Patrick Hénaff

Contrôle bio-inspiré pour l'interaction humain/robot et l'apprentissage sensori-moteur

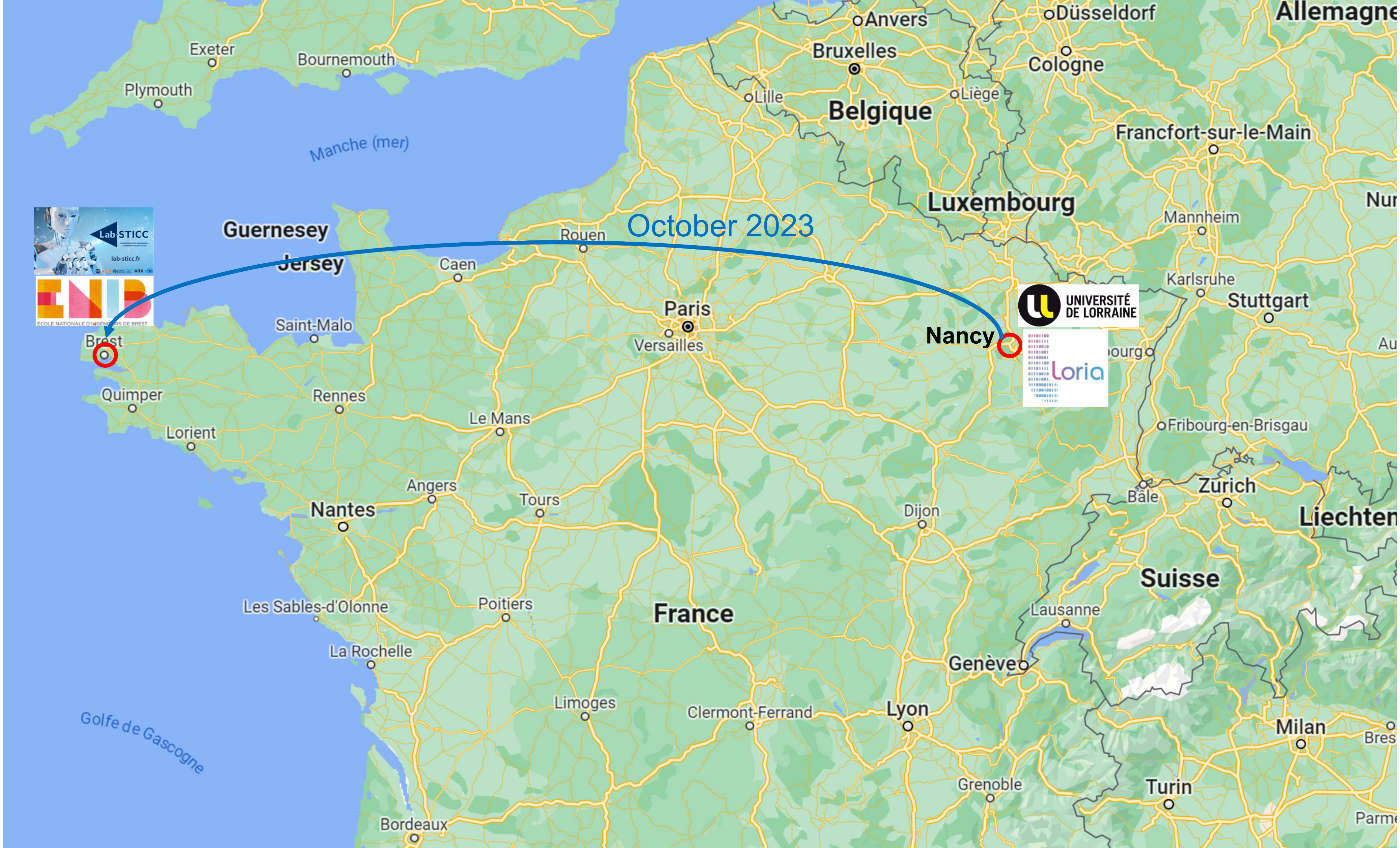
Compétences:

- Interaction humain/robot
- neuroscience computationnelle

ÉCOLE NATIONALE D'INGÉNIEURS DE BREST

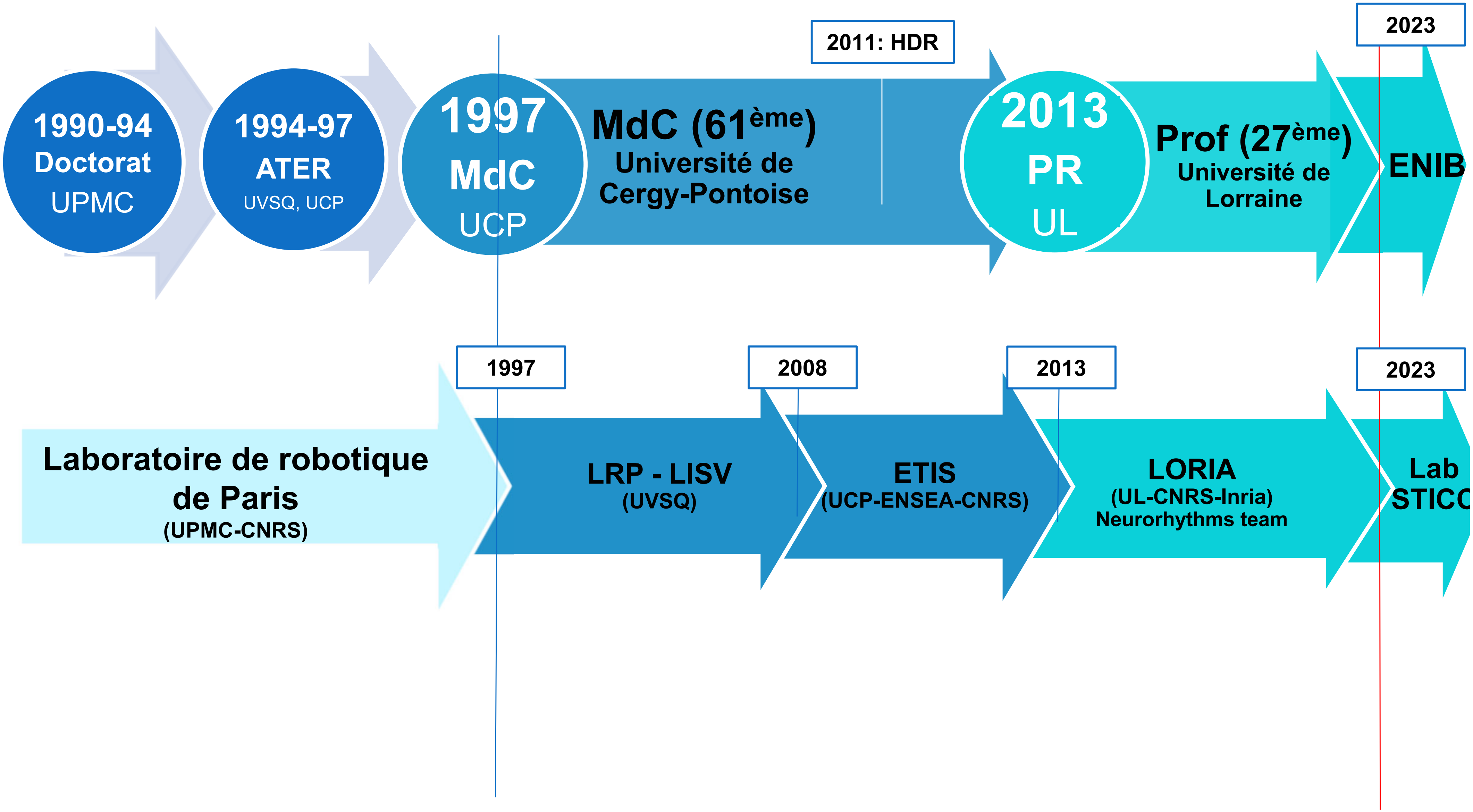
OUTLINE

- **Introduction my carrier**
- **Human rhythmic movements**
  - Interpersonal coordination
  - synchronization
- **Bio-inspired controller for rhythmic movements**
  - Central pattern generators (CPG)
  - Computational models of CPG
- **Experiments of learning motor coordination**
  - Waving back with a robot
  - Coordination of complex rhythmic movements
  - Discrete movements
- **Artificial empathy**
- **Medical & industrial applications**
- **Conclusion**



The work presented here was developed at the LORIA research center (UMRS CNRS - université de Lorraine-Inria), Nancy

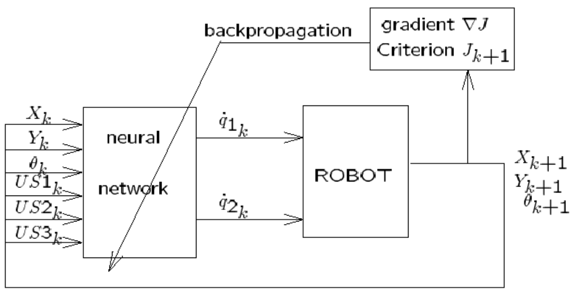
SYNTHÈSE DE MA CARRIÈRE (RECHERCHE)



POINT DE DÉPART : L'APPRENTISSAGE SENSORIMOTEUR INTERACTIF EN BOUCLE FERMÉE

APRENTISSAGE DE COMPORTEMENTS RÉACTIFS POUR LA ROBOTIQUE MOBILE

Neurocontrôleur = Perceptron + rétro-propagation



Apprentissage navigation

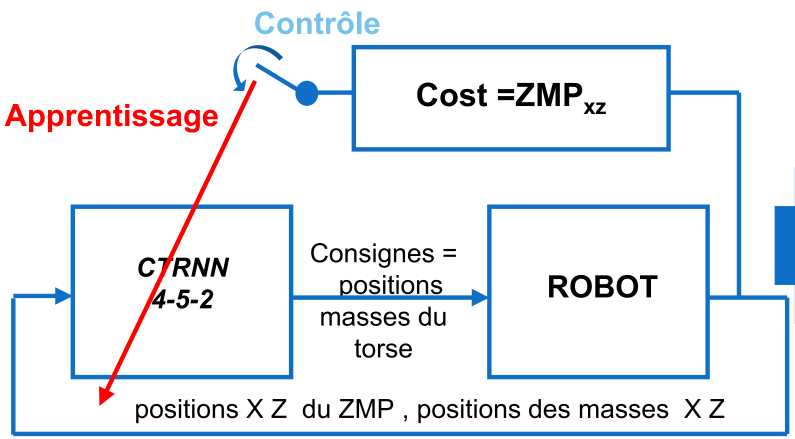
Apprentissage du réflexe

Test navigation + réflexe

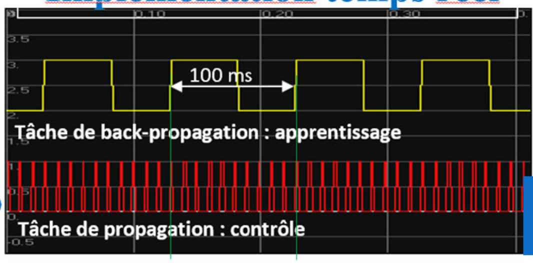
[Hénaff , 1997]

APPRENTISSAGE DE COMPORTEMENTS RÉACTIFS POUR LE CONTRÔLE POSTURAL D'UN ROBOT HUMANOÏDE

Neurocontrôleur = continous time recurrent NN+ rétro-propagation temporelle du gradient (BPTT)

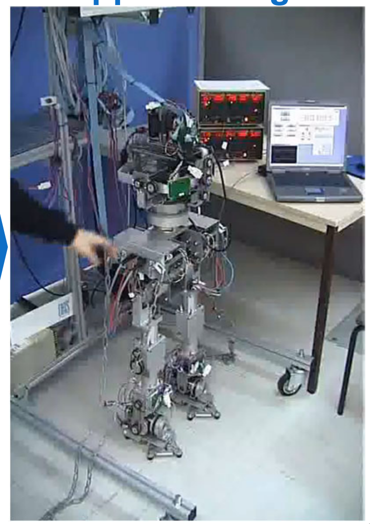


Implémentation temps réel

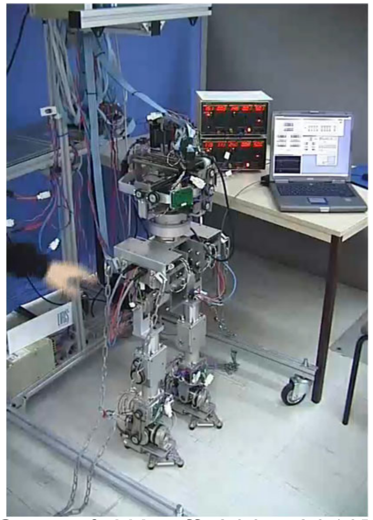


	Propagation	Backpropagation
Complexity	O(n²)	O(TW . n²)
Computational Time (n=10, TW=20)	2 ms	50 ms
Computational Time (n=14, TW=10)	3 ms	60 ms

Apprentissage



Test du contrôle



[Scesa & Hénaff 2005, 2010]

Apprentissage sensorimoteur pour l'interaction humain/robot ?

TRAVAUX DE RECHERCHE 2005-2013

Etude de contrôleurs neuronaux et des mécanismes d'apprentissage de la boucle sensorimotrice en robotique

LISV
Apprentissage pour le contrôle d'équilibre des bipèdes

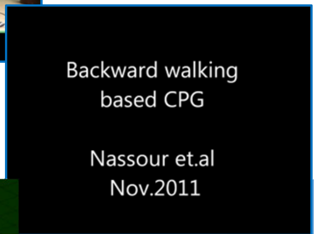
LISV/ETIS
Apprentissage de la marche bipède

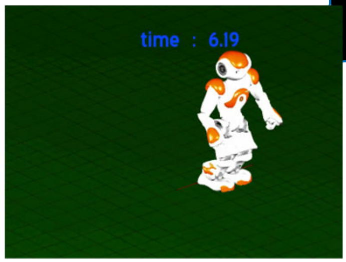
ETIS
Apprentissage d'interactions rythmiques

LISV
Synthèse évolutionniste de réseaux de neurones pour la locomotion

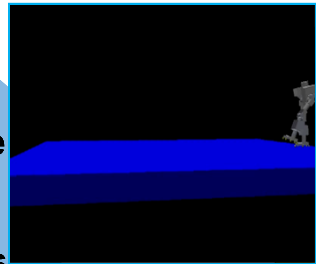
V. Scesa
2006

2011
J. Nassour

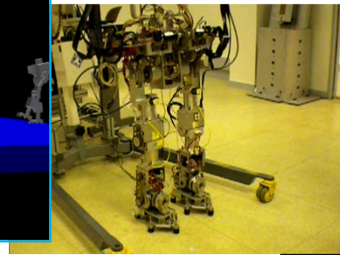




2013



H. Serhan
2009



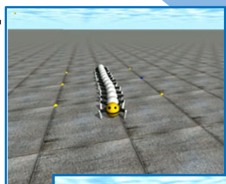
2011

S. Khomenko

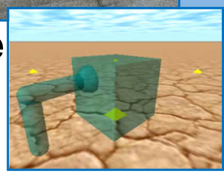
2013

A. Melnyk
2012

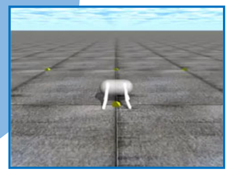
2007



T. Hoinville



2004



T. Hoinville
2005

IA BIO-INSPIRÉE ET APPRENTISSAGE SENSORIMOTEUR POUR L’INTERACTION (NON VERBALE) HUMAIN/ROBOT

HUMAN MOVEMENTS AND INTERPERSONNAL INTERACTIONS

- **Interactions and interpersonal coordinations are often based on rhythmic movements**
- **Rhythmic movements are very primitive and automatic**

Rhythmic movements and discret movements

Rhythmic movements

- Locomotion(walking, running)
- Cleaning, brushing, cooking
- Sports (basket)

Discrete movements

- Static (taking object)
- Dynamic (sport, basket)

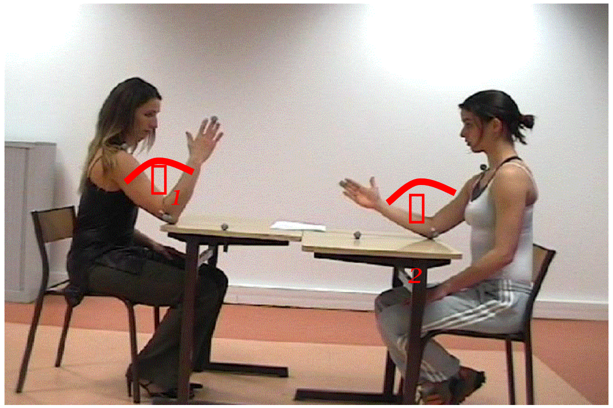
	Rhythmic movements	Discret movements
Upper limbs	« non regular »	« regular »
Lower limbs	« regular »	« non regular »

MAIN PROPERTIES IN INTERPERSONAL INTERACTIONS

Involuntary interpersonal coordination

Phenomenon of emergence of coordination is so powerful that humans can not avoid involuntary dyadic motor coordination

Compromise between movement control and interaction



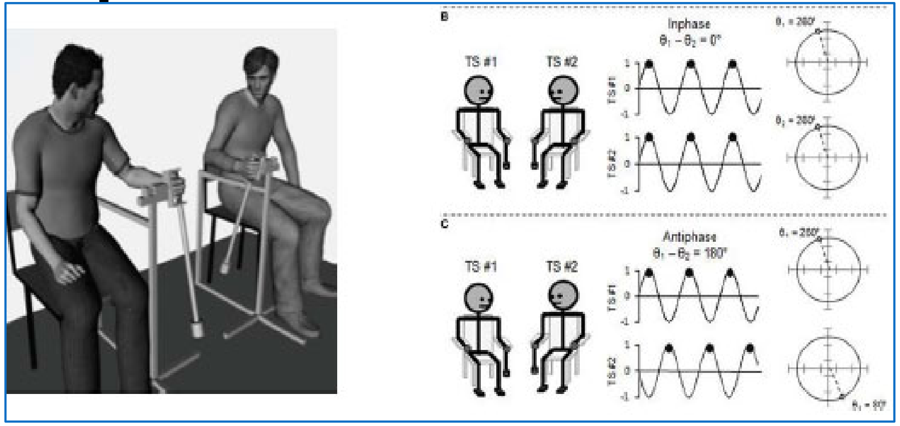
An interaction is always based on **two main aspects**:

- The individual part of each participant
- The share of the coupling in the pair of individuals

➡ **interpersonal coordination is based on synchronization of movements**

WHAT IS SYNCHRONIZATION OF MOVEMENTS?

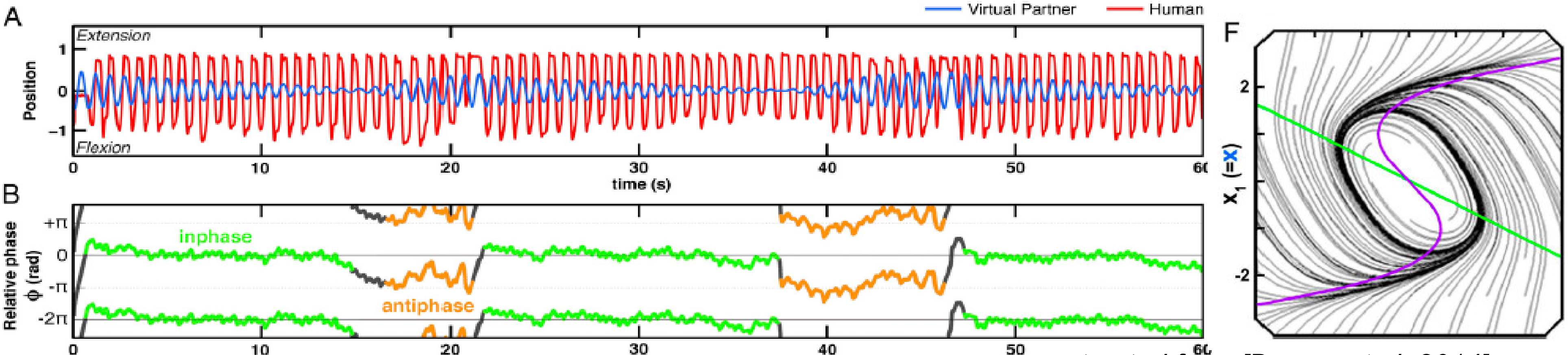
Interpersonal/Interlimb coordination via visual perception



extracted from [Richardson et al, 2007]

Two spontaneously stable coordination patterns appear naturally :
- in-phase (0°)
- anti-phase (180°)

The human dynamic clamp as a paradigm for social interaction

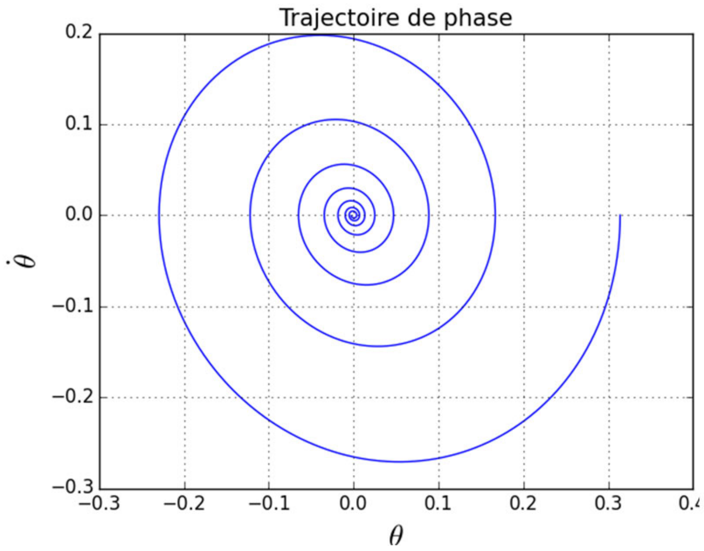


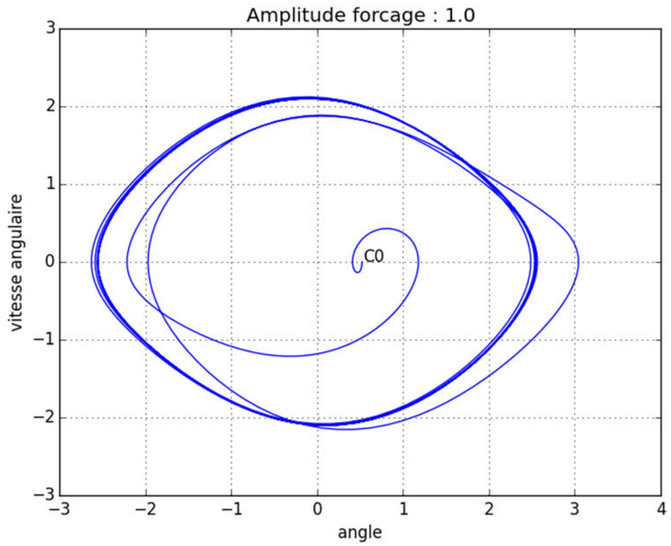
extracted from [Dumas et al, 2014]

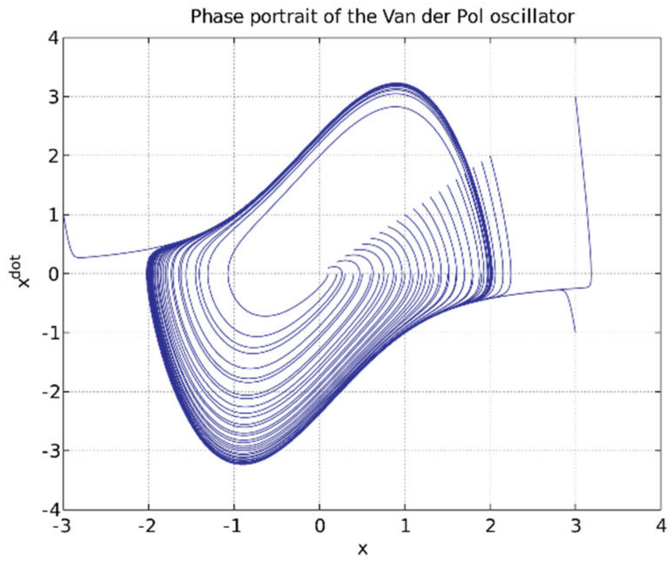
Interpersonal synchronization acts like a dynamical system based on 2 coupled non-linear oscillators

Two independent dynamic systems → emergence of one dynamic system

NON LINEAR OSCILLATORS





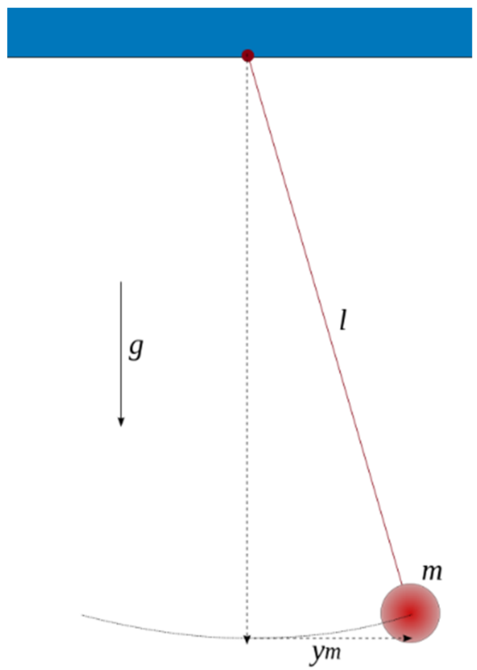


According to parameters :

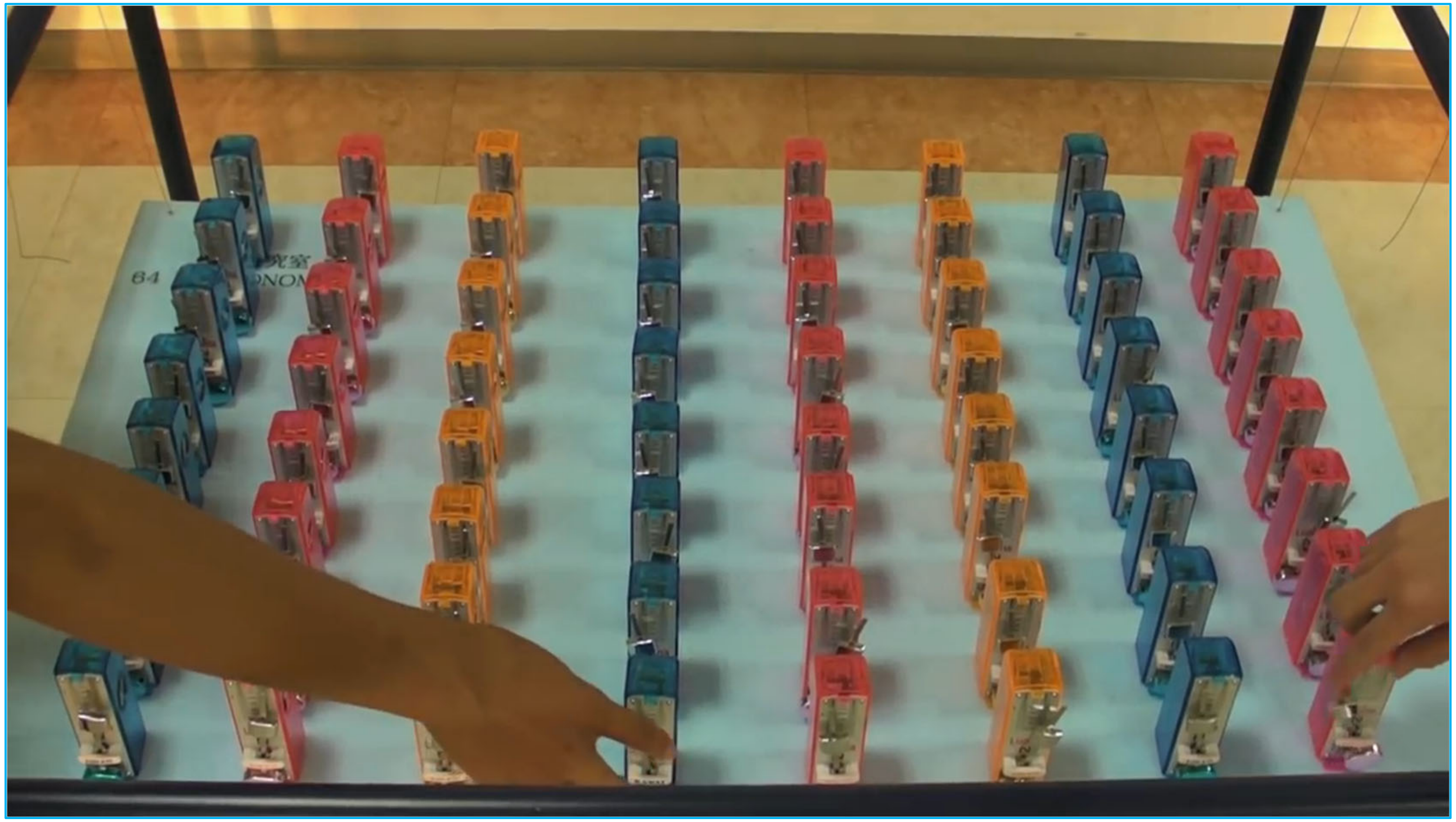
- Emergence of stable limited cycles $\forall$ initial conditions
- Chaotic behavior

Dynamic systems :

- mechanical
- electrical/electronical
- Biological
- Fluids (waves)



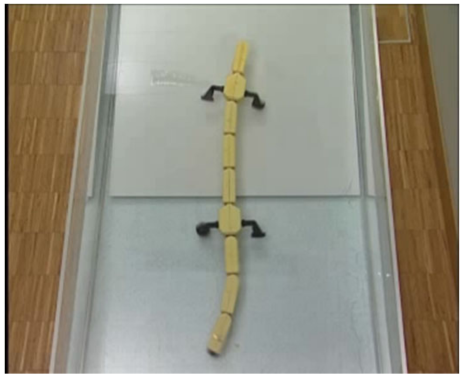
EMERGENCE OF SYNCHRONIZATION BETWEEN COMPLEX DYNAMIC SYSTEMS



Mechanical independant dynamic systems (metronomes) become naturally synchronized

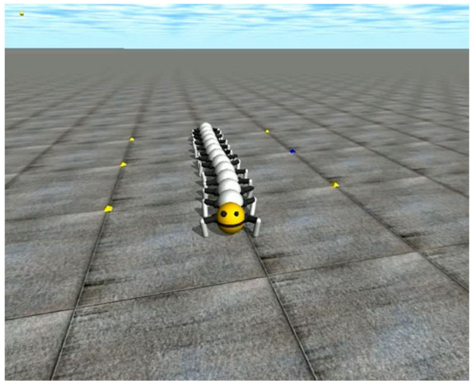
Ikeguchi Lab, Japan

One metronome could be considered as one robot joint



Bio-inspired robots

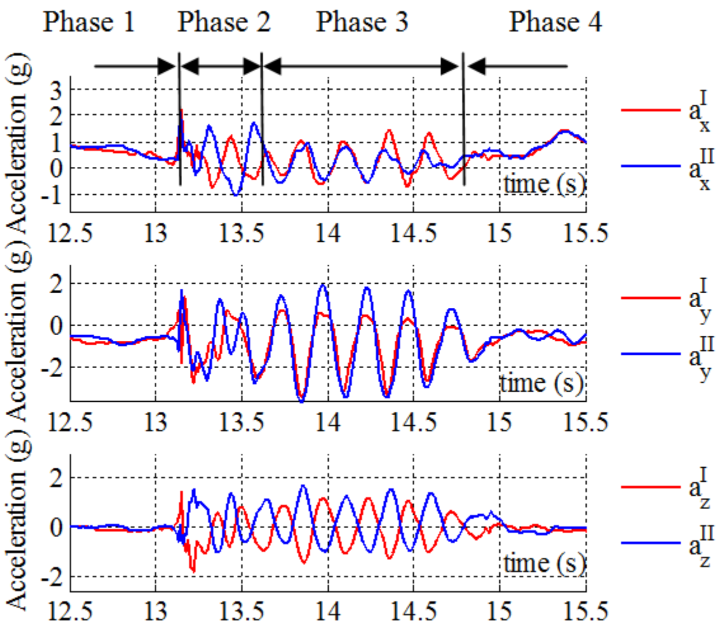
Ijspeert 2007 (Science)



Simulated biological system

Hoinville & Henaff 2007.

EXAMPLE OF INTERPERSONAL SYNCHRONIZATION IN A COMMON PHYSICAL INTERACTION : THE HANDSHAKING

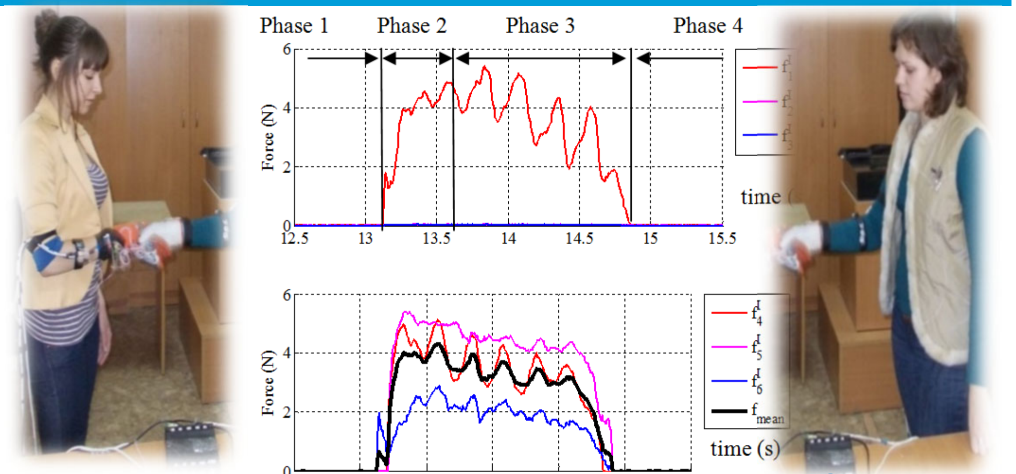


Phase 1 – **SoH**
Start of Handshake

Phase 2 – **PhC**
Physical Contact

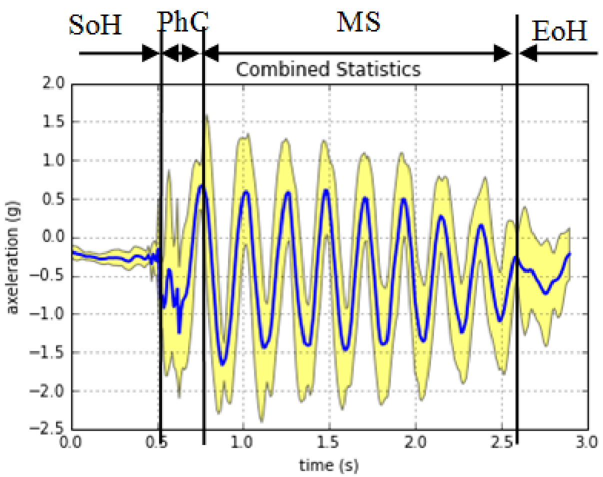
Phase 3 – MS
Mutual Synchrony

Phase 4 – **EoH**
End od Handshake



Subject I **Subject II**

[Melnyk & Henaff, 2014, 2019]



Average of 5 handshakes.

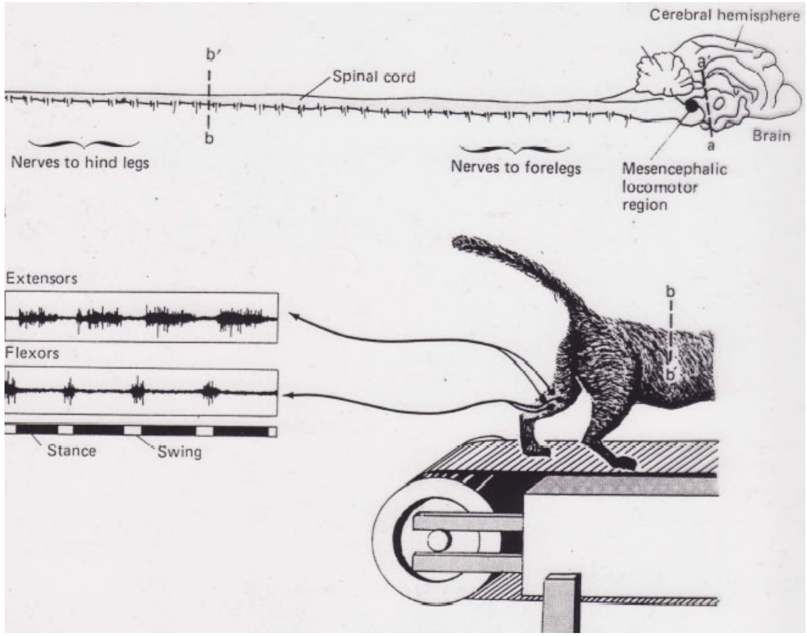
[Tagnes & Henaff & al., 2016]

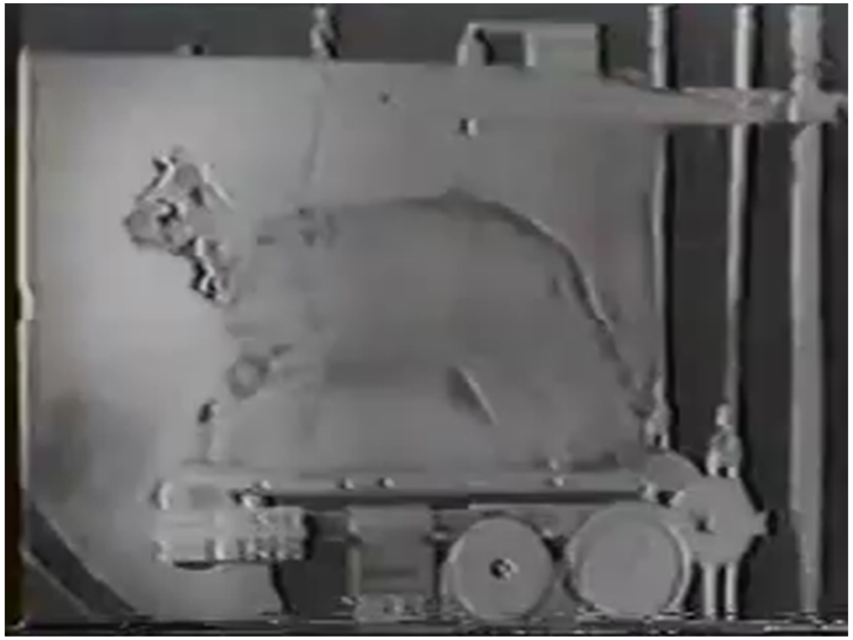
- **Synchronization exists in interpersonal rhythmic physical interactions**
- **Handshaking acts as coupled nonlinear oscillators**

BIOLOGICAL CONTROL OF RHYTHMIC MOVEMENTS

Scientists Shik ML, Orlovsky (1966) have shown :

- That electric tonic stimulation on the remaining part of the Cerebral Trunk (CT) of decerebrate cats resulted in normal walking when the animal was on a treadmill.
- The gait of the animal depended on the intensity of the stimuli and the speed of the treadmill.
- A little stimulation provoked a simple walk whereas a more intense triggered the trot or the gallop

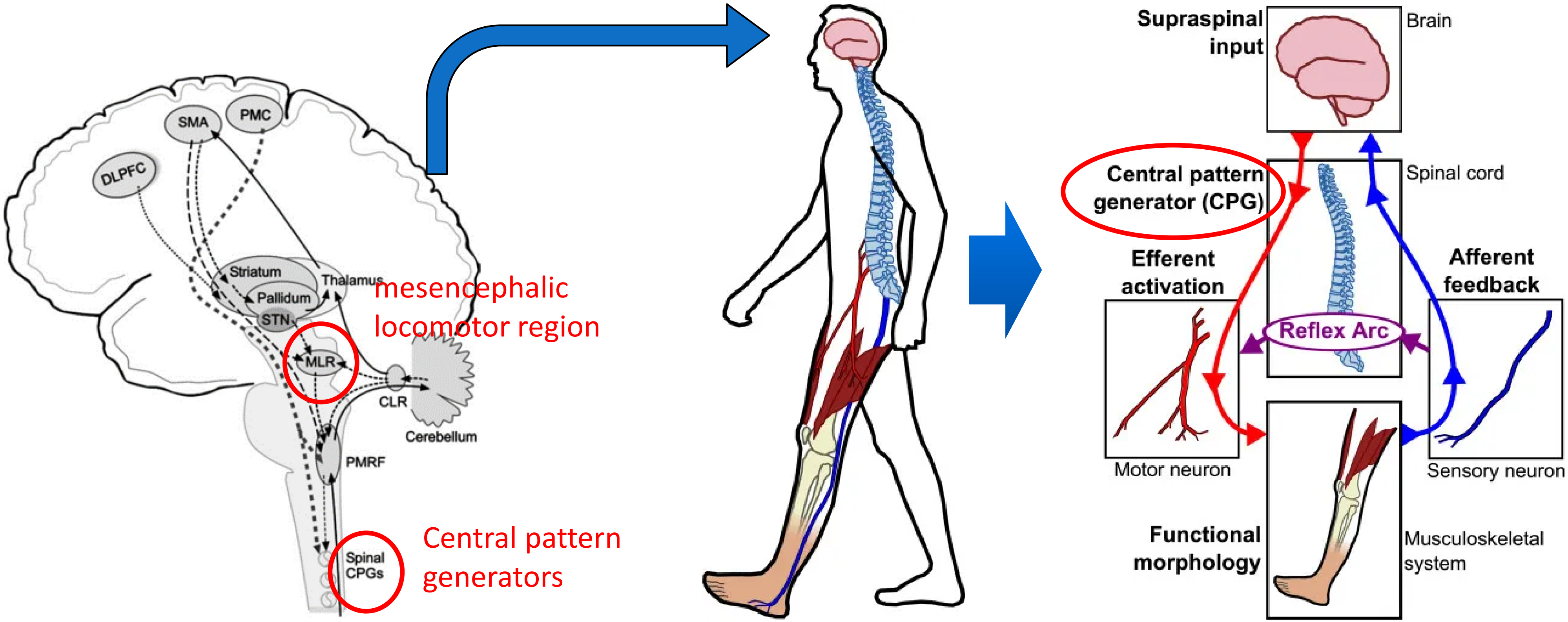




[Shik ML, Orlovsky ,1966]

Specialized neural circuits control the rhythms of locomotion : central pattern generators (CPG)

BIOLOGICAL ASPECTS OF HUMAN MOTOR COORDINATION

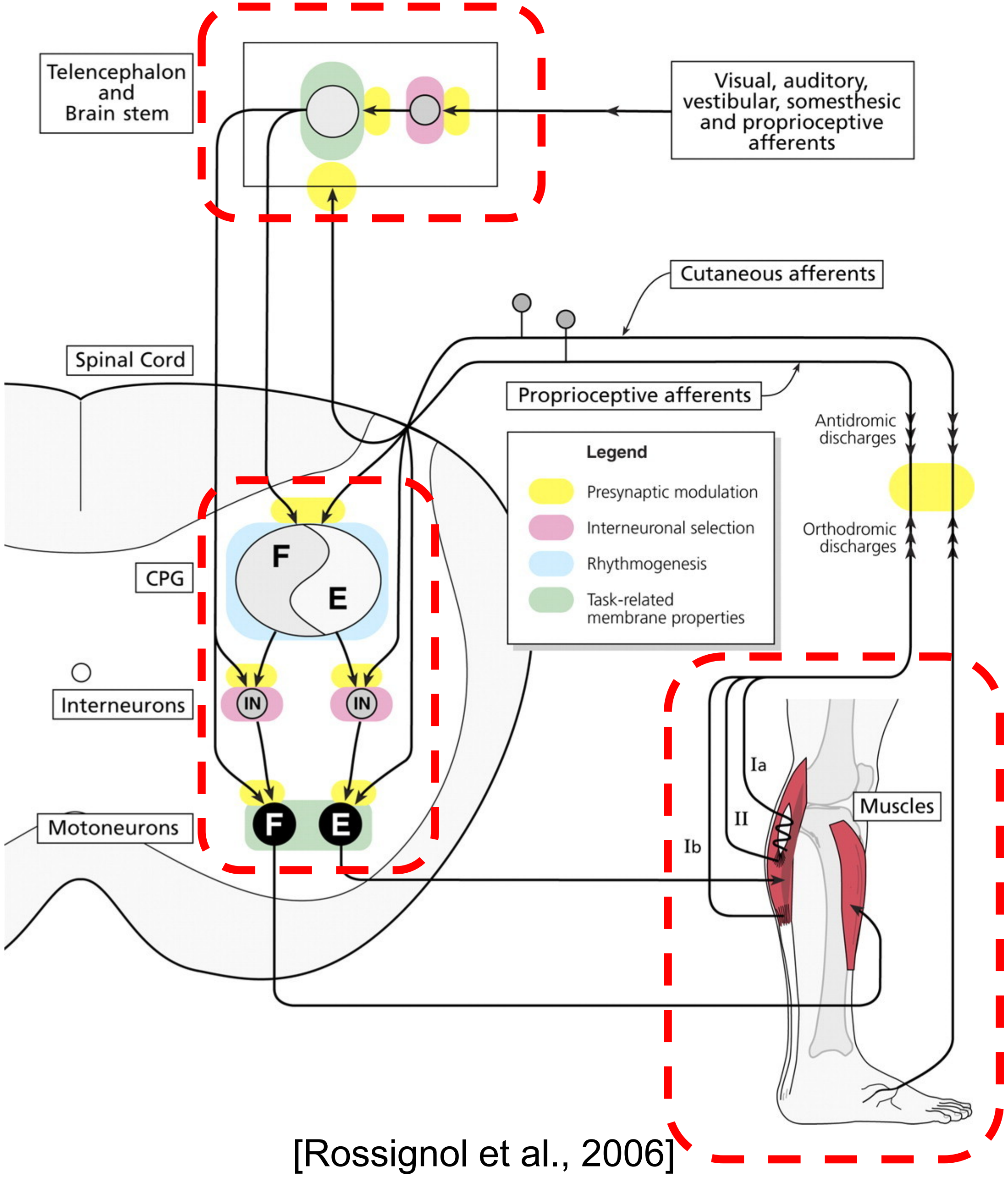


Hypothetical motor pathways in the brain. Extracted from [Chakravarthy, 2010]

Control loop:

- ❑ High-level commands from brain (MLR]
- ❑ **Spinal neurons**:
  - ▪ **Central Pattern Generators**
  - ▪ Reflex arcs
- ❑ Muscles with afferent sensory neurons
- ❑ Feedback to the brain and spinal cord

CENTRAL PATTERN GENERATORS



[Rossignol et al., 2006]

Autonomous neural circuits

- Located in brainstem and spinal cord
- Produce rhythmic signals for:
  - Locomotion
  - Chewing
  - Breathing, etc.

Locomotor CPG:

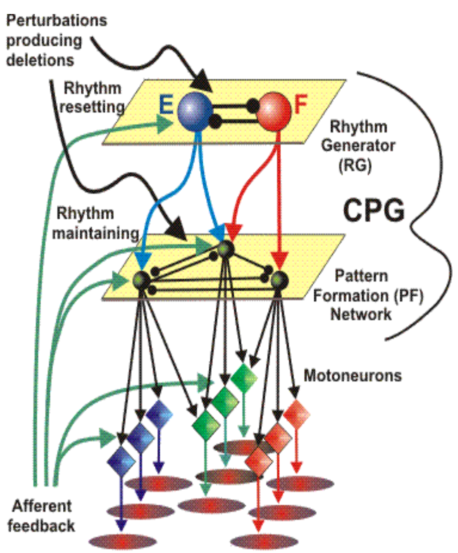
- Excite muscles through motoneurons
- Brain initiates and change gait type
- Sensory feedback affect patterns
- No equilibrium control

Computational model of central pattern generators ?

HUMAN RHYTHMIC MOVEMENTS ARE CONTROLLED BY CENTRAL PATTERN GENERATORS (CPG)

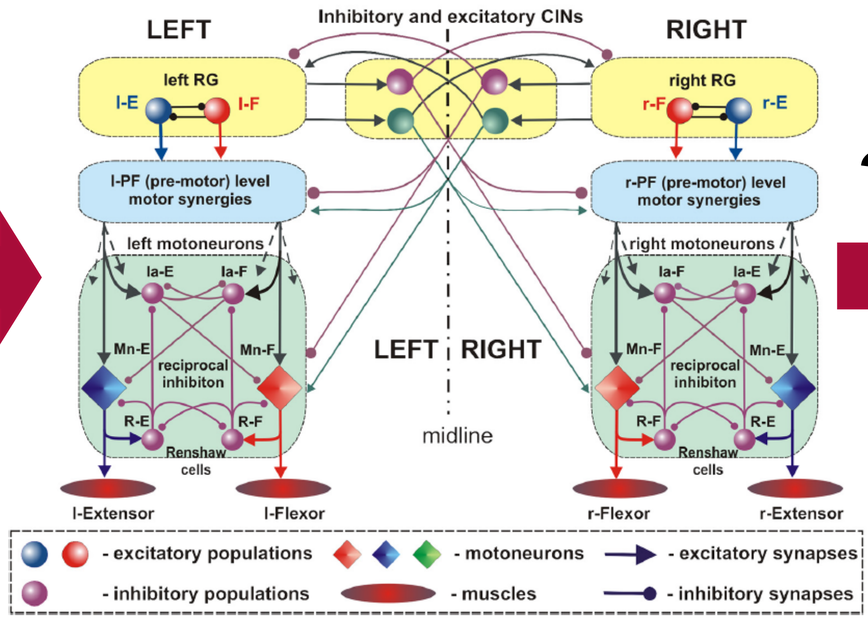
COMPUTATIONAL MODEL OF CPG ?

CPG for lower limbs (locomotion)



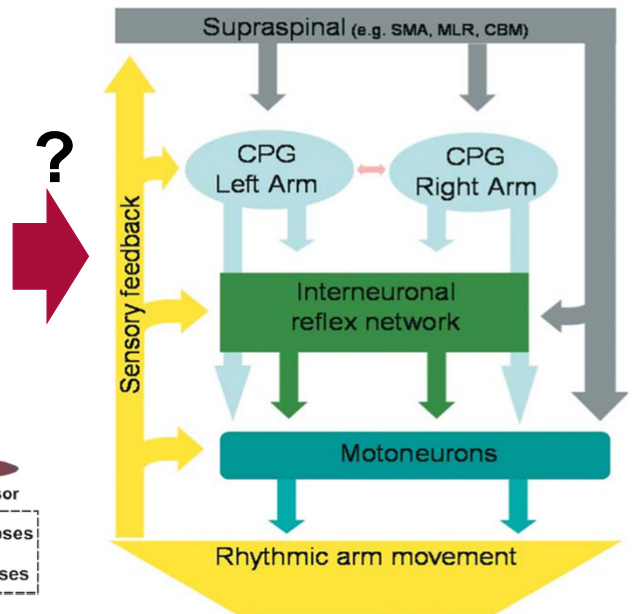
[McCrea & Rybak, 2008]

Bilateral left-right interactions



[Rybak et al. 2015]

CPG for upper limbs



[Zehr, 2006]

Rhytmic generators → rhythmic neurons?

MODELS AND SYNTHESIS METHODS OF BIO-INSPIRED CONTROLLERS

Mesoscopic, macroscopic models

- Neuronal (CTRNN, Ekeberg , Ijspeert, Wörgötter,)
- Oscillators (**Matsuoka**, Kuramoto, Hopf..)

Adaptive mechanisms :

- Neuronal & synaptic plasticity (Beer, Floreano, Husband…)
- Neuromodulation

Synthesis methods

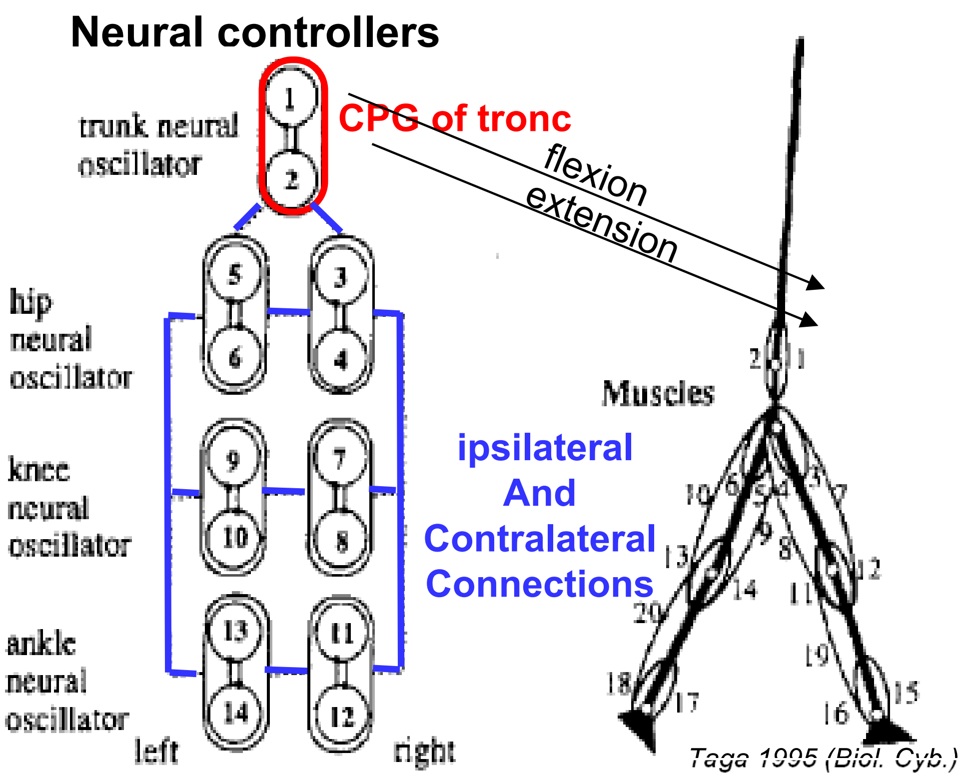
- Manual (Ekeberg, Taga, Ijspeert, Wörgötter, Kasuga…)
- Genetic algorithms for optimisation (Ijspeert, Meyer, Bongard…)
- Learning algorithms (Beer, Endo, Ijspeert…)

Applications in robotics:

- Locomotion : biped, quadruped myriapod, swimming
- human/robot physical interaction : handshaking

COMPUTATIONAL MODEL OF RHYTMHYC NEURONS ?
MATSUOKA NEURON (MESOSCOPIC MODEL)

Neural based CPG controller for biped locomotion (Taga 1995)



Neural controller

- 1 CPG per joint
- 2 coupled neurons per CPG
- Inhibitions: contra and ipsi latéral
- sensori motricity Intégration

Internal coupling of the network

Articular sensory inputs: speeds, forces, contact ground

Model of Neuron i (**Matsuoka** 1985)

$$\tau_{ai}\dot{u}_i = -u_i - \beta f(v_i) + \sum_{j=1}^{14} \omega_{ij} f(u_j) + u_0 + Q_i + S_i$$

$$\tau_{bi}\dot{v}_i = -v_i + f(u_i) \quad et \quad f(u) = \max(0, u)$$

A CPG circuitery is a neural network

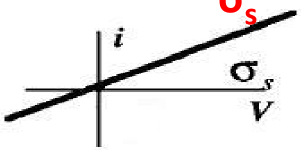
COMPUTATIONAL MODEL OF RHYTMHYC NEURONS ?
A VANDER-POL OSCILLATOR MODEL

Neuron model = Non-linear oscillator (Rowat & Selverston model, 1993)

$$\tau_m \frac{dV}{dt} = -\left(F\left(V,\sigma_f\right) + q - i_{inj}\right)$$

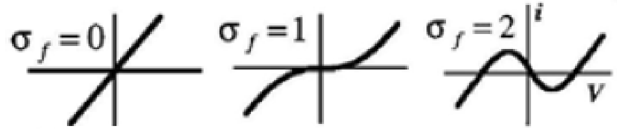
$$\tau_s \frac{dq}{dt} = -q + q_\infty(V) \quad \tau_m < \tau_s$$

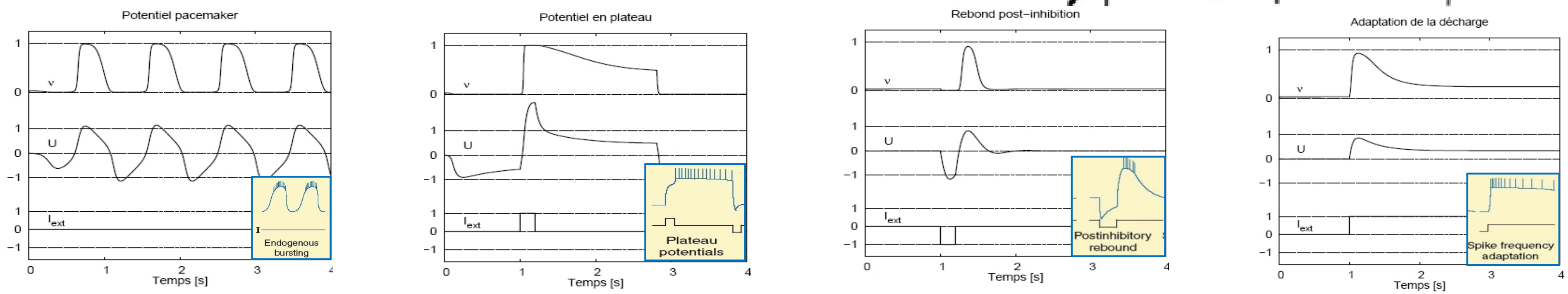
$q_\infty(V) = \sigma_s V$ — σ_s



σ_f

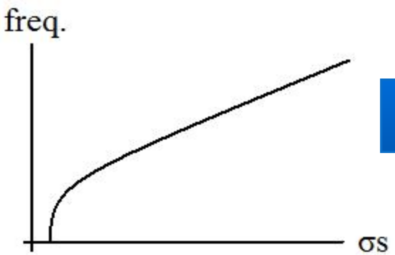
$$F(V,\sigma_f) = V - A_f \tanh\left(\frac{\sigma_f}{A_f} V\right)$$





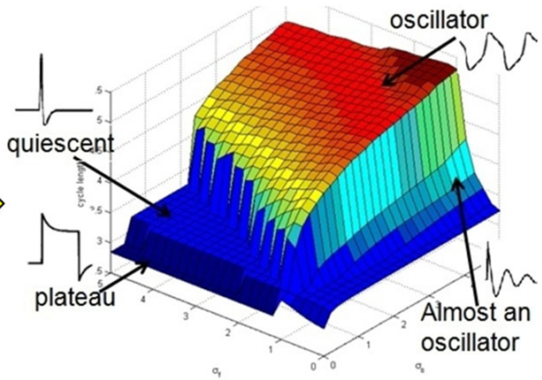
(d) $\sigma_f = 2$; $\sigma_s = 3$ (c) $\sigma_f = 4$; $\sigma_s = 1$ (b) $\sigma_f = 0{,}5$; $\sigma_s = 4$ (a) $\sigma_f = 0$; $\sigma_s = 2$

intrinsic properties of biological neurons , *Marder et al. (2001)*



Articular Cinetic energy index

$$\varepsilon = \int_{t_0}^{t} \dot{\theta}^2 dt$$

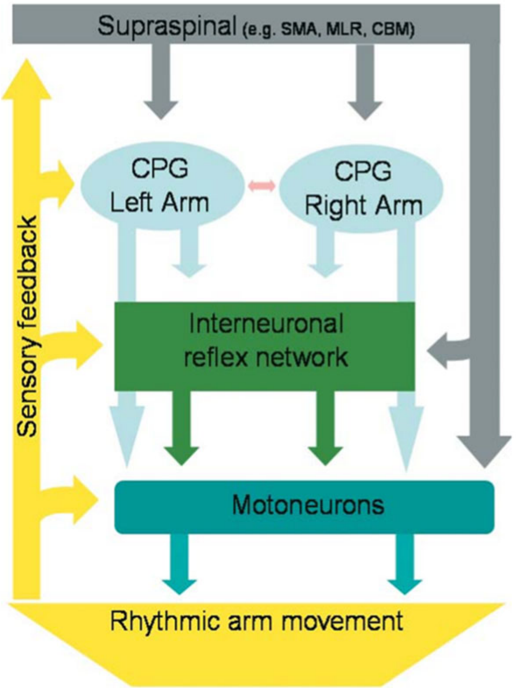


John Nassour, Patrick Hénaff, Fethi Benouezdou, Gordon Cheng (2014), Multi-layered multi-pattern CPG for adaptive locomotion of humanoid robots, Biological Cybernetics, February 2014

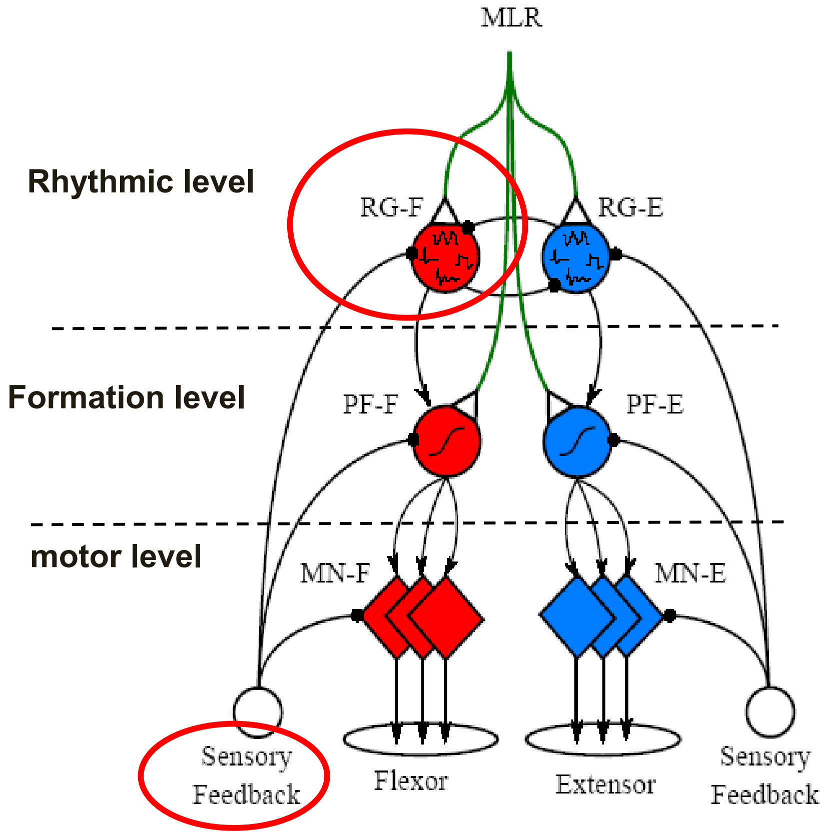
Émergence de coordination motrice due au modèle de neurone de RS : 1 neurone par axe de rotation

COMPUTATIONAL MODEL OF CPG

CPG for upper limbs



Computational CPG for one joint



[Nassour, Hénaff 2014]

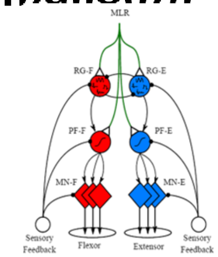
- **Model of Rhythmic generators neuron?**
- **Model of sensory feedback?**

GENERIC CPG CONTROLLER FOR ONE ROBOT JOINT

- **Rhythmic generator cells : Rowat-Selverston model (Van der Pol formalism):**

$$\dot{V} = y$$

$$\dot{y} = \frac{1}{\tau_m}\left(\sigma_f - \frac{\tau_m}{\tau_s} - 1 - \sigma_f \tanh^2\left(\frac{\sigma_f}{A_f}V\right)\right) y - \frac{1+\sigma_s}{\tau_s\tau_m}V + \frac{A_f}{\tau_s\tau_m}\tanh\left(\frac{\sigma_f}{A_f}V\right)$$



- **Interneurons :**

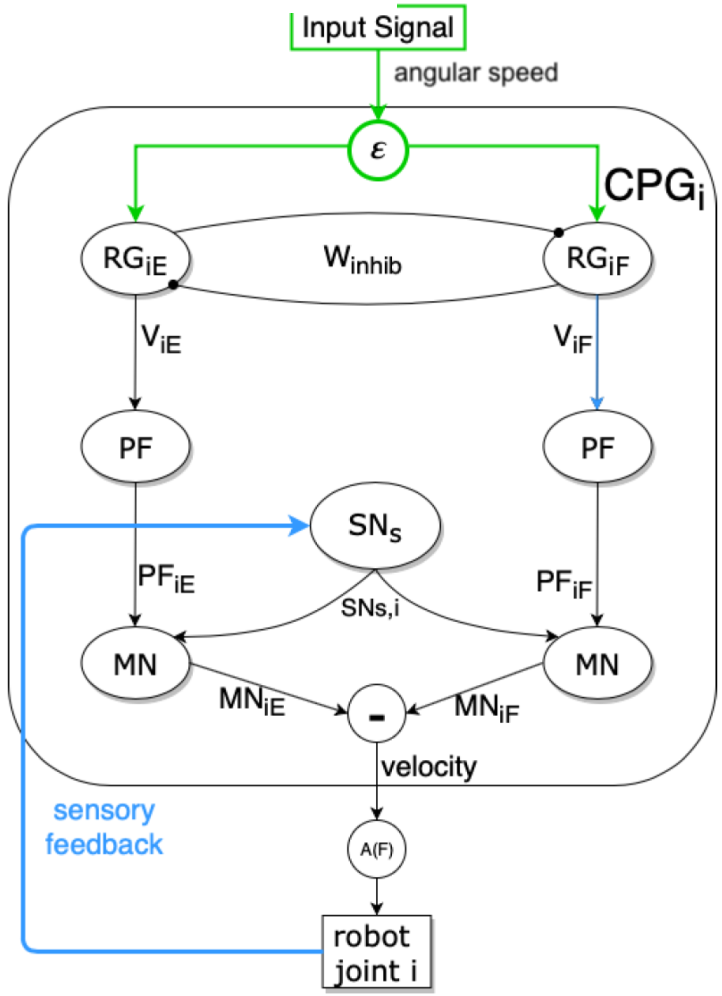
$$PF(V_{i\{E,F\}}) = PF_{i\{E,F\}} = \frac{1}{1+e^{\frac{-V_{i\{E,F\}}}{2}}}$$

$$SN_s(v_{mes_i}) = SN_{i,s} = \frac{1}{1+e^{\alpha_s v_{mes}}}$$

$$MN(PF_{i\{E,F\}}, SN_{i,s}) = MN_{i\{E,F\}} = \frac{1}{1+e^{\alpha_m\left(PF_{i\{E,F\}} - SN_{i,s}\right)}}$$

- **Hebbian Plasticity for frequency learning :**

$$\dot{\sigma_s} = 2\epsilon F\sqrt{\tau_m\tau_s}\sqrt{1+\sigma_s-\sigma_f}\,\frac{y}{\sqrt{V^2+y^2}}$$

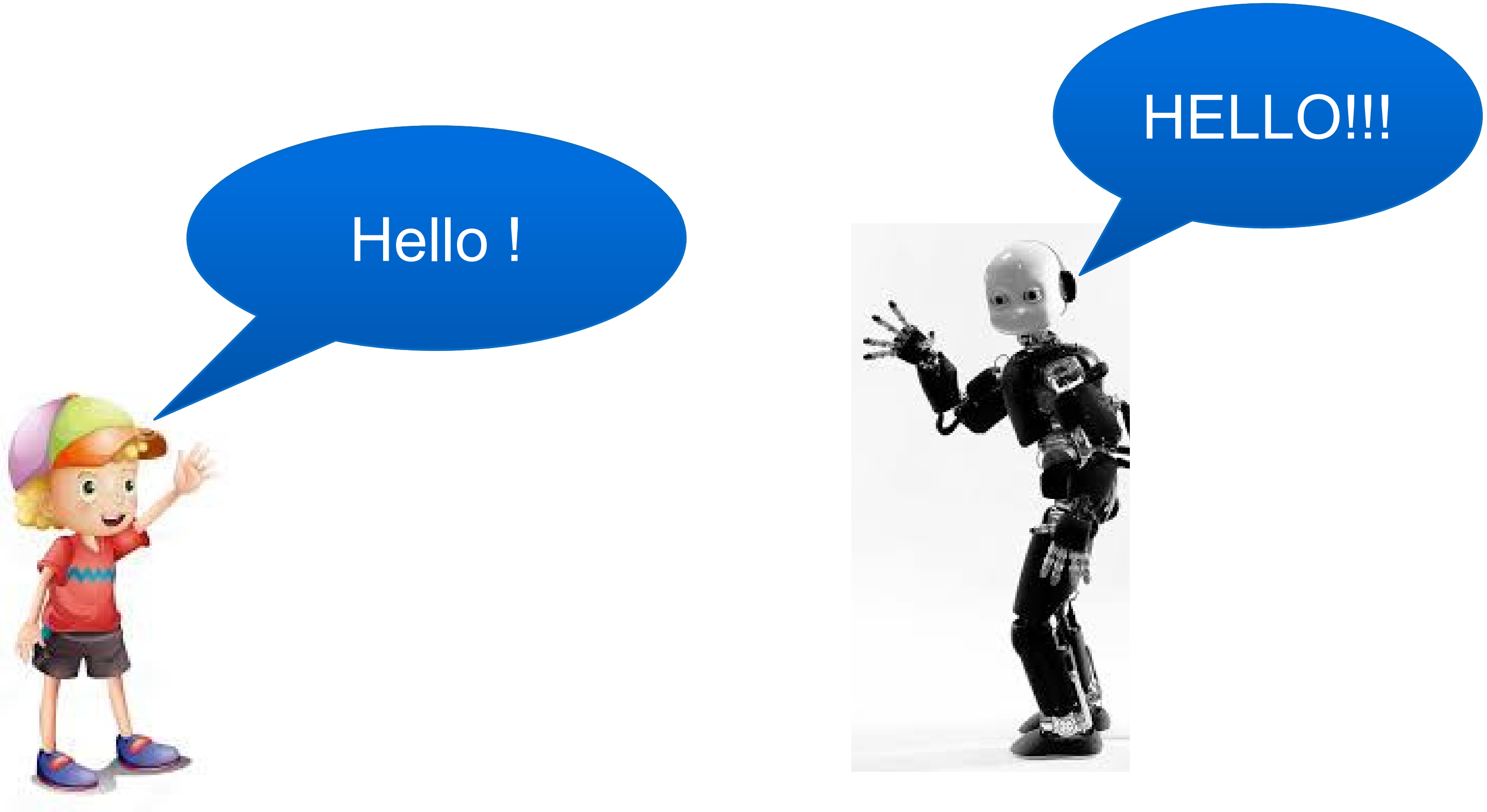


Melanie Jouaiti, Lancelot Caron, Patrick Henaff. Hebbian Plasticity in CPG Controllers Facilitates Self-Synchronization for Human-Robot Handshaking. *Frontiers in Neurorobotics*, Frontiers, 2018,

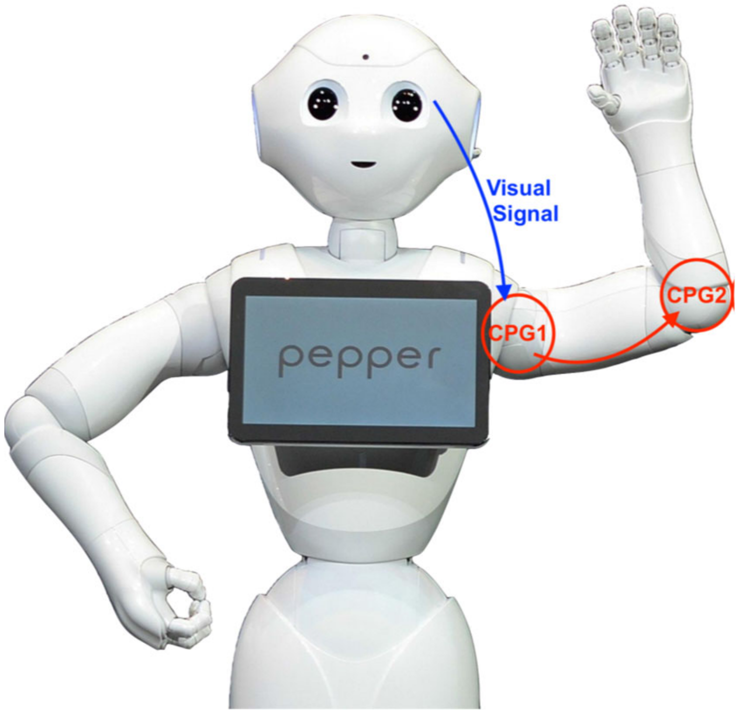
LEARNING SENSORYMOTOR COORDINATION

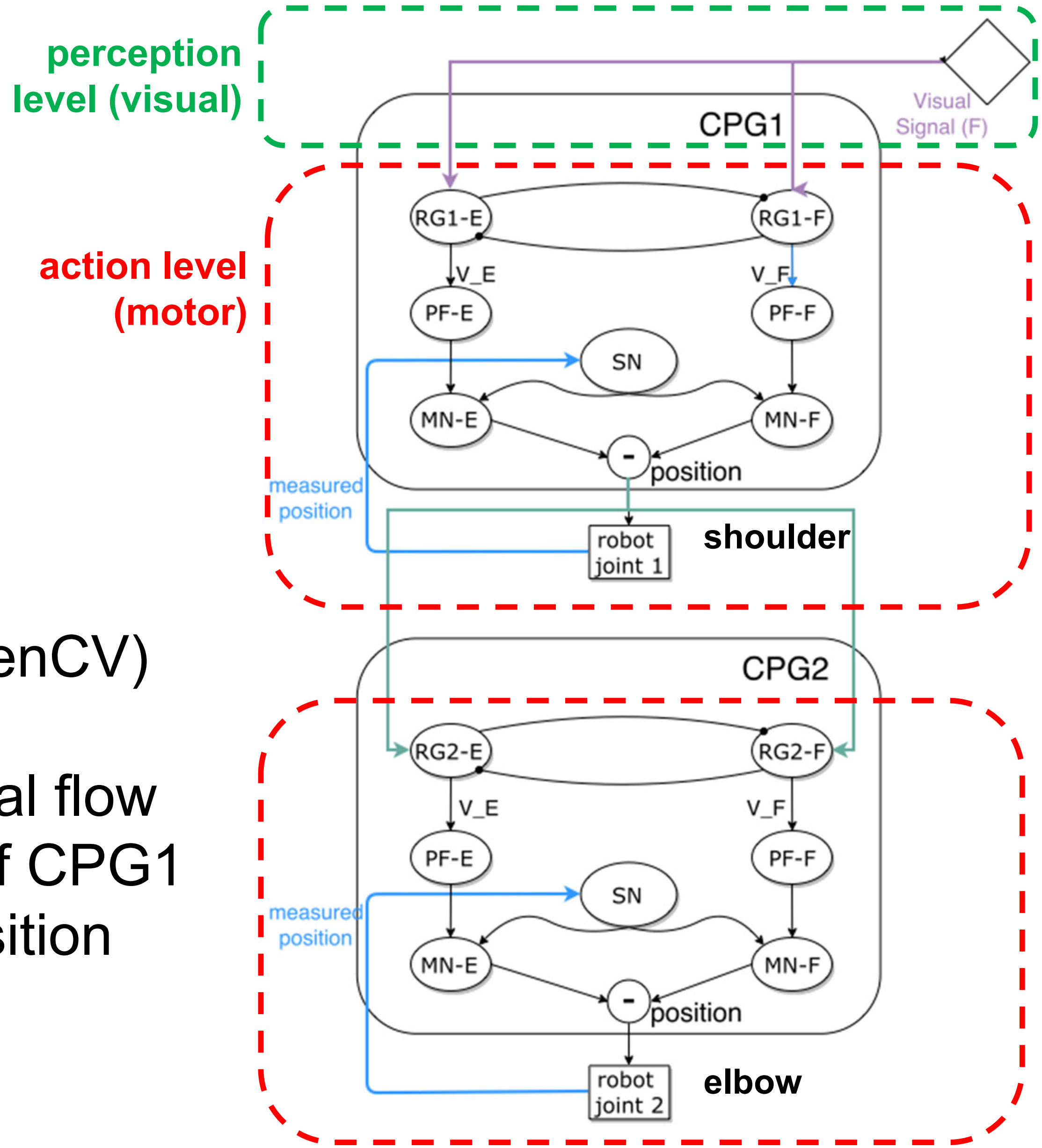
WAVING BACK EXAMPLE

- **Human waves at robot**
- **Optical flow of the hand detected**
- **Robot waves back and adapts to the human frequency**



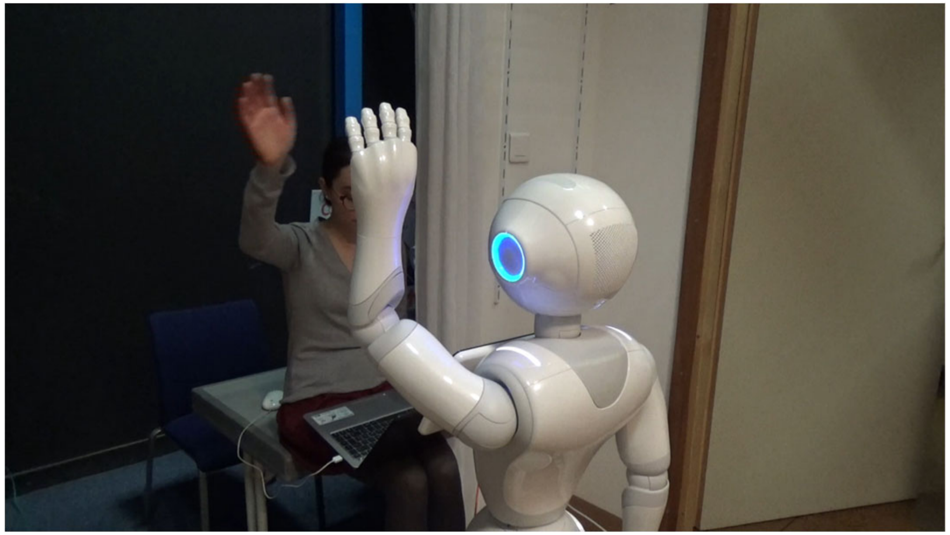
WAVING BACK : CONTROL ARCHITECTURE

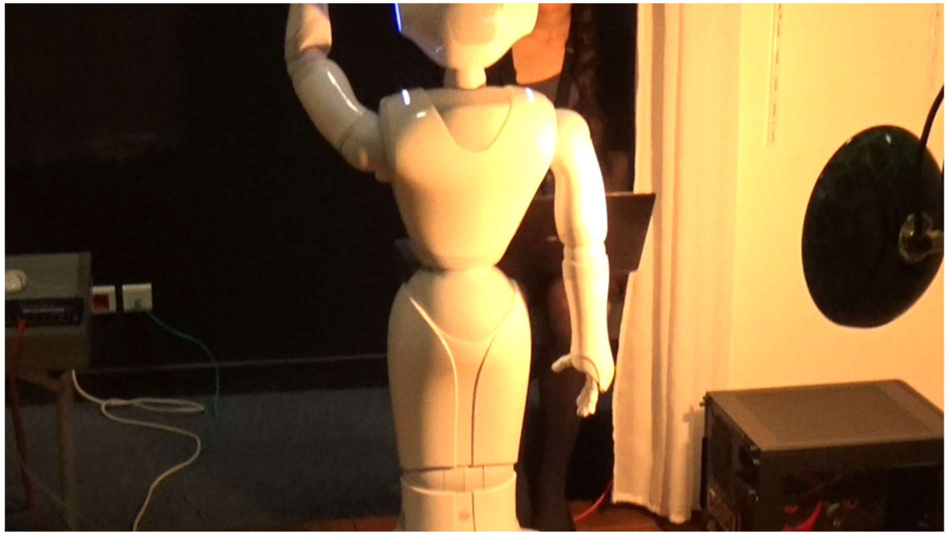




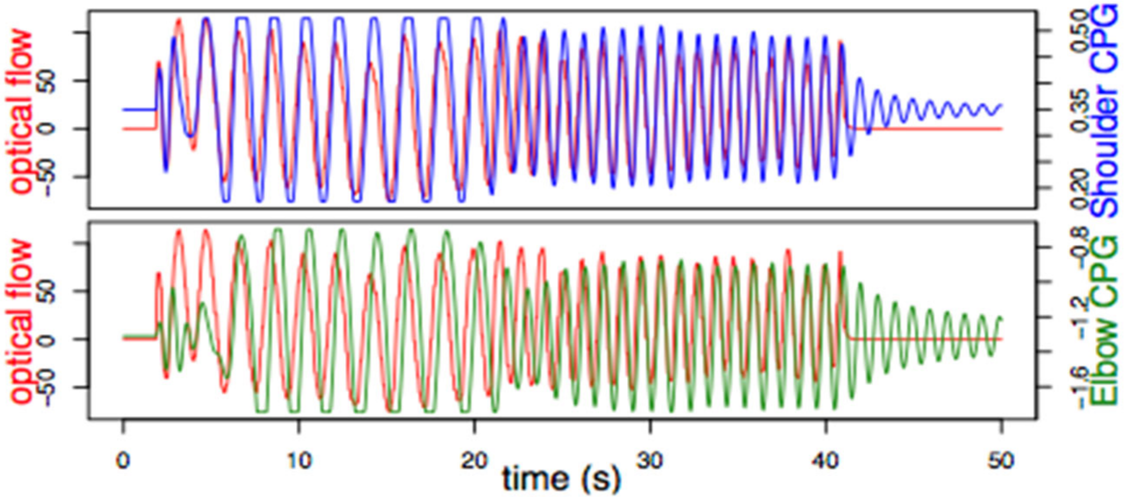
- **Perception : optical flow** (OpenCV)
- **2 joints controlled :**
  - CPG1 input (shoulder) : optical flow
  - CPG2 input (elbow): output of CPG1
  - CPG output: joint angular position
- **interest of plasticity:**
  - faster synchronization

WAVING BACK EXPERIMENT

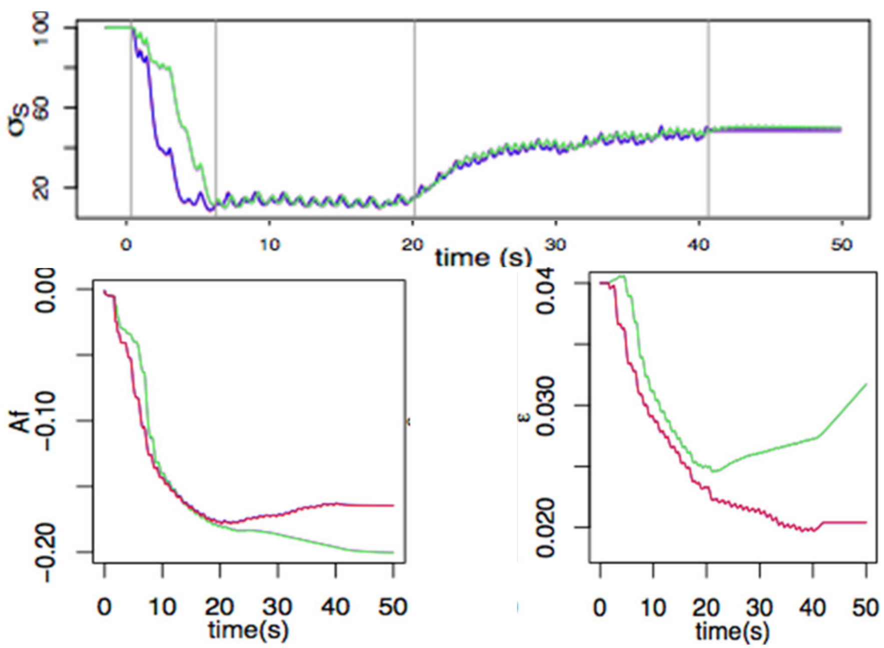




Synchronization between joints and optical flow

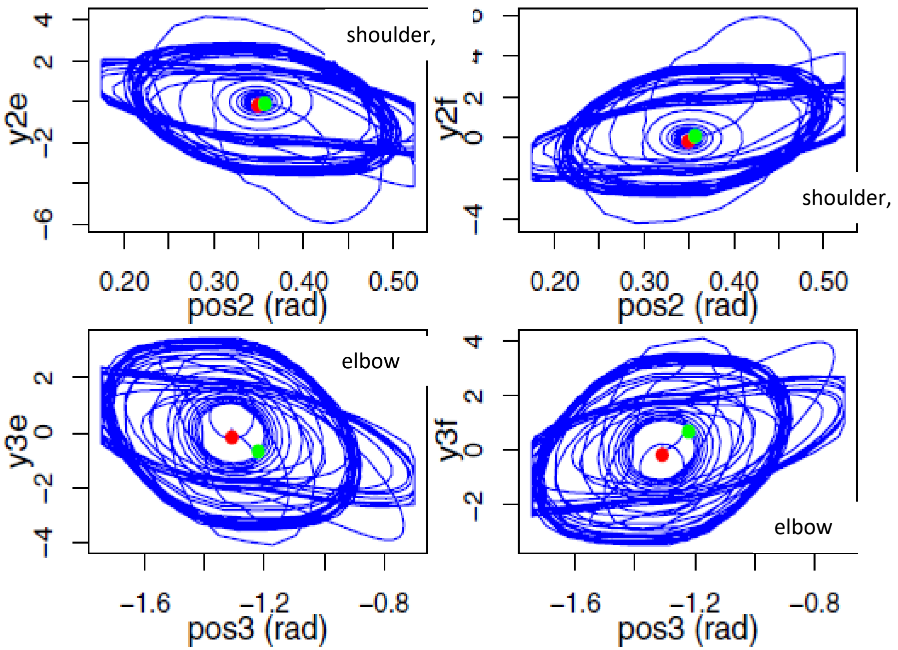


Hebbian plasticity

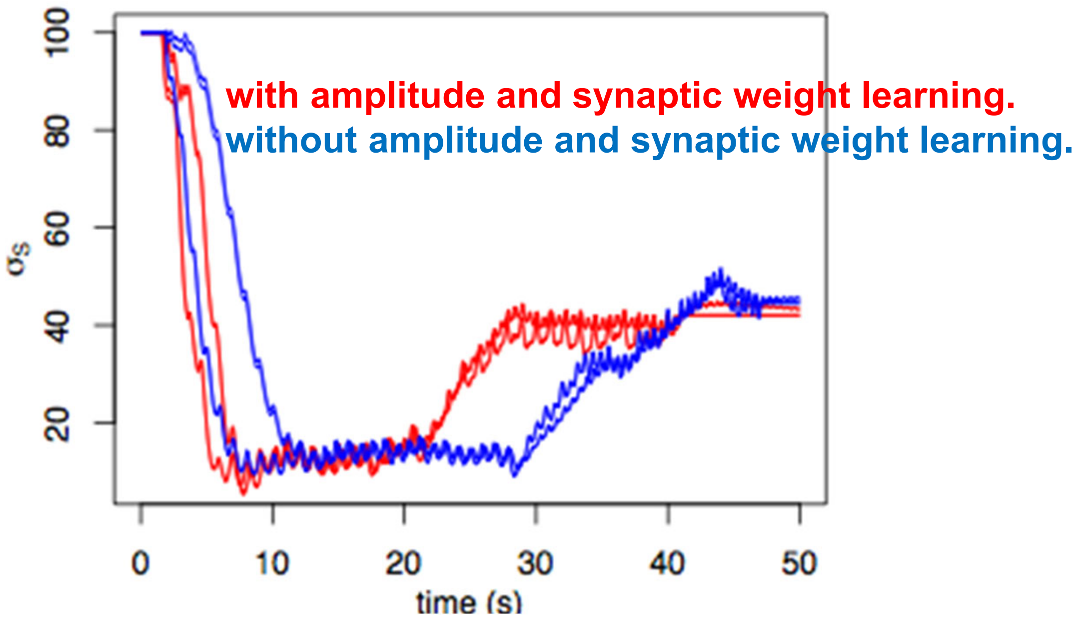


WAVING BACK EXPERIMENT

Phase portrait of rhythmic cells outputs



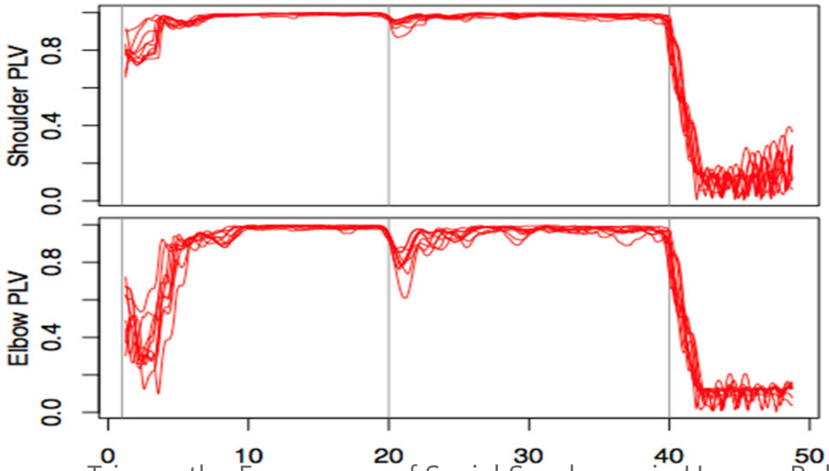
plasticity influences learning speed



Synchronization Measures (10 Wavings)

Phase lock value

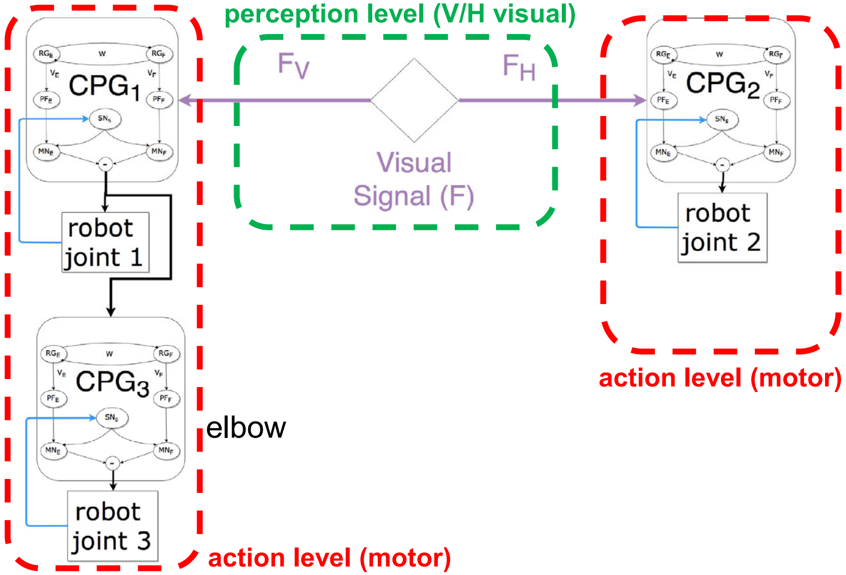
$$PLV(t) = \frac{1}{N}\left|\sum_{i=0}^{N} e^{j(\phi_1(i)-\phi_2(i))}\right|$$



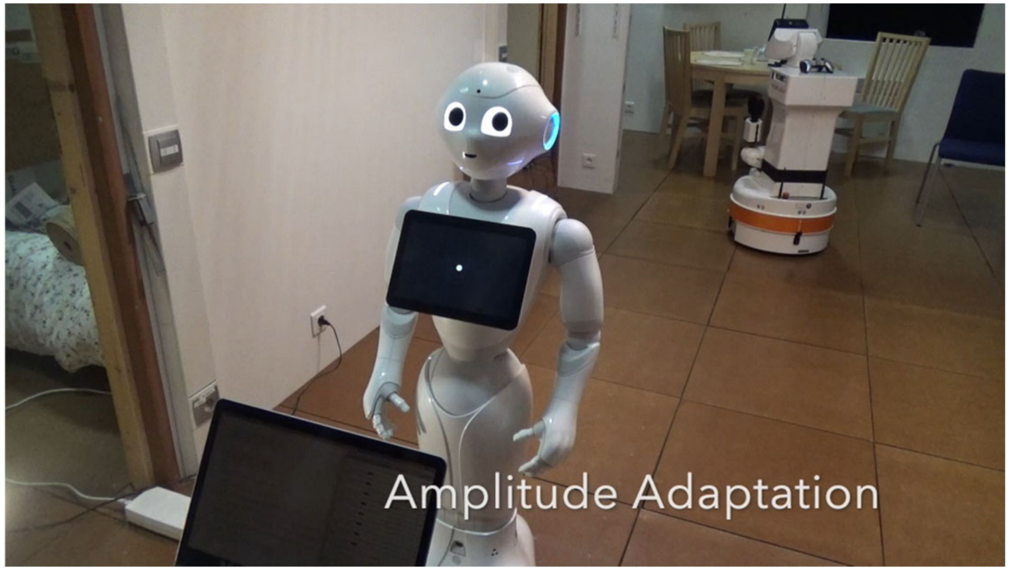
Melanie Jouaiti, Patrick Henaff. CPG-based Controllers can Trigger the Emergence of Social Synchrony in Human-Robot Interactions. IEEE/*ARSO 2018*

COORDINATION OF COMPLEX MOVEMENTS

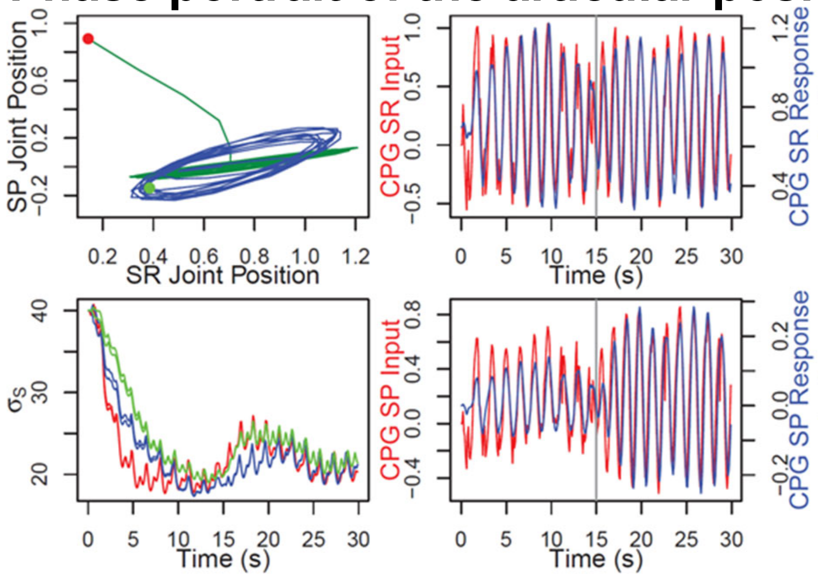
CPGs circuitry



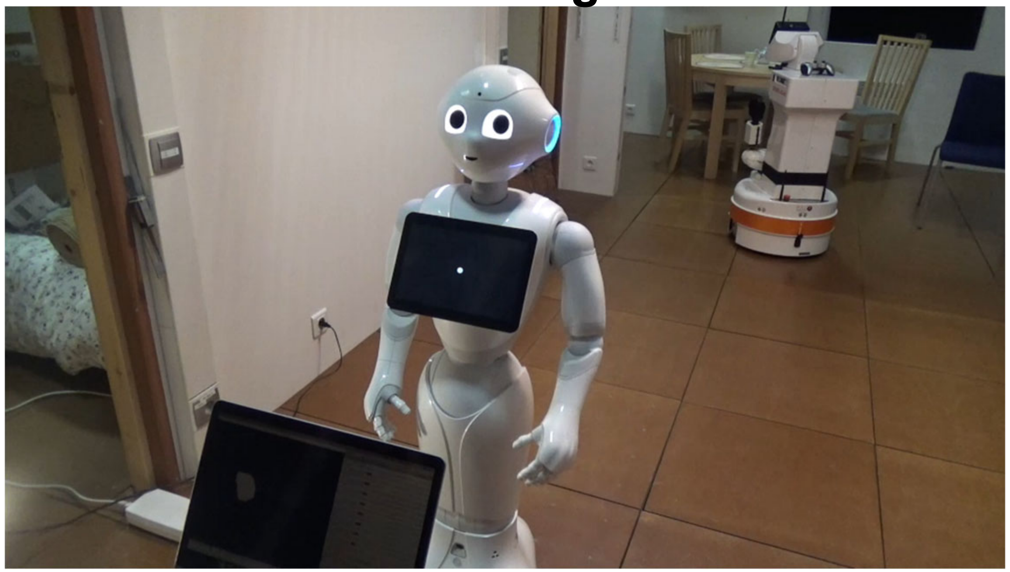
Circles at different speeds



Phase portrait of the articular position



“infinite” sign



M. Jouaiti, P. Henaff. Motor Coordination Learning for Rhythmic Movements. *Development and Learning and Epigenetic Robotics (IEEE/ICDL-Epirob), 2019*

Can CPG achieve both rhythmic and discrete movements?

OSCILLATING NEURON CAN BEHAVE AS A PID CONTROLLER

$$\dot{V} = y + \epsilon F$$

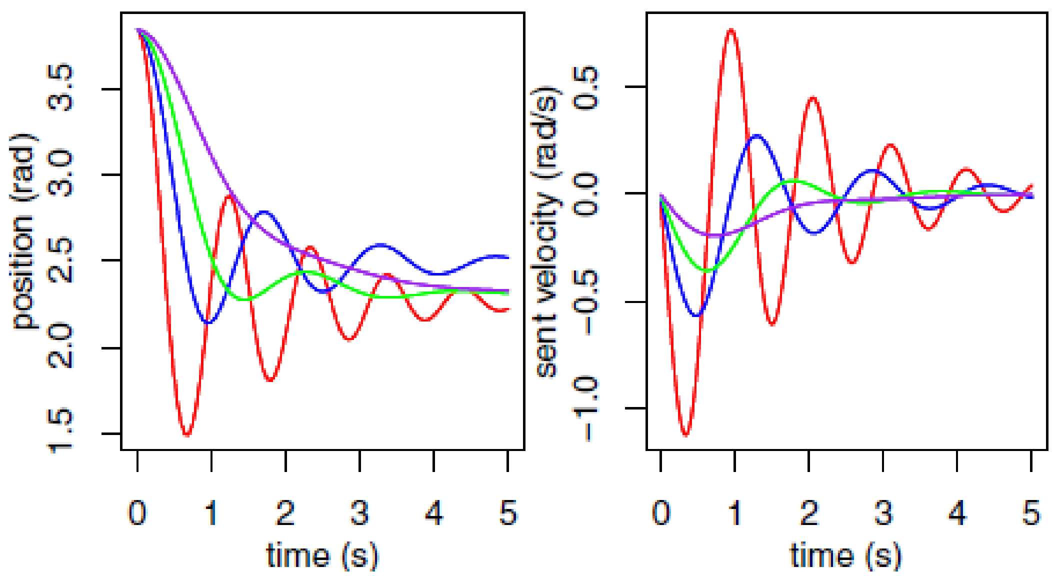
$$\dot{y} = \left(\sigma_f - \frac{\tau_m}{\tau_s} - 1 - \sigma_f \tanh^2\left(\frac{\sigma_f}{A_f}V\right)\right)\frac{y}{\tau_m} - \frac{1+\sigma_s}{\tau_s \tau_m}V + \frac{A_f}{\tau_s \tau_m}\tanh\left(\frac{\sigma_f V}{A_f}\right)$$

Non oscillating : $\sigma_f = 0$

$$\dot{V} = y + \epsilon F$$

$$\ddot{V} + \frac{\tau_s + \tau_m}{\quad}\dot{V} + \frac{1+\sigma_s}{\quad}V = 0$$

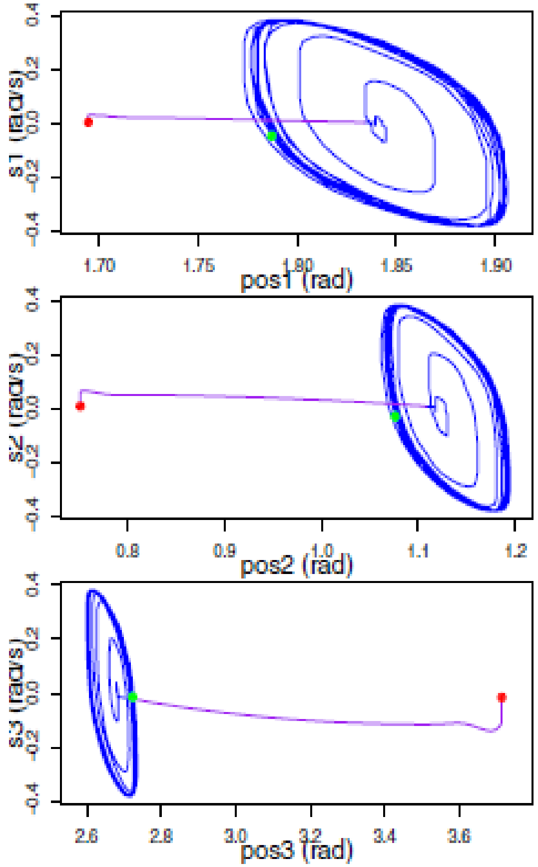
$$\dot{q} = \frac{1}{\alpha b}\left(\underbrace{ae(t) + b\int e(t)dt + \dot{e}(t)}_{\text{PID}}\ \underbrace{-a\ddot{q}}_{\text{robot's dynamic}} \underbrace{-\dddot{q}}_{\text{jerk}}\right)$$



FROM DISCRETE TO RHYTHMIC MOVEMENT : HANDSHAKING EXPERIMENT

- ❑ Robotic arm coupled to a camera detects the hand and raises towards it
- ❑ when the target is reached, the arm oscillates at its own intrinsic frequency

Joint phase portrait

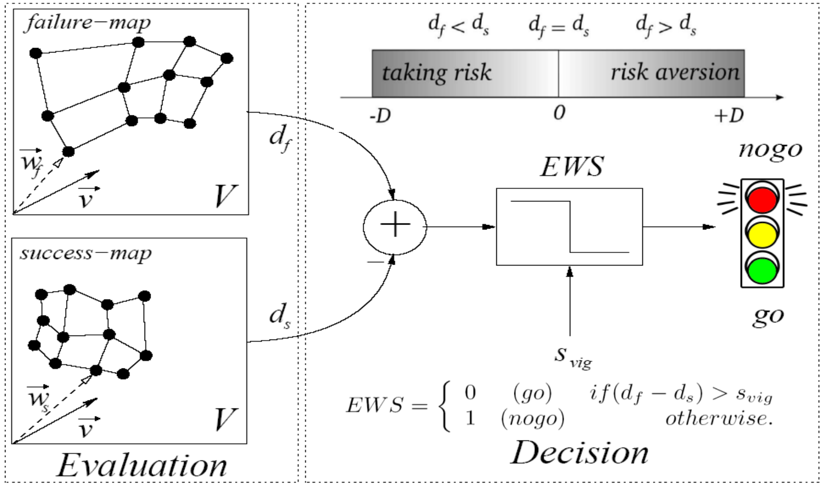


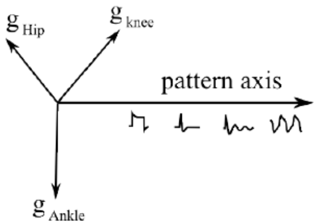
Joint phase portrait

CPG phase portrait

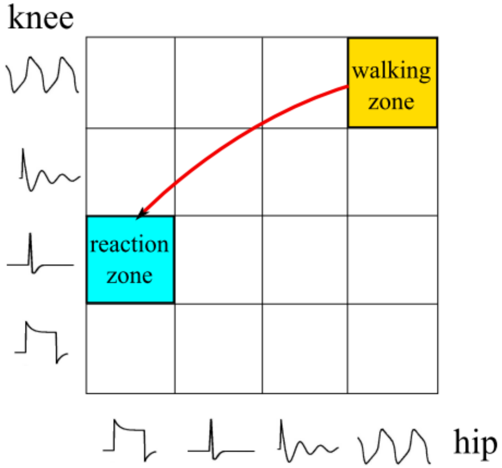
RHYTHMIC/DISCRETE MOVEMENTS SWITCHING IN BIPED LOCOMOTION : BALANCE REFLEX DURING WALKING

Learning based on experiment (SOM)

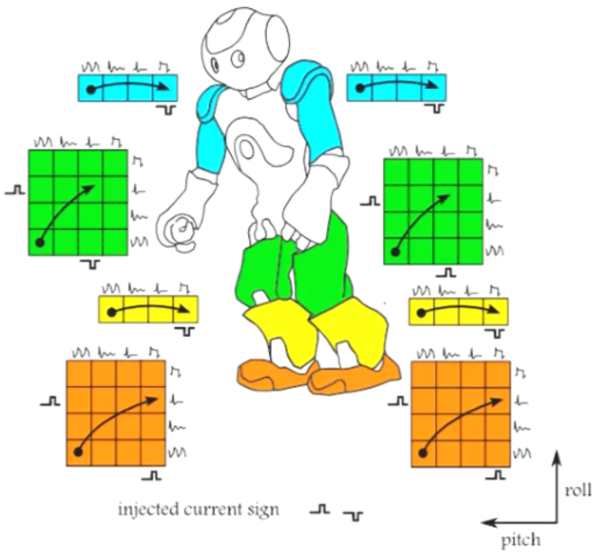


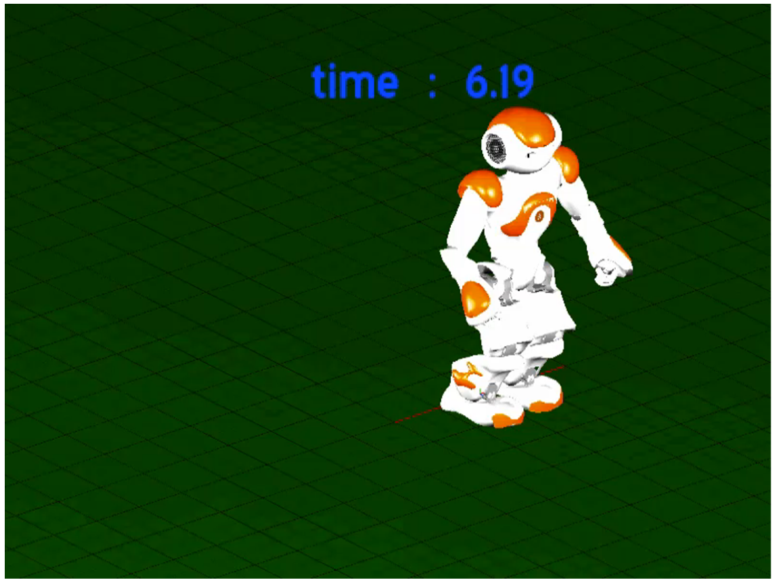


Learning of phase classification of motor neuron gain (σs): phase jumps



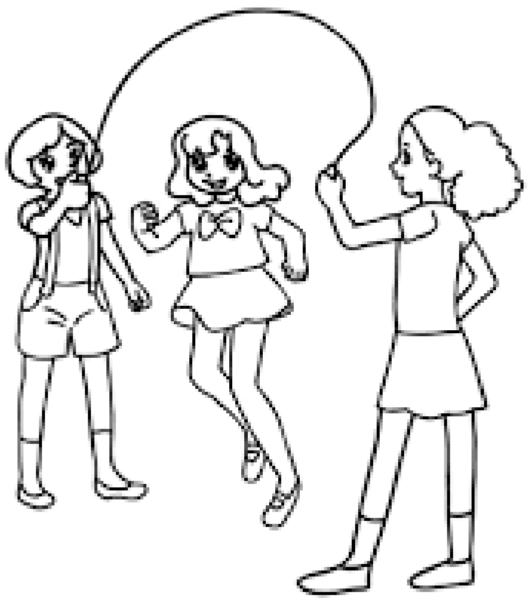
Phase jumps for each joint





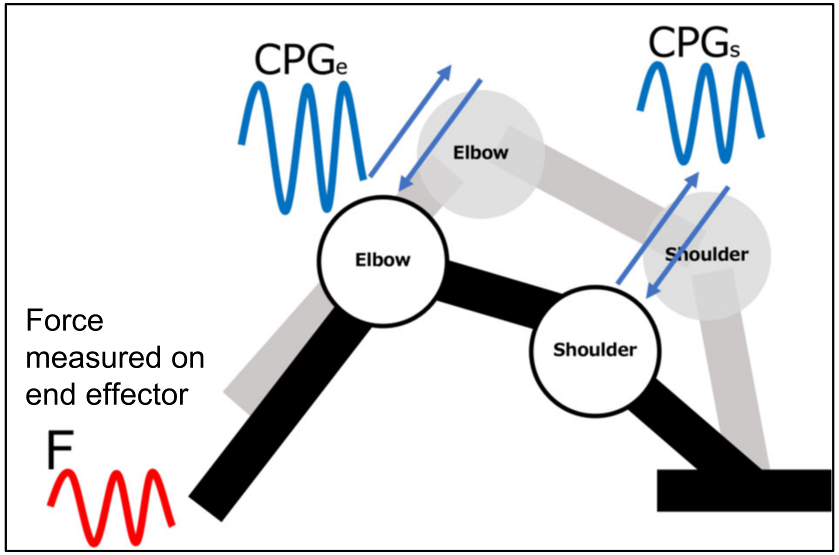
John Nassour, Patrick Hénaff, Fethi Benouezdou, Gordon Cheng (2014), Multi-layered multi-pattern CPG for adaptive locomotion of humanoid robots, Biological Cybernetics, February 2014,

Physical Interactive games between robot and human

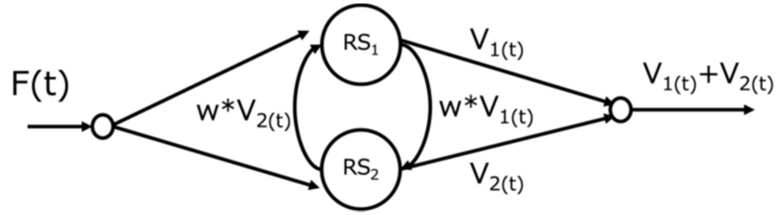


ROPE JUMPING WITH A COLLABORATIVE INDUSTRIAL ROBOT

CPG control scheme

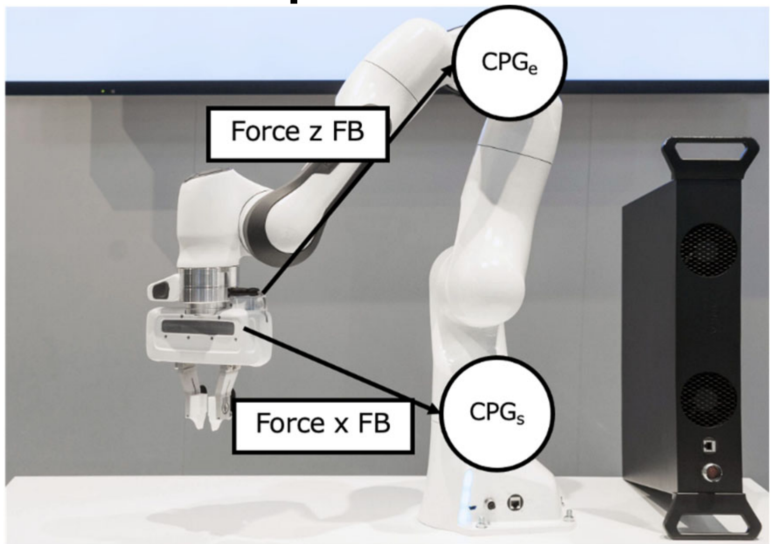


Simplified CPG for each joint



RS = Rowat-Selverston oscillator with hebbian plasticity

Implementation



Yamasaki, Shibata, Hénaff 2023

HANDSHAKING WITH A COLLABORATIVE INDUSTRIAL ROBOT

HR handshaking (Panda+Qb hand)

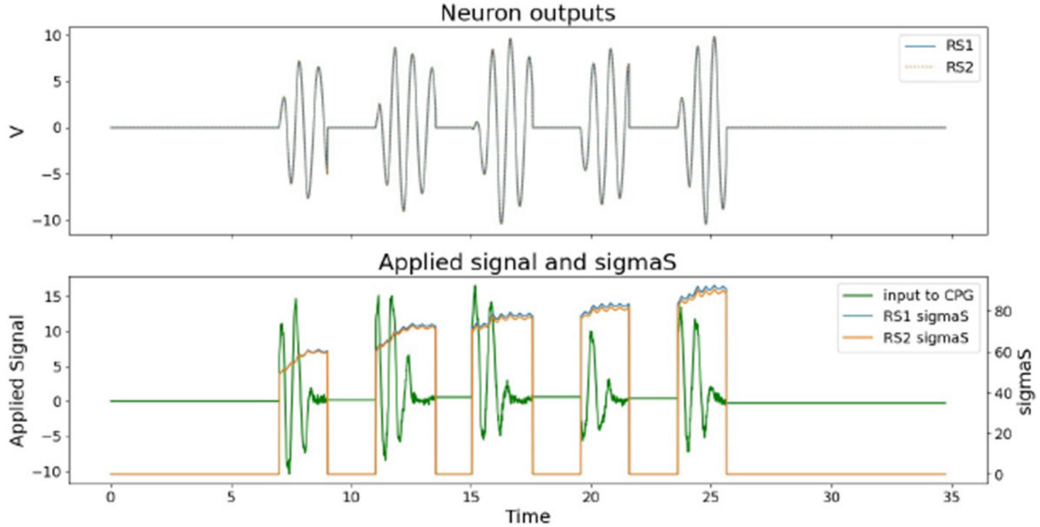
Handshake Robot:
Effects of CPG Controllers on Robot Social Attributes

Kakeru Yamasaki*, Tomohiro Shibata*, Patrick Hénaff**

*The Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Fukuoka, Japan

**LORIA UMR 7503 laboratory, University of Lorraine-INRIA-CNRS, F-54506 Nancy, France

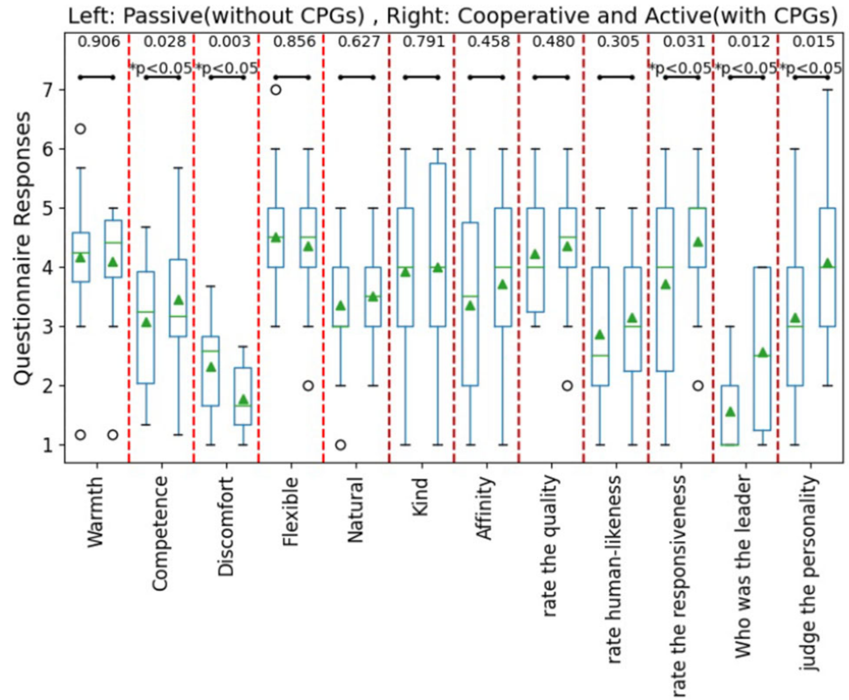
Learning handshake during 5 trials



Comparative RoSAS analysis for 2 robot control modes:

- Impedance control (passive mode)
- Impedance control+ CPG (active mode)

(Accepted to IEEE/Roman 2024)



Artificial Empathy

AFFECTIVE RESONANCE AND SOCIAL INTERACTION

Human face-to-face interaction mutually influences spontaneous postures and gestures → motor resonance

Mühlhoff, R. (2015).

- Coordination
- Synchronization
- Mimicry
- Entrainment
- Attunement

Processes part of Affective Resonance

Does it the same in HRI?

→ Phd thesis of Isabel Casso, cosupervised with Pr. Y. Delevoye , ScaLab, Lille

AFFECTIVE RESONANCE AND SOCIAL INTERACTION

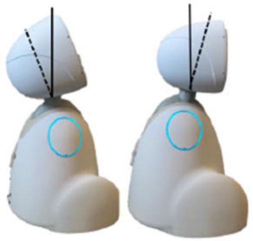
Experiment :

3 robots + no robot condition (speaker)

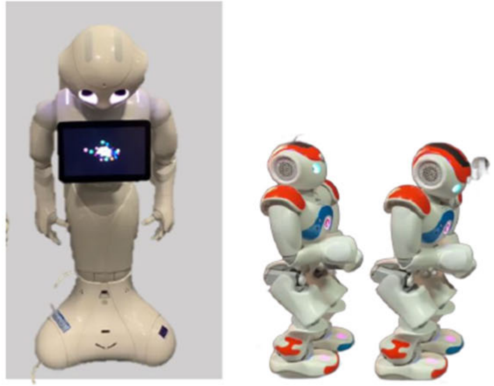
Three oscillation frequencies:

High 0.250 Hz – 4s
Medium 0.125 Hz - 8s
Low 0.083 Hz – 12s

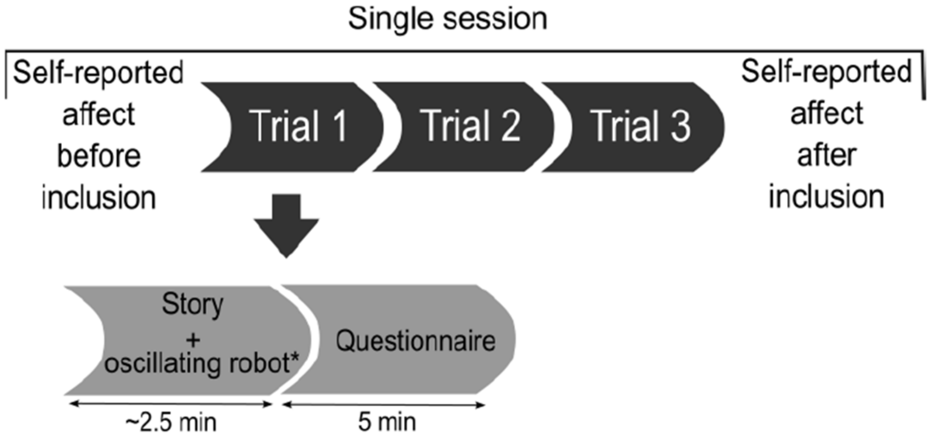
Head movement

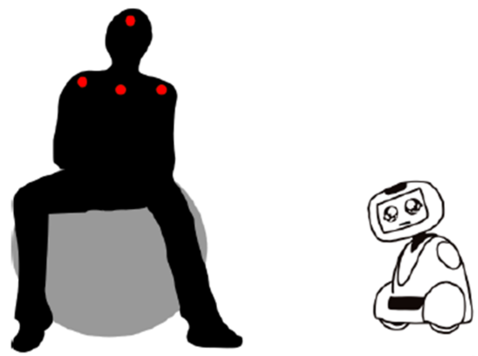


Combined head + torso movement

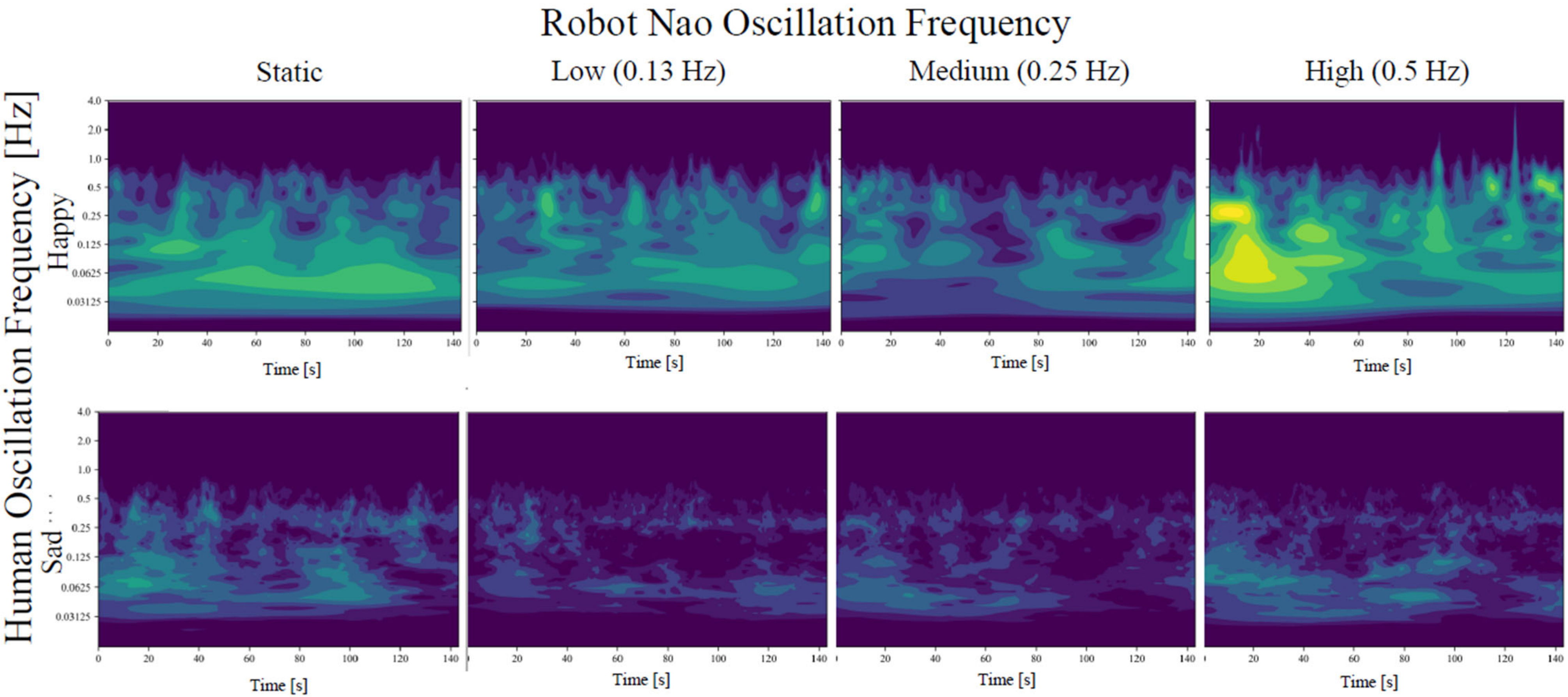


3 fictional stories (approx. 3 min each) expressing happiness or sadness in thefirst person.





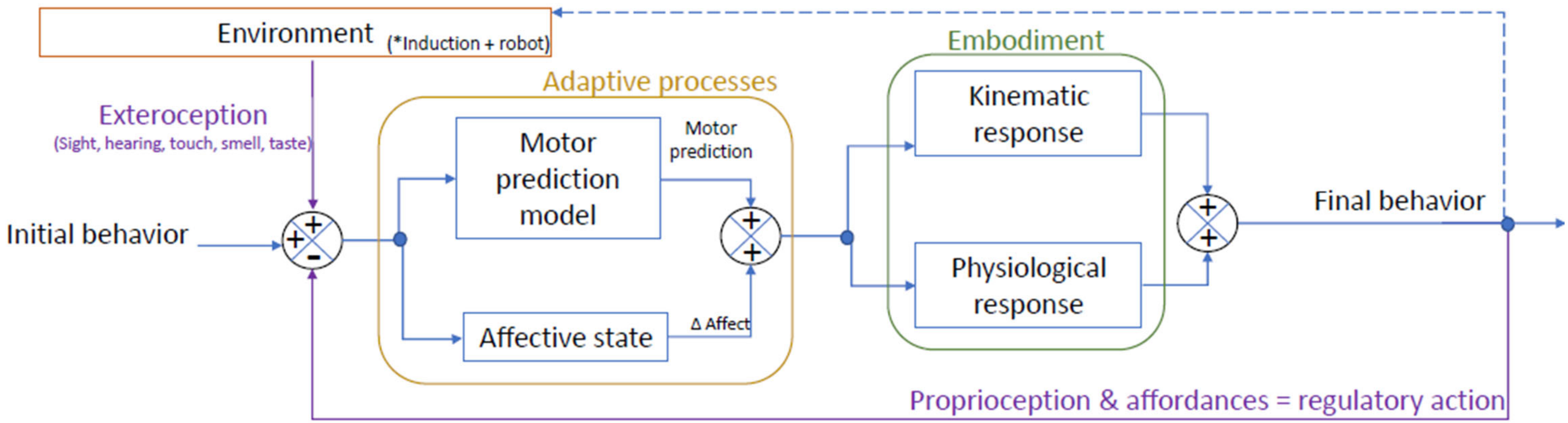
AFFECTIVE RESONANCE AND SOCIAL INTERACTION



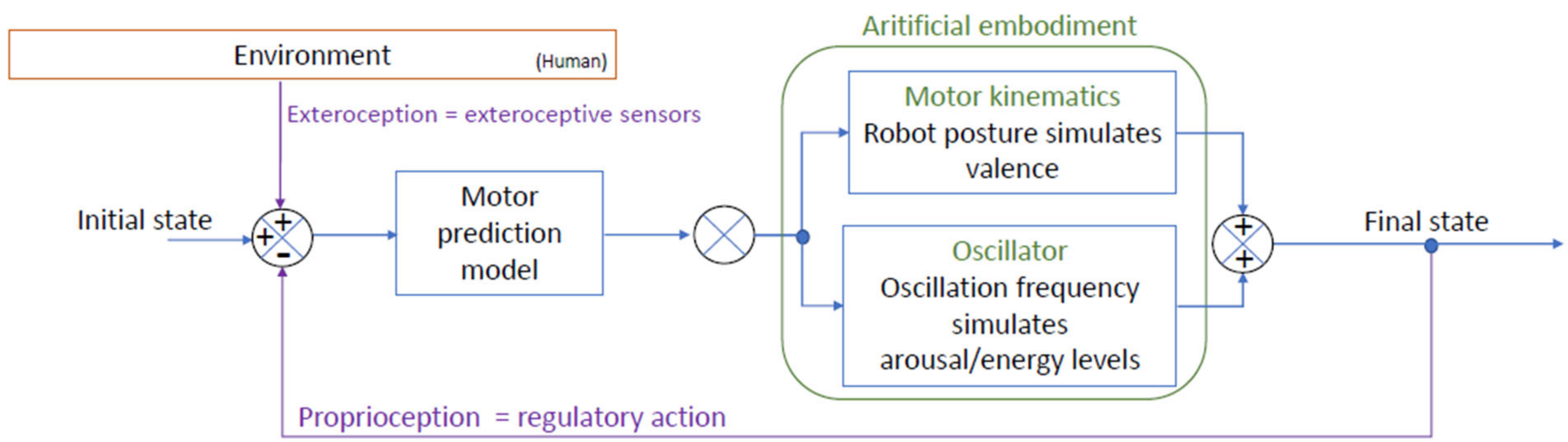
Analysis is on going…

MODEL OF CONTROL IN AFFECTIVE RESONANCE

HUMAN DIAGRAM V4



ROBOTIC CONTROL LOOP V2



Provisional results

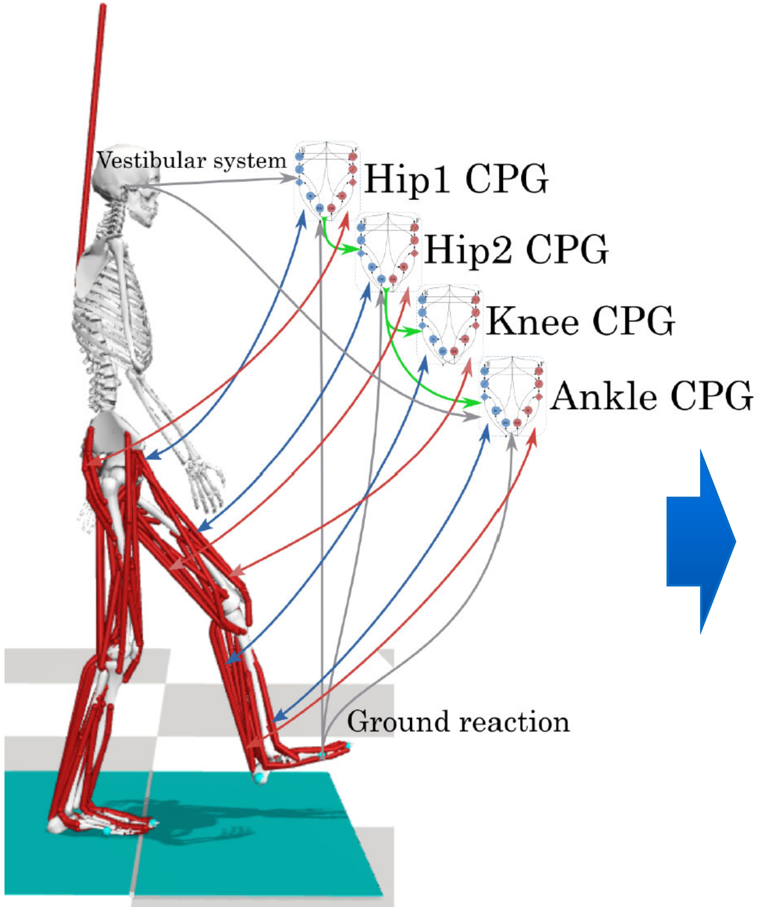
- Robot that elicits more spontaneous movement : Buddy
- No main effect of the oscillation frequency of the robots.
- We observe a tendency of higher spontaneous movement during the MF of every robot.
- When comparing robots that oscillated at MF, participants seem to move more with a non humanoid morphology.
- Participants moved more with a big humanoid robot (Pepper) than with a small humanoid robot (Nao).
- Participants perceived Buddy to be more Animated, Likeable and Intelligent. Nao was rated last on the three categories.

Applications of bioinspired control

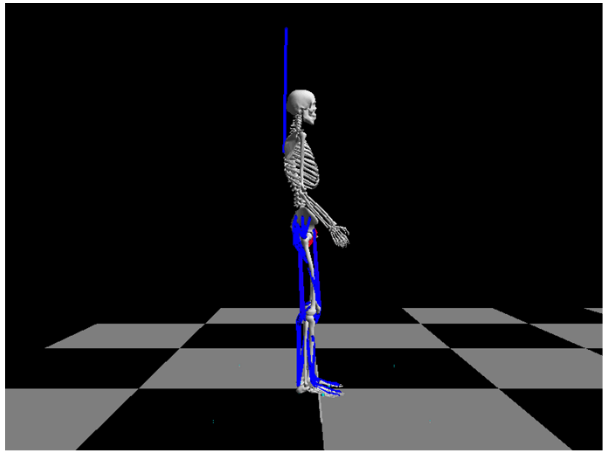
Medical application: Neuro-musculoskeletal simulation of human walk

SIMULATION OF HUMAN WALKING USING CENTRAL PATTERN GENERATORS

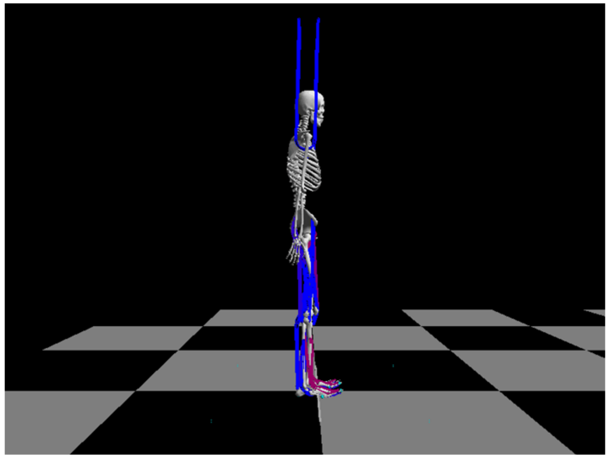
Neuro-musculoskeletal model of human walk healthy and pathotological (Parkinson)



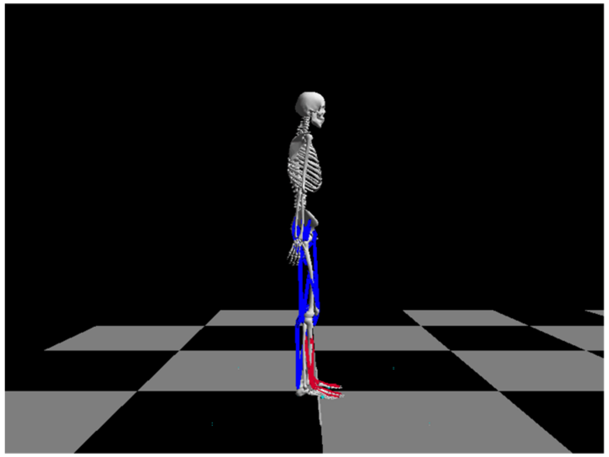
Neuro-Musculoskeletal model with OpenSim (Stanford Univ.) used in a closed loop



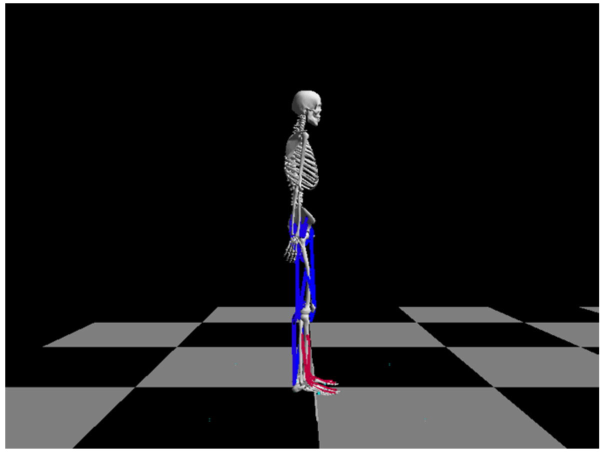
Gait "crunch", depending of CPG parameters



"Freezing of gait" , by reflex inhibition



Back jump



Forward balance reflex

[Shachykov & Henaff, 2017, 2019, 2018,]

Andrii Shachykov, Julien Frere, Patrick Henaff, (2022), Simulation of Spinal Muscle Control in Human Gait using OpenSim, in IEEE Transactions on Medical Robotics and Bionics,

Industrial application : Cobot for steel industry

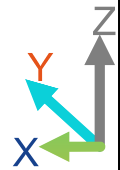
MEASURE AND ANALYZE OF OPERATOR’S MOVEMENTS

Rhythmic movement :

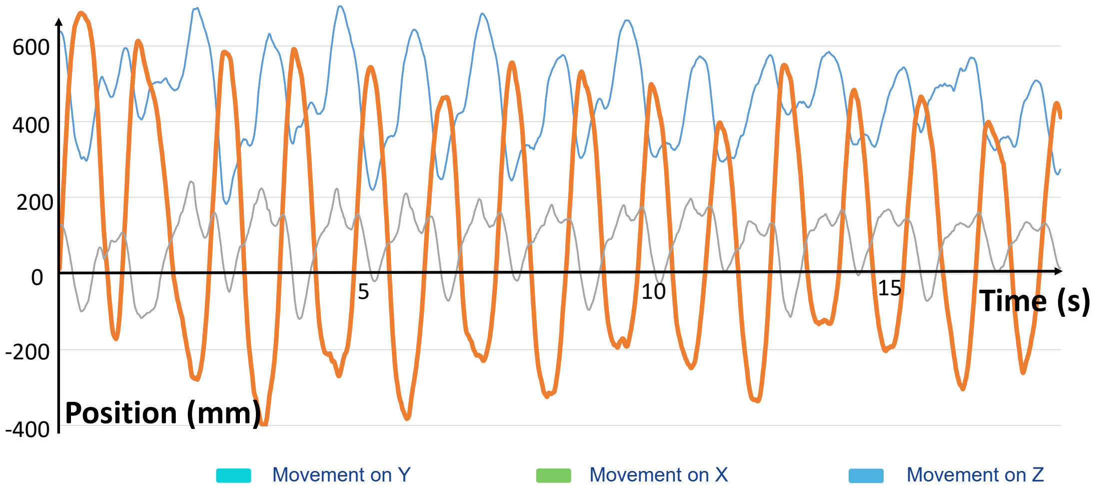
- Main rhythmic movement along Y axis
- Frequency of movement is constant (0.8 Hz)
- This frequency depends on ([Bennet D. et al., 1992]) on stiffness *K* inertia *I* of human arm :

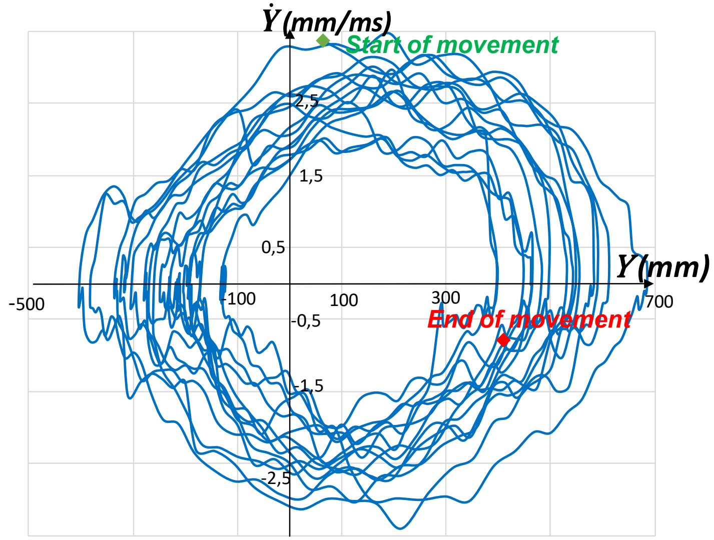
$$\omega = \sqrt{K/I}$$

- Generated by all operator joints
- Rhythmicity movement along Y axis
- Amplitude and frequency (0.8 hz)
- Depend of stiffness *K* and inertia *I* of human arm : $\sqrt{K/I}$



→ Same behavior as dynamic oscillator : limit cycle





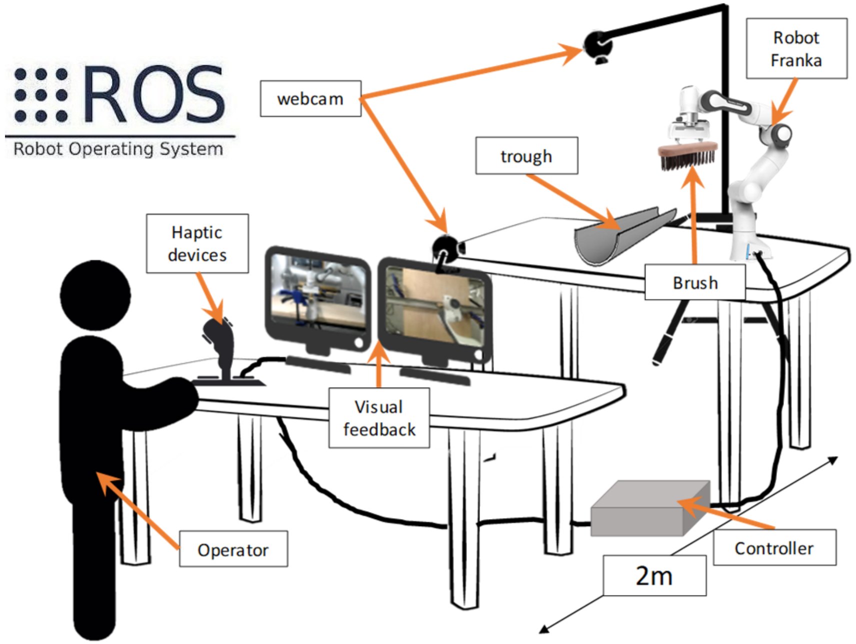
Limit cycle of the brushing movement

→Same behavior as dynamic oscillator (limit cycle)

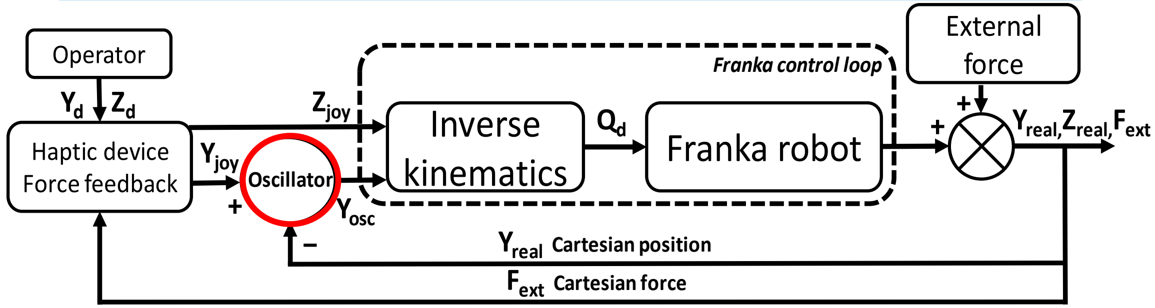
→Control based on dynamic oscillator➔ bio-inspired control

Baptiste Menges, Adrien Guenard, Patrick Henaff. Dynamic Oscillators to Compensate Master Devices Imperfections in Robots Teleoperation Tasks Requiring Dynamic Movements. *CASE 2021 – IEEE 17th International Conference on Automation Science and Engineering (CASE),*

TELEOPERATION SETUP FOR BRUSHING TASK



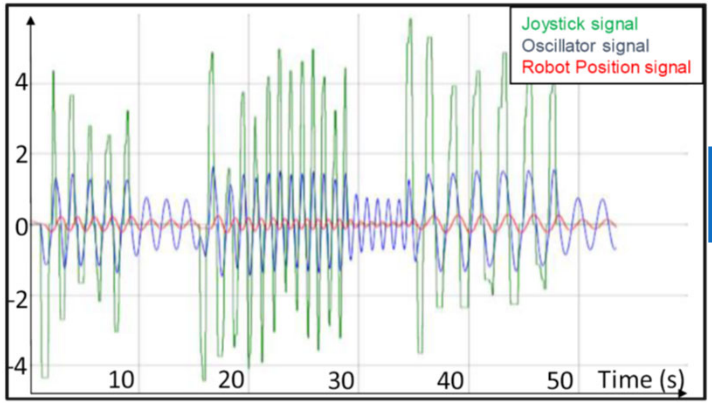
Sensorymotor control loop



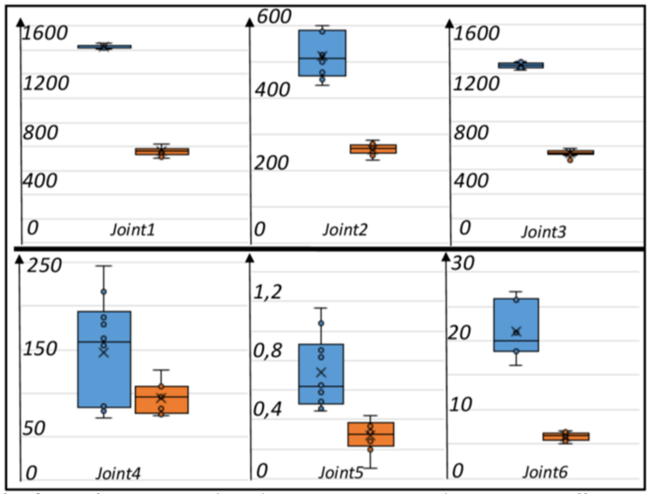
Different master devices

Non Haptic | Falcon : haptic | Geomagic : haptic

Oscillator synchronizes to the movements of operator to control the robot in working space



Joints power consumption



Bio-inspired control reduces the power consumption and compensates imperfection of master device

Baptiste Menges, Adrien Guenard, Patrick Henaff. Improving Control of a Teleoperated Robot Using an Adaptive Oscillator to Perform a Rhythmic Task for Foundry Applications. *ISR 2021 – IEEE International Conference on Intelligence and Safety for Robotics*

CONCLUSION

- Implementation of bio-inspired AI allows the robot active sensorimotor learning when it interacts with humans
- CPG encodes the learned interaction and complex movements
- versatility and efficiency of CPG controller that can adapt to varying frequencies (to varying interactions with human)
- CPG can achieve both discrete and rhythmic movements
- CPG network controls without any complex model of the robot
- Facilitates emergence of interpersonnal synchronisation (motor-coordination)

→ **CPG bases architectures are very efficient for HRI**

→ **need of a coupling with a high level layer to drive CPG learning habilities depending on interactions : social context, emotional state,**

FUTURE WORKS

- motor coordination rehabilitation for elderlies and autistic children (ASD)
- emotion detection and emergence of emotional synchrony between human and robots
- Coupling CPG control and Reinforcement learning
- human/robot physical cooperation for several different rhythmic tasks in dangerous environment (cleaning, scrubbing, brushing..
- Approach can be used in human/cobot physical cooperation for several different rhythmic tasks in dangerous environment: cleaning, brushing, sawing,

MERCI…

Many thanks to my PhD students:

Artem Melnyk (dec. 2014)

Andrii Shachykov (dec. 2019)

Mélanie Jouaiti (June 2020)

Baptiste Menges (dec. 2021)

Isabel Casso (on going)