



## Robotic cloth manipulation for clothing assistance task using Dynamic Movement Primitives

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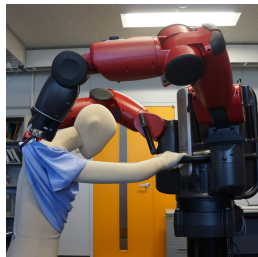


# Outline

- 1 Introduction
- 2 Related Works
- 3 Dynamic Movement Primitives
- 4 Setup and Experiment
- 5 Experiments and results
- 6 Conclusion and Discussion
- 7 Future work

# Introduction

- Clothing assistance is a basic and important assistance activity in the daily life of the elderly and disabled people
- Need of robotic clothing assistance is growing



## Major challenges involved

- Close interaction of the robot with non-rigid clothing article
- Safe human-robot interaction
- Accurate estimation of human-cloth relationship

# Related Works

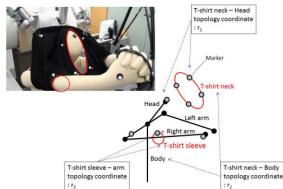
## Towner *et al.*<sup>1</sup>, Identifying and manipulating clothing article by dual-arm robot

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



## Tamei *et al.*<sup>2</sup>, Clothing assistance with dual-arm robot

- ✓ Used Reinforcement learning (RL)
- ✓ Topology coordinates for human and cloth extremities relationship
- ✗ Limited generalization capability for new postures



<sup>1</sup>Marco 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.

<sup>2</sup>Tomoya 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)

## DMP in a nutshell

- It is used for generating a control signal to guide the real system<sup>3</sup>
- It can represent *nonlinear* motion with a set of differential equations

The system is defined as

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

where:

- $y$  is system state and  $g$  is goal state
- $\alpha$  and  $\beta$  are gain terms
- $f$  is nonlinear function defined over time

$f$  is a function of *canonical system*, denoted by  $x$  as  $\dot{x} = -\alpha_x x$

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<sup>3</sup>[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.

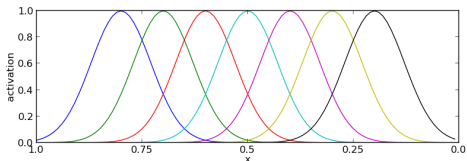
# Forcing function $f$

$f$  is defined as

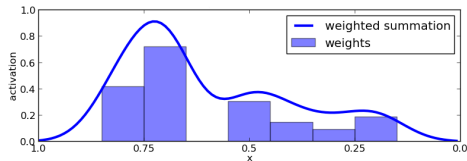
$$f(x, g) = \frac{\sum_{i=1}^N \psi_i w_i}{\sum_{i=1}^N \psi_i} x (g - y_0) \quad (2)$$

where:

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



$\psi$  Activation



Weighted Summation

# Imitating a desired path

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

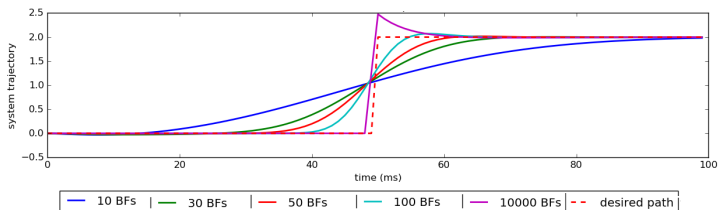
$$\mathbf{f}_d = \ddot{\mathbf{y}}_d - \alpha_y(\beta_y(g - \mathbf{y}) - \dot{\mathbf{y}}) \quad (3)$$

where

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

Choose the weights over the basis functions i.e., minimize<sup>4</sup>

$$\sum_t \psi_i(t) [f_d(t) - w_i \{x(t)(g - y_0)\}]^2 \quad (4)$$



<sup>4</sup>Stefan 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.

# Workflow of *Robotic cloth manipulation* task

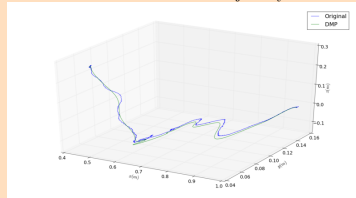
## Teaching Phase



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

## Learn Trajectory

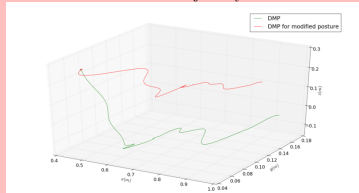
Baxter Left Arm Trajectory



Recorded trajectory is parameterized by DMP

## DMP Generalization

DMP Trajectory



## Testing Phase

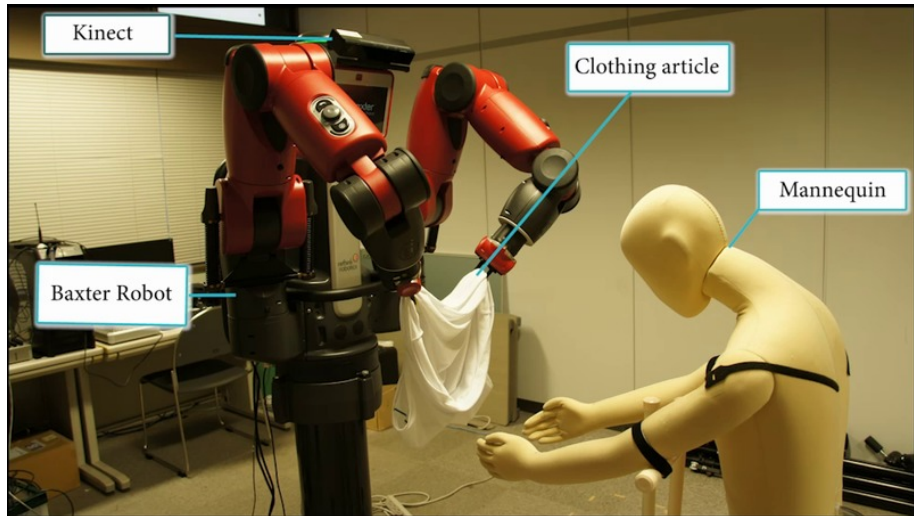
Modified Posture



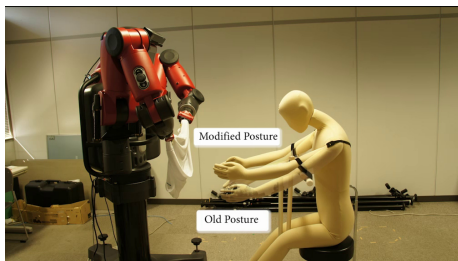
DMP can accommodate any posture by changing goal parameter



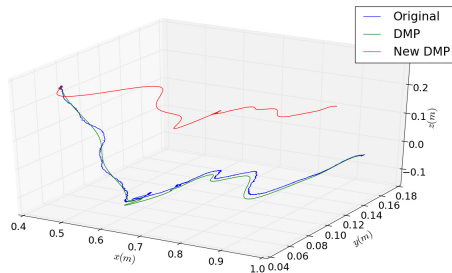
# Setup



# Experiments and results



Old & modified posture of mannequin

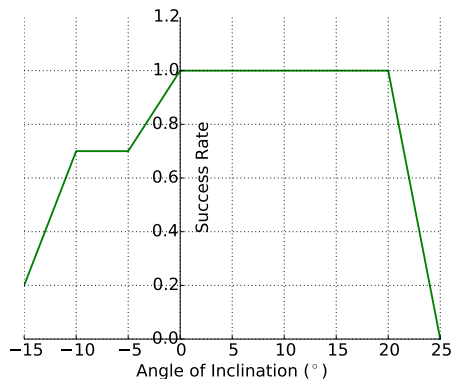
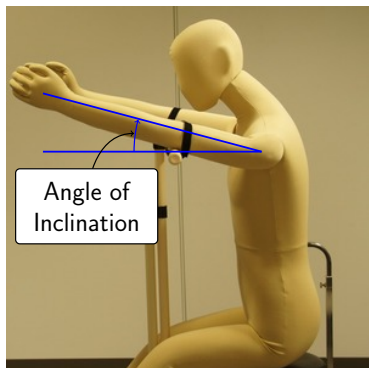


Left arm trajectories of Baxter Robot

[Video demonstration](#)

# Accuracy measurement

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



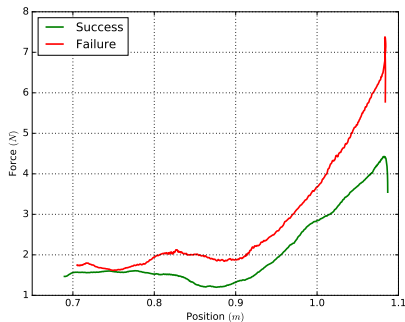
# Failure detection using end-effector forces

## Procedure

- ① Each trajectory is computed by calculating the mean.
- ② The force value is norm of force applied in all three Cartesian directions.



A failure scenario



Forces acting on left arm of Baxter

# Conclusion and Discussion

- Baxter APIs<sup>5</sup> are used to get the end-effector forces. Raw forces are found noisy in nature.
- Result shows that DMPs are able to generalize the movement trajectory
- Proposed failure detection method by using force information can detect failures
- DMP should incorporate orientation information as well

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<sup>5</sup>Cliff Fitzgerald. “Developing baxter”. In: *Technologies for Practical Robot Applications (TePRA)*, 2013 IEEE International Conference on. IEEE. 2013, pp. 1–6.

# 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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Thanks for your attention!

Any questions?

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