STATISTICAL DYNAMICAL SYSTEMS FOR SKILLS ACQUISITION IN HUMANOIDS

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Abstract

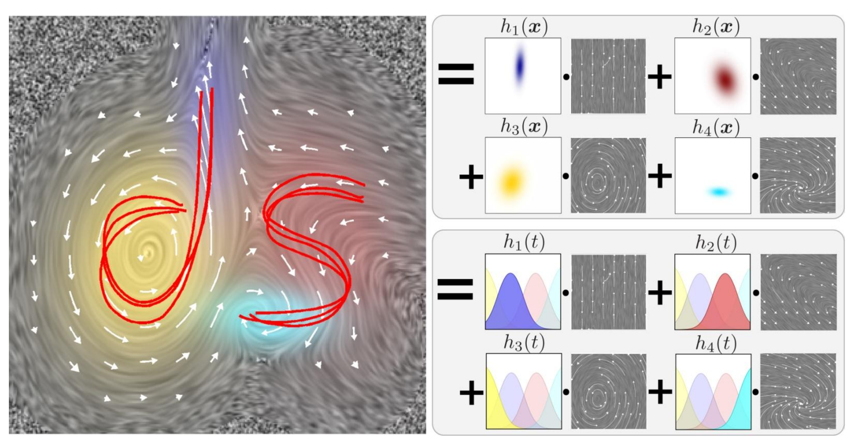
Learning in humanoids is challenging due to the unpredictable environments these robots have to face during reproduction. Two sets of tools are relevant for this purpose:

1) **Probabilistic machine learning** methods that can extract and exploit the regularities and important features of the task.
2) **Dynamical systems** that can cope with perturbation in real-time without having to re-plan the whole movement.

We present a learning by imitation approach combining the two benefits. It is based on a **superposition of virtual spring-damper systems** to drive a humanoid robot's movement. The method relies on a **statistical description of the springs attractor points acting in different candidate frames of reference**. It extends dynamic movement primitives models by formulating the dynamical systems parameters estimation problem as a Gaussian mixture regression problem with projection in different coordinate systems.

The robot exploits local variability information extracted from multiple demonstrations of movements to determine which frames are relevant for the task, and **how the movement should be modulated with respect to these frames**. The approach is tested on the COMAN compliant humanoid with time-based and time-invariant movements, including bimanual coordination skills.

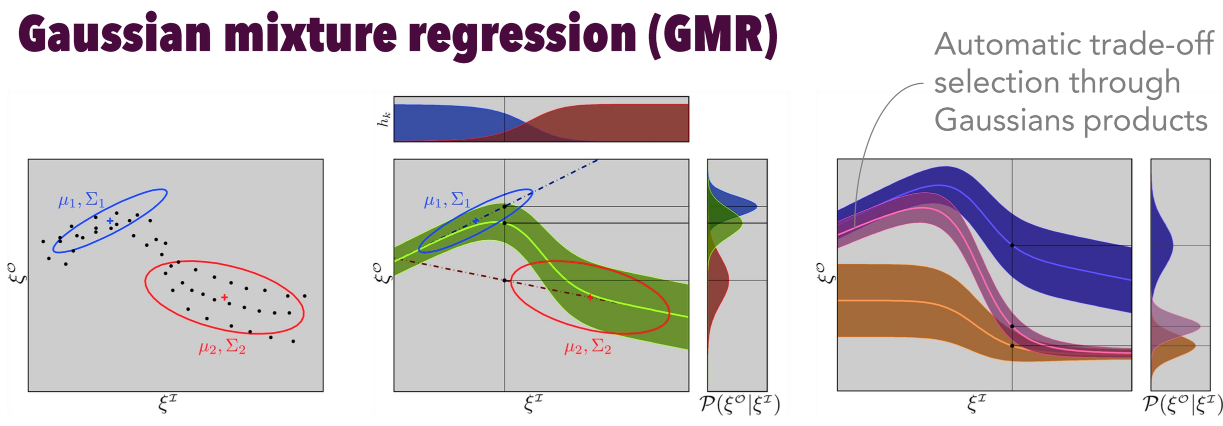
Nonlinear motion encoding with linear systems



Some examples:

- Gaussian Mixture Regression (GMR) [CALINON ET AL, RAM 17(2), 2010]
- Stable Estimator of Dynamical Systems (SEDS) [KHANSARI AND BILLARD, TRO 27(5), 2011]
- Dynamic Movement Primitives (DMP) [IJSPEERT ET AL, IROS'01][HOFFMANN ET AL, ICRA'2009]
- Correlated Dynamic Movement Primitives [CALINON, SARDELLITTI AND CALDWELL, IROS'2010]
- Takagi-Sugeno (TS) fuzzy model [TAKAGI AND SUGENO, IEEE TRANS. SMC 15(1), 1985]

Gaussian mixture regression (GMR)



$\mathcal{P}(\xi^{\mathcal{I}}, \xi^{\mathcal{O}})$ encoded in GMM, $\mathcal{P}(\xi^{\mathcal{O}}|\xi^{\mathcal{I}})$ retrieved through GMR.

Example for time-based trajectories: $\xi^{\mathcal{I}} = t, \ \xi^{\mathcal{O}} = \boldsymbol{x}$.

$$\hat{\boldsymbol{\mu}}^{\boldsymbol{x}} = \sum_{i=1}^{K} h_i(t) \left[\boldsymbol{\mu}_i^{\boldsymbol{x}} + \boldsymbol{\Sigma}_i^{\boldsymbol{x}t} (\Sigma_i^t)^{-1} (t - \mu_i^t)\right] \ \text{with} \ \boldsymbol{\mu}_i = \begin{bmatrix} \mu_i^t \\ \boldsymbol{\mu}_i^{\boldsymbol{x}} \end{bmatrix}, \ \boldsymbol{\Sigma}_i = \begin{bmatrix} \Sigma_i^t & \boldsymbol{\Sigma}_i^{t\boldsymbol{x}} \\ \boldsymbol{\Sigma}_i^{\boldsymbol{x}t} & \boldsymbol{\Sigma}_i^{\boldsymbol{x}} \end{bmatrix}$$

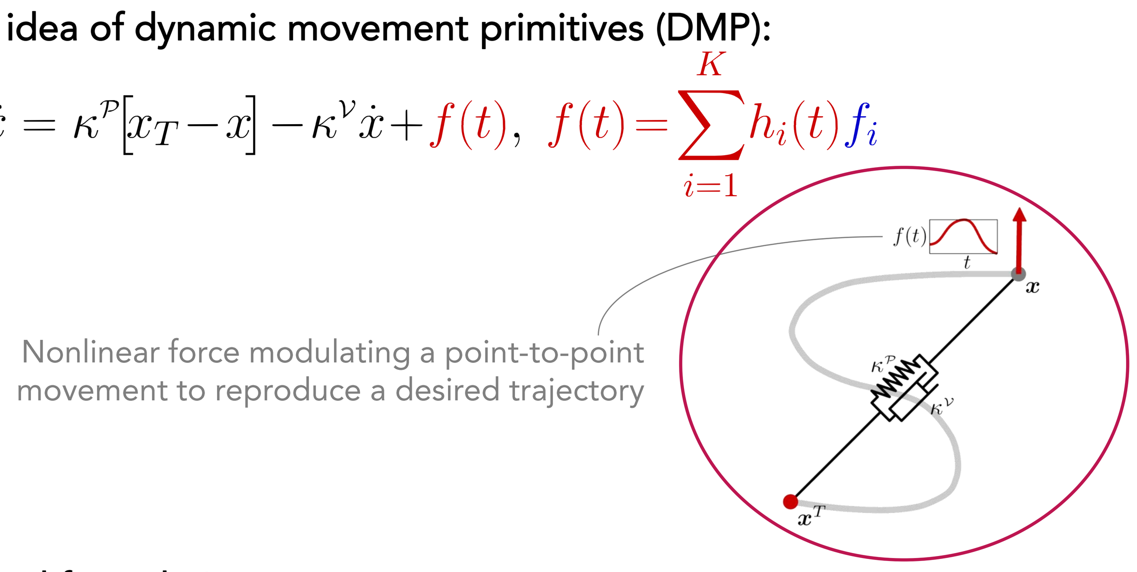
- Learning the model depends linearly on the number of datapoints, while prediction is independent on this number, which makes the approach an interesting alternative to kernel-based regression methods (GMR can retrieve control commands in real-time, independently on the number of datapoints in the training set).
- In GMR, there is no distinction between input and output components when learning the model (any subset of input-output dimensions can be selected, and expectations on the remaining dimensions can be computed in real-time).

[CALINON, GUENTER AND BILLARD, IEEE SMC-B 37(2), 2007]
[HERSCH, GUENTER, CALINON AND BILLARD, IEEE TRANS. ON ROBOTICS 24(6), 2008]
[CALINON, D'HALLUIN, SAUSER, CALDWELL AND BILLARD, IEEE ROBOTICS AND AUTOMATION 17(2), 2010]

Dynamical systems (DS)

Core idea of dynamic movement primitives (DMP):

$$\tau \ddot{x} = \kappa^{\mathcal{P}}[x_T - x] - \kappa^{\mathcal{V}} \dot{x} + f(t), \quad f(t) = \sum_{i=1}^{K} h_i(t) f_i$$



Original formulation:

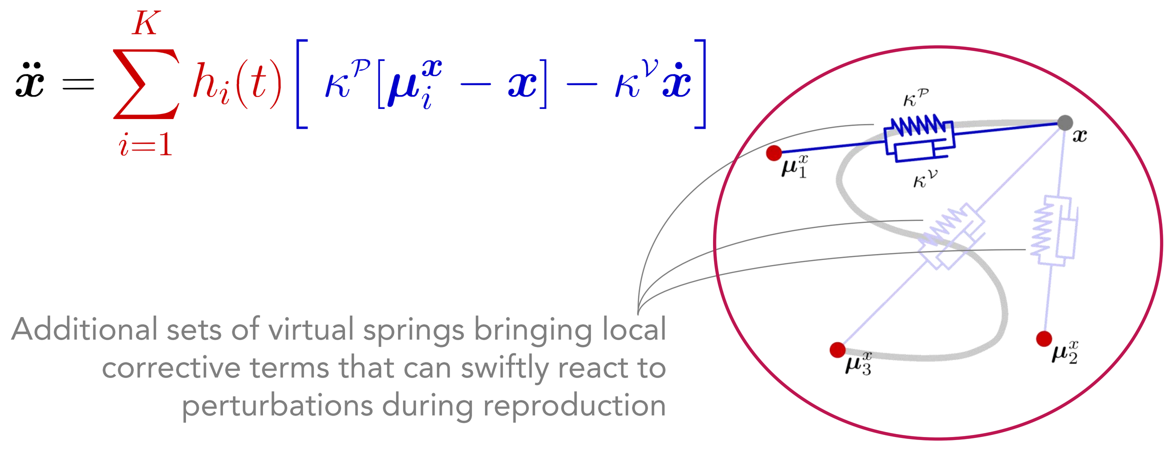
$$\tau \ddot{x} = \kappa^{\mathcal{P}}[x_T - x] - \kappa^{\mathcal{V}} \dot{x} + f(s), \quad f(s) = s\,[x_T - x_0] \sum_{i=1}^{K} h_i(s) f_i$$

$$\tau \dot{s} = -\alpha s$$

[IJSPEERT, NAKANISHI AND SCHAAL, IROS'2001]

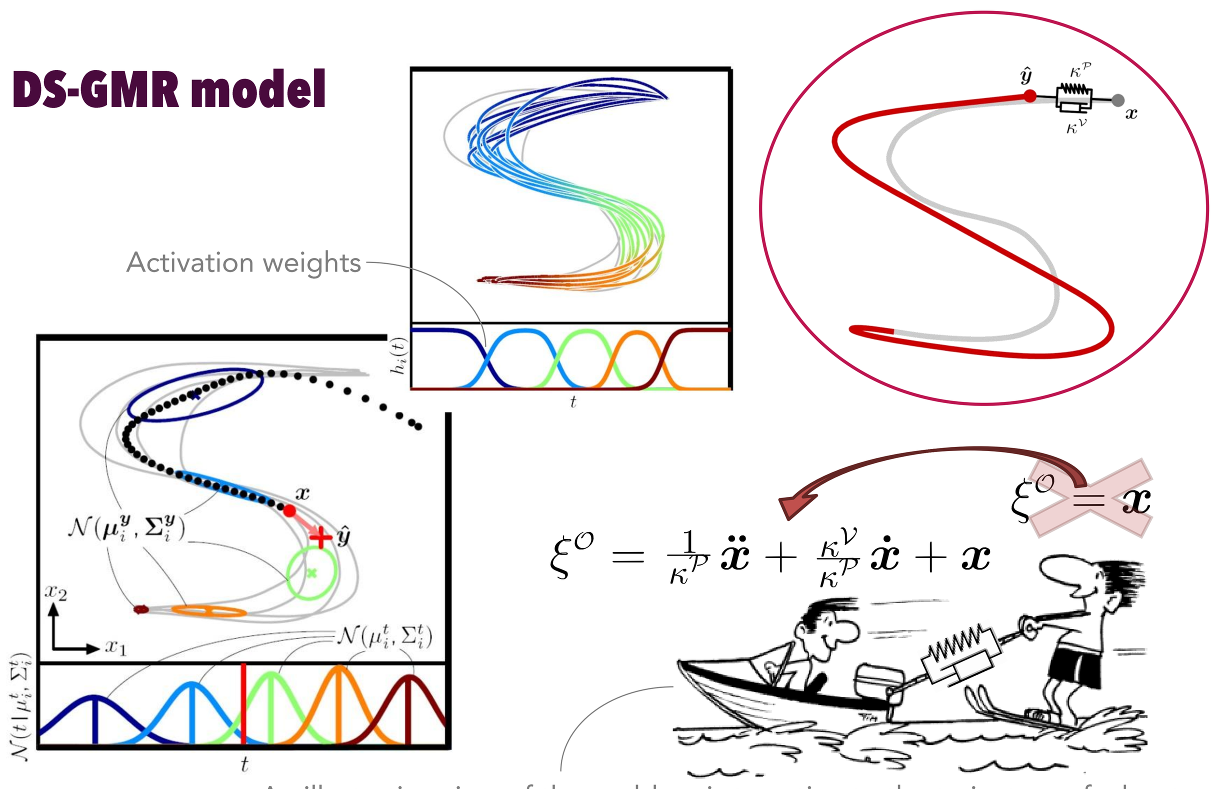
Variant of DMP based on mechanical springs analogy:

$$\ddot{\boldsymbol{x}} = \sum_{i=1}^{K} h_i(t) \left[\ \kappa^{\mathcal{P}}[\boldsymbol{\mu}_i^{\boldsymbol{x}} - \boldsymbol{x}] - \kappa^{\mathcal{V}} \dot{\boldsymbol{x}}\right]$$



[HOFFMANN, PASTOR, PARK AND SCHAAL, ICRA'2009]
[CALINON, D'HALLUIN, CALDWELL AND BILLARD, HUMANOIDS'2009]

DS-GMR model



An illustrative view of the problem is to estimate the trajectory of a boat pulling a water-skier such that the water-skier follows a desired path, with the rope acting as a spring of given stiffness and damping.

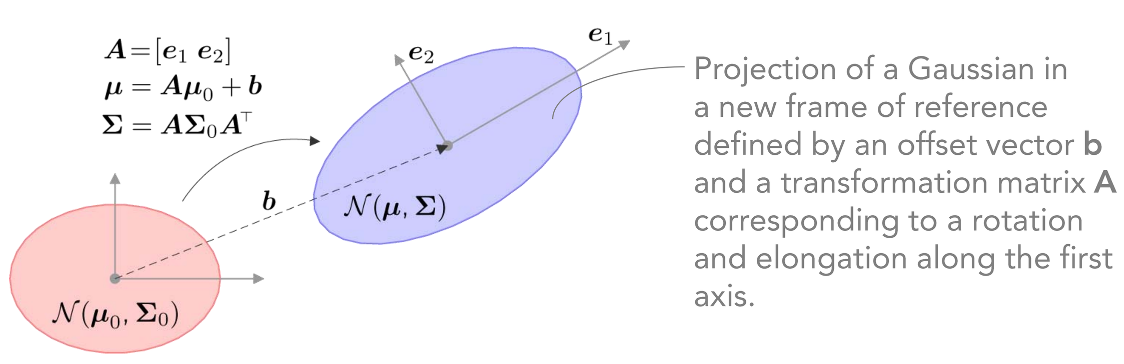
- DS-GMR estimates the path of the attractor point, together with its variability in the form of a covariance matrix.
  The changing stiffness profile can be estimated as being inversely proportional to the variation in the movement.

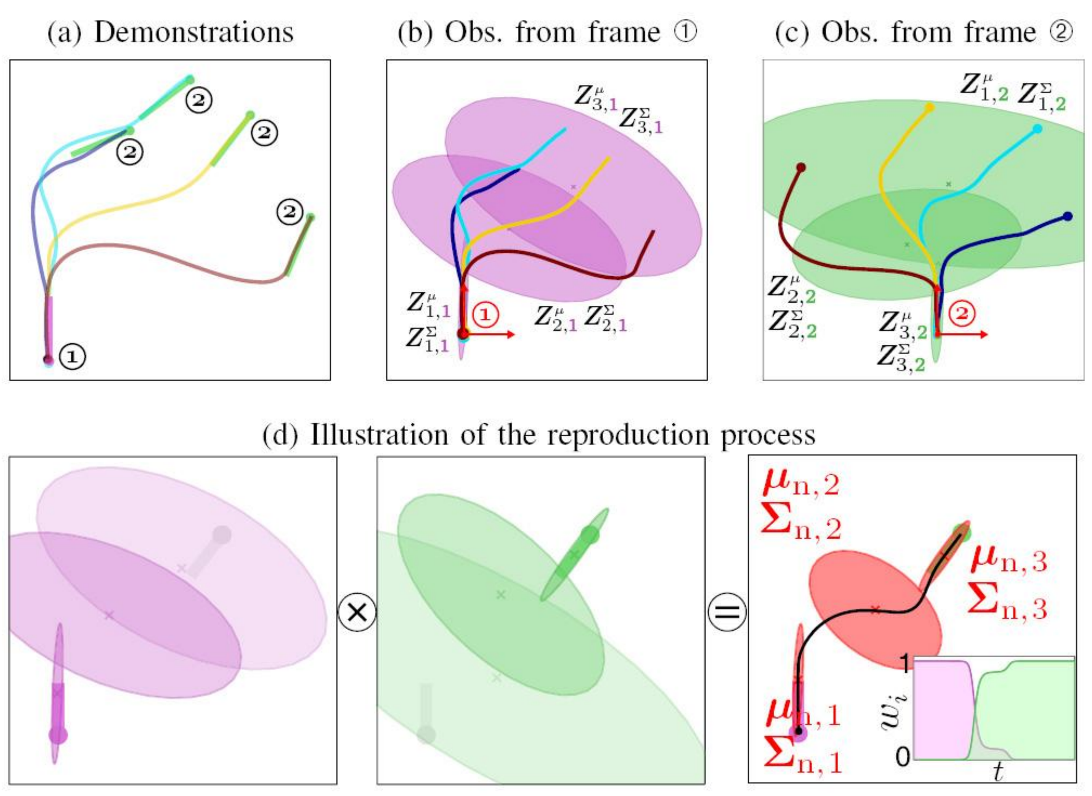
[S. CALINON, I. SARDELLITTI AND D.G. CALDWELL, "LEARNING-BASED CONTROL STRATEGY FOR SAFE HUMAN-ROBOT INTERACTION EXPLOITING TASK AND ROBOT REDUNDANCIES", IROS'2010]

Advantages of the proposed statistical dynamical system:

- DS-GMR automatically adapts the span and position of the activation weights while learning the movement.
- DS-GMR does not only provide a single estimate for each virtual attractor but a Gaussian with full covariance, which can be exploited: 1) to provide additional information when several demonstrations are available; 2) to encapsulate the local relationships between the variables of the task; 3) to regenerate movements with a natural variability that follows the essential characteristics of the task (e.g., for stochastic exploration).
- It extends the approach to models in machine learning compatible with GMM representations, opening up a host of new possibilities (HMM, PHMM, IGMM, DP, etc.).

Extension to task-parameterized skill learning





Reproduction through products of Gaussians:

$$\mathcal{N}(\boldsymbol{\mu}_{n,i}, \boldsymbol{\Sigma}_{n,i}) = \prod_{j=1}^{P} \mathcal{N}\Big(\boldsymbol{A}_{n,j}\boldsymbol{Z}_{i,j}^{\mu} + \boldsymbol{b}_{n,j}\ ,\ \boldsymbol{A}_{n,j}\boldsymbol{Z}_{i,j}^{\Sigma}\boldsymbol{A}_{n,j}^{\top}\Big)$$

Model parameters estimation with expectation-maximization (EM):

E-step:

$$h_{n,i} = \frac{\pi_i \mathcal{N}(\boldsymbol{x}_n | \boldsymbol{\mu}_{n,i}, \boldsymbol{\Sigma}_{n,i})}{\sum_k^K \pi_k \mathcal{N}(\boldsymbol{x}_n | \boldsymbol{\mu}_{n,k}, \boldsymbol{\Sigma}_{n,k})}.$$

M-step:

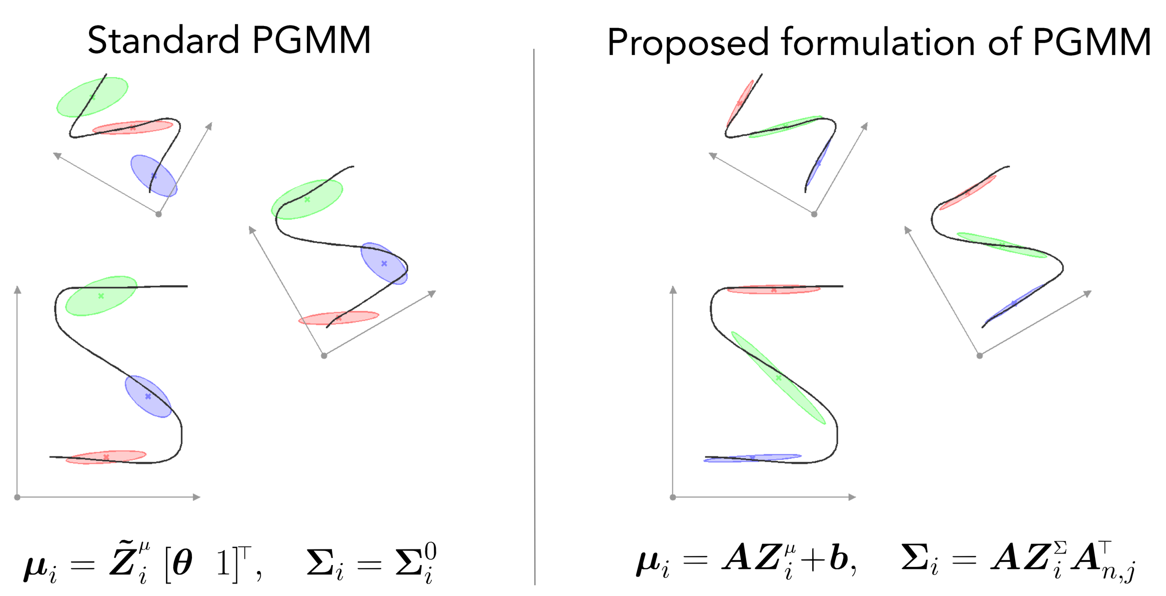
$$\pi_i = \frac{\sum_{n=1}^N h_{n,i}}{N},$$

$$\boldsymbol{Z}_{i,j}^{\mu} = \frac{\sum_{n=1}^N h_{n,i}\, \boldsymbol{A}_{n,j}^{-1}[\boldsymbol{x}_n - \boldsymbol{b}_{n,j}]}{\sum_{n=1}^N h_{n,i}},$$

$$\boldsymbol{Z}_{i,j}^{\Sigma} = \frac{\sum_{n=1}^N h_{n,i}\, \boldsymbol{A}_{n,j}^{-1}[\boldsymbol{x}_n - \tilde{\boldsymbol{\mu}}_{n,i,j}][\boldsymbol{x}_n - \tilde{\boldsymbol{\mu}}_{n,i,j}]^{\top} \boldsymbol{A}_{n,j}^{-\top}}{\sum_{n=1}^N h_{n,i}},$$

$$\text{with} \quad \tilde{\boldsymbol{\mu}}_{n,i,j} = \boldsymbol{A}_{n,j}\boldsymbol{Z}_{i,j}^{\mu} + \boldsymbol{b}_{n,j}.$$

Comparison with parametric hidden Markov model



$$\boldsymbol{\mu}_i = \tilde{\boldsymbol{Z}}_i^{\mu}\,[\boldsymbol{\theta} \ \ 1]^{\top}, \quad \boldsymbol{\Sigma}_i = \boldsymbol{\Sigma}_i^0$$

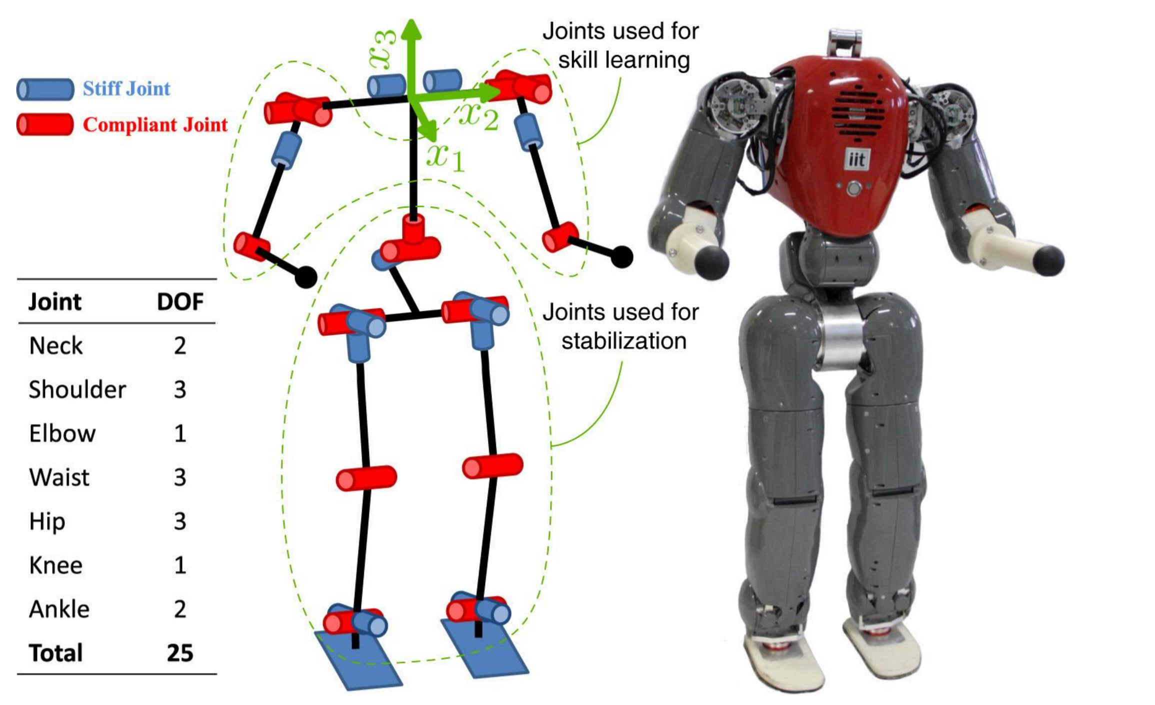
(covariance matrices are shared)

$$\boldsymbol{\mu}_i = \boldsymbol{A}\boldsymbol{Z}_i^{\mu} + \boldsymbol{b}, \quad \boldsymbol{\Sigma}_i = \boldsymbol{A}\boldsymbol{Z}_i^{\Sigma}\boldsymbol{A}_{n,j}^{\top}$$

(covariance matrices are parameterized)

[A.D. WILSON AND A.F. BOBICK, "PARAMETRIC HIDDEN MARKOV MODELS FOR GESTURE RECOGNITION", IEEE TRANS. ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE 21:9, 1999]

COMAN compliant humanoid

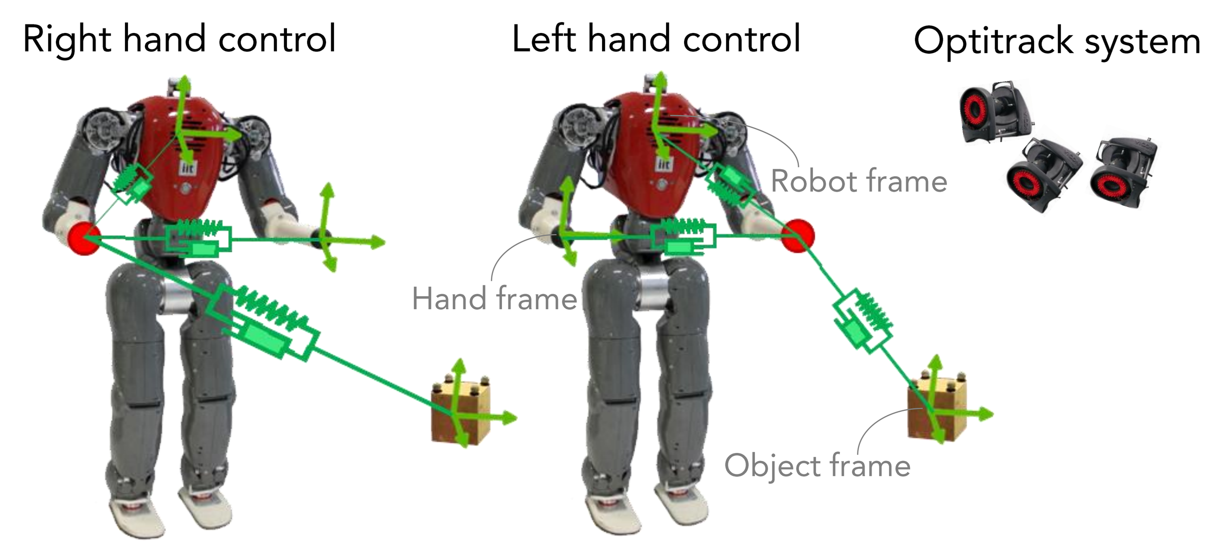


Joint	DOF
Neck	2
Shoulder	3
Elbow	1
Waist	3
Hip	3
Knee	1
Ankle	2
Total	25

- The arms are controlled with an admittance controller to let the user physically interact with the robot by grasping and moving its arms.
- The legs and torso are controlled to let the robot stand by reacting to perturbations with a stabilization control scheme exploiting the intrinsic and controlled compliance of the robot.

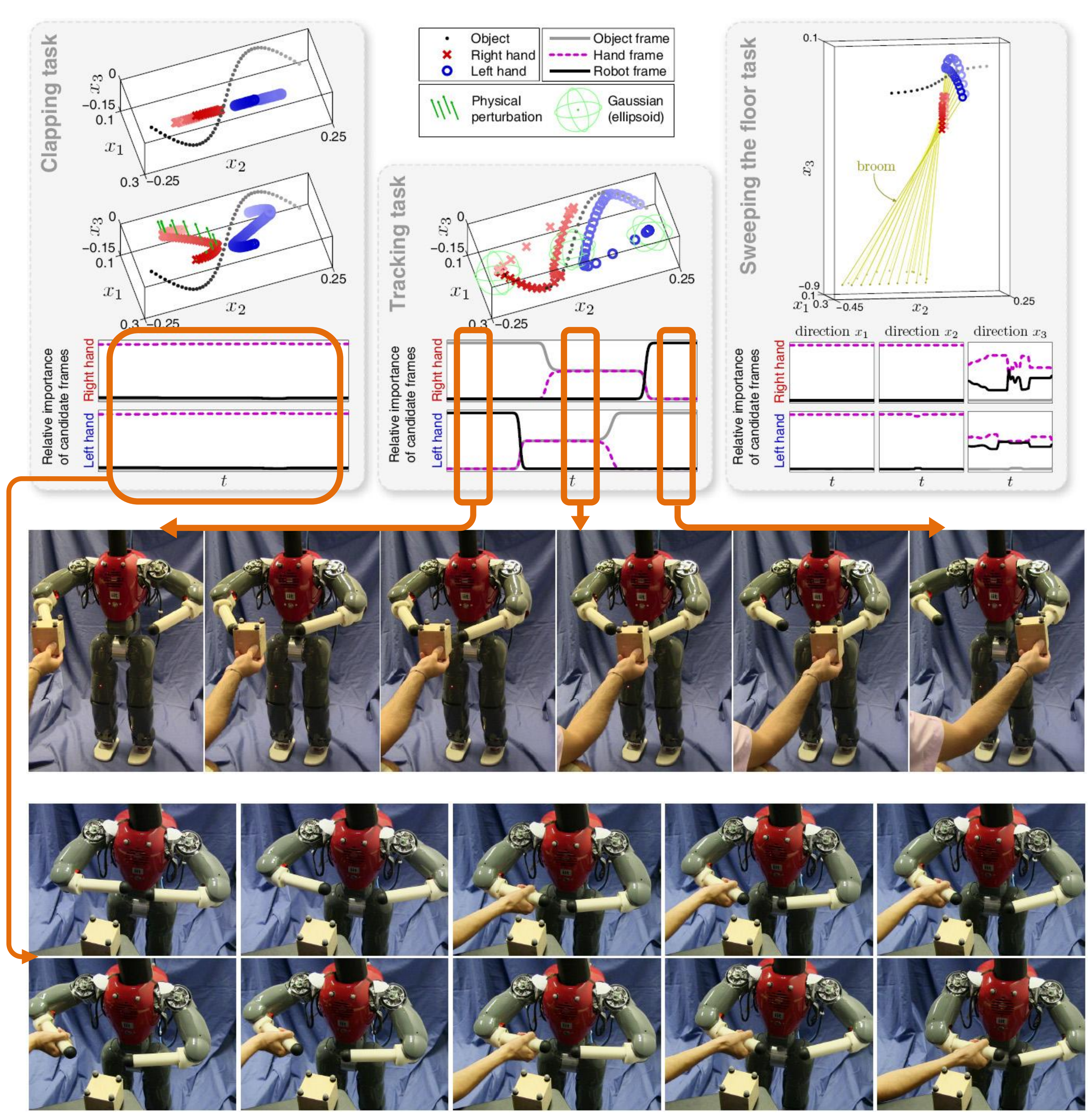
[Z. LI, B. VANDERBORGHT, N.G. TSAGARAKIS, L. COLASANTO AND D.G. CALDWELL, "STABILIZATION FOR THE COMPLIANT HUMANOID ROBOT COMAN EXPLOITING INTRINSIC AND CONTROLLED COMPLIANCE", ICRA'2012]

Candidate frames of reference



- A set of candidate frames of reference is predefined, remaining valid for a wide range of tasks (e.g., hands relevant for most manipulation skills). The role of the robot is to autonomously figure out which frames of reference matter along the task, and in which way the movement should be modulated with respect to these frames.
- Consistent demonstrations will result in stronger springs, while irrelevant connections will vanish.

Experimental results of bimanual skills learning



- **Hands clapping:** The robot extracted that the important aspect of the task is to keep the motion of the hands coordinated (hand frames are extracted as the most important). The robot does not react to the motion of the box (candidate frame irrelevant for the task). If the user grasps one hand of the robot and moves it to a new position, the robot reacts by adapting the movement of the other hand.
- **Tracking task:** the robot learned to smoothly switch from one to two hands reaching (depending on the position of the box used as inputs of the GMR), and to bring back the unused hand to a natural pose. When the box is at reachable distance by the two hands, the relations hand-hand and hand-box are detected to be important for the task (both object frame and hand frame matter).
- **Sweeping task:** The robot correctly extracted that the movement of the two hands requires bimanual coordination, and that the task can be generalized to different positions in the robot's frame, as long as vertical constraints are satisfied.

SEVENTH FRAMEWORK PROGRAMME
AMARSi
STIFF flop

Contact: sylvain.calinon@iit.it Source codes: Programming-by-demonstration.org