Learning Task Constraints for Robot Grasping

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Strategies and Evaluation for Mobile Manipulation in
Household Environments

Overview

“Learning Task Constraints for Robot Grasping”

- Motivation and Problems
- Generative Models – Learning Task Constraint
- Experimental Evaluation
- Conclusion and Future Work

Motivation

We want robots to assist humans in human-centered environments:

1) Interprete human intentions: what does a human want to do?
2) Learn from humans: how to grasp this bottle to *hand-over* (task)?

- However, there are challenges in both **PERCEPTION** and **MOTOR** systems . . .

credits: LAAS-CNRS

Unreliable Perception

What is this?

Unreliable Perception

Ground Truth

It is a cup with:
size: 3-d dimensions
shape: convexity, . . .
weight: 500g
. . .

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Unreliable Perception

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Vision

It looks like a
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It looks like a
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Tactile

It feels like a
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It looks like a **tree, hand** . . .

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Vision+Tactile

It is hollow, like a **tube, cup** . . .

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Tactile

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Vision+Tactile

It is hollow, like a **tube, cup** . . .

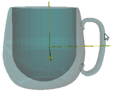
This object is good for containing liquid such as tea, therefore can be used for *pouring* (**task affordance**).

Sensory Data of **Object** $\longrightarrow$ Common Concept!

Unreliable Perception *Cont'ed*

However, a cup affords many tasks: pouring, hand-over, ...

What is a human's intention (or task) when using a cup?



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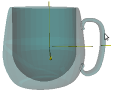

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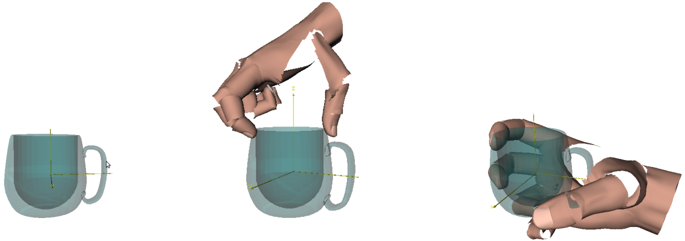

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object+action: moving or hand-over

object+action: pouring or drinking

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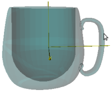

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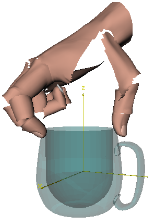

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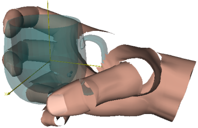

object+action:
pouring or drinking

How to grasp an object puts further constraints on what task(s) the object-grasp combination affords!

Sensory Data of **Object + Action** $\longrightarrow$ Common Concept!

Limited Motor Ability – Correspondence Problem

But even if the robot can interprete human intention,
how can it perform the same task: hand-over an apple?

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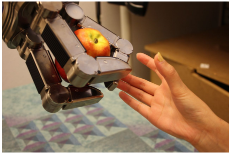

hand is too big:
no free-space for regrasp
Correspondence Problem

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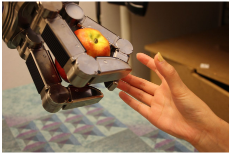

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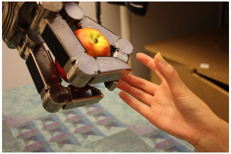

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Correspondence Problem

leave enough **free-space**:
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Constraint variables, that directly characterize task requirements and can be independent of embodiments, may help to solve the correspondence problem in imitation learning.

Goal Directed Imitation

Inspired from Developmental psychology:

Babies can infer human intention, and perform the task through their own means.

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Task Constraint Models

Observe: $\{O, A, C\}^H$

Joint Distribution in **Human** Task Space
$p^H\ (\ T, O, A, C\ )$

Recognize: $\hat{T} = handover$

$p^H(T|O, A, C)$

Joint Distribution in **Robot** Task Space
$p^R\ (\ T, O, A, C\ )$

Decide: Object & Action

$p^R(\hat{T}|O, A)$

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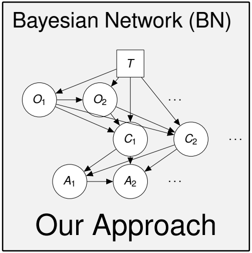

Related Work and Contributions of This Work

Dealing with **sensorimotor uncertainty** through **inference-based** planning and control:

- **Coherent** control, trajectory optimization and action plan architecture (Toussaint *et al.* (2010))
- Dynamic stability in full-body movement using **Dynamic BNs** (Grimes and Rao (2009))

Linking grasps to tasks is rarely addressed, with exceptions:

- Task-oriented quality measure in **force domain** (Li and Sastry (1988))
- **Discrete Bayesian network** modeling the affordances in **simple** manipulation tasks (Montesano *et al.* (2008))

This work focuses on **How to produce not only stable, but also task-oriented grasps by ...**

- evaluating **task affordances** given **object** physical attributes, and embodiment-specific **action** features, and
- **conceptualizing** large range of **continuous** sensory data, helping the robot to understand the world!

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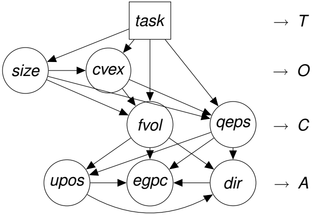
Bayesian Network-Based Task Constraint Model

BN: a probabilistic graphical model that encodes the joint distribution of a set of random variables, $X = \{X_1, \ldots, X_m\}$

Joint distribution $P(X)$ is factorized as:

$$P(X) = P(X|\boxed{\theta, S}) = \prod_{v=1}^{m} P(X_v|\mathbf{pa}_v, \theta_v, S)$$



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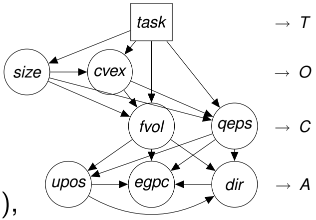

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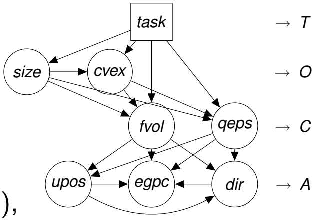

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Learn

S is built by human experts

The variables include **discrete** task T, and **continuous** object, action and constraint features (O, A, C), *i.e.* $X = \{T, O, A, C\}$

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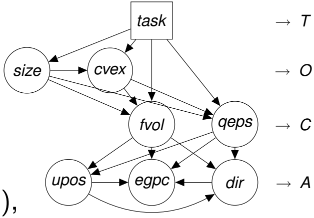

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Inference:

Classify task: $p(T|O, A, C)$,

Infer A distribution: $p(upos|task, size, cvex)$

Experiments

1) “From where should this object be grasped for a given task? ”

2) “Can you imitate this demonstrated task?”

Training Data: $\mathbf{X} = [\mathbf{O}; \mathbf{A}; \mathbf{C}; \mathbf{T}]$

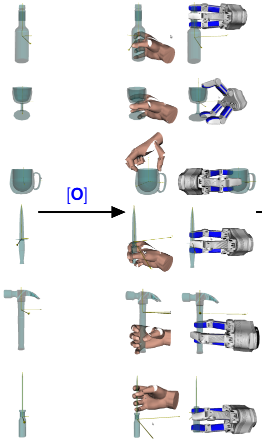
Objects (BADGr, PSB)

Stable Grasps (BADGr, GraspIt2!)

Tasks Labeled (BADGr, GraspIt2!)

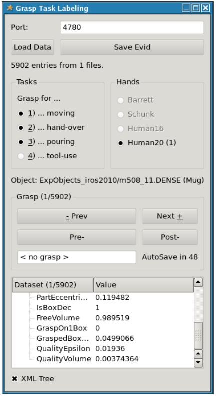
3 tasks: *hand-over, pouring, tool-use*

Mixed BNs (BNT, Matlab®)



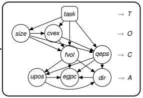
$[\mathbf{O}]$ →

$[\mathbf{O}; \mathbf{A}; \mathbf{C}]^H$
$[\mathbf{O}; \mathbf{A}; \mathbf{C}]^R$ →



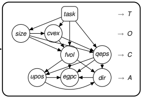
$[\mathbf{O}; \mathbf{A}; \mathbf{C}; \mathbf{T}]^H$ →

Human BN



$[\mathbf{O}; \mathbf{A}; \mathbf{C}; \mathbf{T}]^R$ →

Robot BN



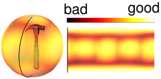
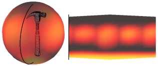
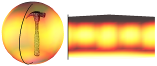
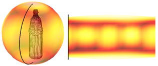
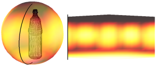
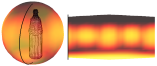
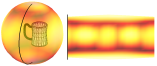
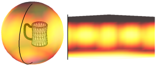
Song *et al.* (2010), to appear in IROS
Huebner and Kragic (2008)
Miller and Allen (2004)
Murphy (1997)

1) "From where (*upos*) should this object be grasped for a task? "

Goal: To identify how the three tasks influence the position of the grasps on 3 objects:

$P(upos \mid task, size, cvex)$

Results: Distribution of unified position conditioned on tasks and object features:

	$T = t_1$, *hand-over*	$T = t_2$, *pouring*	$T = t_3$, *tool-use*
Hammer:	 ⥀ unwrap the sphere →		
Bottle:			
Mug:			

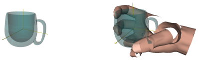
Details: BNs are trained for Schunk hand
Training data ~ 3500 *cases*: from 22 objects, leaving out the 3 objects (see table)
Testing data ~ 500 *cases*: from the three testing objects

2) "Can you imitate this demonstrated task?"

Goal: To demonstrate the use of the task constraint BNs in an imitation setup.

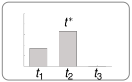
Results: Three steps for goal-directed imitation:

Scenes	Reward Functions
Step 1 Human demonstration: recognize task t^*	$P^H(\,t \mid \mathbf{o}^H, \mathbf{a}^H, \mathbf{c}^H)$

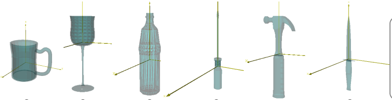


$\mathbf{o}^H$ $\quad$ $\mathbf{a}^H$

t_1 = *hand-over*
t_2 = *pouring*
t_3 = *tool-use*

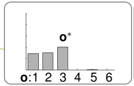


Step 2 Select object $\mathbf{o}^*$: matching t^*, or also similar to $\mathbf{o}^H$

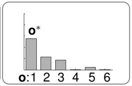


$\mathbf{o}_1$ $\mathbf{o}_2$ $\mathbf{o}_3$ $\mathbf{o}_4$ $\mathbf{o}_5$ $\mathbf{o}_6$

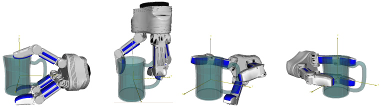
$P^R(\,t_2 \mid \mathbf{o})$



$P^R(\,t_2 \mid \mathbf{o}) \cdot 0.2 + S(\mathbf{o},\, \mathbf{o}^H | t_2) \cdot 0.8$

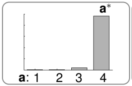


Step 3 Select action $\mathbf{a}^*$: matching t^*, or also similar to $\mathbf{a}^H$

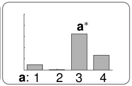


$\mathbf{a}_1$ $\mathbf{a}_2$ $\mathbf{a}_3$ $\mathbf{a}_4$

$P^R(\,t_2 \mid \mathbf{o}^*, \mathbf{a})$



$P^R(\,t_2 \mid \mathbf{o}^*, \mathbf{a}) \cdot 0.2 + S(\mathbf{a},\, \mathbf{a}^H | t_2) \cdot 0.8$



Details: BNs are trained for Human and Schunk hands
Training data $\sim$ 3400 *cases*: from 19 objects, leaving out the 6 testing objects (see table)

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Goal: To demonstrate the use of the task constraint BNs in an imitation setup.

Results: Three steps for goal-directed imitation:

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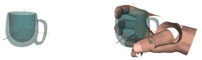
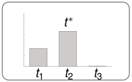
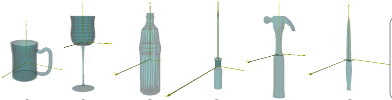
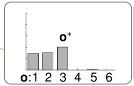
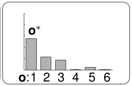
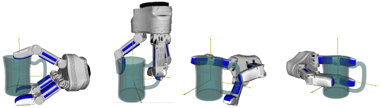
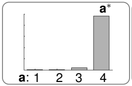
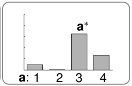
Step 1 Human demonstration: recognize task t^*  t_1 = *hand-over* t_2 = *pouring* t_3 = *tool-use*	$P^H(\, t \mid \mathbf{o}^H, \mathbf{a}^H, \mathbf{c}^H)$ 	
Step 2 Select object $\mathbf{o}^*$: matching t^*, or also similar to $\mathbf{o}^H$ 	$P^R(\, t_2 \mid \mathbf{o})$ 	$P^R(\, t_2 \mid \mathbf{o}) \cdot 0.2 + S(\mathbf{o},\, \mathbf{o}^H \vert t_2) \cdot 0.8$ 
Step 3 Select action $\mathbf{a}^*$: matching t^*, or also similar to $\mathbf{a}^H$ 	$P^R(\, t_2 \mid \mathbf{o}^*, \mathbf{a})$ 	$P^R(\, t_2 \mid \mathbf{o}^*, \mathbf{a}) \cdot 0.2 + S(\mathbf{a},\, \mathbf{a}^H \vert t_2) \cdot 0.8$ 

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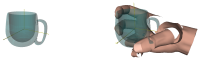

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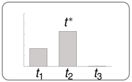

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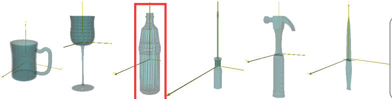

$\mathbf{o}_1$ $\mathbf{o}_2$ $\boxed{\mathbf{o}_3}$ $\mathbf{o}_4$ $\mathbf{o}_5$ $\mathbf{o}_6$

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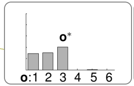

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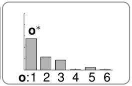

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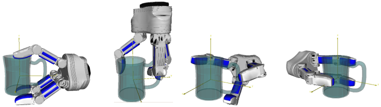

$\mathbf{a}_1$ $\mathbf{a}_2$ $\mathbf{a}_3$ $\mathbf{a}_4$

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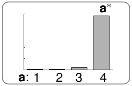

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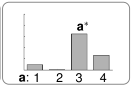

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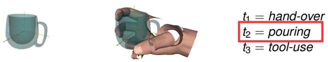

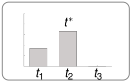

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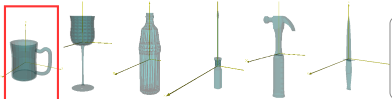

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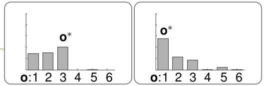

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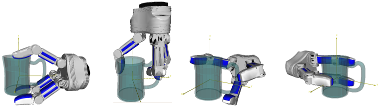

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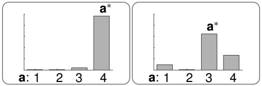

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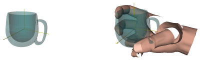

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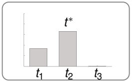

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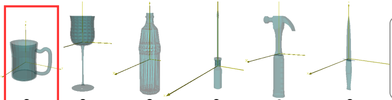

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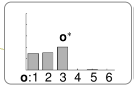

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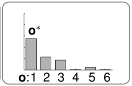

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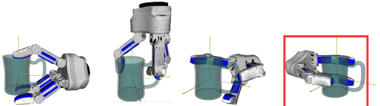

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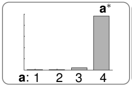

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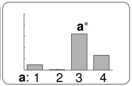

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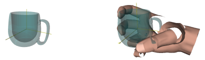
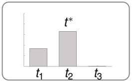
 t_1 = *hand-over* t_2 = *pouring* t_3 = *tool-use*		
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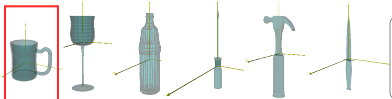	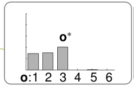	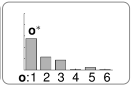
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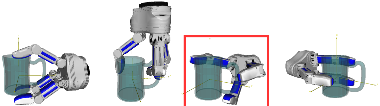	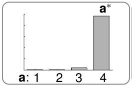	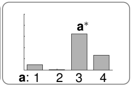

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Conclusion

- We introduced a semi-automated method for acquiring manually annotated, task-related grasps.
- Mixed Bayesian networks were used to encode the probabilistic relationships between task-, object- and action-related features.
- The obtained task constraint BN represents an embodiment-specific concept of affordance, which maps symbolic representations of task to the continuous constraints.
- This network could be applied in multiple ways, such as: task classification, goal-oriented object selection and grasp planning.

Future Work

BNs are limited in modeling high-dimensional, multi-channeled sensory streams: $\{O, A, C\}$. When number of nodes is high, the training and inference become intractable.

Explore latent-space representation of tasks using sensory features in $\{O, A, C\}$:

- Discover task-(ir)relevant features $\rightarrow$ what are their properties?
- Identify the relationships between features $\rightarrow$ learn BN structures.

Thanks

For your attention!

EU project IST-FP7-IP-215821

paco | plus
perception, action and cognition
through learning of object-action complexes

EU project IST-FP6-IP-027657

Swedish Foundation for Strategic Research

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