Learning and Generalization of Motor Skills by Learning from Demonstration

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Introduction

'Is Imitation learning the route to humanoid robots?'
(St. Schaal: Trends in Cognitive Sciences, 1999)

Crucial for the widespread of anthropomorphistic robots that shall assist humans: easy programming (e.g.: learning from demonstration).
Introduction cont.

Three challenges need to be mastered for imitation:

- **Correspondence problem**
  (human links/ joints might not match the links/ joints of the robot)

- **Generalization**
  (important, that movement can be generalized to a different context)

- **Robustness against perturbation**
  (dynamic environment → obstacle avoidance)
Introduction cont.  *DMP*

**Dynamic Movement Primitive (DMP) framework**

A recorded movement is represented with a set of differential equations.

Advantages:

- Perturbance can automatically be corrected for by the dynamics of the system (robustness)
- Adaption to a new goal is simply achieved by changing a goal parameter (generalization)
- The movement trajectory is represented in end-effector space (correspondence problem)
Introduction cont.  

**How to deal with complex motion?**

Build a library out of movement primitives out of which complex motion can be composed by sequencing!

*example:* grasping – placing – releasing

*Due to the generalization ability of each dynamic movement primitive, an object may be placed between two arbitrary positions.*
DMP \quad \textit{set of differential equations}

\textbf{Transformation System:}

\begin{align*}
\tau v' &= K(g-x) - Dv + (g-x_0)f \\
\tau x' &= v
\end{align*}

$x, v$ position, velocity of the system

$x_0, g$ start and goal position

$\tau$ temporal scaling factor

$K$ acts like a spring constant

$D$ damping term

$f$ non-linear function that can be learned
DMP cont. set of differential equations

Non-linear fcn and canonical system (4):

\[ (3) \quad f(s) = \frac{\sum_i w_i \psi_i(s)s}{\sum_i \psi_i(s)}, \quad \psi_i(s) = \exp(-h_i(s-c_i)^2) \]

\[ (4) \quad \tau s' = -\alpha s \]

\[ \alpha \quad \text{pre-defined constant} \]

\[ c_i, h_i, w_i \quad \text{center, width and adjustable weights of Gaussian basis functions} \]
DMP cont. Learning from demonstration

- Movement $x(t)$ is recorded, $v(t)$ and $v'(t)$ are computed for each time step $t = 0, ..., T$
- $s(t)$ is computed for appropriate adjusted $\tau$

- $f_{\text{target}}(s) = \frac{-K(g - x) + Dv + \tau v'}{g - x_0}$, $x_0 = x(0)$, $g = x(T)$

- Finding $w_i$ by minimizing the error criterion:

$$J = \sum_s (f_{\text{target}}(s) - f(s))^2$$
DMP cont. *Generating a movement plan*

A movement plan is generated by reusing $w_i$, specifying $x_0$, $g$ and setting $s = 1$
DMP cont. *Drawbacks*

**Drawbacks of the original DMP formulation:**

- $x_0$, $g$ are the same $\rightarrow$ system will remain in $x_0$
- Scaling of $f$ problematic if $(g - x_0)$ close to zero
- If $(g_{\text{new}} - x_0)$ changes its sign compared to $(g_{\text{original}} - x_0)$, the resulting generalization is mirrored
DMP cont.  Modified DMP

Replacing the Transformation system

(1) \[ \tau v' = K(g-x) - Dv - K(g-x_0)s + Kf(s) \]

(2) \[ \tau x' = v \]

\( K(g - x_0) \) is required to avoid jumps at the beginning of a movement.

Learning and propagating DMPs is achieved with the same procedure as before, except:

\[ f_{\text{target}}(s) = \frac{\tau v' + Dv}{K} - (g-x) + (g-x_0)s \]
DMP cont. *Modified DMP*

**Comparison of goal-changing results**

between old (left) and new (right) DMP formulation
DMP cont. *Modified DMP*

**Obstacle Avoidance**

Adding a coupling term \( p(x, v) \):

\[
\tau v' = K(g - x) - Dv - K(g - x_0) s + Kf(s) + p(x, v)
\]

Derived from Fajen / Warren (2003):

\[
p(x, v) = \gamma R v \phi \exp(-\beta \alpha)
\]

- \( R \): rotational matrix with axis \( r = (x-o) \times v \) and angle of rotation of \( \pi/2 \)
- \( \gamma, \beta \): constant
- \( \phi \): angle between direction of end-effector towards obstacle / end-eff.'s velocity relative to the obstacle
Motion Library

Conceptual sketch of an imitation learning system:
Additional information is needed!

Traditional AI planning algorithms formalize the domain scenario by defining a set of pre- and post-conditions.

→ Such algorithms are based on discrete symbolic representations of object and action.
Motion Library cont. *Combination of MP*

**Minimum – jerk movements**

Jumps in the acceleration signal are avoided by initializing the succeeding DMP by

\[ v_{\text{pred}} \rightarrow v_{\text{succ}} \text{ and } x_{\text{pred}} \rightarrow x_{\text{succ}} \]

Different switching times:
A lighter color indicates an earlier switching time.
Experiment: Sarcos Slave arm

7 DOF anthropomorphic arm with 3 DOF end-effector
Experiment cont. 10 dimensional DMP

Involved variables:

End-effector's position \((x, y, z)\) in Cartesian space

End-effector's orientation \((q_0, q_1, q_2, q_3)\) in quaternion space

Finger position \((\theta_{TL}, \theta_{TV}, \theta_{FAA})\) in joint space
Experiment cont.

Water-serving task:
Experiment cont.
Online adaption & obstacle avoidance

Pick and place:  http://www-clmc.usc.edu
Conclusion & Outlook

Done yet:

- Extension of the DMP framework to action sequences that allow object manipulation
- Adding of semantic information

Future work:

- Extension of the movement library
- Focus on associating objects with actions
- Application of this framework on a humanoid robot
Thank you for your attention...