Learning Task Constraints for Robot Grasping using Graphical Models

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Overview

" Learning Task Constraints for Robot Grasping using Graphical Models"

- Motivation
- Model – Bayesian Network
- Data Acquisition
- Experiments
- Conclusions

Motivation

What is a GOOD GRASP?

Our answer:

A good grasp should not only be stable, but also afford the desired post-grasp action – TASK.

Motivation

credits: LAAS-CNRS

Robots assist humans in human-centered environments, interpreting human intention, and learning from humans.

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

Unreliable Perception

What is this?

Ground Truth

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

Vision

It looks like a
tree, hand . . .

Tactile

It feels like a
carved stone . . .

Vision+Tactile

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

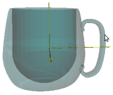
This object is good for containing liquid such as tea, therefore can be used for *pouring* (**task affordance**).

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

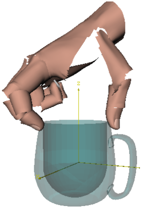
Unreliable Perception *Cont'ed*

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

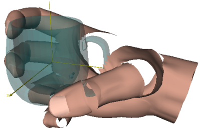
What is a human's intention (or task) when using a cup?



only **object** features:
not sure



object+action:
moving or hand-over



object+action:
pouring or drinking

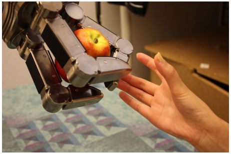
How to grasp an object puts further constraints on what task(s) the object-grasp combination affords!

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

Limited Motor Ability

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

Learn from human by copying human grasp?



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

leave enough **free-space**:
task constraint!

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

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

Goal-Directed Imitation

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

Decide: Object & Action

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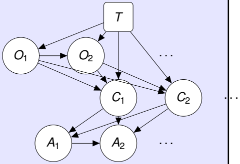
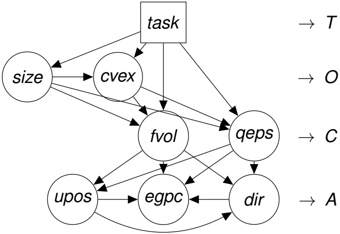
Our Approach:

Bayesian Network (BN)



Montesano *et al.* (2008)

Bayesian Network (BN)



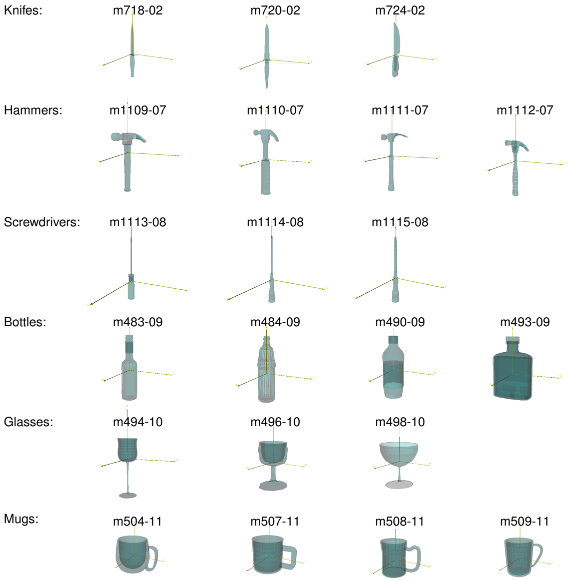
- Factorization of joint distribution through directed graphs.
- Inference by Junction-Tree Algorithm (Cowell *et al.*, 1999).

Training Data

** Generated by **BADGr** – a Toolbox for Box-based Approximation, Decomposition and GRasping | *Workshop on Grasp Planning and Task Learning by Imitation* (Huebner, 2010) .

- Simulation environment: GraspIt2! (Miller and Allen, 2004).
- 25 objects with 6 object classes: bottles, glasses, mugs, knives, hammers, and screwdrivers (Shilane *et al.*, 2004).
- 2 hand models: Human hand and Schunk Dexterous Hand (SDH).
- 3 tasks: *hand-over, pouring*, and *tool-use*.

Data Acquisition



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

- Object approximation – box decomposition
- Grasp hypotheses – approaching box facades
- Feature extraction – $[\mathbf{O}; \mathbf{A}; \mathbf{C}]$
- Manual task labeling – $[\mathbf{T}]$ by human | All in BADGr (Huebner, 2010)

Three Experiments:

1) "Which task is this object-grasp configuration good for?"
2) "From where should this object be grasped for a given task? "
3) "Can you imitate this demonstrated task?"

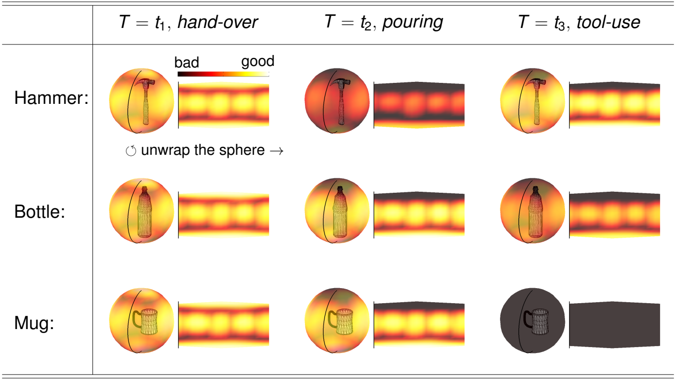
1) Which task is this object-grasp configuration good for?

	$T\|O$			$T\|O,A$			$T\|O,A,C$		
hand-over	0.51	0.15	0.34	0.56	0.35	0.09	0.70	0.21	0.09
pouring	0.22	0.78	0.00	0.13	0.87	0.00	0.11	0.89	0.00
tool-use	0.15	0.10	0.75	0.12	0.00	0.88	0.11	0.00	0.89

Task classification given different amount of observations:

- Object features contain a lot of task-relevant information for *pouring* and *tool-use* tasks.
- Action features improve classification for *pouring* and *tool-use*.
- Constraint features significantly improve classification rate of *hand-over*.

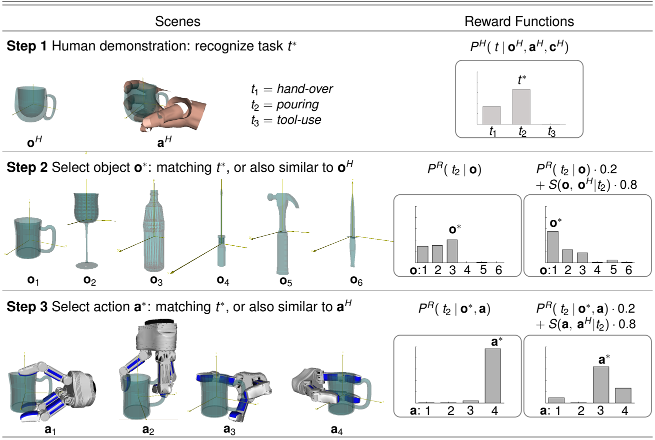
2) From where should this object be grasped for a task?



Grasp position conditioned on tasks and objects:

- Generative mapping on continuous action features.
- Allowing plan and control at low-level sensorimotor systems.

3) Can you imitate this demonstrated task?



Goal-directed imitation:

- Achieving same task based on robot's own motor capabilities.

Conclusions

- 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

- Multivariate discretization for learning BN structures from high-dimensional continuous data, – ICRA 2011 submission.
- Including dynamic features (e.g. trajectories of hand+object)

Thanks

Thanks for your attention!

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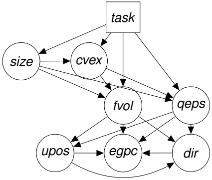
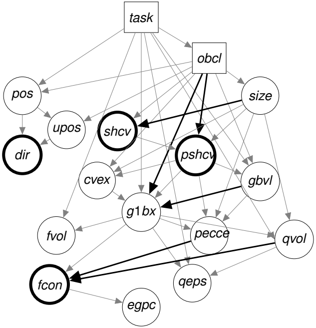
ICRA 2011 submission

IROS 2010: 8 nodes
Structure Built by Experts



ICRA 2011: 17 nodes
Structure Learned from Data

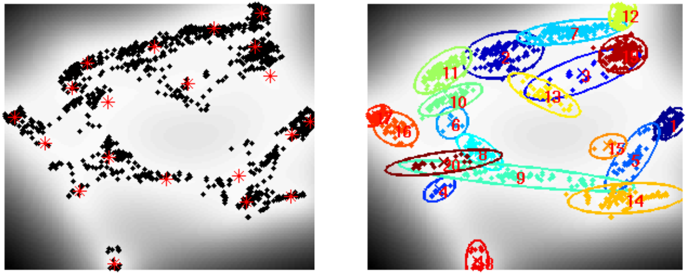


Structure learning from discretized data

- Improved task classification.
- Allow generative mapping on many more continuous variables.

ICRA 2011 submission

a) Step1: GP-LVM → 2D Latent Space b) Step2: GMM → Discretization



Sparse GP-LVM based discretization for 20-D *fcon*

- Two-dimensional latent space learned using sparse GP-LVM with 20 inducing points (red stars).
- Discretization on the latent space using GMM.

ICRA 2011 submission

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hand-over	0.70	0.12	0.17	0.74	0.09	0.17	0.86	0.04	0.10	
pouring	0.12	0.88	0.00	0.05	0.95	0.00	0.15	0.85	0.00	ICRA 2011
tool-use	0.16	0.00	0.84	0.03	0.00	0.97	0.04	0.01	0.95	

Improved task classification rate

- Especially for *hand-over* task.
- More feature variables with learned BN structure are beneficial.