FEATURE SELECTION ALGORITHMS FOR CORTICOMUSCULAR COHERENCE-BASED BRAIN-COMPUTER INTERFACES

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FIELD OF APPLICATION:
NEUROENGINEERING

ARTIFICIAL INTELLIGENCE
TASK

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TYPE OF FEATURE

Introduction

Brain-Computer Interfaces for post-stroke rehabilitation

Stroke

Stroke is a condition in which **cells** in the **brain** suddenly **die** because of lack of oxygen caused by an obstruction in the blood flow or by a hemorrhage.

> In 2021, stroke was responsible for **over 7 millions deaths**, approximately **10%** of the total **global** deaths. It is one of the main reasons for abnormal human death.

Stroke: **Post-stroke patients**

In recent years there has been a noticeable **increase** in the **survival rate** of **post-stroke patients**.

Who survive is usually left with **disabilities**, affecting especially **upper limb movement**.

Patients lose their ability to **control** their **muscles** in the **physiological manner**.

Post-stroke rehabilitation

Rehabilitation makes the difference in **overcoming** or not motor **disabilities**.

Among the recent advanced **rehabilitation techniques,** there are the ones based on **Brain-Computer Interfaces (BCIs).**

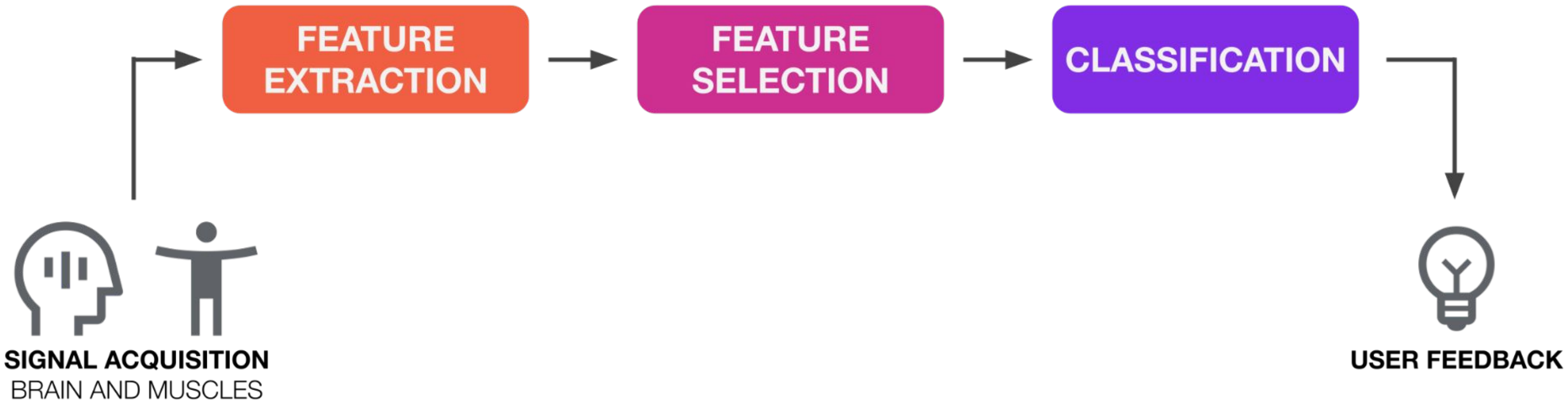
Pichiorri et al. 2023

Post-stroke rehabilitation: **Brain-Computer Interface (BCI)**

BCI provides a way to develop **interaction** between a **brain** and a **computer**. This interaction is achieved by using control signals arising due to the **brain activity**.

In this work, the type of BCI used is called **Hybrid BCI** which also acquires **muscle activity** as peripheral signal.

Post-stroke rehabilitation: **Pipeline**



Pipeline: **Feature selection**

Feature selection is a crucial step usually performed by a **high specialized neurophysiologist**.

It is important to select features that take into account **neurophysiological** and **rehabilitative** principles.

FEATURE EXTRACTION → FEATURE SELECTION → CLASSIFICATION

Pipeline: **Automated feature selection**

The focus of my research is on **automated** feature selection step which does **not** require **high specialized** neurophysiological competence.

The aims are:

- expand BCI use to users with **limited**:
  - **expertise** on BCI;
  - **knowledge** of the **neurophysiological principles** that guide the selection of the features.
- improve the choice by also considering the **classification performance.**

Dataset and problem

Feature selection in a binary classification task

Datasets: Data acquisition

This study is focused on **healthy subjects** who execute movements in a repeatable way intra/inter individuals.

The **processed** data used in this work was **provided by** IRCCS Santa Lucia Foundation, Rome, Italy.

SANTA LUCIA

Data acquisition: **Movements**

The data was collected from 14 healthy subjects performing four different movements:

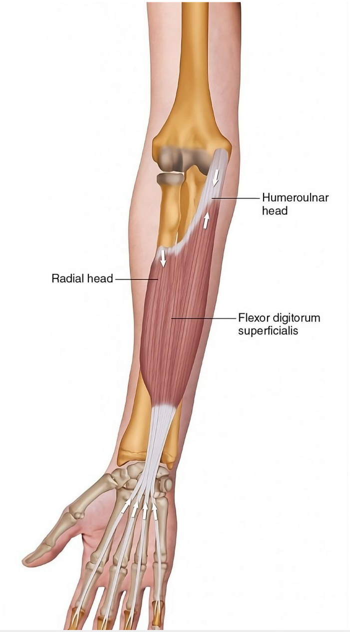
- **GraspL:** Finger grasping with the left hand;
- **GraspR:** Finger grasping with the right hand;
- **ExtL:** Finger extension with the left hand;
- **ExtR:** Finger extension with the right hand;

Each movement was studied **independently** from the others

Data acquisition: **GraspL**

For the sake of brevity, during this presentation, the explanation is **focus** on only **finger grasping** `GraspL`.

The same procedure explained in the following was applied also to the other movements.



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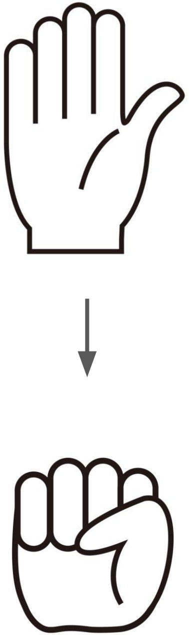
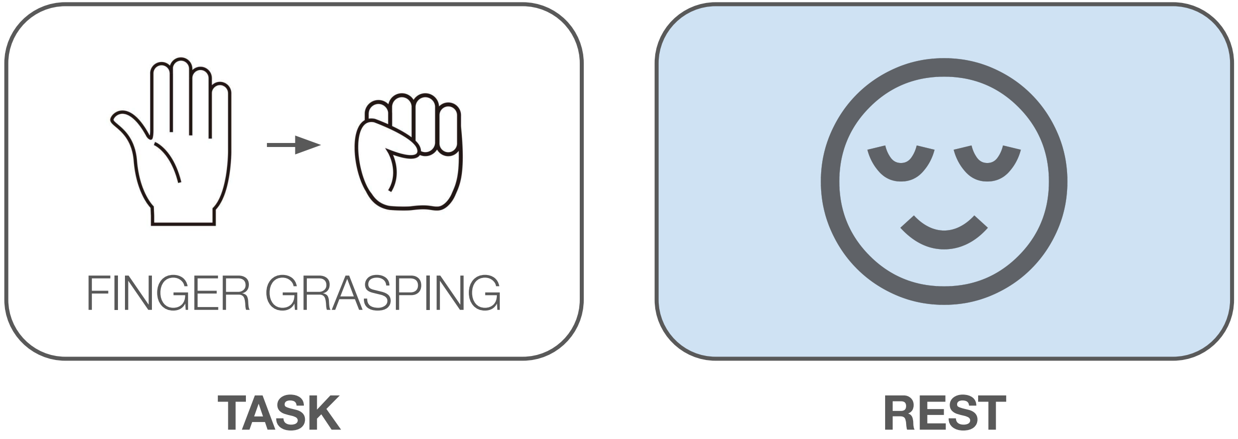


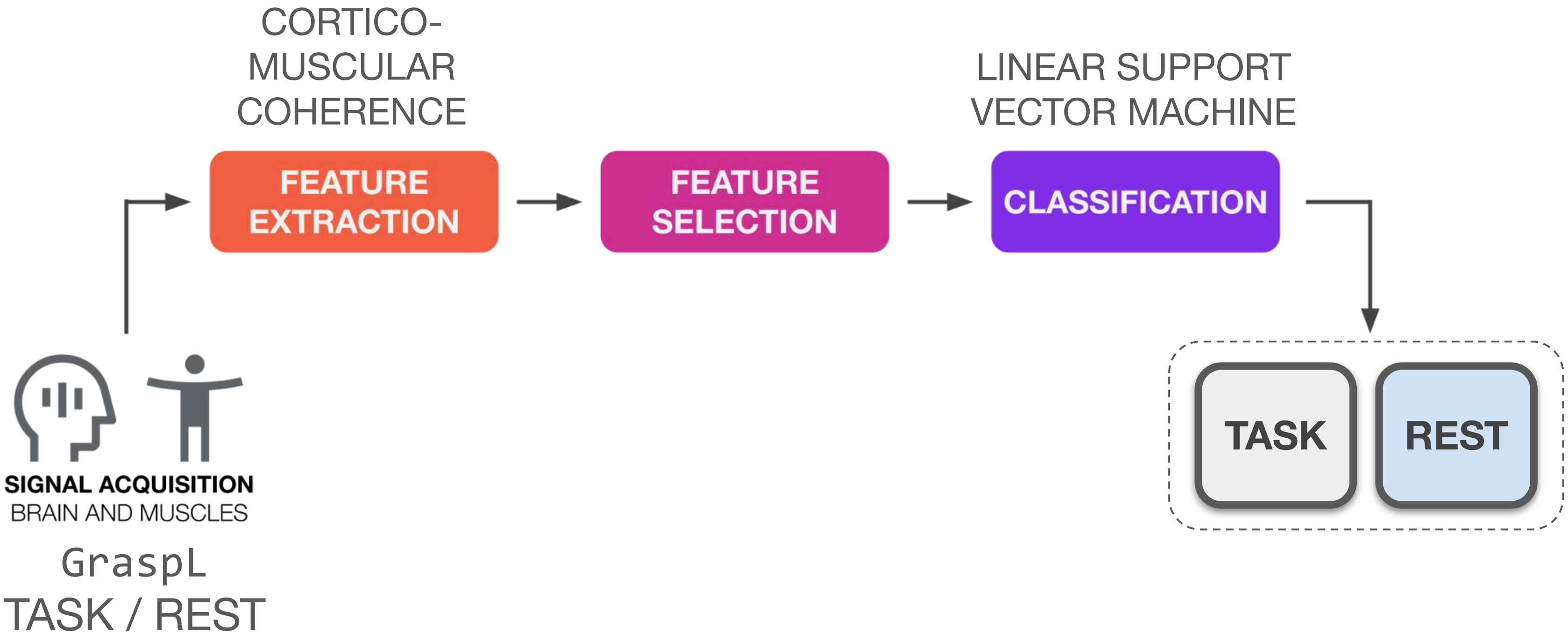
GRASPING
GraspL

GraspL: **Rest and Task**

During **data acquisition**, the subject **alternates** moments where he performs the **movement** and moments where he is at **rest**:

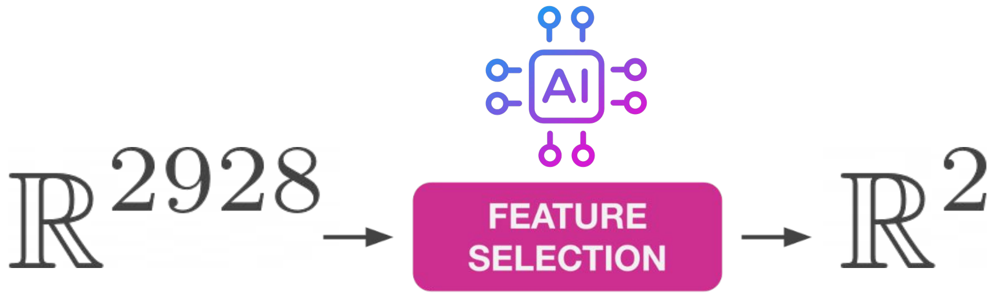


GraspL: **Pipeline**



Pipeline: **Automated feature selection**

From the initial 2928 features, the **two** most **relevant features** must be selected to optimize the classification performance.



Different feature selection algorithms were **compared**.

Proposed solution

State-Of-The-Art

and Random Planet

State-Of-The-Art: Feature selection algorithms

In this field, some of the State-Of-The-Art feature selection methods are:

- **Mutual Information:** Statistical measure-based method;
- **Stepwise Regression:** Statistical search oriented approach;
- **Genetic Algorithm:** Metaheuristic search technique;
- **Decision Tree:** Common method in Machine Learning;
- **Random Forest:** Ensemble of Decision Tree models.

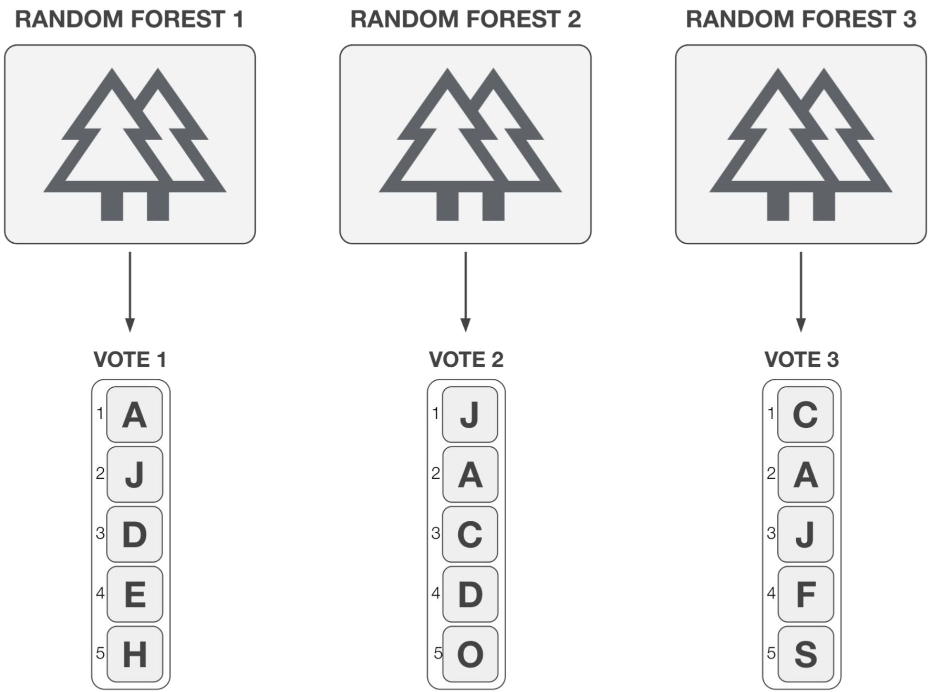
> Both **Decision Tree** and **Random Forest** have **low stability**, namely the features selected are highly **influenced** by the initial conditions (i.e., **random seed** adopted).

Random Planet

Random Planet is a **novel method** introduced in this work to **improve stability** of Decision Tree and Random Forest.

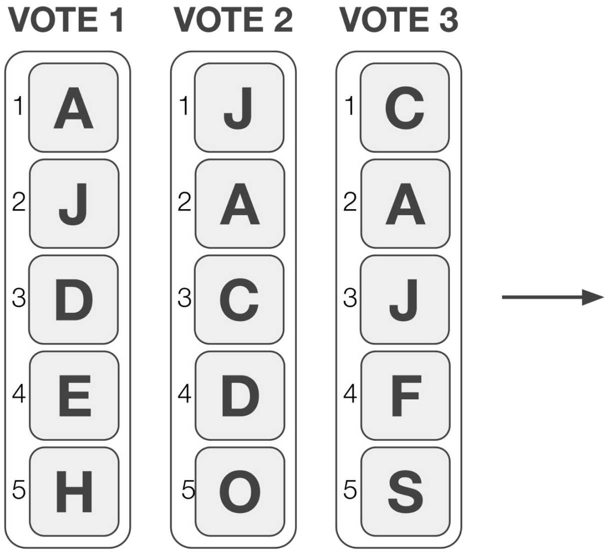
Random Planet is an **ensemble** of Random Forest models:

Random Planet: **Example - Collection of votes**



PROPOSED SOLUTION

Random Planet: **Example - Most voted features**



A = 3
J = 3
C = 2
D = 2
E = 1
F = 1
H = 1
S = 1
O = 1

Random Planet: **Example - Tie-breaker**

A = 3
J = 3
C = 2
D = 2
E = 1
F = 1
H = 1
S = 1
O = 1

Classification performance obtained by a linear SVM using **only** feature A

A = 3 + 0.82
J = 3 + 0.89

Classification performance obtained by a linear SVM using **only** feature J

FINAL RANKING

1 **J**
2 **A**

PROPOSED SOLUTION

Feature selection algorithms compared

The feature selection algorithms compared are:

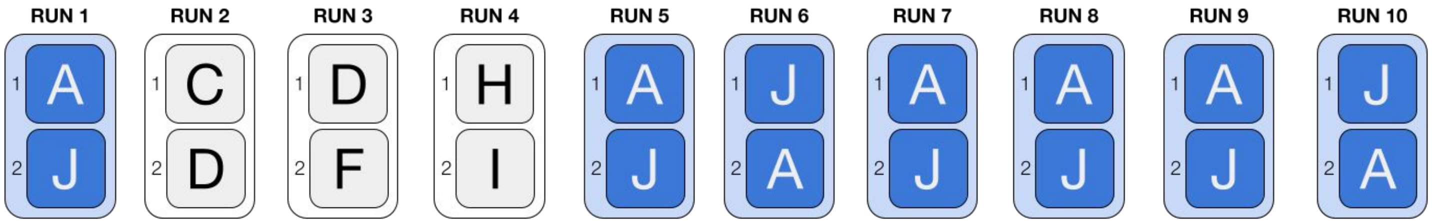
- **Decision Tree** `(DTree);`
- **Genetic Algorithm** `(GAAM):` **9** hyperparameter combinations tested;
- **Mutual Information** `(MInfo);`
- **Random Planet** `(RPlanet):` **45** hyperparameter combinations tested;
- **Stepwise Regression** `(StepwiseR).`

> **Hyperparameter tuning** procedures based on **statistical analysis (ANOVA)**, were performed for **Genetic Algorithm** and **Random Planet**.

Feature selection algorithms compared: **Metrics**

The metrics adopted to compared the feature selection algorithms are:

- Area Under Curve (**AUC**) of the Receiver Operating Characteristic curve;
- **F1 Score**;
- **Soft Stability (SoftS):** Metric defined in this study to measure the stability.



$$\text{SoftS} = 7/10 = 0.7$$

Result

Algorithms comparison

GraspL: Performance comparison

Mean **Soft Stability** (SoftS) of each algorithm and mean **classification** performance obtained using the features selected by each method.

Means computed over the 14 subjects. (Mean ± std)

Method	AUC Train	AUC Test	F1 Train	F1 Test	SoftS
DTree	0.959 ± 0.02	0.957 ± 0.02	0.957 ± 0.02	0.955 ± 0.03	0.343 ± 0.28
GAAM	0.984 ± 0.02	0.975 ± 0.02	0.984 ± 0.02	0.975 ± 0.02	0.443 ± 0.17
MInfo	0.957 ± 0.03	0.952 ± 0.04	0.954 ± 0.04	0.948 ± 0.05	1.0 ± 0.0
RPlanet	0.960 ± 0.02	0.954 ± 0.03	0.958 ± 0.02	0.951 ± 0.03	0.671 ± 0.27
StepwiseR	0.966 ± 0.02	0.964 ± 0.02	0.964 ± 0.03	0.962 ± 0.03	1.0 ± 0.0

Performance comparison: **Statistical significance**

AUC Test performances were compared using **statistical** methods (ANOVA).

Significant **differences** were found only between Mutual Information and Genetic Algorithm with this last having **higher** mean AUC performance.

Method	AUC Test
DTree	0.957±0.02
GAAM	0.975±0.02
MInfo	0.952±0.04
RPlanet	0.954±0.03
StepwiseR	0.964±0.02

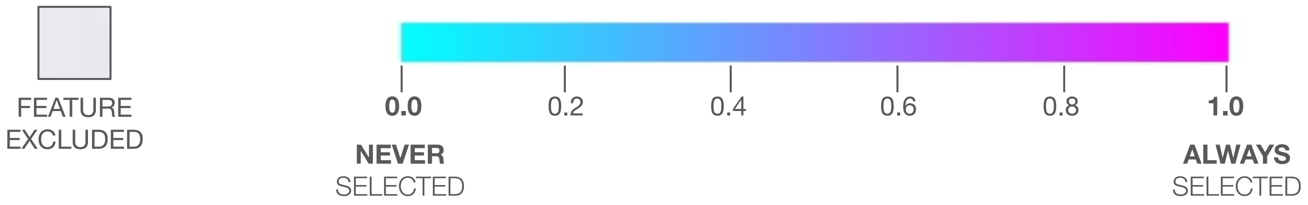
GAAM > MInfo

GraspL: **Selected Features**

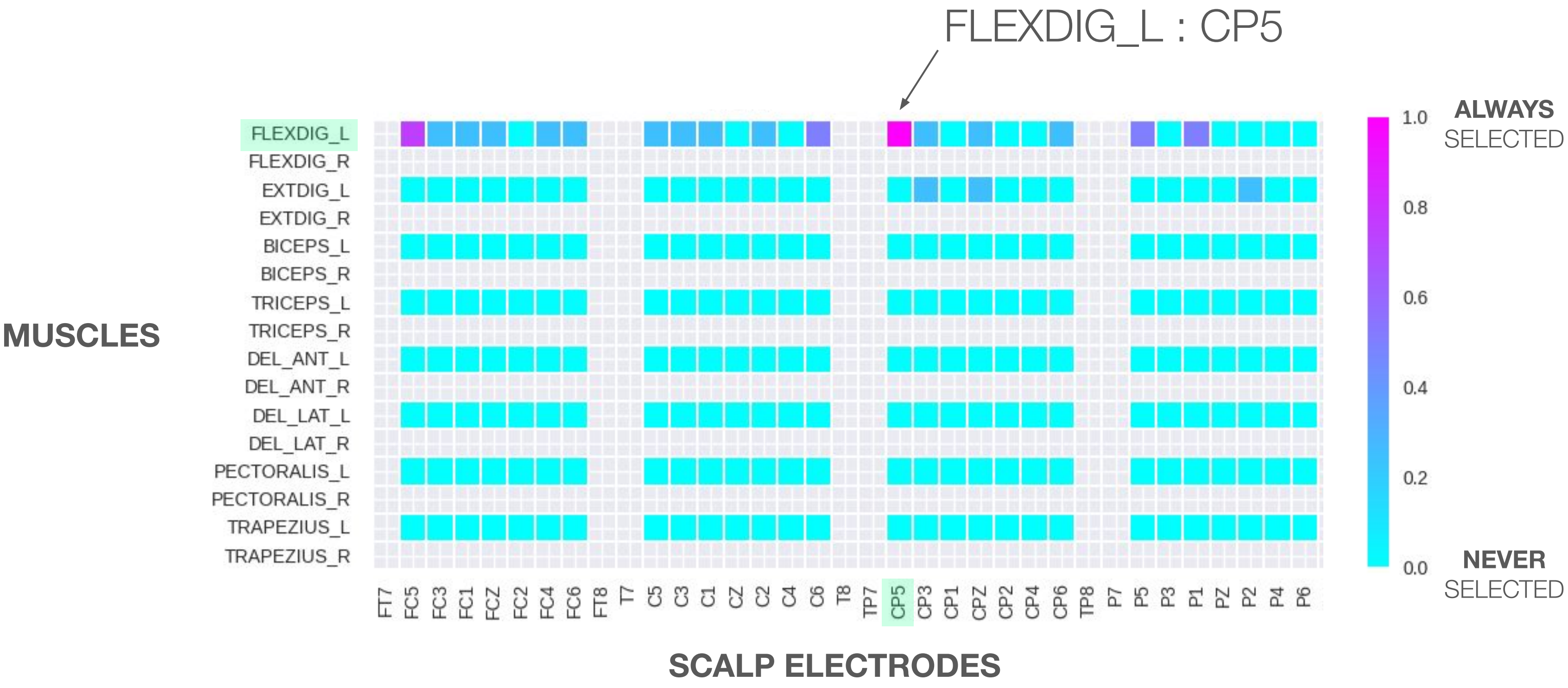
Restricting the initial feature space taking into account **neurophysiological constraints**, it is interesting to see the different features chosen by each method.

This information is represented as an **heatmap** with values ranging from 0 to 1:

- **Value ≃ 0:** the feature was **never** or rarely selected in one of the subjects.
- **Value ≃ 1:** the feature was selected as the best for **most** of the subjects.



Selected Features: **Random Planet**



GraspL, GraspR, ExtL, ExtR

Similar results were obtained for the **other movements** (`GraspR`, `ExtL`, `ExtR`) and using **different features domains** (spatial filtering, brain/muscles channels).

All the feature selection algorithms tested allow to obtain **high classification** performance (AUC-F1 Score Test > 0.9) without **statistical significant** differences most of the time.

GraspL, GraspR, ExtL, ExtR: **Overall perspective**

From an **overall perspective**:

- Genetic Algorithm has the **same** AUC performance of Stepwise Regression
    - Genetic Algorithm has a **lower stability**

- Decision Tree and Random Planet have the **same** AUC performance
    - As desired, Random Planet has always **higher stability**

Future works

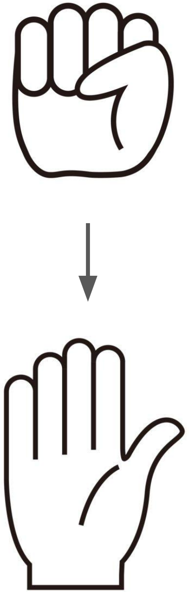
Neurophysiology expert consulting of the heatmaps is necessary to further considerations on what algorithms select the most **relevant** features from a **physiological point of view**.

The comparison should be **extended** to **post-stroke patients** considering also the features a **neurophysiologist** would select as **reference**.

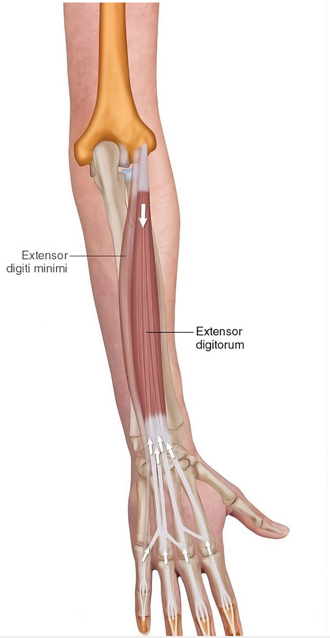
Thanks for your attention

End of the presentation

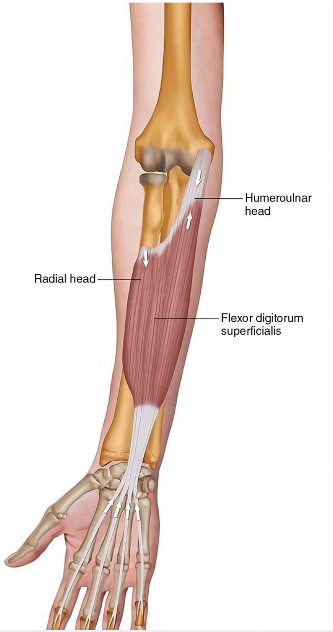
Finger Extension and Grasping



EXTENSION
Ext



EXTENSOR DIGITORUM



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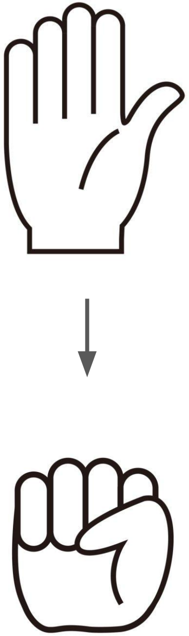


GRASPING
Grasp

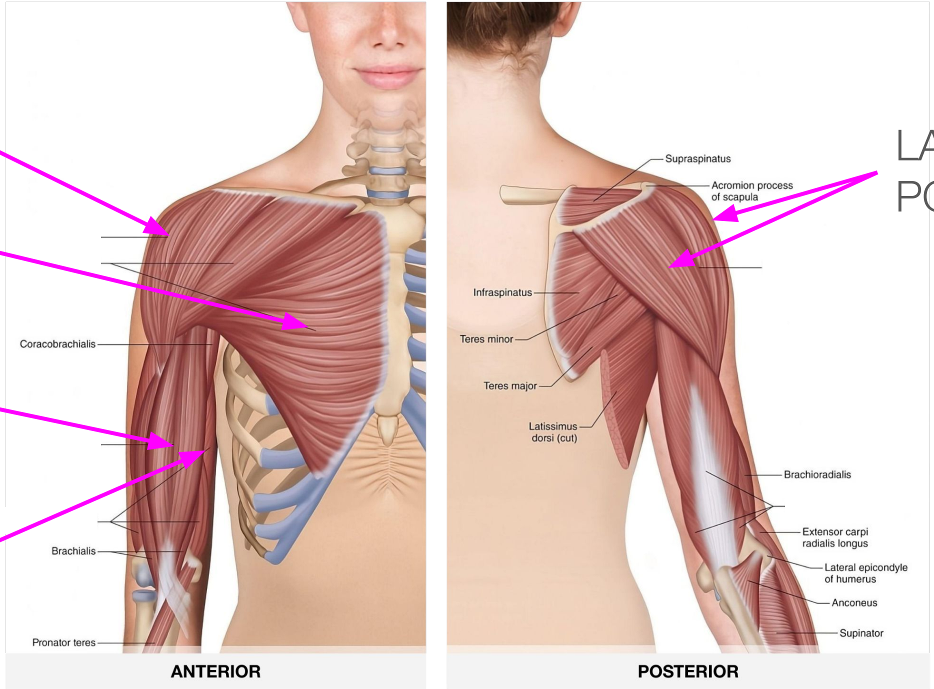
Upper limb muscles

ANTERIOR DELTOID

PECTORALIS MAJOR

BICEPS BRACHII

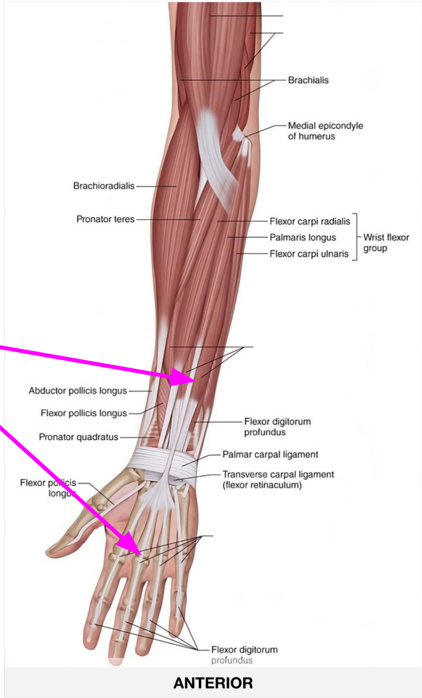
TRICEPS BRACHII

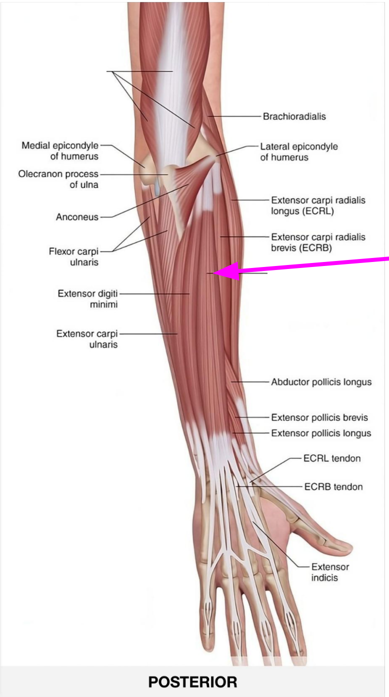


LATERAL AND POSTERIOR DELTOID

Upper limb muscles

FLEXOR
DIGITORUM
SUPERFICIALIS





EXTENSOR
DIGITORUM

APPENDIX

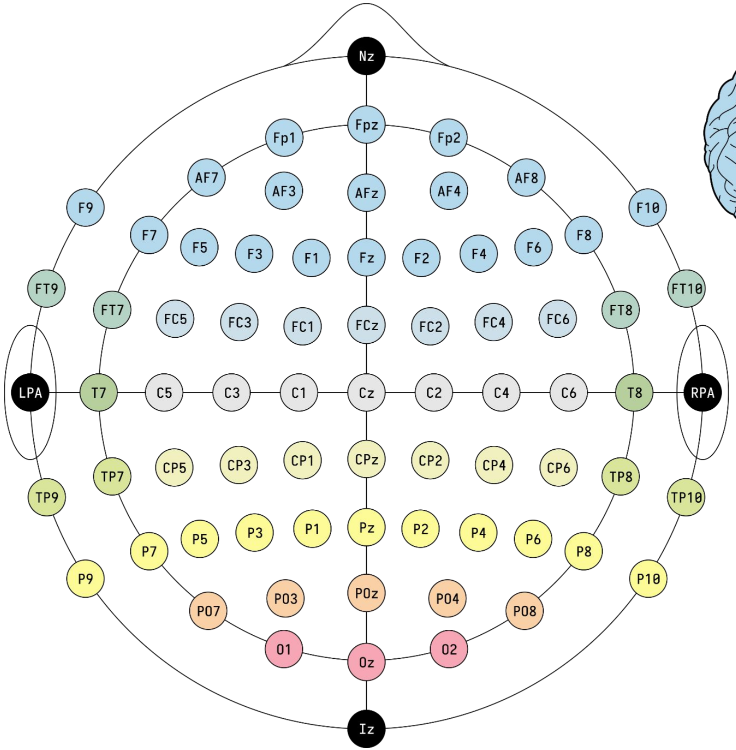
Brain signal: Scalp electroencephalography (EEG)

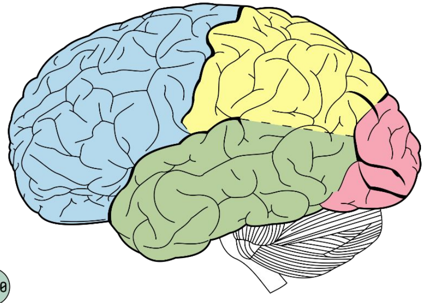
EEG is the **most common** technique to acquire brain signal:

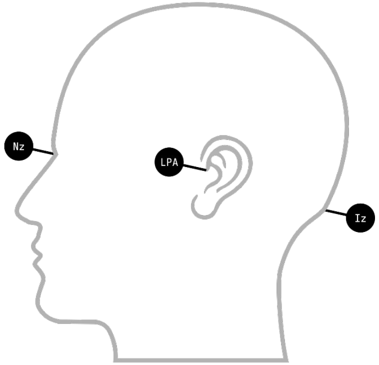
- non-invasive
- high temporal resolution
- relative cheap
- relative easy to use
- scalable

EEG: **10-10 International Electrodes system**

The placement of the electrodes on the scalp follows specific patterns called electrode systems

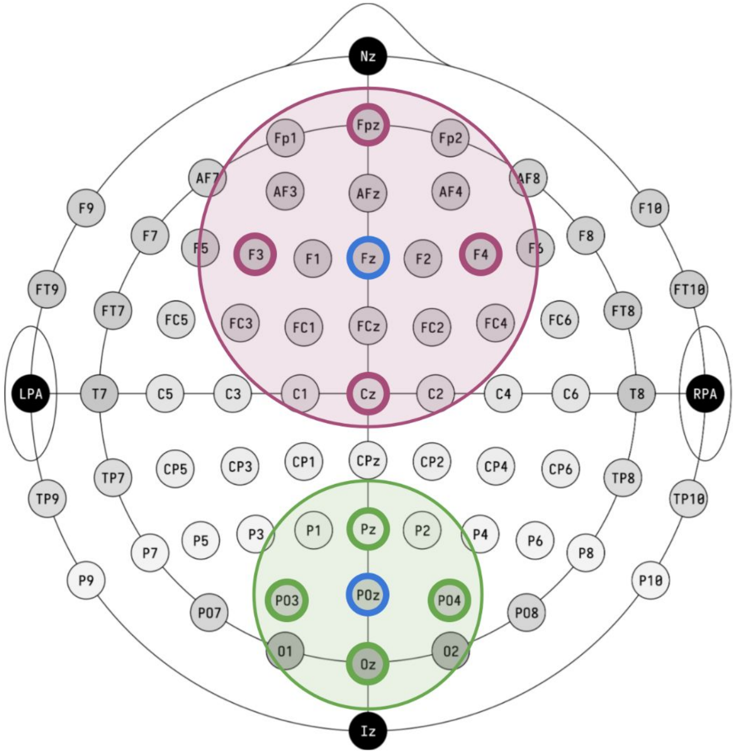






APPENDIX

EEG: **Laplacian filtering**



LARGE LAPLACIAN

$$\overline{F_Z} = F_Z - \frac{1}{4}(F_{PZ} + C_Z + F3 + F4)$$

SMALL LAPLACIAN

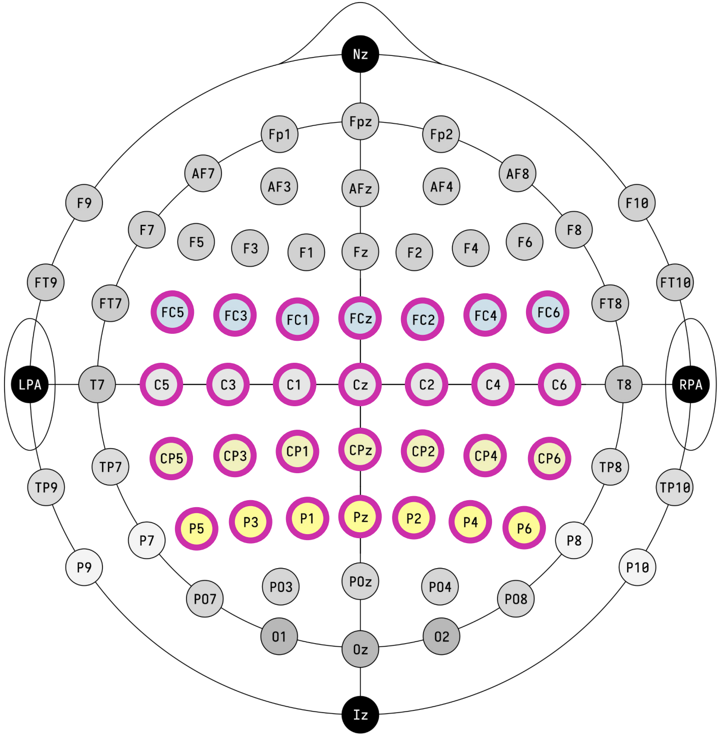
$$\overline{P_{OZ}} = P_{OZ} - \frac{1}{4}(P_Z + O_Z + PO3 + PO4)$$

EEG: **Sensorimotor area**

The brain region of **interest** during limb **rehabilitation** is **sensorimotor area**.

It is responsible for:

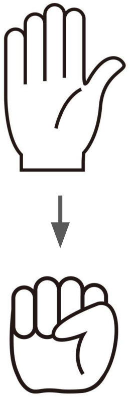
- movement planning
- movement execution
- proprioception
- touch and pain

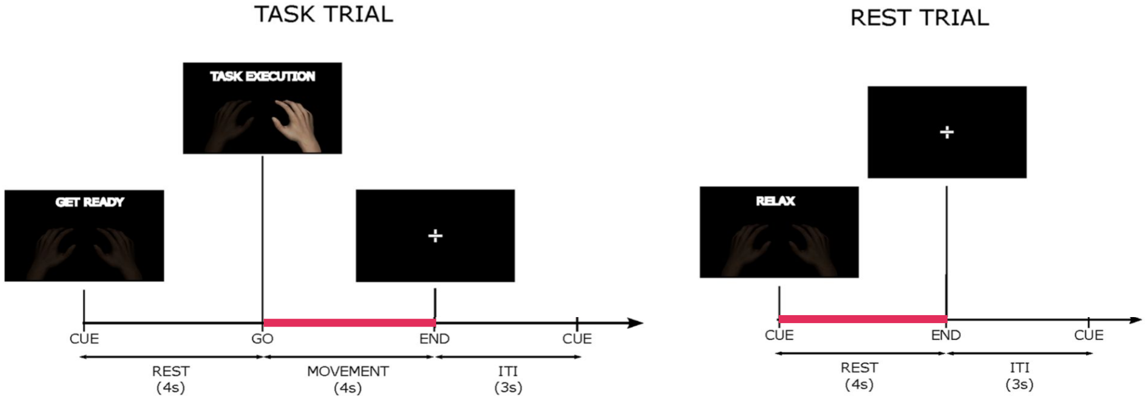


GraspL: **Rest and Task**

For each subject, the recording was repeated randomly for 40 times (i.e., 40 trials):

- **20 task trials:** subject performs `GraspL` movement;
- **20 rest trials:** subject at rest;





APPENDIX

CorticoMuscularCoherence (CMC)

CMC features combines a **EEG** channel `x` and a **EMG** channel `y`:

$$CMC_{xy}(f) = |S_{xy}(f)|^2$$

where `Sxy` is the Cross Power Spectral Density

CMC corresponds to the **linear correlation** between a EEG channel `x` and a EMG channel `y` at a given **frequency** `f`

End of the presentation