# A Whole Systems Approach to Robot Imitation Learning of Object Movement Skills

**Manuel Mühlig**

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| Vorsitzender: | apl. Prof. Dr.-Ing. Franz Kummert |
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| Zweiter Berichterstatter: | Dr.-Ing. Michael Gienger |
| Dritter Berichterstatter: | Dr.-Ing. Tamim Asfour |
| Dekan: | Prof. Dr. Jens Stoye |

Berichte aus der Robotik

**Manuel Mühlig**

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*Meinen Eltern*

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# Abstract

Imitation learning has become a popular paradigm to extend the abilities of robots by demonstrating new skills. Many methods have been proposed that allow a robot to detect such demonstrations and to learn from them. However, there is a significant drawback with state-of-the-art imitation learning approaches. Most of them consider imitation learning of object movement skills as an isolated, data-driven method for learning object trajectories. They neglect much of the information that is provided by the human interaction partner and therefore miss many opportunities for increasing the generalization capabilities.

The work at hand addresses this drawback by proposing a whole systems view on imitation learning. The main contribution of this thesis is an architecture for interactive imitation learning of object movement skills. Its purpose is to enable learning skills from only a few demonstrations, but still to be able to extensively generalize to new situations. This is achieved by various methods. Firstly, a probabilistic learning scheme in combination with movement optimization is suggested. It allows to exploit the variance information from multiple demonstrations. While imitating, the robot can diverge from variant parts of the movement to respect additional criteria regarding the robot's limits. Furthermore, a novel method for automatically selecting skill-dependent task spaces is presented. These task spaces represent a skill in relative coordinates of specific object feature points, such as their top or bottom sides. That way, the learned skill is decoupled from specific objects and from the robot's embodiment. In particular, it enables the robot to perform a skill in different ways, such as one-handed or bimanually. This is achieved by introducing the concept of a dynamic body schema. All of the presented methods respect that learning is performed in interaction with a human tutor. The tutor is modelled by the system, which allows to detect certain postures for instructing the robot. Additionally, the model is used to estimate the non-measurable internal state of the tutor, like the effort or discomfort of certain poses. This allows to deduce skill-relevance of specific phases of a demonstrated movement. The presented system also comprises an attention mechanism, which is directly coupled to the robot control scheme using the novel concept of linked objects. Consequently, the tutor can highlight relevant objects, from which the robot either learns or to which it applies a learned skill.

All of the proposed methods are not presented in isolation. Instead, the thesis emphasizes the whole systems view by integrating them into a consistent architecture. The generalization capabilities of this architecture go beyond the state of the art, which is validated by several experiments. For instance, one experiment shows that a child-sized humanoid robot with 26 degrees of freedom is able to learn the skill of stacking objects. In addition to imitating the skill as demonstrated, the robot is able to generalize it to different objects, situations that contain obstacles, and to a bimanual performance. Even more, the skill learned by the humanoid robot can also be reproduced by other robots.

# Contents

# Symbols

**General notation:**

| | |
|---|---|
| $x$ | A scalar value |
| $\boldsymbol{x}$ | A vector |
| $\boldsymbol{X} = \begin{pmatrix} x_{1,1} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,m} \end{pmatrix}$ | The matrix $\boldsymbol{X}$ with its elements $x_{i,j}$ |
| $\boldsymbol{X}^T$ | The transpose of matrix $\boldsymbol{X}$ |
| $\boldsymbol{X}^{(i)}$ | A matrix $\boldsymbol{X}$ can refer to a subsumption of multiple matrices. In this case the $i$ is used to refer to the according sub-matrix. |
| $\hat{x}$ | An estimation for the value of expression $x$ |

**Special notation:**

| | |
|---|---|
| $\boldsymbol{v}$ | A linear velocity vector |
| $\boldsymbol{\omega}$ | An angular velocity vector |
| $\boldsymbol{r}$ | A radius vector |
| $p(x)$ | The probability of expression $x$ |
| $D$ | Space dimensionality |
| $K$ | Number of Gaussian components in a GMM |
| $\pi_k$ | The a priori probability of the Gaussian component $k$ |
| $\boldsymbol{\mu}_k$ | The mean vector of the Gaussian component $k$ |
| $\boldsymbol{\Sigma}_k$ | The covariance matrix of the Gaussian component $k$ |
| $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ | The multivariate normal distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ |
| $\mathcal{N}(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ | The probability of data vector $\mathbf{x}$ with regard to the normal distribution $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ |
| $\mathcal{L}$ | Log-likelihood |
| $q$ | A joint angle |
| $\boldsymbol{m}$ | The gravity force vector for a mass m |