



Robotic cloth manipulation for clothing assistance task using Dynamic Movement Primitives

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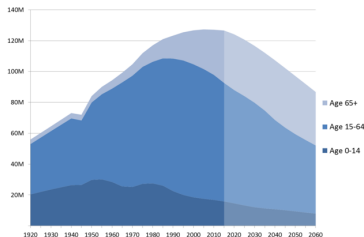
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Introduction

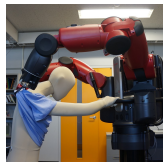
- Japan is a super-aging society
- In 2030, 1.8 person is supposed to care 1 elderly
- 400,000 care givers are lacking now
- Clothing is one of the most suffering daily activities for elderly



Japan population growth¹

Major challenges involved

- Close interaction of the robot with cloth
- Safe human-robot interaction
- Estimation of human-cloth relationship



¹JonMcDonald. Chapter 2: Population and Households, table 2-7 (Ministry of Internal Affairs and Communication, Statistics Bureau, retrieved 13 January 2016) and Population Projections for Japan (January 2012): 2011 to 2060, table 1-1 (National Institute of Population and Social Security Research, retrieved 13 January 2016). URL: https://en.wikipedia.org/wiki/Aging_of_Japan#/media/File:Japan_Population_by_Age_1920-2010_with_Projection_to_2060.png.

Related Works

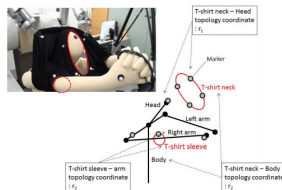
Towner *et al.*², Manipulating clothing article by dual-arm robot

- Used Hidden Markov Model for tracking
- Triangulated mesh model for simulating clothing article
- Highly depends on simulated contour information.



Tamei *et al.*³, Clothing assistance with dual-arm robot

- Used Reinforcement learning (RL)
- Topology coordinates for human and cloth extremities relationship
- Via-point trajectory with minimum jerk criterion



²Marco Cusumano-Towner *et al.* "Bringing clothing into desired configurations with limited perception". In: *Robotics and Automation (ICRA), 2011 IEEE International Conference on.* IEEE. 2011, pp. 3893–3900.

³Tomoya Tamei *et al.* "Reinforcement learning of clothing assistance with a dual-arm robot". In: *Humanoid Robots (Humanoids), 2011 11th IEEE-RAS International Conference on.* IEEE. 2011, pp. 733–738.

Dynamic Movement Primitives (DMP)

Used for generating control signal to guide real system⁴

Why DMP?

- A *non-linear* dynamical system used for policy parameterization
- Can adapt to complex motor-skills
- Also perform target tracking and obstacle avoidance

The system is defined as

$$\ddot{y} = \alpha (\beta (g - y) - \dot{y}) + f$$

where:

- y is system state and g is goal state
- α and β are gain terms
- f is nonlinear function defined over time

f is a function of *canonical system*

⁴[Stefan Schaal](#). “Dynamic movement primitives-a framework for motor control in humans and humanoid robotics”. In: *Adaptive Motion of Animals and Machines*. Springer, 2006, pp. 261–280.

Forcing function f

f is defined as
$$f(x, g) = \frac{\sum_{i=1}^N \psi_i w_i}{\sum_{i=1}^N \psi_i} x (g - y_0)$$

where:

- y_0 is the initial state of the system
- w_i is a weighting for a given basis function ψ_i
- $\psi_i = \exp\left(-h_i (x - c_i)^2\right)$ is Gaussian with mean c_i and variance h_i

Imitating a desired path

The desired forcing term f which affects the system acceleration, is written as

$$\mathbf{f}_d = \ddot{\mathbf{y}}_d - \alpha_y (\beta_y (g - \mathbf{y}) - \dot{\mathbf{y}})$$

Choose the weights over the basis functions i.e., minimize⁵

$$\sum_t \psi_i(t) [f_d(t) - w_i \{x(t)(g - y_0)\}]^2$$

⁵Stefan Schaal, Christopher G Atkeson, and Sethu Vijayakumar. “Scalable techniques from nonparametric statistics for real time robot learning”. In: *Applied Intelligence* 17.1 (2002), pp. 49–60.

Example of DMP

Workflow of *Robotic cloth manipulation* task

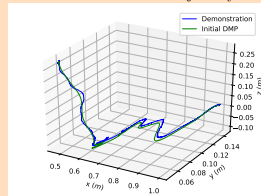
Teaching Phase



A demonstration is performed by moving the Baxter arms in the appropriate trajectory

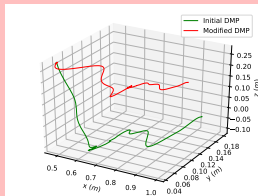
Learn Trajectory

Baxter Left Arm Trajectory



Recorded trajectory is parameterized by DMP

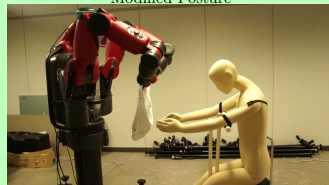
DMP Generalization



Arms posture of the mannequin is changed. Accordingly goal parameter of DMP is modified

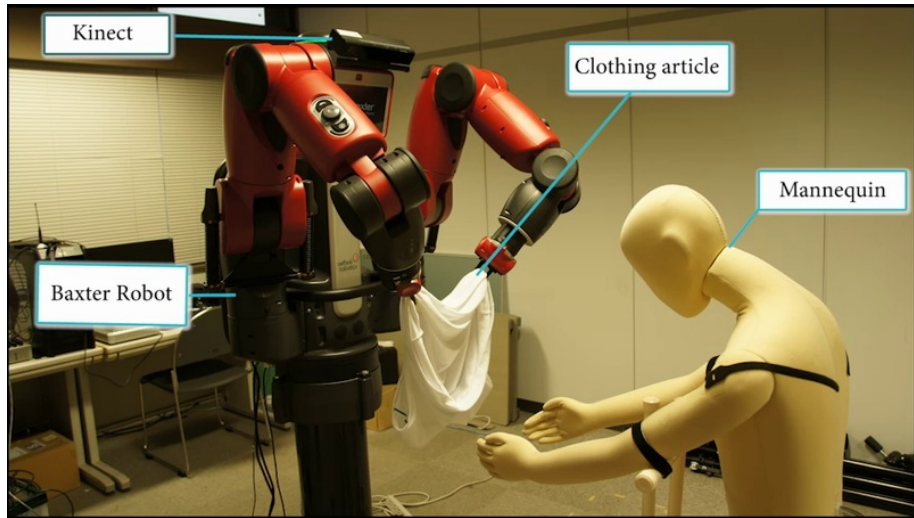
Testing Phase

Modified Posture

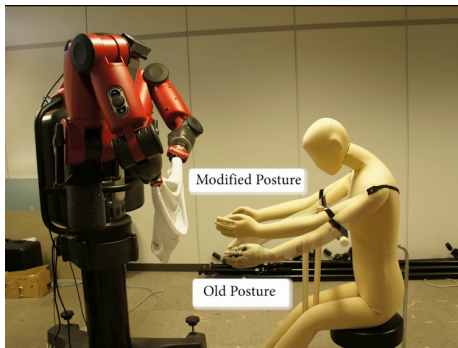


DMP can accomodate any posture by changing goal parameter

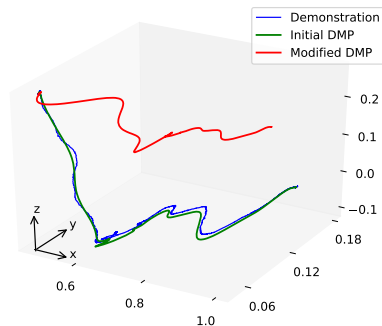
Setup



Experiments and Results



Old & modified posture of mannequin

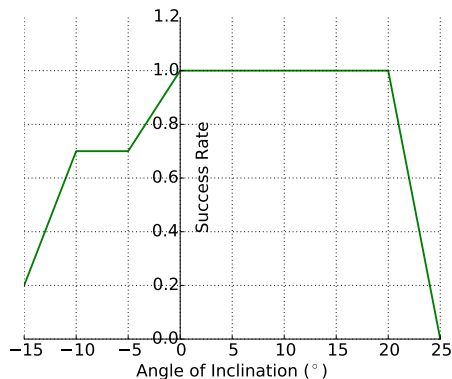
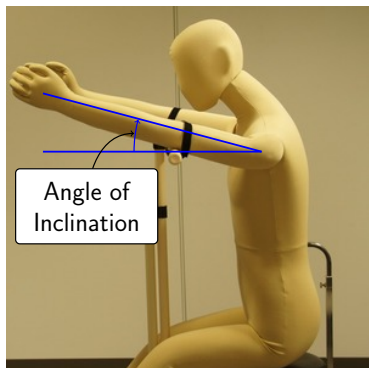


Left arm trajectories of Baxter Robot

[Video Demonstration](#)

Accuracy measurement

Angle of Inclination measures the bending of arms w.r.t. horizontal line in two-dimensional space



Discussion and Conclusion

- Robotic clothing assistance is challenging since it requires cooperative manipulation
- Clothing article inherits non-rigid and highly deformable properties
- Result shows that DMPs are able to generalize the movement trajectory
- DMP should incorporate orientation information as well

Future work

- Make approach more robust by using combination of visual and force information
- Need for designing an adaptive controller
 - For real-time tracking of mannequin
 - To adapt various failure scenarios

Acknowledgments

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Ijspeert, Auke Jan, Jun Nakanishi, and Stefan Schaal. “Movement imitation with nonlinear dynamical systems in humanoid robots”. In: *Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on*. Vol. 2. IEEE. 2002, pp. 1398–1403.



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Schaal, Stefan. “Dynamic movement primitives-a framework for motor control in humans and humanoid robotics”. In: *Adaptive Motion of Animals and Machines*. Springer, 2006, pp. 261–280.



Schaal, Stefan, Christopher G Atkeson, and Sethu Vijayakumar. “Scalable techniques from non-parametric statistics for real time robot learning”. In: *Applied Intelligence* 17.1 (2002), pp. 49–60.



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Thanks for your attention!

Any questions?

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supplemental here

Dynamic Movement Primitives (DMP)

DMP in a nutshell

- A method of trajectory control/planning⁶
- Complex movements are considered as composed of sets of primitive action ‘building blocks’
 - Executed in sequence *and/or* in parallel
 - DMPs are a proposed mathematical formalization of these primitives.
- It can represent *nonlinear* motion with a set of differential equations
- These equations can be adapted to generate any movement trajectory

⁶Schaal, Stefan. “Dynamic movement primitives-a framework for motor control in humans and humanoid robotics.” *Adaptive Motion of Animals and Machines*. Springer Tokyo, 2006. 261-280.

Formulation of DMP

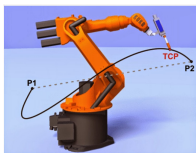
DMP is for generating a control signal to guide the real system

Underlying Idea⁷

- 1 Take a dynamical system with well specified stable behaviour
- 2 Add another term that makes it follow some interesting trajectory

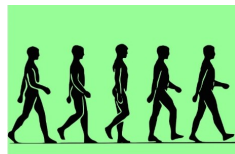
There are two kinds of DMP:

DISCRETE DMP



Point to Point Motion

RHYTHMIC DMP



Human Walking

⁷Ijspeert, A. J., J. Nakanishi, and S. Schaal. "Learning control policies for movement imitation and movement recognition." Neural information processing system. Vol. 15. 2003.

Formulation of DMP

Let's start with point attractor dynamics⁸

$$\ddot{y} = \alpha_y(\beta_y(g - y) - \dot{y}) \quad (1)$$

where:

- y is system state and g is goal state
- α and β are gain terms

Now add a forcing term f on eq(1) that will let us to modify this trajectory

$$\ddot{y} = \alpha_y(\beta_y(g - y) - \dot{y}) + f \quad (2)$$

f is nonlinear function defined over time.

- * The introduced system in eq(2) is called the *canonical system*.
- * It is denoted by x as $\dot{x} = -\alpha_x x$

⁸Ijspeert, Auke Jan, Jun Nakanishi, and Stefan Schaal. "Movement imitation with nonlinear dynamical systems in humanoid robots." Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on. Vol. 2. IEEE, 2002.

Formulation of DMP

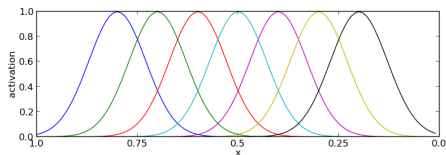
The forcing function f is defined as a function of the canonical system:

$$f(x, g) = \frac{\sum_{i=1}^N \psi_i w_i}{\sum_{i=1}^N \psi_i} x (g - y_0) \quad (3)$$

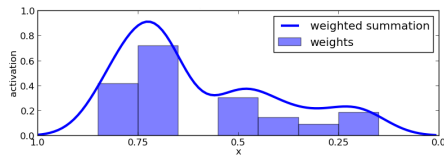
where:

- y_0 is the initial state of the system
- w_i is a weighting for a given basis function ψ_i
- $\psi_i = \exp(-h_i(x - c_i)^2)$ is Gaussian with mean c_i and variance h_i

Forcing function f is a set of Gaussians that are *activated* as the canonical system x converges to its target.



ψ Activation



Weighted Summation

Imitating a desired path

The forcing term f which affects the system acceleration, can be re-written as

$$\mathbf{f}_d = \ddot{\mathbf{y}}_d - \alpha_y(\beta_y(g - \mathbf{y}) - \dot{\mathbf{y}}) \quad (4)$$

where

- \mathbf{y}_d is desired trajectory, given by $\ddot{\mathbf{y}}_d = \frac{\partial}{\partial t} \dot{\mathbf{y}}_d = \frac{\partial}{\partial t} \frac{\partial}{\partial t} \mathbf{y}_d$

Forcing term

- Comprised of weighted summation of basis functions
- We can use optimization technique like LWR⁹
 - * To choose the weights over our basis functions
 - * Minimize

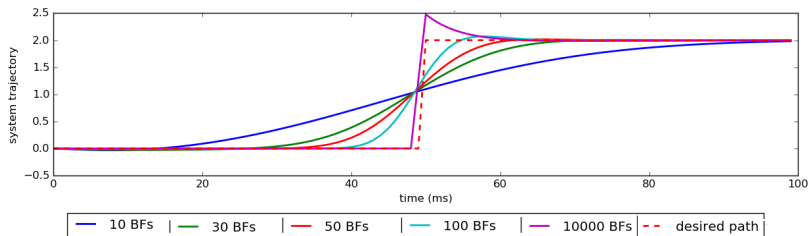
$$\sum_t \psi_i(t) (f_d(t) - w_i(x(t)(g - y_0)))^2 \quad (5)$$

⁹Cleveland, William S. "Robust locally weighted regression and smoothing scatterplots." Journal of the American statistical association 74.368 (1979): 829-836.

Imitating a desired path

The solution¹⁰ of eq(5) $w_i = \frac{\mathbf{s}^T \boldsymbol{\psi}_i \mathbf{f}_d}{\mathbf{s}^T \boldsymbol{\psi}_i \mathbf{s}}$
where

$$\mathbf{s} = \begin{pmatrix} x_{t_0}(g - y_0) \\ \vdots \\ x_{t_N}(g - y_0) \end{pmatrix} \text{ and } \boldsymbol{\psi}_i = \begin{pmatrix} \psi_i(t_0) & \dots & 0 \\ 0 & \ddots & 0 \\ 0 & \dots & \psi_i(t_n) \end{pmatrix}$$



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¹⁰Schaal, Stefan, Christopher G. Atkeson, and Sethu Vijayakumar. "Scalable techniques from nonparametric statistics for real time robot learning." Applied Intelligence 17.1 (2002): 49-60.