Towards Symbiotic Robots: Learning Human-Robot Collaboration from Human-Human Demonstrations

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Symbiotic Human-Robot Collaboration

**Human:** intelligence, reasoning, dexterity  
**Robot:** precision, force, speed
Requirements

Challenges:
- How do we specify collaborative behavior?
- How can robots anticipate human action?
- How can robots generate responses?
Specifying Collaborative Behavior

Can we learn interaction by imitation?
Imitation Learning
(Single-Agent) Imitation Learning

Motion Recording → Representation: Dynamic Motor Primitives → Motion Reproduction

x

time
Dynamic Motor Primitives

- Adaptive representation of trajectories
- Encode trajectory as dynamical system
- Goal position acts as attractor in dynamical system

\[ \ddot{y} = \left( \alpha_y (\beta_y (g - y) - (\dot{y})/\tau)) + f(x) \right) \tau^2 \]
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- $f(x)$ is sum of weighted basis functions
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$$f(x) = \sum_{i=1}^{m} \psi_i(x) w_i x$$

$$\theta = [w_1, \ldots, w_N]^T$$
DMP: 2D Example

Changing start positions
DMP Successful Applications

[Kober et al., NIPS2009]  [Kormushev et al., IROS2010]  [Ben Amor et al., IROS 2012]
(Multi-Agent) Imitation Learning

Recording Human-Human Demonstrations → ? → Reproduction during Interaction

**Required:**
- Model correlations between agents
- Mutual dependencies

**Nice to have:**
- Allow anticipation
- Recognition

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Interaction Primitives
Interaction Primitives

- Inspired by dynamic motor primitives
- Probabilistic encoding of joint-behavior
- Bayesian reasoning to generate responses
Interaction Primitives: Concept

**Modeling** correlations among agents as a joint probability distribution of DMP parameters

$$p(person1, person2)$$

Demonstration
Generating Responses

**Condition** on current observation in order to generate best response
Inferring Predictions and Responses

\[ \tau_o \]

Human

Robot

Time
Inferring Predictions and Responses

Human

Robot

Prediction

$\tau_o$  \quad  $\theta^A$

Time
Inferring Predictions and Responses

Predictive distribution:

\[
p(\theta | \tau_o) \quad \text{with} \quad \theta = \left[ \theta^A, \theta^B \right]^T
\]
Inference

Conditioning on partial observation $\tau_o$ yields distribution with

**Mean**

$$\mu_{\theta|\tau_o} = \mu_{\theta} + \Sigma_{\theta} \Omega^T A^{-1} (\tau_o - \Omega \mu_{\theta})$$

**Covariance**

$$\Sigma_{\theta|\tau_o} = \Sigma_{\theta} - \Sigma_{\theta} \Omega^T A^{-1} \Omega \Sigma_{\theta}$$

Closed form solution for posterior → No sampling required!

Better inference: **InteractionProMPs** [Maeda et al. 2015]
Example

Demonstrations  Learning  Conditioning  Response

\[ \theta = \begin{bmatrix} \theta^A, \theta^B \end{bmatrix}^T \]

Prediction Performance

[Graph showing prediction performance over time for different stages of movement, labeled 'After 40% of Movement' and 'After 60% of Movement'.]
Learning to Receive

Learning an Interaction Primitive

Human-Human Data → Trajectories → Joint Probability

Agent A

Agent B

Robot Control

Collaborative Task → Bayesian Inference → Action Generation

Human

Robot

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Example

Human

Agent A (Observed)

Noisy observation

Agent B (Controlled)

Robot

X amplitude

Time (s)

Initial distribution

Current prediction

Example

Combining Interaction Primitives

Combinations and sequences of interaction primitives can be used to solve complex tasks

(a) Handing over a plate
(b) Handing over a screw
(c) Holding the screw driver

M. Ewerton et al., 2015 "Learning Multiple Collaborative Tasks with a Mixture of Interaction Primitives", ICRA 2015
Combining Interaction Primitives

Interaction Primitive = Building block

Complex Interactions = Combinations of blocks
Action Recognition

Hand over plate

Hold screwdriver

Hand over screw

What is the most likely current task $k$ given observation $\tau_o$?

$$p(k|\tau_o) \propto p(\tau_o|\theta_k) \ p(k)$$

Posterior  Likelihood  Prior

Solution $\arg\max_k p(k|\tau_o)$
Assembly Assistants
Assembly Assistant
Effects of Conditioning
Recent Results

[D. Vogt et al., 2015] "Learning Continuous Human-Robot Interactions from Human-Human Demonstrations", Submitted
On-going: Projecting Robot Intentions
Projecting Robot Intention

So far: robot infers human intention

Important: human understands robot intention
Projecting Robot Intention
Example

Mutual understanding of the state of the collaboration!

Summary

**New methodology** collaborative skills from human-human demonstrations

**Interaction Primitives** represent joint-behavior

**Compositions of Interaction Primitives** for complex sequential tasks
Collaborators

- Geri Neumann
- Marco Ewerton
- Guilherme Maeda
- Jan Peters
- Erik Berger
- David Vogt
- Bernhard Jung
- Steve Grehl