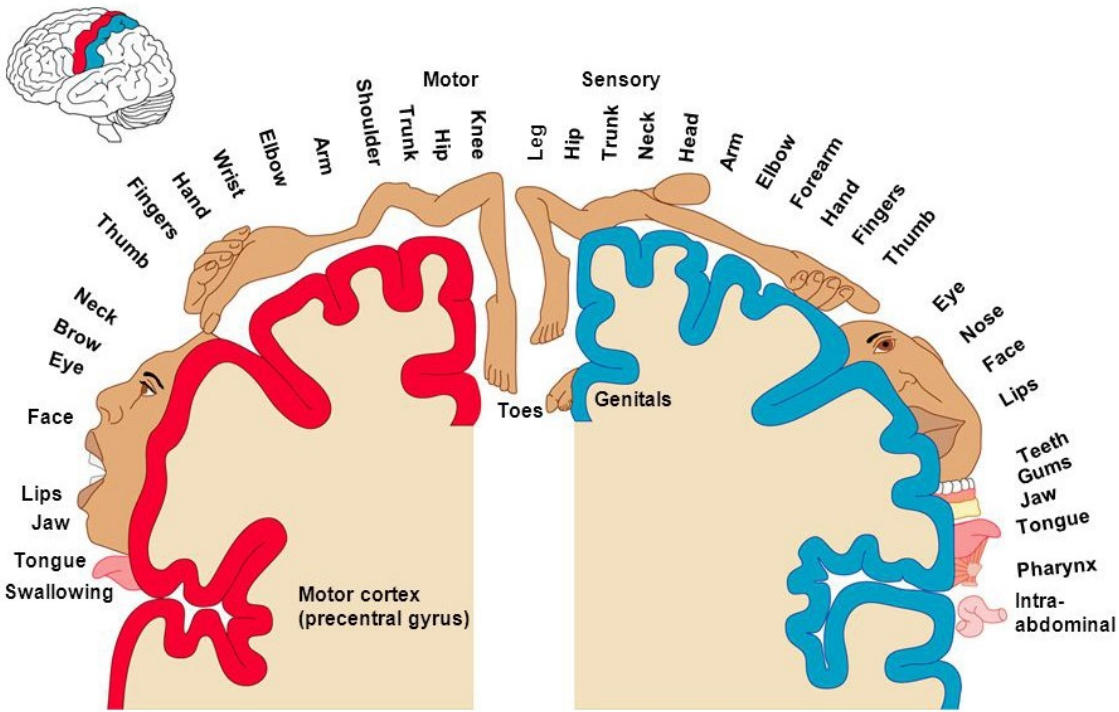
- Communication with Locked In subjects (auditory).



Sensorimotor paradigms

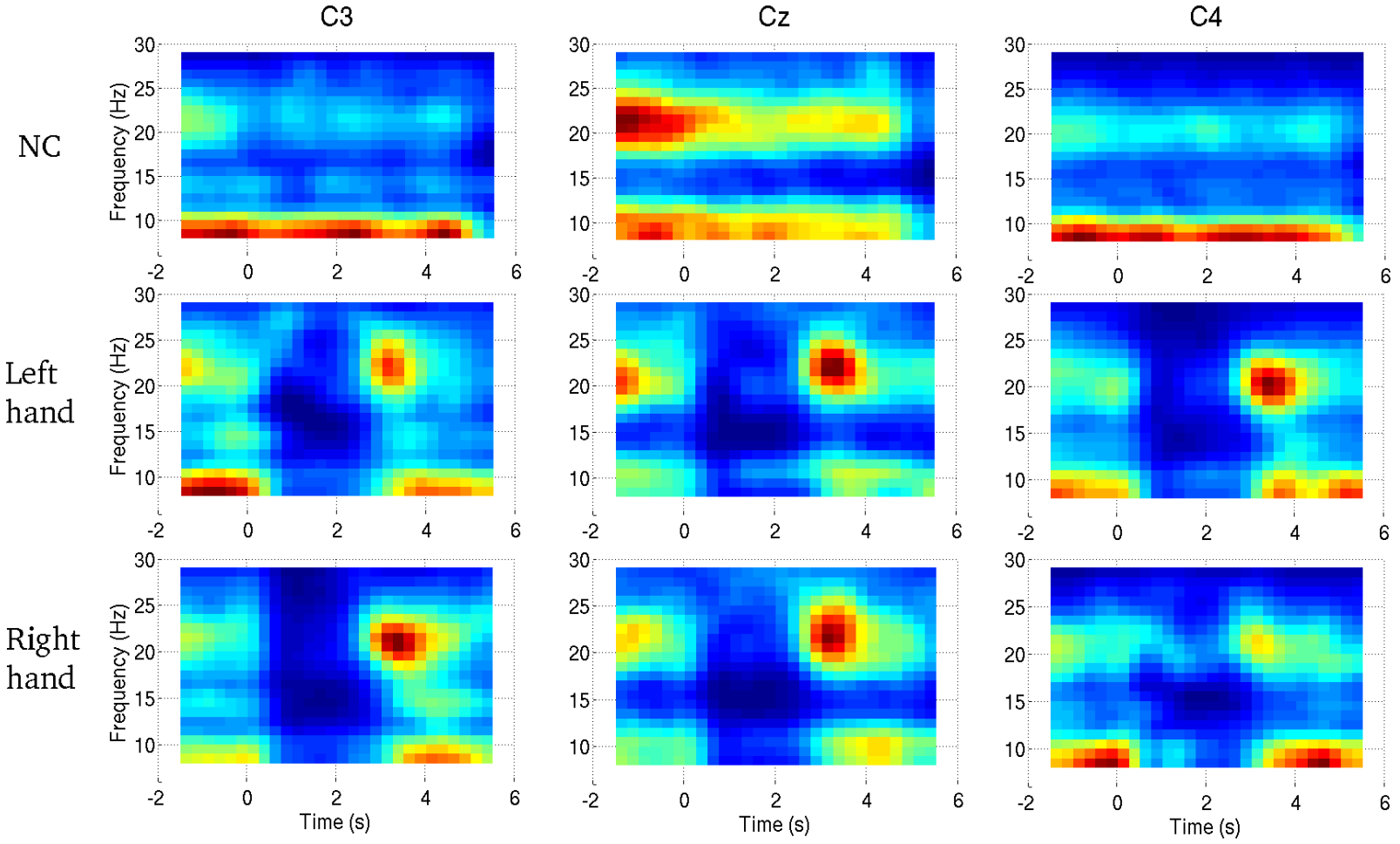
- **Real or imaginary activity.**
- Event related Desynchronisation / Synchronisation (ERD / ERS).
- Topography characteristic of the body part.





https://learnsomatics.ie/

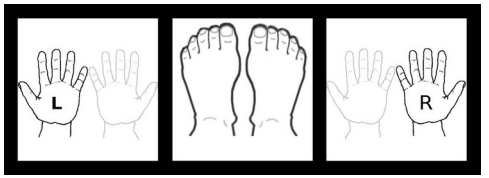
Sensorimotor brain rythms



Sensorimotor task selection

Goal: asynchronous commands, “self-paced”.

- Identify adequate motor tasks



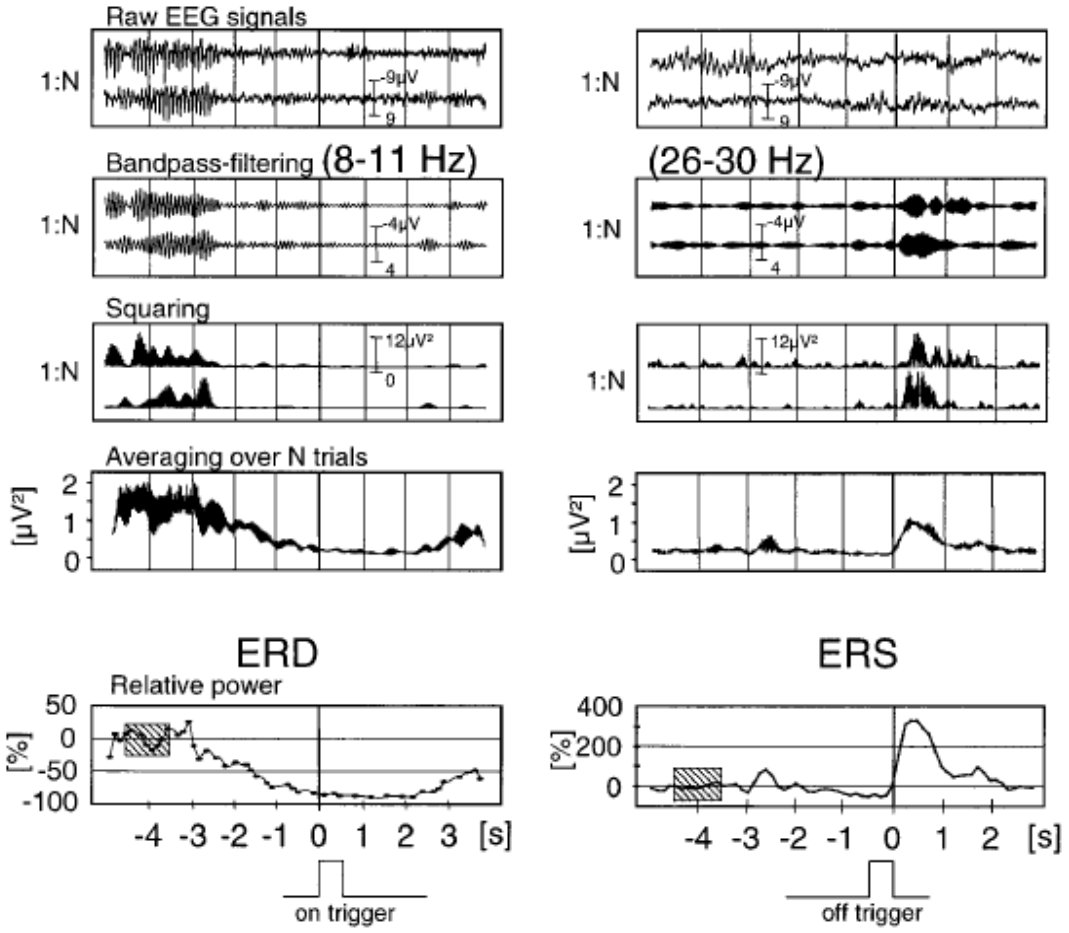
- Detect the occurrence of such tasks in resting periods (ERS). → Discrete command button

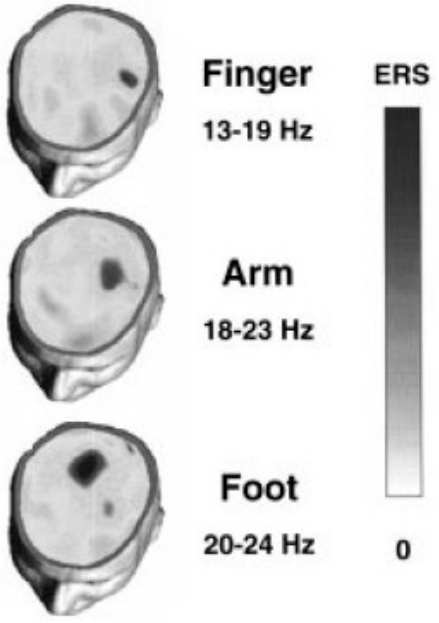
- Measure the task duration (ERD). → Continuous command cursor

Note: non motor tasks are possible (mental calculus, 3D mental rotation, verbal tasks, …).



Sensorimotor BCIs: Features

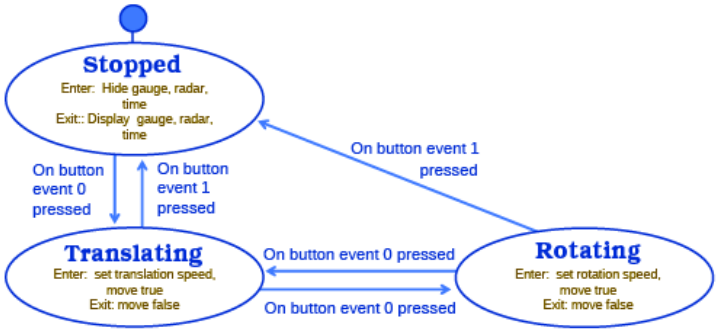




Pfurtscheller, 1999.

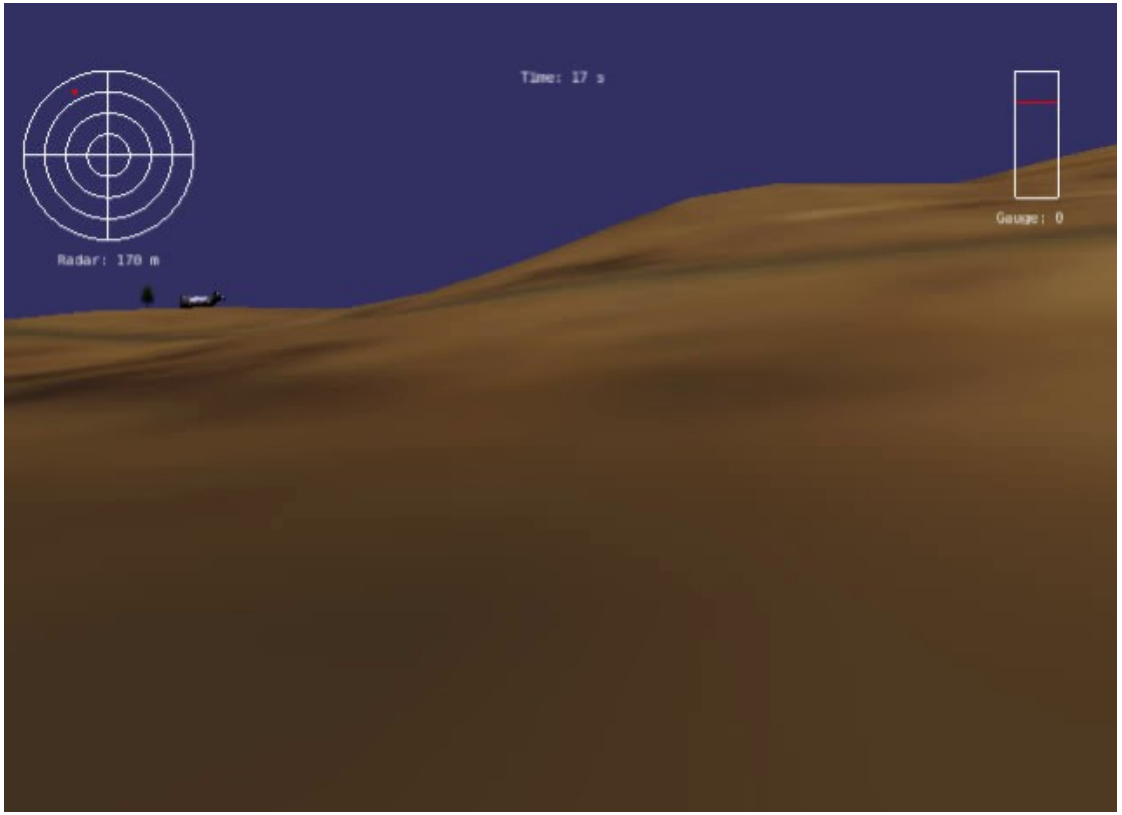
Sensorimotor paradigms: Demo

Discrete command: button based on beta rebound.
Application: **Navigation** in a virtual environment.



Logo turtle strategy.

Importance of the interface !!!

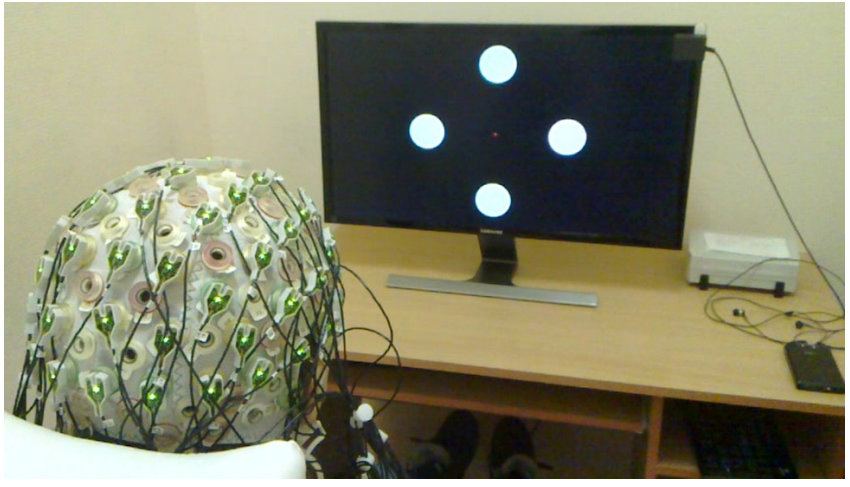


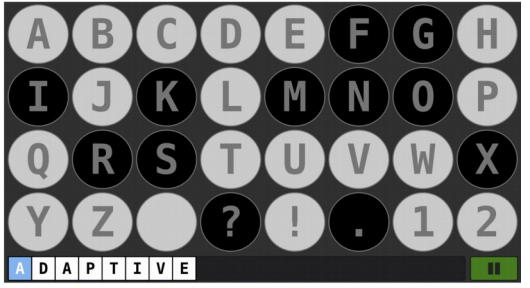
YouTube link

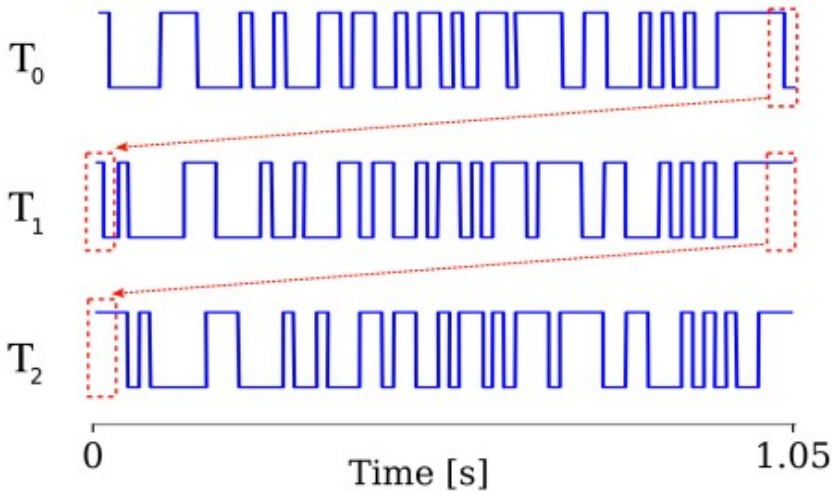
Visually Evoked Potentials (VEP)

Information encoded as:

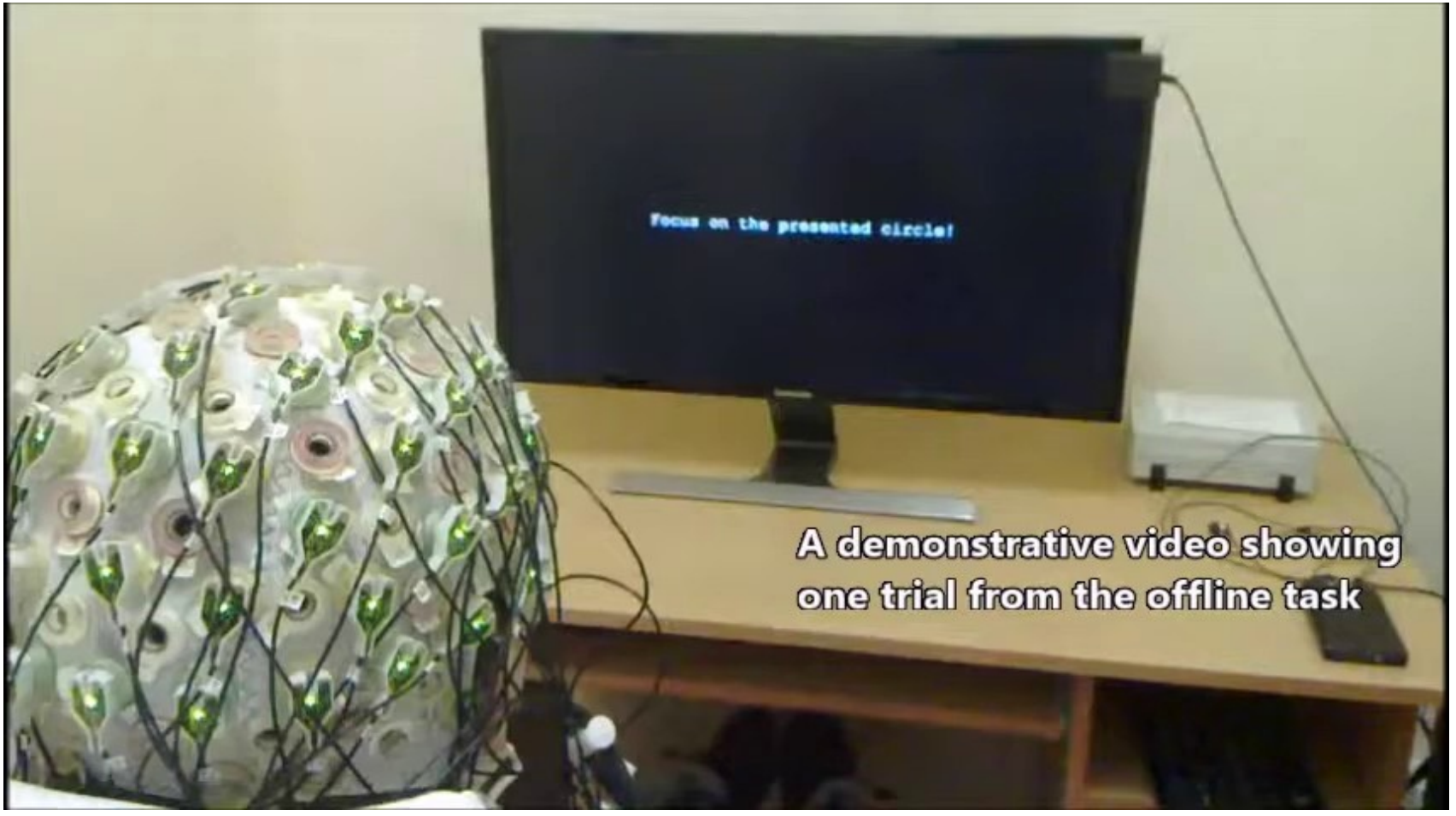
Frequencies (SSVEP) or Code modulations (c-VEP) / Time codes.
Gold (maximally uncorrelated) sequences.







Visually Evoked Potentials: Demo



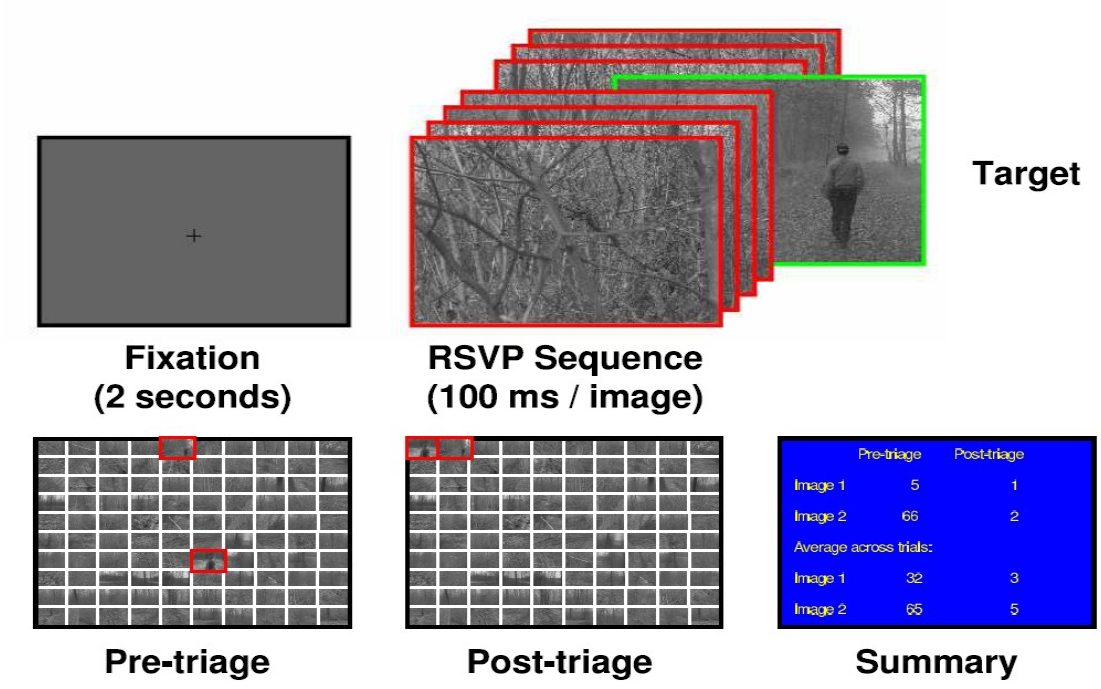
YouTube link

Ethical issues

- Augmented human.
- Instrumentalization.
- Brain “reading”.
- Reliability: wrong message or command.

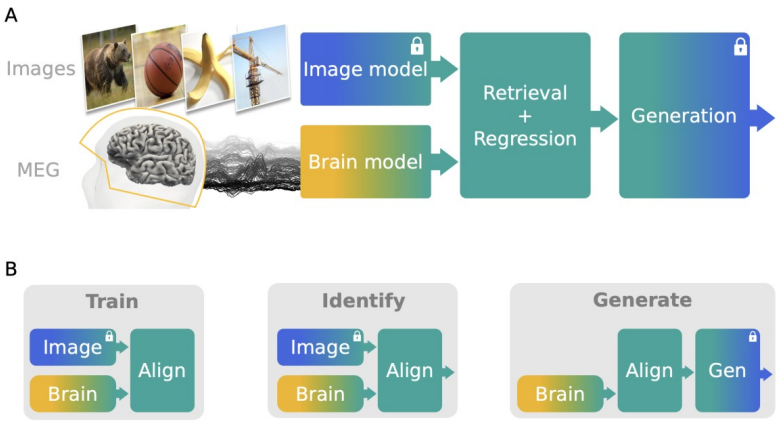
Ethical issues

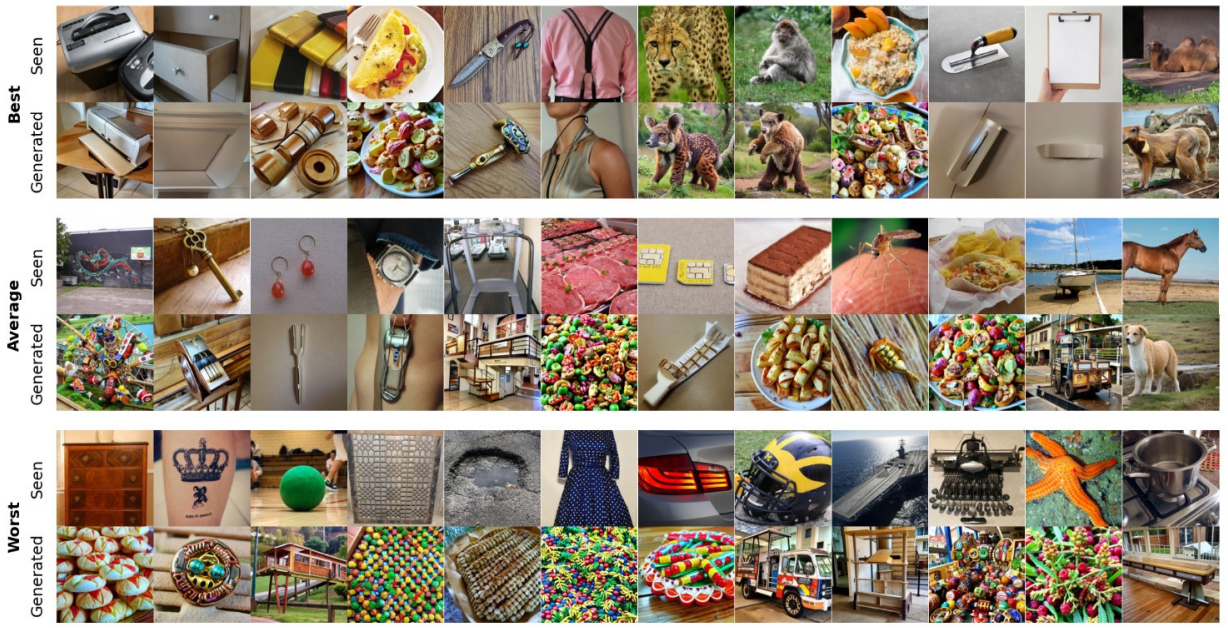
Cortically Coupled Computer Vision for Rapid Image Search.



DARPA: Neurotechnology for Intelligence Analysts

Ethical issues: Brain reading (MEG or fMRI)





MEG example:

- Combination of Deep Learning pipelines: Image encoding, Brain Signal Encoding, **learned mapping between the two** and Image generation.

Benchetrit, Banville, King @ Meta / PSL, 2023.

Thank you !!!

