



Human into the loop

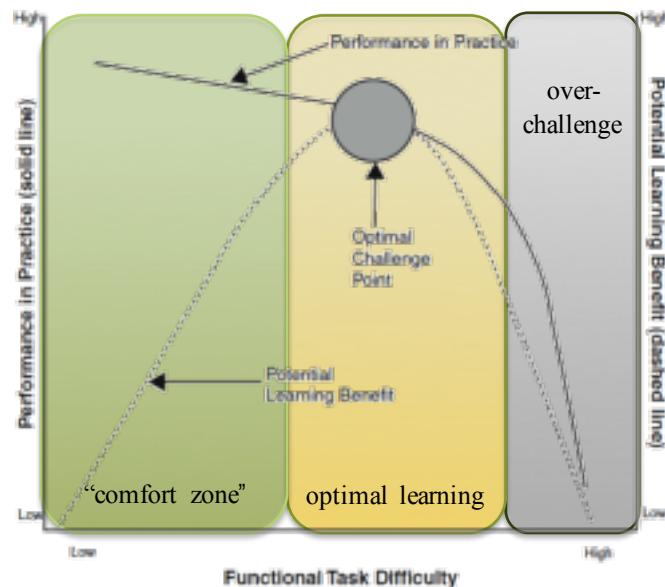
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Contents

- 1. Introduction**
2. Physiological signals and patient's emotional state
3. Biomechanical analysis
4. Dynamic adaptive system for robot-assisted motion rehabilitation
5. Experimental validation
6. Conclusions and future work

Introduction



Challenge beyond present capabilities

Learning is optimal when difficulty is out of “comfort zone”.

Enable training in optimal conditions

Support and guidance can help to avoid “over-challenge”.



Training should be adjusted for each patient for an optimal challenge. The optimal learning difficulty is not identical with the difficulty under which performance is greatest.

Introduction

- Conventional rehabilitation devices: **not efficient** patient-robot interaction
- “**If-then**” **algorithm** → predefined unidirectional action
- Patient intentions and needs are ignored
- **Biomechanical** and **physiological** effects are not considered

(Riener et al., 2010)

- Monitoring of **patient movements** and **internal states** for adapting to user needs
- Next generation of robotic therapy devices: use of patient information

(Louriero et al., 2011)

- Protocols based on **patient biomechanical performance, strength and emotional state**



Faster learning and recovery time

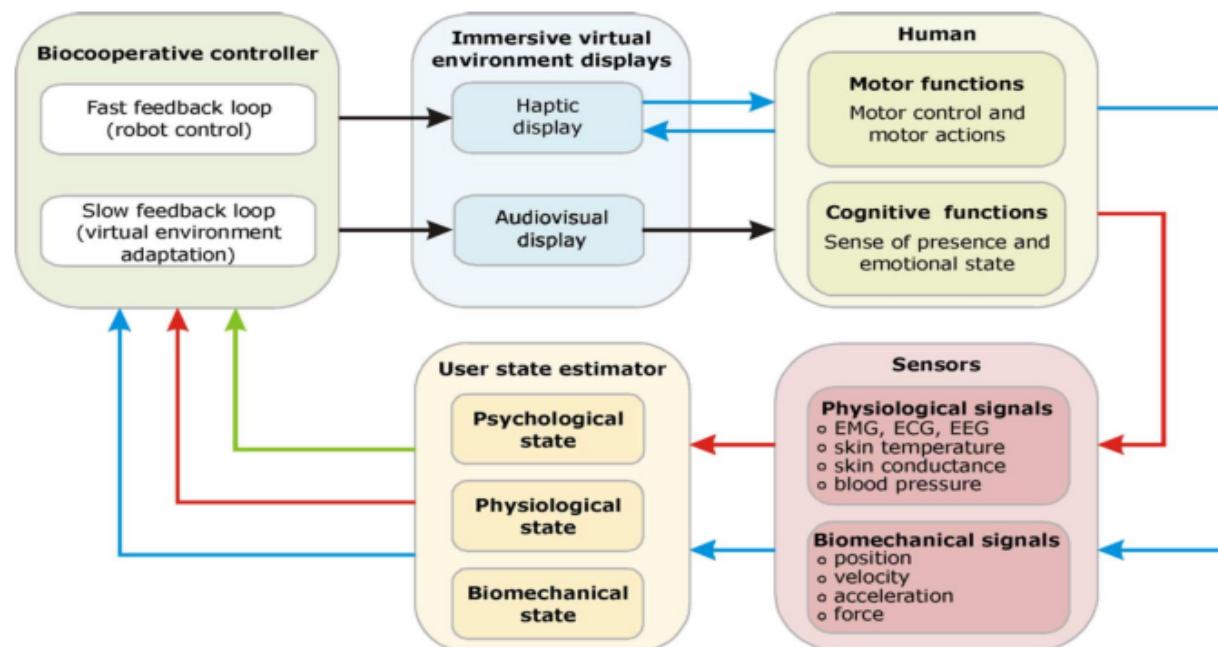
(Van der Loos et al., 2011)

Introduction: Human into the loop

How do they work?

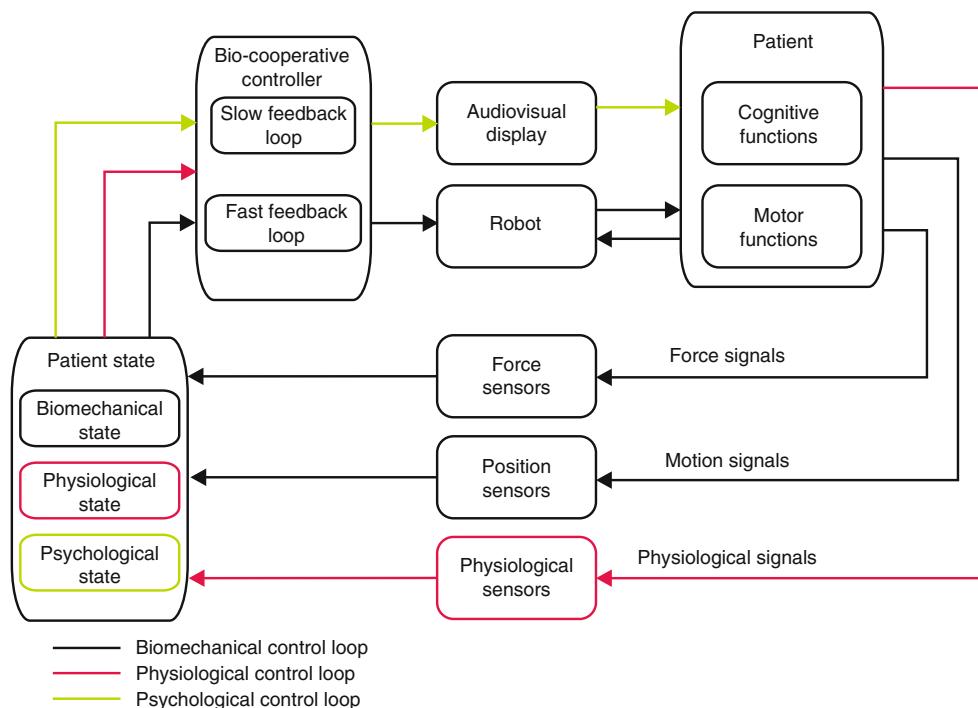
- Bio-cooperative controllers place the human **into the control loop** by feeding back the biomechanical and physiological information.
- He/she is more than just a sender of the command to the device or the passive receiver of a device action.

(Riener et al, 2010)



Introduction: Human into the loop

The human closes the loop by feeding back the biomechanical and physiological information to a processing unit.



Biomechanical integration makes the rehabilitation system safe, ergonomically acceptable, and “user cooperative.”

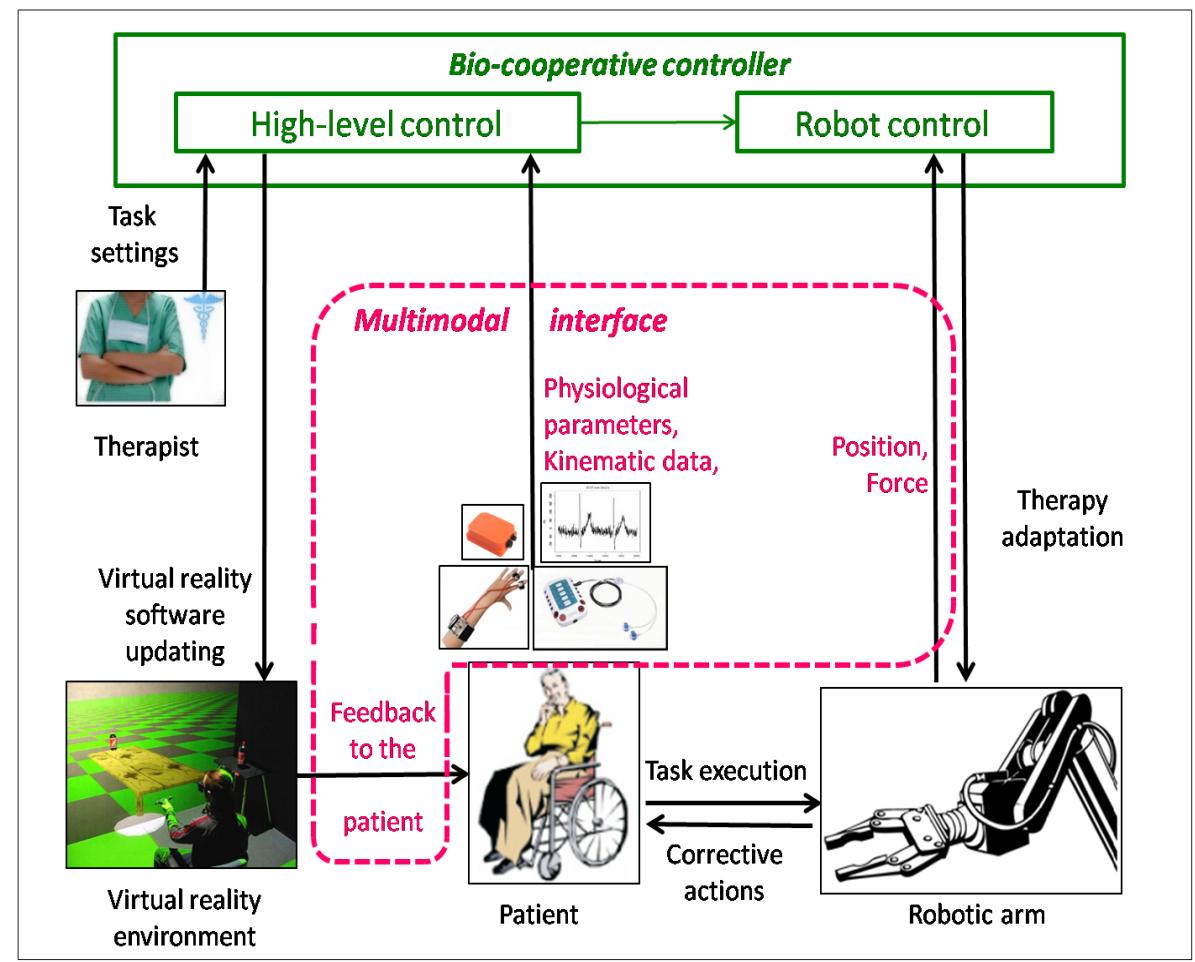
- Thus, with respect to rehabilitation robotics, the robot assists the human in a compliant way, with just as much force as needed so that the patient can contribute to the movement with his own voluntary effort.

Psychophysiological integration involves recording and controlling the patient's physiological reactions so that the patient receives appropriate stimuli and is challenged in a moderate but engaging and motivating way without causing undue stress or harm. Including physiological or psychological interpretations into the loop makes the system “**bio-cooperative**.”

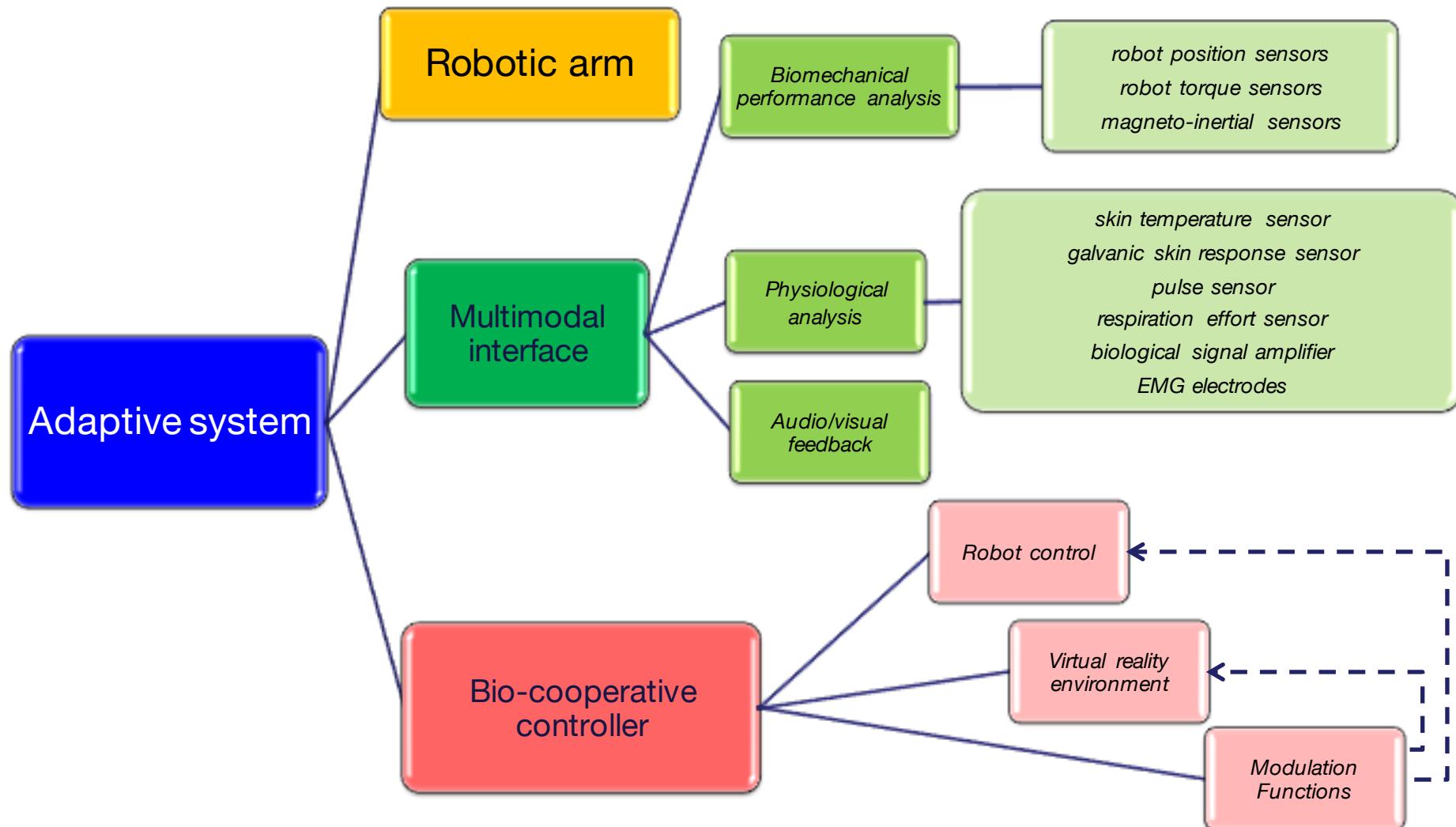
Bio-cooperative control system

*Developing a novel rehabilitation system made of a **multimodal interface** and a **bio-cooperative controller** that, including the **patient in the control loop**, is able to:*

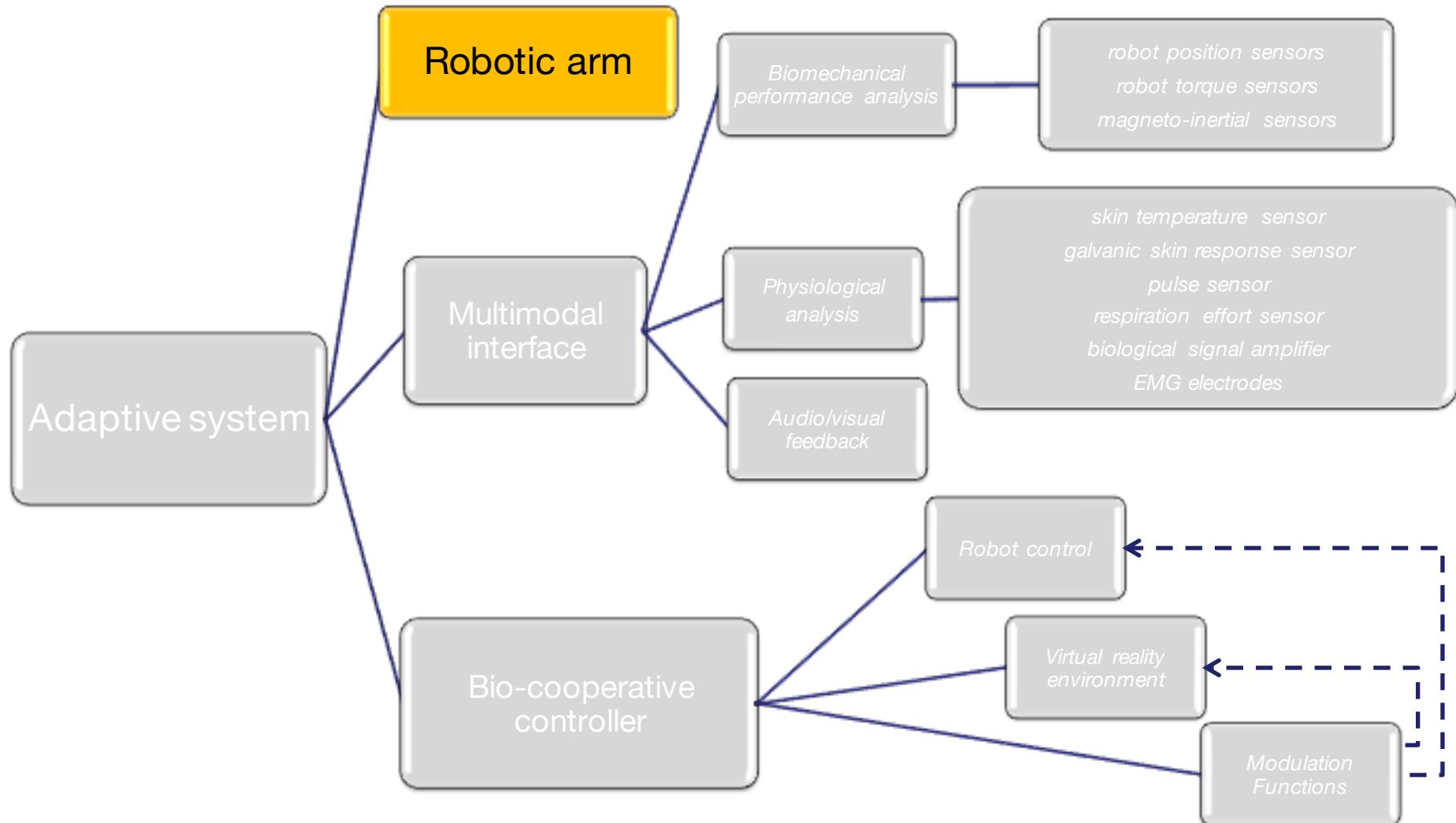
1. *Adaptively and dynamically change the complexity of the exercise in accordance with patient requirements;*
2. *Update robot control and apply corrective actions;*
3. *Continuously assess the progress of the recovery from the functional viewpoint;*
4. *Maximize patient motivation and involvement in the therapy by favoring her/his active role.*



Bio-cooperative control system: components



Robotic arms



Robotic arms

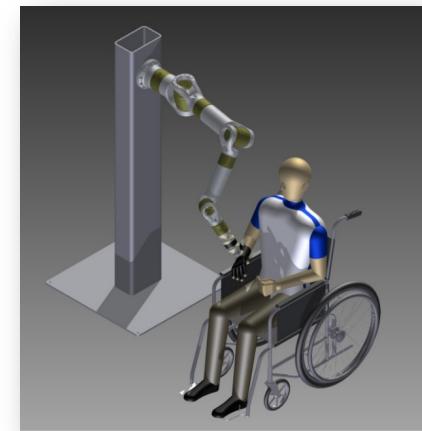
ROBOTHERAPIST 2D:

- 2 DOF for planar movements
- Pneumatic actuators
- High backdrivability

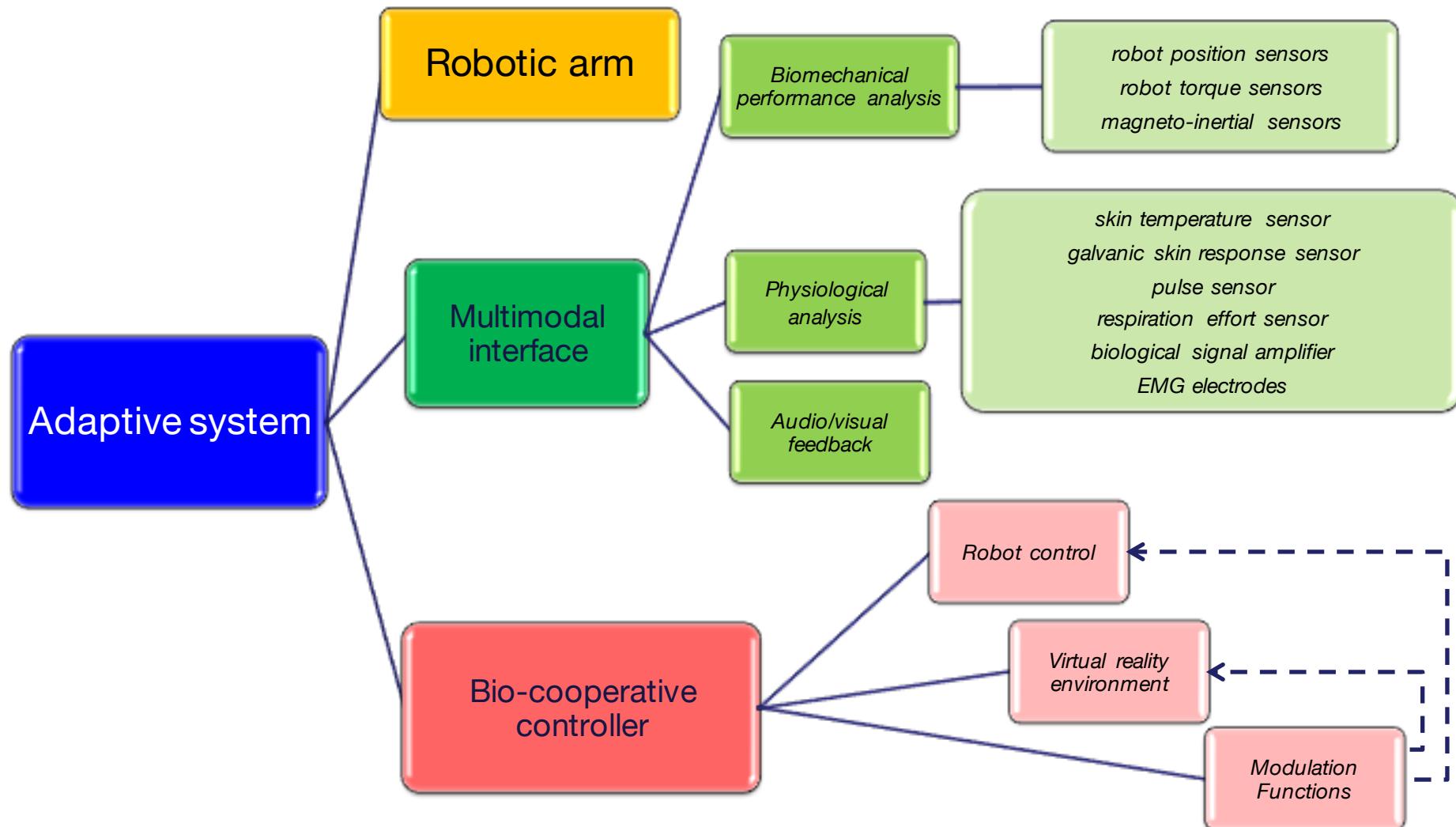


GENERAL PURPOSE ROBOT:

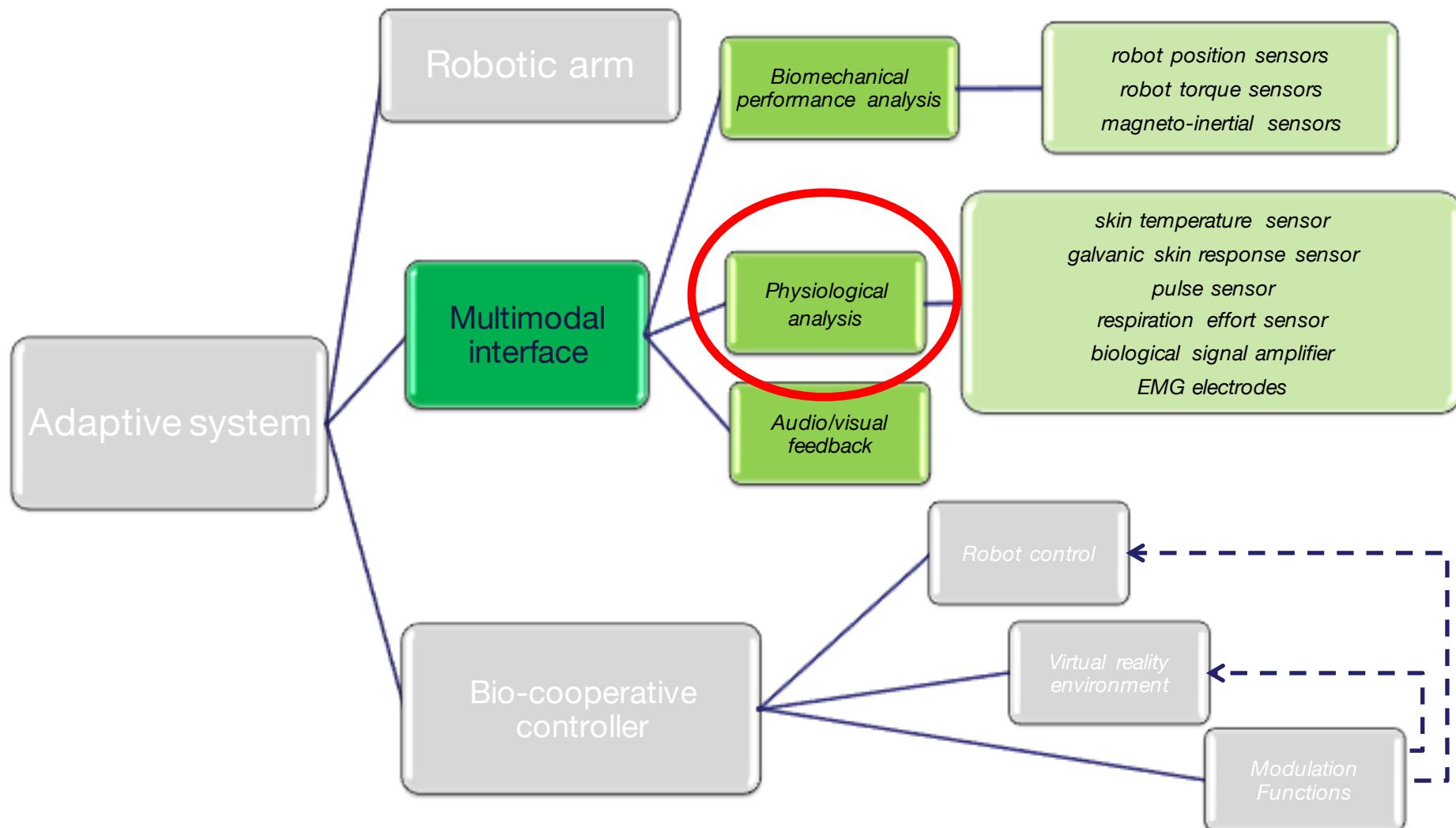
- Electric actuation.
- 7 DOF.
- 6 axes Force/Torque sensor



Bio-cooperative control system: components



Physiological signals



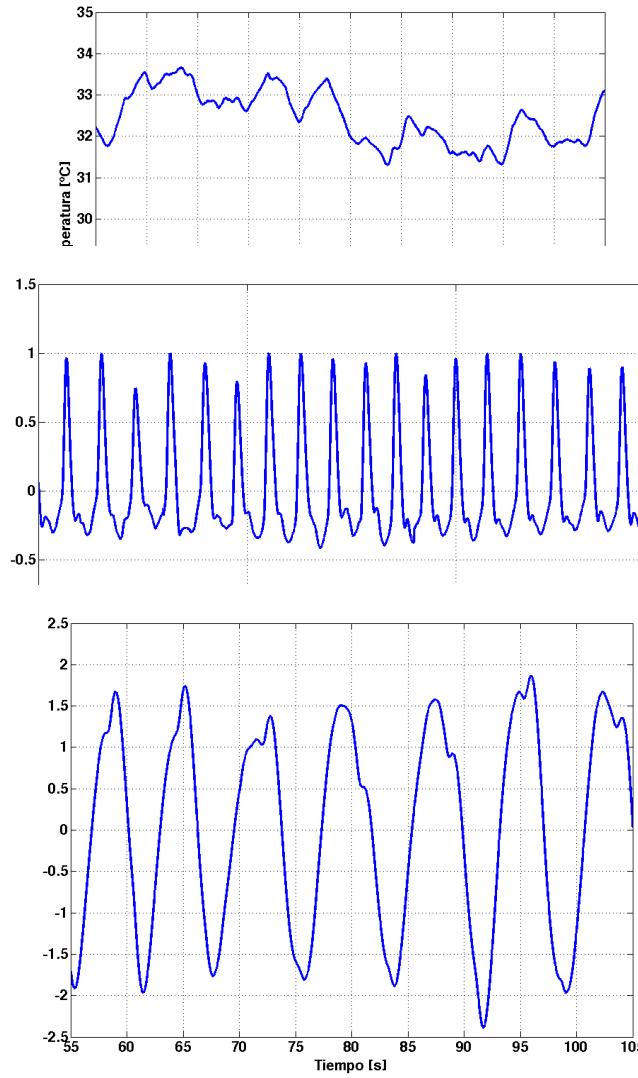
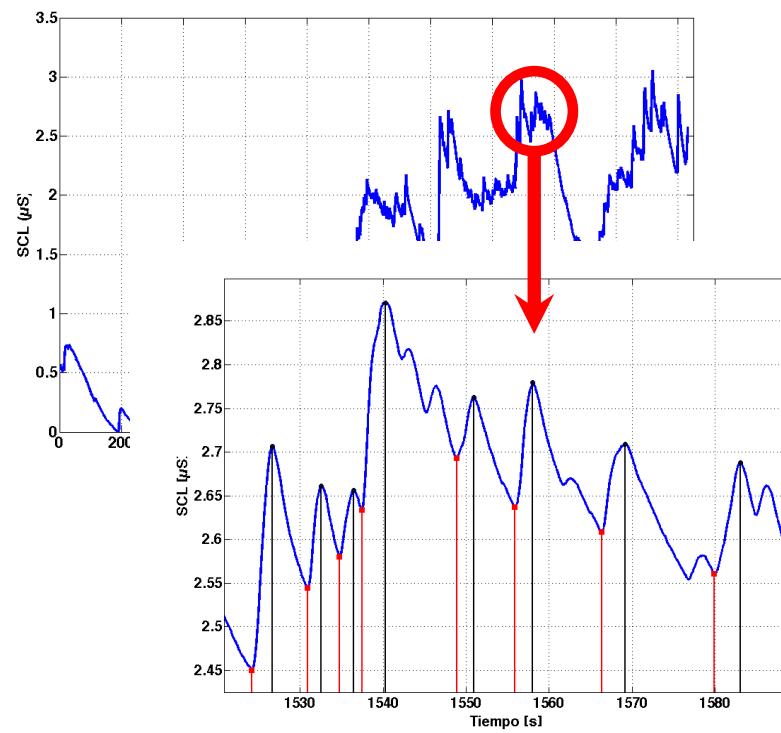
Contents

1. Introduction
- 2. Physiological signals and patient's emotional state**
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4. Dynamic adaptive system for robot-assisted motion rehabilitation
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Physiological signals and patient's emotional state

Physiological signals:

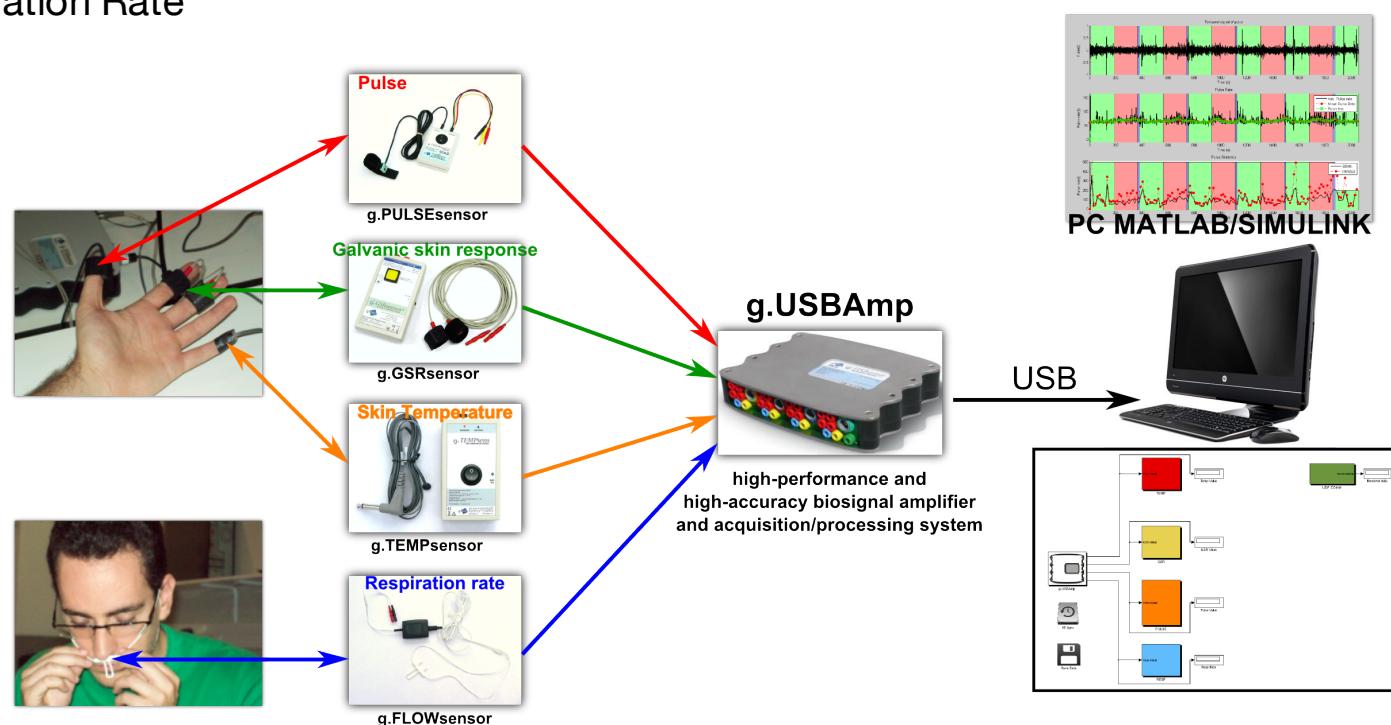
- Skin Temperature
- Galvanic Skin Response (SCL and SCR)
- Pulse
- Respiration Rate



Physiological signals and patient's emotional state

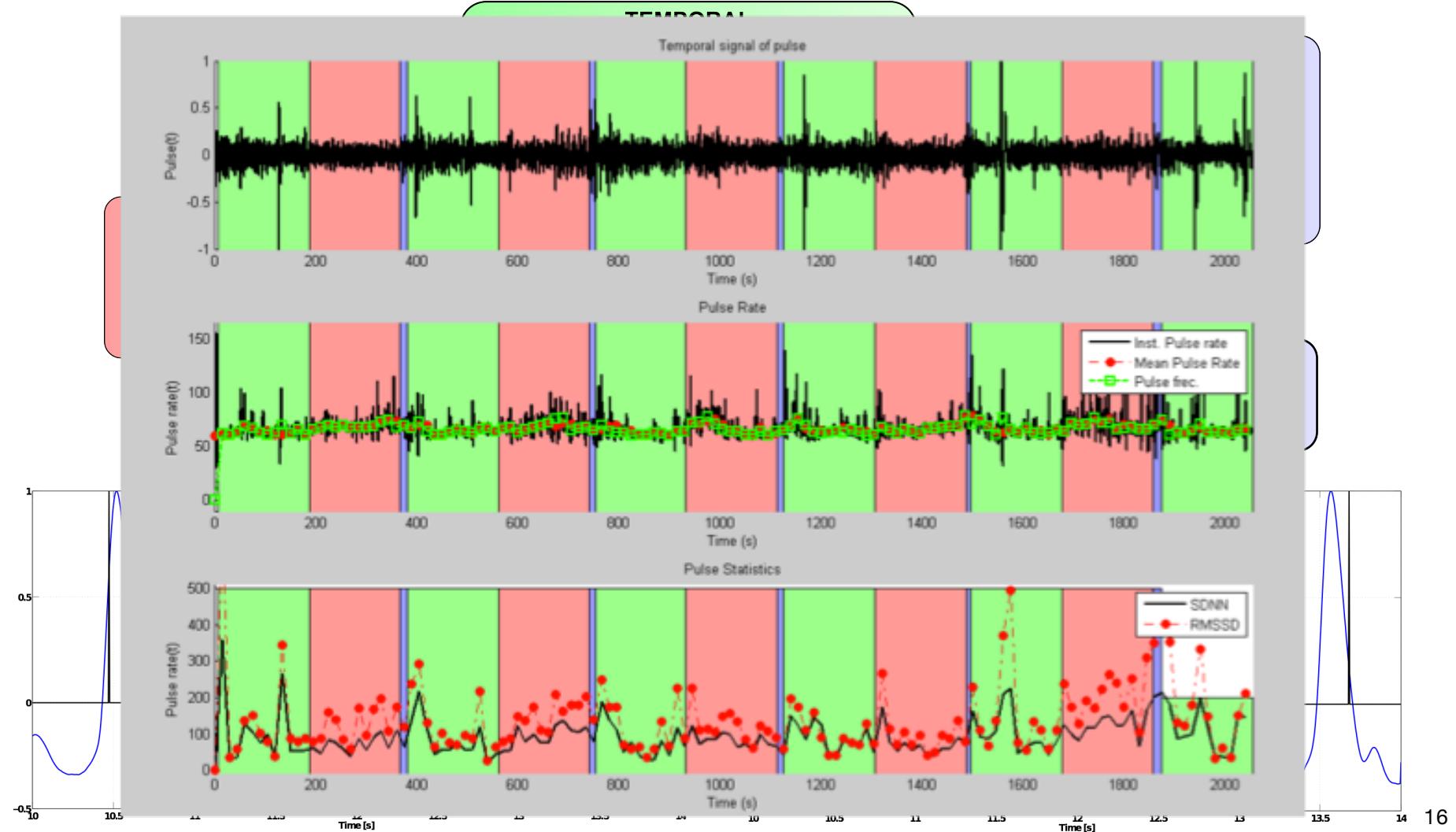
Physiological signals:

- Skin Temperature
- Galvanic Skin Response (SCL and SCR)
- Pulse
- Respiration Rate



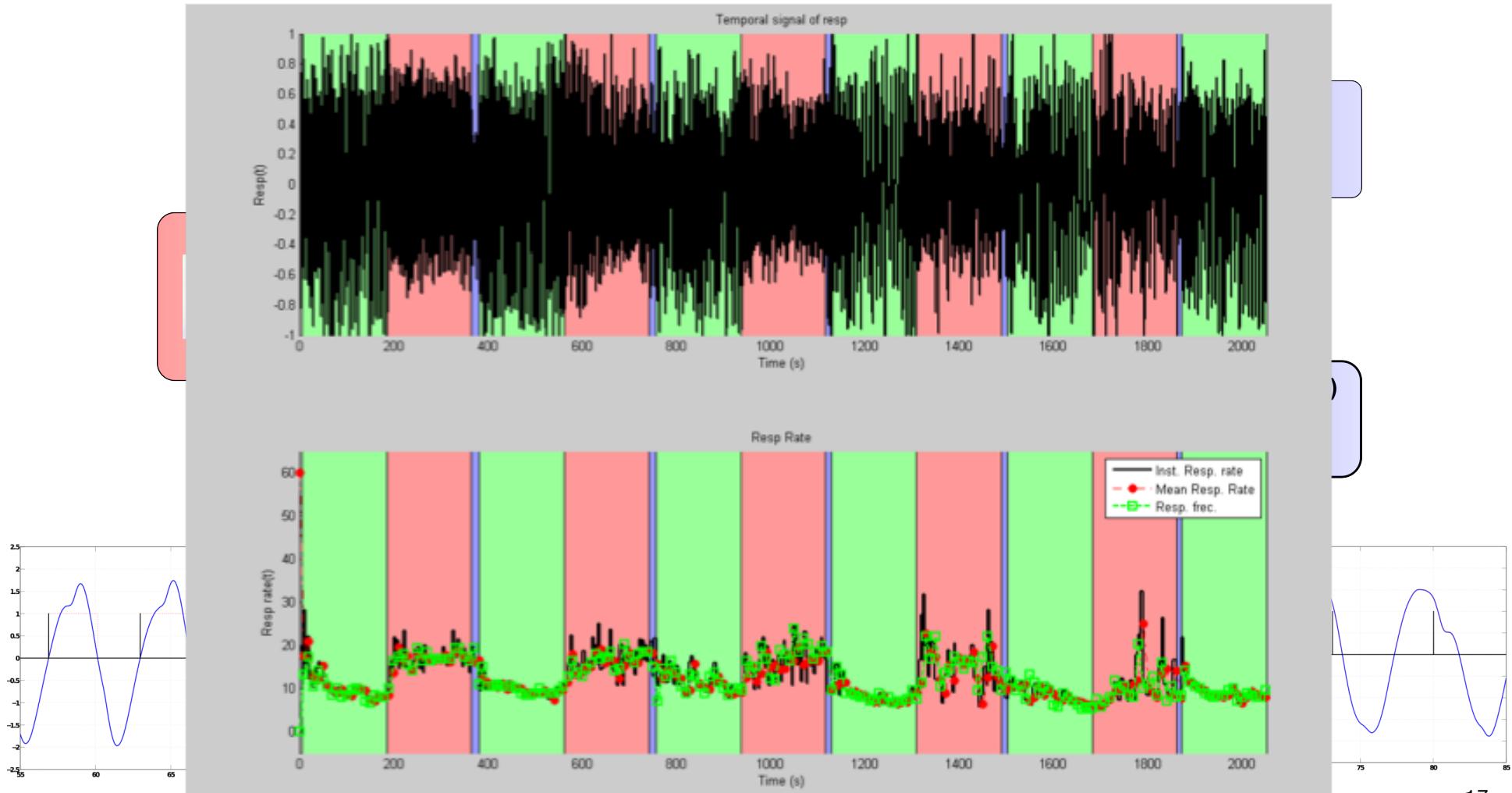
Physiological signals and patient's emotional state

Pulse



Physiological signals and patient's emotional state

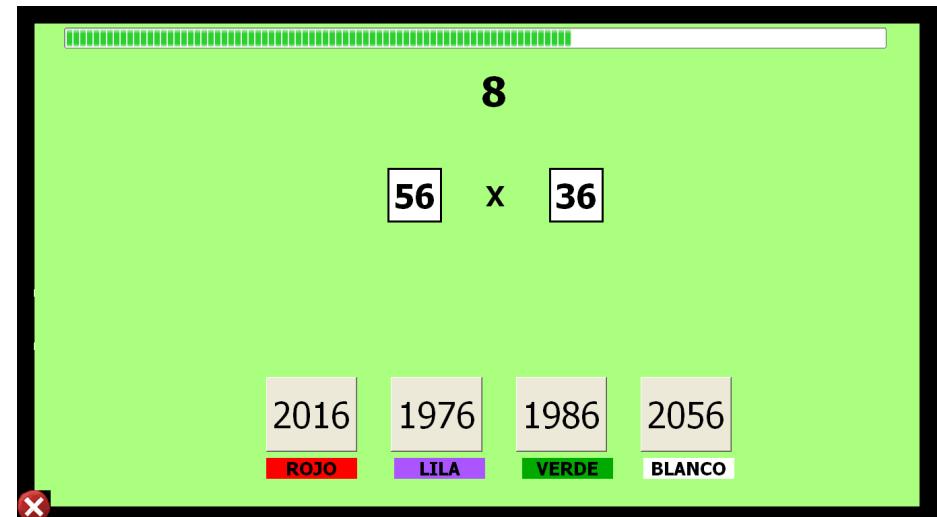
Respiration Rate



Physiological signals and patient's emotional state

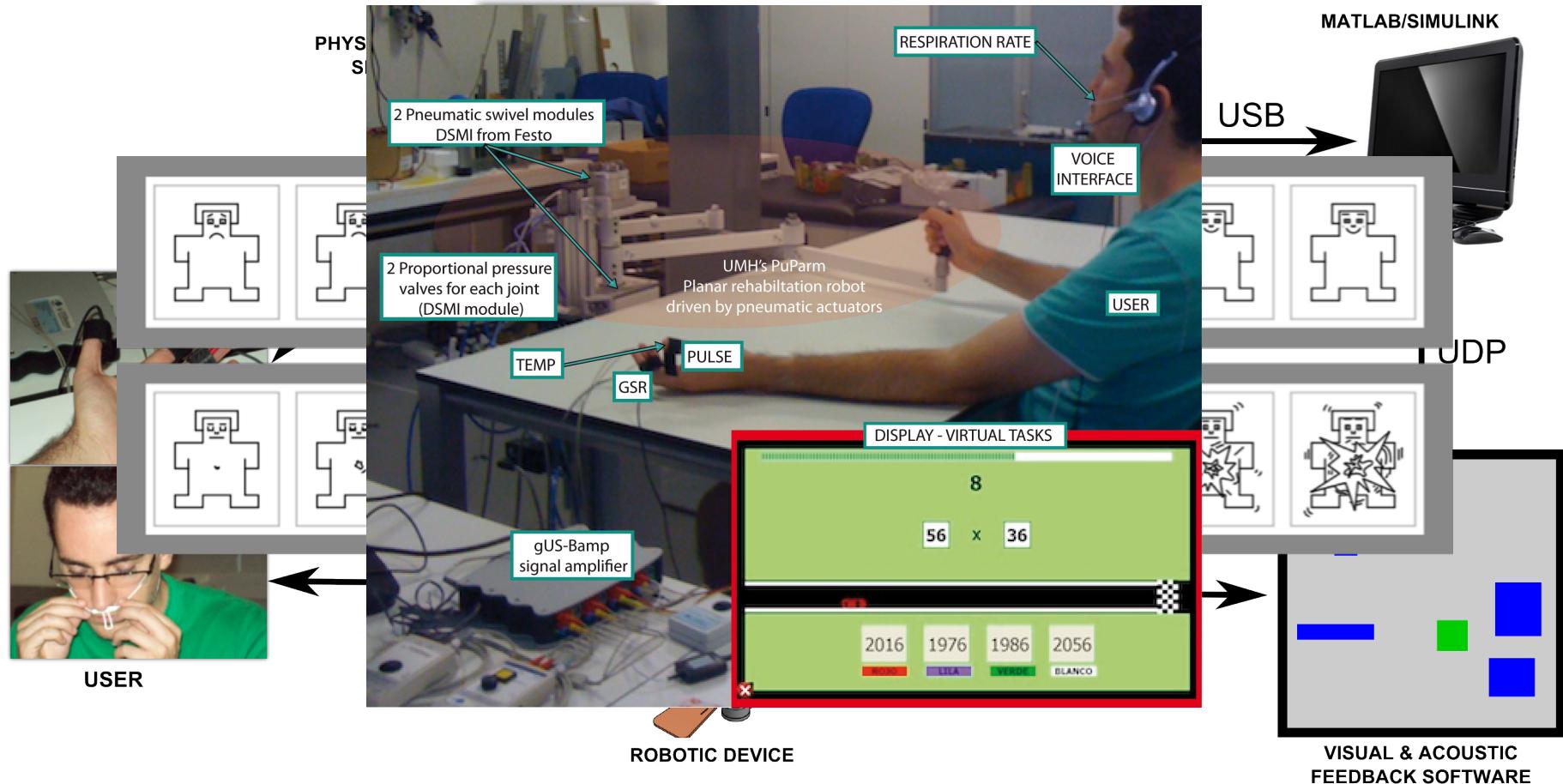
First experiment

- Is it possible to use physiological responses to differentiate between different levels of physical workload and between different levels of cognitive workload?
- 15 subjects
- Five tasks:
 1. Physical/coordination
 2. Physical/coordination + disturbance
 3. Cognitive
 4. Cognitive + Physical/coordination
 5. Cognitive + Physical/coordination + disturbance



Physiological signals and patient's emotional state

Experiment Setup



Physiological signals and patient's emotional state

Experiment Protocol:



Physiological signals and patient's emotional state

Results

	TASK 1			TASK 2			TASK 3		
	Mean	Std. Deviation	P	Mean	Std. Deviation	p	Mean	Std. Deviation	p
PULSE RATE	3,343541667	3,24902265	0,001	5,965816667	6,253152882	0,001	1,380883333	8,897741198	0,027
SDNN	-2,4439	74,59971547	0,783	40,79455833	102,6239799	0,795	-47,54663333	106,9855433	0,104
RMSSD	10,45891667	116,3706145	0,8	83,96063333	173,3166428	0,397	-74,082375	169,9344861	0,106
PNN50	3,752391667	25,7565764	0,684	13,86935	22,08986707	0,359	-18,04566667	24,3925181	0,003
RESP. RATE	-0,169933333	4,272592642	0,733	-0,773366667	5,17079653	0,962	0,633241667	3,915629411	0,751
TEMP	-0,283116667	0,443463957	0,015	-0,3063	0,279974242	0,004*	-0,408708333	0,538461214	<0.001
SCL	0,372983333	0,267167016	0,006	0,775708333	0,376405114	<0.001	0,536125	0,673929808	0,001
SCR	0,031481481	0,029995635	0,002	0,060185185	0,043605294	<0.001	0,027777778	0,070987898	0,01

	TASK 4			TASK 5		
	Mean	Std. Deviation	p	Mean	Std. Deviation	p
PULSE RATE	6,50005	5,748315737	<0.001	11,99294167	7,725351042	<0.001
SDNN	10,7112	59,18057767	0,974	41,9134	117,5803287	0,026
RMSSD	18,05615	96,77649738	0,974	72,44796667	202,5048038	0,018
PNN50	-3,026283333	16,85220297	0,287	1,710825	35,30824531	0,605
RESP. RATE	-0,977	3,750583723	0,859	-0,094808333	3,340629716	0,578
TEMP	-0,501366667	0,482663693	0,012*	-0,557575	0,559021473	0,001
SCL	0,655258333	0,645313292	<0.001	0,855283333	0,615859511	<0.001
SCR	0,049537037	0,069930956	0,002	0,062037037	0,062037665	<0.001

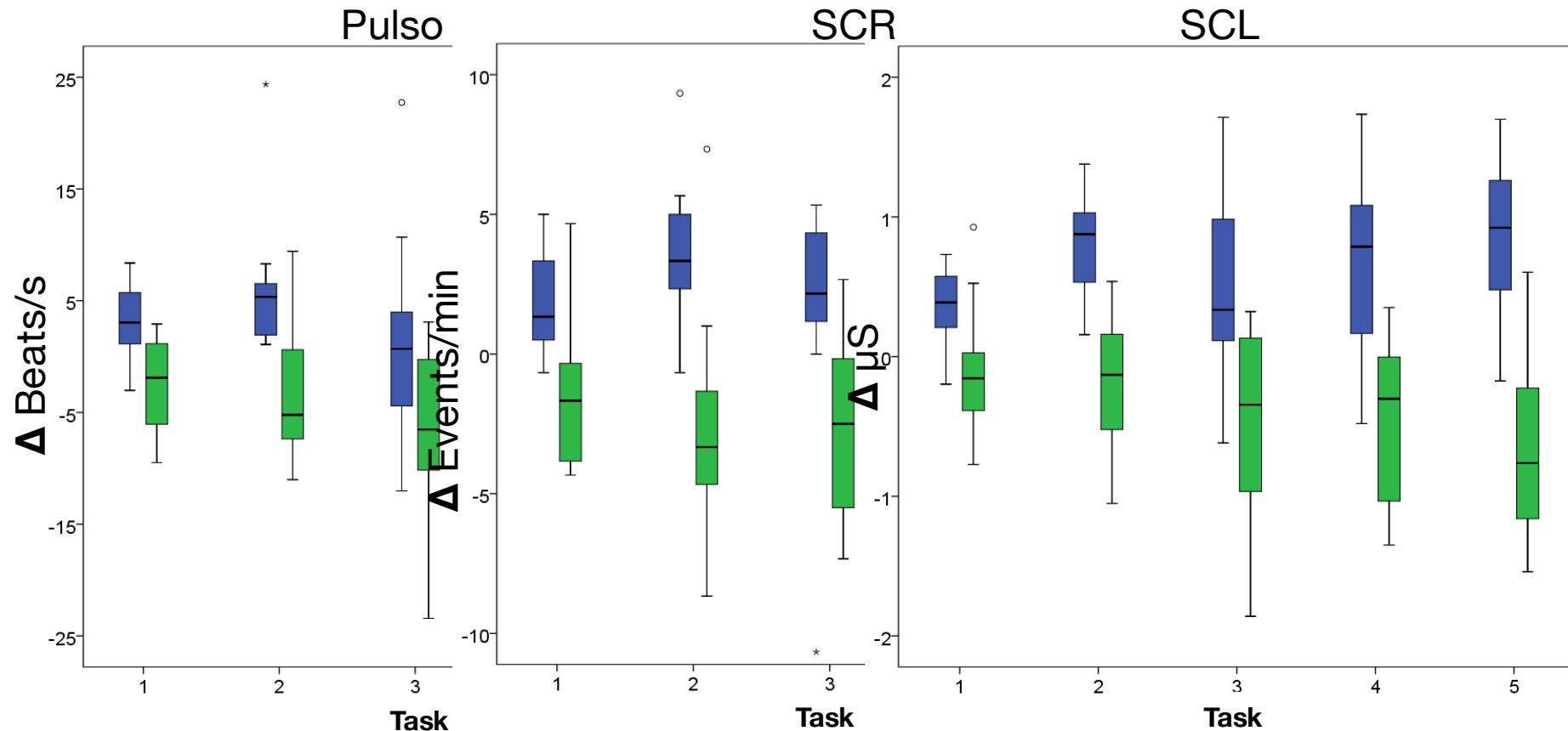


F. Javier Badesa, Ricardo Morales, Nicolás García-Aracil, José María Sabater, Carlos Pérez-Vidal and Eduardo Fernández,
"Multimodal Interfaces to Improve Therapeutic Outcomes in Robot-Assisted Rehabilitation", IEEE Transactions on Systems
 Man and Cybernetics Part C-Applications and Reviews

Physiological signals and patient's emotional state

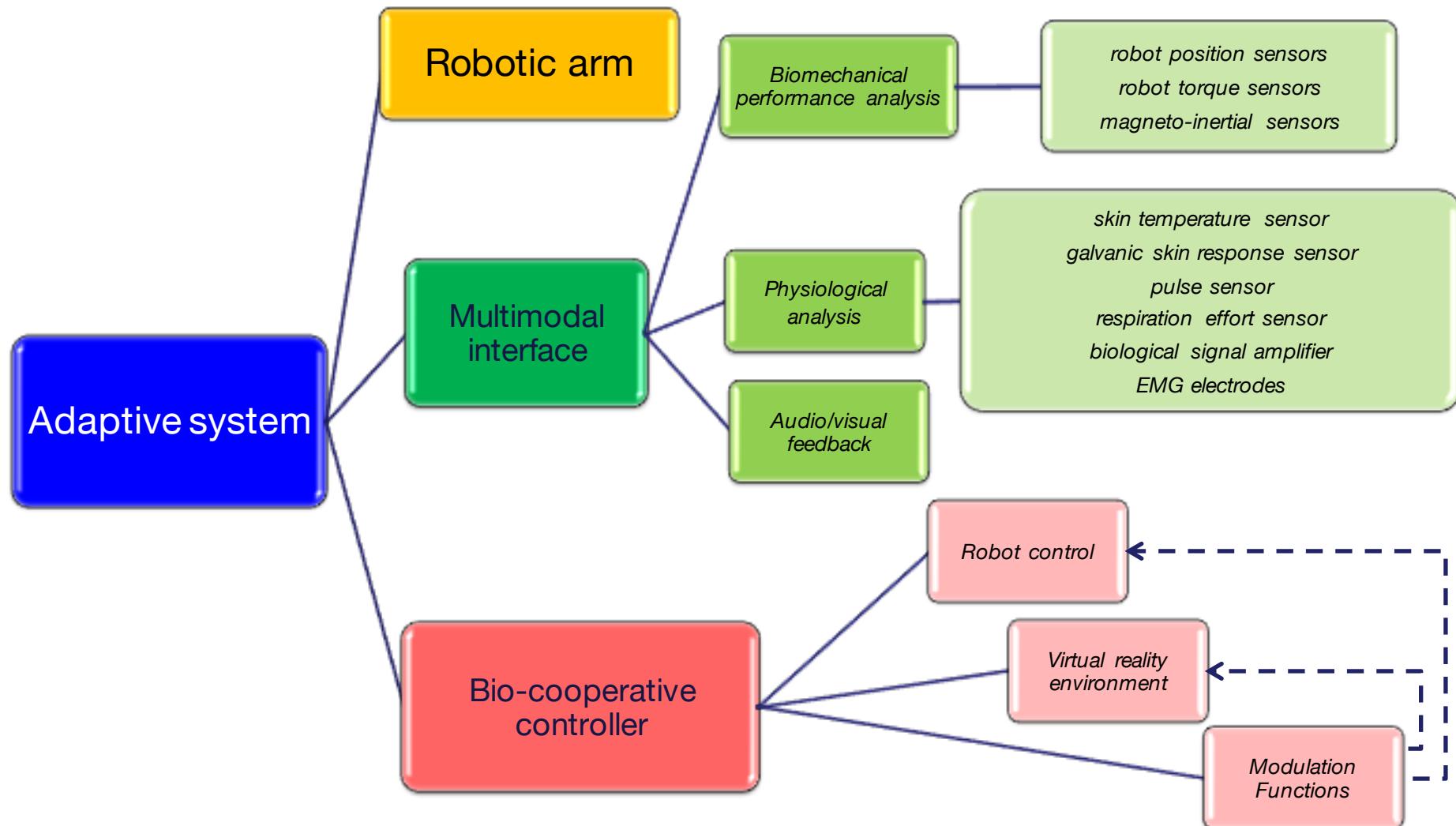
Results

 Task-Rest
 Rest-Task

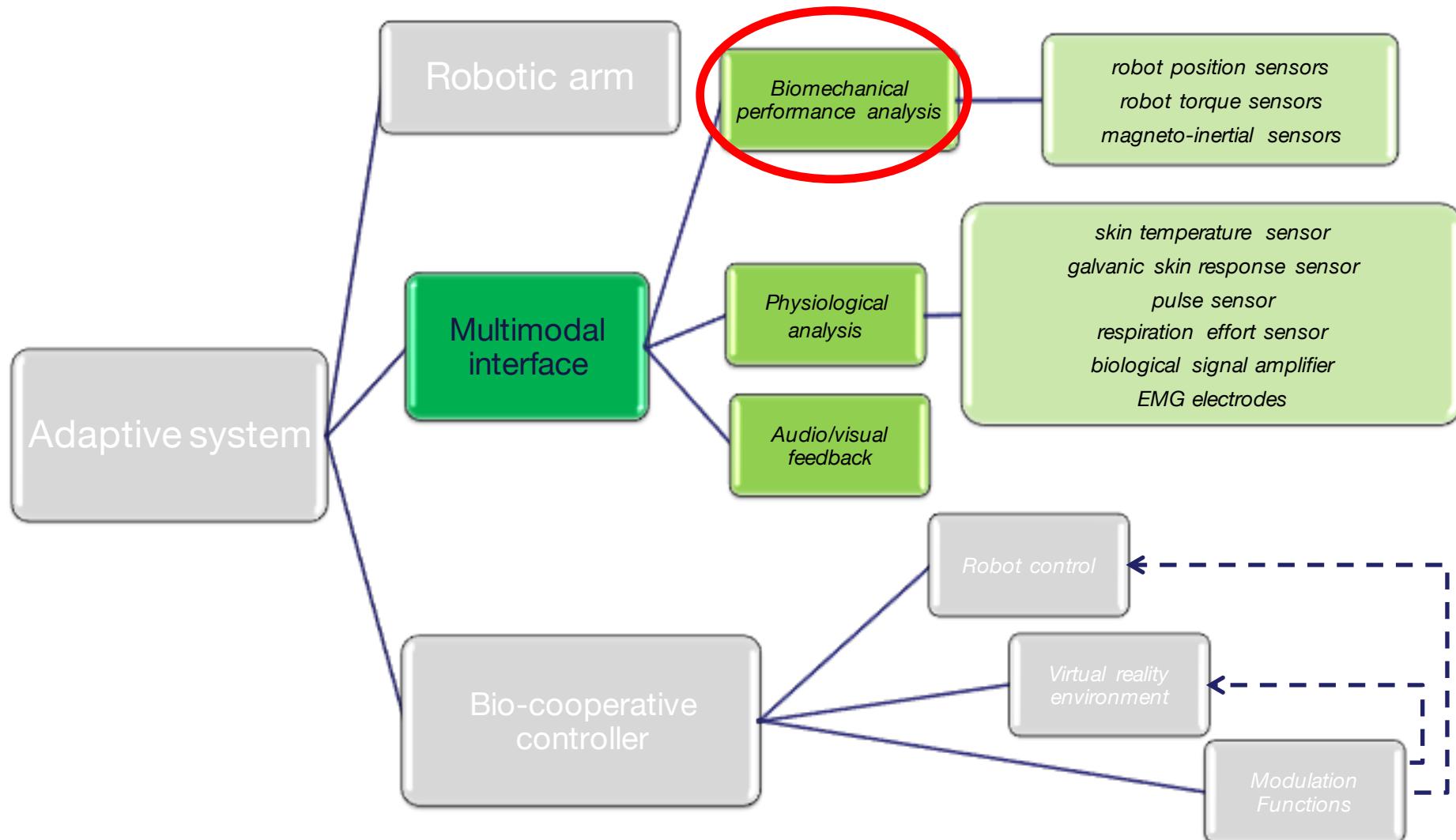


F. Javier Badesa, Ricardo Morales, Nicolás García-Aracil, José María Sabater, Carlos Pérez-Vidal and Eduardo Fernández,
“Multimodal Interfaces to Improve Therapeutic Outcomes in Robot-Assisted Rehabilitation”, IEEE Transactions on Systems
Man and Cybernetics Part C-Applications and Reviews

Main Objective



Biomechanical analysis



Contents

1. Introduction

2. Physiological signals and patient's emotional state

3. Biomechanical analysis

4. Dynamic adaptive system for robot-assisted motion rehabilitation

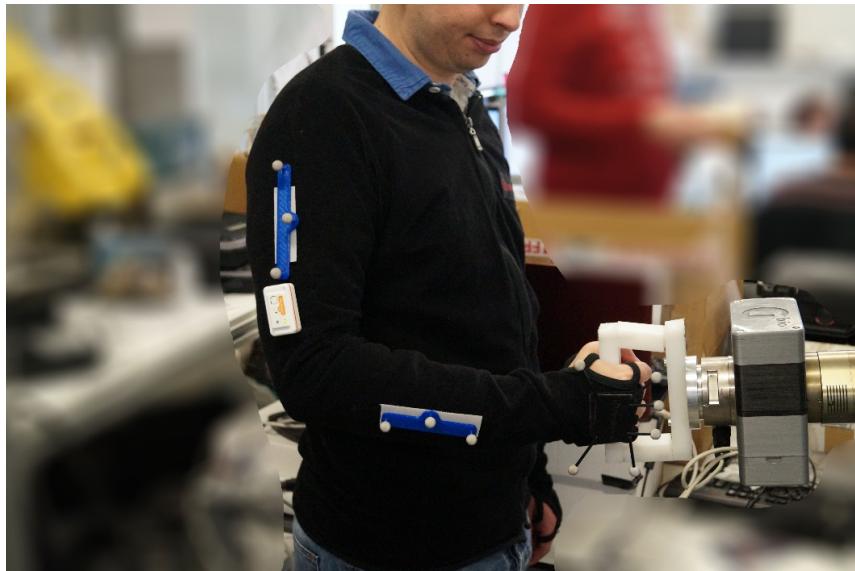
5. Experimental validation

6. Conclusions and future work

Biomechanical analysis

Kinematic reconstruction: Rehabilitation robots

- Hermes Robot: tridimensional movements, 7 DoFs reconstruction
- PUPArm Robot: planar movements, 5 DoFs reconstruction.



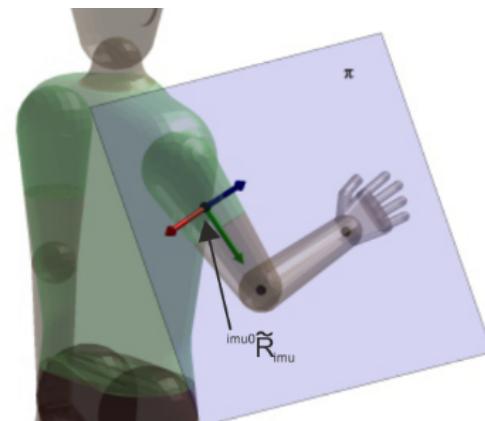
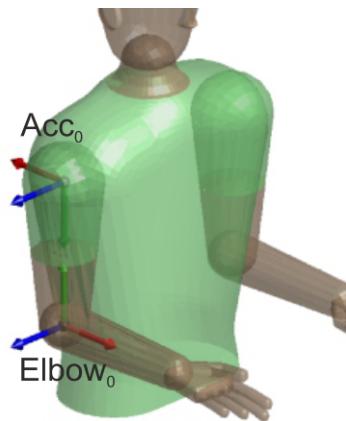
Biomechanical analysis

Kinematic reconstruction: Rehabilitation robots

- Reconstruction algorithm:
$$\vec{q}(t_{k+1}) = \vec{q}(t_k) + \dot{\vec{q}}(t_k)\Delta t.$$

$$\dot{\vec{q}} = J^{-1}(\vec{q})\{\dot{\vec{v}}_d + K \cdot \overrightarrow{err}\}$$
- 7 DoFs reconstruction:
 - **Fixed shoulder** is assumed.
 - **One accelerometer** placed onto the upper arm.
 - Free arm movement.
- 5 DoFs reconstruction:
 - **Shoulder movements are computed.**
 - **One accelerometer** placed onto the upper arm and **one IMU** placed onto the shoulder.
 - Wrist joint is fixed.

Biomechanical analysis

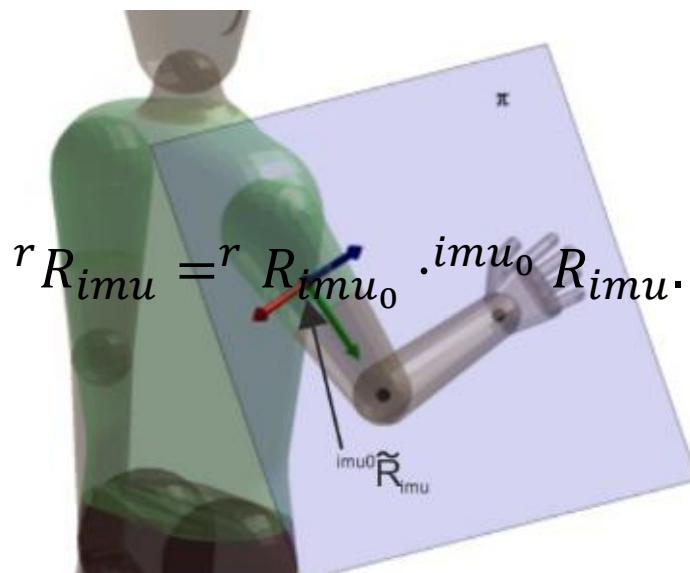


$${}^{imu0}V_g = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

$${}^{imu0}V_g = {}^{imu0}\tilde{R}_{imu} {}^{imu}V_g.$$

Biomechanical analysis

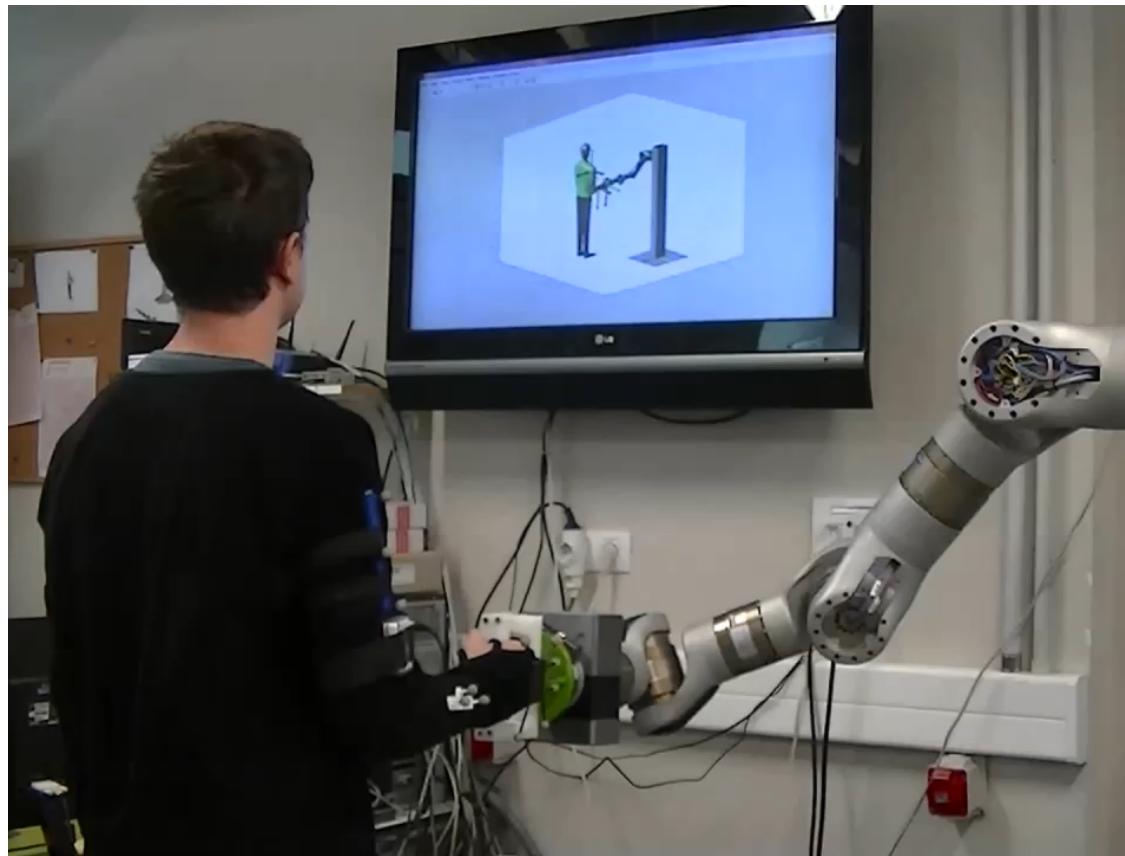
- 7 DoFs reconstruction **direct data**:
 - Shoulder point: position and orientation.
 - Wrist point: position and orientation.
- 5 DoFs reconstruction **direct data**:
 - Elbow point: position.
 - Wrist point: position and orientation.



$$d(\tilde{H}, \Pi) = \frac{|A_\Pi \tilde{H}_x + B_\Pi \tilde{H}_y + C_\Pi \tilde{H}_z + D_\Pi|}{\sqrt{{A_\Pi}^2 + {B_\Pi}^2 + {C_\Pi}^2}} = 0$$

$$\begin{aligned} \tilde{H} = & (g \cdot \hat{H})g + \cos(\theta)(\hat{H} - (g \cdot \hat{H})g) - \\ & - \sin(\theta)(g \times \hat{H}) \end{aligned}$$

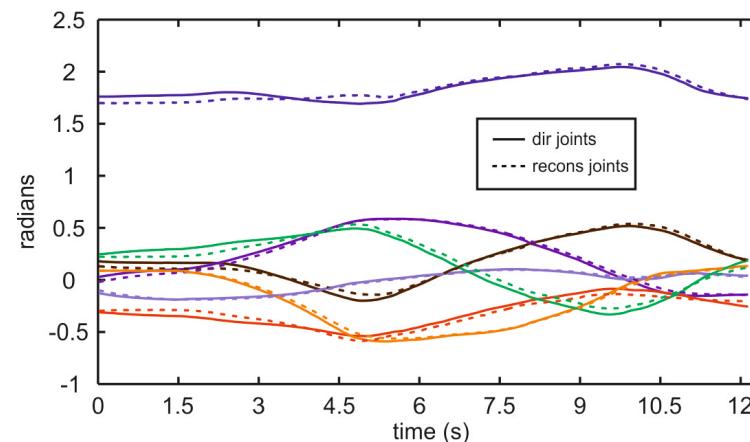
Biomechanical analysis



Biomechanical analysis

- 5 healthy subjects
- Three trials of the same exercise.

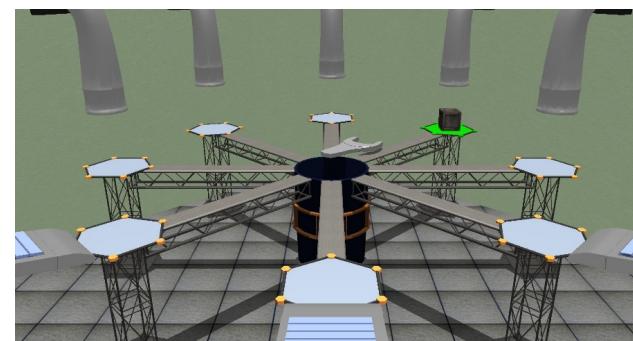
Error committed on each joint (rad)							
ID	Joint 1	Joint 2	Joint 3	Joint 4	Joint 5	Joint 6	Joint 7
1	0.029	0.021	0.042	0.015	0.041	0.010	0.048
2	0.044	0.058	0.091	0.019	0.091	0.033	0.087
3	0.034	0.026	0.047	0.013	0.044	0.015	0.043
4	0.091	0.037	0.010	0.014	0.112	0.022	0.110
5	0.047	0.014	0.073	0.012	0.065	0.018	0.089
Mean	0.049	0.031	0.071	0.014	0.070	0.020	0.075



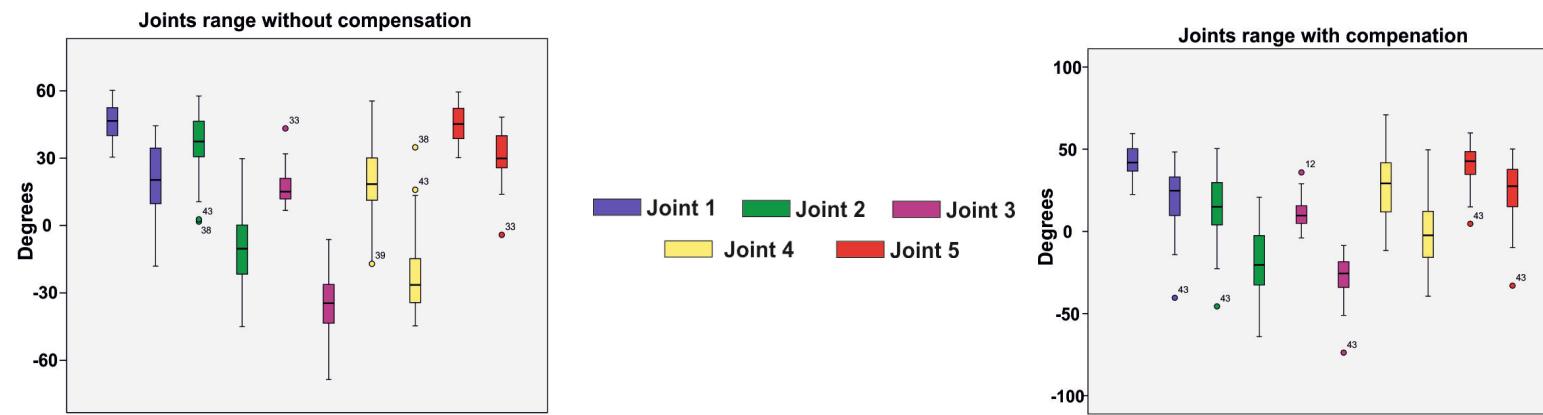
Biomechanical analysis

Kinematic reconstruction: Experimental results 5 DoFs

- 50 healthy subjects.
- Two different exercises:
 - Without trunk compensation.
 - With trunk compensation.
- 3D roulette activity.
- 16 movements.

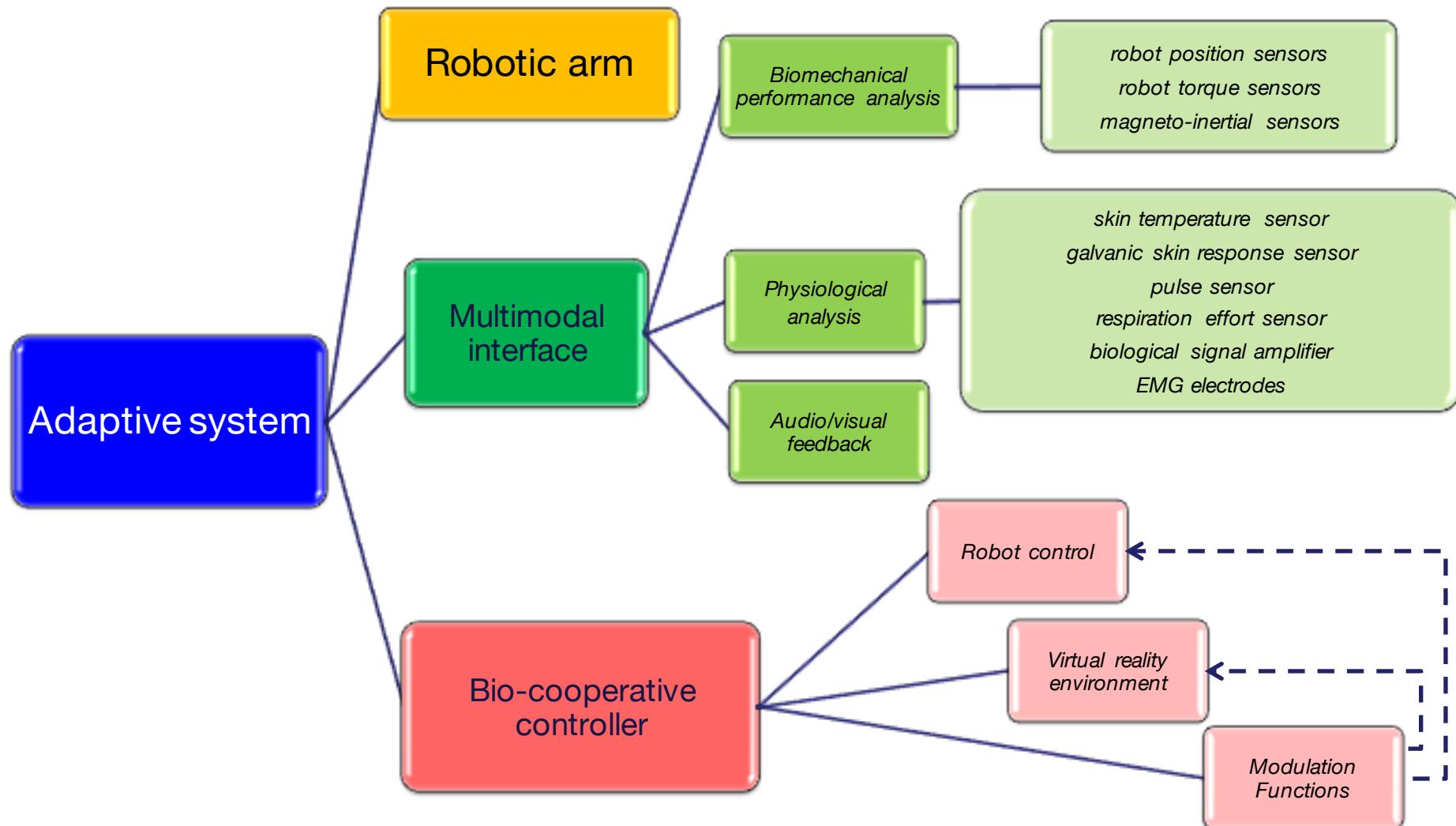


Biomechanical analysis

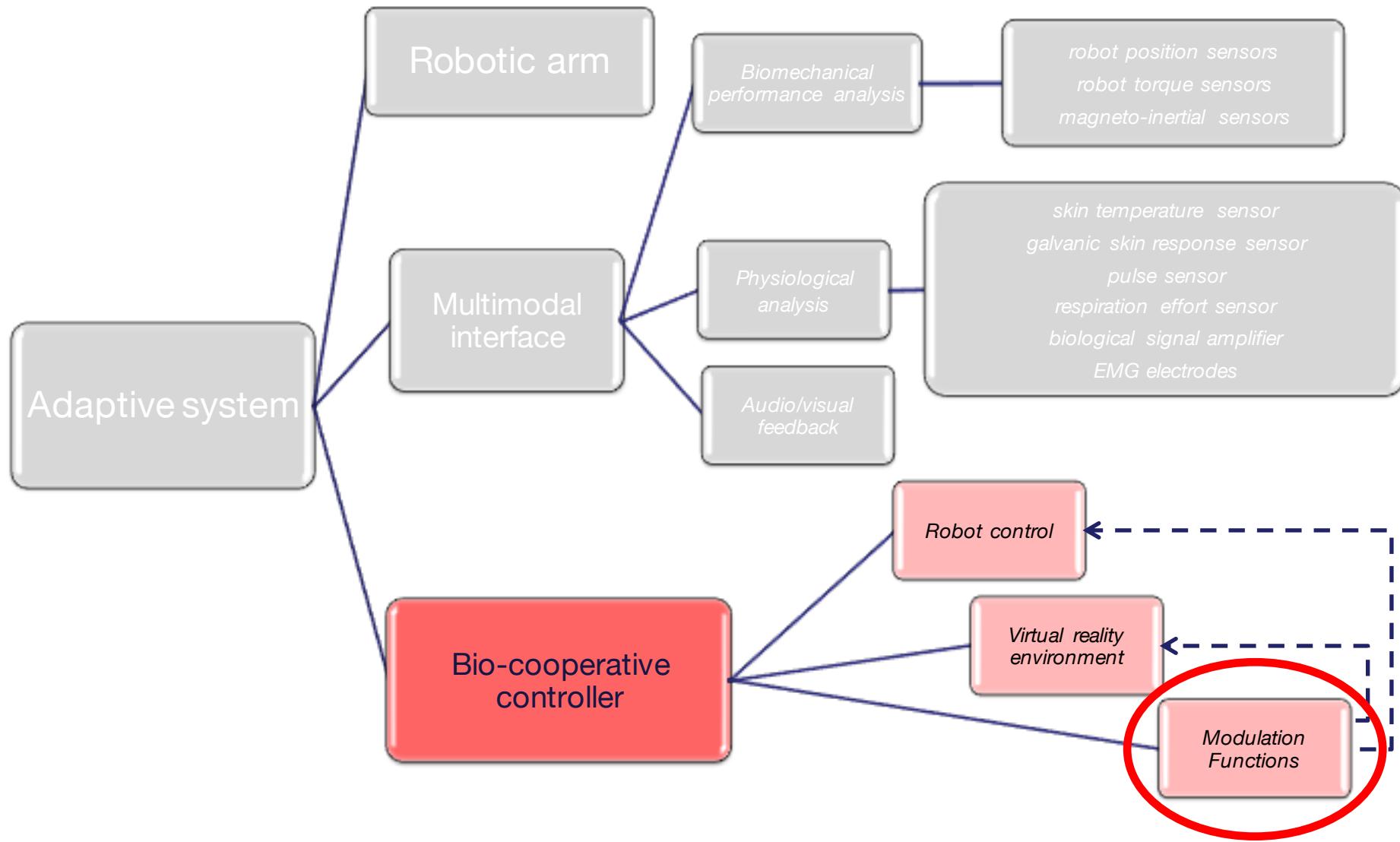


Joint Ranges	Without Compensation		With Compensation	
	Mean (deg)	STD (deg)	Mean (deg)	STD (deg)
Shoulder Abd/Add	27.6	12.3	22	12.8
Shoulder Flex/Ext	46.4	9.8	33.5	11.9
Shoulder Rotation	52.9	12.7	37.7	14.1
Elbow Flex/Ext	41.7	10.5	29.1	11.5
Forearm Prono/Sup	13.8	5.7	15.7	7.7

Main Objective



Main Objective



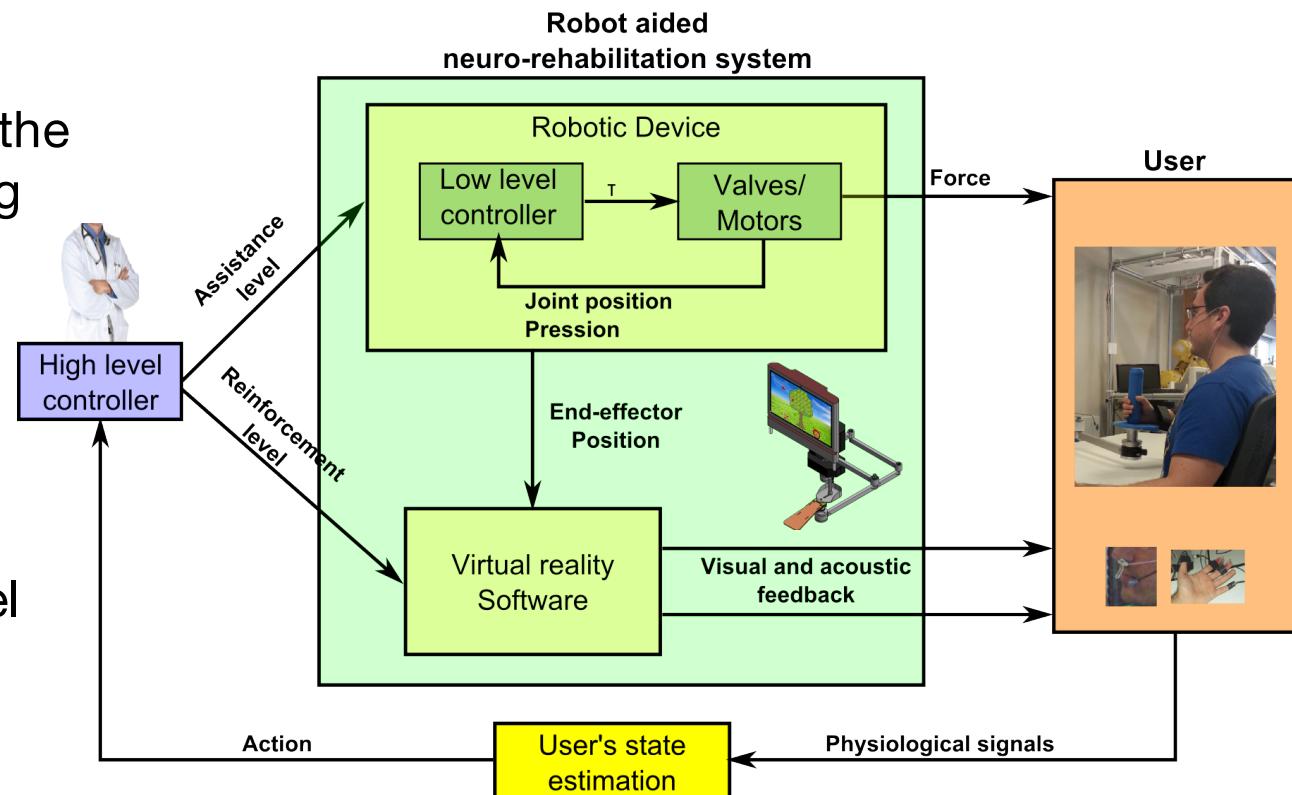
Contents

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Dynamic adaptive system for robot-assisted motion rehabilitation

Main objective

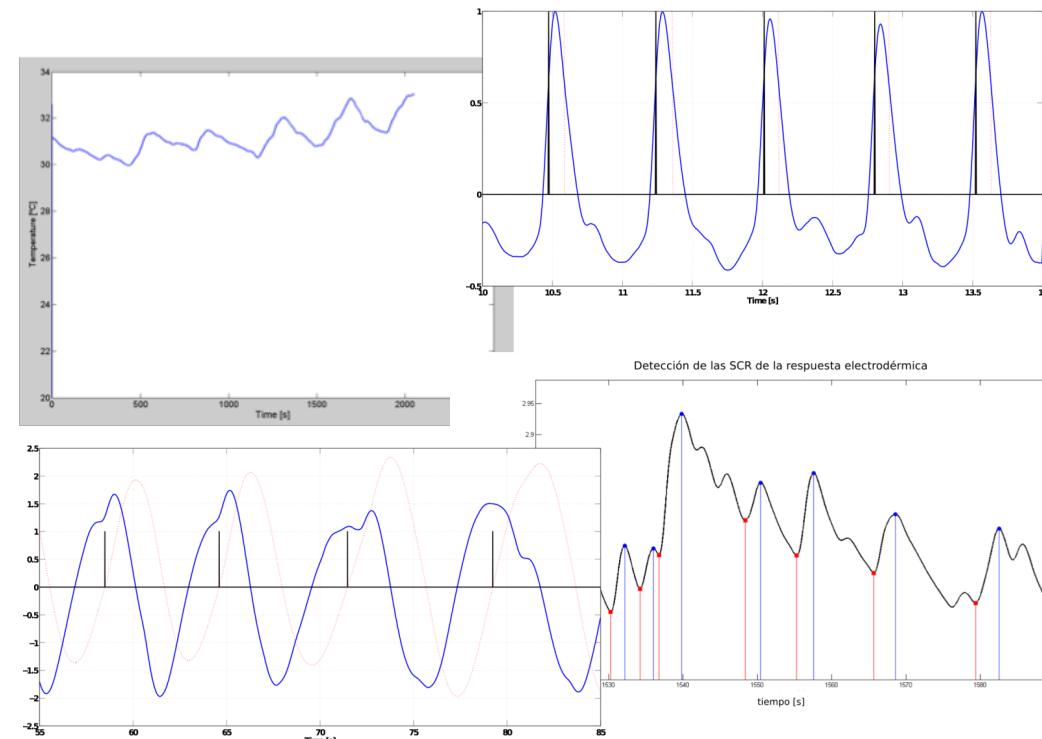
- Place the human into the control loop by feeding back the physiological information
- Physiological states:
 - Relaxed
 - Medium stress level
 - Over-stressed



Dynamic adaptive system for robot-assisted motion rehabilitation

Acquisition, signal processing and feature extraction

- Physiological Signals:
 - Skin Temperature
 - GSR: SCL y SCR
 - Pulse
 - Respiration Rate
- Matlab/Simulink:
 - Real-Time Simulink® Scheme
 - UDP Communication



Dynamic adaptive system for robot-assisted motion rehabilitation

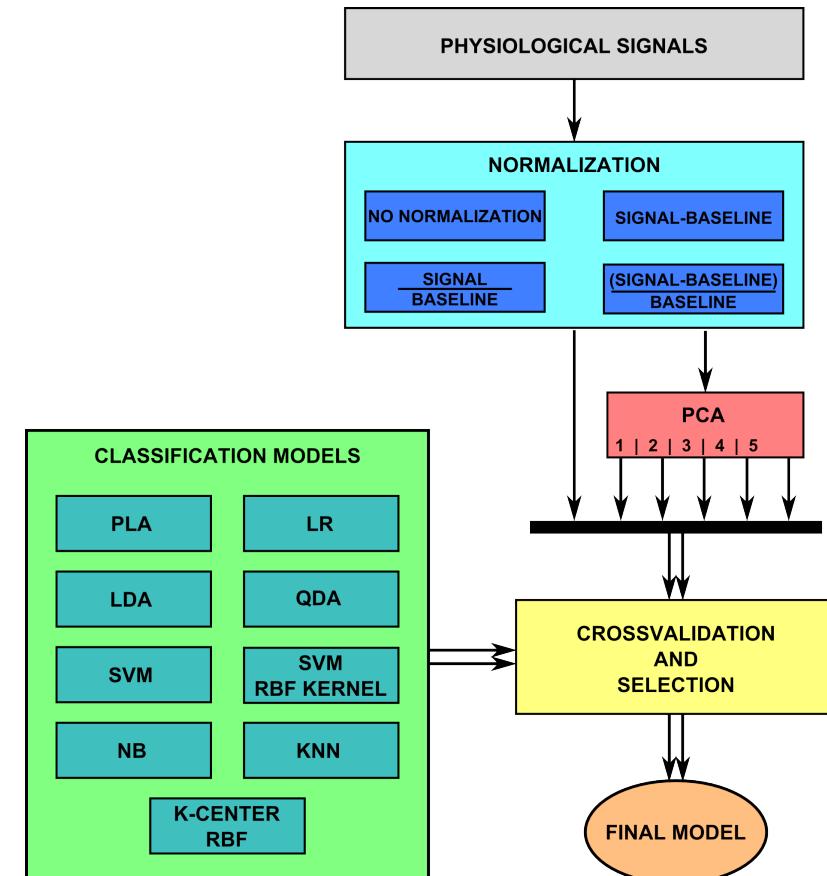
Patient's emotional state estimation:

- **Classification**

- 9 classification techniques
- One vs One multi-class strategy
- Leave-one-out cross-validation

- **Regression**

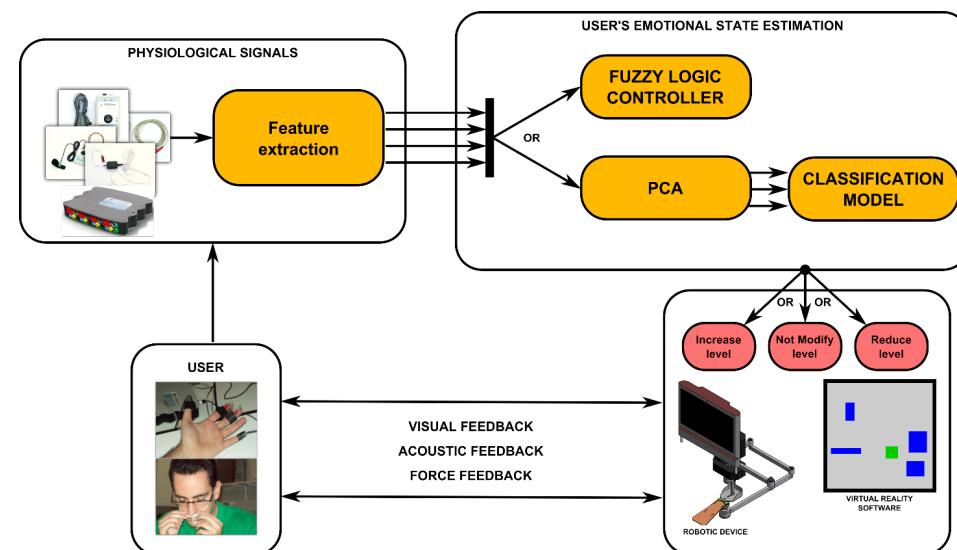
- Fuzzy logic controller
 - Valence and arousal estimation
- Matlab® Fuzzy Logic Toolbox



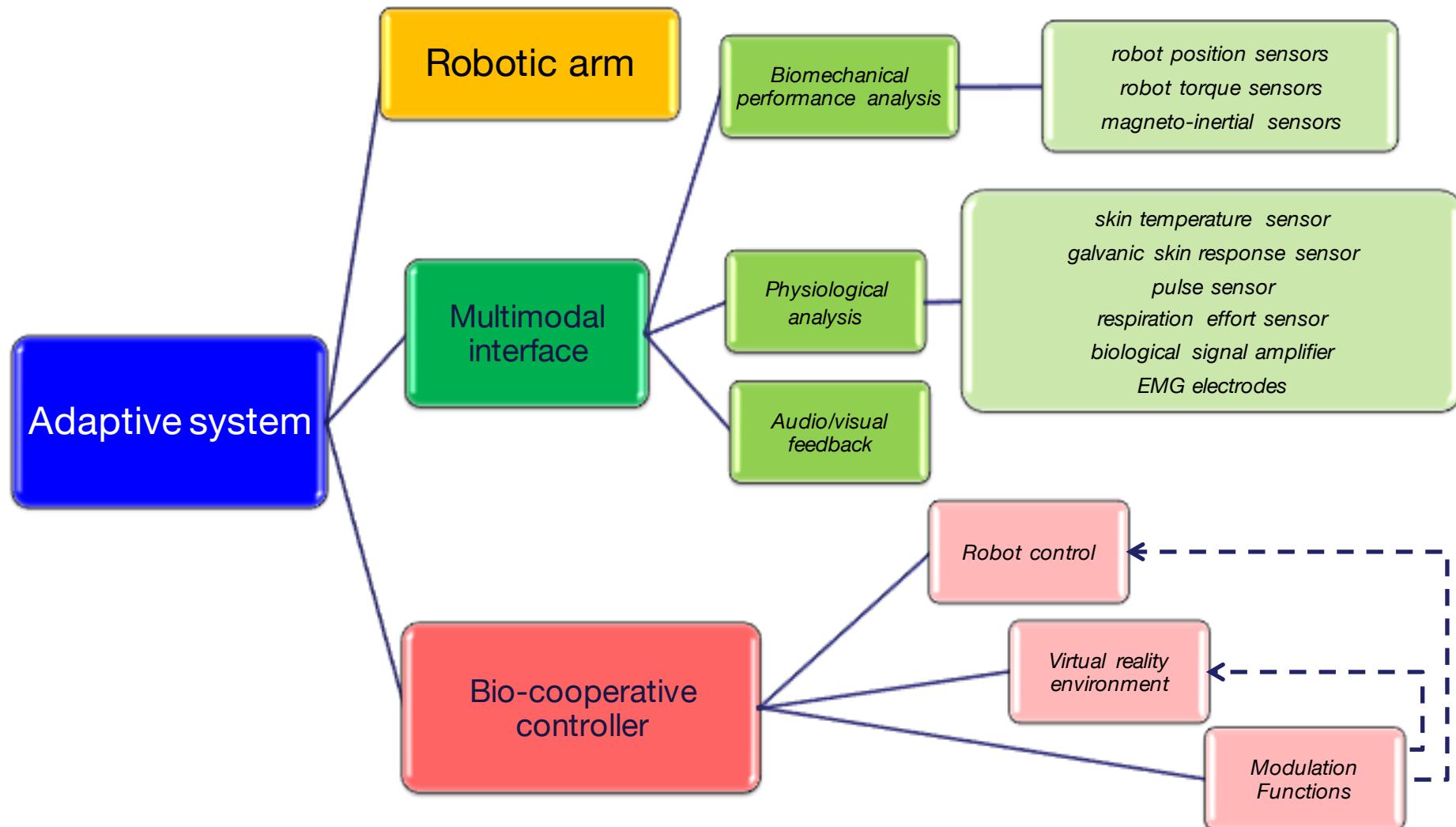
Dynamic adaptive system for robot-assisted motion rehabilitation

Bio-cooperative Control

- Signal processing, feature extraction and estimation of user's emotional state implemented with Matlab/Simulink
- UDP communication
- Emotional state block sends every 30 seconds one of the following actions:
 - Over-stressed, reduce level
 - Medium stress level, not modify
 - relaxed, increase level



Main Objective



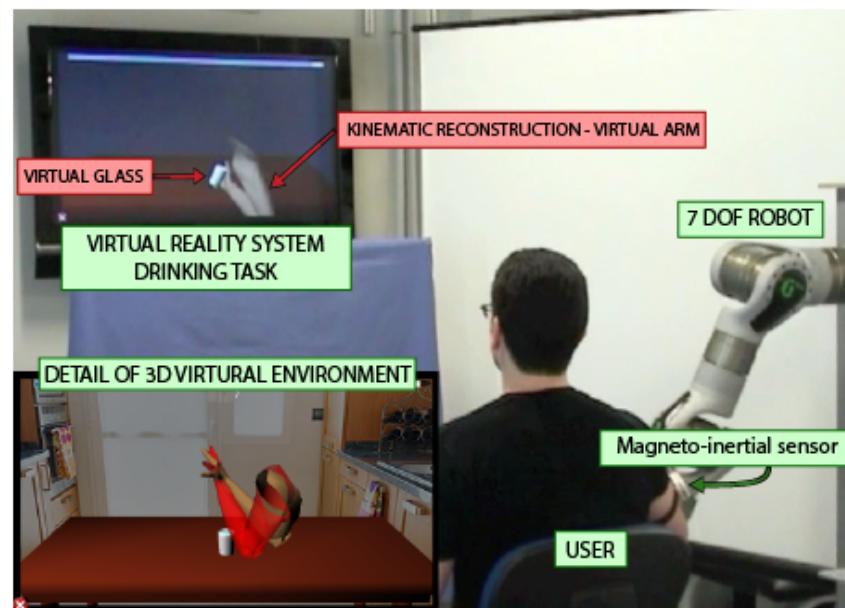
Contents

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Experimental validation

Assistive Experiment

- Bio-cooperative control using fuzzy logic controller
- Drinking task
- Two step experiment
- Three different levels for models training:
 - high gain
 - very low gain
 - negative gains



Experimental validation



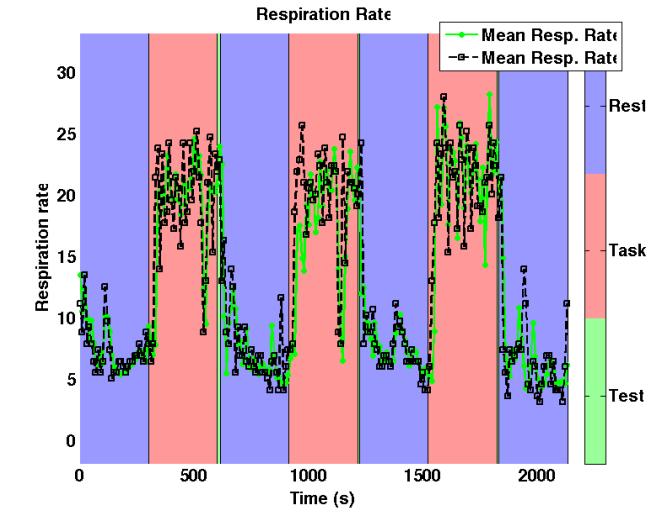
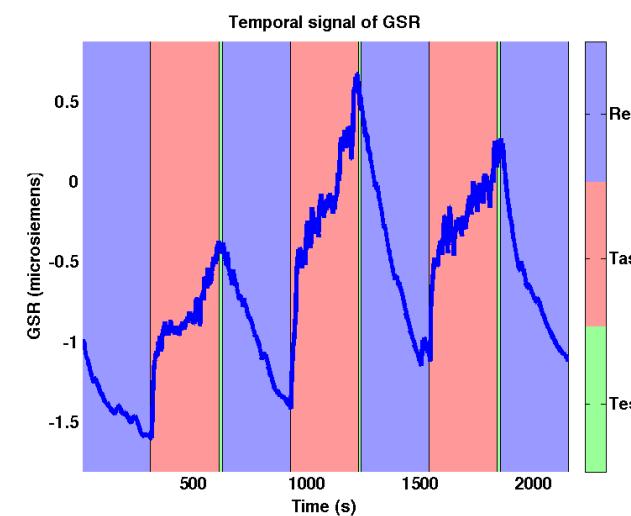
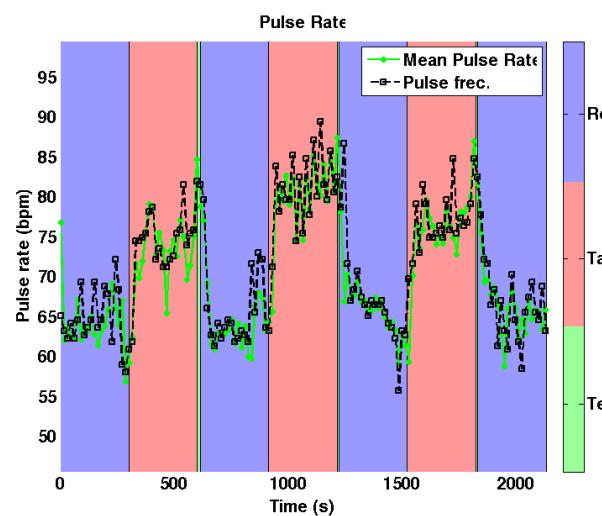
Development of an Intelligent Multimodal Assistive Robot

*Franciso J. Badesa, Ricardo Morales, Nicolas Garcia-Aracil, Carlos
Perez-Vidal, Jose M. Sabater
Eugenio Papaleo, Antonino Salerno, Loredana Zollo, Eugenio Guglielmelli*

Experimental validation

Training step

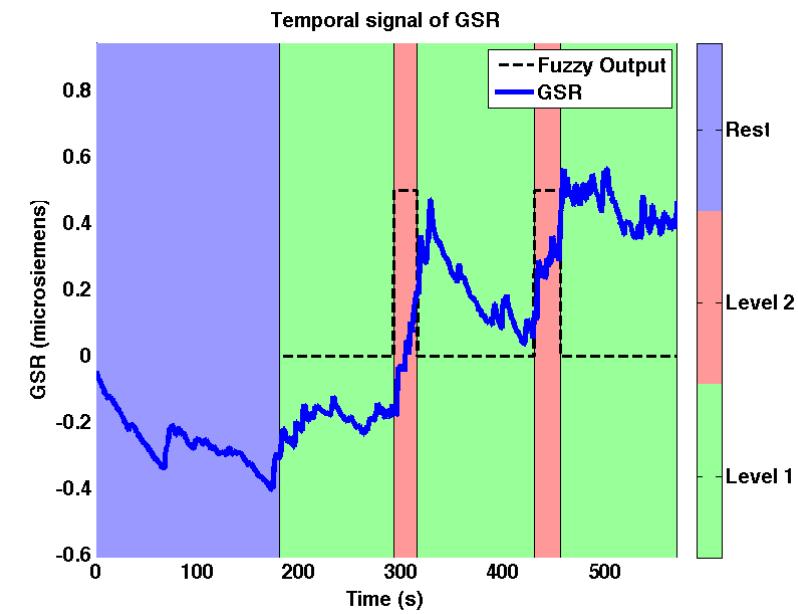
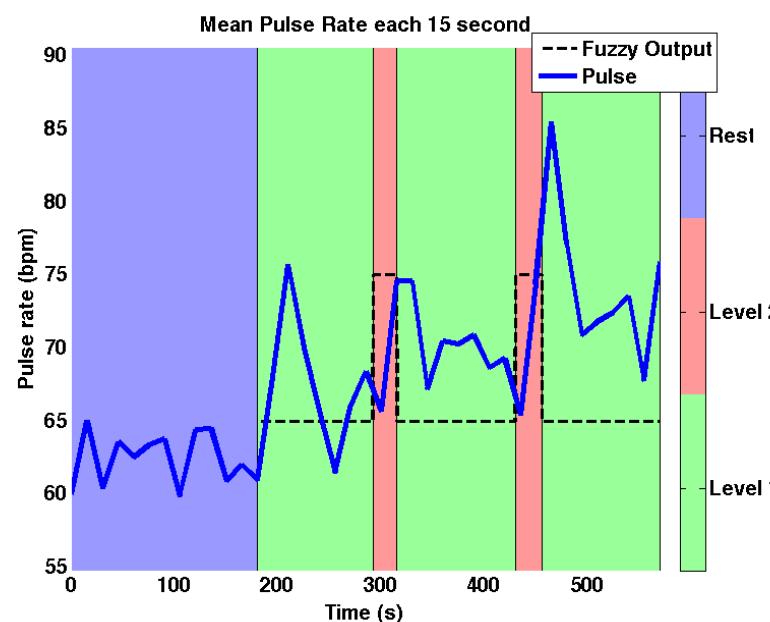
- Fuzzy Logic Controller
- Histograms of the differences between the signal with respect to the baseline
- Use of statistical characteristics
 - Mean
 - Standard deviation



Experimental validation

Validation step

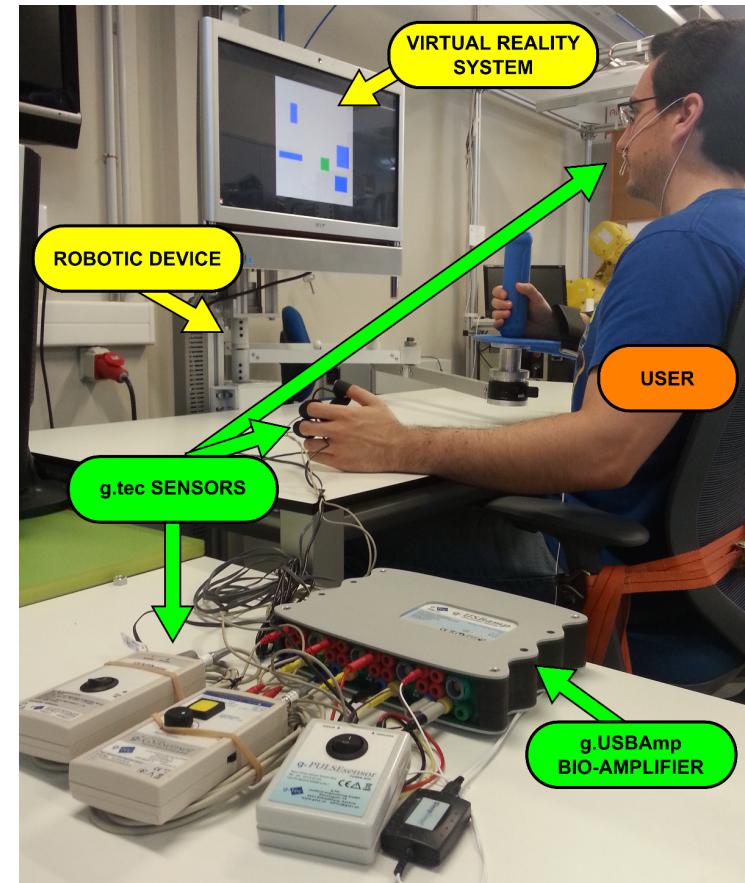
	Drinking tasks		Time (seconds)	
	Mean	Std. Deviation	Mean	Std. Deviation
Task 1	14.43	4.04	15.43	6.38
Task 2	7.71	2.29	36.15	4.20
Task 3	8.00	2.00	25.75	1.05



Experimental validation

Rehabilitation Experiment

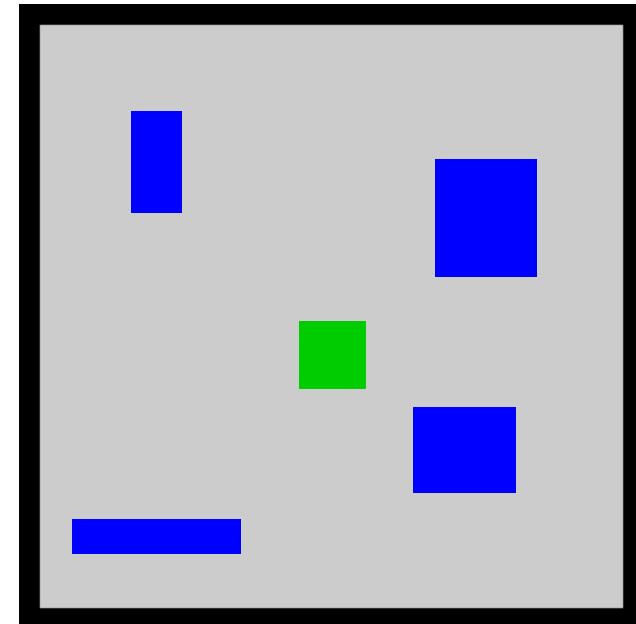
- 2 steps:
 1. Data recording:
 - Classification models training.
 - Fuzzy logic controller membership functions.
 - 3 different levels of the same task.
 2. Validation:
 - 10 minutes task.
 - 5 different levels
 - 2 bio-cooperative controllers
 - ➡ Classification models
 - ➡ Fuzzy logic



Experimental validation

1. Data recording:

- Protocol:
 - Experiment is explained
 - Adaptation period of few minutes
 - Rest period 5 min
 - Task 5 min
 - Self-assessment manikin (SAM)
- Three different levels:
 - Relax level: One blue rectangle, low speed.
 - Medium level: Three blue rectangles, medium speed.
 - Stress level: Four blue rectangles, high speed.



Experimental validation

1. Data recording: Classification models training

- LOOCV
- Normalization:
Signal - baseline
baseline

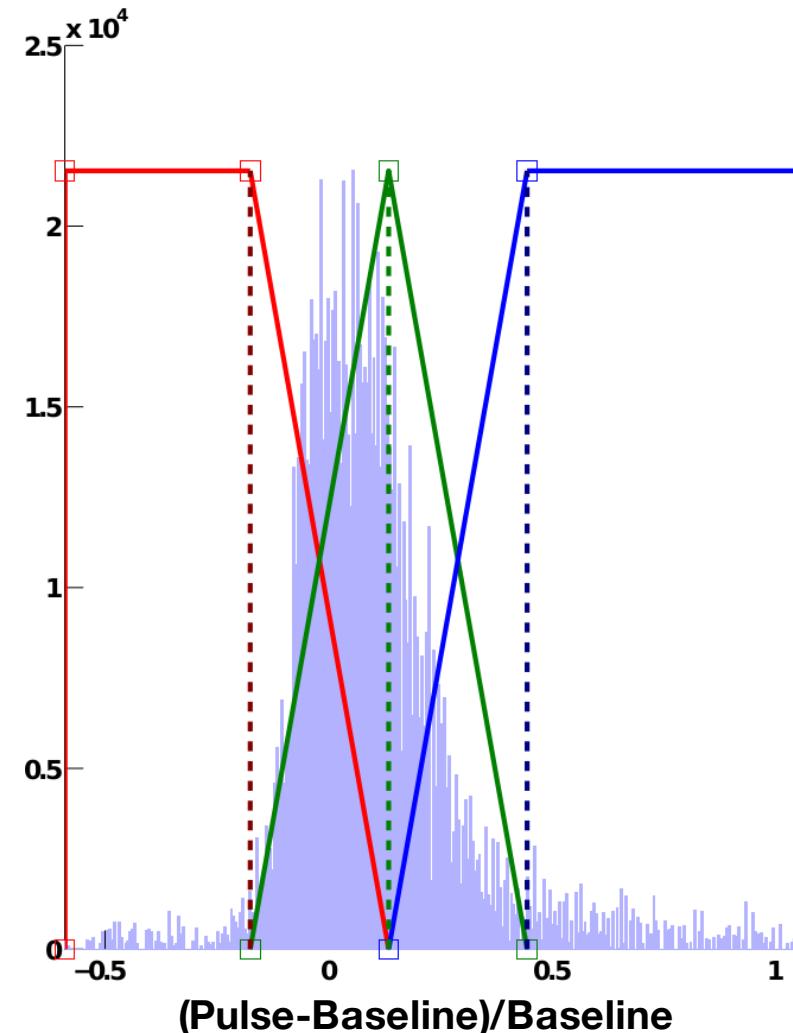
Algorithm	PCA 1 PC	PCA 2 PC	PCA 3 PC	PCA 4 PC	PCA 5 PC	NO PCA
PLA	56.57	81.90	83.05	82.86	82.10	83.05
LR	61.90	65.71	84.76	83.81	85.71	85.71
LDA	50.48	64.76	74.29	74.29	76.19	76.19
QDA	49.52	63.81	75.24	78.10	78.10	78.10
SVM Lineal	60.00	67.62	86.67	85.71	85.71	85.71
SVM con RBF	78.10	80.00	91.43	91.43	91.43	91.43
NB	49.52	61.90	66.67	64.76	60.00	53.33
KNN	64.76	72.38	80.95	80.95	80.95	80.95
RBF	58.10	57.05	56.10	56.10	56.29	56.19



Experimental validation

1. Data recording: Fuzzy logic controller

- Membership functions:
 - Data collecting
 - Normalization
 - Histogram for each signal
 - Mean and STD values to implement membership functions
- Matlab® Fuzzy Logic Toolbox
- 65,71% LOOCV



Experimental validation

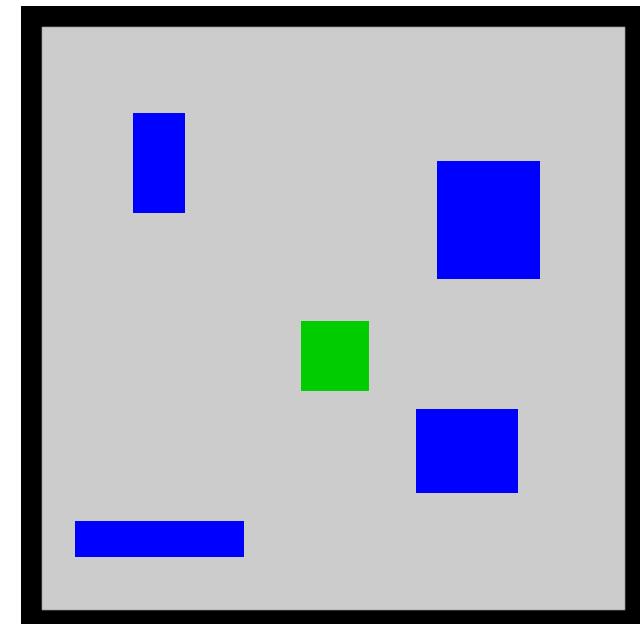
2. Bio-cooperative control validation:

- Protocol:

- Experiment is explained
- Adaptation period of few minutes
- Rest period 5 min
- Task 10 min

- Automatic level changes:

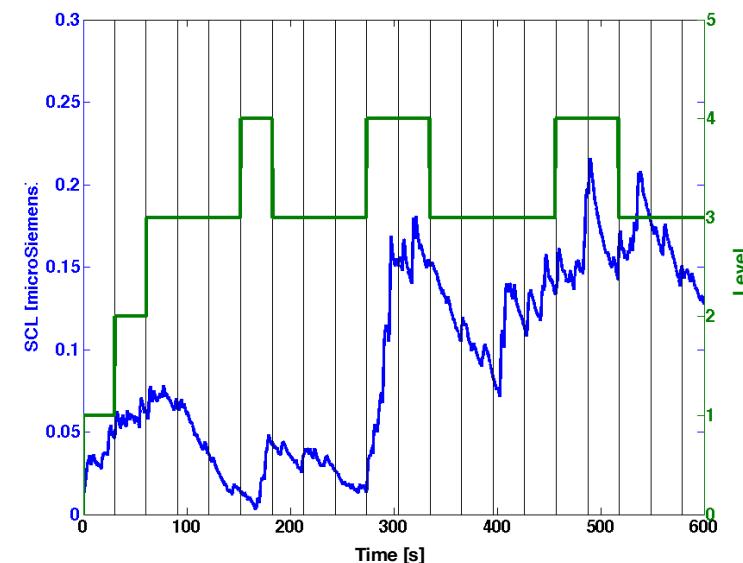
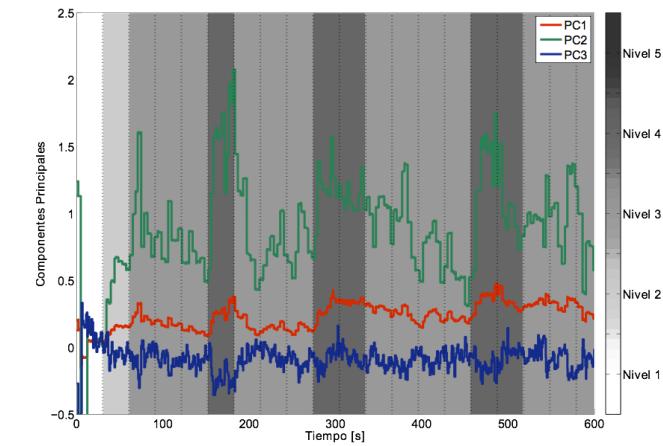
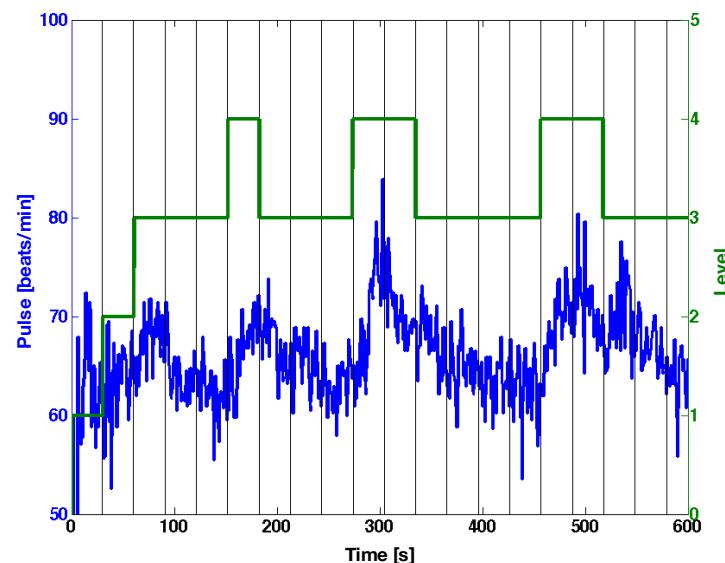
- Only one blue rectangle with low speed.
- Three blue rectangle with low speed.
- Three blue rectangle with medium speed.
- Four blue rectangle with medium speed.
- Four blue rectangle with high speed.



Experimental validation

2. Bio-cooperative control validation:

- Classification techniques
- SVM with RBF kernel
- PCA, 3 principal components

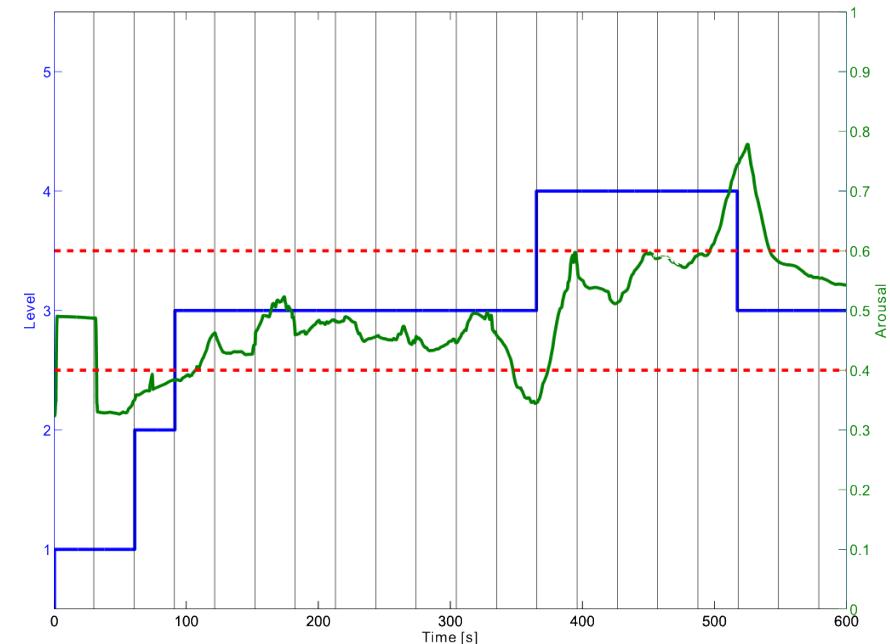
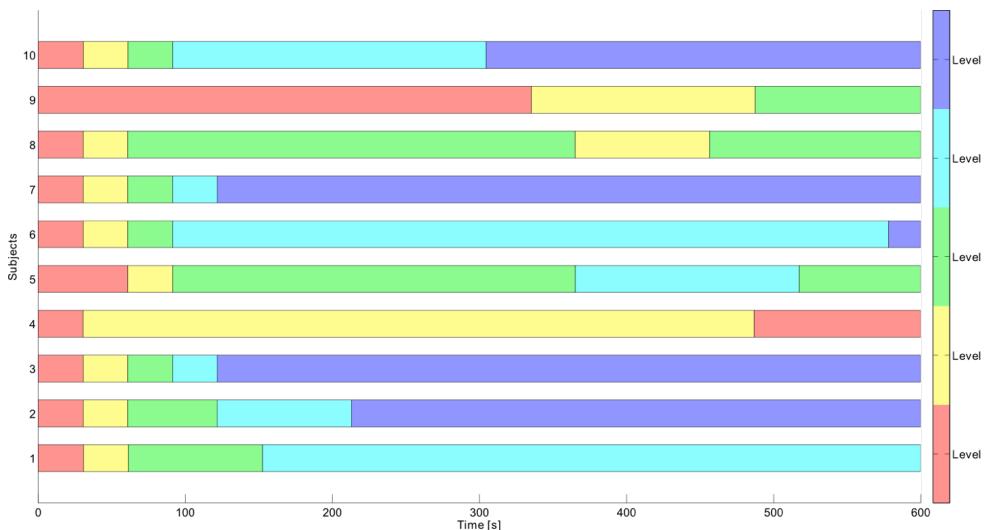


F. Javier Badesa, Ricardo Morales, Nicolas Garcia-Aracil, Alicia Casals, Loredana Zollo, "Auto-adaptive robot-aided therapy using machine learning techniques", Computer Methods and Programs in Biomedicine

Experimental validation

2. Bio-cooperative control validation:

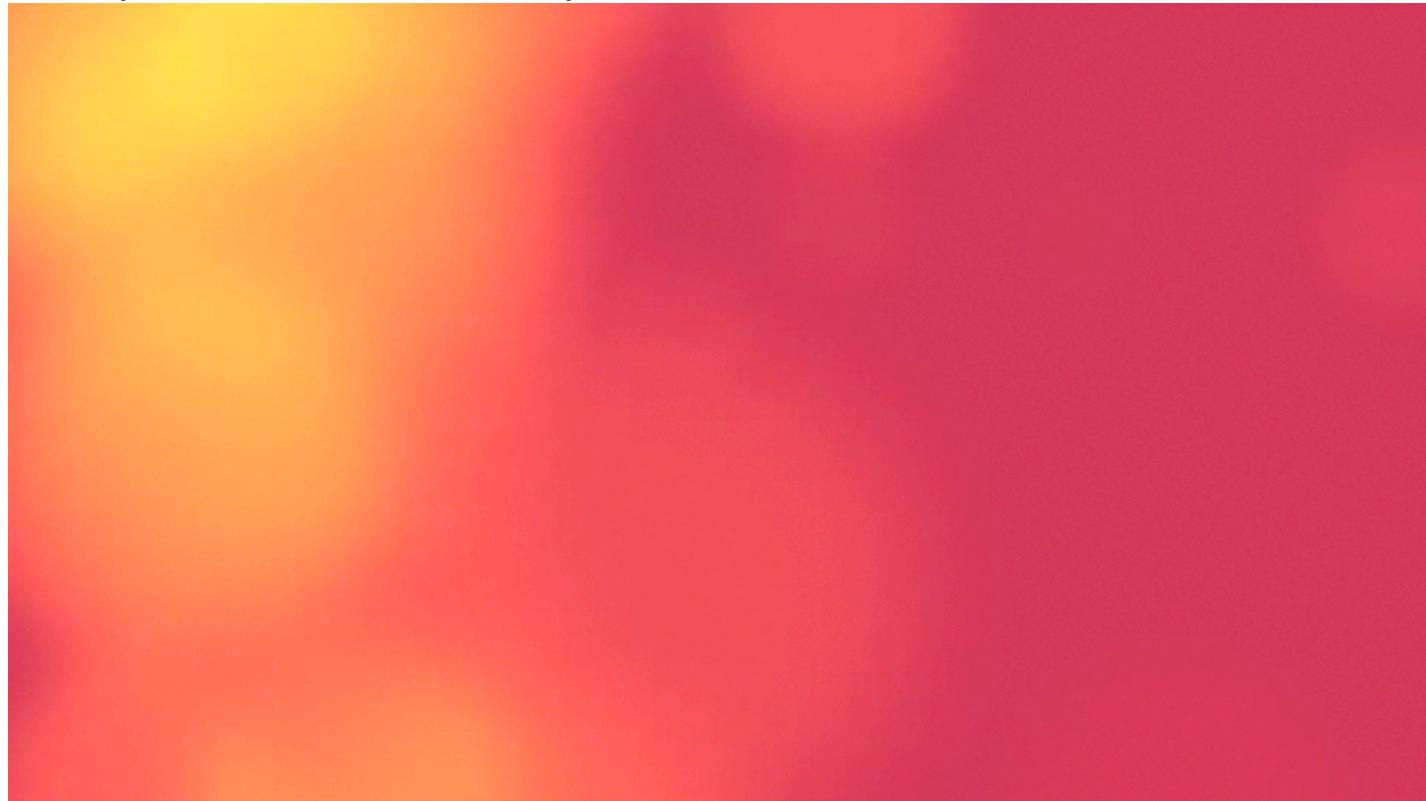
- **Fuzzy logic controller**
- Three different actions:
 - Arousal < 0.4 → increase level
 - 0.4 < Arousal < 0.6 → no change
 - Arousal > 0.6 → reduce level



Experimental validation

First clinical trials with post-stroke patients:

- Bio-cooperative control using classification techniques(Two step experiment)
- Three different levels for training (5 cm distance, easy task for the patient; 10 cm distance, adequate level task for the patient; 15 cm distance, too difficult task for the patient.)



Experimental validation

First clinical trials with post-stroke patients: Classification models training

- Normalization:

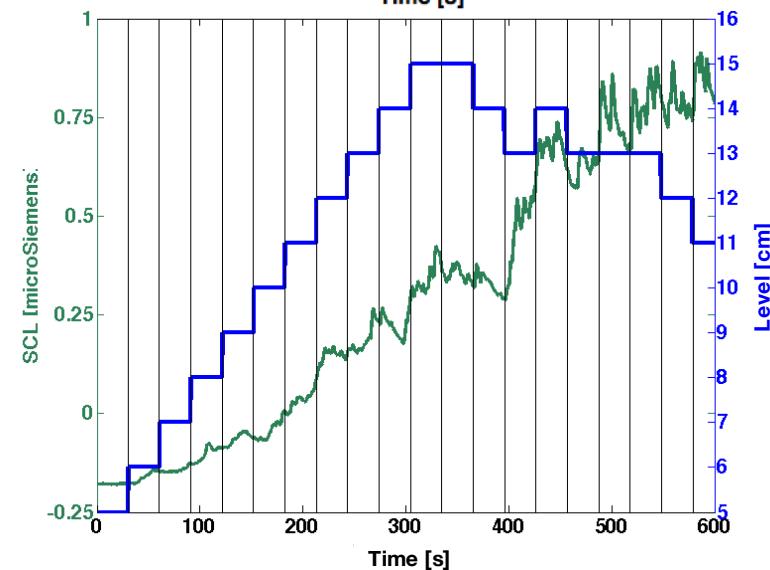
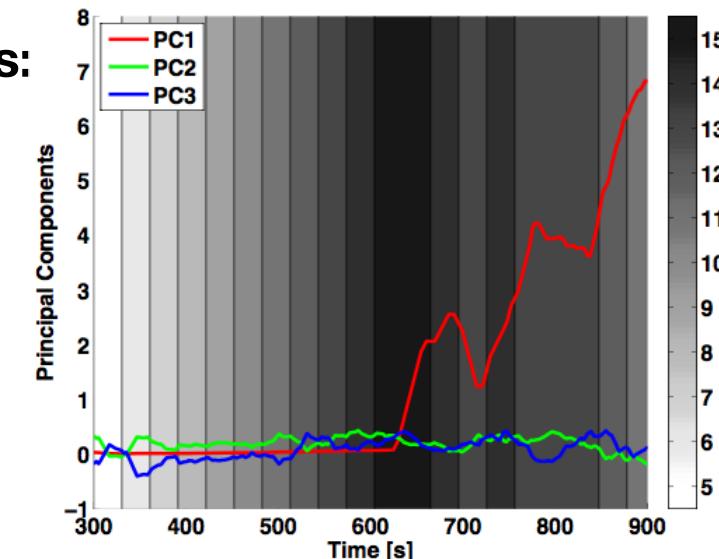
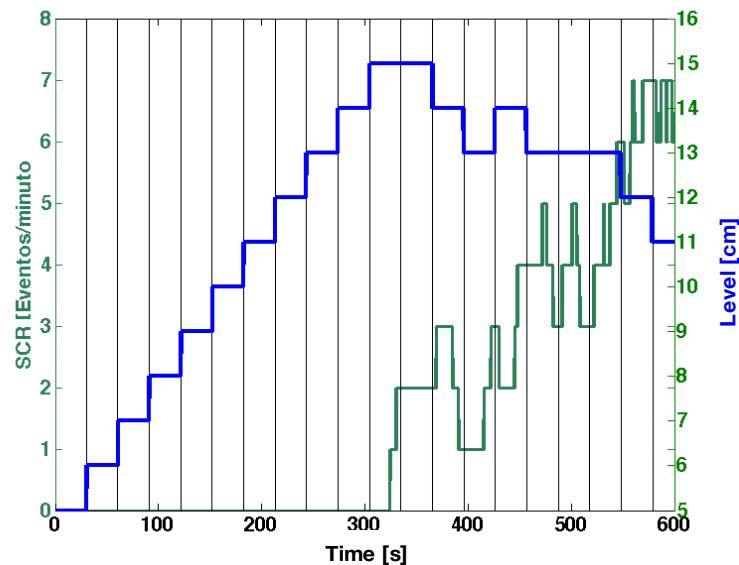
Signal - baseline
baseline

Algorithm	PCA 2 PC	PCA 3 PC	PCA 4 PC	PCA 5 PC	NO PCA	Mean
PLA	38,11	66,76	70,00	68,65	69,19	62,542
LR	54,05	66,22	68,92	63,51	63,51	63,242
LDA	56,76	71,62	67,57	66,22	66,22	65,68
QDA	56,76	60,81	64,86	66,22	66,22	62,97
SVM Lineal	58,11	70,27	68,92	68,92	68,92	67,03
SVM con RBF	56,76	70,27	71,62	71,62	71,62	68,38
NB	56,76	63,51	64,86	60,81	44,59	58,11
KNN	50,00	52,70	52,70	52,70	52,70	52,16
RBF	43,24	43,24	41,89	41,89	41,89	42,43

Experimental validation

First clinical trials with post-stroke patients:

- Classification techniques Validation
- SVM with RBF kernel
- PCA, 3 principal components



Contents

1. Introduction
2. Physiological signals and patient's emotional state
3. Biomechanical analysis
4. Dynamic adaptive system for robot-assisted motion rehabilitation
5. Experimental validation
- 6. Conclusions**

Conclusions

- Bio-cooperative control:
 - Three emotional states
 - 9 machine learning classification models.
 - SVM with RBF kernel: 91,43 % LOOCV
 - Fuzzy logic controller:
 - Histogram for membership functions
 - 65,71 % LOOCV
- It is currently undertaking the first exploratory clinical trials with post-stroke patients:
 - SVM with RBF kernel
 - 5 acquisition data sessions
 - first results are promising

