"Lucy, Take the Noodle Box!": Domestic Object Manipulation Using Movement Primitives and Whole Body Motion

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Introduction

Learning from demonstration [1] is a popular alternative to randomised motion planners that replaces explicitly programmed motion models by demonstrating feasible and predictable motions to a robot by a human.

Dynamic motion primitives (DMPs) [2] can be used to create manipulation models that are easy to analyse and interpret; however, mobile manipulators complicate such models since they need the ability to synchronise arm and base motions for performing tasks.

We analyse DMPs in the context of a Toyota Human Support Robot (HSR) and introduce a small extension of DMPs that makes it possible to perform whole body motion with a mobile manipulator.

Whole Body Motion Using DMPs

We represent manipulator trajectories using DMPs [2] in Cartesian space.

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

$$f(x) = \frac{\sum_{i=1}^{k}\Psi_i(x)w_i}{\sum_{i=1}^{k}\Psi_i(x)}x(\mathbf{g}-\mathbf{y_0})$$

$$\Psi_i(x) = \exp\left(-\frac{1}{2\sigma_i^2}(x-c_i)^2\right)$$

Joint velocity commands are then calculated using an inverse kinematics solver [3].

$$\dot{\mathbf{q}} = J^{-1}\dot{\mathbf{y}}$$

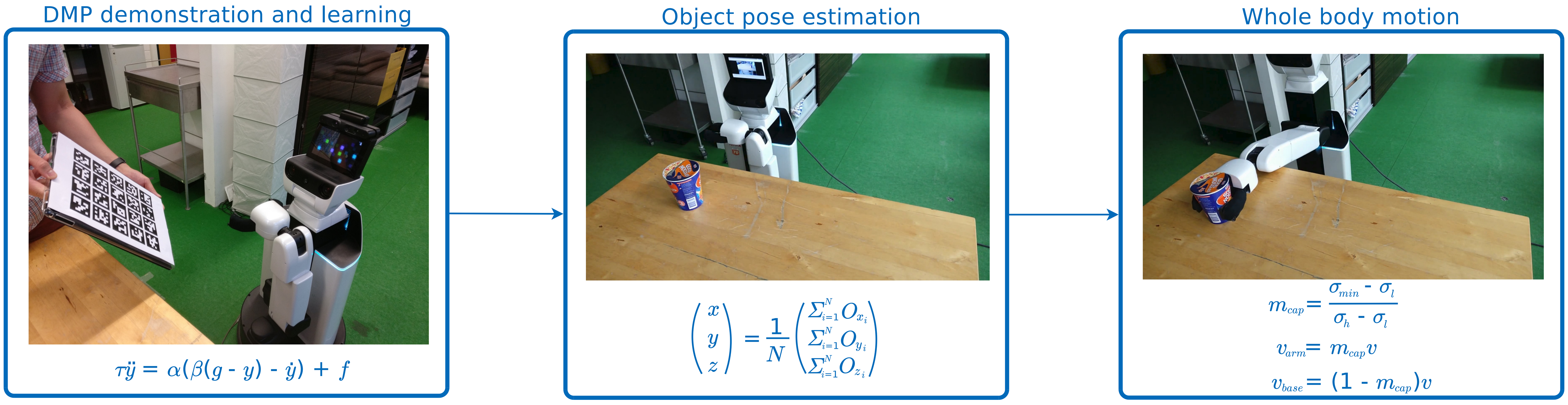
Whole body motion is achieved by splitting the motion between the base and the arm depending on the singular values of the manipulator Jacobian [4].

$$m_{cap} = \frac{\sigma_{min} - \sigma_l}{\sigma_h - \sigma_l}$$

$$\mathbf{v}_{ee} = m_{cap}\mathbf{v}$$

$$\mathbf{v}_b = (1 - m_{cap})\mathbf{v}$$

Primitive Acquisition and Whole Body Motion Pipeline



Grasping Experiment Setup

For evaluation, we recorded a grasping primitive for the HSR and performed experiments involving grasping 15 different objects from two surfaces - an ordinary dining table and a living room table.

In both cases, one object at a time was placed at different positions on the table. The robot had to detect the object, estimate its pose, and then grasp it (10 times for each object-surface combination), resulting in 300 grasping experimental trials in total.

We use SSD [5] trained on the COCO dataset for object detection.

Results

Object \ Surface	Dining table	Coffee table
Noodles	5	9
Salt box	10	4
Light ball	10	0
Duct tape	9	10
Coffee cup	9	10
Cup	9	10
Mug	7	10
Toy	8	7
E-stop	4	0
Sponge	10	9
Bowl	7	9
Stress ball	10	10
Cookies	8	10
Shampoo	10	8
Pringles can	6	9
Total successful	122	115

Future Work

- Incorporating the orientation of the end effector in the motion execution process
- Including dynamic information about the environment, such as obstacles that are in the way of a robot [6]
- Using kinesthetic teaching for demonstrating motion trajectories [1]
- Adaptation of primitives to different contexts and tasks (e.g. multiple grasping strategies)
- Improving the object pose estimation method for taking into account the shape of the object
- Using primitives for modelling and predicting execution failures
- More extensive evaluation in cluttered environments and with different robot platforms

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