Intelligent Robots - How grasping technology evolved from simulation to the real-world

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In This Presentation

Robot Grasping

Deep Learning for Grasping

Deep Reinforcement Learning for Grasping and Manipulation
Robot Grasping
Grasping: A Foundational Skill

Moravec (1988): "it is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility"
# Types of Grasps

## Human Grasp Taxonomy

<table>
<thead>
<tr>
<th>Grasp Type</th>
<th>Power</th>
<th>Intermediate</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palm</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Pad</td>
<td>2.5</td>
<td>Side</td>
<td>Side</td>
</tr>
<tr>
<td>Side</td>
<td>2</td>
<td>2</td>
<td>2.5</td>
</tr>
</tbody>
</table>

### Thumb Adducted

- 1: Large Diameter
- 2: Small Diameter
- 3: Medium Diameter
- 4: Finger Finger
- 5: Light Tool
- 6: Pinch

### Thumb abducted

- 11: Index Finger
- 12: Adjacent Finger
- 13: Power Grip
- 14: Lateral Tension
- 15: Parallel Tension

## Robot Grasp Taxonomy

- Robot Image
# Robot Grasping

<table>
<thead>
<tr>
<th>Commercial</th>
<th>Soft Robotics</th>
<th>Kindred</th>
<th>Right Hand Robotics</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td><img src="image2.png" alt="Image 2" /></td>
<td><img src="image3.png" alt="Image 3" /></td>
<td><img src="image4.png" alt="Image 4" /></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Academic</th>
<th>Google Research</th>
<th>UC Berkeley</th>
<th>Google Research</th>
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<tbody>
<tr>
<td><img src="image5.png" alt="Image 5" /></td>
<td><img src="image6.png" alt="Image 6" /></td>
<td><img src="image7.png" alt="Image 7" /></td>
<td><img src="image8.png" alt="Image 8" /></td>
</tr>
</tbody>
</table>
Amazon picking challenge 2016 winner
Streamlining manual grasping from shelves
Data-driven Grasp Synthesis

1. Success is sensitive to sensor noise & exceptions.
2. There is no standard heuristic for all objects & grippers.
Deep Learning for Computer Vision

AlexNet (Krizhevsky et al. 2012)

The class with the highest likelihood is the one the DNN selects

When AlexNet is processing an image, this is what is happening at each layer.

First Deep Learning: 2012

Image source: CrowdAI.org
Deep Learning for Grasping

Pinto and Gupta 2015

MIT-Princeton Team, APC 2017
Dex-Net 4.0: Deep Learning from Simulation

Training from 5 Million simulated grasp attempts

Dex-Net 4.0: Deep Learning from Simulation

- Deep Learning for features
- Deep Learning for grasp point selection
- Same AI for different grippers & item sets.
- Near 100% grasp success.

Deep Reinforcement Learning for Grasping and Manipulation
A Brief History of Reinforcement Learning

Simulations and Games
- 1992: TD for Backgammon
- 2013: ATARI suite challenge
- 2015: Nature: Deep RL for ATARI
- 2016: Science: AlphaGo
- 2017: Poker
- 2018: DOTA 2
- 2019: Starcraft II

Physical Skills
- 2016: Data Center Cooling
- 2017: Open-loop grasping in clutter
- 2018: QT-OPT: Grasping learned in HW
- 2018: OpenAI Dactyl learned in sim.
- 2018: Kindred SenseAct challenge suite
Can responsive behavior be learned?

Output: Joint torques

Deep Neural Network

Input: Joint angles, velocities

Random parameters in network

Learned parameters in network (learning algorithm: PPO)
Kindred Research: SenseAct

• Open-Source toolkit for learning with physical robots: https://github.com/kindredresearch/SenseAct

• Research focus areas:
  • Learning vs. classic control
  • Can learning create new and useful robot behaviors
  • Simulation vs. learning in the real world
OpenAI: Project Dactyl

“We hope to go further beyond what hand-programmed robots can do”
Learning Responsive Grasping

Google/Princeton “TossingBot”

For more information

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