Learning objects by autonomous exploration and human interaction

Serena Ivaldi
Team LARSEN, INRIA
serena.ivaldi@inria.fr
8 Research Centres in France

Inria Research Centres

Local sites

Paris
Saclay
Île-De-France
Rennes
Bretagne
Atlantique
Bordeaux
Sud-Ouest
Grenoble
Rhône-Alpes
Sophia Antipolis
Méditerranée
Nancy
Grand Est
Lille
Nord Europe

Centre de recherche Inria
Antenne

Strasbourg
Pau
Lannion
Nantes
Montpellier
Lyon

Inria Nancy / Loria Team Larsen

smart apartment

Pepper Tiago

arena

Franka

iCubNancy01

Talos
Outline

Learning the visual appearance of objects from scratch - with curiosity-based autonomous exploration and social guidance

Learning by demonstration whole-body manipulation on humanoids

HEAP project - Incorporating human preferences to improve grasping of irregular objects in a heap
Learning the visual appearance of objects from scratch - with curiosity-based autonomous exploration and social guidance

Learning by demonstration whole-body manipulation on humanoids

HEAP project - Incorporating human preferences to improve grasping of irregular objects in a heap
Learning like a child

- Sensorimotor learning
- Object exploration
- Social guidance

MACSi
Object learning through interaction

autonomous learning of visuomotor models

object learning through active exploration

object learning through joint attention

powerful learning tools

intrinsic motivation + aut. exploration + social guidance

social guidance

IROS 2012

IEEE TAMD 2014

Front. Neurorob. 2013
Multimodality for object learning

- **observation**
  (pure vision: models and entities)

- **active exploration**
  (manipulation, better models)

- **exploration and interaction**
  (better models with categories)
Multimodality for object learning

exploration and interaction
(better models with categories)

active exploration
(manipulation, better models)

observation
(pure vision: models and entities)
Multimodality for object learning

Robot object human

- Vision
- Proprioception
- Objects + categories
- Entities + views
- Vision
- Proprioception
- Identified entity
- Identified view
- Mid-level dictionary
- Low-level dictionary
- HSV superpixels
- SURF points
- Depth contours
- Optical flow
- Depth data
- KLT points
- Mid-level features
- Low-level features
- Model, category
- Segmented proto-object
Observation alone is not enough

The robot learns the objects demonstrated by the human.

The robot has not yet learnt to identify its body, hence all entities are labeled by an "unknown" category.

Acquire better models through action

Active exploration of objects

**action does not change the view**

<table>
<thead>
<tr>
<th>pre</th>
<th>post</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="pre image" /></td>
<td><img src="image2" alt="post image" /></td>
</tr>
</tbody>
</table>

**action provokes a new view**

<table>
<thead>
<tr>
<th>pre</th>
<th>post</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3" alt="pre image" /></td>
<td><img src="image4" alt="post image" /></td>
</tr>
</tbody>
</table>
Active exploration & social guidance

Intrinsic motivation
SGIM-ACTS

Exploration strategy
actor → action → object

Social exploration
Robot asks human to manipulate the object

Autonomous exploration
Robot lifts the objects, then makes it fall on the table
Robot pushes the object
Curiosity-driven exploration of objects

• Focusing on the objects that are not yet learned
• choosing the appropriate action for each object

• with the “bad” teacher the robot takes and throws more the objects (41% vs 24%)

• the “good” teacher has a catalysing effect: learning process is 25% faster

• with intrinsic motivation, the robot spends most of its time in learning the cube (54% and 51% with bad and good teacher respectively)
Better learning with action and interaction

Better object recognition

Better object recognition

This is open-ended!!
No limit to the number of objects, they are learned incrementally.

The limit is how much you are patient and interact with the robot :) 

Outline

Learning the visual appearance of objects from scratch - with curiosity-based autonomous exploration and social guidance

Learning by demonstration whole-body manipulation on humanoids

HEAP project - Incorporating human preferences to improve grasping of irregular objects in a heap
Towards whole-body manipulation

Grasping an object is a particular task adding to the balancing and locomotion tasks of the whole-body robot controller.
Towards whole-body grasping & manipulation

Tele-operation/retargeting is the whole-body kinesthetic teaching

Transfer paradigm: from humans to robots

Human partner  Robot  Operator  Ground control

human partner monitor  robot monitor  operator monitor
Towards whole-body grasping & manipulation

Can we make sure that the robot controller can execute in principle any retargeted human motion in real-time?
Auto-tuning the controller for teleoperation

Learning the control structure and the parameters that enable the robot to perform a variety of motions
Auto-tuning the controller for teleoperation

WE RECORD A SEQUENCE OF DOUBLE SUPPORT MOVEMENTS FROM A HUMAN OPERATOR
Auto-tuning the controller for teleoperation

Learning the control structure and the parameters that enable the robot to perform a variety of motions
Demonstrating whole-body manipulation
Whole-body co-manipulation with a human

- Take into account the entire human dynamics in a multi-task QP controller for collaborative manipulations
- Joint level controller for the robot, but capable of reacting to the human

Whole-body co-manipulation with a human

Proposed approach:
- Model the human as a robot → multi-robot QP controller
- Reason in terms of balance of the couple human+robot, not robot only

\[
\begin{align*}
\text{minimize} & \quad \sum_k w_k \| \ddot{g}_k - \ddot{g}_k^{des} \|^2 \\
\text{subject to} & \quad M\ddot{q} + N = J_0^T F^0 + (J_1 - \Psi^T J_2) F^- + S\tau \\
& \quad J_0 \dot{q} = 0 \\
& \quad (J_1 - \Psi^T J_2) \dot{q} = 0 \\
& \quad f \in C \\
& \quad \text{torque limits, joint limits, collision avoidance}
\end{align*}
\]

Individual or combined tasks (e.g. combined CoM for balance)
Equal and opposite contact forces between robots
Non-slipping contacts between robots

Whole-body co-manipulation with a human

EXPERIMENT 1: PICK AND PLACE

Learning the visual appearance of objects from scratch - with curiosity-based autonomous exploration and social guidance

Learning by demonstration whole-body manipulation on humanoids

HEAP project - Incorporating human preferences to improve grasping of irregular objects in a heap
EU Project HEAP

Human guided learning of robotic heap sorting

Why do we need human guidance?
Human guidance / expertise / preference → Grasping algorithms
Why do we need human guidance

We already have plenty of grasping algorithms that we can use to find the best candidate grasp for the objects in the scene…

=> Dexnet 2.0
Malher et al., RSS 2017

https://github.com/BerkeleyAutomation/gqcnn
Dex-Net 4.0: Learning Ambidextrous Robot Grasping Policies

Science Robotics Journal 2019
berkeleyautomation.github.io/dex-net
=> Dexnet 2.0, Malher et al., RSS 2017

https://github.com/BerkeleyAutomation/gqcnn
Why do we need human guidance

1) Because some objects challenge our cameras

➡ Crystals
Why do we need human guidance

1) Because some objects challenge our cameras

➡ Mirror
Why do we need human guidance

2) Because the best grasp candidate automatically computed by a grasping algorithm (here: Dexnet 2.0) is not the best choice according to the human, it is not what the human would do.

➡ Pipe
Why do we need human guidance

2) Because the best grasp candidate automatically computed by a grasping algorithm (here: Dexnet 2.0) is not the best choice according to the human, it is not what the human would do

➡ Broom
Why do we need human guidance

3) Because grasping algorithms do not reason about the objects fragility

⇒ the Duplo tower will break during grasping and transportation
Integrating human preferences

**GRASP PREDICTIONS**

**BAD DEXNET GRASP SELECTION**

**BETTER DEXNET GRASP SELECTION**

Good demonstrations

Bad demonstrations
Integrating human preferences

Learning grasp preference models for classes of objects
Human guidance & preferences

Tests with different number of targeted classes
Top Training
Bottom validation

(unsupervised - k-means & u-maps)
Human guidance & preferences

Classes of objects that were automatically created

Still work in progress…
Summary

Autonomous curiosity based exploration
Human guidance in exploring objects

Methods for demonstrating whole-body manipulation (open-ended, without constraints)

Incorporating human preferences and learning class-specific grasp preferences (incrementally)
Acknowledgments


L. Penco, J.B. Mouret, V. Modugno, W. Gomes

L. Vianello, Y. Fleytoux, A. Ma, J.B. Mouret
Thank you! Questions?


L. Penco, J.B. Mouret, V. Modugno, W. Gomes

L. Vianello, Y. Fleytoux, A. Ma, J.B. Mouret