Statistical Dynamical Systems for Skills Acquisition in Humanoids

Sylvain Calinon, Zhijin Li, Tohid Alizadeh, Nikos G. Tsagarakis and Darwin G. Caldwell
Learning & Interaction Lab – Department of Advanced Robotics – Istituto Italiano di Tecnologia (IIT)

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 various attractor points acting in different candidate frames of reference. It extends dynamical 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 humanoid humanoid with time-varying and time-invariant movements, including bimanual coordination skills.

Nonlinear motion encoding with linear systems

Gaussian mixture regression (GMR)

P(ξ1, ξ2) encoded in GMM, P(ξ1, ξ2) retrieved through GMR.

Example for time-based trajectories: Z1 = t, Z2 = z.

DS-GMR model

Activation weights:

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.

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 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 physical 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, GMM, DP, etc.).

Extension to task-parameterized skill learning

Gaussian mixture regression (GMR)

P(ξ1, ξ2) encoded in GMM, P(ξ1, ξ2) retrieved through GMR.

Example for time-based trajectories: Z1 = t, Z2 = z.

Dynamical systems (DS)

Core idea of dynamical movement primitives (DMP):

\[ \tau \ddot{z} = \kappa [p - z] - \kappa' z + f(t), \quad f(t) = \sum_{i=1}^{K} h_i(t) \Phi_i \]

Nonlinear force modulating a point-to-point reproduction to a desired trajectory.

Variant of DMP based on mechanical springs analogy:

\[ \ddot{z} = \sum_{i=1}^{K} h_i(t) \left[ \kappa_i [p - z] - \kappa' z \right] \]

Comparison with parametric hidden Markov model

Standard PHMM

Proposed formulation of PHMM

Model parameters estimation with expectation-maximization (EM):

E-step:

M-step:

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.