Operational space control in the context of model learning

First workshop for young researchers on Human-friendly Robotics
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A word about me

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Background

- Studied Engineering and Automatic Control at ENI in Tarbes.
- Exchange student at NTU (Singapore).
- M. Sc. and PhD in Automatic Control from INP in Toulouse.
- Postdoc in Prof. O. Khatib research Group at Stanford University (CA, USA).

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Current status

- Assistant Professor at Université Pierre et Marie Curie since Sept. 2007 : Teaching Computer Science and Control for Robotics
- Research at l'Institut des Systèmes Intelligents et de Robotique :
  - Reactive control and motion generation for redundant systems
  - Simulation and evaluation software | Collision detection
  - iCub...

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  From Astrophysics to Zoology...

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Institut des Systèmes Intelligents et de Robotique

- A "young" lab. born from the fusion of three different labs in jan. 2007.
- 100 people among which 30 faculties.
- Lab. director : Prof. Philippe Bidaud.
- 3 research groups :
  - Interactive Systems : micro/nano-manipulation, surgical robotics
  - Mobile and autonomous Systems : bio-inspired robotics, mobile robotics, autonomous systems
  - Perception and Motion : Human and artificial perception, motion analysis, rehabilitation, humanoid robots control

Outline

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Model free, learning-based (NN, RL) control

- No a priori knowledge required, on-line adaptation
- Stability of the resulting controllers is hard to prove
- Deriving a generic control method is not easy
  $\Longrightarrow$ Same conclusion !

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First steps...

- Equip our robots with a redundant number of sensors and actuators (humanoids ?)
- Stop actuating robots with DC motors and high gear ratios.
- Use the nice framework offered by model-based control.
- Don't trust models and put some learning in the loop.

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FIG.: A CAD view of the iCub robot - credit : the RobotCub Consortium

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It relates the task space (what I want to control) to the joints space (what I can actually control)

- At the geometric level : $\mathbf{x} = h(\mathbf{q}) \rightarrow$ non-linear : too complex
- At the kinematic level : $\dot{\mathbf{x}} = J(\mathbf{q})\dot{\mathbf{q}}$
- At the dynamic level : $\mathbf{\Gamma} = M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) + \mathbf{\Gamma}_{ext}$
- In a combined fashion : $\mathbf{f} = \Lambda(\mathbf{q})\ddot{\mathbf{x}} + \mu(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{p}(\mathbf{q}) + \mathbf{f}_{ext}$ [Khatib 87]

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  - Hands, feet, head, CoG velocities...
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Some state of the art literature results for humanoids :
<u>**Reactive approach**</u> : J. Park, L. Sentis, O. Khatib at Stanford University (2004-2008).

<u>**Motion planning based approach**</u> : E. Yoshida, M. Poirier, J.P.Laumond, O. Kanoun, F. Lamiraux, R. Alami and K. Yokoi at the French-Japanese Joint Robotics Lab. at LAAS CNRS (Toulouse, France) (2008).

What is nice about model-based control ? An Example...

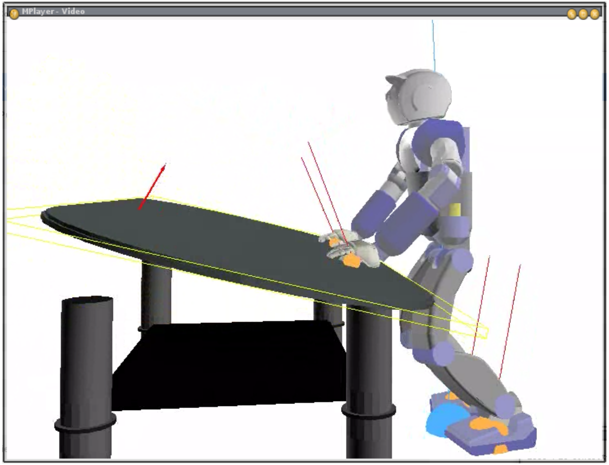

FIG.: A virtual humanoid in the SAI environment - credit : Luis Sentis

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Does it exist already ?

- Yes : Locally Weighted Projection Regression [Vijayakumar et al. 00]

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- Uses a combination of linear models (called Receptive Fields (RFs)) (RLS)
- Each model is valid on an elliptic zone of the inputs space
- The prediction made by LWPR for a given input vector is a weighted sum of the results of all the active surroundings RFs.
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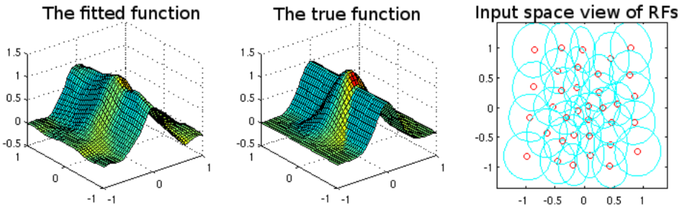

FIG.: Example of LWPR learning on a sample function - credit : Sethu Vijayakumar

Our approach to combine OSC and learning

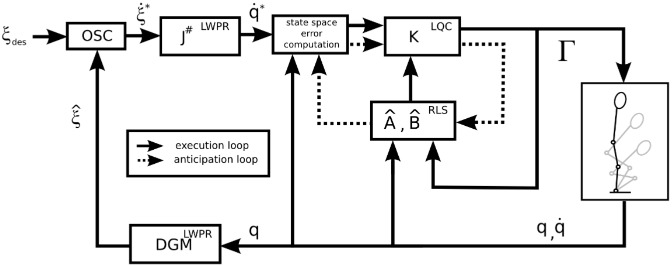

FIG.: Some example of OSC and learning combination - credit : Camille Salaün (Abials, 2008)

Some results in simulation and using a toy-like robot

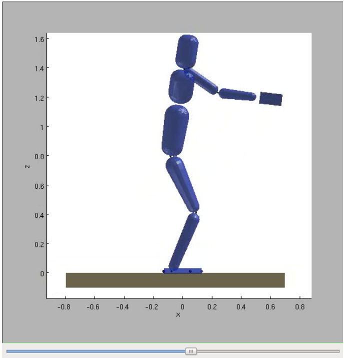

Fig.: A standing and reaching task using learnt models - credit : Camille Salaün (Abials, 2008)

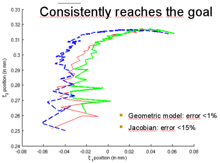

Fig.: A standing task using learnt models on a Bioloid robot - credit : Paul Tonelli

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From a theoretical point of view

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- Increase the number of DoFs
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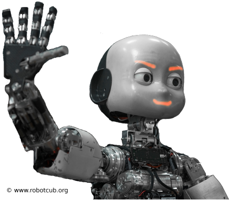
From a practical point of view

- Use this robot as a real demonstrator !



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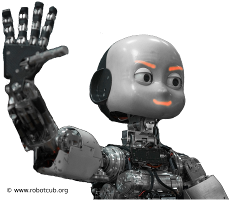
From a practical point of view

- Use this robot as a real demonstrator !
- Guide learning using Human/Robot interaction (teaching, imitation, curiosity)



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Can we get an idea of what is the optimal motion criteria using motion capture data and learnt direct and inverse models ? This vision of human motion is a bit simplistic. But we may try !

Acknowledgements

- Prof. Philippe Bidaud (always thank the boss !)
- Camille Salaün (PhD student)
- Prof. Olivier Sigaud (Senior colleague)
- Paul Tonelli (Master Student)
- The RobotCub consortium and Giorgio Metta in particular (always thank the robot provider !)

Questions ?