CT CPNL

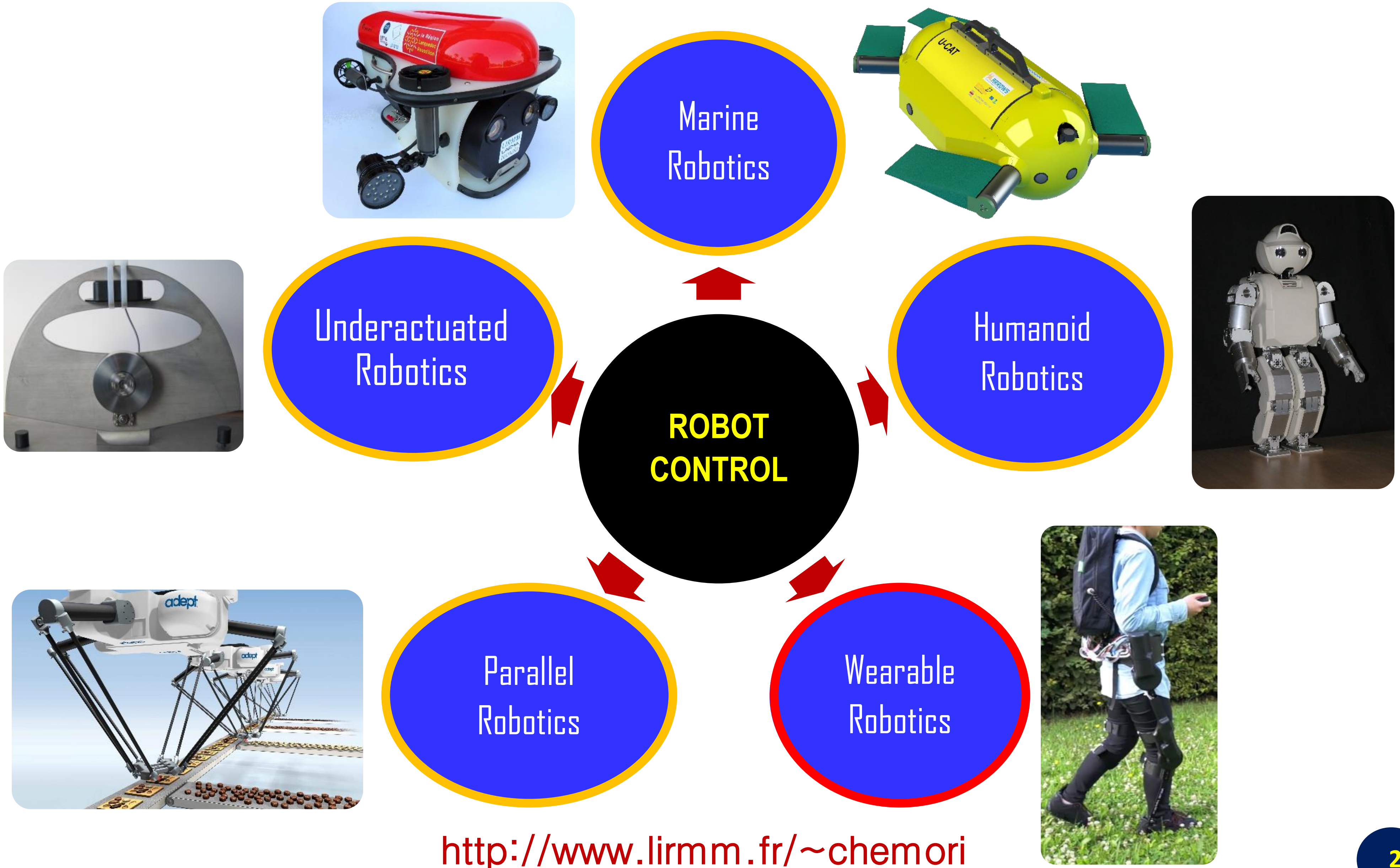
Friday, June 03, 2022

An assistive MPC-Based Framework for a Robotic Knee Rehabilitation Exoskeleton

Ahmed CHEMORI

Laboratoire d'**I**nformatique, de **R**obotique
et de **M**icroélectronique de **M**ontpellier
LIRMM, CNRS/Université de Montpellier
161, rue Ada 34095
www.lirmm.fr/~chemori
Email : Ahmed.Chemori@lirmm.fr

My research activities in Robot Control



http://www.lirmm.fr/~chemori

Speaker : **A. CHEMORI**

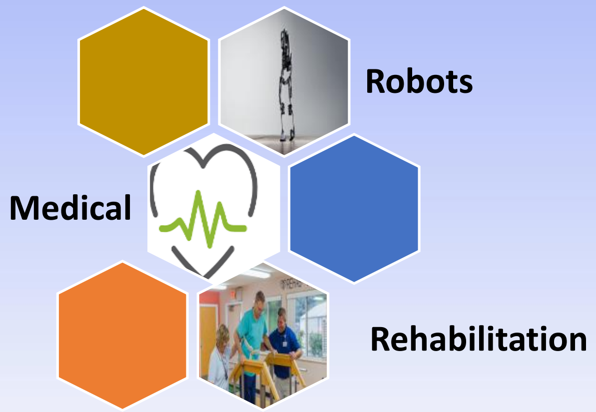
Outline

Outline of the presentation

- Introduction & Context
- Some basic definitions & Main applications
- A brief historical overview & Some examples of today
- Experimental setup: EICOSI Orthosis (@LISSI – UPEC)
- Proposed control solutions (L1 adaptive , MPC)
- Real-time experimental results
- Conclusion

Speaker : A. CHEMORI

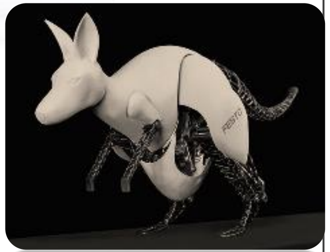
Introduction & Context



Speaker : **A. CHEMORI**

Introduction & Context

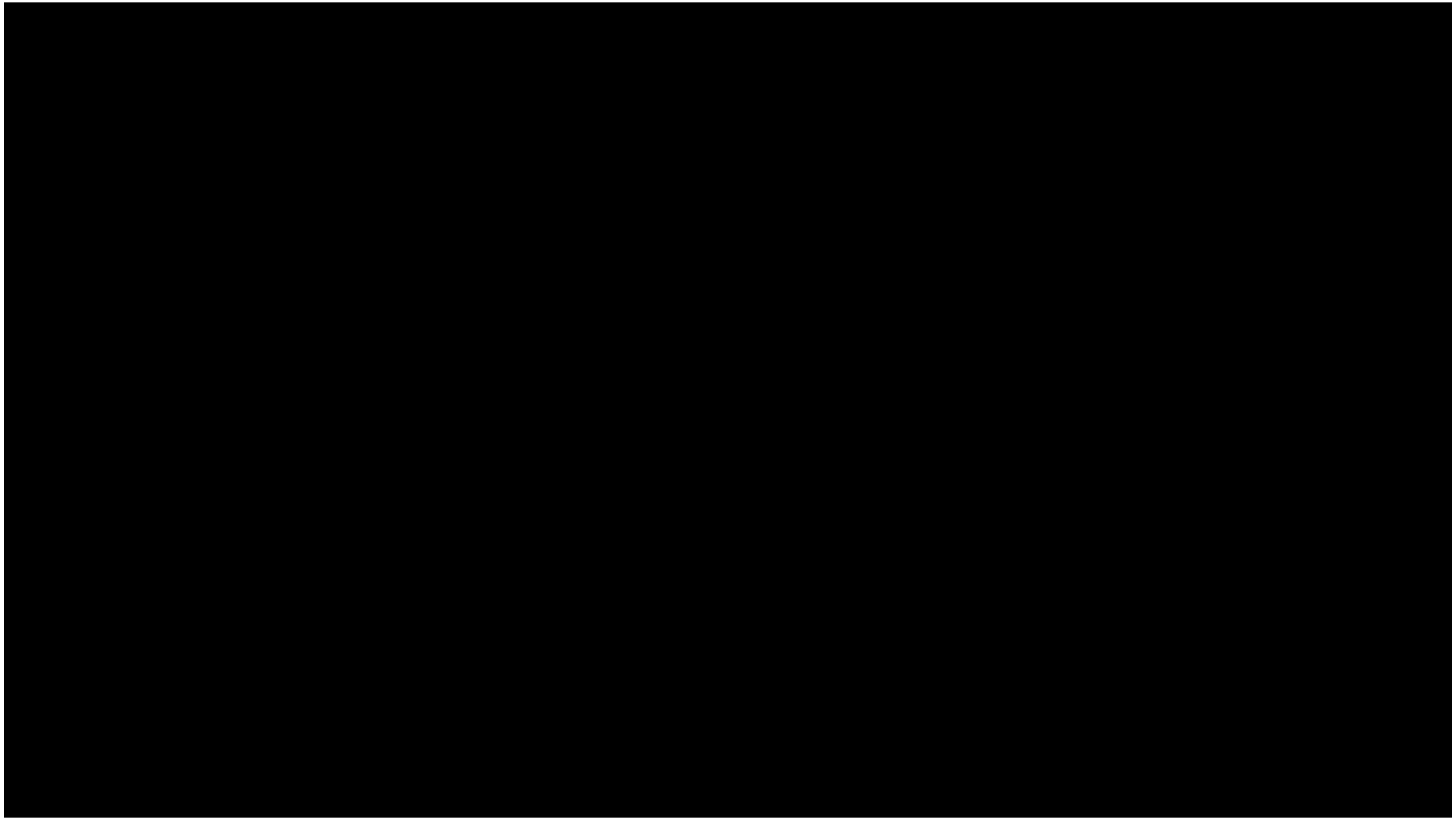
Speaker : **A. CHEMORI**



ROBOTICS

- **Wearable** Robotics
- **Industrial** Robotics
- **Mobile** Robotics
- **Bioinspired** Robotics
- **Legged & Humanoid** Robotics
- **Aerial** Robotics
- **Micro** Robotics
- **Marine** Robotics
- **Medical** Robotics
- **Service** Robotics

Introduction & Context



Speaker : **A. CHEMORI**

Introduction & Context

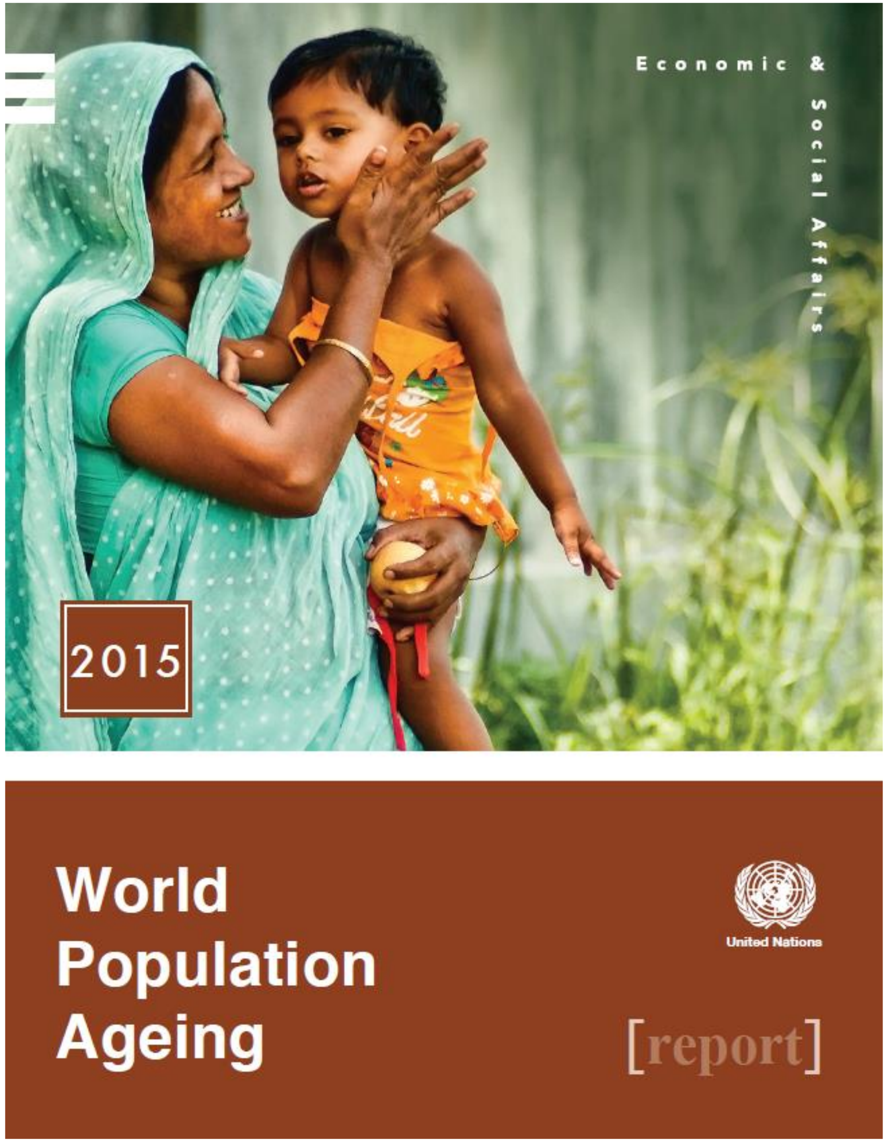
Introduction & Context

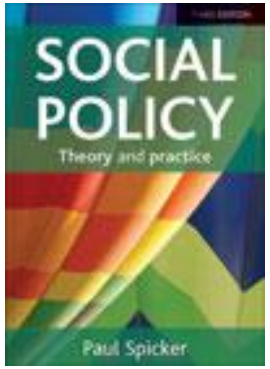






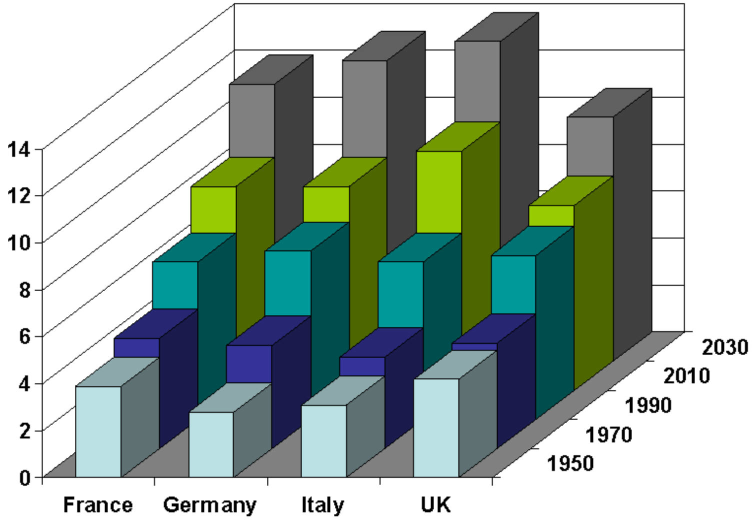
How we can help them ?



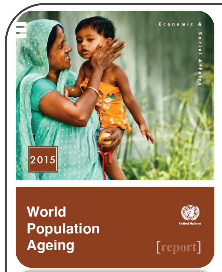


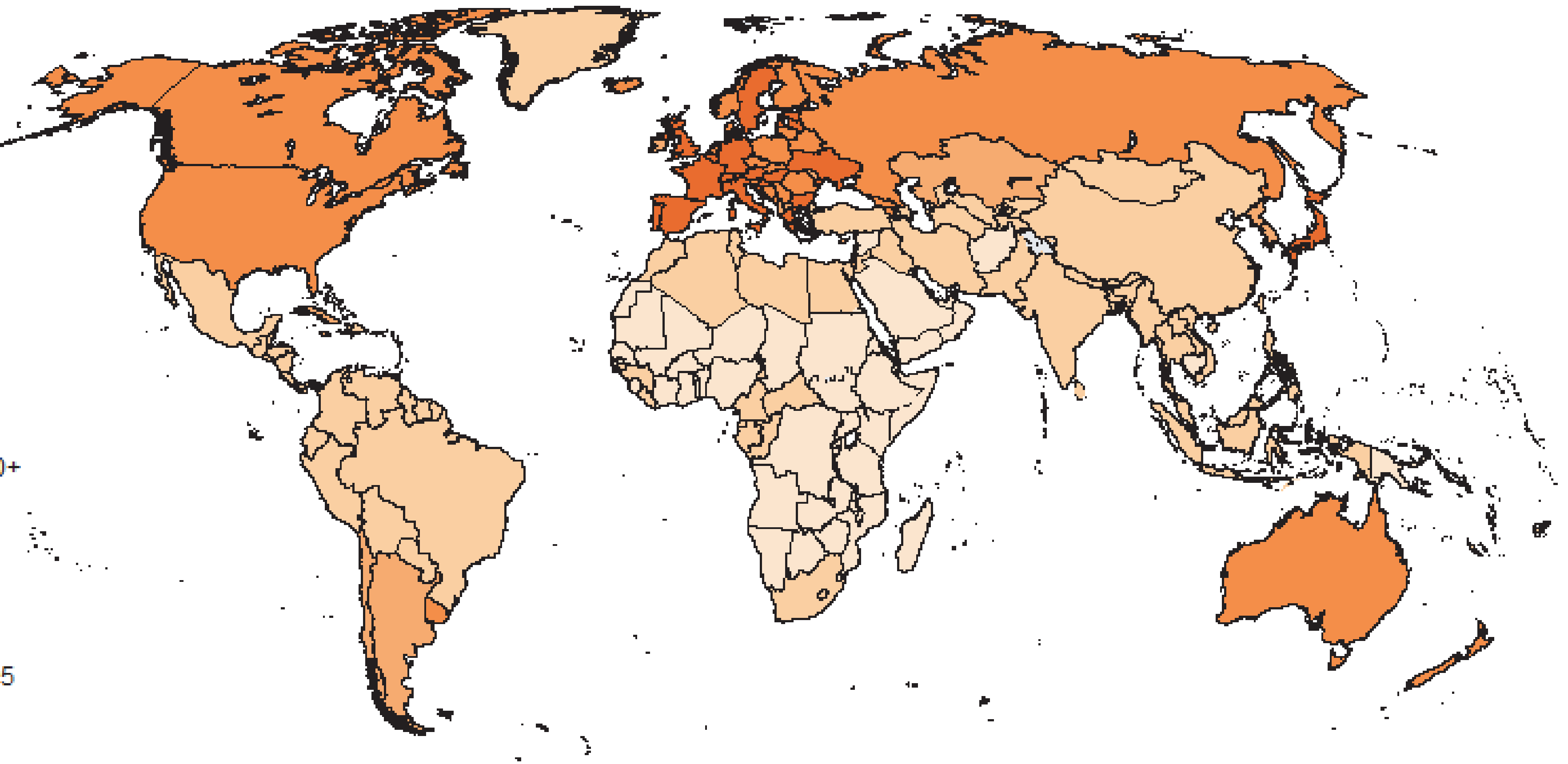
By
Paul Spicker

% of population over 65

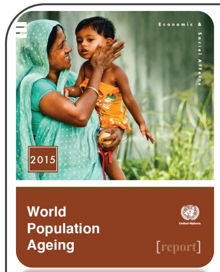


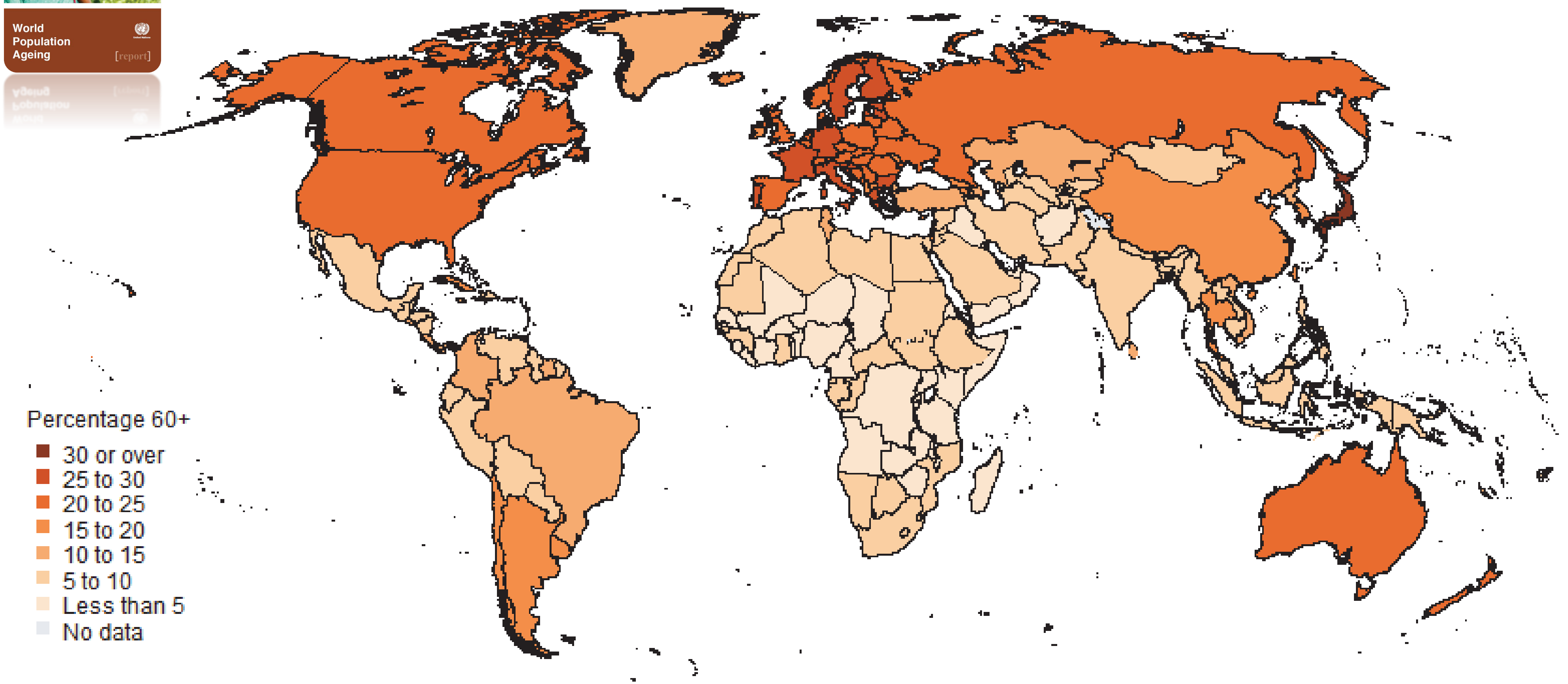
Introduction & Context





Data source: United Nations (2015). World Population Prospects: The 2015 Revision





Data source: United Nations (2015). World Population Prospects: The 2015 Revision

Introduction & Context

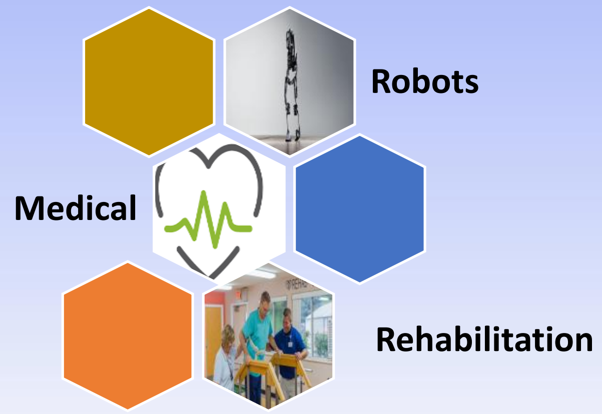
Number of old people is rising faster than ever !

2050

What would be the solution to their **mobility** problems ?

Speaker : **A. CHEMORI**

Some basic definitions



Speaker : **A. CHEMORI**

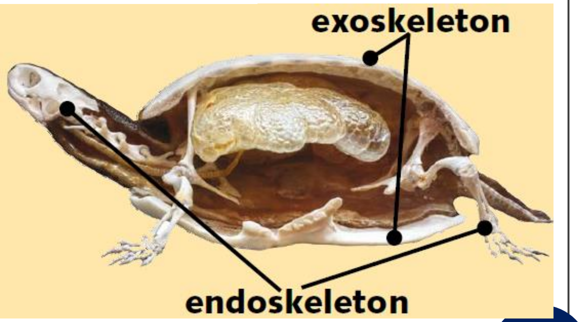
What is an exoskeleton ?

- ✓ Animals and humans have **skeletons**
- ✓ To **protect** and support **inner working** of their bodies
- ✓ **Muscles** are attached to skeletons so be able to **move**
- ✓ Skeletons **inside** bodies are called **endoskeletons**


- ✓ Some animals have skeletons on the **outside** of their bodies, they are called **exoskeletons**
- ✓ Animals with exoskeletons live on land and in water,
- ✓ Include : **Crustaceans** and **insects**
- ✓ Like : **Spiders**, **shrimps**, **crabs**, etc



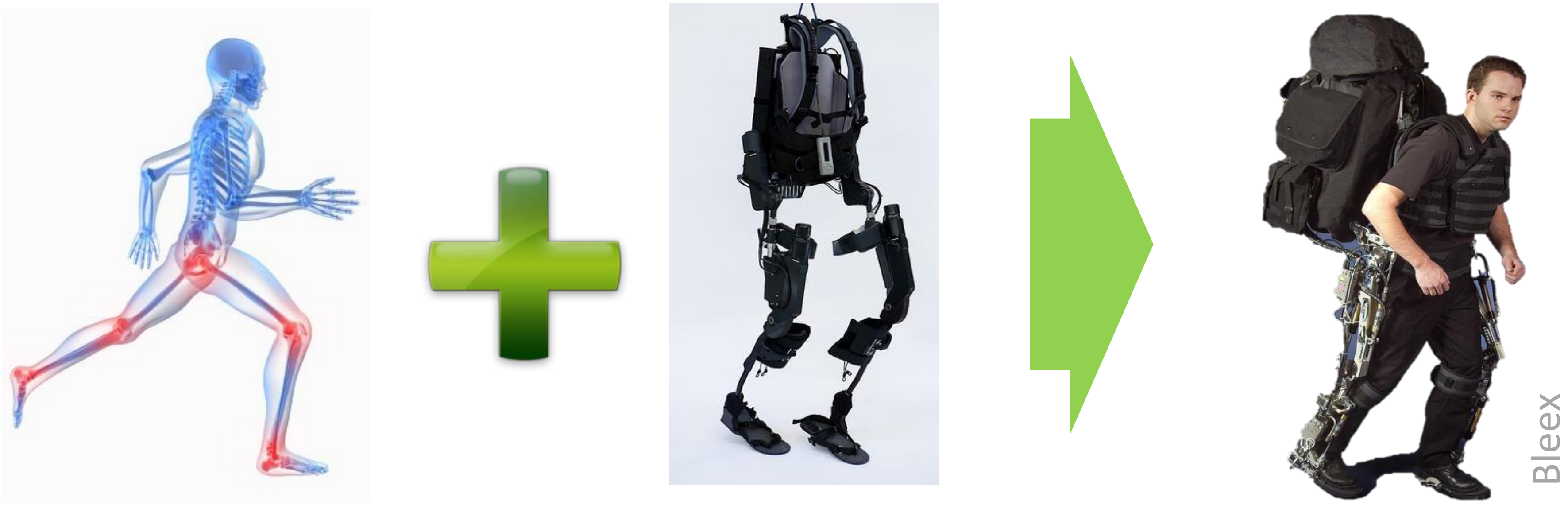

- ✓ Other animals have both **endo** and **exoskeletons** like turtles



Speaker : A. CHEMORI

What is an exoskeleton ?

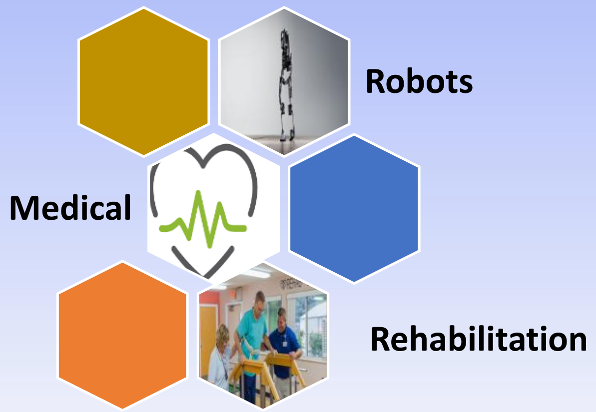
- ✓ It is a **mechanical frame** designed to be **worn by a human** being
- ✓ **Designed** around the **function** and **shape** of the **human body**



- ✓ It **moves** with the **wearer**, adding **strength** and **durability**
- ✓ **Additional** strength/protection/support, benefit people in **dangerous/tiring jobs** or **mobility** issues
- ✓ Developped **initially** for **military** applications

Speaker : **A. CHEMORI**

Main Applications

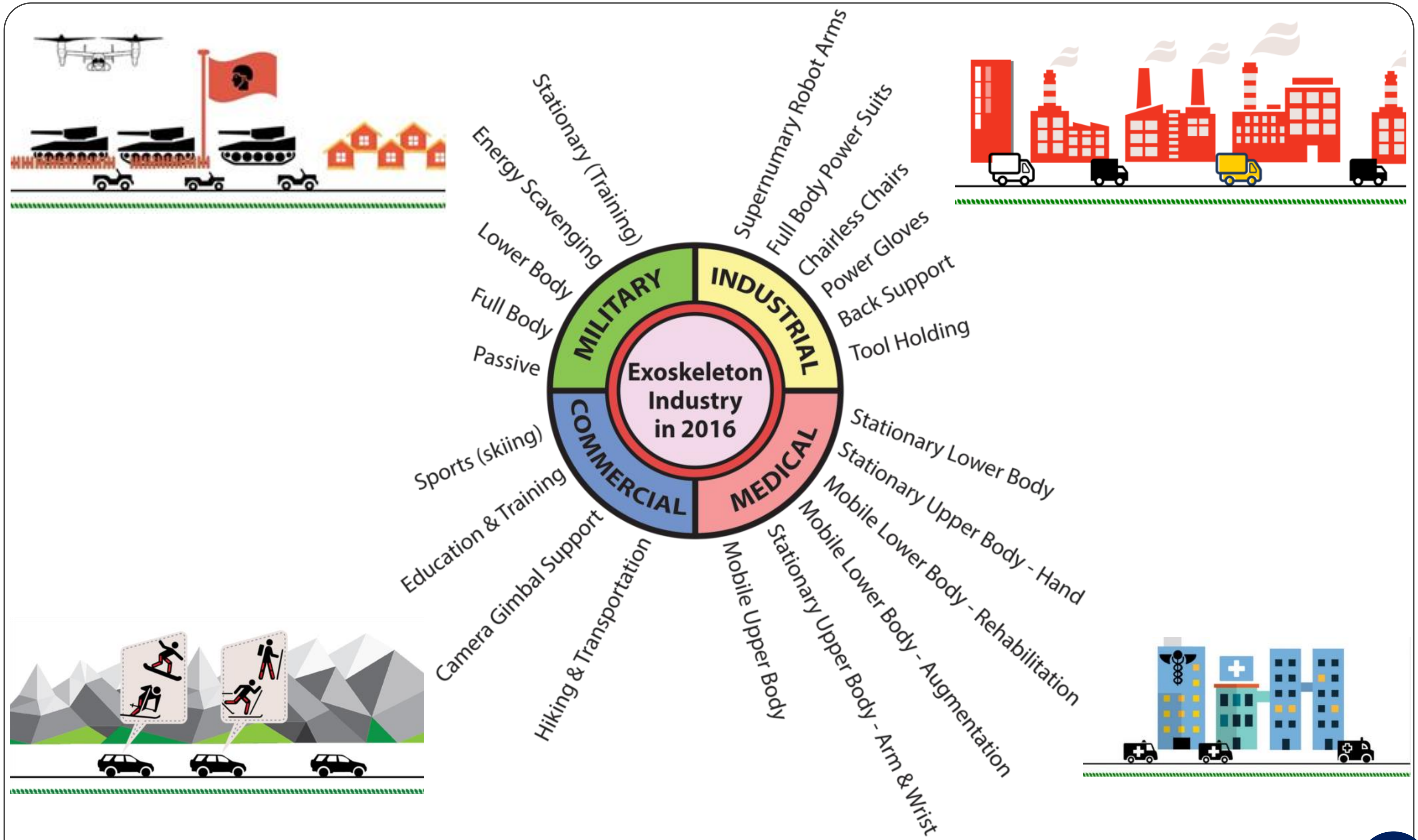


CNRS LIRMM Université de Montpellier

- Context
- **Definitions**
- Brief history
- Prototypes
- Controllers
- Results
- Conclusion

Speaker : **A. CHEMORI**

Where exoskeletons are used ?

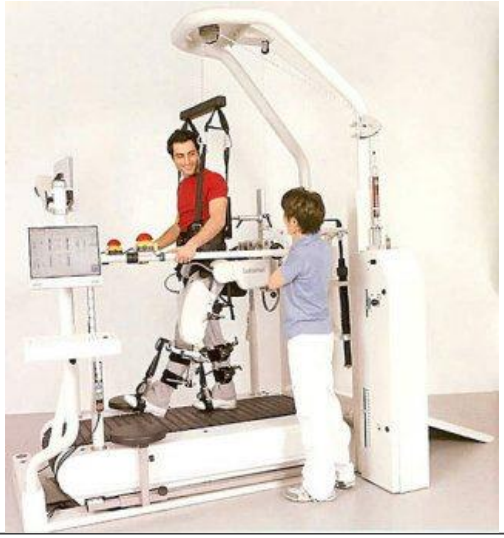


Source : https://exoskeletonreport.com/2016/08/exoskeleton-industry-2016/

Where exoskeletons are used ?

Medical applications : Assistive devices in physical therapy (rehabilitation), amplify muscles' strenght, restore locomotion to paralyzed persons, stroke, spinal cord injury, etc.




Where exoskeletons are used ?

Consumer/Civilian applications : Assist humans in daily life tasks and also eldery persons (balance, carry loads, site to stand, etc)

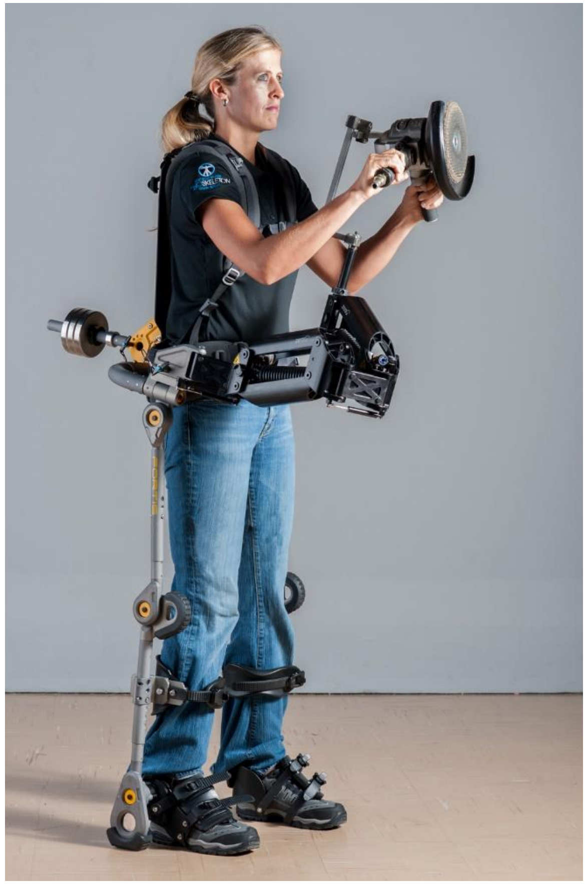
HAL Exoskeleton

Ekso Bionics Exoskeleton

PANASONIC Exoskeleton

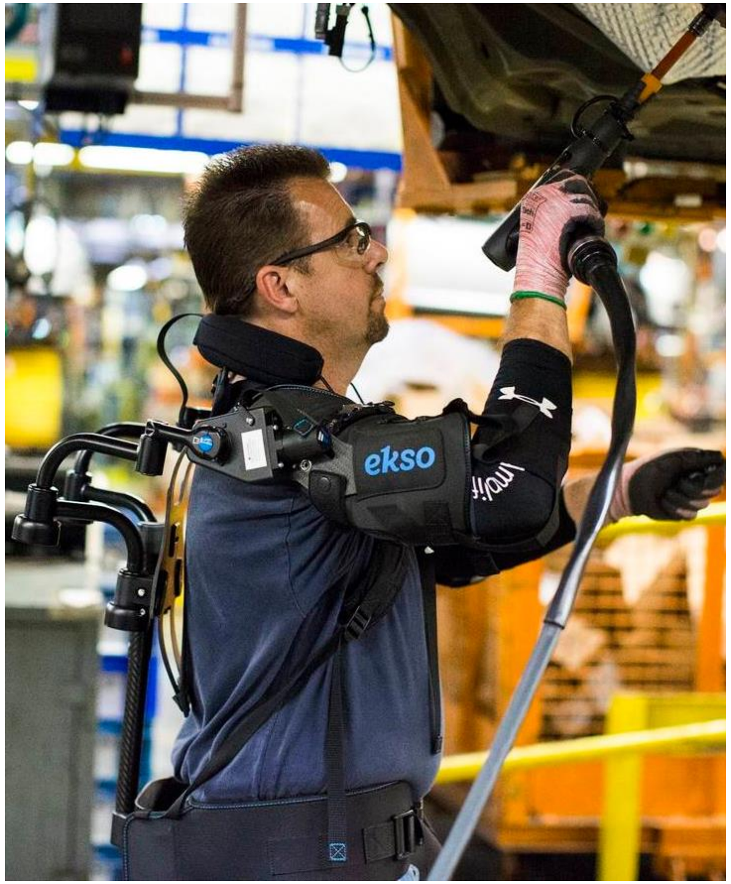
Where exoskeletons are used ?

Work/Industry applications : To ease physical exertion in industry (force multiplier, Distributes weight to reduce user strain, reduce fatigue, etc)



FORTIS Exoskeleton

DAEWOO Exoskeleton



FORD Exoskeleton

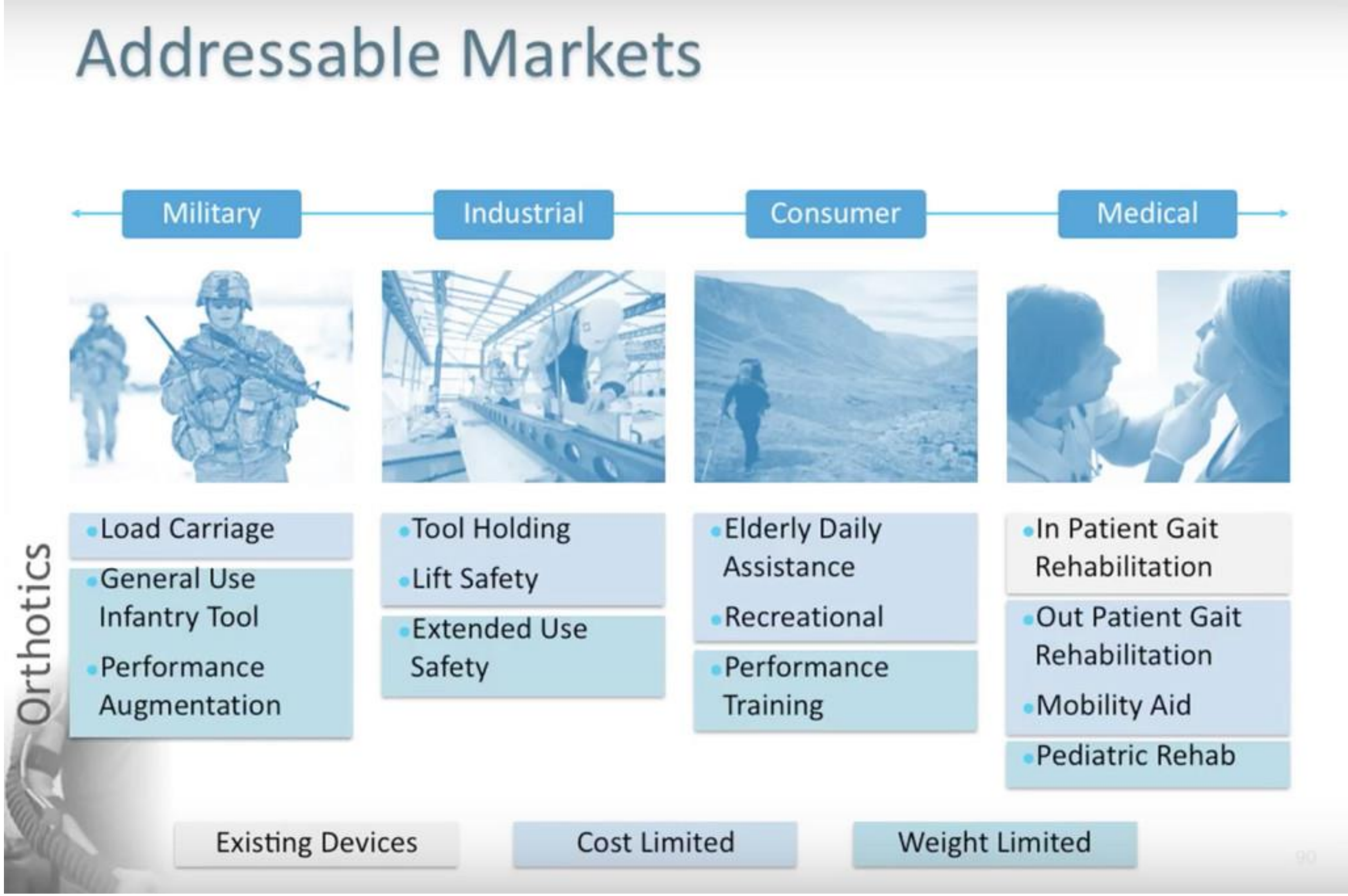
Where exoskeletons are used ?

Military applications : To enhance soliders' ability, protect soliders, amplify strengh, increase endurance, improve effeciency, etc

HULC, EKSO BIONICS

XOS 2, SARCOS/RAYTHEON

Where exoskeletons are used ?



Source : https://exoskeletonreport.com/2016/08/exoskeleton-industry-2016/

Stationary vs mobile / Lower body vs upper body

Stationary | **Mobile**

Lower body

Hocoma – Lokomat

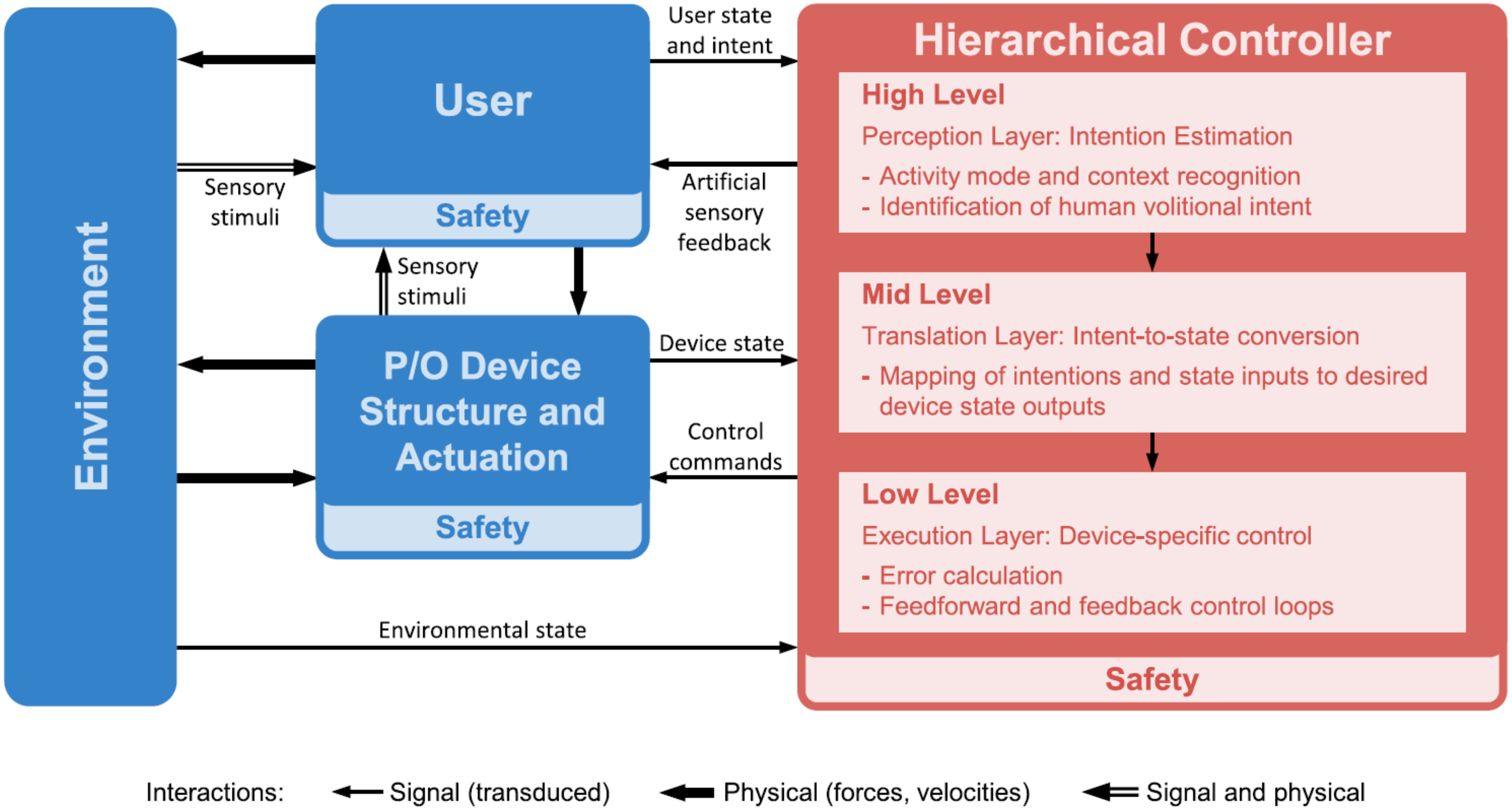
HANK by Gogoa

Upper body

InMotion Arm, Bionik Lab

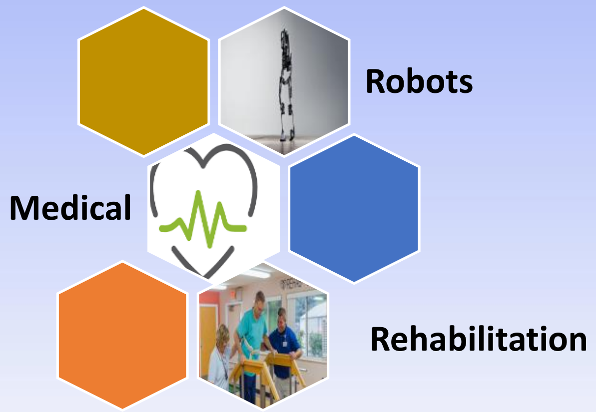
MyoPro by Myomo

Control framework



[Ticker et al. 2015]

A brief historical overview

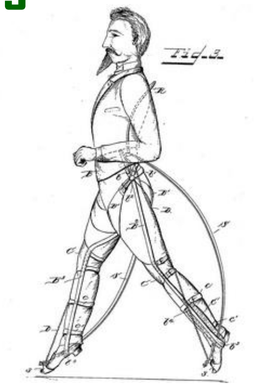


A brief historical overview

Brief historical overview

Yagn's running aid

1890



- ✓ Never build
- ✓ Concept studies drawing
- ✓ Simple bow/leaf–Spring

Hardiman

1960's

- ✓ 680 kg, 30 DOFs
- ✓ Full-body hydraulically powered
- ✓ Amplify drastically human force

Mihailo Pupin

1971

- ✓ Pneumatic actuators
- ✓ Flex/Ext : hip, knee, and ankle
- ✓ Abduction/adduction : hip

Berkley Bleex

2004

- ✓ 7dof/leg : 3dofs/hip, 1dof/knee, and 3dofs/ankle
- ✓ First "load-bearing and energetically autonomous"
- ✓ 4 dof actuated (2 hip, 1knee, 1 ankle)
- ✓ Linear hydraulic actuators

A brief historical overview

Brief historical overview

Sarcos XOS suit

2006

- ✓ For military applications
- ✓ 25x strength amplification, Still tethered
- ✓ weighs 68 kg and allows lifting 90 kg

Rewalk

2011

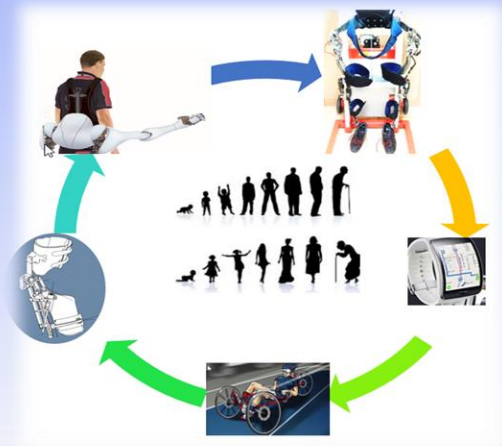
- ✓ For disabled people
- ✓ Light wearable brace support suit
- ✓ DC motors at the joints, rechargeable batteries
- ✓ Physiological and psychological benefits

HAL 5

2012

- ✓ Designed to support and expand the physical capabilities of its users
- ✓ For people with physical disabilities
- ✓ Allow carrying loads
- ✓ Weight only 10 Kg

Some examples of exoskeletons



10 examples of exoskeletons

Examples of commercialized exoskeletons

http://exoskeletonreport.com/2015/04/12-commercial-exoskeletons-in-2015/

Speaker : **A. CHEMORI**

Examples of commercialized exoskeletons

❶ ReWalk

❷ Ekso

❸ Indego

❹ REX

Examples of commercialized exoskeletons

❺ Lokomat

❻ HAL

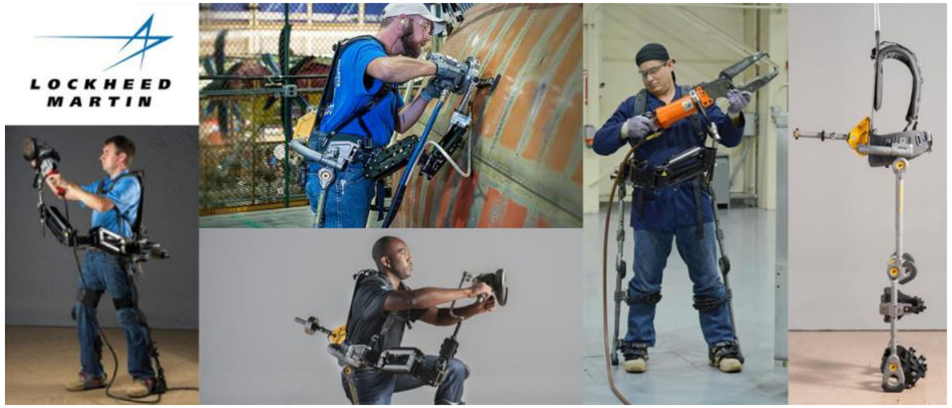
❼ Walking Assist

❽ Hercule

Examples of commercialized exoskeletons

9 DSME

10 Exoatlet

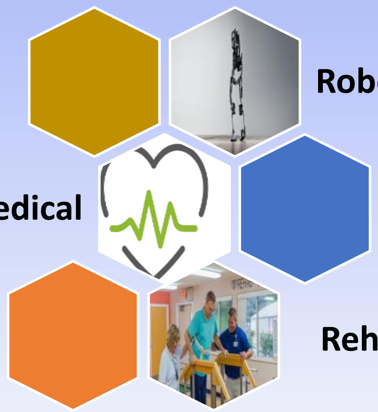


11 FORTIS

12 AGAINER

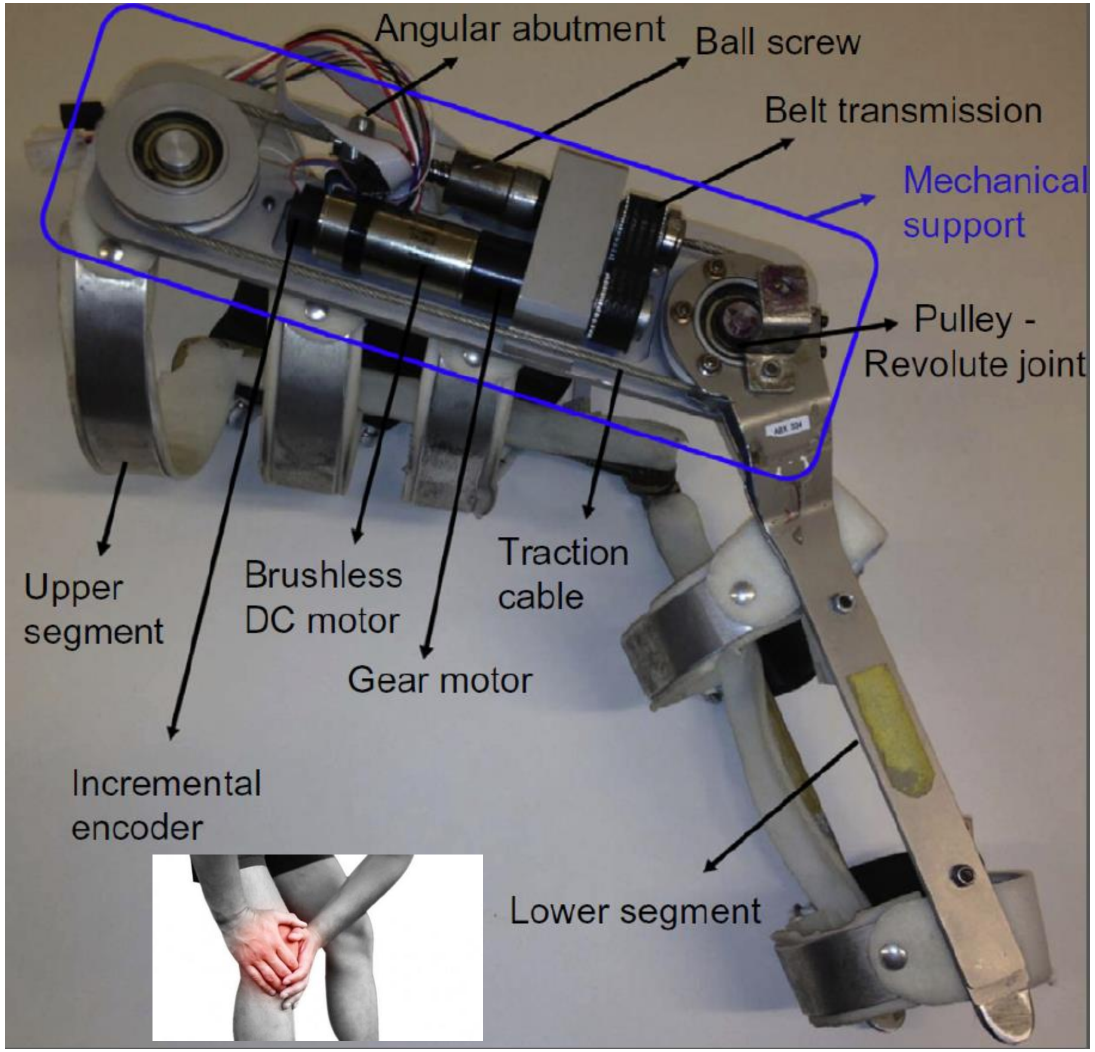
Speaker : **A. CHEMORI**

Our experimental setups



Experimental setups

Overview of **EICOSI** exoskeleton (LISSI – UPEC)

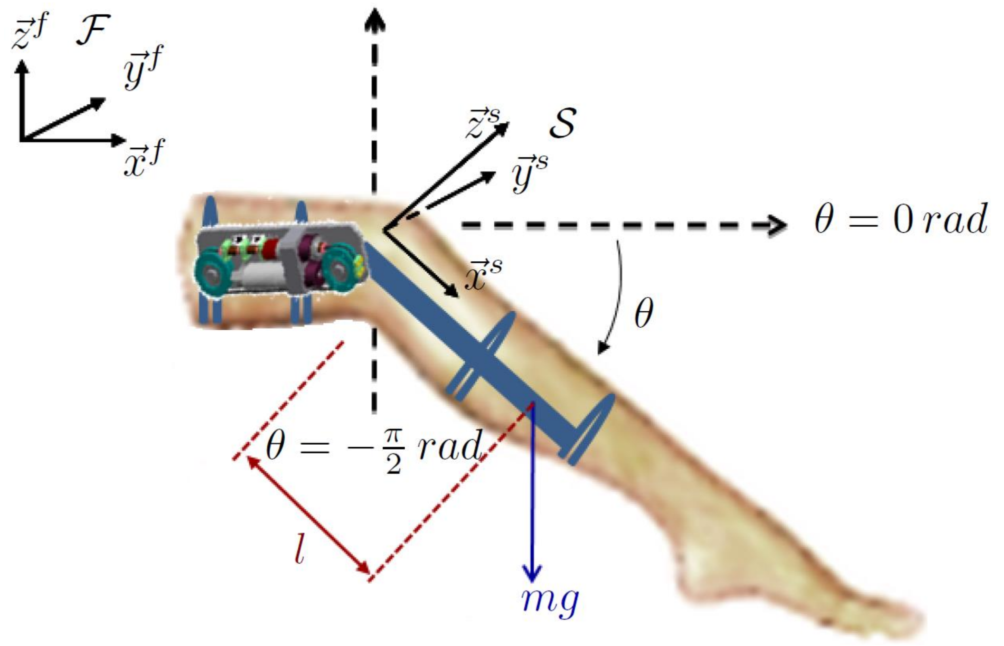


For
knee Rehabilitation

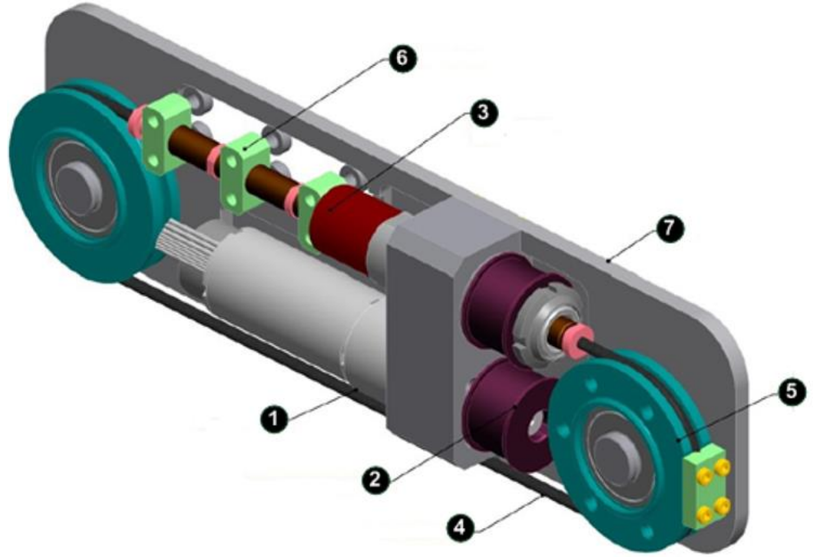
EICOSI : **E**xoskeleton **I**ntelligently **CO**mmunicating and **S**ensitive to **I**ntention

Modelling & actuation of **EICOSI** exoskeleton

Its kinematics with human leg



Its actuation system

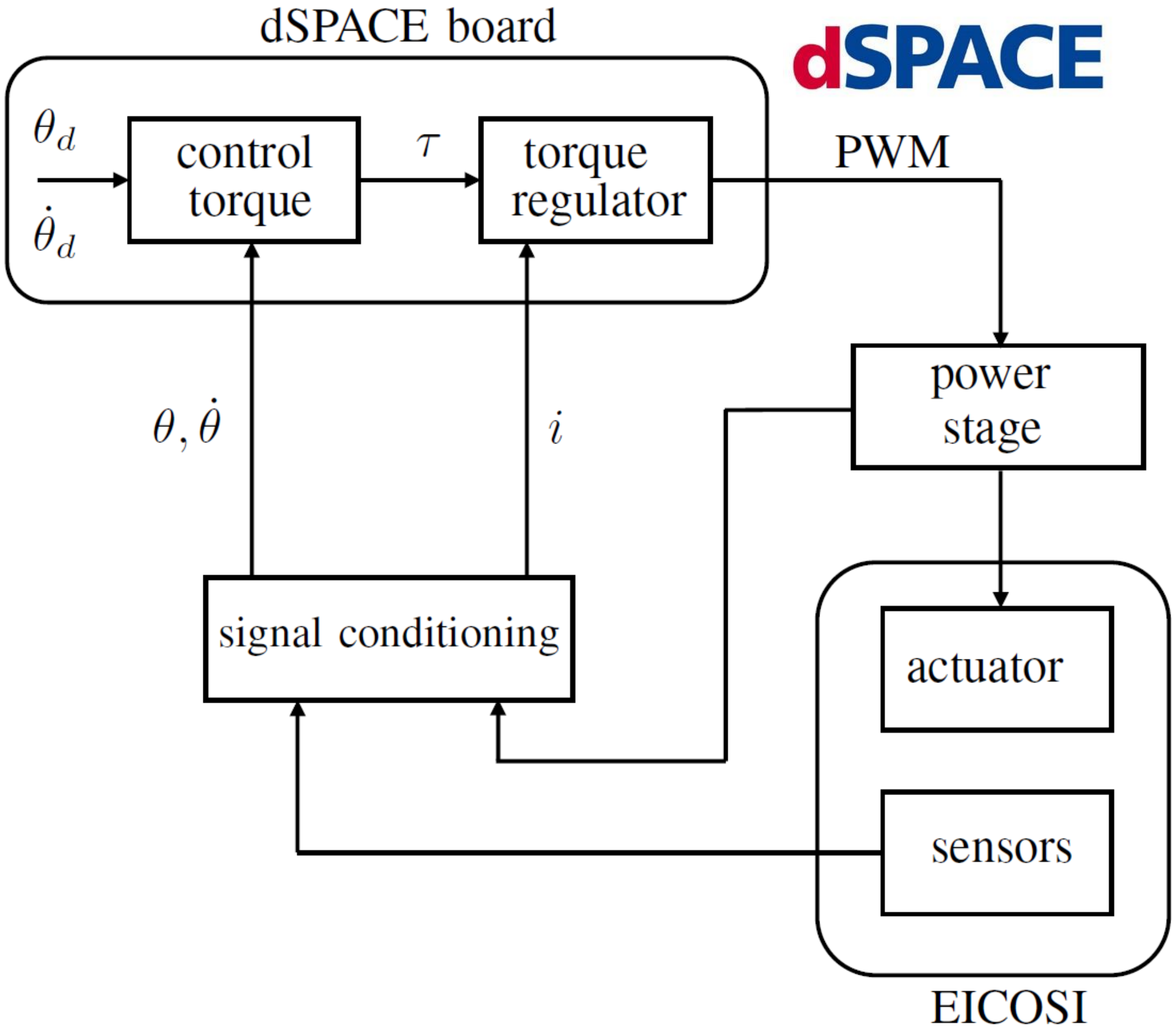


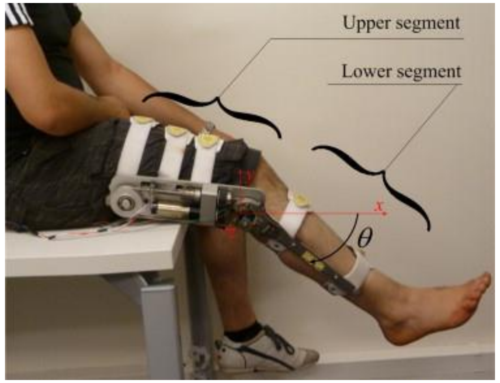
Its dynamic model

$$J\ddot{\theta} = -T_g \cos(\theta) - A\text{sign}(\dot{\theta}) - B\dot{\theta} + u + T_h$$

Experimental setups

View of the hardware architecture of **EICOSI** exoskeleton

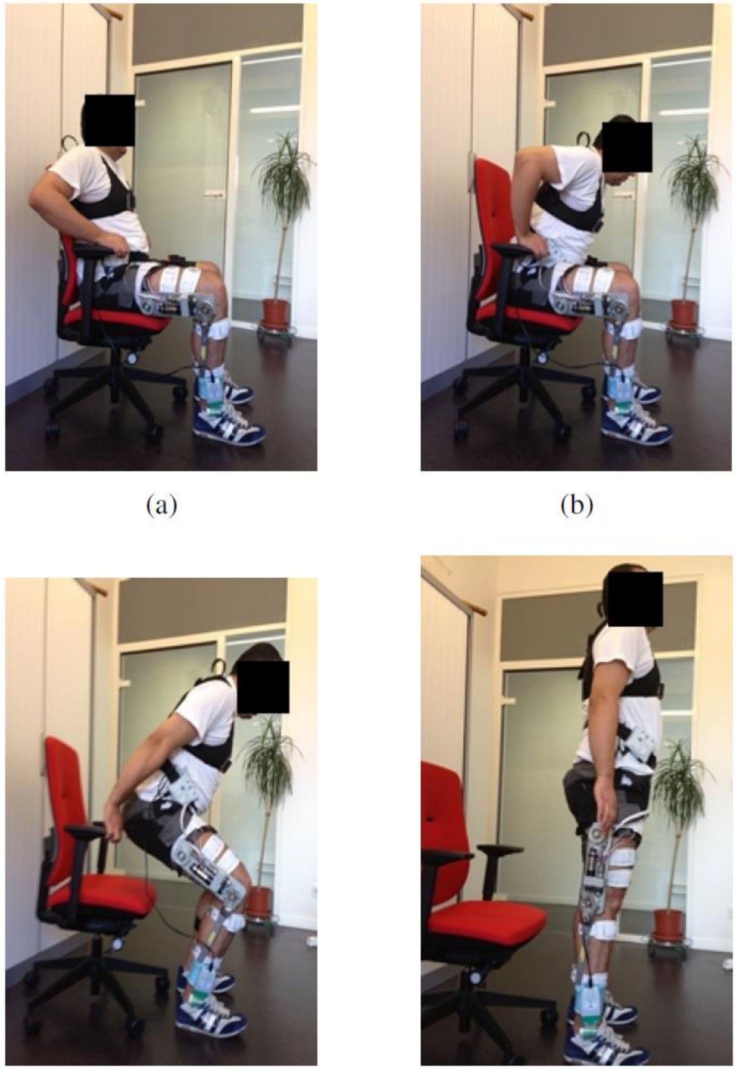




Speaker : **A. CHEMORI**

Experimental setups

Typical applications of **EICOSI** exoskeleton



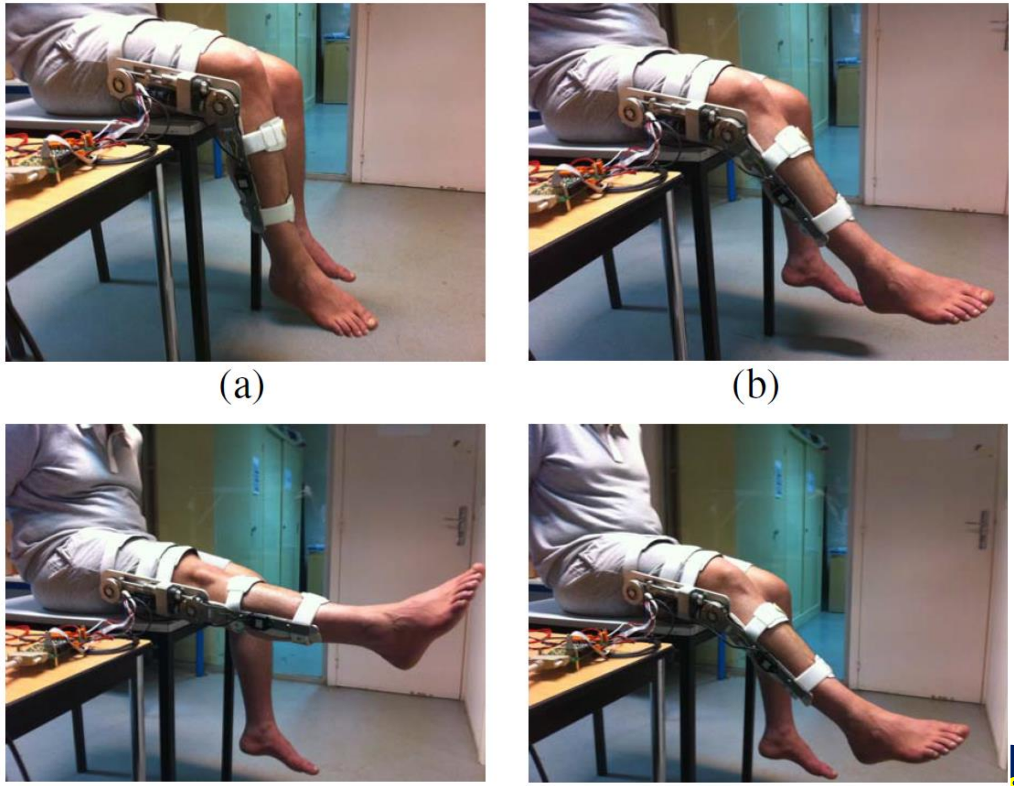
(a) (b)

(c) (d)

Site to stand task

LISSI — Laboratoire Images, Signaux et Systèmes Intelligents

Flexion-extension rehabilitation task



(a) (b)

(c) (d)

Context

Definitions

Brief history

Prototypes

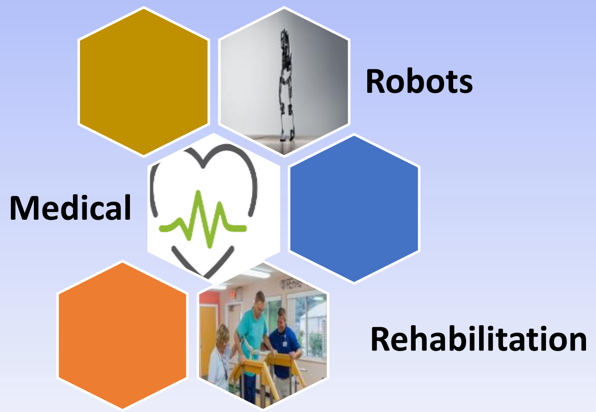
Controllers

Results

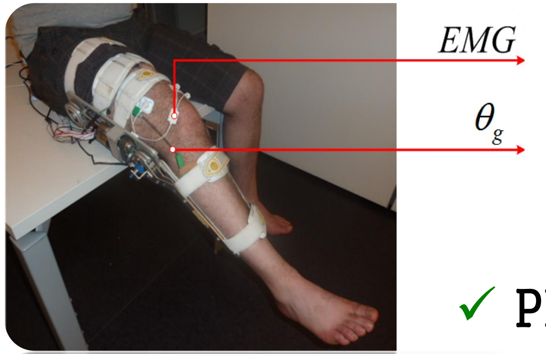
Conclusion

Speaker : **A. CHEMORI**

Proposed control solutions



Proposed control solutions



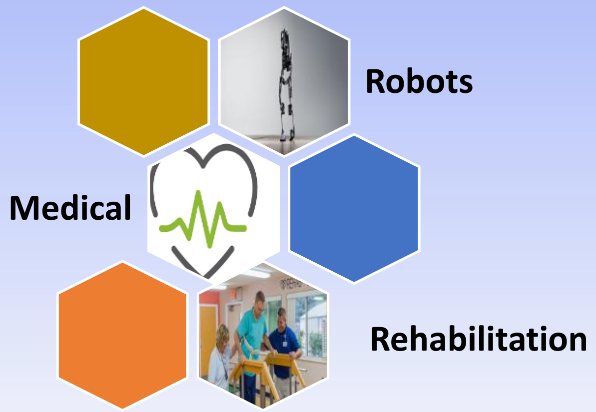
Three types of rehabilitations

1. Passive rehabilitation
2. Assistance as needed
3. Resistive rehabilitation

- ✓ PID controller
- ✓ Inverse dynamics control
- ✓ Sliding mode control
- ✓ **Model Predictive Control**
- ✓ **L1 adaptive control**
- ✓ Backstepping control
- ✓ RISE control
- ✓ NASF Control

Speaker : **A. CHEMORI**

L1 Adaptive Control



Why L1 adaptive control ?

1. Model parameters should be adequately initialized
2. Appropriate excitation is needed for parameters convergence
3. High adaptation gains can destabilize the system

Proposed Solution

Decouple Robustness and Adaptation

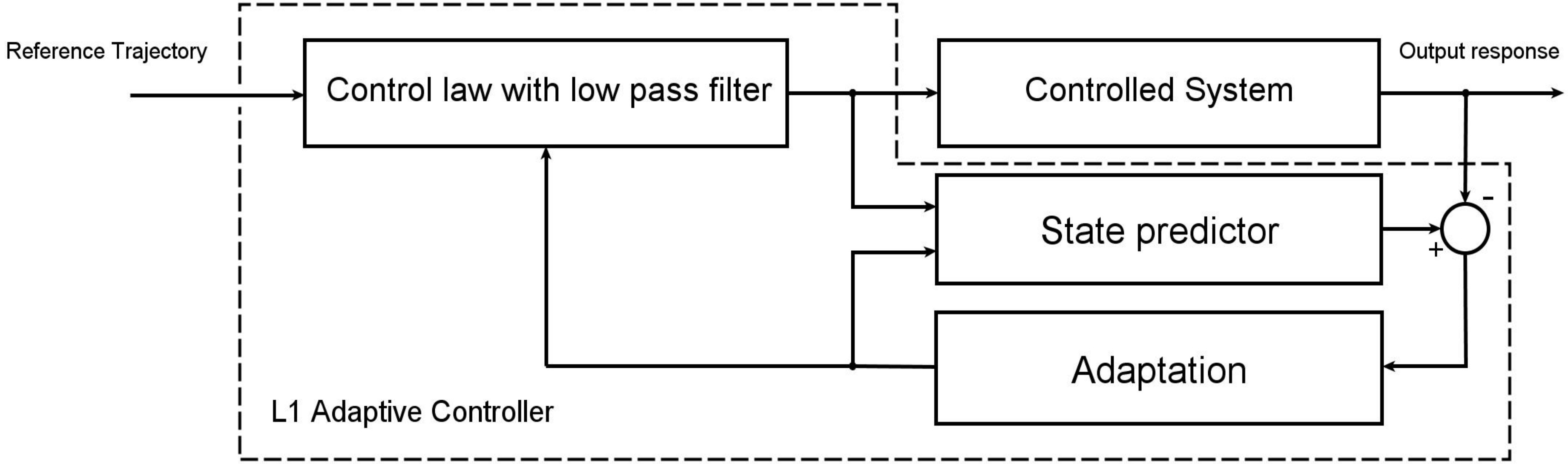
Possibility of zero parameter initialization	Large gains lead to fast adaptation with stability guaranteed	Parameter excitation not needed for parameter convergence

Solution : $\mathcal{L}_1$ Adaptive controller [Hovakimyan2010]

L1 Adaptive control

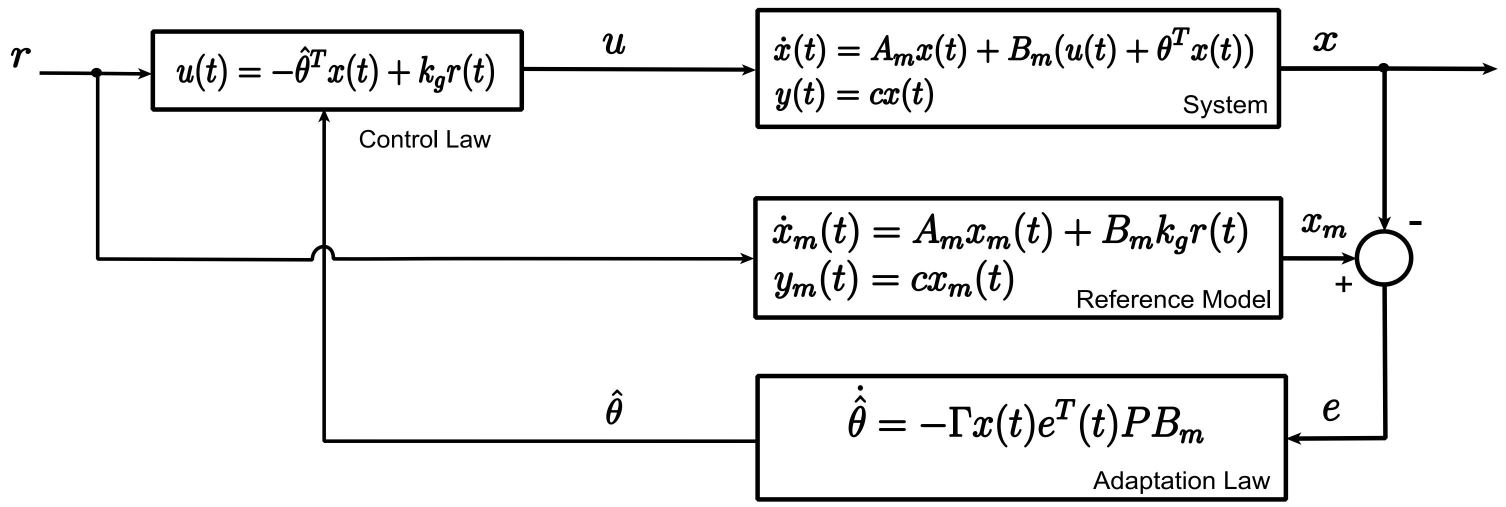
Main features

- ✓ Recently developed controller [Hovakimyan 2010]
- ✓ Inspired from MRAC controller (+ low pass filter)
- ✓ Fast adaptation can be guaranteed
- ✓ Validated on various systems (mainly in aerospace)



L1 Adaptive control

✓ Inspired by direct MRAC (Model Reference Adaptive Control)



r : is a piecewise-continuous bounded reference signal

θ : is a vector of unknown constant parameters

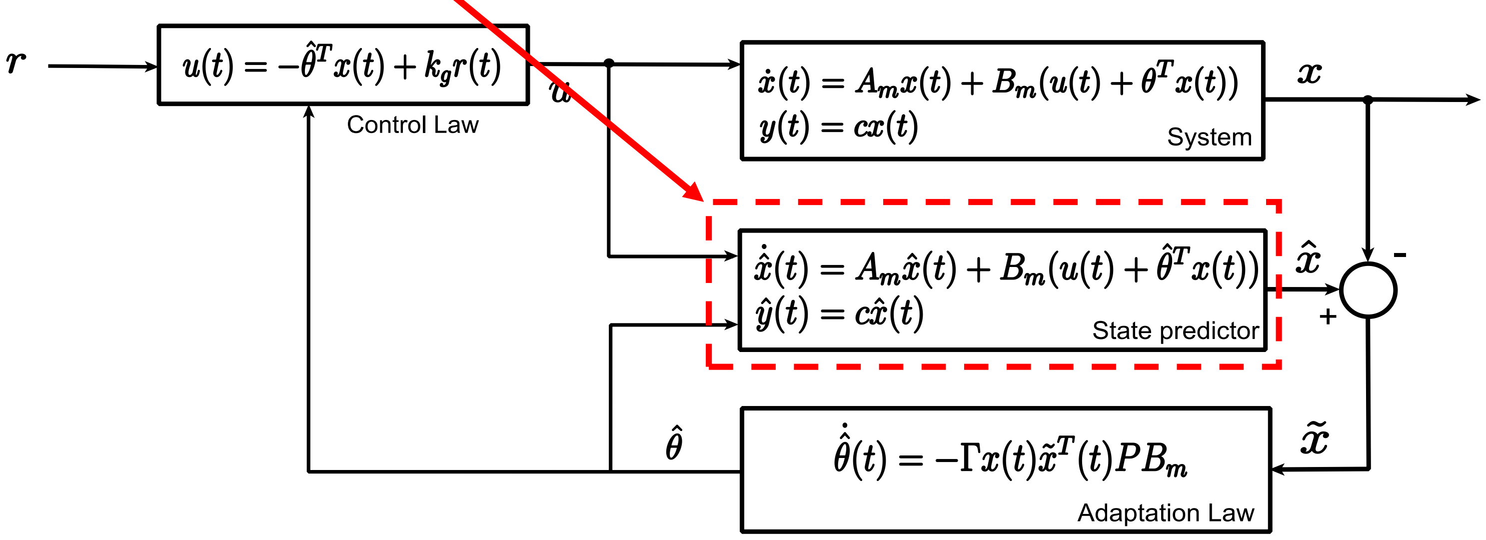
$\hat{\theta}$: is the estimate of θ

$$k_g = \frac{-1}{cA_m^{-1}B_m}$$

$$P = P^T$$
$$A_m^T P + P A_m = -Q$$
$$Q = Q^T > 0$$

L1 Adaptive control

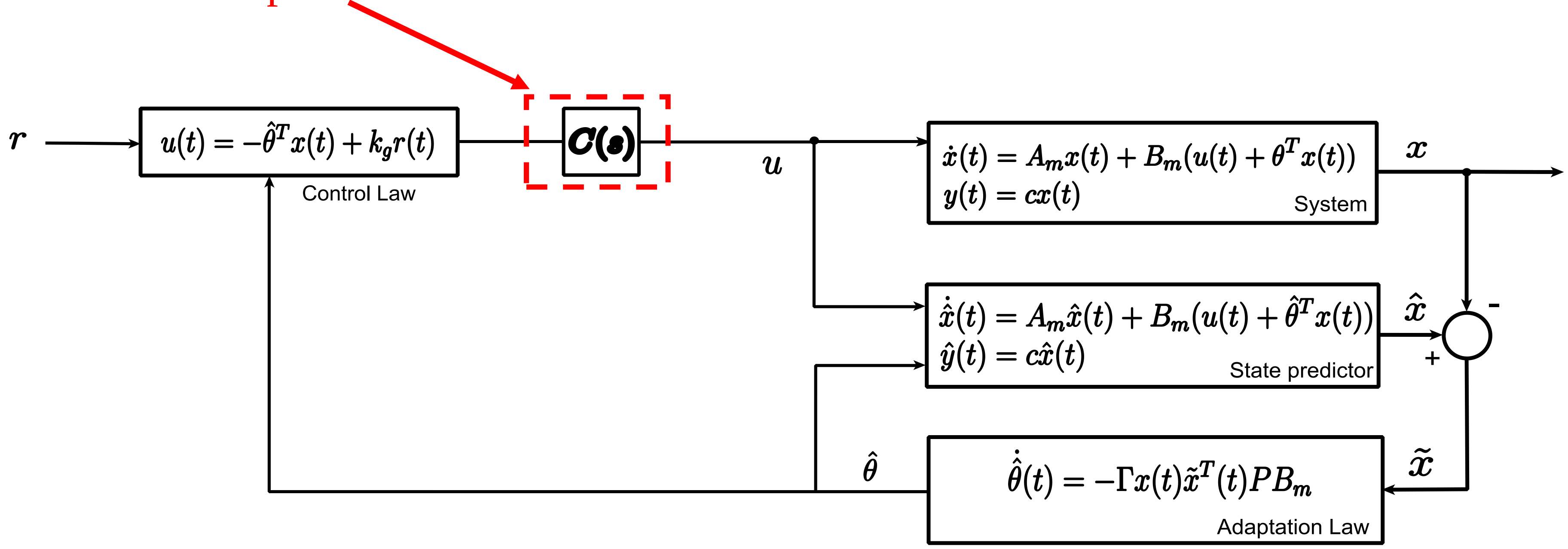
- ✓ Inspired by direct MRAC (Model Reference Adaptive Control)
- ✓ With a State predictor instead of the reference model



- ✓ The tracking error is replaced by the prediction error

L1 Adaptive control

- ✓ Inspired by direct MRAC (Model Reference Adaptive Control)
- ✓ With a State predictor instead of the reference model
- ✓ With low pass filter

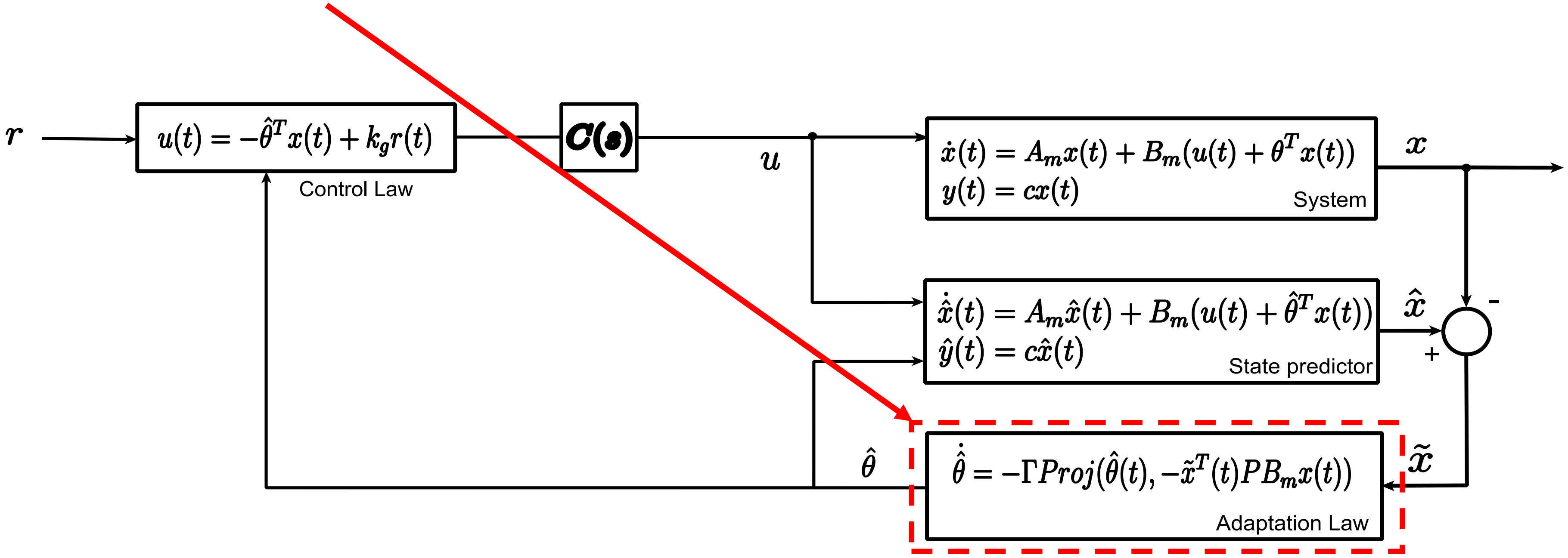


C(s) : is a stable and strictly proper transfer function

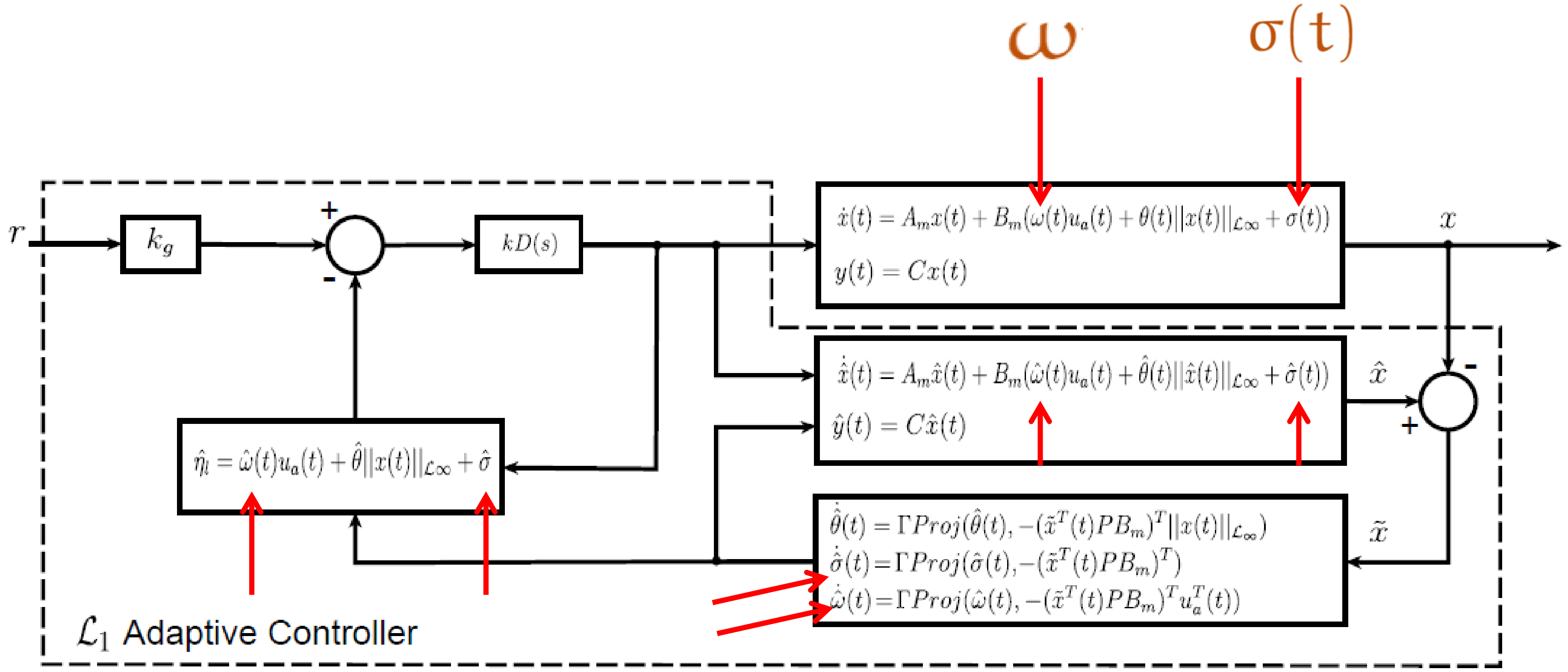
C(s) = 1 → Direct MRAC

L1 Adaptive control

- ✓ Inspired by direct MRAC (Model Reference Adaptive Control)
- ✓ With a State predictor instead of the reference model
- ✓ With a low pass filter
- ✓ With a projection operator to bound the estimated parameters



Case of Multi-Input Multi-Output form with 2 additional parameters to estimates



Motivation : Time lag limitation

Consider the following system [Hovakimyan 2010]

$$\dot{x}(t) = Ax(t) + B\big(u(t) + \theta(t)^T x(t)\big) \quad , \quad x(0) = x_0$$
$$y(t) = Cx(t)$$

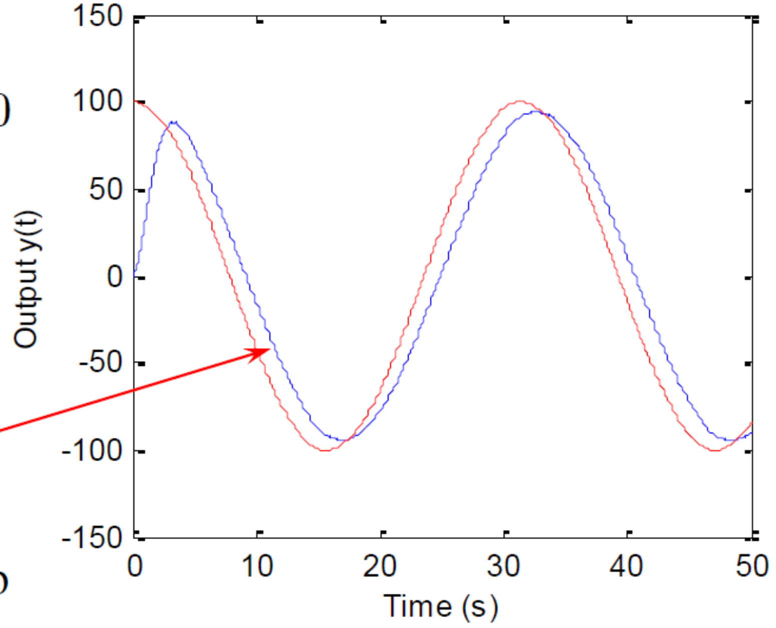
$$A = \begin{bmatrix} 0 & 1 \\ -1 & -1.4 \end{bmatrix} \; ; \; B = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \; ; \; C = \begin{bmatrix} 1 & 0 \end{bmatrix} \; ; \; \theta = \begin{bmatrix} 4 \\ -4.5 \end{bmatrix}$$

The proposed design parameters are the following:

$$C(s) = \frac{\omega k D(s)}{1+\omega k D(s)} = \frac{160}{s+160} \; , \; \Gamma = 10000 \; , \; k_m = 0$$

For a bounded reference trajectory to be tracked :

$$r(t) = 100\cos(0.2t)$$

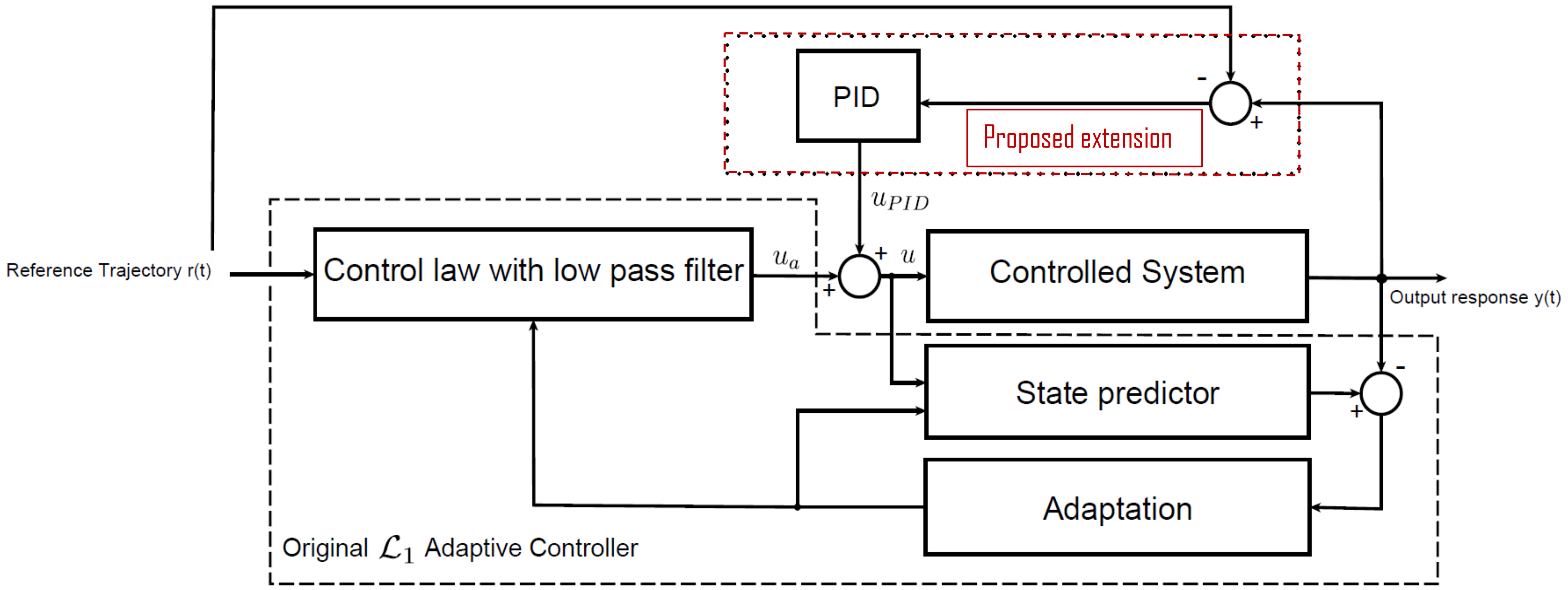


A time lag in the tracking is noticed

Due to the presence of the filter in the control loop

Augmented L1 Adaptive control

Proposed solution : Basic idea



The new control law in this case : $u = u_a + u_m + u_{PID}$

- The adaptive term (u_a)
- The state-feedback term (u_m)
- The proposed extension term (u_{PID})

First validation : Back to the example

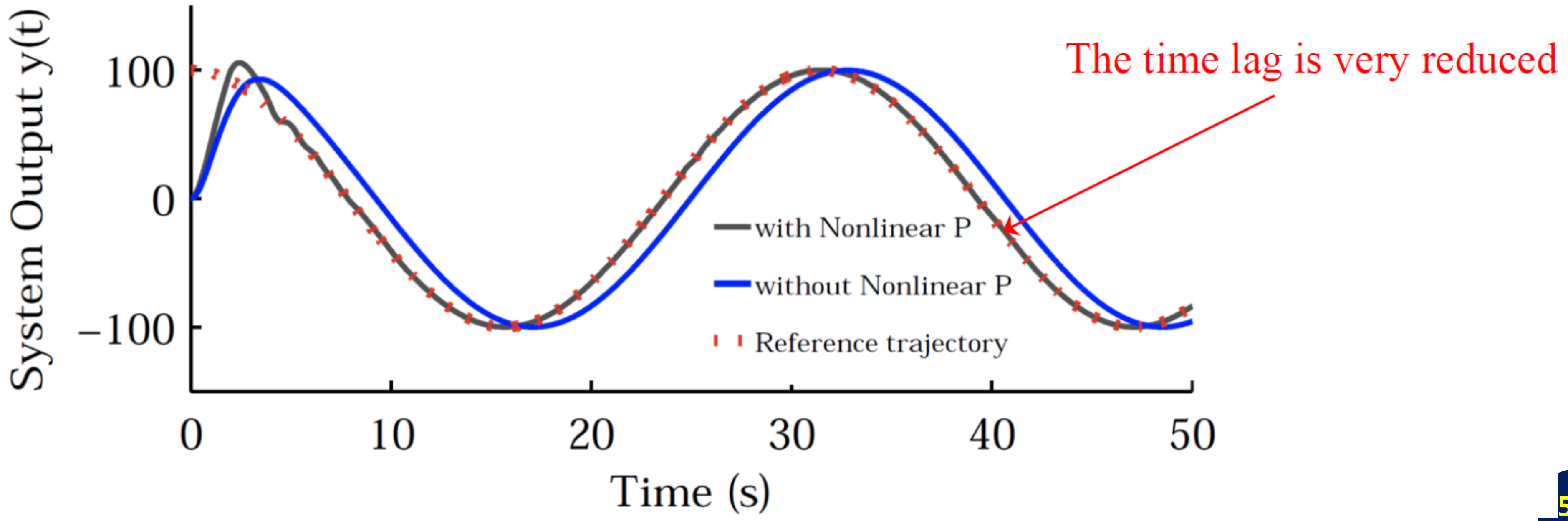
The proposed design parameters are the same:

$$C(s) = \frac{160}{s+160} \quad , \quad \Gamma = 10000 \quad , \quad k_m = 0$$

The same reference trajectory to be tracked :

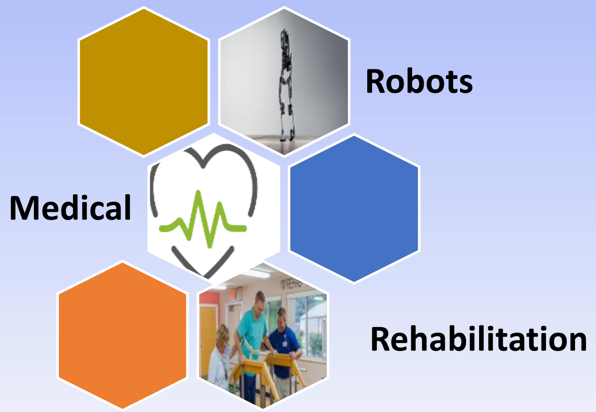
$$r = 100\cos(0.2t)$$

The obtained tracking for both controllers :



Speaker : **A. CHEMORI**

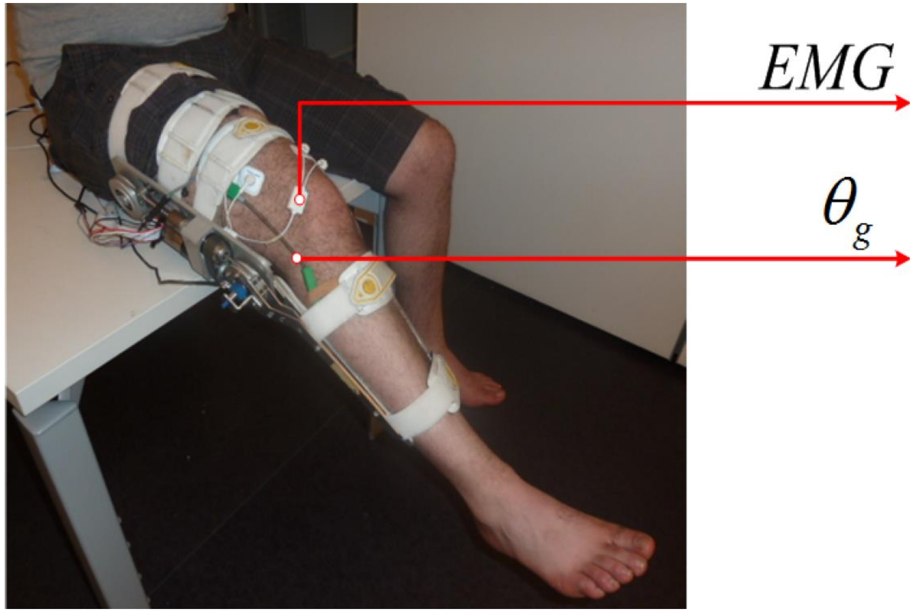
Experimental results
L1 Adaptive



Real-time experimental results

Some experimental issues

- ✓ Performed on a healthy male subject,
- ✓ 23 years old,
- ✓ Weighing 65 Kg, and
- ✓ Measuring 178 cm



EMG electrodes are used :

- ✓ At the **rectus femoris** (RF) acting as a quandriceps muscle and the **biceps femoris** long head (BF) acting as hamstring muscle
- ✓ The EMG measurements are presented only to show the muscles activity and are not used in the control law

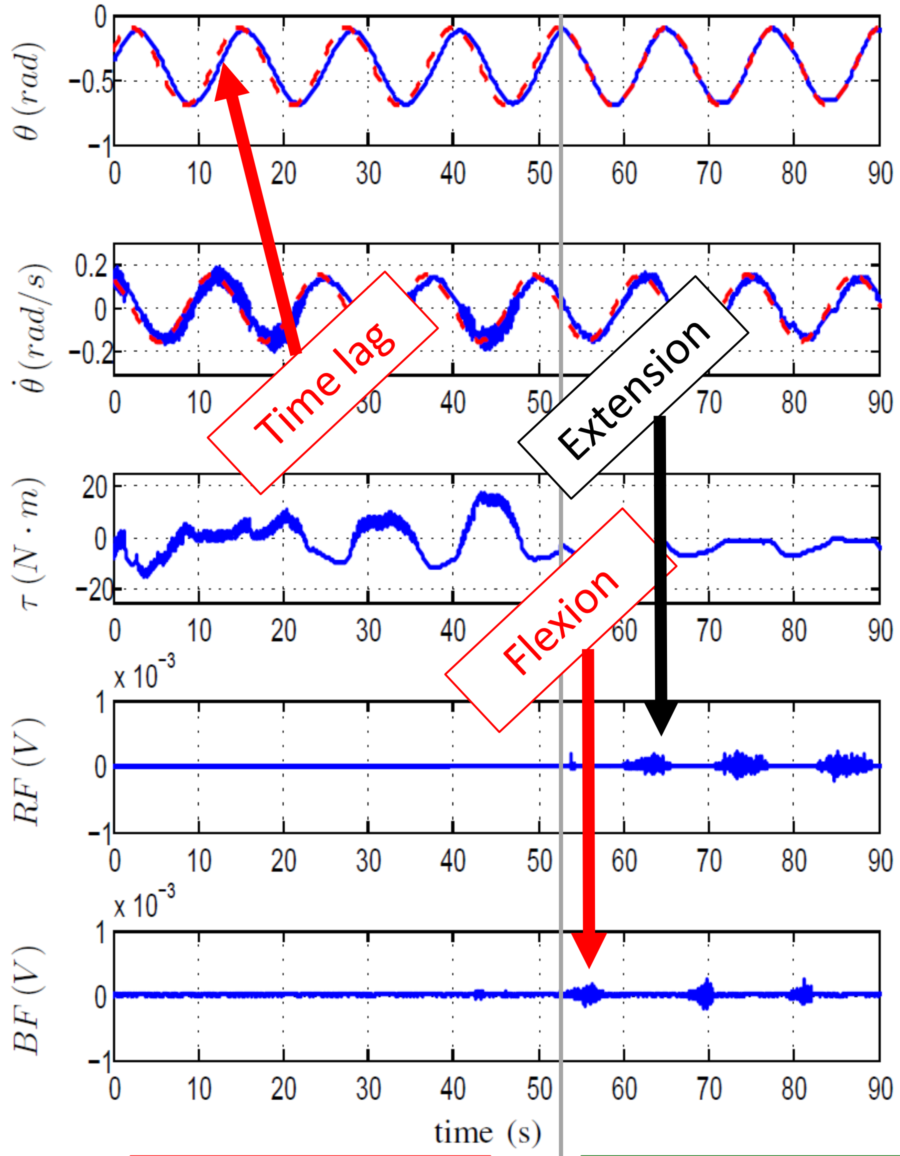
Some experimental issues

- ✓ All the estimated parameters have been initialized to zero
- ✓ The parameters of the state feedback are taken as: $k_{m1} = 1$ and $k_{m2} = 1{,}4$
- ✓ **Classical** and **augmented L1** adaptive control laws are compared

Three case studies have been performed :

- ✓ **Scenario 1** : Passive rehabilitation
- ✓ **Scenario 2** : Assistance as needed
- ✓ **Scenario 3** : Resistive rehabilitation

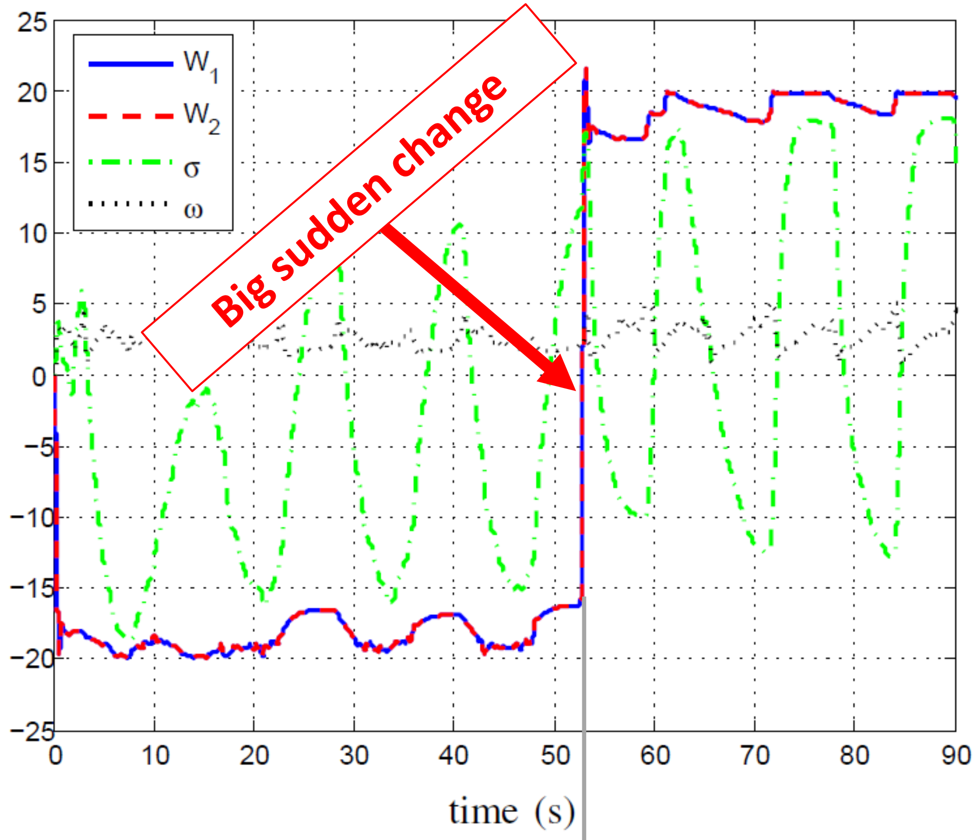
Real-time experimental results



Passive wearer | Active wearer

Scenario 2 : Assistance as needed

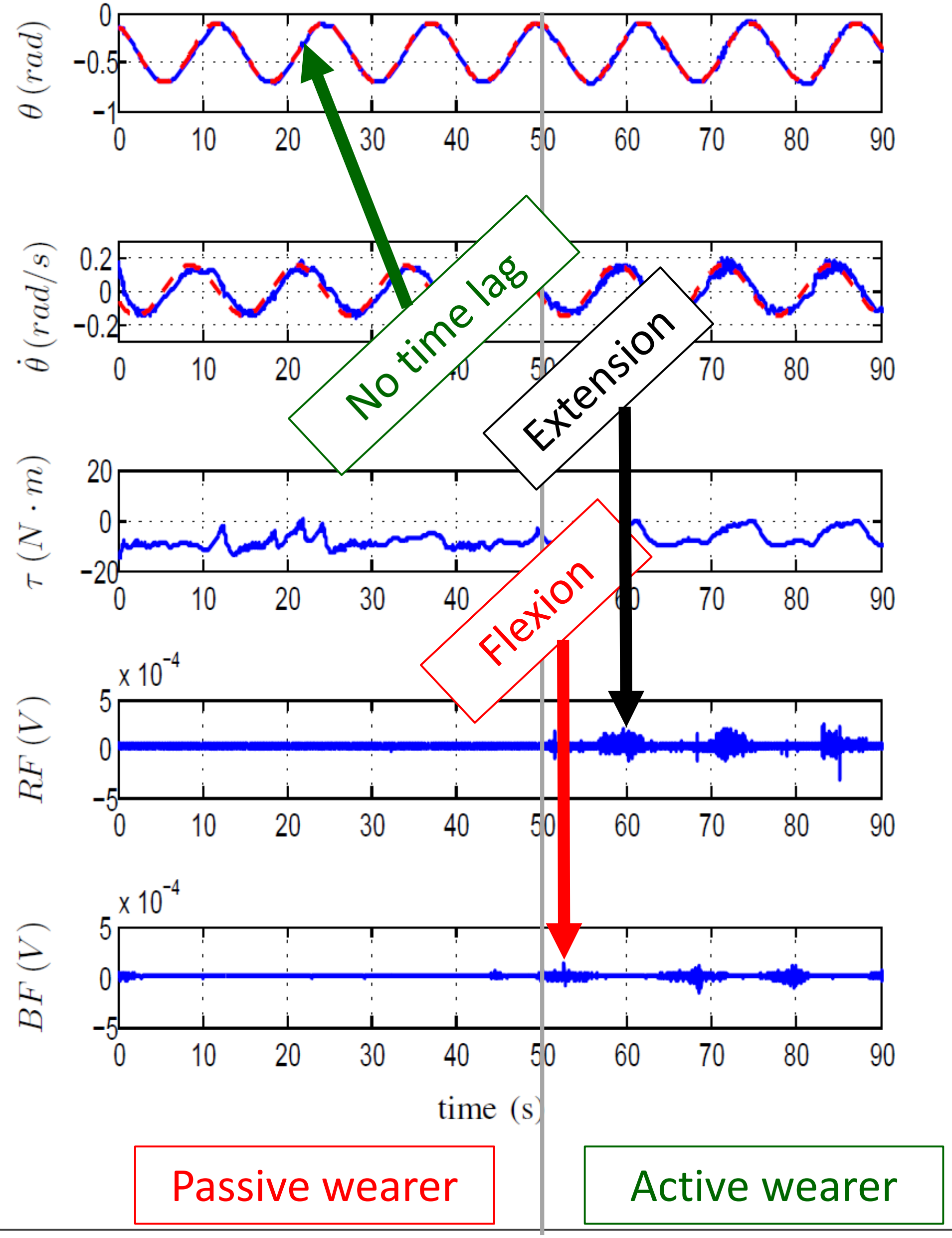
L1 adaptive control



Passive wearer | Active wearer

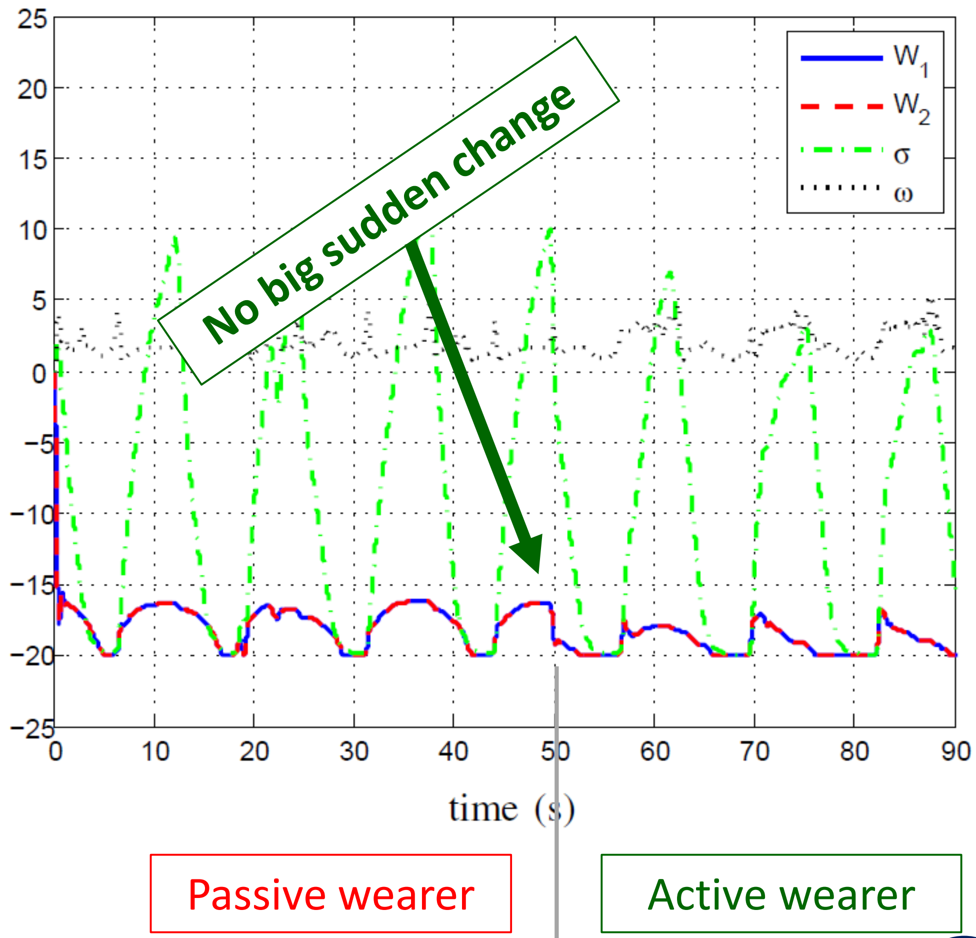
Speaker : **A. CHEMORI**

Real-time experimental results

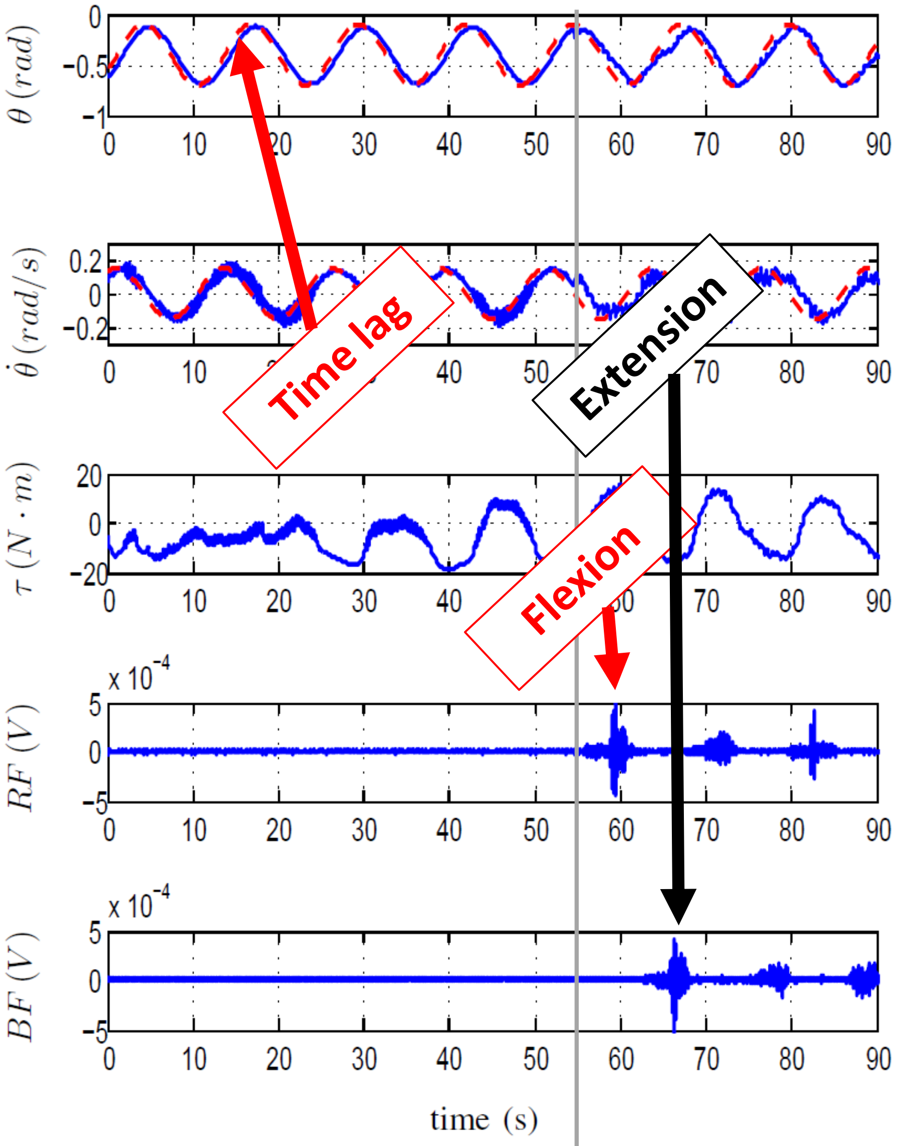


Scenario 2 : Assistance as needed

Augmented L1 adaptive control



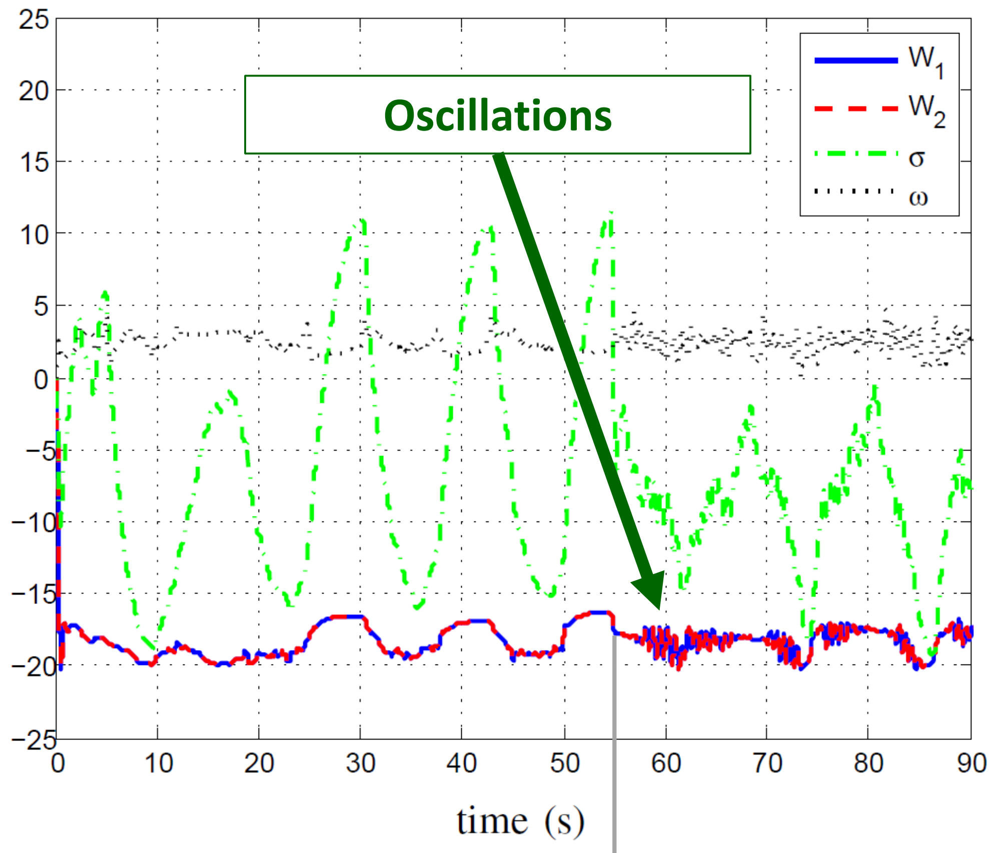
Real-time experimental results



Passive wearer
Active wearer

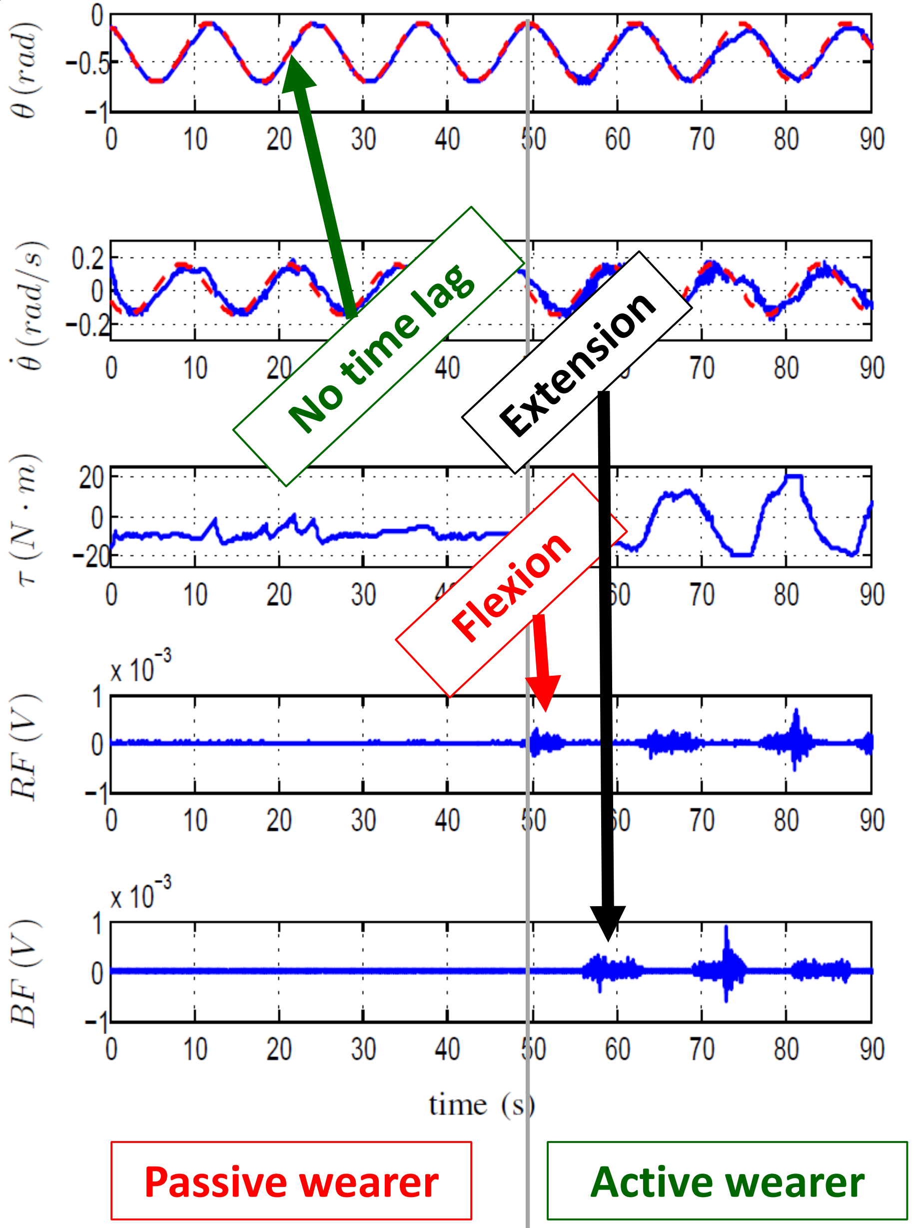
Scenario 3 : Resistive rehabilitation

L1 adaptive control



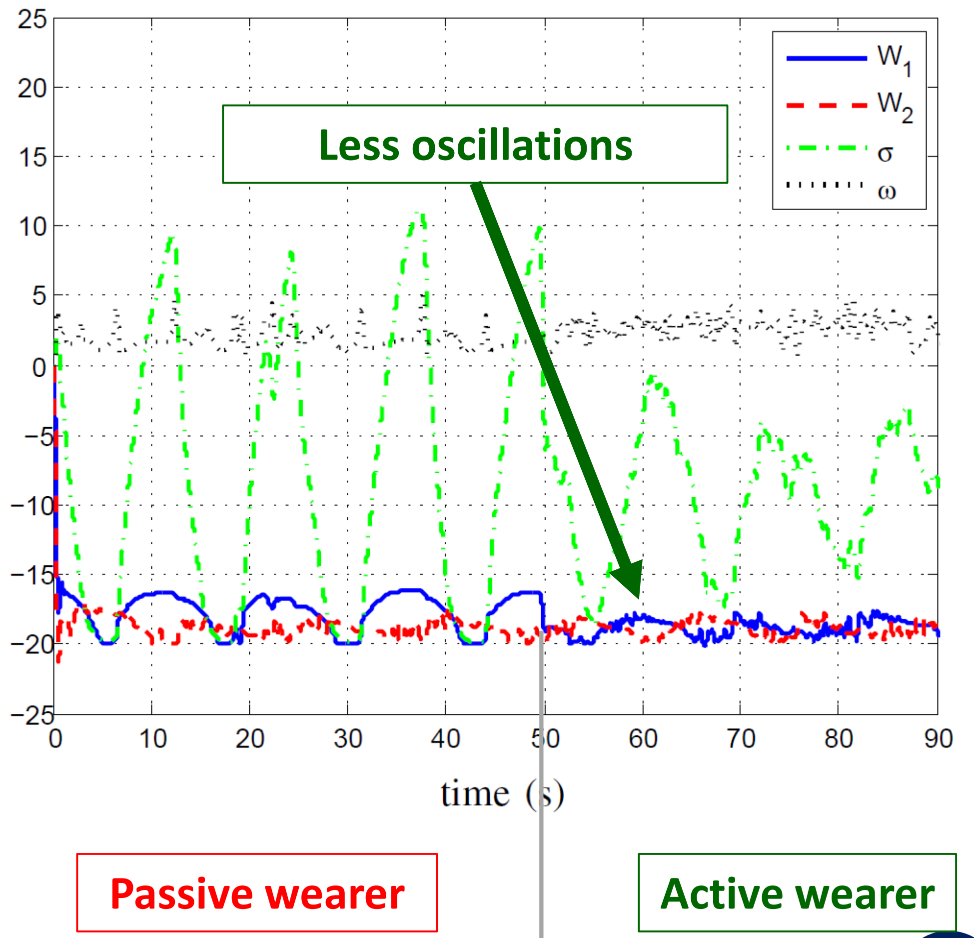
Passive wearer
Active wearer

Real-time experimental results



Scenario 3 : Resistive rehabilitation

Augmented L1 adaptive control



Speaker : A. CHEMORI

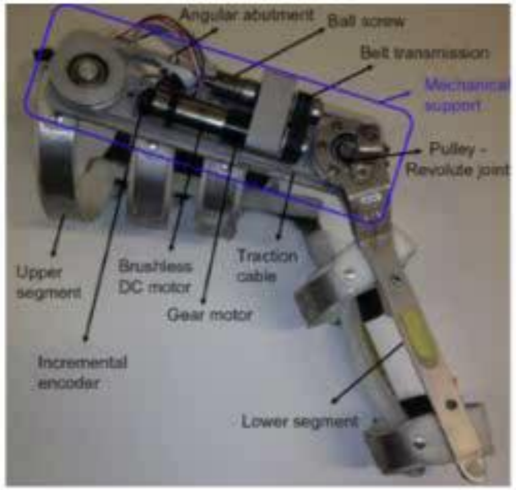
Real-time experimental results

LISSI UPEC — LIRMM CNRS

Augmented L1 Adaptive Control of an Actuated Knee Joint Exoskeleton

- Real-Time Experimental results -

H. Rifai[1], M.S. Ben Abdessalem[1], A. Chemori[2], S. Mohammed[1] and Y. Amirat[1]

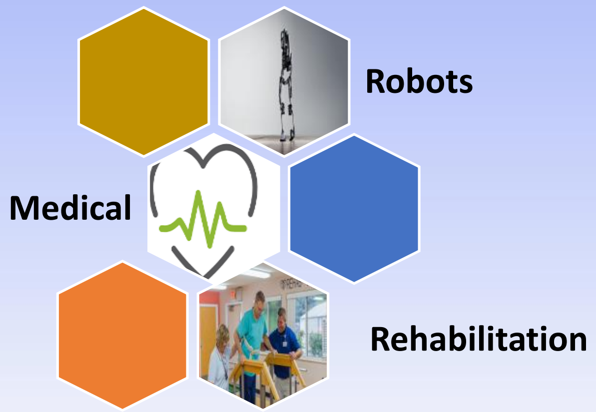


[1] **LISSI-lab**
Université de Paris-Est Créteil (UPEC)
122 rue Paul Armangot
94400 Vitry-Sur-Seine, France,

[2] **LIRMM** - UMR CNRS 5506
Université de Montpellier
161 rue Ada,
34095 Montpellier, France

[Rifai et al 2016] H. Rifai, M-S. Ben Abdessalem, A. Chemori, S. Mohammed and Y. Amirat, "Augmented L1 Adaptive Control of an Actuated Knee Joint Exoskeleton: From Design to Real-Time Experiments", IEEE ICRA'16, Stockholm, Sweden, 2016.

MPC – Based Control



Speaker : **A. CHEMORI**

Context

Definitions

Brief history

Prototypes

Controllers

Results

Conclusion

Speaker : **A. CHEMORI**

MPC based control

An Assistive Explicit Model Predictive Control Framework for a Knee Rehabilitation Exoskeleton

Ines Jammeli, Ahmed Chemori, *Senior Member, IEEE*, Huiseok Moon, Salwa Elloumi, and Samer Mohammed, *Senior Member, IEEE*

***Abstract*—This article focuses on the control of an actuated knee joint orthosis. The proposed solution is a novel model predictive control framework dedicated to assistive and rehabilitation purposes. This framework includes 1) an exact input-to-state feedback linearization, 2) a model predictive controller (MPC or EMPC), considering input/output constraints, 3) a least-squares dynamic parameters identification, 4) a nonlinear disturbance observer for the estimation of the wearer's torque, 5) a Lyapunov-based stability analysis of the resulting closed-loop system, and 6) a reference trajectory generator. The proposed framework has been validated via real-time experiments performed on three healthy subjects wearing the knee joint orthosis. Various experimental scenarios have been considered, including assistive and resistive rehabilitation tasks in a sitting position and walking with normal/abnormal gait patterns. The obtained results indicate the efficiency of the proposed predictive controllers with respect to a conventional proportional-integral-derivative (PID) controller in terms of tracking performance, required torque, and wearer comfort.**

***Index Terms*—Assistive robotics, knee joint powered orthosis, model predictive control (MPC), rehabilitation.**

I. Introduction

WITH recent medical advances, life expectancy increases steadily. According to the World Health Organization, the world population aged 60 years and older is expected to reach a total of 2 billion by 2050; however, it was approximately 900 million in 2015. This population is exposed to health risks caused by weakened muscle strength, which hinders their ability to walk as frequently as normal and adversely affects their walking stability, thereby making them dependent on others. Consequently, the aging of the population and the physical deterioration of the elderly have become a global socioeconomic problem [1]. This issue calls for considerable attention on how to assist this population, as well as people with lower and/or upper-limb pathologies in their daily life, especially regarding mobility and autonomy [2].

One of the best remedies for reduced mobility is rehabilitation. Conventional intensive therapies are usually adopted in clinical centers to help people recover their voluntary movements. However, the problem with these therapies is that they are only effective when they are intensive [3]. Furthermore, repetition is a key element in this case, which allows the brain to reprogram the motion sequence. Therefore, this process is time and capital intensive, and requires the strength of both the patient and therapist. However, intensive long-term rehabilitation therapy is not always an option owing to its expensive cost, and the insufficiency of qualified staff.

To reduce the burden on care services, several initiatives have been set up to promote assistive technologies, such as the promising technologies based on wearable robots. These devices are mechatronic systems, equipped with sensors and actuators, and embodied by the human upper and/or lower-limbs, which provide the following functions: 1) augmenting physical human capabilities at upper/lower-limbs, 2) assisting people with reduced mobility for achieving daily living activities, and 3) automating the rehabilitation of human joints and muscles to recover and improve the control of the wearer's limbs [4]. This considerable focus on wearable robots can be explained by their ability to reproduce repetitive tasks that require strength and robustness. They can autonomously perform these tasks faster than therapists, with a better level of accuracy, without getting tired, and without requiring a third party. Hence, they may promote a reduction in patient fatigue. They enable long training sessions with optimal consistency, as well as measurements for the user to track the desired gait patterns, which may help to accelerate the rehabilitation process [5].

Sitting and standing up movements are essential for most human activities. Given their importance, several wearable robots have been developed to help weakened people perform these movements. Shepherd *et al.* [6] designed a knee exoskeleton

Manuscript received January 26, 2021; revised July 1, 2021 and October 24, 2021; accepted November 3, 2021. Recommended by Technical Editor J. A. Schultz and Senior Editor M. BASIN. *(Corresponding author: Ahmed Chemori.)*

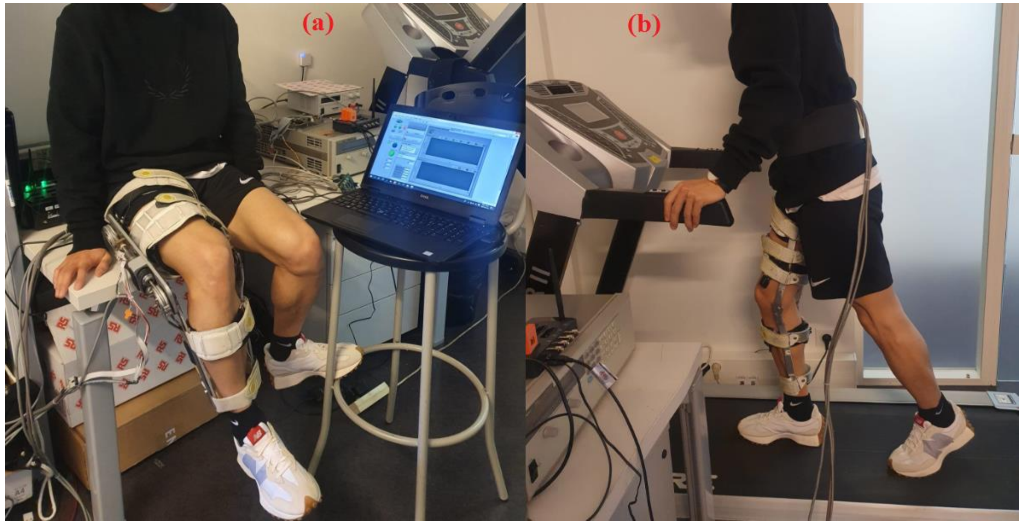
Ines Jammeli and Salwa Elloumi are with the LSA, Polytechnic School of Tunisia, University of Carthage, Tunis 1054, Tunisia (e-mail: jammeli.ines@gmail.com; salwa.elloumi@gmail.com).

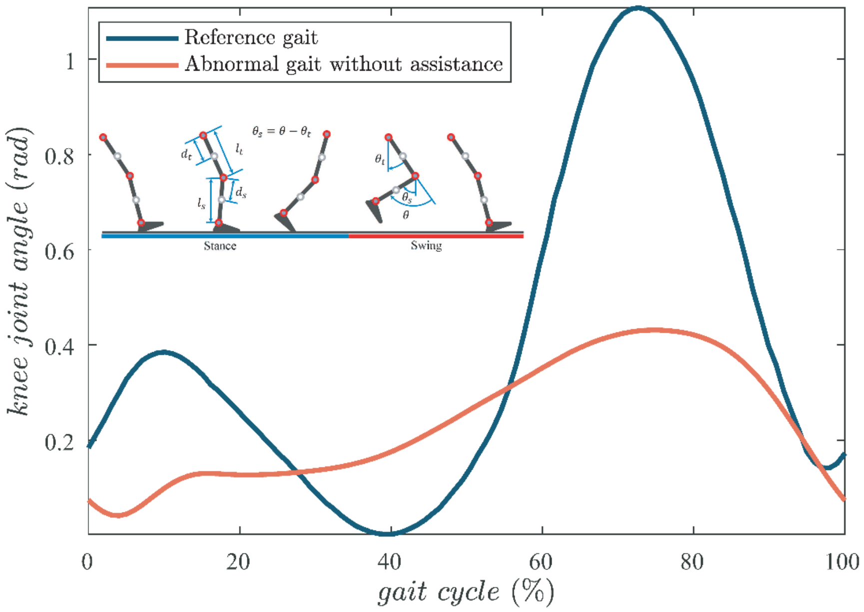
Ahmed Chemori is with the LIRMM - Laboratoire d'informatique, de Robotique et de microélectronique de Montpellier, Centre National de la Recherche Scientifique, University of Montpellier, 34000 Montpellier, France (e-mail: ahmed.chemori@lirmm.fr).

Huiseok Moon and Samer Mohammed are with the Univ Paris Est Creteil, LISSI, F-94400 Vitry, France (e-mail: huiseok.moon@paris-est-sup.fr; samer.mohammed@u-pec.fr).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TMECH.2021.3126674.

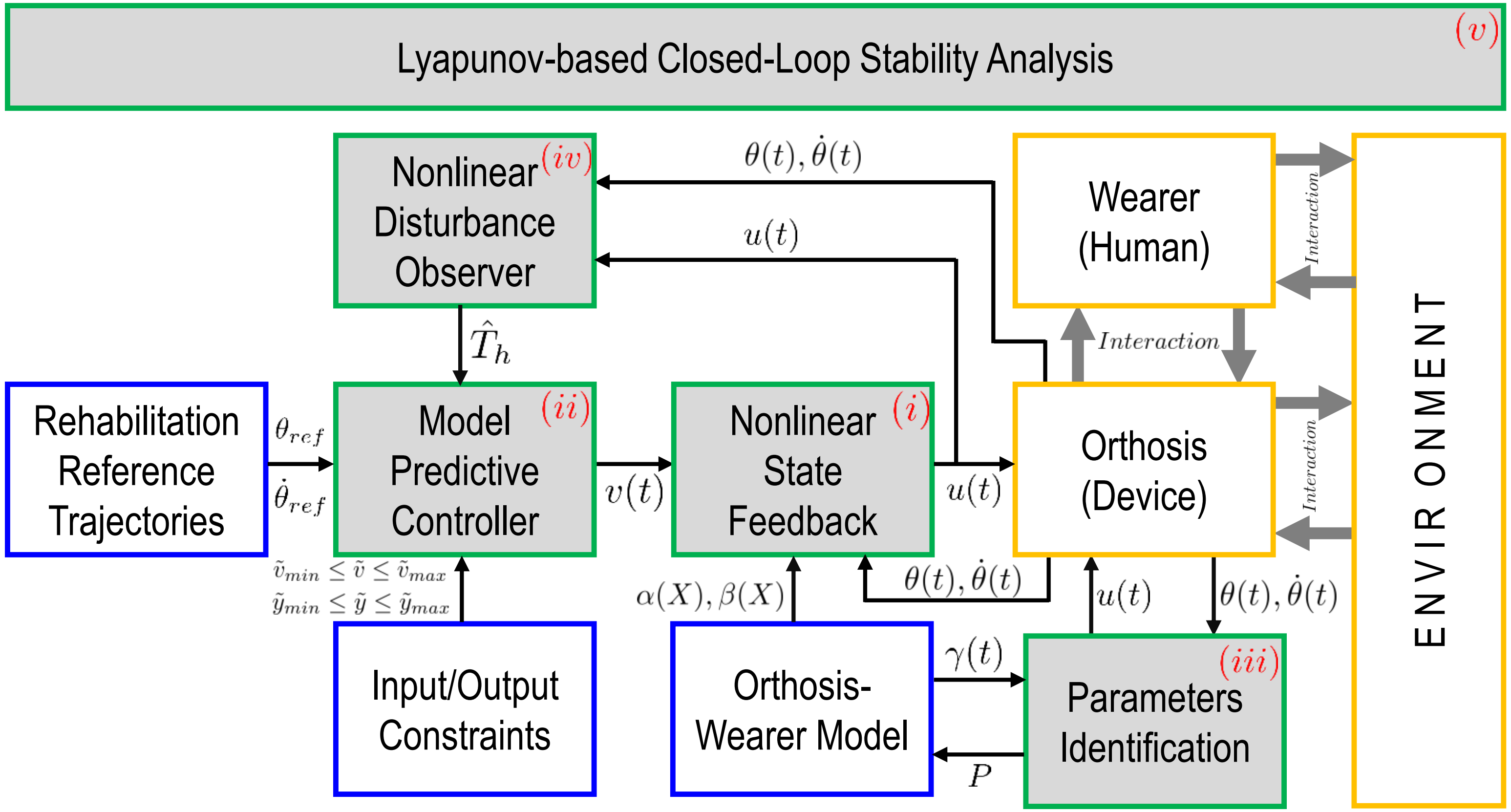
Digital Object Identifier 10.1109/TMECH.2021.3126674





Context
Definitions
Brief history
Prototypes
Controllers
Results
Conclusion

Proposed MPC-Based control framework



Speaker : **A. CHEMORI**

Identification of dynamic parameters

(iii) Parameters Identification

- ✓ The subject wear the exoskeleton, stay passive in a sitting position
- ✓ The human-orthosis is considered to be a single system
- ✓ Its inverse dynamic model can be represented as:

$$\tau_e = J\ddot{\theta} - T_g \cos(\theta) + ASign(\dot{\theta}) + B\dot{\theta}$$

- ✓ Which can be rewritten in an affine in the parameters as follows:

$$\tau_e(t) = \begin{bmatrix} -\cos(\theta(t)) & Sign(\dot{\theta}(t)) & \dot{\theta}(t) & \ddot{\theta}(t) \end{bmatrix} \begin{pmatrix} T_g \\ A \\ B \\ J \end{pmatrix}$$

$$= \gamma^T(t) P$$

- ✓ A least square method is used

Parameter	Symbol	S1	S2	S3
Static friction coefficient $(N.m)$	A	2.0082	1.2067	0.7613
Viscous friction coefficient $N.m.s.rad^{-1}$	B	1.713	3.238	2.4539
Inertia $Kg.m^2$	J	0.4325	0.2594	0.2525
Gravity torque $(N.m)$	T_g	9.4199	10.4741	3.4379

Speaker : A. CHEMORI

Input-to-state feedback linearization

Nonlinear State Feedback $^{(i)}$

- ✓ Let us consider the nonlinear state feedback:

$$\tau_e = \alpha(X) + \beta(X)v$$

- ✓ For the sitting position, we set:

$$\begin{cases} \alpha(X) = -T_g \cos(\theta) + ASign(\dot{\theta}) + B(\dot{\theta}) - \tau_h \\ \beta(X) = J \\ X = [x_1 \ x_2]^T = [\theta \ \dot{\theta}]^T \end{cases}$$

- ✓ Then the resulting nonlinear state feedback writes:

$$\tau_e(t) = -T_g \cos(\theta) + ASign(\dot{\theta}) + B(\dot{\theta}) - \tau_h + Jv.$$

- ✓ For the standing position, we set:

$$\begin{cases} \alpha(X) = T_g \sin(\theta - \theta_t) + ASign(\dot{\theta}) + B(\dot{\theta}) - \tau_h + \tau_l \\ \beta(X) = J \\ X = [x_1 \ x_2]^T = [\theta \ \dot{\theta}]^T \end{cases}$$

- ✓ Then the resulting nonlinear state feedback writes:

$$\tau_e(t) = T_g \sin(\theta - \theta_t) + ASign(\dot{\theta}) + B(\dot{\theta}) - \tau_h + \tau_l + Jv \qquad (1)$$

Input-to-state feedback linearization

Nonlinear State Feedback (i)

- ✓ The nonlinear state feedback, replaced in the orthosis dynamics leads to:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = v \\ y = x_1 \end{cases}$$

- ✓ The discretization of the resulting linear dynamics using Euler's method leads to :

$$\begin{cases} \tilde{X}(k+1) = A\tilde{X}(k) + B\tilde{v}(k) \\ \tilde{y}(k) = C\tilde{x}(k) \end{cases}$$

- ✓ With:

$$A = \begin{pmatrix} 1 & T_s \\ 0 & 1 \end{pmatrix}, \; B = \begin{pmatrix} 0 \\ T_s \end{pmatrix} \; , \text{and} \quad C = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

- ✓ The proposed MPC controller is designed based on this dynamics.

Speaker : **A. CHEMORI**

MPC based control

Proposed MPC controller

Model Predictive Controller (ii)

✓ The associated optimization problem can be expressed as:

$$V(k) = min(\tfrac{1}{2}\tilde{v}_{\to k}^{T} H \tilde{v}_{\to k} + \tilde{X}(k)^T F \tilde{v}_{\to k}) + \tfrac{1}{2}\tilde{X}(k)^T Y \tilde{X}(k)$$

$$\begin{cases} \text{s.t} \quad \theta_{min} \leq \theta(k+i) \leq \theta_{max} \quad \text{for} \quad i = 1..N_c \\ \dot{\theta}_{min} \leq \dot{\theta}(k+i) \leq \dot{\theta}_{max} \quad \text{for} \quad i = 1..N_c \\ \tilde{v}_{min} \leq \tilde{v}(k+i) \leq \tilde{v}_{max} \quad \text{for} \quad i = 1..N_c \\ \tilde{X}(0) = \tilde{X}(k) \\ \tilde{X}(k+i+1) = A\tilde{X}(k+i) + B\tilde{v}(k+i) \;\; \text{for} \;\; k \geq 0 \\ \tilde{y}(k+i) = C\tilde{X}(k+i) \quad \text{for} \quad k \geq 0 \end{cases}$$

✓ Iterating the discrete dynamics over the prediction horizon gives:

$$\begin{pmatrix} \tilde{X}(k+1) \\ \tilde{X}(k+2) \\ \vdots \\ \tilde{X}(k+N) \end{pmatrix} = \begin{pmatrix} A \\ A^2 \\ \vdots \\ A^N \end{pmatrix} \tilde{X}(k) + \begin{pmatrix} B & 0 & \cdots & 0 \\ AB & B & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ A^{N-1}B & \cdots & AB & B \end{pmatrix} \begin{pmatrix} \tilde{v}(k) \\ \tilde{v}(k+1) \\ \vdots \\ \tilde{v}(k+N-1) \end{pmatrix}$$

MPC based control

Proposed MPC controller

Model Predictive Controller (ii)

- ✓ Let us now consider the following cost function:

$$V(k) = \sum_{i=0}^{N-1} (\| \tilde{X}(k+i) \|_Q^2 + \| \tilde{v}(k+i) \|_R^2) + \tilde{X}(k+N)^T Q_f(N) \tilde{X}(k+N)$$

- ✓ Which can be rewritten in the following compact form:

$$V(k) = \sum_{i=0}^{N-1} l(\tilde{X}(k+i), \tilde{v}(k+i)) + F(\tilde{X}(k+N))$$

- ✓ By substituting $\tilde{X}(k+i) = A^i \tilde{X}(k) + \sum_{j=0}^{i-1} A^j B \tilde{v}_{k+i-1-j}$ in the previous costs yields:

$$\begin{cases} V(k) = min(\frac{1}{2}\tilde{v}_{\to k}^T H \tilde{v}_{\to k} + \tilde{X}(k)^T F \tilde{v}_{\to k}) \\ \quad + \frac{1}{2}\tilde{X}(k)^T Y \tilde{X}(k) \\ \text{s.t} \;\; G\tilde{v}_{\to k} \leq W + E\tilde{X}(k) \end{cases}$$

- ✓ The solution is obtained by zeroing $grad_{\tilde{v}_{\to k}} V(k)$

Nonlinear$^{(iv)}$ Disturbance Observer

Nonlinear Disturbance observer

- ✓ In typical rehabilitation scenarios, when the wearer is asked to develop a muscle activation, the human torque is considered an external disturbance
- ✓ We propose an NDO to estimate its values
- ✓ The dynamics of the system can be rewritten as follows:

$$\dot{X} = F_1(X) + G_1(X)\tau_e + G_2(X)d$$

- ✓ Where:

$$G_1(X) = G_2(X) = \begin{pmatrix} 0 \\ \frac{1}{J} \end{pmatrix}$$

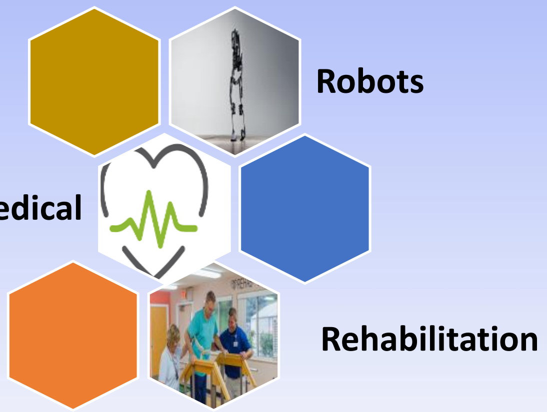
- ✓ The proposed nonlinear observer is designed as follows:

$$\begin{cases} \hat{d} = z + p(X) \\ \dot{z} = L(-F_1(X) - G_1(X)\tau_e - G_2(X)(z + p(X))) \end{cases}$$

- ✓ Where:

$$\hat{d} = \hat{\tau}_h, p(X) = k_1\theta + k_2\dot{\theta}, L = \frac{\partial p(X)}{\partial X} = (k_1 \; k_2)$$

Experimental results MPC



Speaker : **A. CHEMORI**

Real-time experimental results

LSA - SYSTEMES AVANCES
Laboratoire de Recheche - EPT

Video of the real-time experiments of the paper

An Assistive Explicit Model Predictive Control Framework for a Knee Rehabilitation Exoskeleton

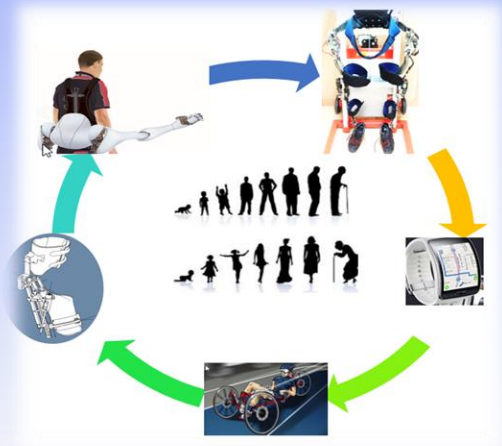
Submitted to : IEEE/ASME Transactions On Mechatronics

Ines Jammeli*, Ahmed Chemori** Senior Member, IEEE, Huiseok Moon***, Salwa Elloumi* and Samer Mohammed*** Senior Member, IEEE

* LSA, EPT, University of Carthage BP. 743, 2078 La Marsa, Tunis, Tunisia.
** University of Montpellier, CNRS, Montpellier, France
*** LISSI, EA 3956 – UPEC, 122 rue Paul Armangot, 94400 Vitry-Sur-Seine, France

[Jammeli et al 2021] I. Jammeli, A. Chemori, H. Moon, S. Elloumi and S. Mohammed,"An Assistive Explicit Model Predictive Control Framework for a Knee Rehabilitation Exoskeleton", IEEE/ASME Transactions on Mechatronics, DOI: 10.1109/TMECH.2021.3126674, 2021.

Conclusion



Conclusion

Problem

- Control of wearable robotic devices
- Those mechanical frames designed to be worn by humans
- For : **Civilian, work/industry, medical, military applications**

Challenges

- ✘ Deal with complex structures
- ✘ Uncertainties, nonlinearities, friction, …
- ✘ Interaction with the wearer (human)
- ✘ Safety aspects

Solutions

- ✓ Different advanced control schemes (linear and nonlinear)
- ✓ L1 Adaptive, MPC-Based control schemes

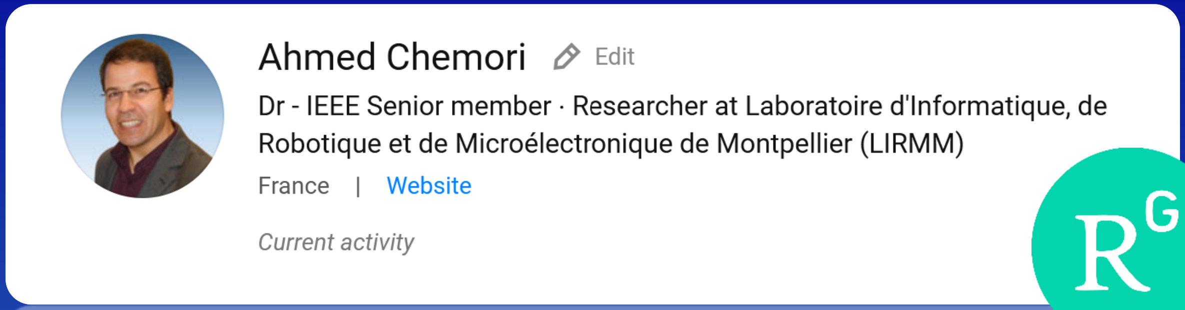
Validations

- ✓ Validation in simulation (different scenarios)
- ✓ Real-time experiments → EICOSI exoskeleton
- ✓ Rehabilitation applications

Speaker : **A. CHEMORI**

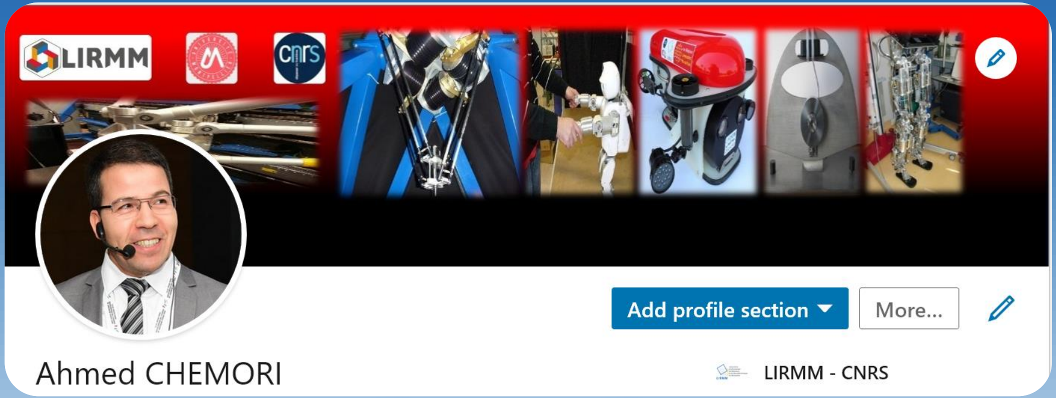
www.lirmm.fr/~chemori/

ResarchGate



Email : chemori@lirmm.fr

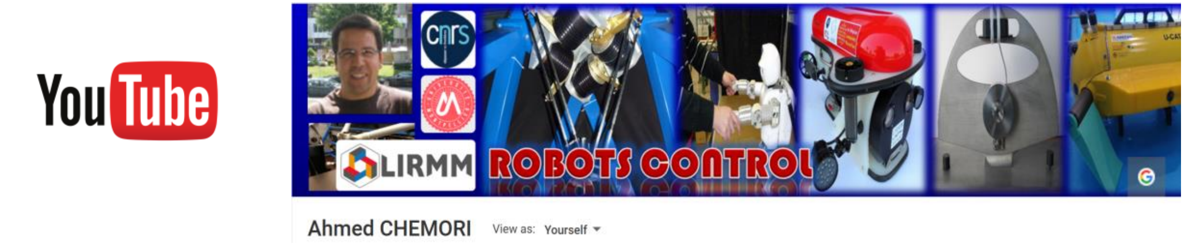
LinkedIn



More videos of experiments on :

Find more videos on Ahmed CHEMORI's YouTube channel:

Robot Control



Thank you for your attention ...