IEEE SMC 2014
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SYSTEMS, MAN, AND CYBERNETICS

Tutorial: Brain-Machine Interaction: From Neural Decoding to Real-World Applications

BMI control of robotic exoskeletons

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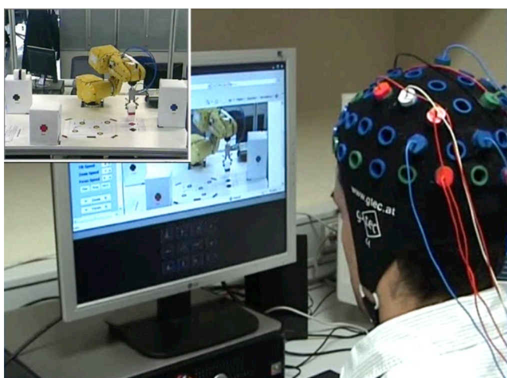

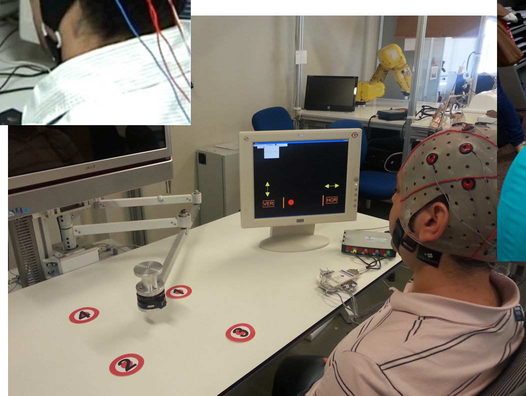

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Outline

- Brain2Motion: BMI control of upper-limb exoskeleton
  - Spontaneous BMI
  - Detection of movement intention

- BioMot: BMI control of lower-limb exoskeleton
  - Cognitive mechanisms related to self-adjustments during walking
  - Decoding of locomotion from EEG signals
  - Cognitive attention mechanisms

Brain2Motion

Exoskeletal – Neuroprosthesis Hybrid Robotic System for the Upper Limb controlled by a multimodal brain-neural interface

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Instituto Cajal, CSIC, Spain
(José L. Pons)

Dates: 01.01.2012-31.12.2014

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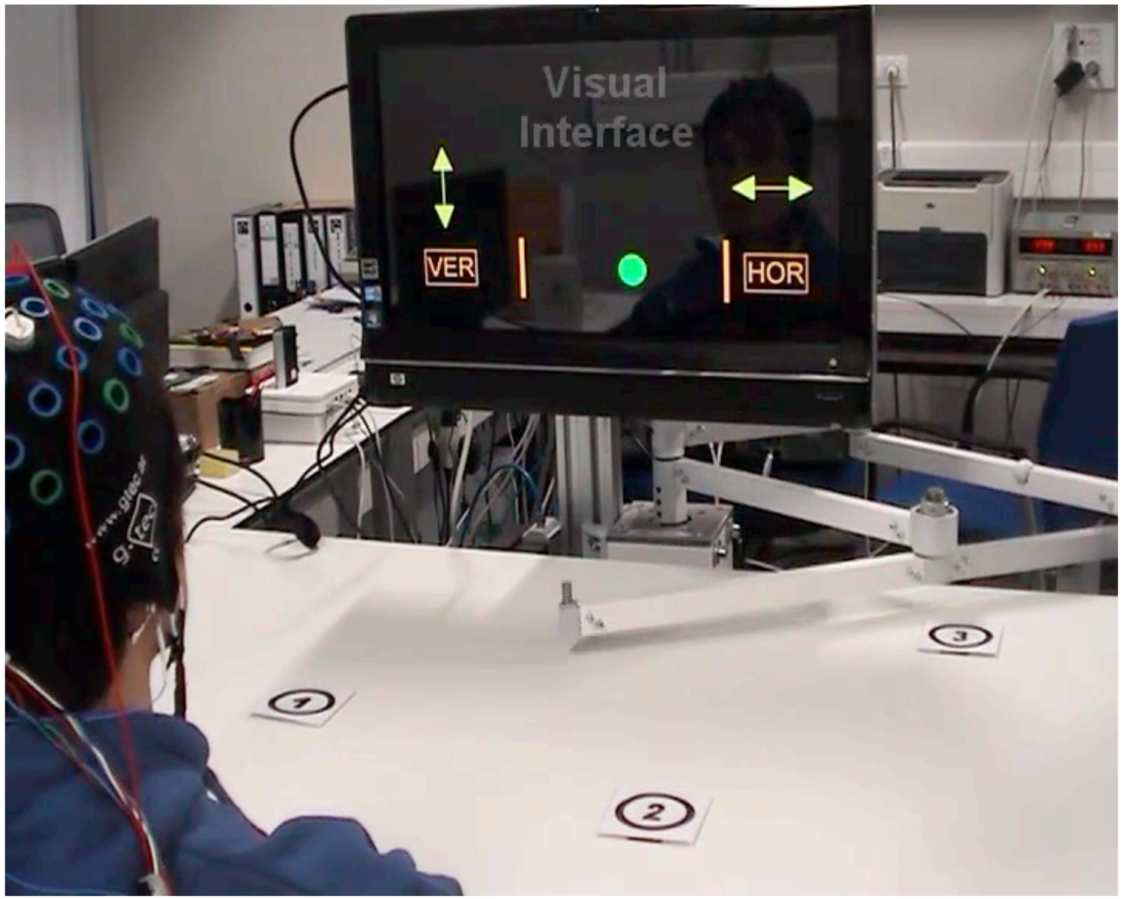
INSTITUTO CAJAL CSIC

GOBIERNO DE ESPAÑA MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD

Brain2Motion

- Goals
  - Control of an upper limb exoskeleton by motor imagery (mental tasks)
  - Control of an upper limb exoskeleton detecting movement intention
  - Usability tests with patients

Spontaneous BMI based on 2 mental tasks

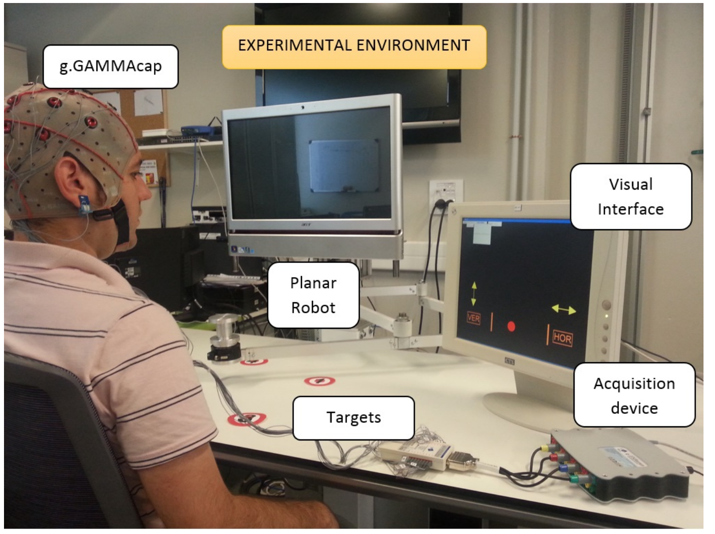


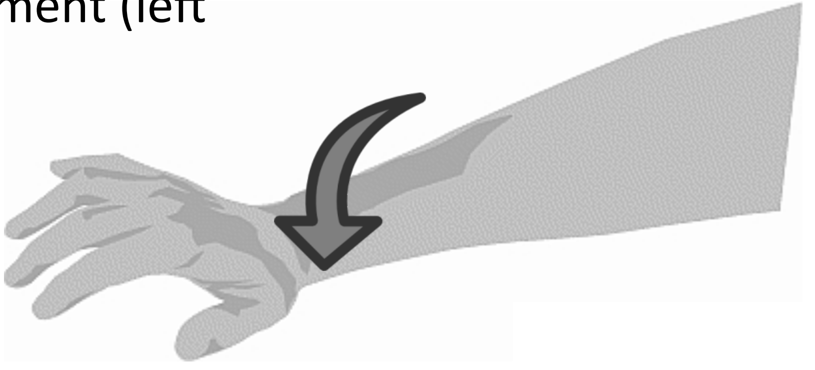
Enrique Hortal

E. Hortal, A. Úbeda, E. Iáñez, J.M. Azorín, “Control of a 2 DoF Robot Using a Brain-Machine Interface”, Computer Methods and Programs in Biomedicine, 116(2), 169-176, 2014.

Main characteristics

- Control of a planar robot (2 DoF)
- BMI classifier based on Periodogram and Support Vector Machine
- Two mental tasks related to motor imagery
  1. Imagination of the right arm movement (right task)
  2. Imagination of the left arm movement (left task)

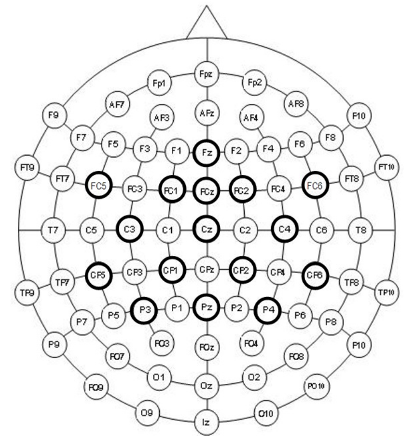




Register, Processing & Classification

<u>Processing:</u>

1. Sample frequency: 256 Hz
2. Internal Band-Pass Filter: 0.5-100 Hz
3. Notch Filter: 50 Hz
4. Band-Pass Filter: 5-40 Hz
5. Laplacian Smoothing Filter
6. Normalized
7. Periodogram
   - 8-36 Hz
   - Resolution: 1 Hz



<u>Classifier:</u>

Support Vector Machine

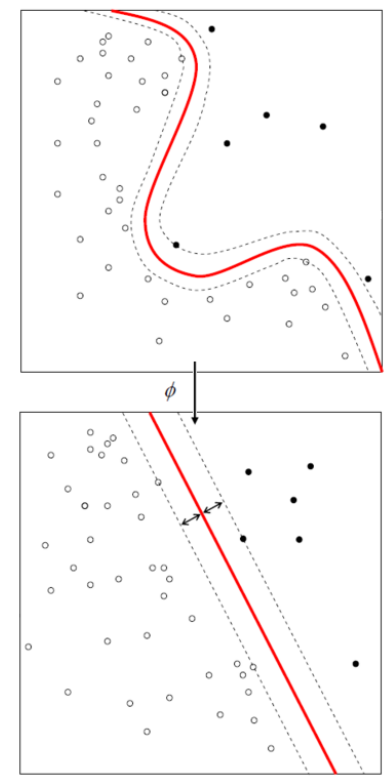
Kernel: Radial Basis Function (RBF)

C = 512

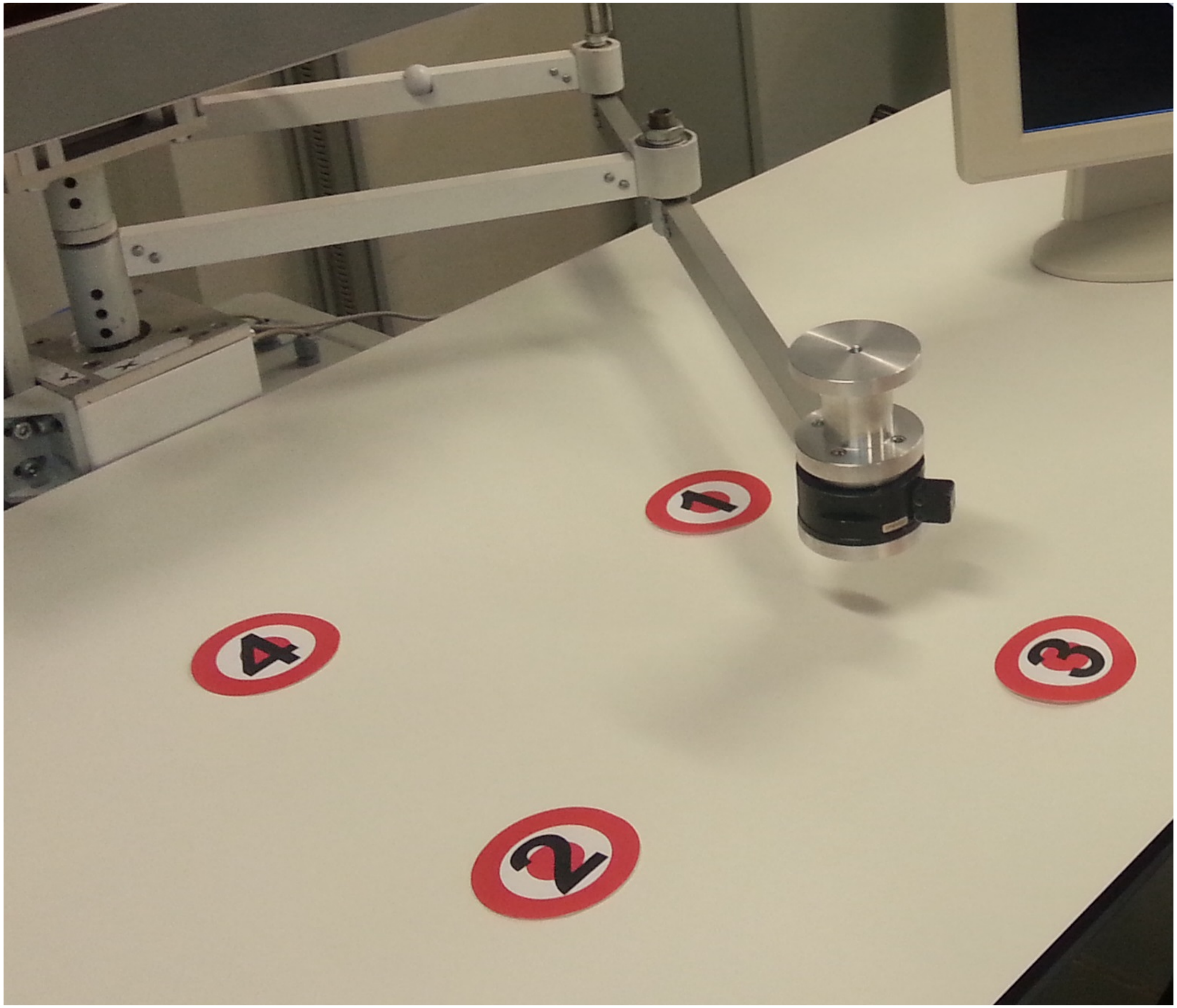
ϒ = 0,002

Mode:

4 detections in the last 5

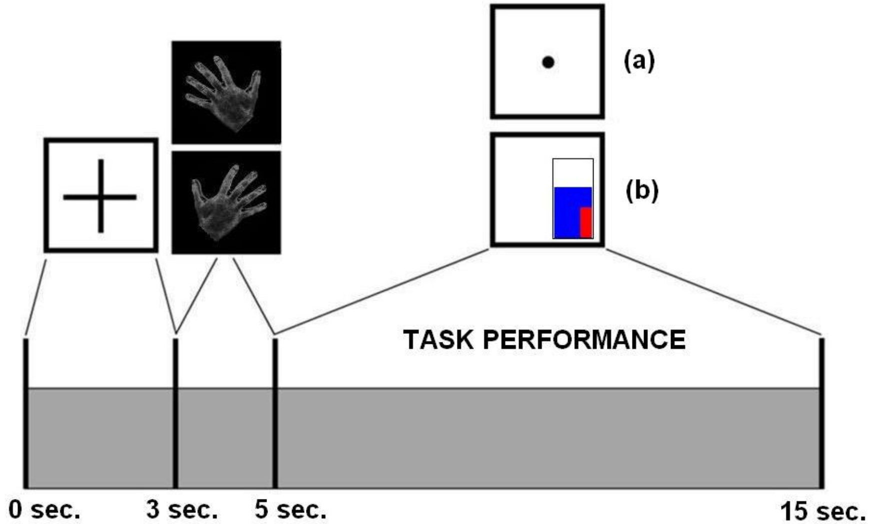


Planar Robot



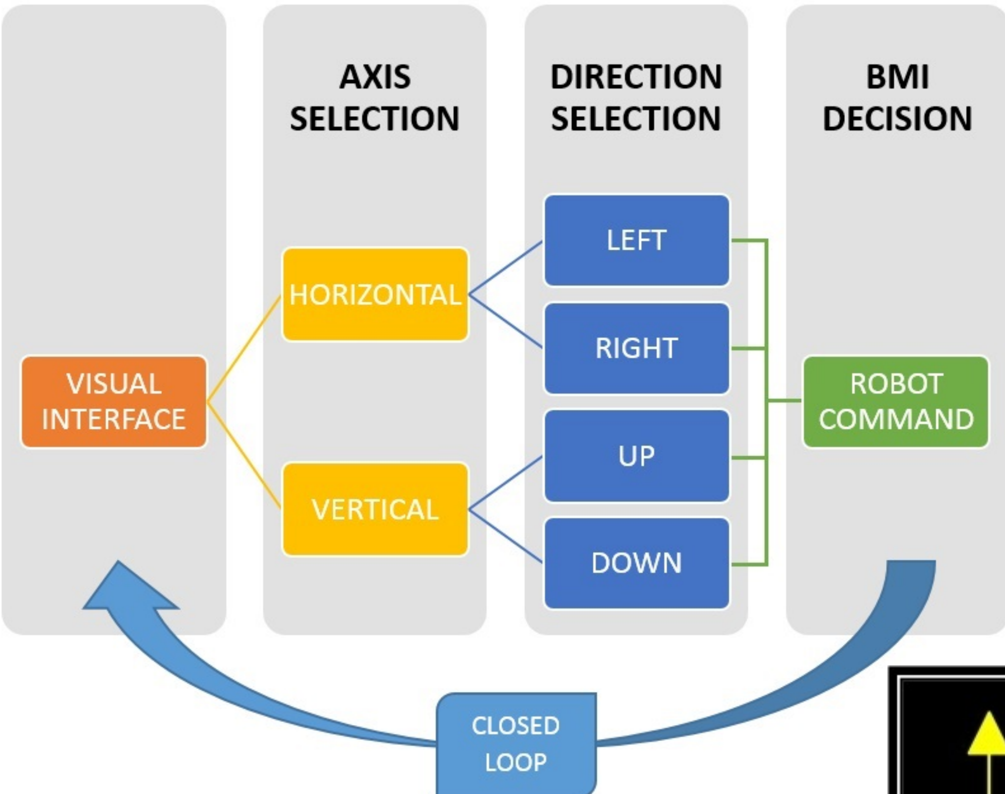
Training Protocol

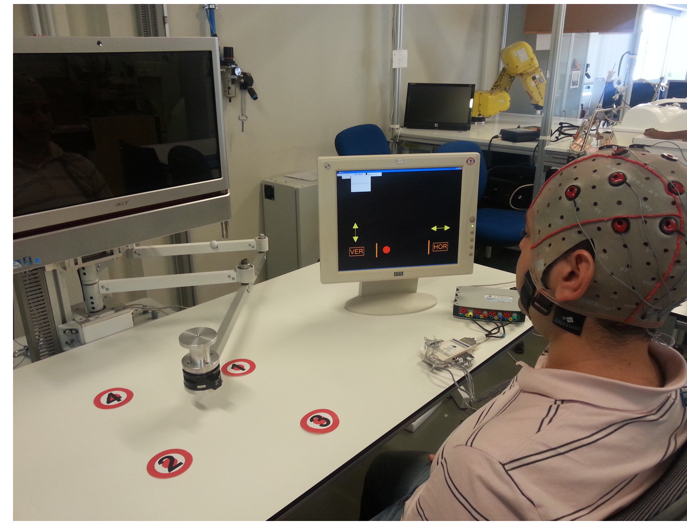
1. Session of 12 offline register (no visual feedback)
   – Selection of the best combination of tasks
2. Offline session using the best combination of tasks (no visual feedback)
   – Temporary model creation
3. Online session (visual feedback)
   – Final model creation

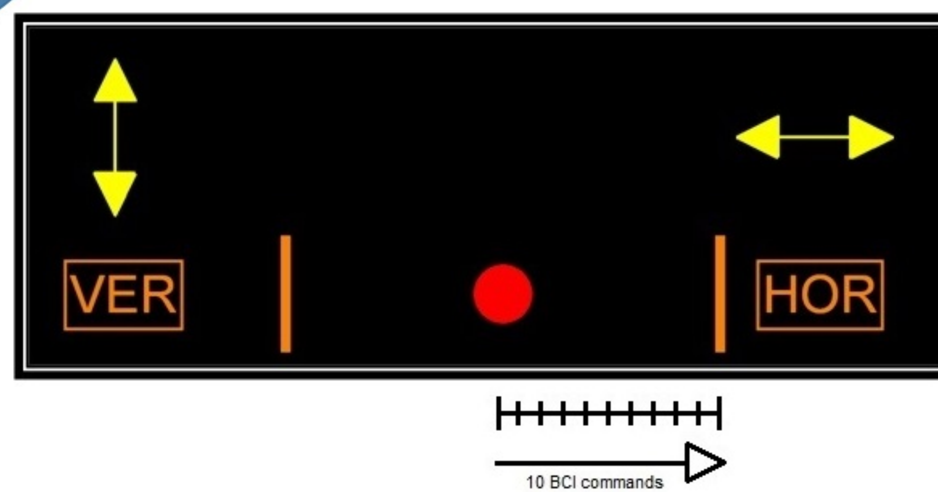


USER	SUCCESS	ERROR	UNCERTAIN	GSR
A	77,55	10,21	12,24	88,39
B	72,93	9,26	17,80	88,64
C	66,26	11,74	22,00	84,93
Mean	71,93	10,72	17,36	86,95

Hierarchical Control

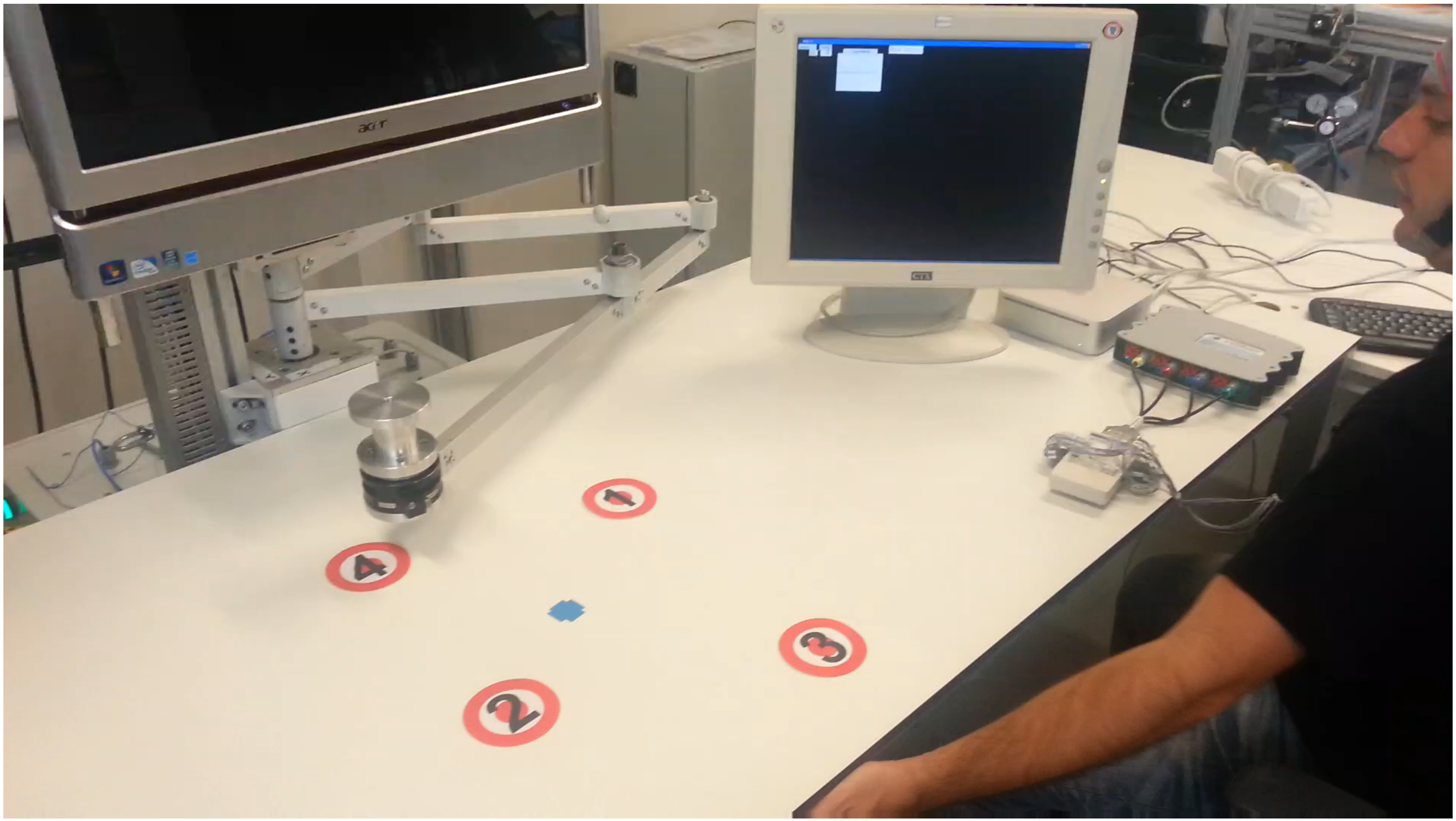






Movement: 50 mm

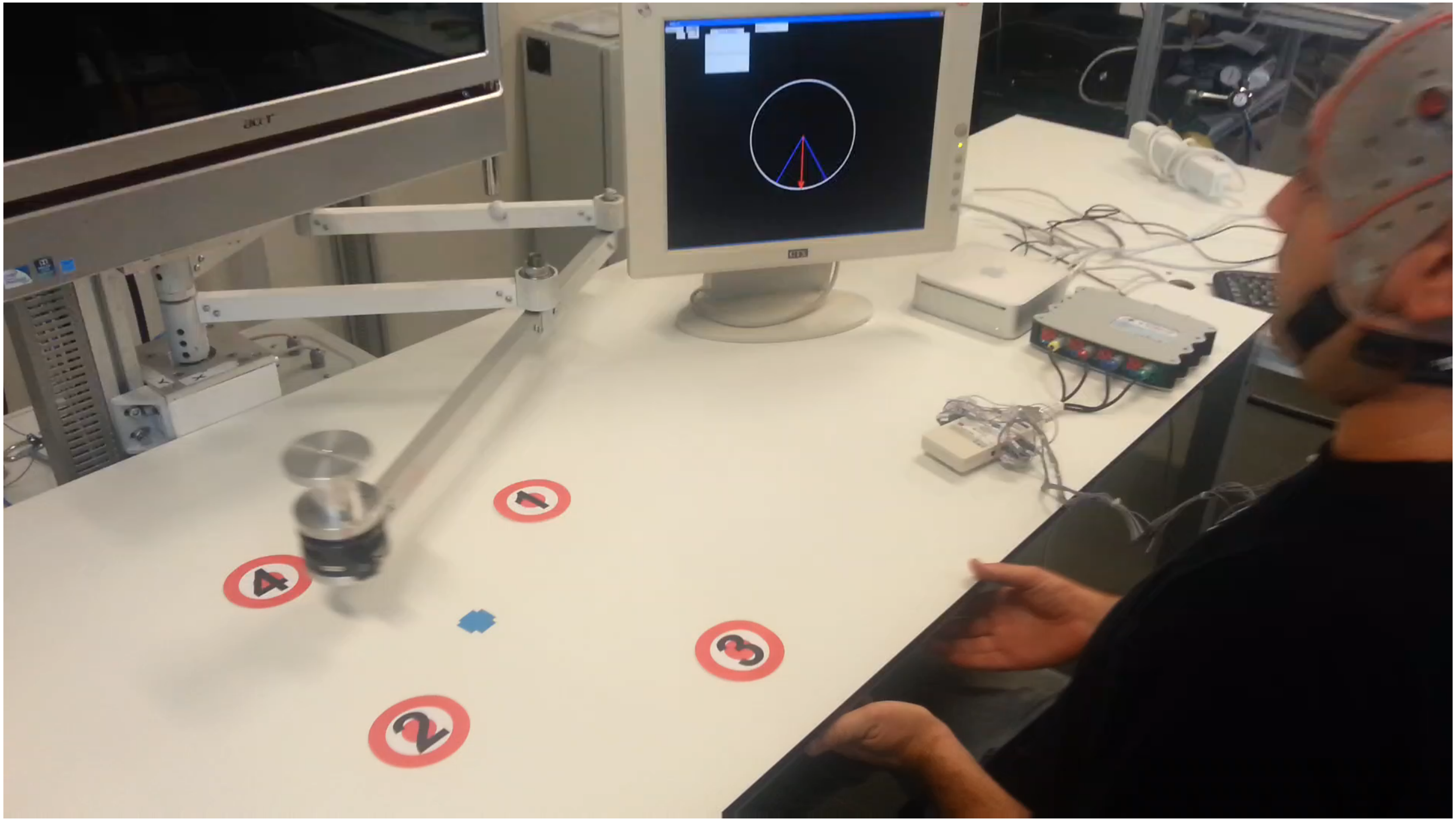
Hierarchical Control - Online



Directional Control

Time: 5 s
Movement: 25 mm

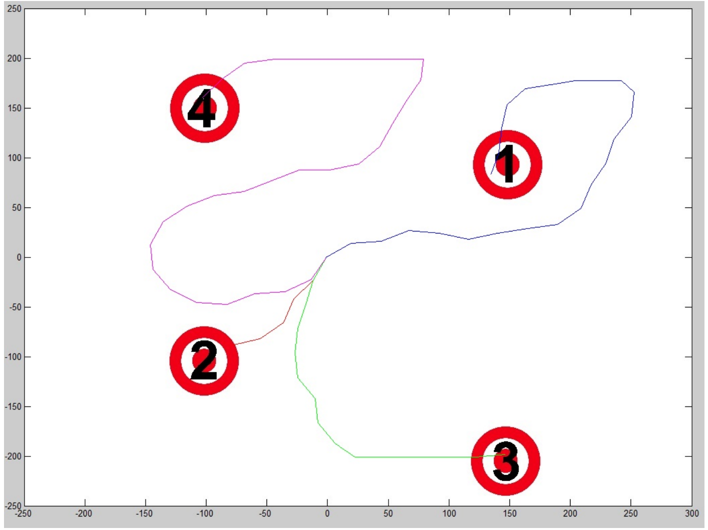
Directional Control - Online



Results

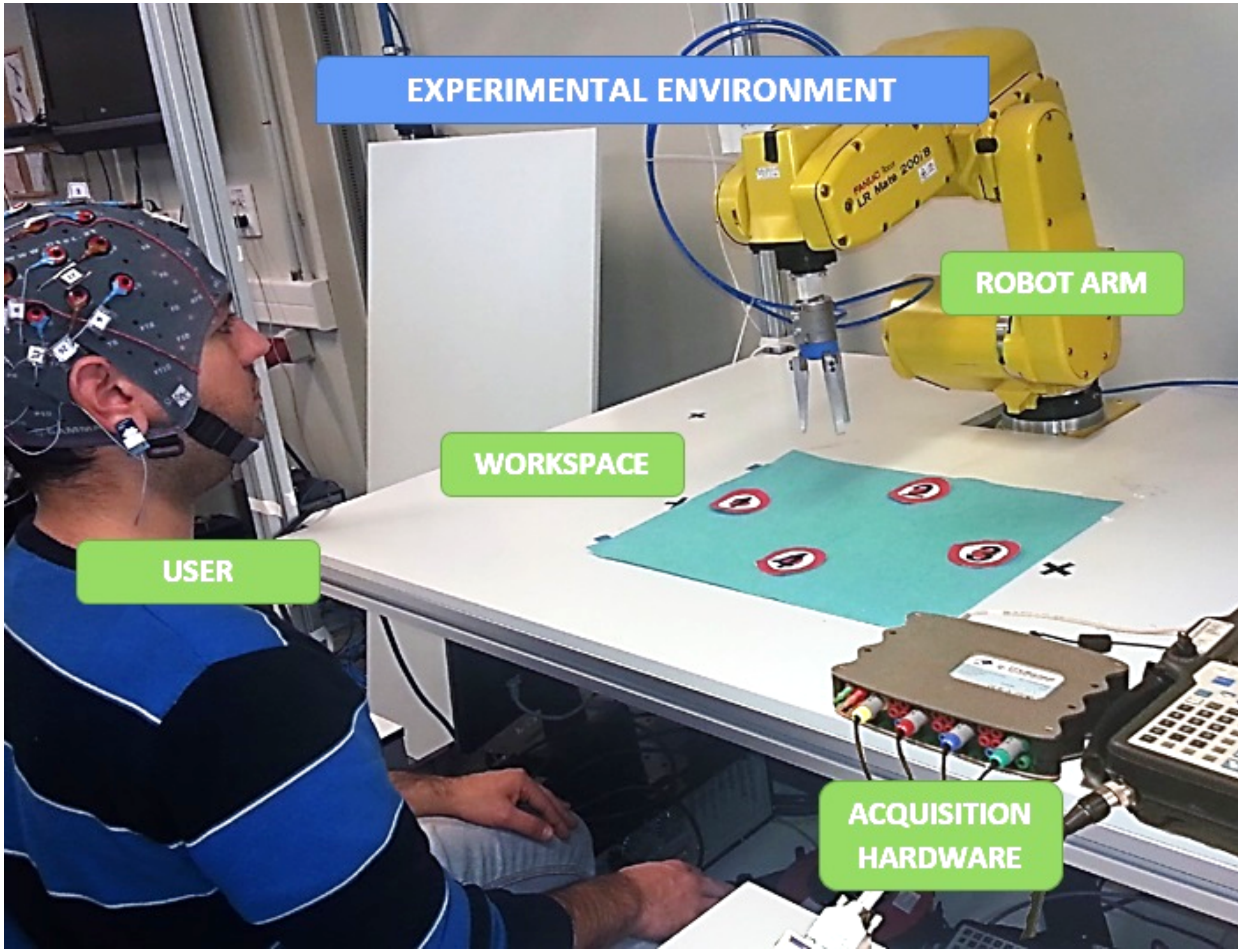
User	Test	Target	*Hierarchical control* Trials	E/D	Test time(s)	*Directional control* Trials	Test time(s)
A	1	1	2	0/5	93	2	189
		2	1	5/14	269	2	128
		3	1	1/9	221	1	58
		4	1	2/9	206	1	165
		Total time (s)			**789**		**540**
A	2	1	1	1/7	180	1	97
		2	1	0/4	76	1	32
		3	1	0/7	114	1	67
		4	1	0/5	106	2	251
		Total time (s)			**476**		**447**
B	1	1	2	0/5	116	1	105
		2	1	0/4	27	1	108
		3	1	1/9	52	2	243
		4	2	0/5	238	1	88
		Total time (s)			**433**		**544**
B	2	1	1	1/7	179	1	217
		2	1	2/8	111	1	27
		3	1	0/7	173	1	77
		4	1	0/5	148	1	152
		Total time (s)			**611**		**473**

Directional Control



- Hierarchical control is more reliable but slower
- Directional control is easier to manage and faster, but less precise

Spontaneous BMI based on 4 mental tasks

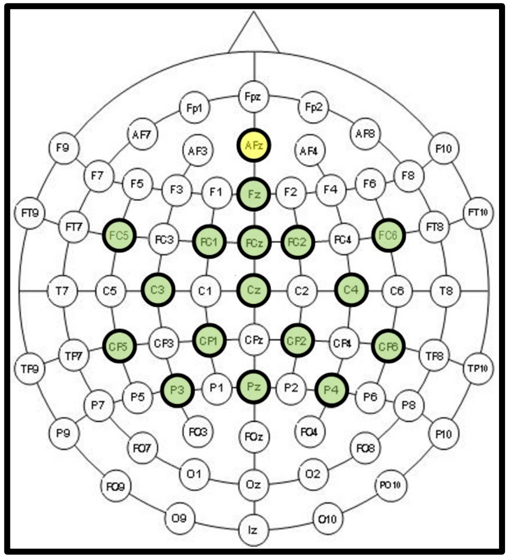


Enrique Hortal

E. Hortal, D. Planelles, A. Costa, E. Iáñez, A. Úbeda, J. M. Azorín, "Brain-Machine Interface based on four mental tasks for controlling a robot arm", Neurocomputing (in press).

EEG processing & classifier

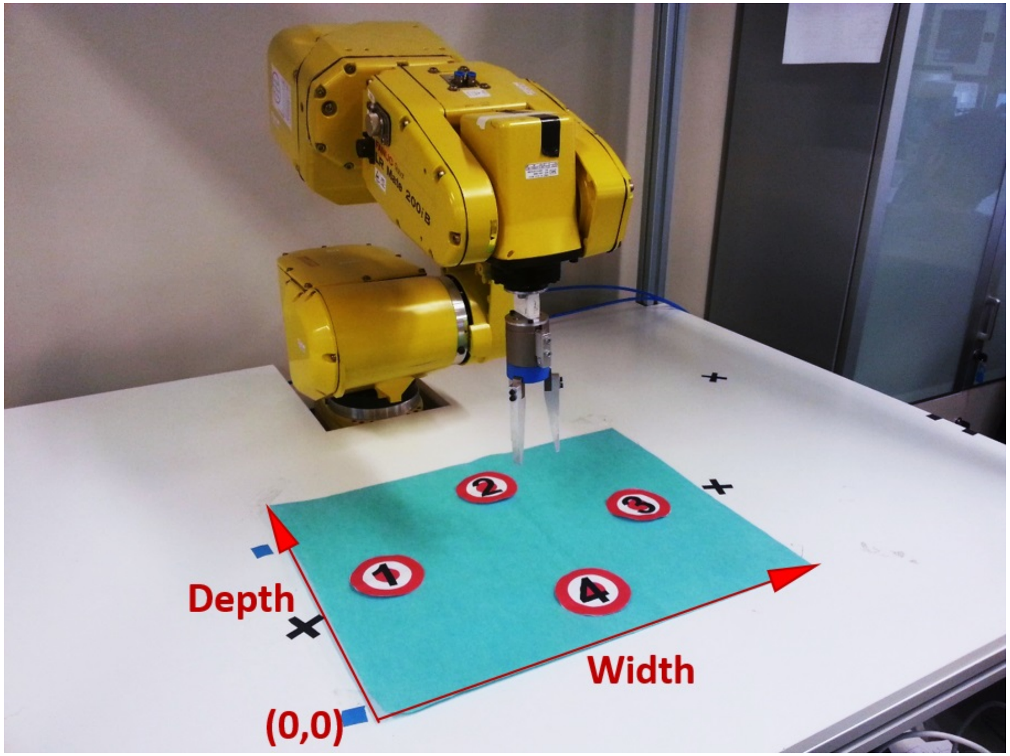
- Sampling frequency
  - 256 Hz
- Filter
  - Notch: 50 Hz
  - Band pass: 5 – 40 Hz
  - Laplacian
- Feature extraction
  - Periodogram (8 – 36 Hz every 2 Hz)



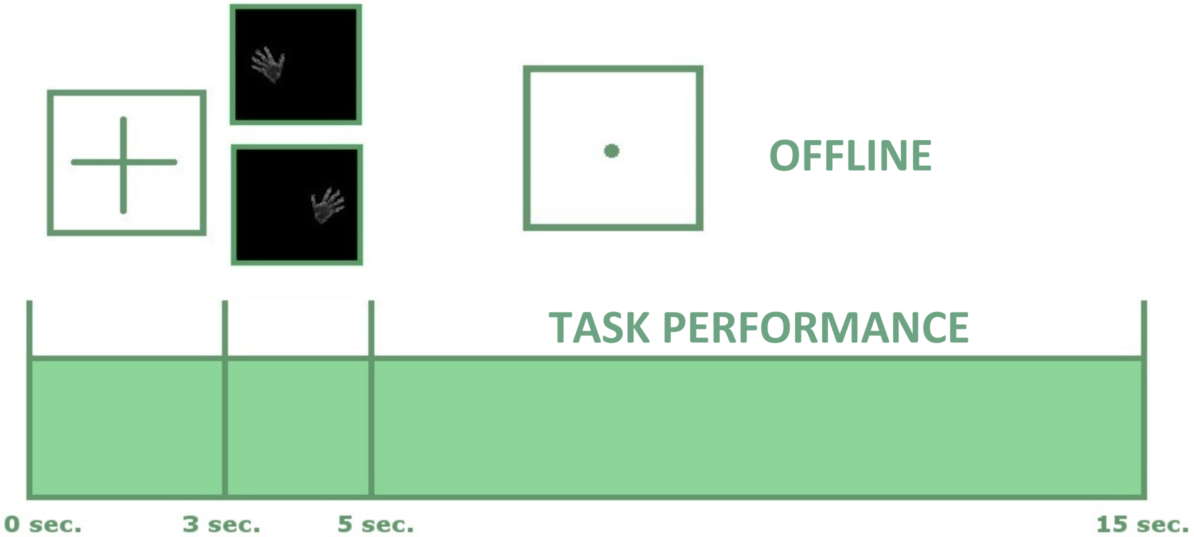
- Classifier: Support Vector Machine
- 4 tasks
  - Motor (both hands)
  - Concentration (countdown and alphabet)
- Uncertain values
  - 4 equal classifications in 5 consecutive ones

Experimental tests

- Test protocol
  - Creation of the classification model
  - Training
  - Real time test
    - 4 targets
    - 5 repetitions

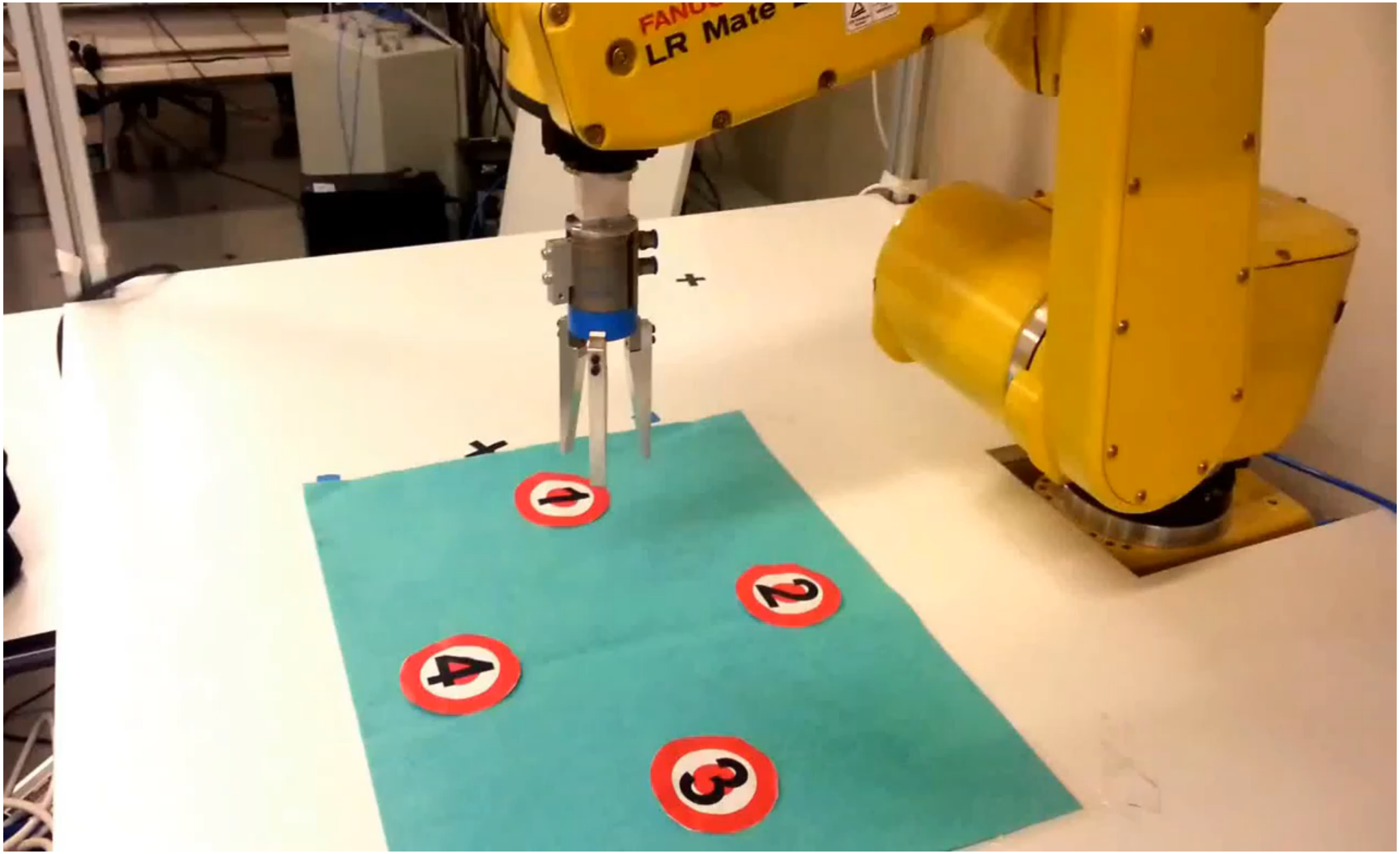


Creation of the classification model



USER	RIGHT HAND	LEFT HAND	COUNT DOWN	ALPH. BACKW.	Mean
A	85,00	91,10	51,27	68,64	**74,00**
B	78,39	89,41	61,86	61,44	**72,78**

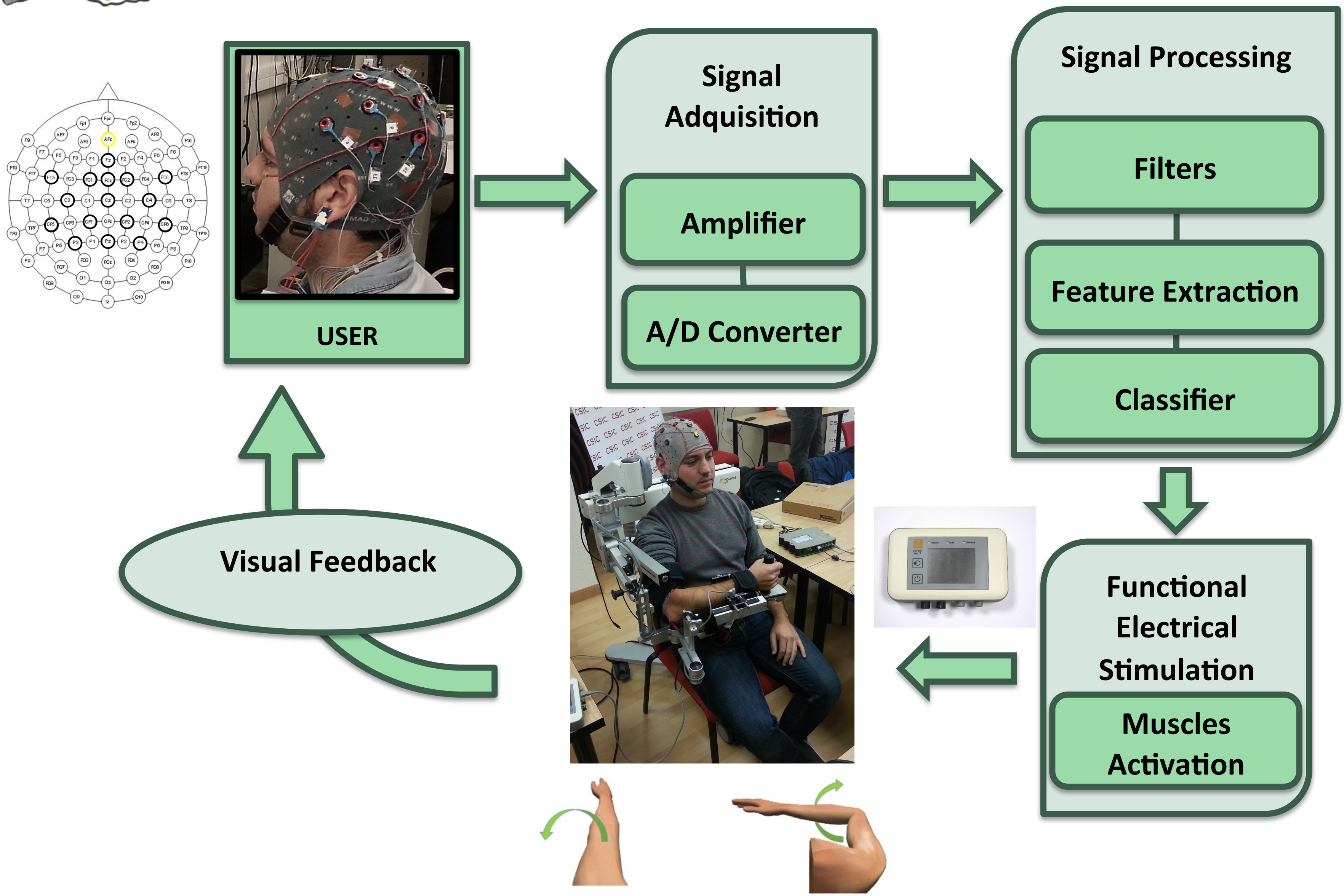
Real time test



Real time tests - Results

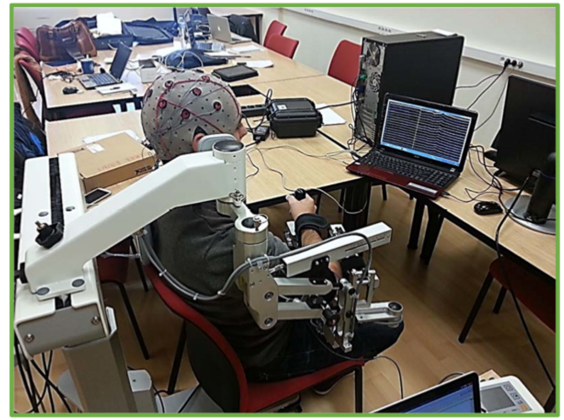
USER	REPETITION	TARGET				TOTAL
		1	2	3	4	
A	1	13,87	28,88	23,07	106,19	**172,01**
	2	5,99	19,28	50,34	11,72	**87,33**
	3	5,89	49,11	106,46	28,41	**189,87**
	4	4,73	31,93	87,57	39,58	**163,81**
	5	5,13	15,63	109,34	107,76	**237,86**
B	1	7,13	86,16	40,93	11,29	**145,51**
	2	5,06	39,29	37,61	16,57	**98,53**
	3	6,01	32,59	58,07	23,70	**120,37**
	4	5,19	23,55	84,94	35,11	**148,79**
	5	5,98	53,76	134,52	21,07	**215,33**

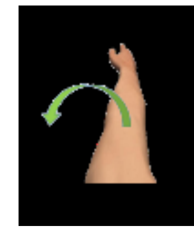
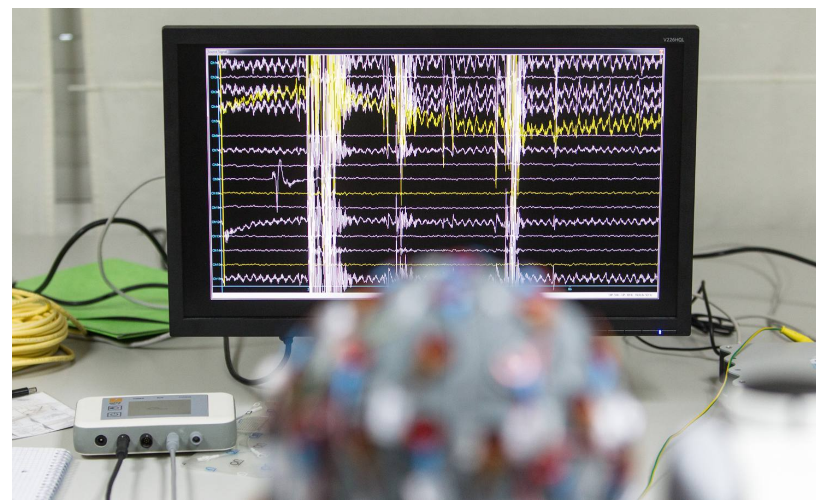
Application to the upper-limb exoskeleton



BMI based on motor imagery

- One mental task related to motor imagery:
  - Imagination of hand movement
- Feature Extraction:
  - Periodogram
- Classifier:
  - SVM



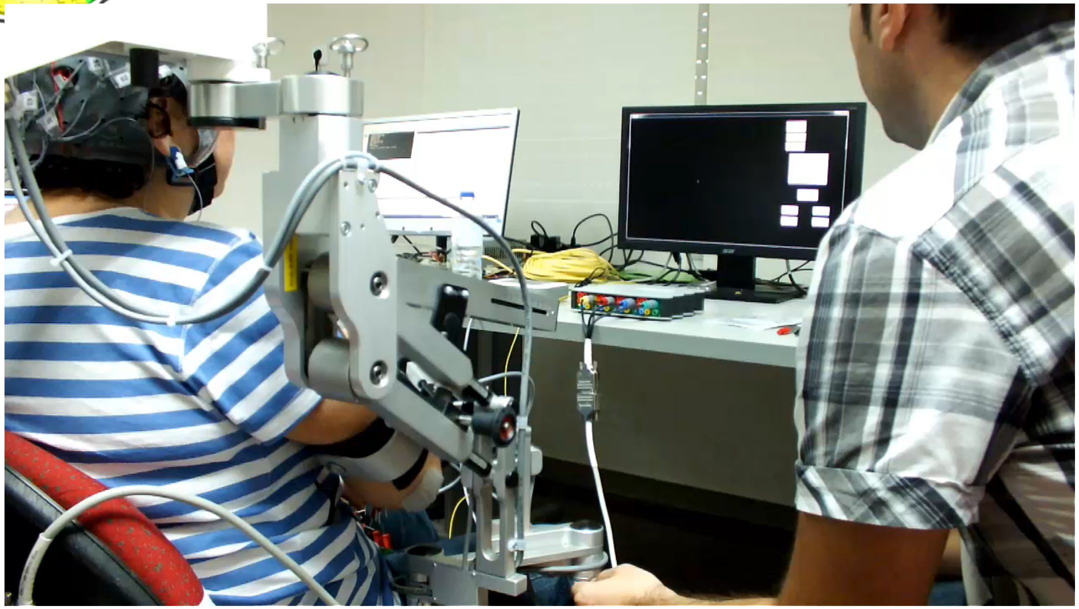



Participants in the experiments

Alicante Hospital, Spain
Rehabilitation Department
Jose M. Climent, MD, PhD

- 5 patients (P1-P5) participated in the usability tests of the system
- Patients:
  - 4 patients suffered a stroke and they are affected by hemiplegia (P1-P4)
  - The last one (P5) suffered a traumatic brain injury and quadriplegia

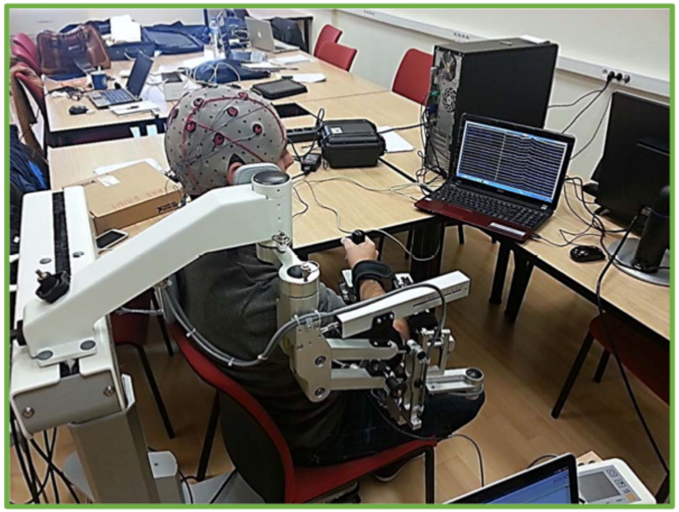
BMI based on motor imagery

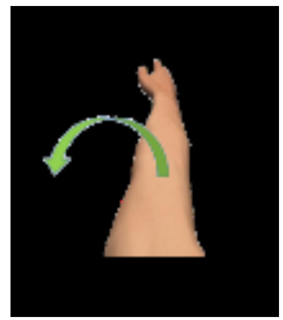


Experiments

USER	P1	P2	P3	*P5	Average
Correct detections	17	20	23	13	18.3
Percentage of correct detect.	42.5	50.0	57.5	32.5	45.6
False positives	7	2	5	10	6.0
Percentage of false positives	17.5	5.0	12.5	25.0	15.0
Percentage of Accuracy	**62.5**	**72.5**	**72.5**	**53.8**	**65.3**

Detection of the movement intention of the upper limb





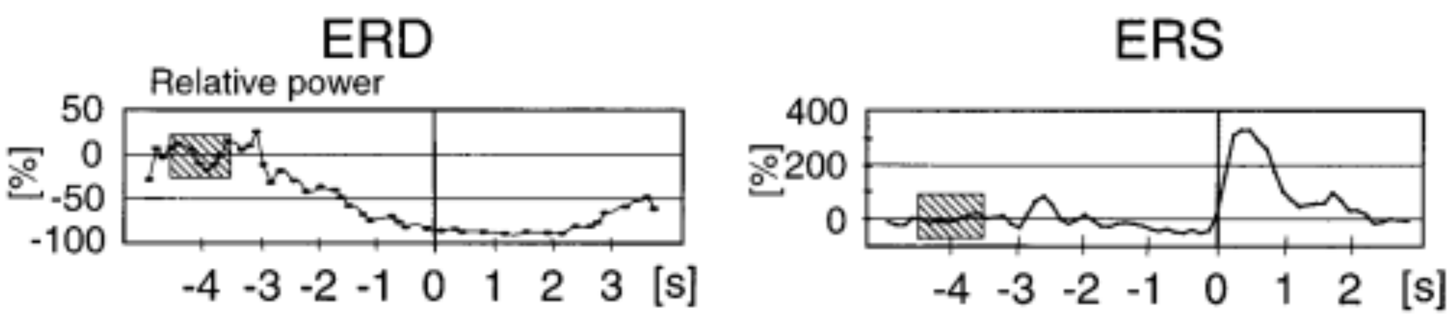
D. Planelles

- Objective:
  - Detect the intention to perform a movement of the upper limb before it really happens using EEG signals (ERD phenomenon)
- Motivation:
  - Control of an exoskeleton attached to user's upper limb

D. Planelles, E. Hortal, A. Costa, A. Úbeda, E. Iáñez, J. M. Azorín, "Evaluating Classifiers to Detect Arm Movement Intention from EEG Signals ", Sensors, 14(10), 18172-18186, 2014.

Detection of the movement intention of the upper limb

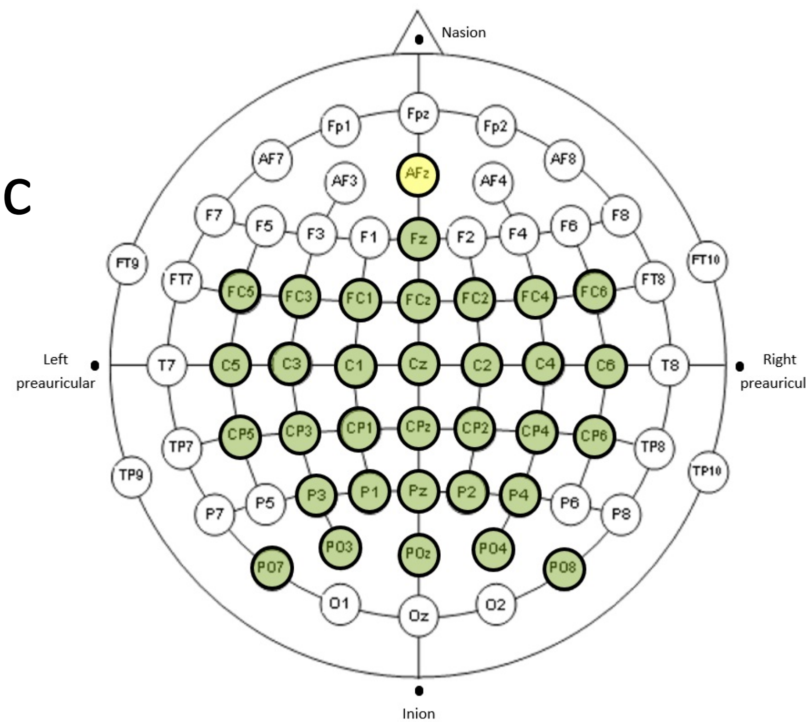
- Sensorimotor rhythms
  - Event-Related Desynchronization (ERD)
    - Up to 2 seconds before movement onset
  - Mu and beta frequency bands (8-30 Hz)
  - Decrease of spectral power just before performing a movement
  - Event-Related Synchronization (ERS)
    - After performing the movement



Detection of the movement intention of the upper limb

Register

- Sampling frequency: 256 Hz
- GammaCap and 2 g.tec amplifiers
- 32 EEG electrodes + Ground: AFz. Reference: Ear lobe.



Detection of the movement intention of the upper limb

Signal processing & classifier

- Notch filter (50 Hz)
  - Eliminate power interference
- Bandpass filter
  - 4th orden Butterworth from 5-40 Hz
  - Isolate mu and beta frequency bands
- Spatial filter
  - Laplacian Surface (LAP)
  - Reduce contribution of surrounding electrodes
- Features extraction
  - Fast Fourier Transform (FFT)
  - The sum of 8-12 Hz power spectral per each electrode: 32 features
- Classifier
  - Support Vector Machine

Detection of the movement intention of the upper limb

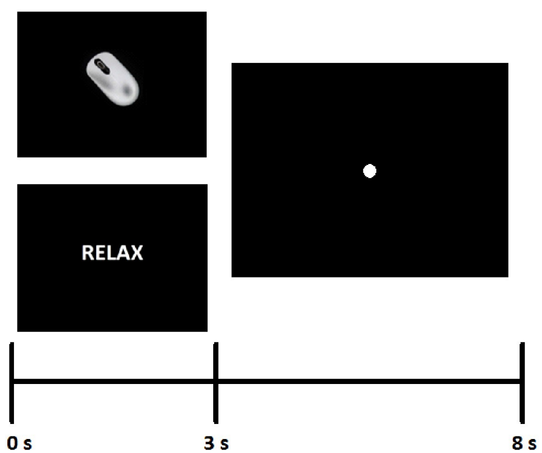
Results

Offline: 10-fold cross validation

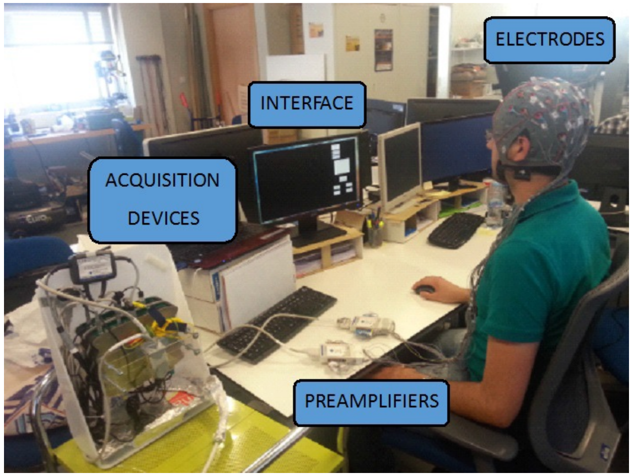
USER	TPR %	FPR %
A	67,00 ± 10,59	30,00 ± 22,11
B	83,00 ± 14,18	18,00 ± 9,19

Online: Real time test

USER	TPR (%)	FPR (%)	ACC (%)
A	69,31	22,27	72,50
B	93,33	15,38	88,33



10 runs with 10 movements each to train the model



BMI based on movement intention of the upper limb

Experiments

User	True Positive (%)	False Positives (%)	System Accuracy (%)
P2	70,2	6,1	80,0
P3	89,4	24,7	81,3
P4	75,1	24,4	75,0
*P5	38,2	30,3	47,5
Patients Avg	**68,2**	**21,4**	**71,0**

BioMot

Smart Wearable Robots with Bioinspired Sensory-Motor Skills

VII Programme Framework:

FP7-ICT-2013-10 (GA no. 611695)

Dates: 01.10.2013-30.09.2016

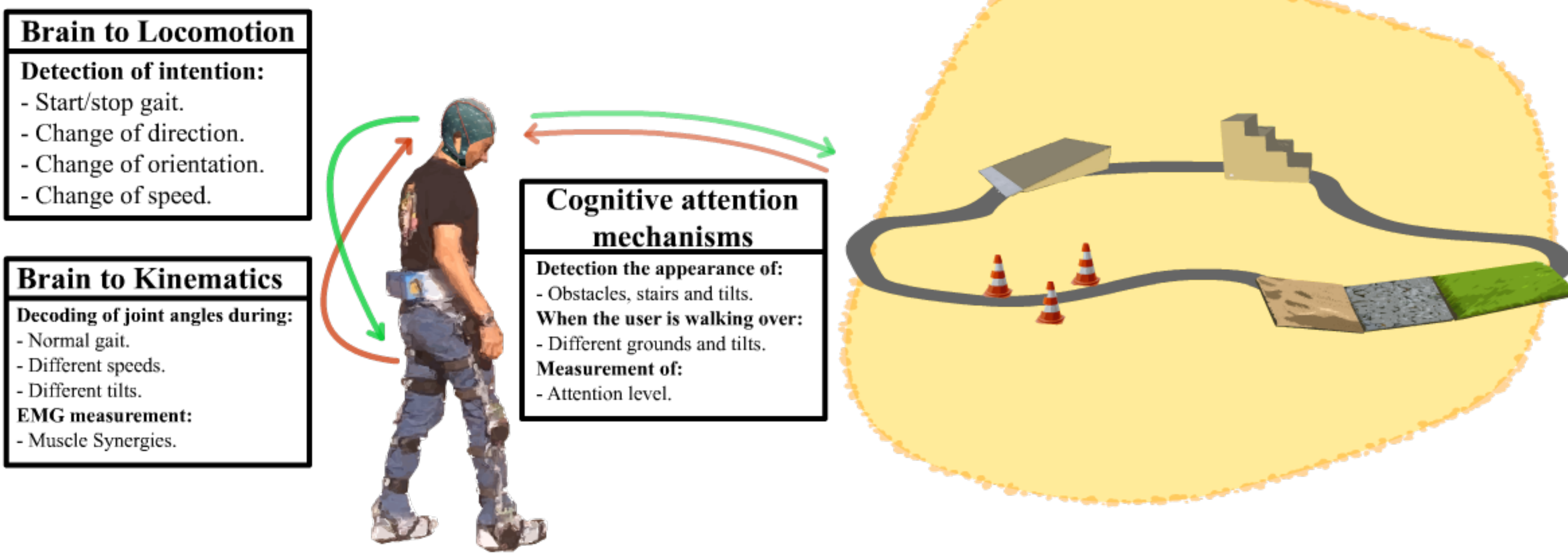
Coordinators: José L. Pons (PI), Juan C. Moreno (co-PI)

Goal: improve existing robotic exoskeletons exploiting dynamic sensory-motor interactions and developing cognitive capabilities that can lead to symbiotic gait behavior in the interaction of a human with a wearable robot

BioMot

To study the <u>cognitive mechanisms related to initiation/termination of the gait</u> and to changes in direction/orientation during walking

Environment

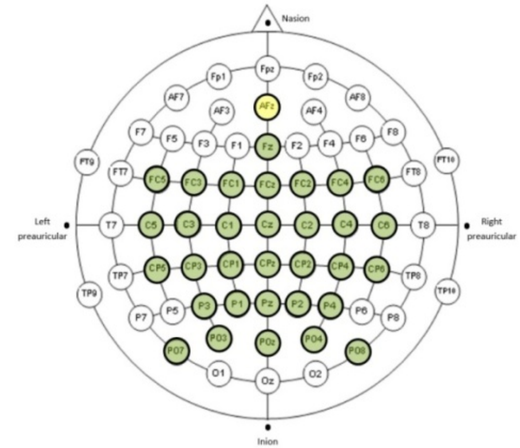


To design models to <u>decode the locomotion during walking from EEG</u> signals

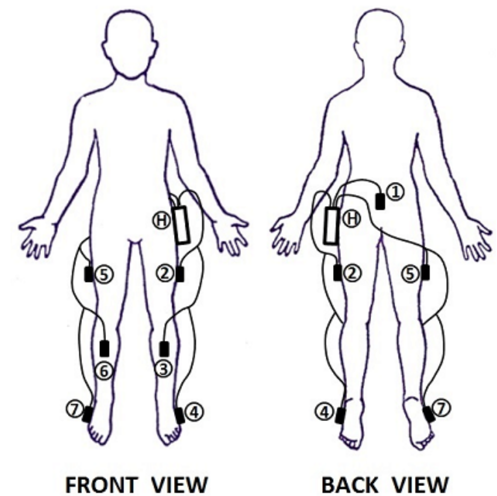
To understand <u>cognitive attention mechanisms</u> related to stability and adaptation to environment

Experimental equipment

- EEG signals:
  - two g.USBamp amplifiers (g.tec)
  - 32 g.LadyBird active electrodes



- Joint angles:
  - 7 inertial measurement units (IMUs) (Technaid)

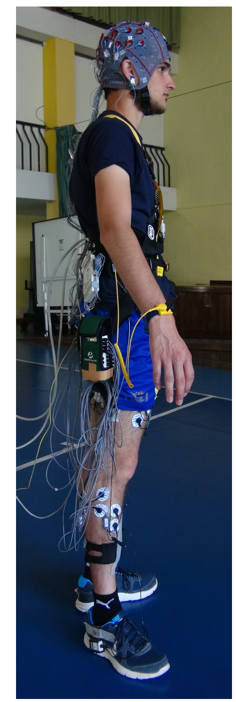


- A treadmill:
  - Model Pro-Form Performance 750
  - different tilts and speeds can be set

D. Planelles, A. Costa, A. Úbeda, E. Iáñez and J. M. Azorín. "Experimental Architecture To Analyse Brain Signals During Walking", International Conference on NeuroRehabilitation (ICNR), Aalborg, Denmark, 24-26 June 2014.

Cognitive mechanisms related to self-adjustments during walking

- Goals:
  - Detect from EEG signals the intention of the user to:
    - Start/stop gait cycle (Priority 1)
    - Change the walking direction (Priority 2)
    - Change gait velocity from EEG signals (Priority 2)
- Motivation:
  - Control of an exoskeleton attached to the lower limb

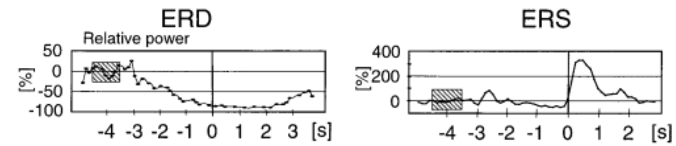


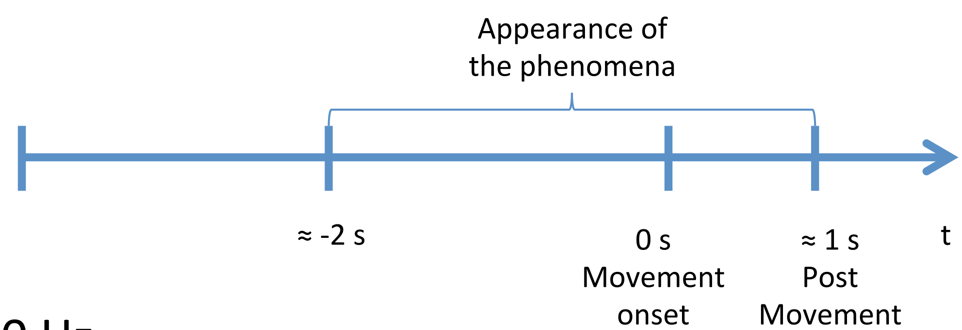
D. Planelles

D. Planelles, E. Hortal, A. Costa, E. Iáñez, J.M. Azorín. "First steps in the development of an EEG-based system to detect intention of gait initiation", 8th Annual IEEE International Systems Conference, Ottawa, Canada, 31 Mar - 3 Apr 2014.

Detect gait initiation intention

- Event-Related Desynchronization (ERD)
  - Up to 2 seconds before movement onset
- Mu and beta frequency bands (8-30 Hz)
- Decrease of spectral power just before performing a movement



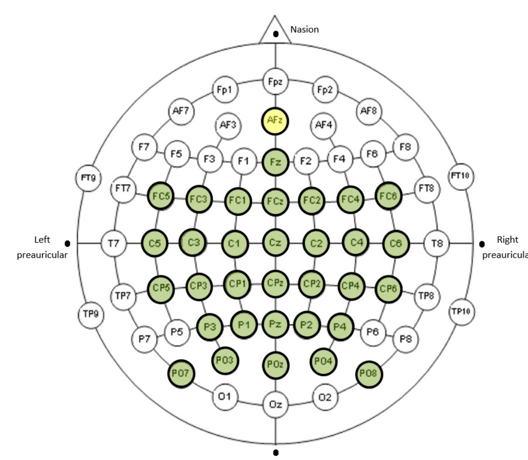


EEG Register

- Sampling frequency: 1200 Hz
- GammaCap and 2 g.tec amplifiers
- 32 EEG electrodes +

  Ground: AFz.

  Reference: Ear lobe.



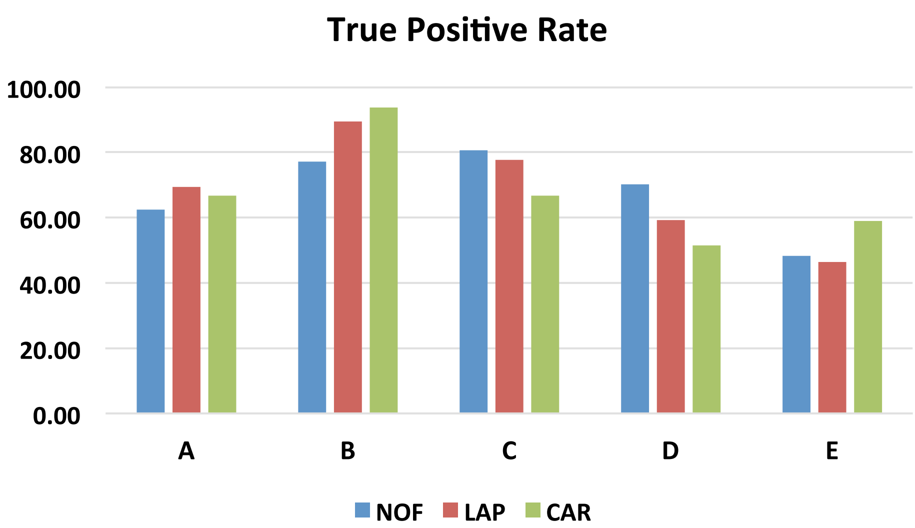
Detect gait initiation intention

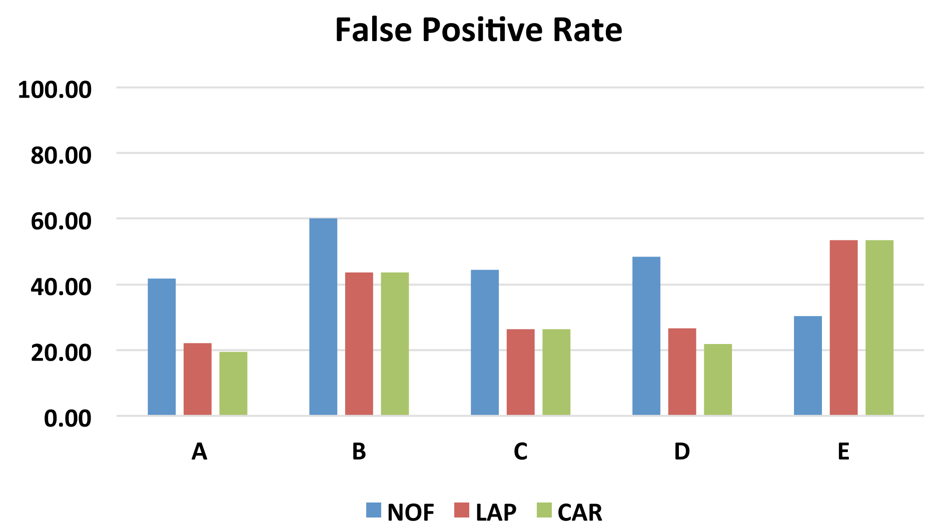
<u>Signal processing & classifier</u>

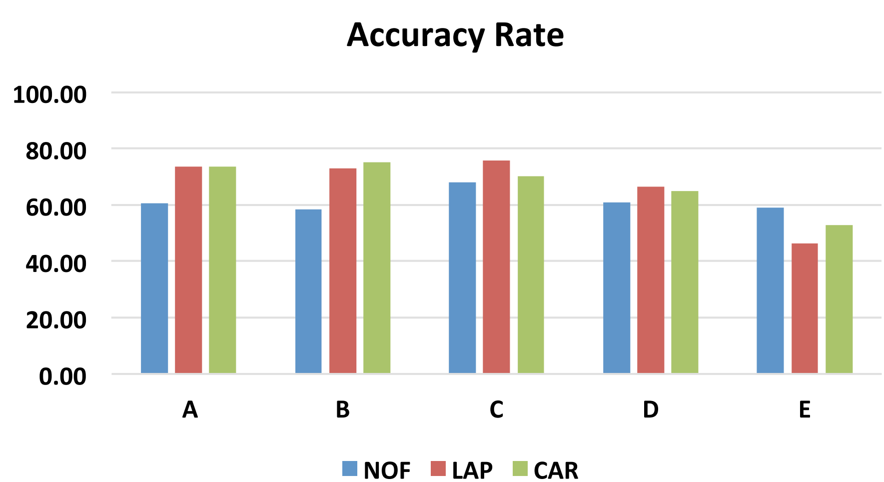
- Notch filter (50 Hz)
  - Eliminate power interference
- Bandpass filter
  - 4th orden Butterworth from 5-40 Hz
  - Isolate mu and beta frequency bands
- <u>Spatial filter</u> (one choice):
  - No filter (NOF)
  - Surface Laplacian (LAP)
  - Common Average Reference (CAR)
- Features extraction:
  - <u>6th order autoregresive model:</u> 6 features per electrode
- Classifier:
  - Support Vector Machine

Detect gait initiation intention

Offline results

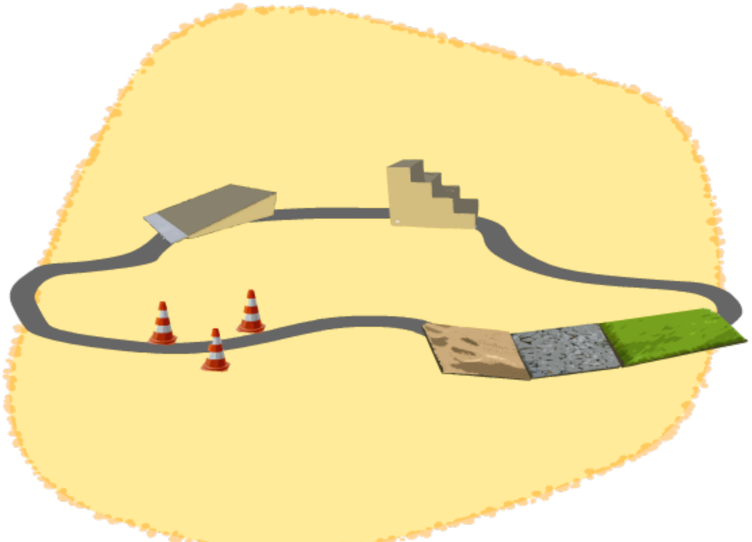






Cognitive attention mechanisms contributing to stability and adaptation to environment

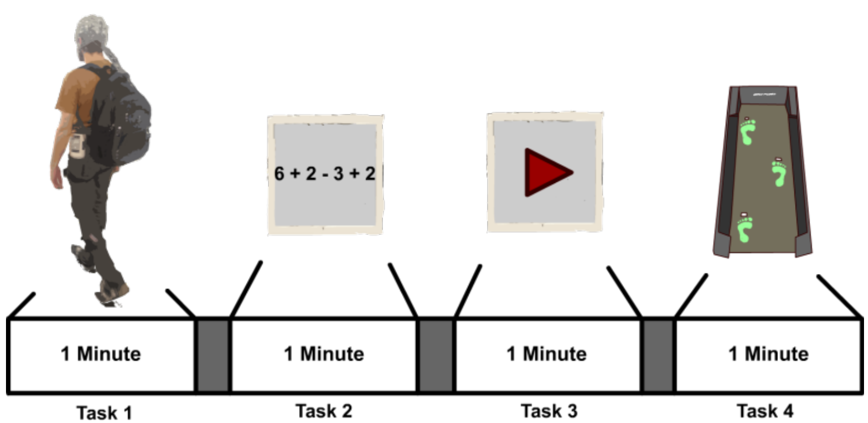
- Goals:
  1) Determine the degree of human's attention on walking
  2) Studying how different tilts affect on gait attention
  3) Detection of obstacles in the environment
  4) Detection of different environments



Classify attention level during gait

A. Costa

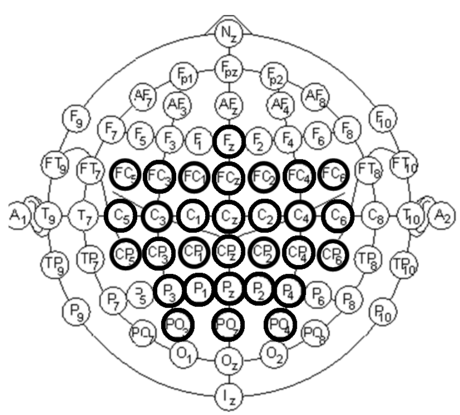
- Classify attention level during gait:
  - Standard attention level
    - Normal walk on the treadmill without distractions
  - Low level
    - The user has to perform mathematical operations or to watch videos
  - High level
    - The user has to follow some adhesive marks placed over a treadmill



Classify attention level during gait

Register

- Active Electrodes → improve signal/noise ratio
- 32 channels →motor cortex
- Ground → Az
- Monoauricular reference → rigth earlobe
- 50 Hz notch filter → remove power line interference
- Bandpass filter → 5-100 Hz



Processing

- Data window → 1000 ms
- Data overlap → 500 ms
- 3-nearest neightbors Laplacian Filter → Remove neighbors electrode contribution.
- Spectrum features → Welch method
- 32 features → 1 per electrode → sum of frequencies from 8 to 40 Hz.

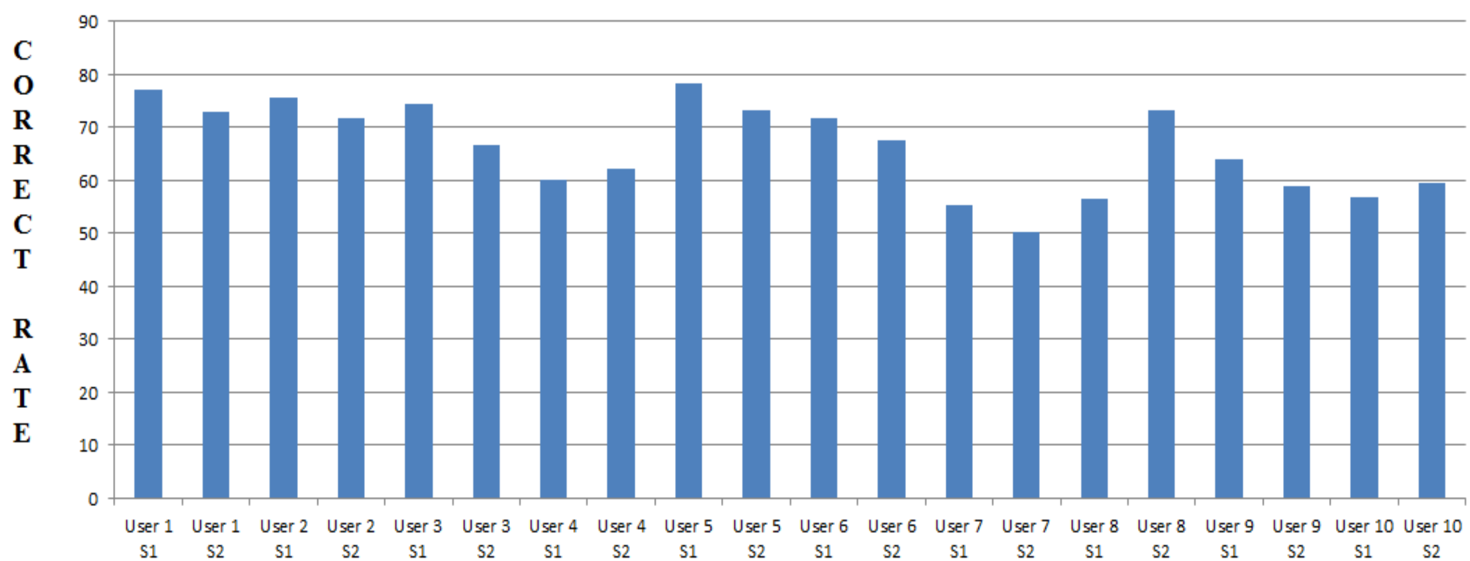
Classification

- Linear Discriminant Analysis (LDA)

Classify attention level during gait

Healthy people – Offline Results

- Offline results: 8-fold cross validation between sessions
- Average correct rate: 66%
  - This value is significantly above the chance level for a 4-task classification system (25%)

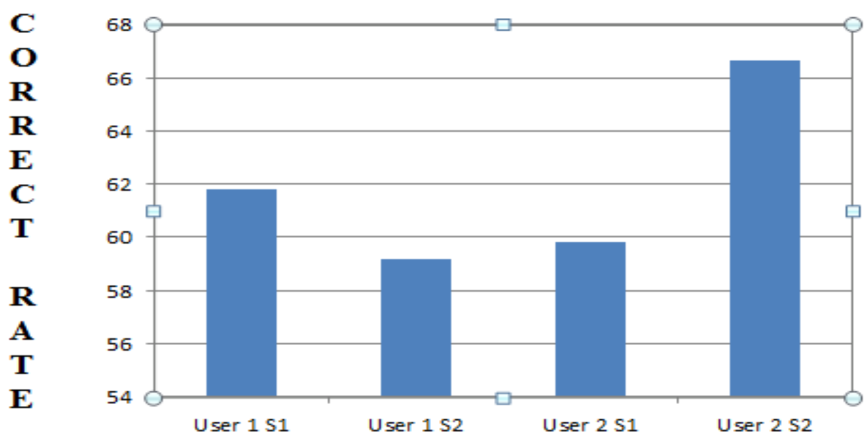


A. Costa, E. Iáñez, A. Úbeda, D. Planelles, E. Hortal, J.M. Azorín. "Experimental Setup and First Results of a BCI System for Attention Levels Classification During Gait", Workshop on Neuro-Robotics for Patient-Specific Rehabilitation, 13th International Conference on Intelligent Autonomous Systems, Padova, Italy, 15-19 July 2014.

Classify attention level during gait

Healthy people – Online Results

- Experimental tests with 2 sessions for 2 healthy users finished
- Online results: 7 runs → train model; 1 run→ test model
- Average correct rate: 62%
  - This value is significantly above the chance level for a 4-task classification system (25%)



Classify attention level during gait

Experiments with Patients

National Hospital for Spinal Cord Injury, Toledo (Spain)

<u>Patients:</u>

Complete spinal cord injured patients (Level of injury below D7)

Incomplete spinal cord injured patients (Level between C2 and D12)

Classify attention level during gait
Results with patients

- Patients C01 and C02 perform 3 runs (3 minutes for each attention level)
- Patient C04 performs 2 runs: (2 minutes for each attention level)
- Healhty user A02 also performs 3 runs: (3 minutes for each attention level)

User	Laplacian filter	Classifier	Success percentaje of 4 attention levels
C01	4 neighbors	LDA	58%
C02	3 neighbors	LDA	60%
C04	3 neighbors	LDA	50%
A02	*4 neighbors*	*LDA*	*74%*
C01	3 neighbors	KNN citiblck 1 neighbor	57%
C02	1 neighbor	KNN citiblck 1 neighbor	69%
C04	5 neighbors	KNN citiblck 1 neighbor	63%
A02	*4 neighbors*	*KNN citiblck 1 neighbor*	*81%*

- After laplacian filter, 32 features (sum of frequencies from 20 to 90 Hz) were used by the classifier

Detection of obstacles in the environment

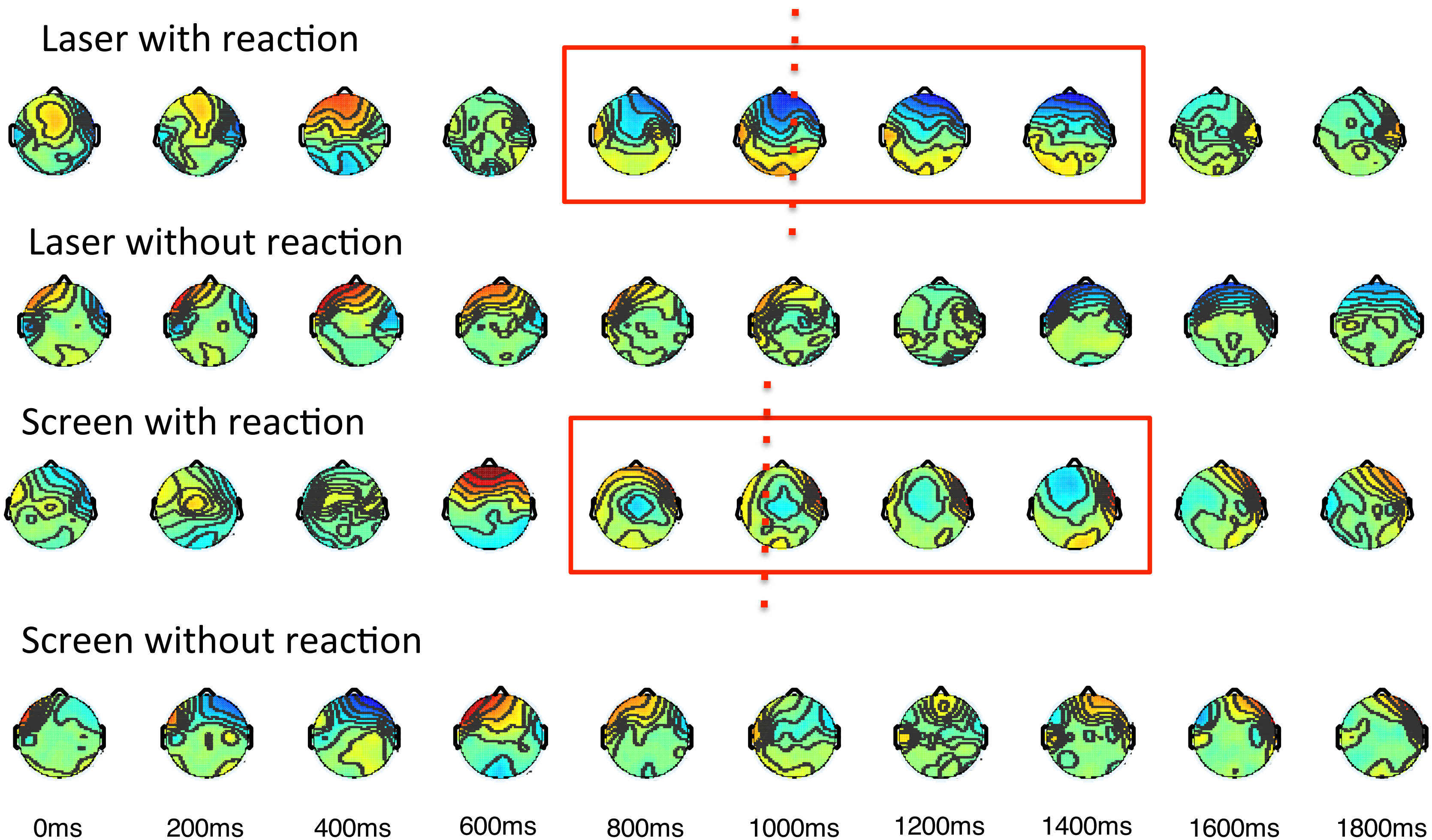

R. Salazar

- Obstacles are presented to user in two ways:
  - A line laser is projected on the treadmill during 5 sec.
  - A change of the color screen during 5 sec.
- Experiments:
  - Reaction. When the obstacle appears, the user stops their gait one secod and then continue it.
  - No reaction. When the obstacle appears, the user ignores it (the user does not stop their gait).
  - Free. The user freely changes their gait without obstacle presence.

Detection of obstacles in the environment

Spatial distribution

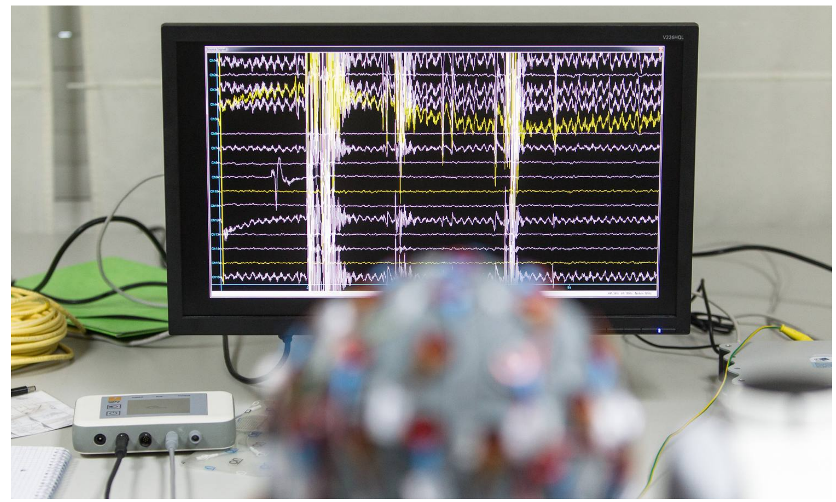
Bandpass filter 0.2-4Hz + CAR



Detection of obstacles in the environment

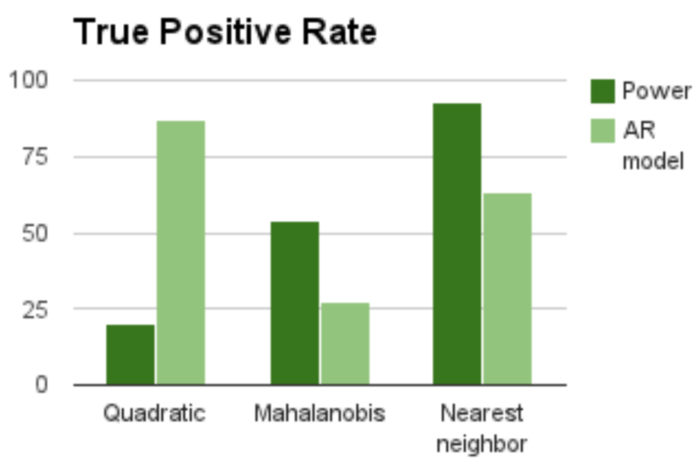
Processing & Classifier

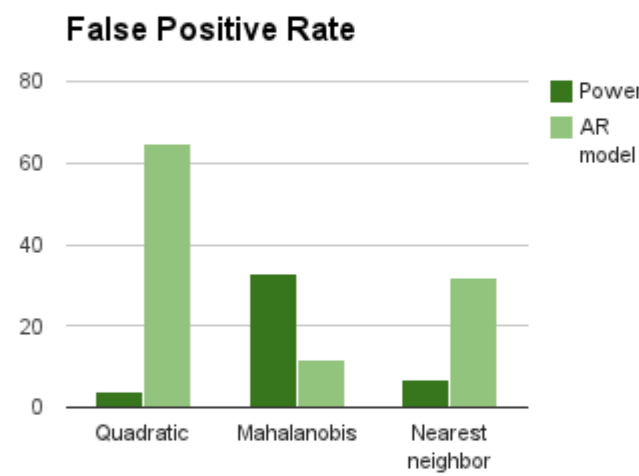
- Two classes are considered:
  - To avoid the obstacle
  - Normal walk
- Data window of 1 second.
- Filtering:
  - Band pass filter 0.2-4Hz
  - Common Average Reference
- Features:
  - Power in the frontal zone.
  - 6th order autoregresive model
- Classifiers:
  - Quadratic
  - Mahalanobis
  - Nearest neighbors

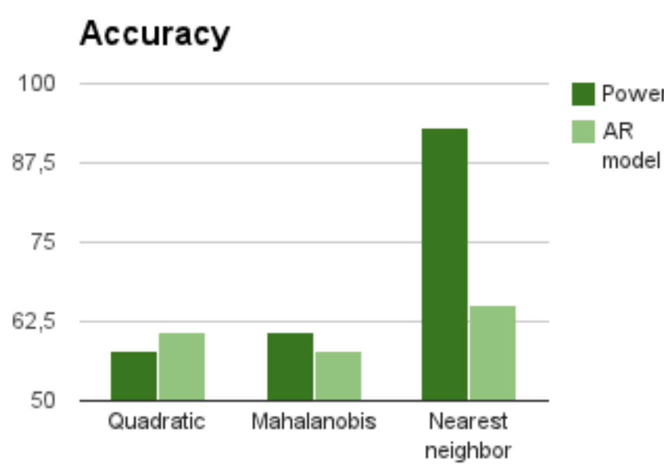


Detection of obstacles in the environment

Preliminary results: One subject







Decoding of locomotion during walking from EEG

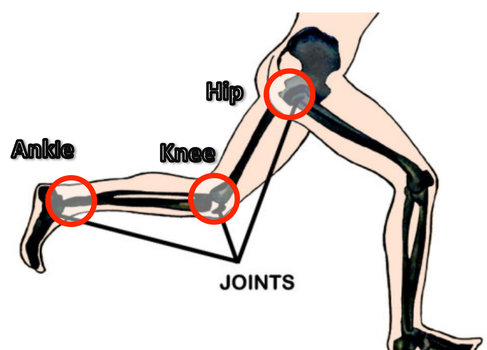
A.Úbeda et al. Decoding Knee Angles from EEG signals for Different Walking Speeds. IEEE SMC conf 2014

A. Úbeda

- Decode the state of lower-limb joints (hip, knee and ankle) during walking through EEG signals.

- Approach for decoding
  - EEG Signals are bandpass filtered (4th order Butterworth) below 2 Hz
  - EEG data from each electrode is standardized by subtracting the mean and dividing the result by the standard deviation
  - Multidimensional linear regression is applied

$$x[t] = a + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nk} S_n [t-k]$$



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Patients and relatives

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