
# User-Centred BCI for Mechatronic Actuation by Spatio-Temporal P300 Monitoring

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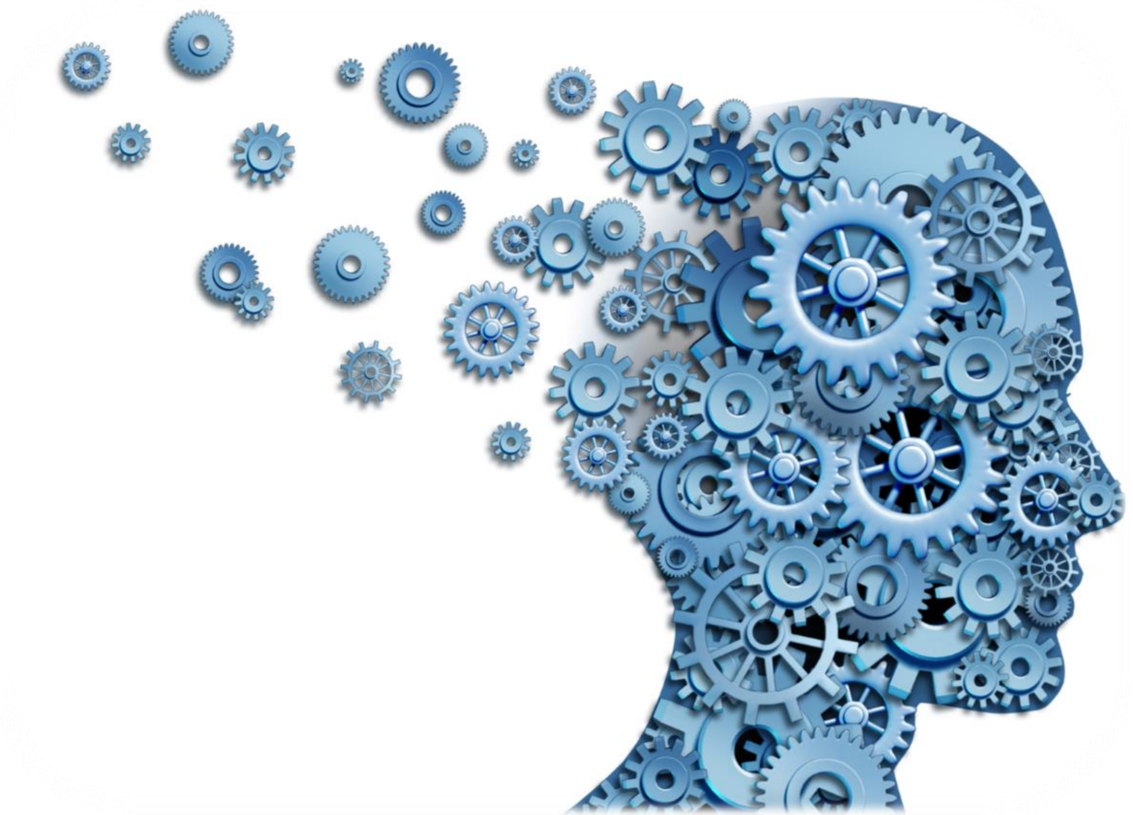
# Outline

- Introduction: the “Brain Computer Interface”
- Methods: the Overall Architecture and Algorithm
  - Machine Learning
  - Features Management
  - Classification
- Experimental Results
- Conclusions



# The “Brain Computer Interface”

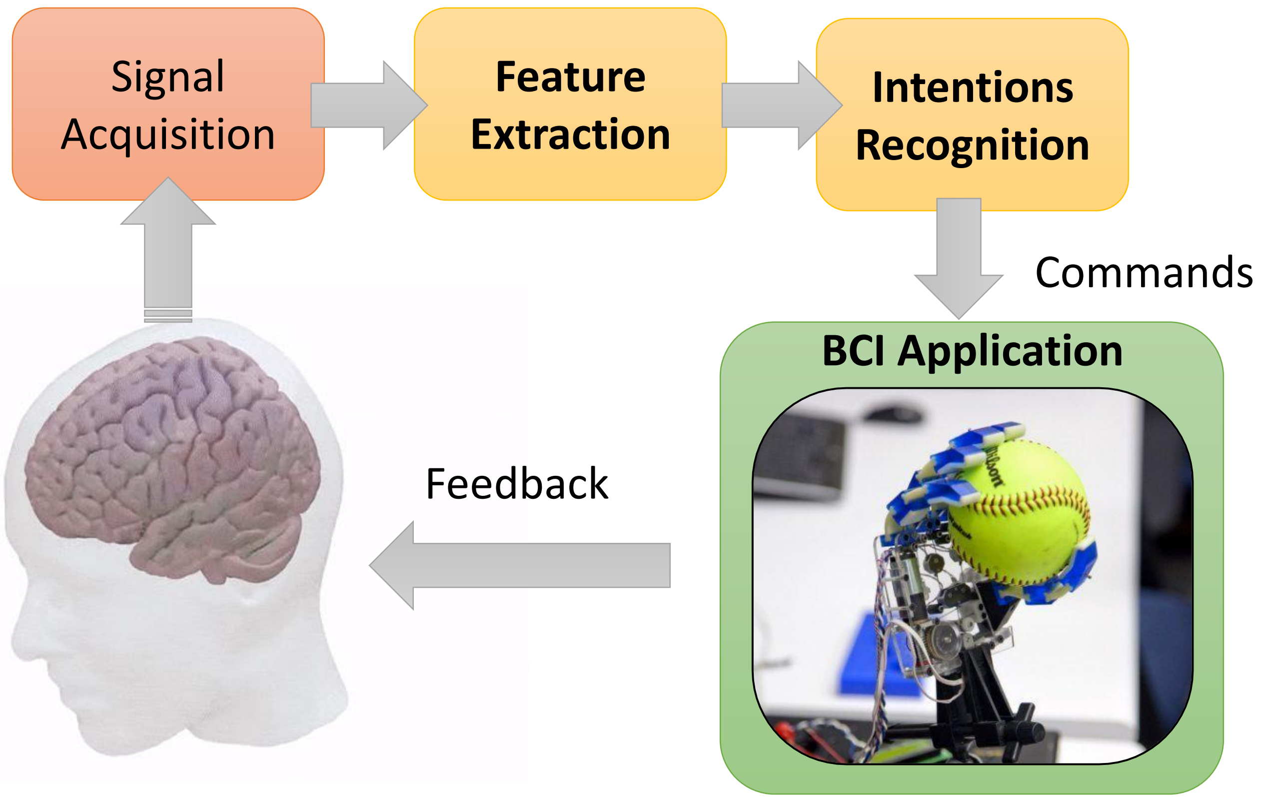


A "Brain-Computer Interface" (BCI) is the **control loop platform** between the **human brain** and **mechanical devices**.

↓

**Goal:** To create **enabling technology,** even for disabled people, controlling devices **by their mind**

## General BCI Control System



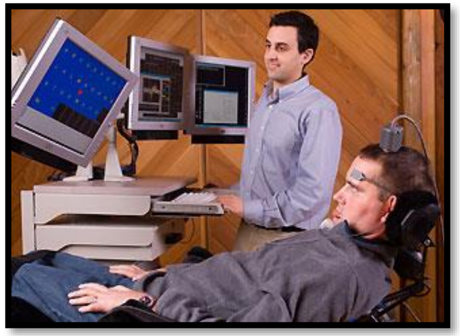
# The "Brain Computer Interface"



The BCI is based on the **recognition** of a particular **Brain Activity Pattern (BAP)**, that is excited during a particular mental task. Some of the most used (state of the art):

- ❑ **Event related potentials (ERP)**
- ❑ Slow cortical potentials (SCP)
- ❑ Event-related synchronization potentials (ERD/ERS)
- ❑ Steady state visual potentials (SSVP)
- ❑ Sensorimotor rhythms (SMR)

Cursors and Speller



*Hochberg et al.(2006)*

Car Driving

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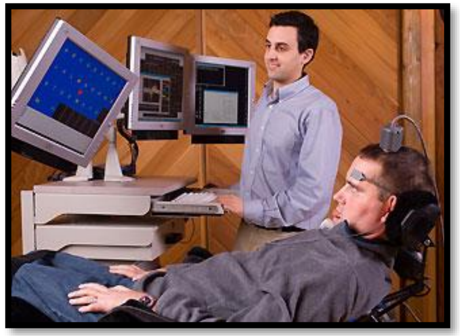

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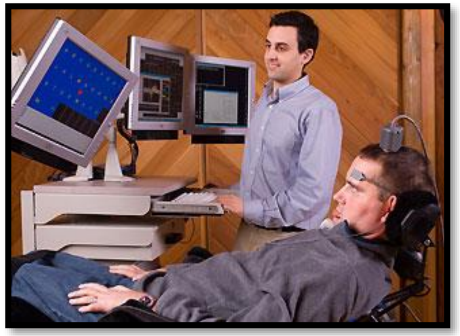

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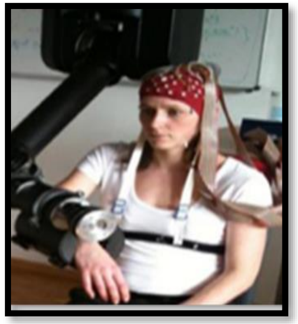
Prothesis



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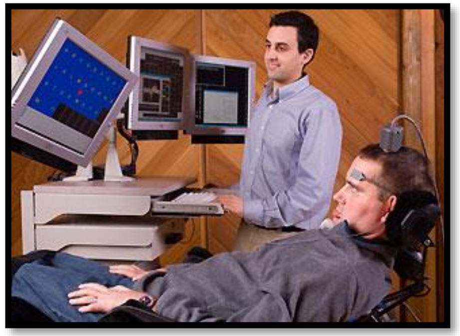

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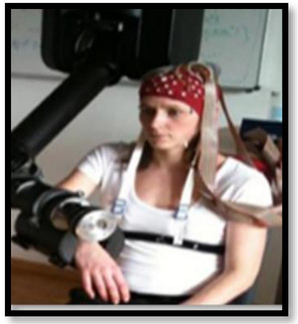

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Neuro-games

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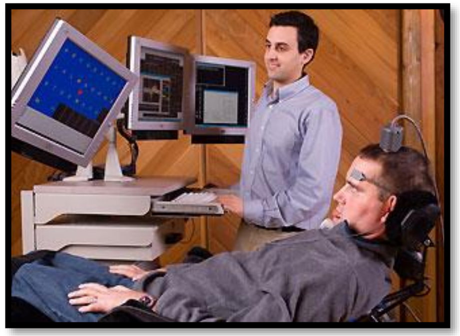

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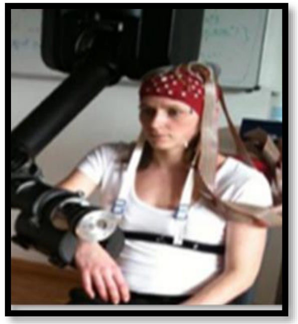

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Robotics Control

*Bogue et al. (2014)*

Car Driving

*Duan Feng et al. (2015)*

Neuro-games

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# State of the Art

| Signal | Physiological Phenomena (Occurrence Time) | Number of choices | Training Time | Transfer rate | Mean[1] Accuracy |
|---|---|---|---|---|---|
| | | (Opt: ≥4) | (Opt: ≤1h) | (Opt: ≥30 bits/min) | (Opt: >80%) |
| SSVP (or VEP) | Neural activity elicited by a visual stimulus (~10-70ms - **AS**) | <12 | Hours | 60-100 bits/min | 80% |
| SCP | Slow Cortical Potentials are shifts in the cortical electrical activity (200ms BS to 300 ms **AS**) | 2 -4 | Weeks | 5-12 bits/min | 86% |
| **P300** | **Positive peaks due to the occurrence of single or rare stimulus (~150-450ms AS)** | **<9** | **Hours** | **20-25 bits/min** | **84%** |
| SMR | Modulations in sensorimotor rhythms (up to 8s AS) | 2-5 | Weeks | 3-20 bits/min | 85% |

[1]Mean accuracy evaluated on work that operates on single trial classification; **AS:** after stimulus; **BS:** before stimulus

Not in line with the BCI needs Could be improved In line with the BCI needs

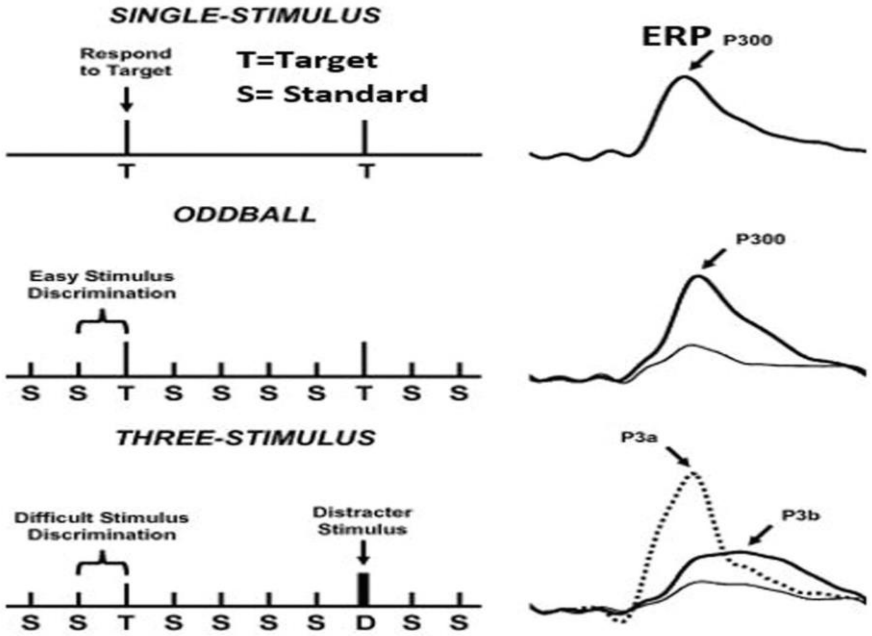
# Our Aim is…



| Signal | Physiological Phenomena | Number of choices | Training Time | Transfer rate | Mean Accuracy |
|---|---|---|---|---|---|
| P300 | Positive peaks due to single or rare stimulus | <9 | Hours ↓ | 20-25 bits/min ↑ | 84% ↑ |

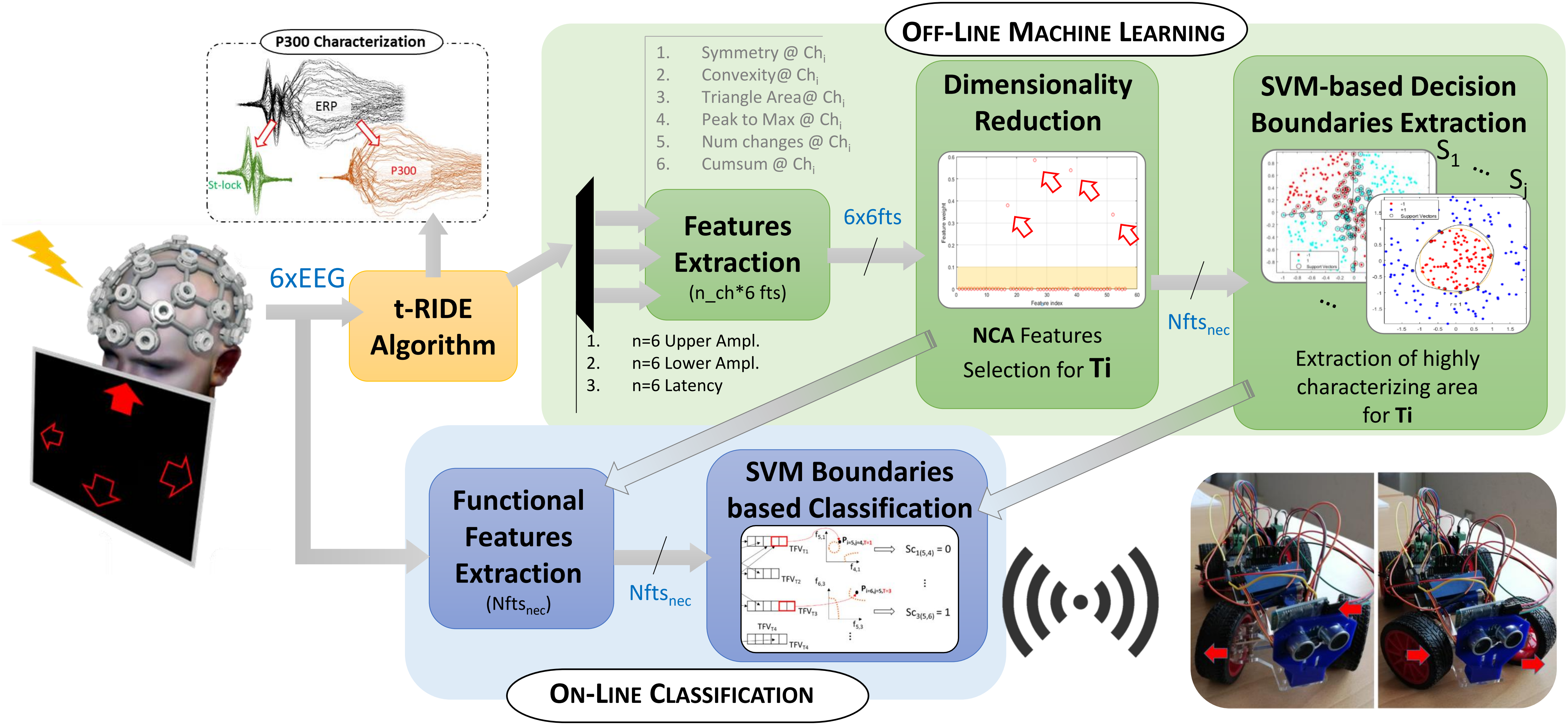
Create a **P300-based BCI system** for the remote control of mechatronic device, which ensures:

- ❑ **High accuracy in detection**
- ❑ **Fast User-Centered Machine Learning Stage**
- ❑ **Computationally easy algorithms for portable hardware (Raspberry Pi, Microcontrollers, FPGAs, etc.)**
- ❑ **No brain signals modulation request**
- ❑ **Quick and accurate intention recognition**



# The architecture



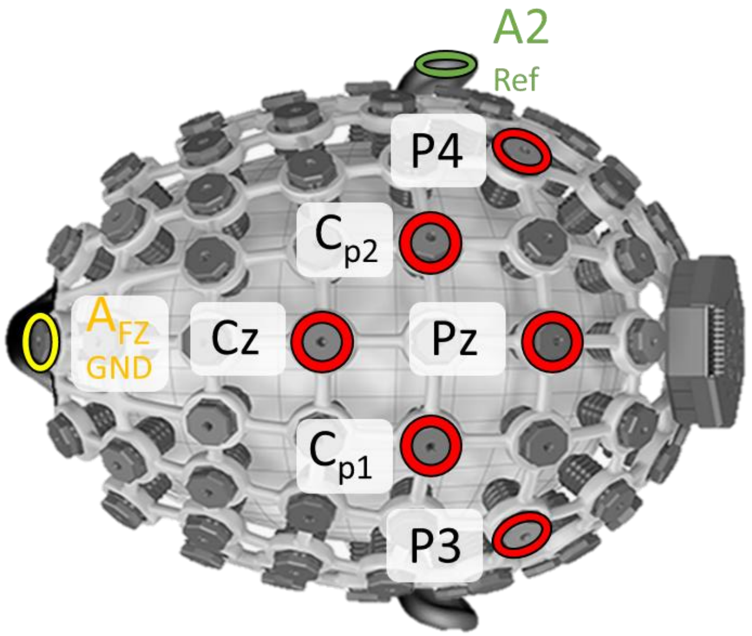


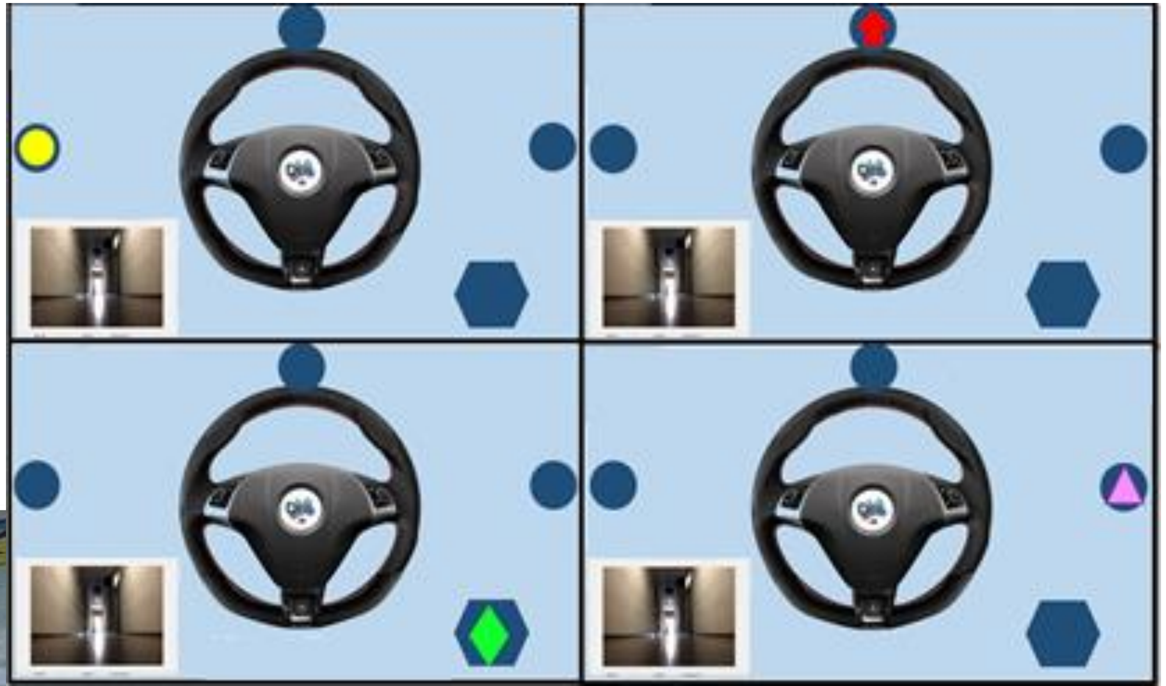
# The Hardware & Environment



The adopted stimulation protocol is a custom visual **oddball paradigm**:

- **visual stimulation.**
- **random flash** on a display (**25%** occurrence).
- inter-stimuli (**ISI**) time **500ms**.



# The Hardware & Environment



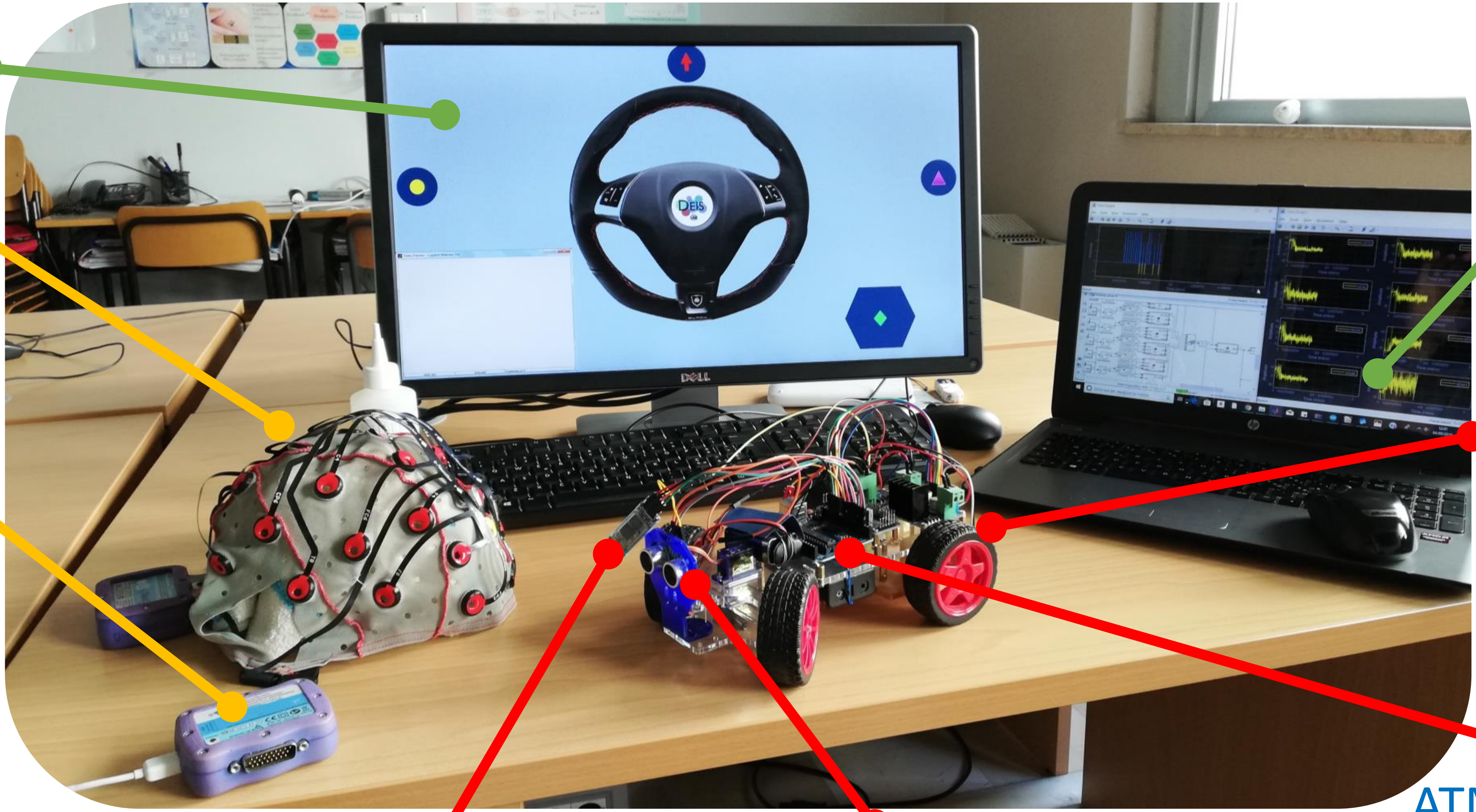
Stimulation Terminal

EEG Headset

EEG Base Station

BCI Simulink Control System

**Prototype Car System (PCS)**




ATMega328 P-PU PCS Core

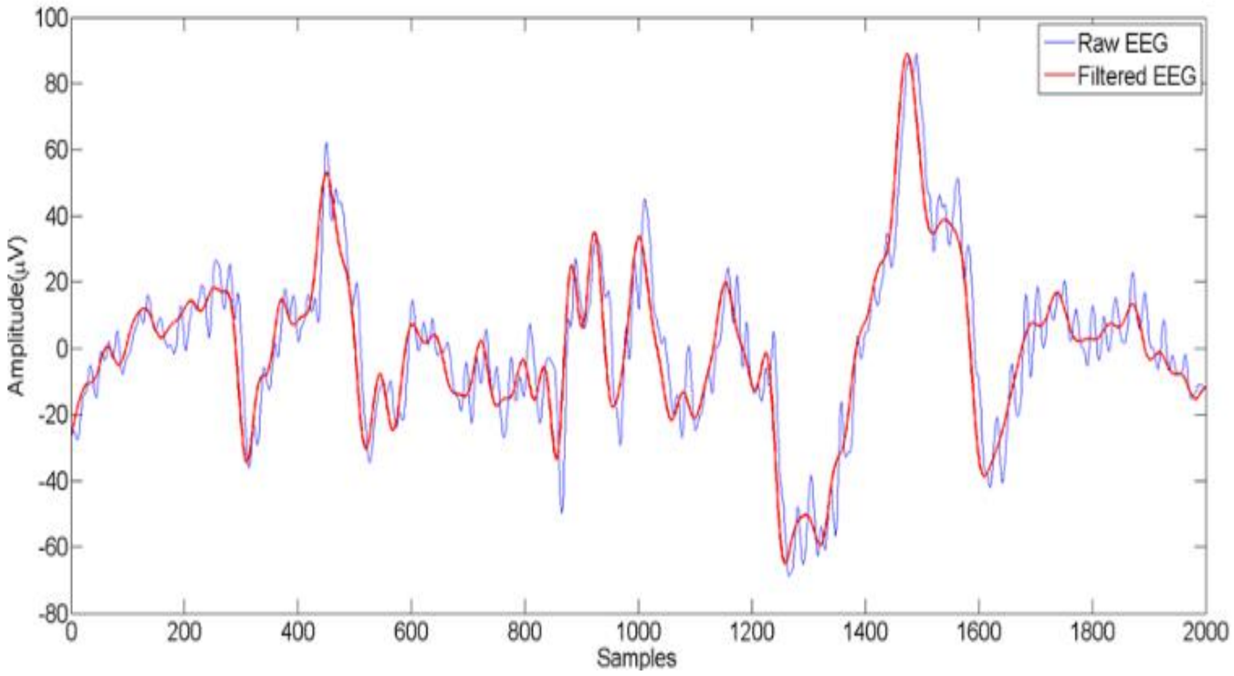
Bluetooth Interface

Ultrasonic Sensors

# The Machine Learning Stage



## The Pre-Processing

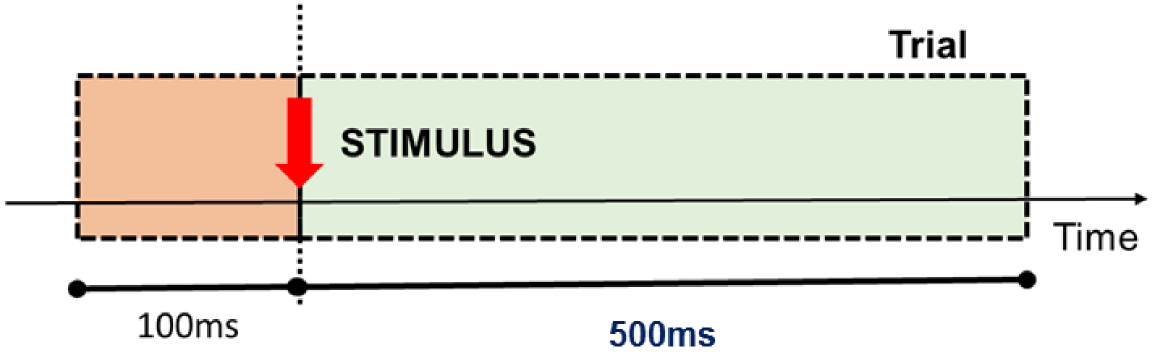



**Filtering:**

- ❑ Bandpass Filtering (8th order Butterworth Filter: **0.5 – 30 Hz)**
- ❑ 4th order Notch Butterworth : 48 – 52 Hz
- ❑ 4th order Low Pass Butterworth : **13 Hz**

**Data slicing:**

The EEG data are decomposed in data blocks (observation) of 600ms.



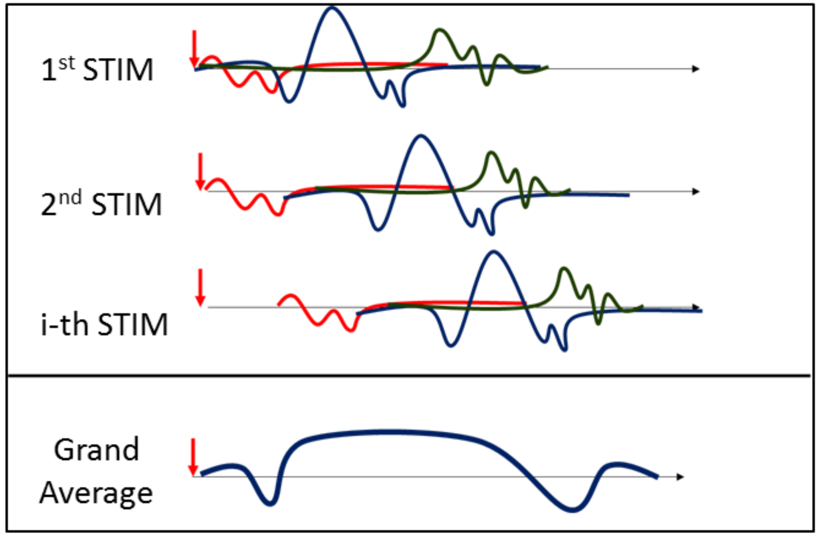
# The Machine Learning Stage

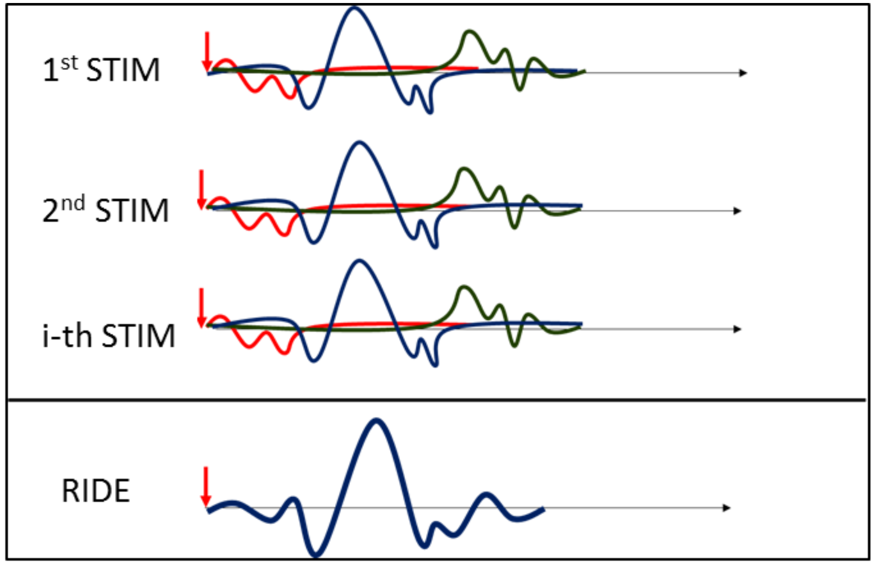
## T-RIDE: P300 CHARACTERIZATION

The ML stage is entrusted to the **tuned - Residue Iterative Decomposition (t-RIDE)** approach [1]. It is based on the hypotesis of **well-structured brain response.**

**t-RIDE** divides the signal into two (or three) components:

- ❑ **Stimulus recognition**
- ❑ **Stimulus Classification: P300**
- ❑ **(Optional) Active Response**



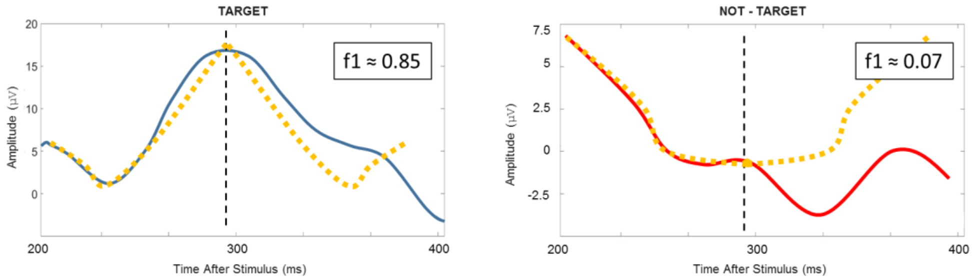

[1] D. De Venuto, V. F. Annese and G. Mezzina, "Remote Neuro-Cognitive Impairment Sensing Based on P300 Spatio-Temporal Monitoring," in *IEEE Sensors Journal*, vol. 16, no. 23, pp. 8348-8356, Dec.1, 2016.doi: 10.1109/JSEN.2016.2606553

# The Machine Learning Stage

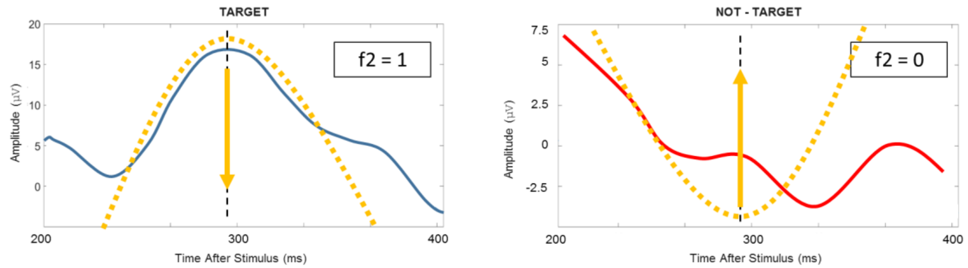


## The P300 Feature Extraction

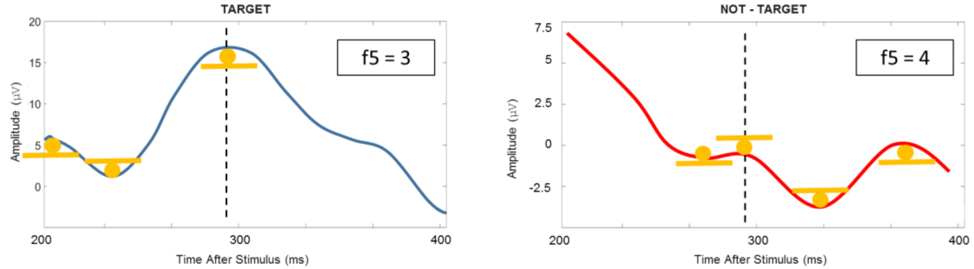
### Feature #1: Symmetry



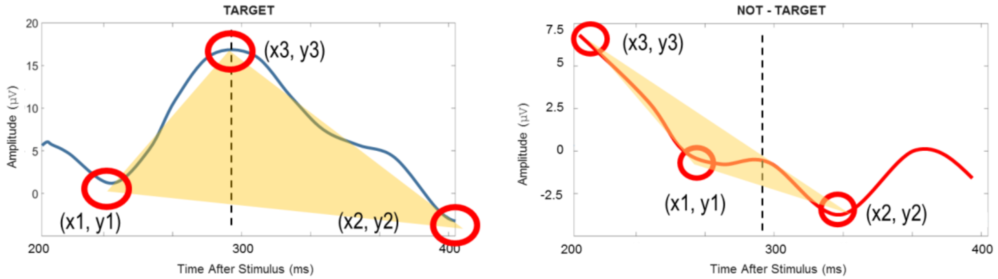

### Feature #2: Convexity



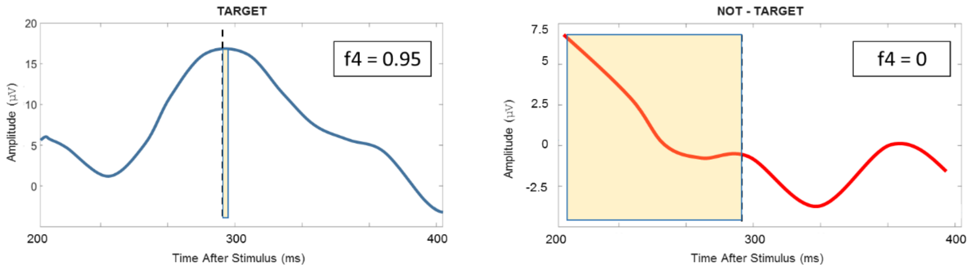

### Feature #5: NSC



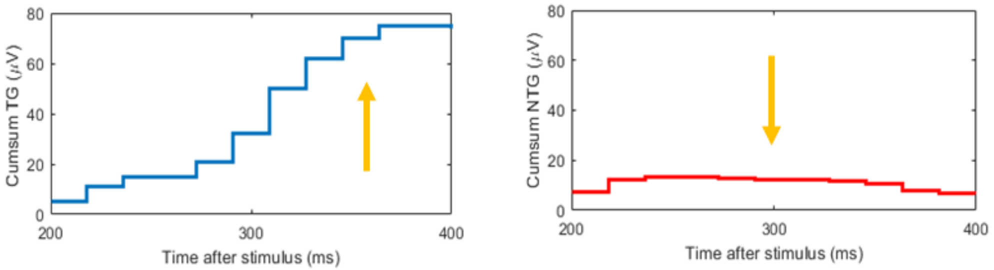

### Feature #3: ITA




### Feature #4: PPD




### Feature #6: Cumulative Sum



# The Dimensionality Reduction



With 6 features per channels, a general classifier extracts the decision boundaries on the 2-by-2 combinations. In this case it will work on 630 2D subspaces. To address the issue, in case of real-time prediction, the NCA algorithm for features selection has been implemented in the ML chain.

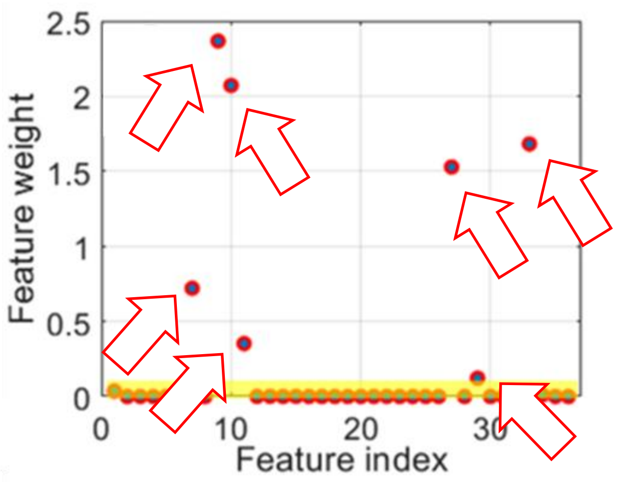
The **Neighborhood Component Analysis approach** defines the average probability of correct classification as:

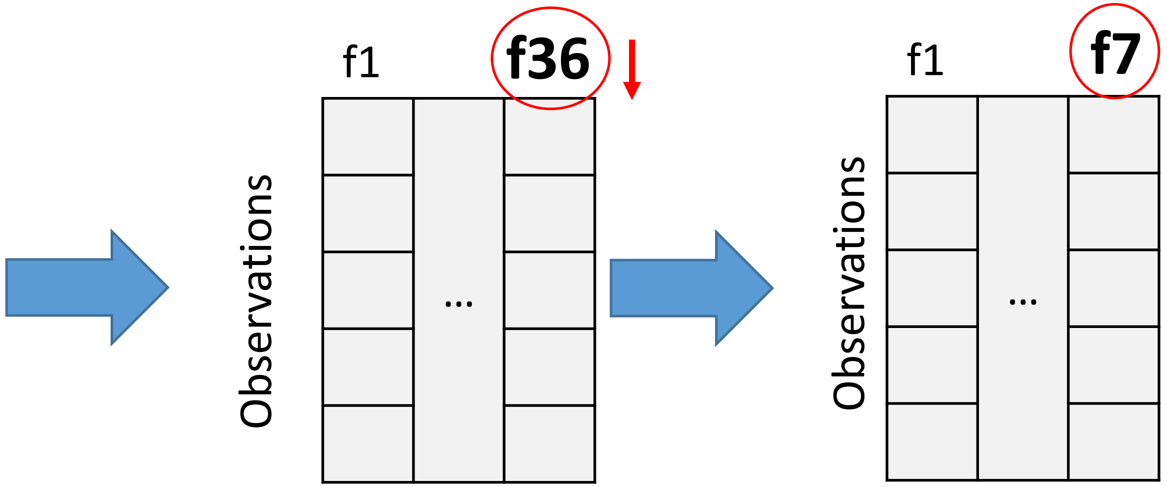
$$F(w) = \sum_{i=1}^{No} p_i - \lambda \sum_{r=1}^{Nf} w_r^2$$

$p_i$ : probability of correct classification of the observation.

$w_r$: desired feature weights. λ: regularization parameter.

The system automatically **maximize F(w)**, **choosing** opportunely **λ**.



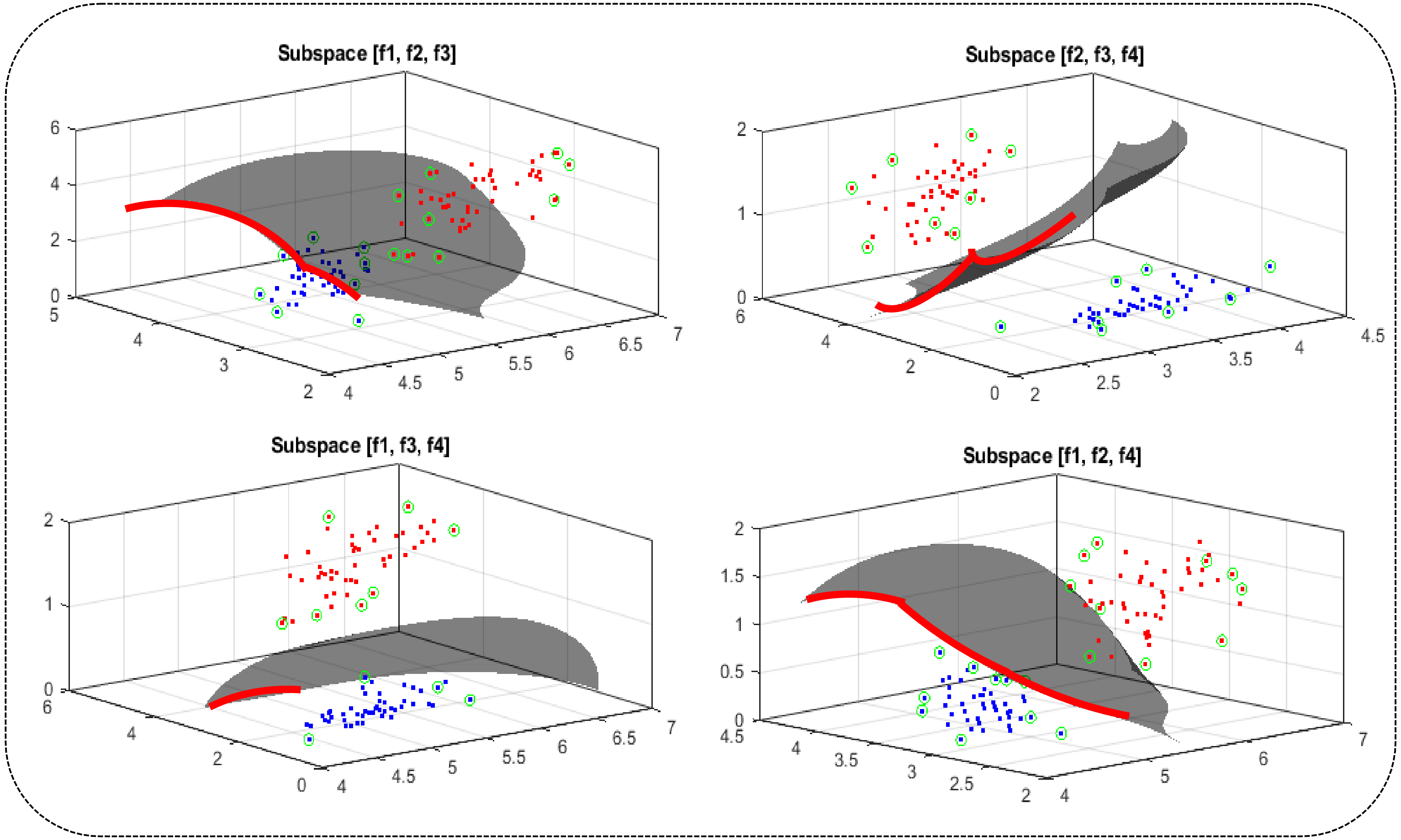



# The Machine Learning Stage



## The Classification Boundaries

The **features** are used to train an **“One vs All”** Support Vector Machine (**SVM**).




Separating criterion: **Radial basis (Gaussian)**.

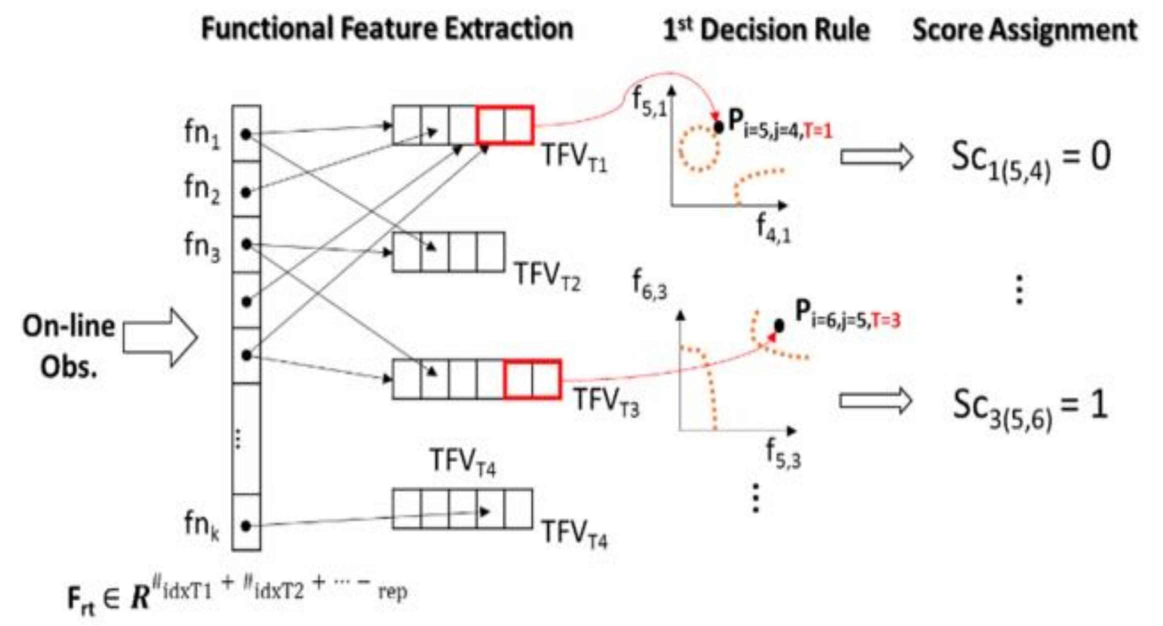
It isolates the i-th target from the others, defining, on each subspace

$$N_{sub-sp} = \frac{N_{fts}!}{2! \cdot (N_{fts} - 2)!}$$

**area in which only the desired target can be present.**

# The Real Time Classification






**Rule #1.** If **P**i,j,T is in the areas delimitated by the SVM-based boundaries $(SVMb_{i,j,T})$, **F → 1**

$$\boldsymbol{SCORE_T = \frac{\sum_{i=1}^{N_{sub-sp,T}} F(P_{i,j,T} < SVMb_{i,j,T})}{N_{sub-sp,T}}}$$

The target with the highest relative score is labelled as the choice.

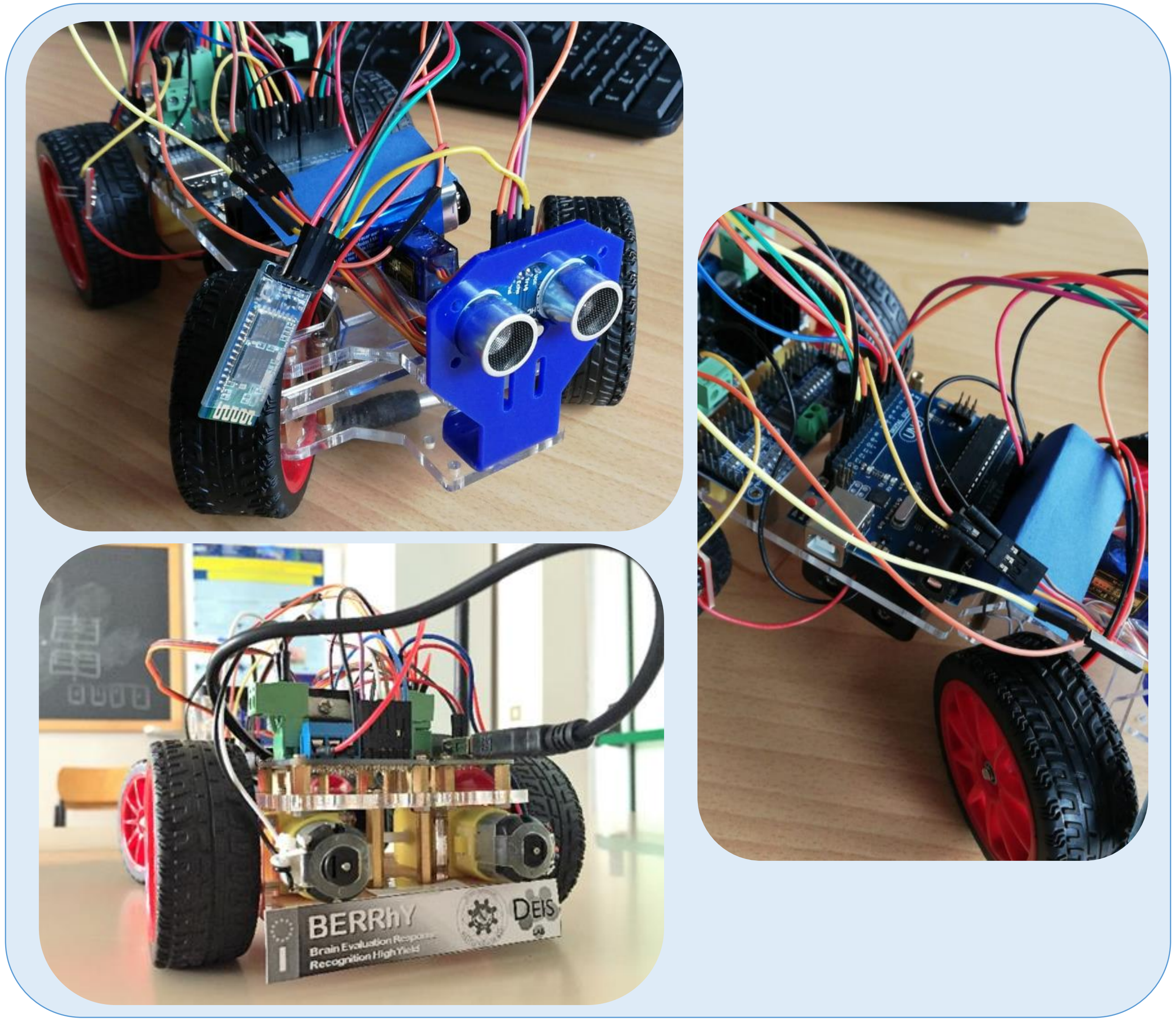
**Rule #2.** The score of the ambiguous targets is then re-assigned in a weighted version as:

$$\boldsymbol{SCORE_T{}^w = \frac{\sum_{i=1}^{N_{sub-sp,T}} W_T(i) * F(P_{i,j,T} < SVM_{i,j,T})}{N_{sub-sp,T}}}$$

with $\boldsymbol{W_T}(i)$ the vector that contains the features weights.

# The PCS: Mechatronic Actuator



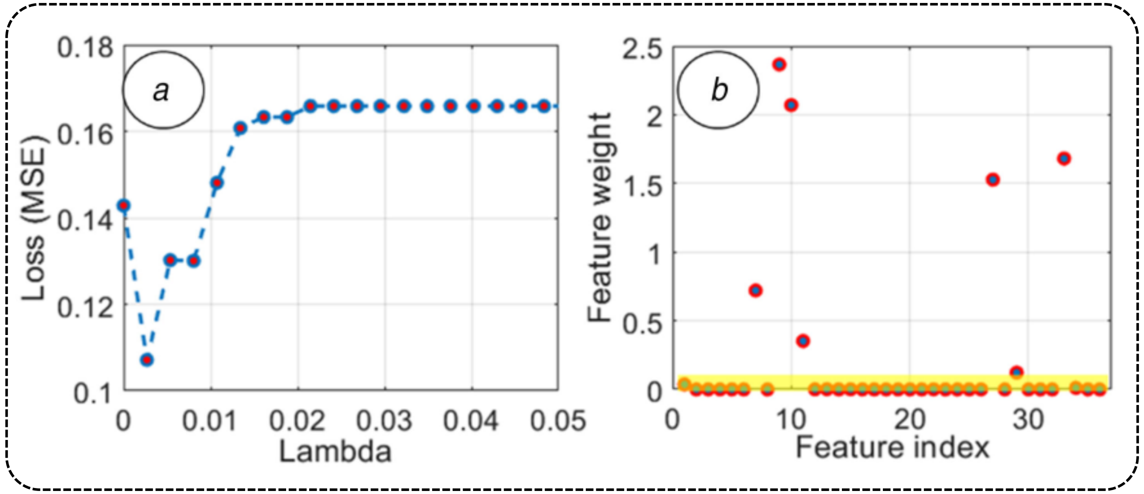



- ❑ **Central Unit:** Arduino UNO Rev 3 (ATMega 328 P-PU Microcontroller);
- ❑ **2 DC motors** control the propulsion of the vehicle
- ❑ **1 Servomotor** controls the steering;
- ❑ **3 ultrasonic sensors** for automated navigation System;
- ❑ **Other components:** 1 DC-DC converter; 1 HC-05 Bluetooth Module, 1 h-bridge; 18650 batteries (3.7V and 2700mAh)

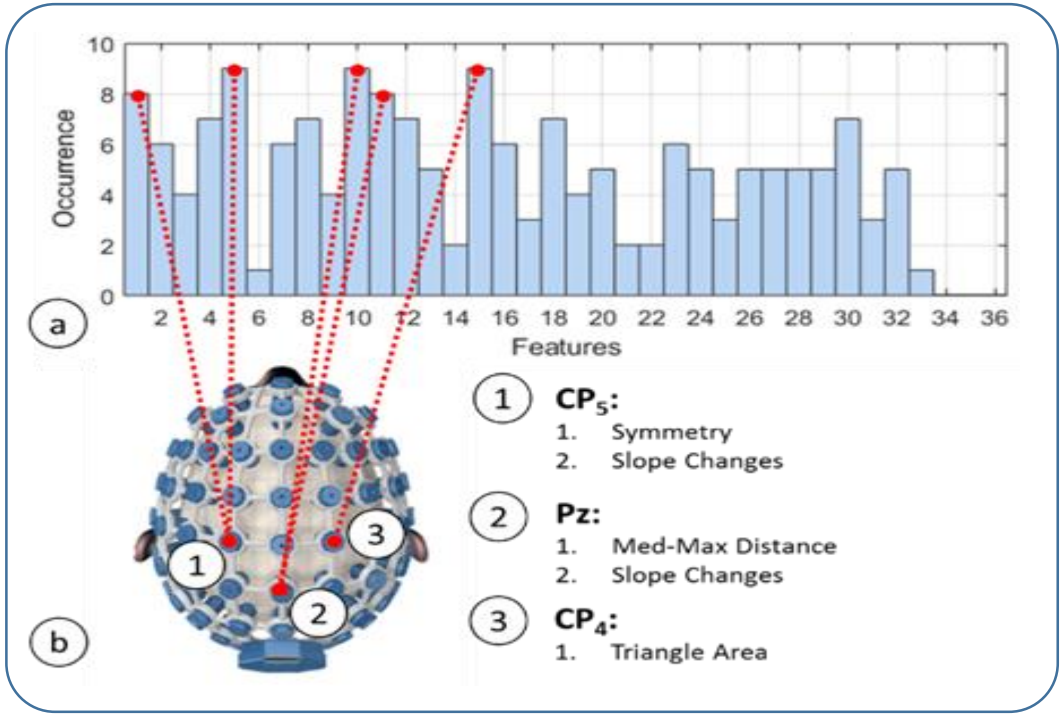
# The Experimental Results



Dimensionality reduction allows passing from, i.e., **F** $\in \mathbb{R}^{300,\ 36}$ → **Fn** $\in \mathbb{R}^{300,\ 7}$, by minimizing the CIL loss. For example, **the 7 selected features allow the classifier extracting decision boundaries on 21 subspaces w.r.t. 630 ones.**



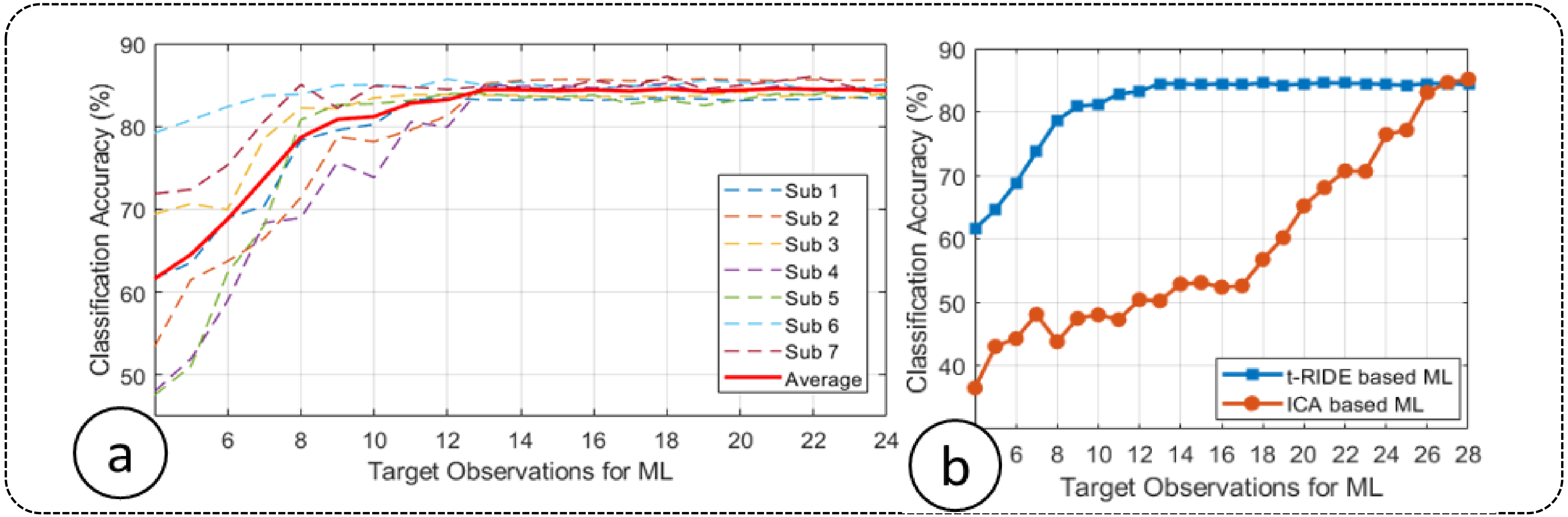

*(a) Classifier in loop loss vs λ (b) selected features*




The P300 is easily recognizable on CP1 by its symmetry and number of change (low), on Pz by the Latency-Max distance and an high triangle area distinguishes the P300 on CP2.

*(a) Occurrence of the extracted features (b) Physical significance of the main features*

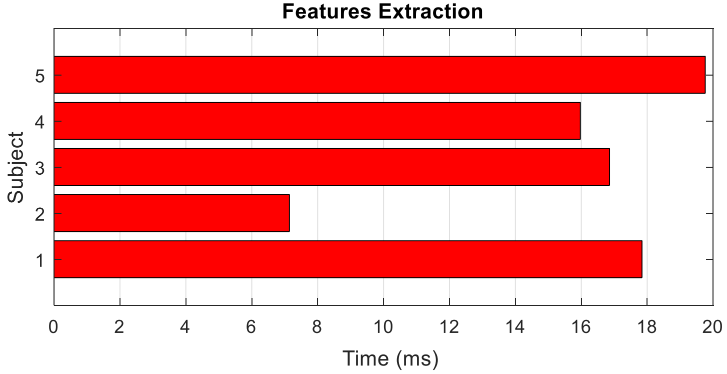
# The Experimental Results

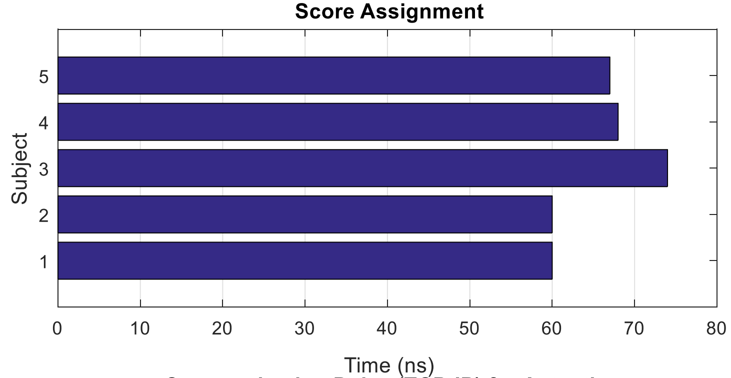


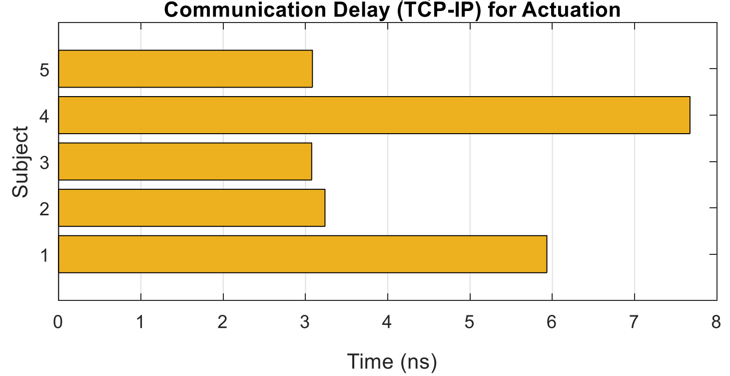

- The system accuracy is, on average ( 7 subjects), **84.28 ± 0.87 %** (Figure a).
- The accuracy increasing reaches the **steady-state accuracies** only after 13 targets and 52 not targets (**ML timing ~ 33 s**).
- An **Independent Component Analysis** approach has been used to train the same system, (Figure b). ICA-trained system needs higher number of trials (26 targets and 104 not targets) to reach an accuracy slightly higher than a t-RIDE-trained BCI but later (**ML timing >60s**).

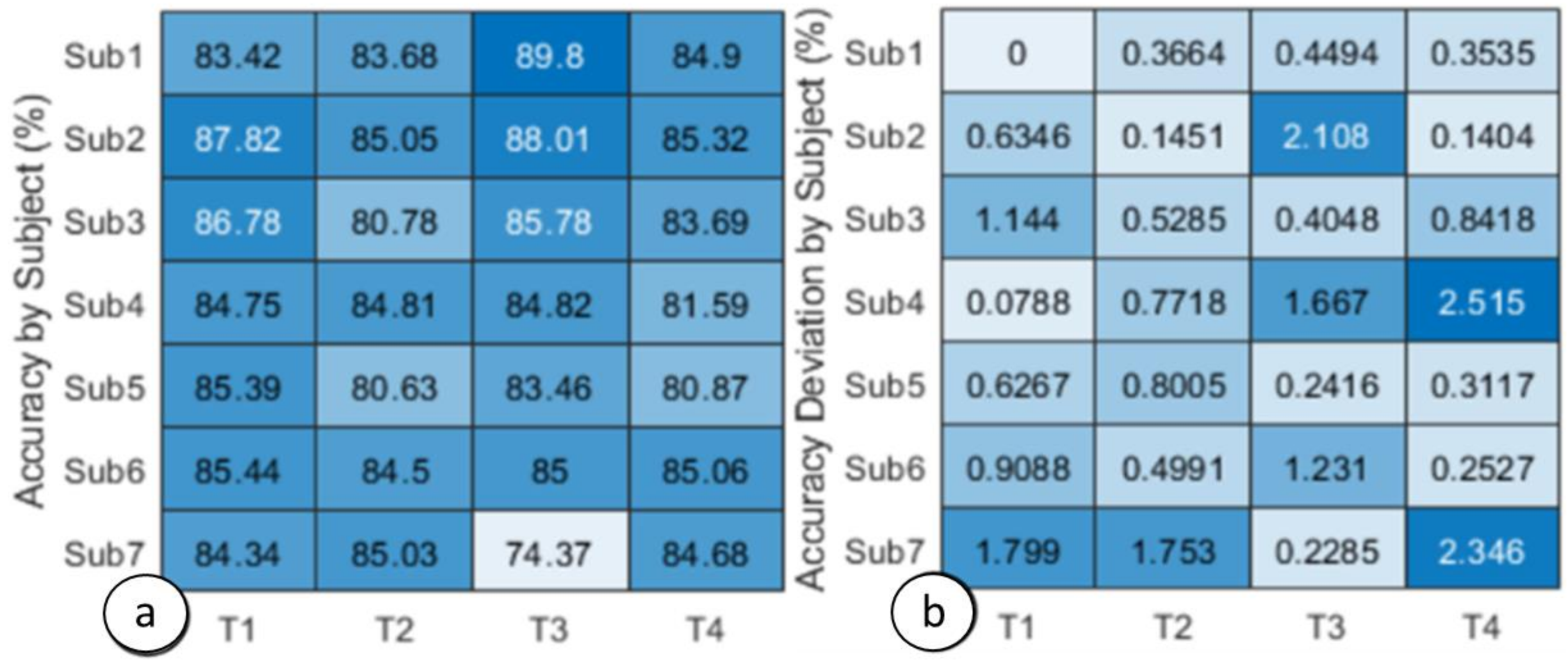
# The Experimental Results






*(a) Heatmap of Subject mean accuracies vs directions (b) Heatmap of Subject accuracies standard deviations vs directions*

## Timing*1:

- ❑ Buffer: 500ms
- ❑ Complete FE stage : 19.58±9.7ms
- ❑ Decision: 0.067±0.008ms
- ❑ Communication BCS-PCS: 3.5 ns

*1 The system has been implemented on a PC with Intel i5 processor and 16 GB RAM

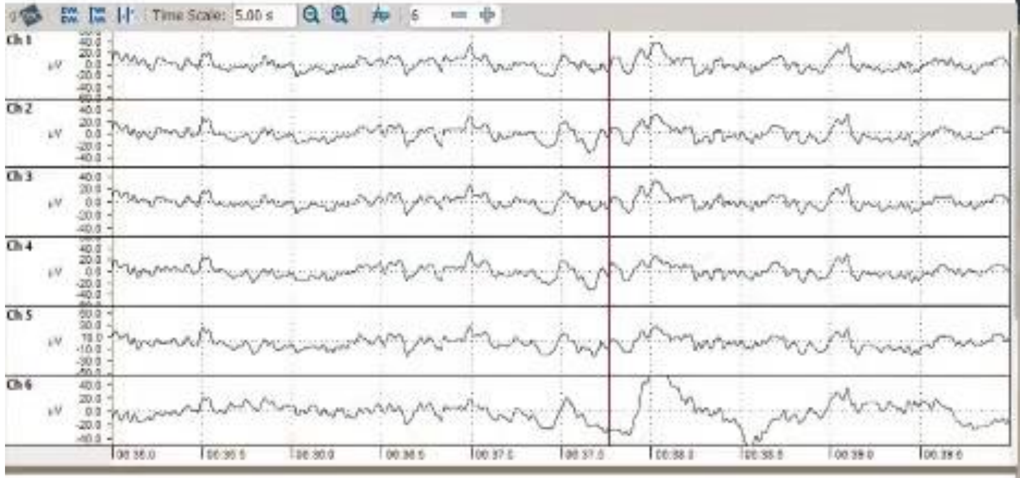
# Video Demonstration



Intention – Action Sequence


Experimental Setup

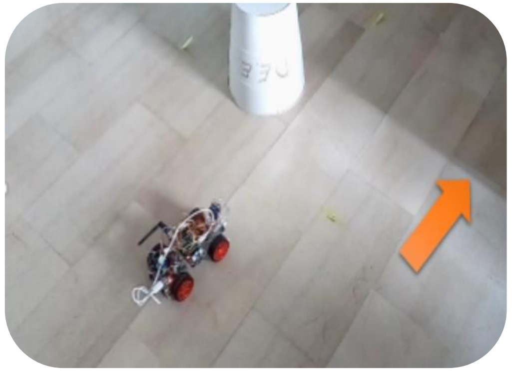
Monitored Electrodes




Event Triggered Obstacle Overcoming

# Conclusions





The BCI is promising method in assistive technology, diagnostic and rehabilitative application field but can be used also to assist the autonomous driving.

- A P300-based BCI has been developed, realized and tested on a **prototype car** based on Arduino UNO.
- The ML stage uses an **innovative architecture**, which guarantees a **good operation speed** and a **reduction of requested amount of data**
- The implementation of a **subjectivity-based feature selection**, allows **fast user's intention recognition**
- **The Support Vector Machine-inspired classifier shows** classification accuracy of 84.28 ± 1.24 % (tested on 7 subjects)