Tutorial on Learning from Demonstration

Part 1: Introduction

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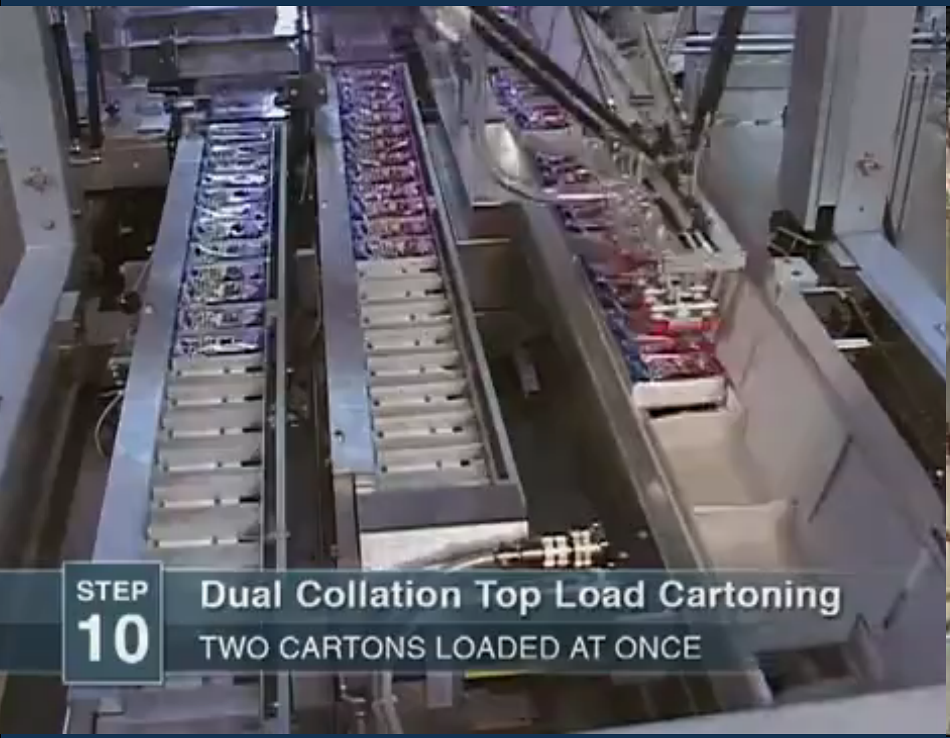
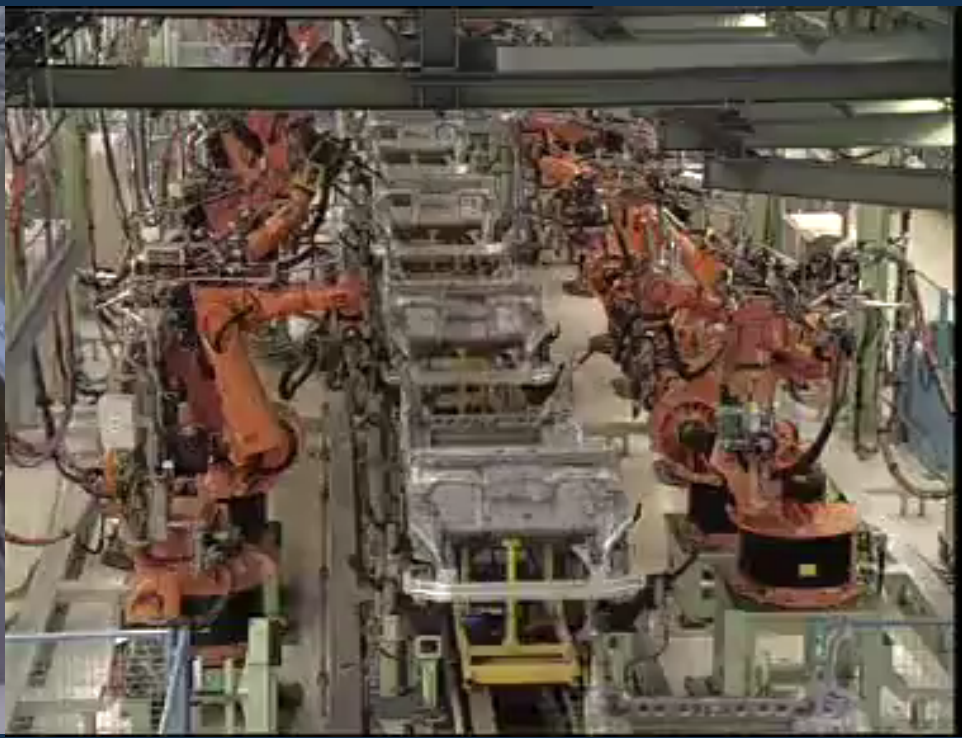
Factory Robots





Industrial tasks still performed by Humans

- Manipulation tasks that require high dexterity
  → precise position and force control.
- Tasks that are versatile with limited series.

Polishing

Precise insertion

Learning from Human Demonstrations: Principle

- Transfer to the robot skills that took years for the humans to master.
- Human can quickly re-train the robot to adapt to task changes.
- The human teaches by showing how to perform the task.

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The Multiple Promises

It offers a user-friendly means of teaching
→ No need to learn how to program the robot

It bootstraps learning by starting from a “good” example
→ Reduces search space for a good solution

Not Just Record and Replay: Generalize!

Hypotheses

Take humans as example

→ Hypothesis: Human is a good example!

Human teaches the robot by showing how to perform the task

→ Hypothesis: There is an interface to teach the robot

Which interface?

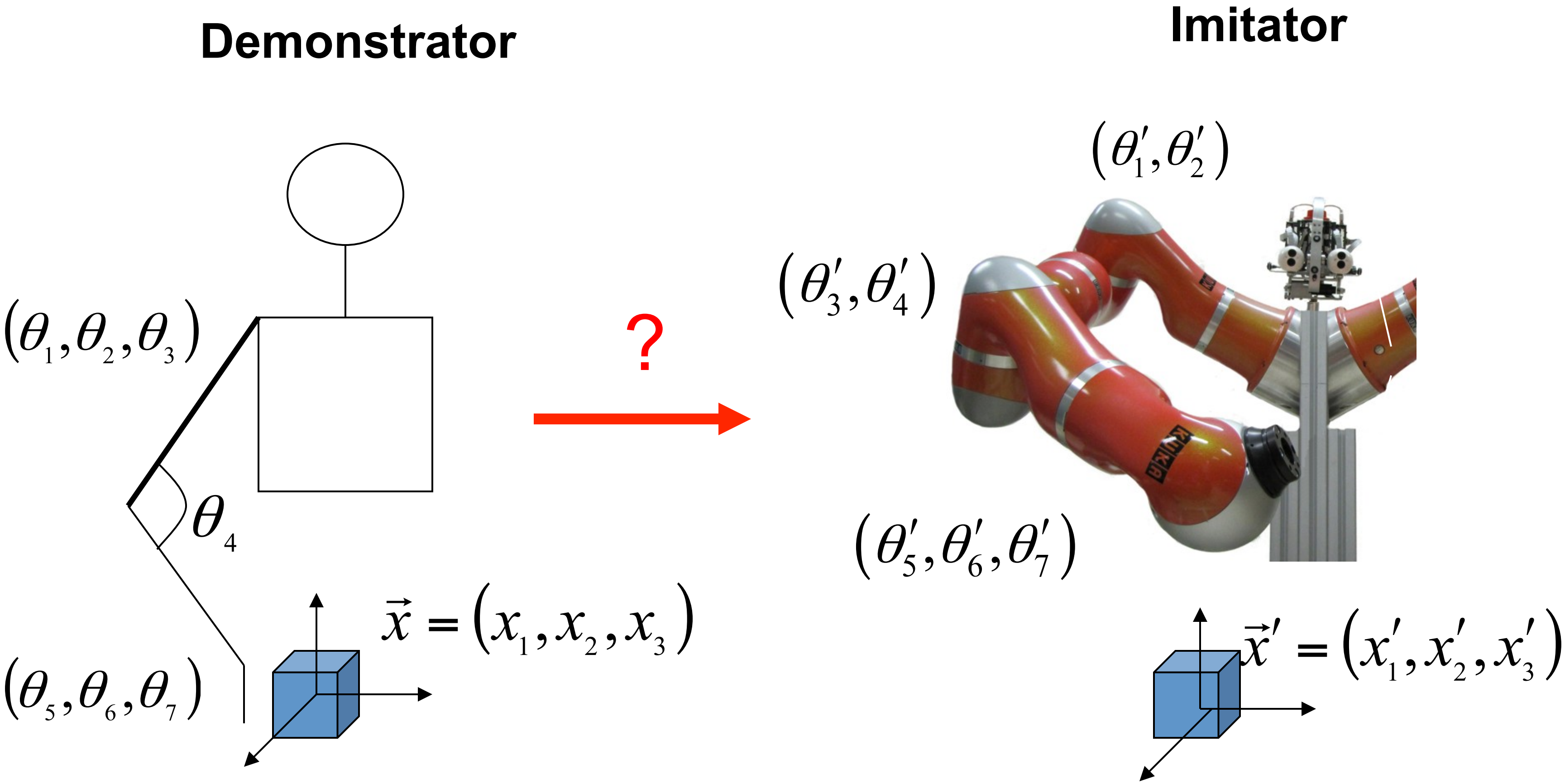
Vision:

Pros:
- Unobtrusive
- Record information on whole body.

Cons:
- Correspondence problem.
- No haptic information

Full body motion tracking using vision. Ude et al 2004

Correpondence Problem



Establish a correspondence across degrees of freedom when feasible.

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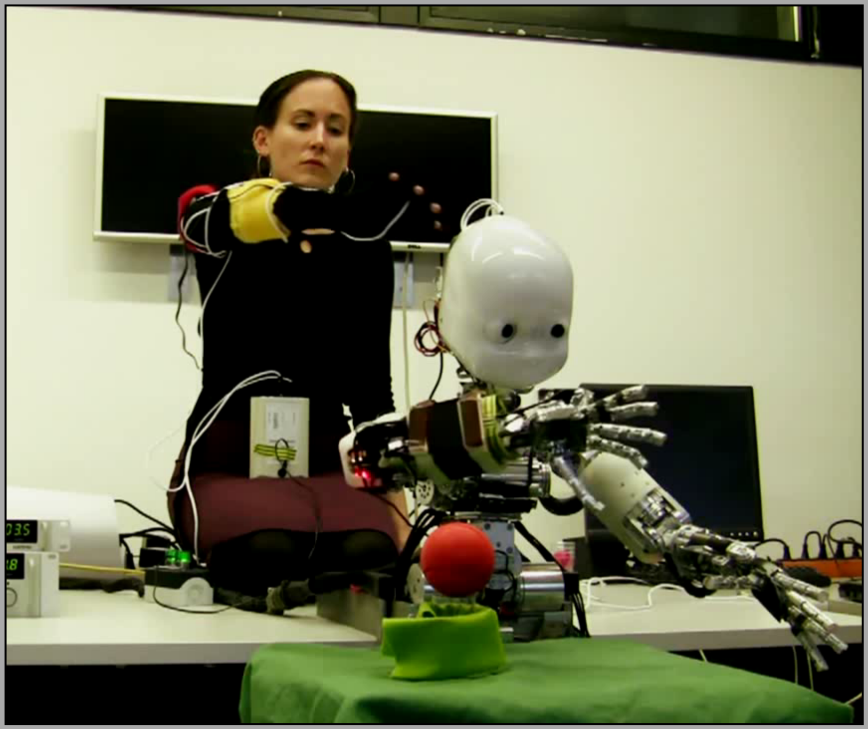
Which interface?



Motion sensors:

Pros:

- Real-time kinematic information
- Solve correspondence problem

Cons:

- Require to wear the system
- No haptic information

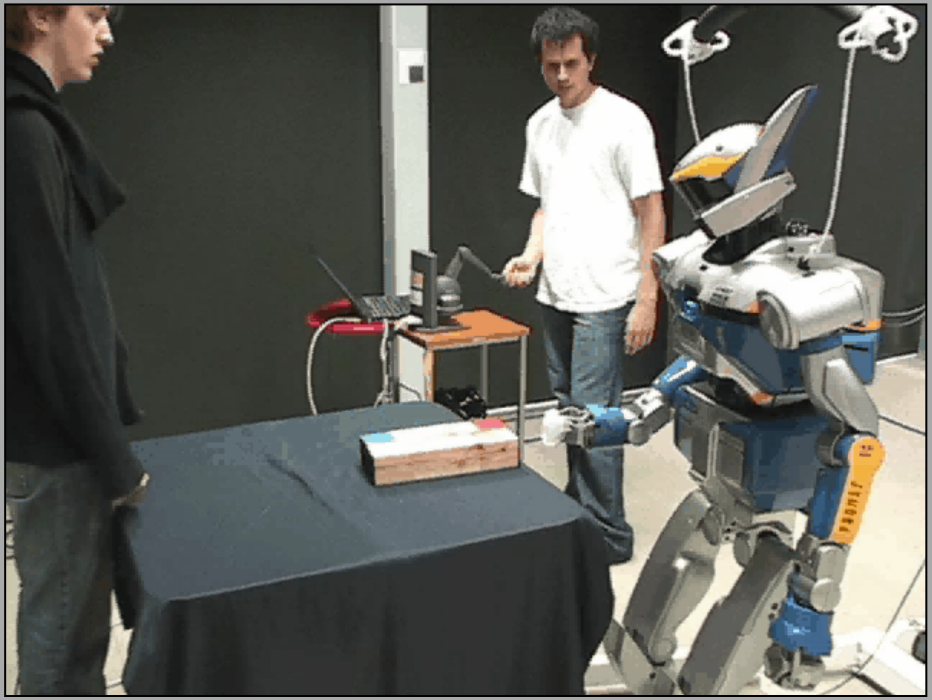
Which interface?

Kinesthetic Teaching:

Pros:
- Solve correspondence problem
- Transmit kinematic & haptic information

Cons:
- Need two hands to teach movements of a few DOFs

Which interface?



Haptic devices:

Pros:
- Solve correspondence problem
- Transmit kinematic & haptic information

Cons:
- Requires training
- User far from task location

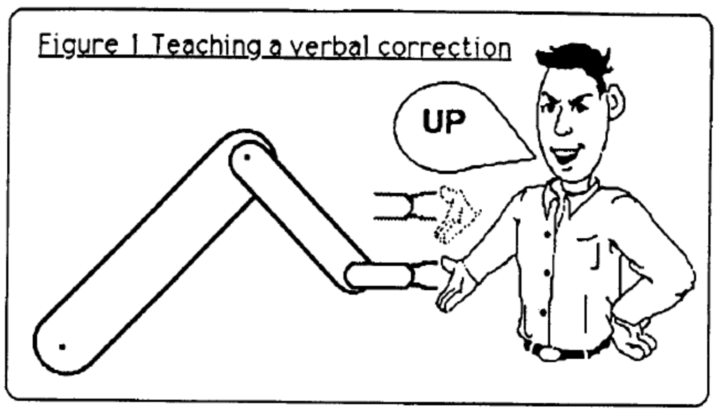
Equivalent Terms in the Literature

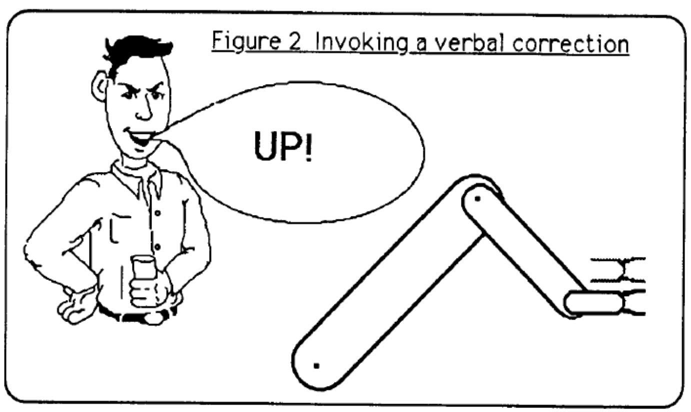
Robot Programming by Demonstration
Imitation Learning in Robots
Apprenticeship Learning
Robot Learning from Demonstration

Short History

• Programming by examples (Lauriere, 1978; Bauer, 1979)

• MacDonald, Bruce A., and Witten, Ian H. "Programming computer controlled systems by non-experts." (1987).





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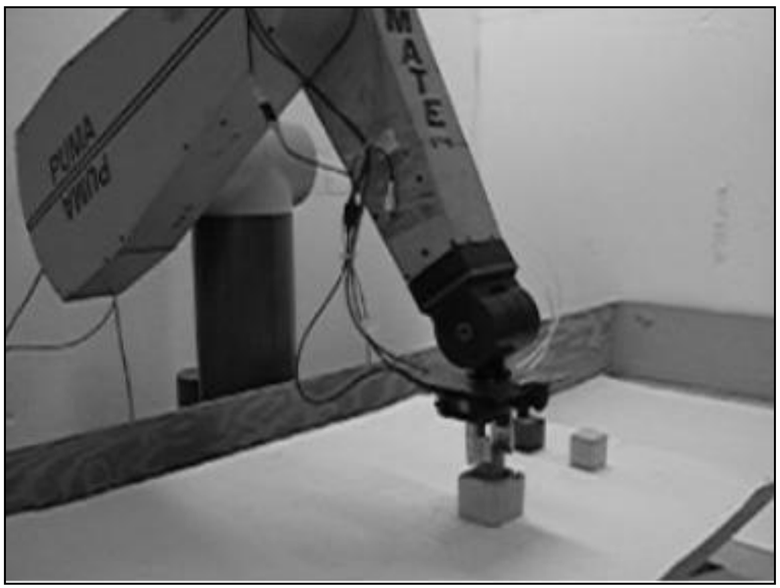
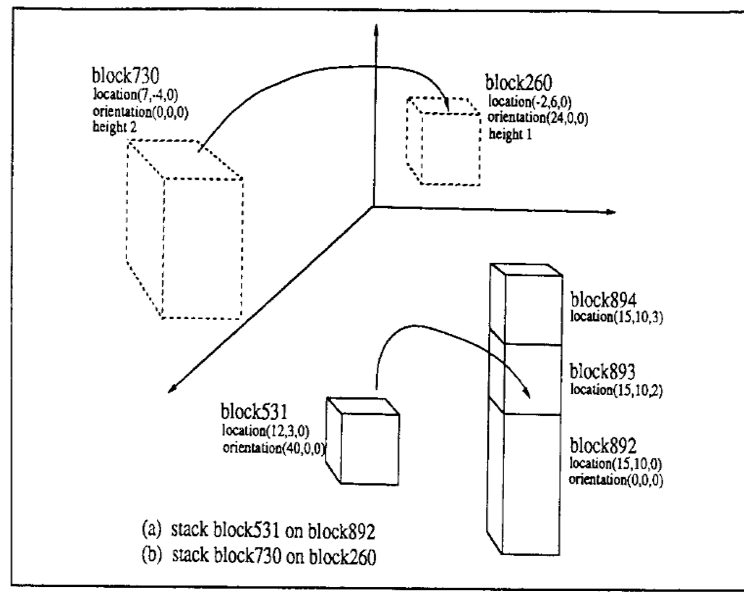
Short History

- Discrete State and Action System :
  - Block world + Predefined set of actions
- Learn sequencing across state-actions





Block world

- Heise, 1989, Tech. Report, Univ. of Alberta
- Kuniyoshi et al. IEEE Trans. on Robotics and Automation,1994.

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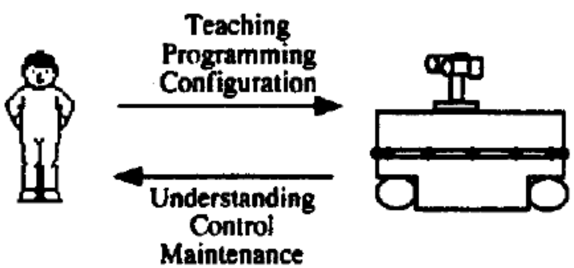
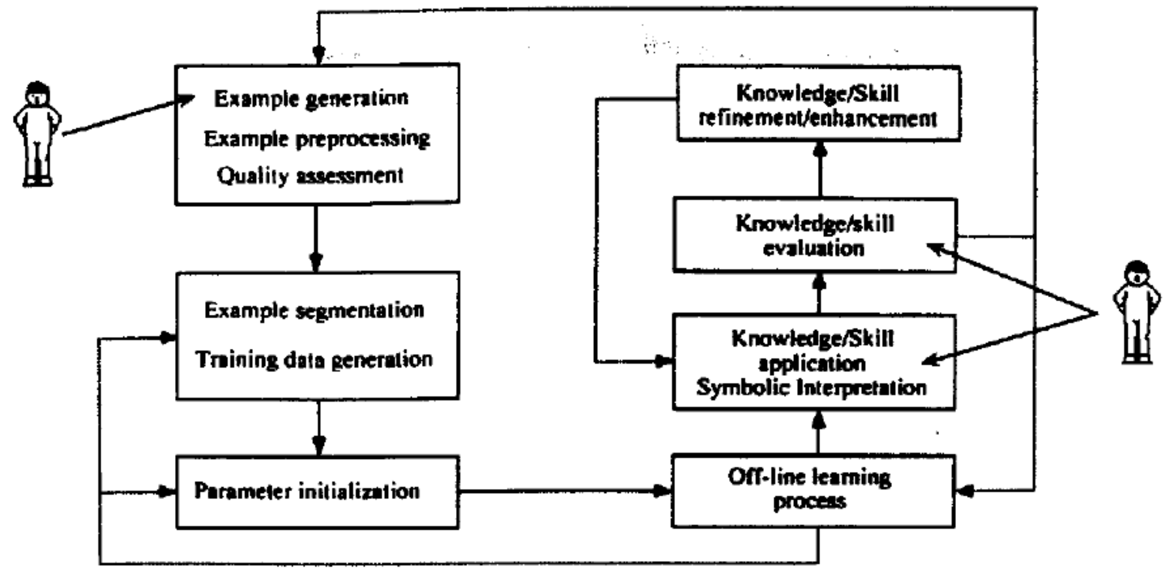
Short History

First work to question how to correct bad teaching:
→ detects wrong / unnecessary / inefficient manipulations
→ do not burden the human to redo a demonstration when imperfect





• Kaiser, Holger and Dillmann. "Obtaining good performance from a bad teacher." *Programming by Demonstration vs. Learning from Examples Workshop at ML*. Vol. 95. 1995.
• Holger, Kaiser, and Dillmann. "What can robots learn from humans?." *Annual Reviews in Control* 20 (1996): 167-172.

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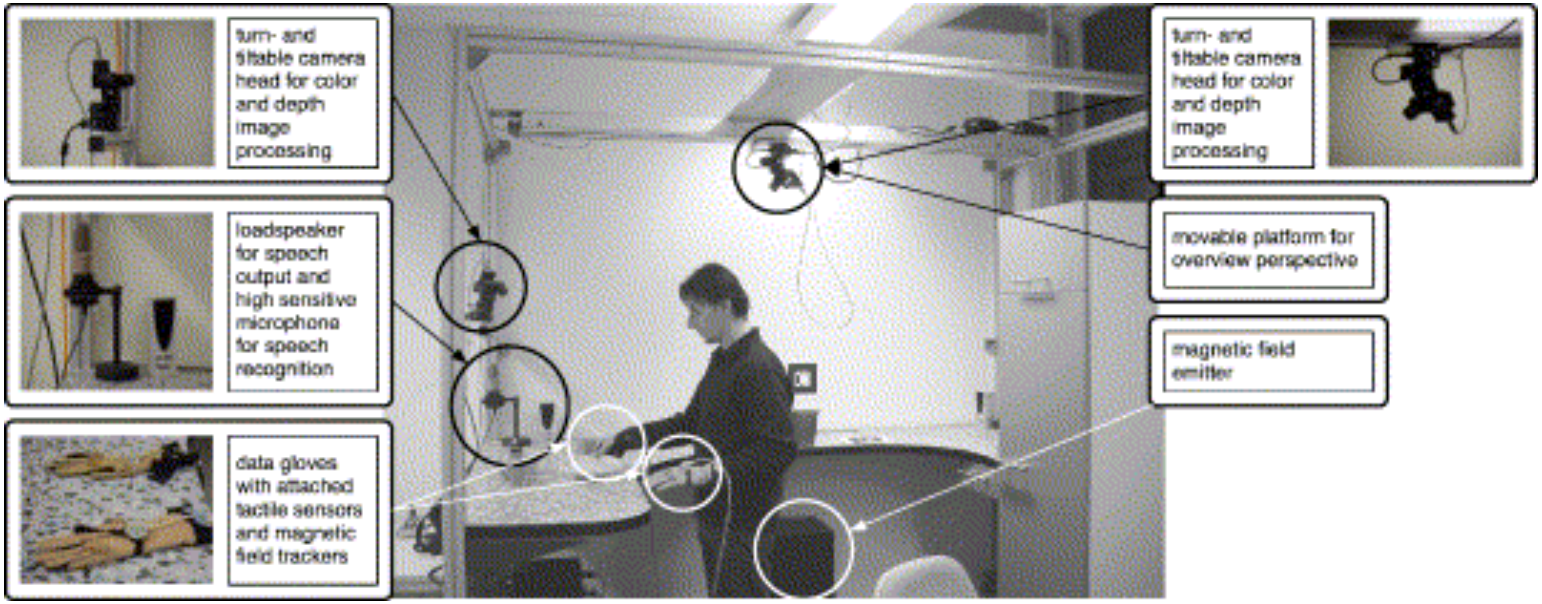
Short History

One-Short Learning

- Segmentation of demonstration into primitives
- Classification of gestures into predefined states (e.g. grasp, collision)
- Built-in controller for producing sequences of states



- Dillmann et al, Robotics & Autonomous Systems, 2001.
- Steil et al., Robotics and Autonomous Systems, 2004
- Aleotti et al, Robotics & Autonomous Systems, 2004.

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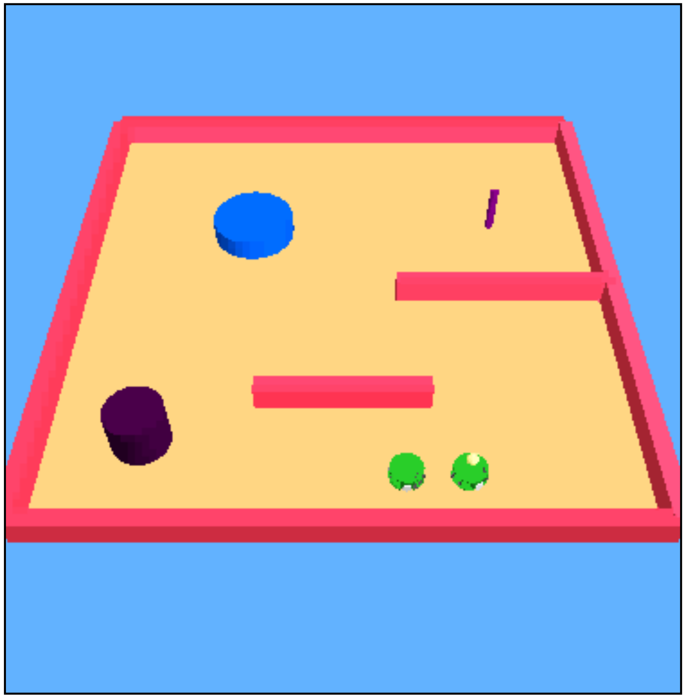
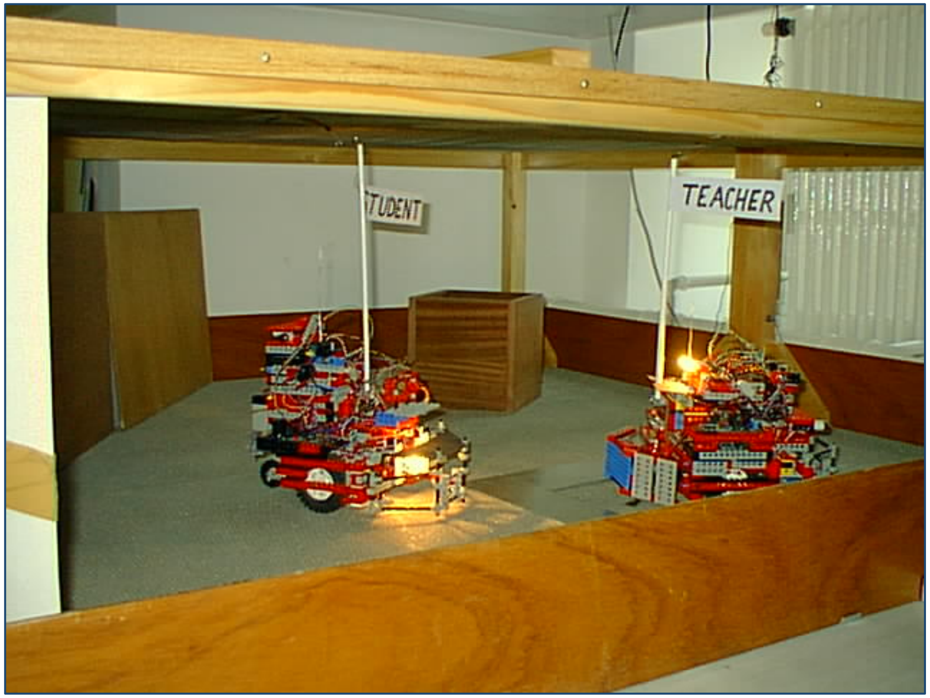
Short History

Following: simple imitation mechanism / while following the teacher, the learner robot learns to associate a word with a meaning in terms of sensory inputs.





Demiris & Hayes, 1994, 1996;
Dautenhahn, *Robotics & Autonomous Systems* 1995
Billard & Dautenhahn, *Robotics & Autonomous Systems*, 1998
Moga, Gaussier, Applied Artificial Intelligence, 2000
Kaiser et al, *Robotics & Autonomous Systems, 2002*

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Overview of current research areas

Low-Level Skills
- Trajectories
- Force profiles

High-Level Skills
- Combination of actions
- Speech-directed teaching

Batch learning versus incremental learning

Combined with other techniques
- Bootstrap reinforcement learning
- Inverse optimal control

User-studies to assess:
- Interfaces
- Effectiveness of algorithm

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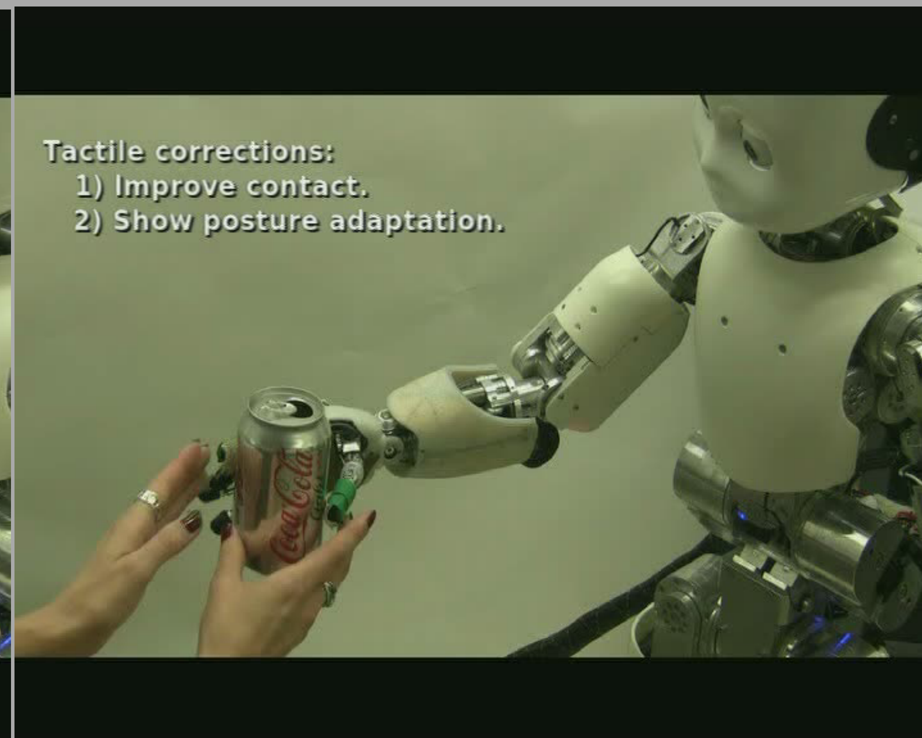
http://www.scholarpedia.org/article/Robot_learning_by_demonstration

Kinesthetic Teaching using Tactile Sensing

No Adaptation



Teaching adaptive behavior

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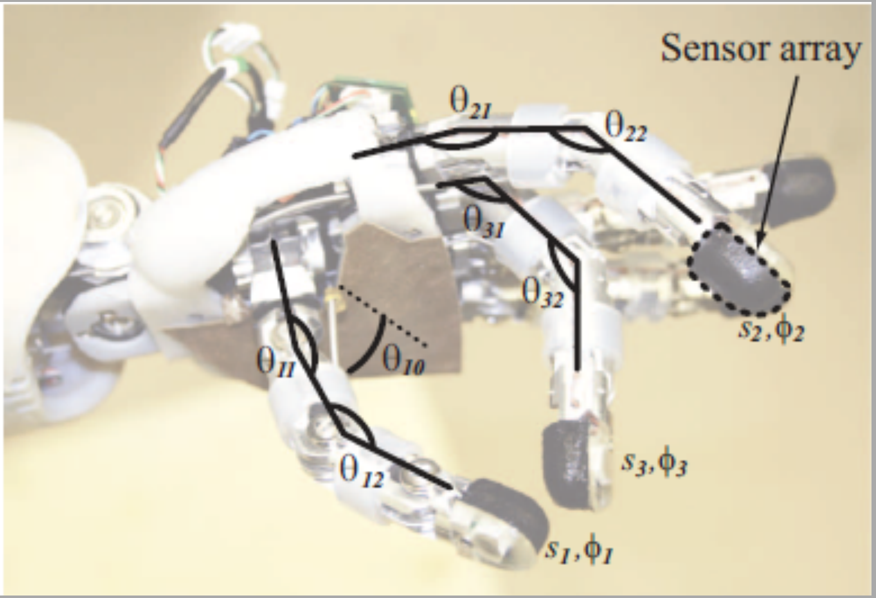
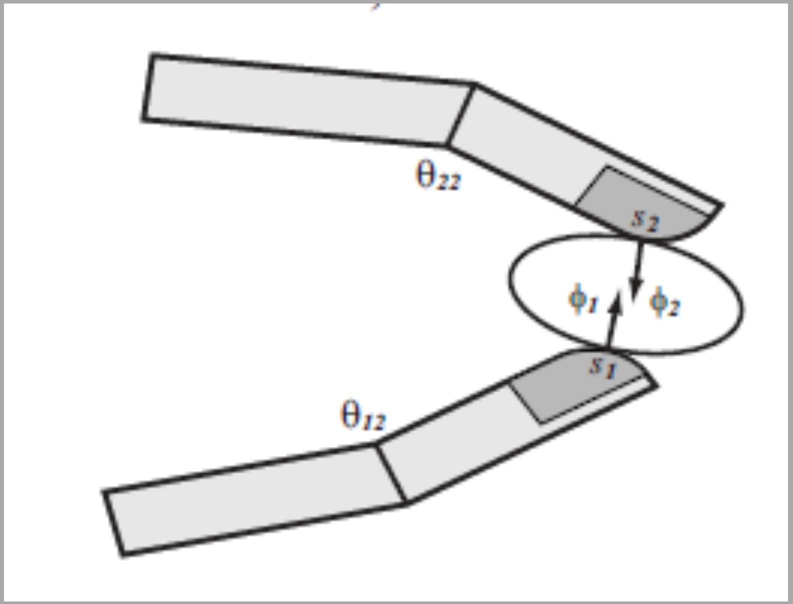
Sauser, Argall, Metta and Billard, Autonomous Robots, 2011

Kinesthetic Teaching using Tactile Sensing

Learn a probabilistic mapping $p(\phi, s, \theta)$ between contact signature of the object (normal force ϕ and tactile response s) and fingers' posture θ.





Sauser, Argall, Metta and Billard, Autonomous Robots, 2011

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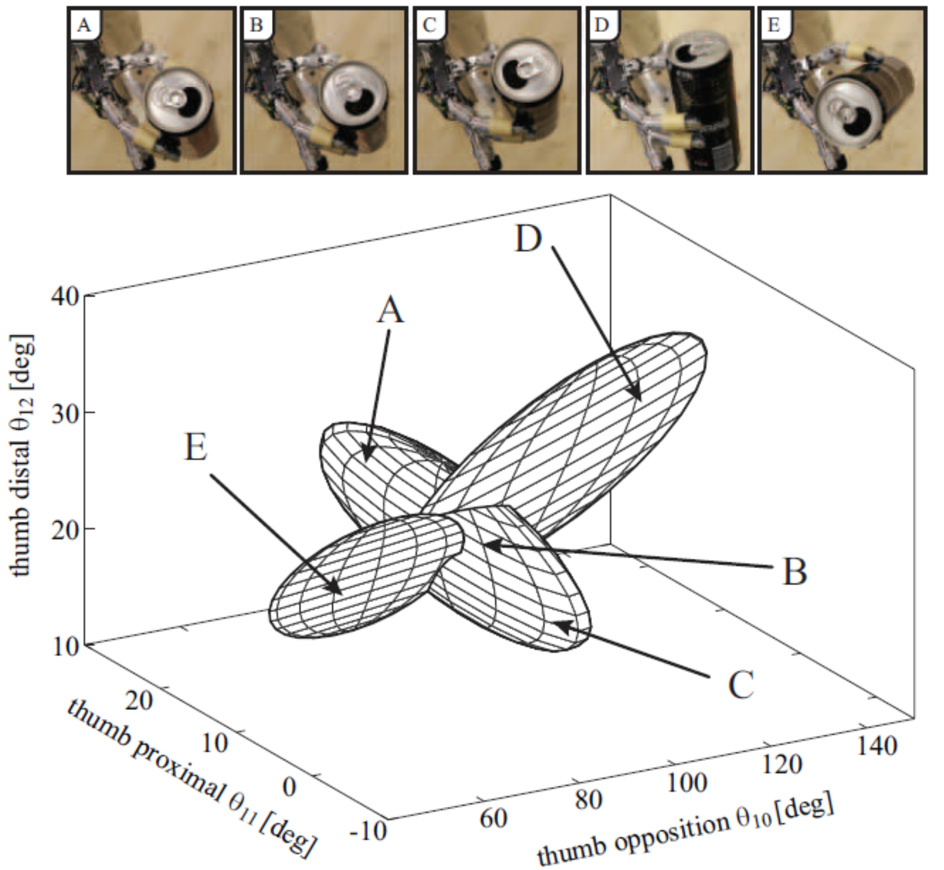
Kinesthetic Teaching using Tactile Sensing



$$\hat{\theta} = E\left\{p\left(\theta \mid s,\phi\right)\right\}, \quad \hat{s} = E\left\{p\left(s \mid \theta,\phi\right)\right\}$$

Sauser, Argall, Metta and Billard, Autonomous Robots, 2011

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LEARNING ALGORITHMS AND SYSTEMS LABORATORY

Teaching Compliant Control

Too stiff – Spills the liquid

Too compliant – spill the liquid outside the glass

Kronander and Billard, IEEE Trans. on Haptics, 2013

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Teaching Compliant Control

Decrease stiffness

Increase stiffness

Kronander and Billard, IEEE Trans. on Haptics, 2013

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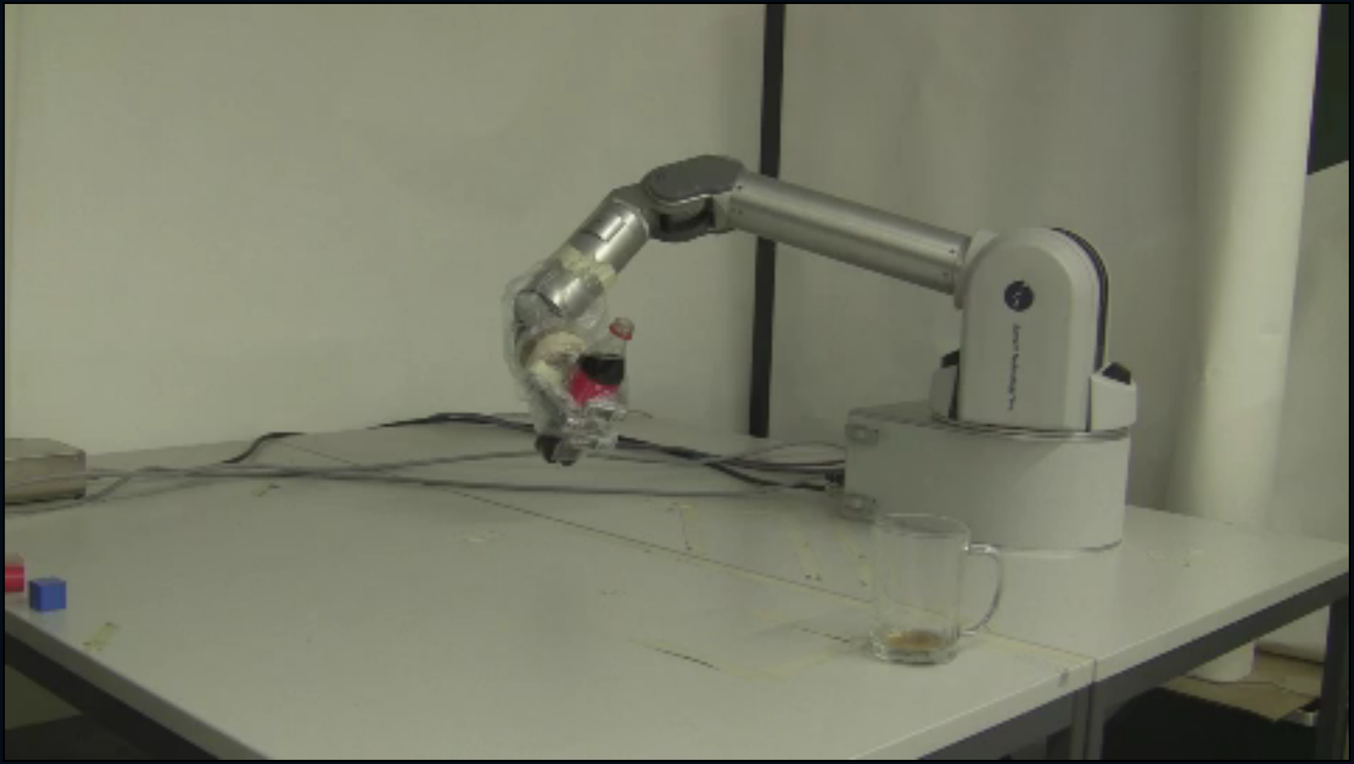
Teaching Compliant Control



Kronander and Billard, IEEE Trans. on Haptics, 2013

Swiss National Centre of Competence in Research

Combining LfD with Optimal Control

- One cannot use directly demonstration as the dynamics of robot differ from human dynamics
- Use human demonstrations to learn the reward of a LQR controller.
- Use optimal control (LQR) to generate trajectories close to demonstrations.

Atkeson & Schaal, Intern. Conf. on Machine Learning, 1997;

Combining LfD with Reinforcement Learning

- Use human demonstrations to initialize the parameters of the controller.
- One cannot use directly demonstration as the dynamics of robot differ from human dynamics
- User reinforcement learning to search for solutions nearby the demonstrations.

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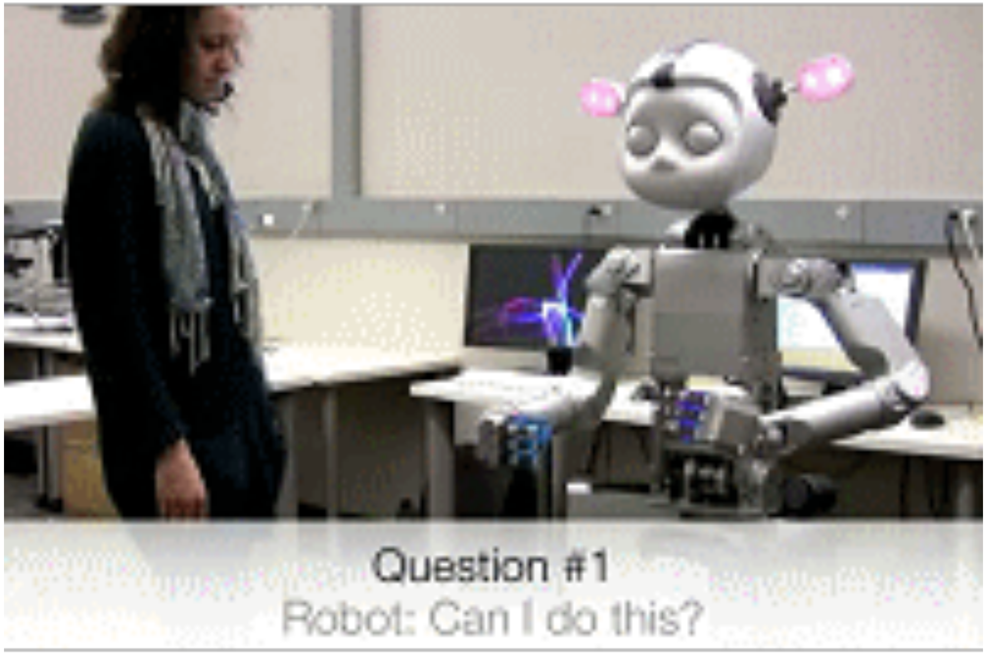
Kormushev et al, Int. Conf. on Robotics and Intelligent Systems,2010

Refinement through verbal interaction

- Robot has initial set of reaching skills
- Robot provided with a dialogue system to query the teacher
- Teacher modifies the controller through verbal guidance



Cakmak & Thomaz, Intern. Conf. on Human-Robot Interaction, 2012

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Companies selling LfD/PbD products

Yumi robot by ABB

Baxter Robot by Rethink Robotics

LWR by KUKA

UR3, Universal Robotics

Welding Robots, Robotik

Carbon Robotics

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