

Learning to Grasp through Self-Supervision

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Agenda

- 1 Introduction
- 2 Examples
- 3 Comparison
- 4 Demonstration
- 5 Questions & Discussion





Introduction





Photo: Pinto and Gupta

Goals

- Provide answers/insights to the following:
 - What is a Grasp/Grasp-Process?
 - What are the benefits of self-supervised learning for grasping?
 - How can we achieve successful grasps through selfsupervised learning?
 - An alternative approach that is neither supervised nor unsupervised.
- Create an intuition to solve such and similar problems



Grasp Process



Tools to Grasp

2-Jaw Gripper





3-Finger Gripper



Vacuum

Gripper



Bionic Hand

Universität Hamburg

Tools used for Research

- Literature Review from Newburry et al., 2022, about grasp synthesis with Deep Learning (6DoF), 85 reviewed papers.
 - Most commonly used gripper: Two-Finger parallel jaw (51 times)
 - Most commonly used robot: Robotic arm (66 times)

Manufacturer	Model	Popularity	DoF
Robotiq	2F	10	1
Robotiq	3F	5	1
Franka Emika	Panda Gripper	12	1
Barret	BarretHand	7	5
Kinova	2F	3	1
Kinova	3F	1	2
Wonik Robotics	Allegro Hand	4	16
Rethink Robotics	Baxter Gripper	4	1
Shadow Robot Company	Shadow Hand	2	20
	Custom	2	
	Other	32	

Input Format	Number of times used
Point Cloud	34
Depth Image	18
RGB-D Image	15
Voxel Grid	12
Segmentation Mask	9
Other	10



Grasp Pose



3-DoF

7-DoF





6/7-DoF



Methods for Grasp Synthesis

- Analytical Methods
 - Requires an accurate model of the object (hard to get)
- Supervised / Human labeling
 - Biased
 - Human working time
- Self-Supervised Learning
 - Autonomous label generation/learning (without human bias/effort)
 - Labeling through Trial-and-Error
 - Simulation / Roboter working time
- Reinforcement Learning





Examples





Three different Approaches

- 1. Supersizing Self-supervision: Learning to Grasp from 50K Tries and 700 Robot Hours.
 - L. Pinto and A. Gupta, 2015, Carnegie Mellon University.
- 2. Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection.
 - S. Levine, P. Pastor, A. Kryzhevsky and D. Quillen, 2017, Google.
- 3. GraspNet-1Billion: A Large-Scale Benchmark for General Object Grasping
 - H.-S. Fang, C. Wang, M. Gou. C. Lu, 2020, Shanghai Jiao Tong University.



Supersizing Self-Supervision

- Pinto and Gupta (2015), Carnegie Mellon University
 - RGB-Camera (known Position)
 - Pretrained Convolutional Layers (AlexNet trained on ImageNet)
 - Random attempts and evaluation
 - Classification into 18 different angles, 3-DOF annotation



Query Kinect image



Find objects via MOG subtraction



Approach random object

Execute random grasp



Verify grasp success



Supersizing Self-Supervision: CNN

The Convolutional Neural Network (CNN) Architecture

- Input: Image patch centered at the presumed grasp point
- Output: 18 scores





UH

Supersizing Self-Supervision: Dataset

- 50k+ grasp attempts
 - Random 40k for the training set and 3k for the test set
 - 7k with pretrained network

Data Collection Type	Positive	Negative	Total	Grasp Rate
Random Trials	3,245	37,042	40,287	8.05%
Multi-Staged	2,807	4,500	7,307	38.41%
Test Set	214	2,759	2,973	7.19%
	6,266	44,301	50,567	



Supersizing Self-Supervision: Staged Learning

Staged Learning

- 1. Trained classification CNN-Model as prior
- 2. Previous stage with seen and unseen objects





Supersizing Self-Supervision: Learning/Dataset



Binary classification of the test set (single stage)

The success rate is 66% for unseen and 73% for seen objects



Hand-Eye Coordination

- Levine et al. (2016), Google
 - RGB-Camera (unknown position)
 - Tries to learn the best next move to a grasp
 - "Can react to changes during the grasp process"





Hand-Eye Coordination: CNN





Hand-Eye Coordination: Learning Process

Staged Learning

- 1. Start with random motor commands (half of the data), single step
- 2. Trained model from the last stage
 - Cross Entropy Method (CEM) to find the next move
 - Projection of the "best" next move to the table height
- 3. Increasing max steps by two (till 10), and train again



Hand-Eye Coordination: Learning/Dataset



GraspNet-1Billion

- Fang et al. (2020), Shanghai Jiao Tong University
- Grasp annotation of real-world data through analytical computation on sim objects
 - Depth cloud (RGB-D camera) (multiple viewpoints)
 - The DNN tries to adapt depth clouds from real objects to eighty-eight known 3D-Models
 - Capable of 7-DoF grasp synthesis and collision detection



GraspNet-1Billion: Grasp/Pose Synthesis



GraspNet-1Billion: Dataset

Dataset

- 97k Images from 190 cluttered scenes
- 88 objects
- Leads to more than 1 Billion
 6-DoF grasp annotations

6D-Pose









Instance Masks

Rectangle-based

Rectangle-based Grasp Poses



GraspNet-1Billion: DNN



GraspNet-1Billion: Ablation Study

Comparison of grasp score (s) and success rate

Object	s=1	s=0.5	s=0.1	Object	s=1	s=0.5	s=0.1
Banana	98%	67%	21%	Apple	97%	65%	16%
Peeler	95%	59%	9%	Dragon	96%	60%	9%
Mug	96%	62%	12%	Camel	93%	67%	23%
Scissors	89%	61%	5%	Power Drill	96%	61%	14%
Lion	98%	68%	16%	Black Mouse	98%	64%	13%



Conclusion





Comparison

	50k Tries	Eye-Hand Coordination	GraspNet
Dataset Size	50k	3000k	1000k
Sensor	RGB-Camera	RGB-Camera	RGBD-Camera
Main Feature	Simple CNN	Motion Planning Risk of collisions	7-DoF Pose Big data set

(No direct comparison of performance due to different setups, objects and goal parameters)



Conclusion

- Importance of Large-Scale Data and Multi-Stage learning
- Improving grasping models in robotics
- There are various approaches to solve the same problem





Demonstration



Picture: GraspNet



fang2020graspnet

GraspNet: 7-DoF Grasp Pose Synthesis









Sourcecode: https://github.com/graspnet/graspnetbaseline

Questions & Discussion



Picture: www.unsplash.com



5

References

- H.-S. Fang, C. Wang, M. Gou. and C. Lu, GraspNet-1Billion: A Large-Scale Benchmark for General Object Grasping. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, USA, 2020, pp. 11441-11450. https://doi.org/10.1109/CVPR42600.2020.01146.
- S. Levine, P. Pastor, A. Krizhevsky, J. Ibarz, D. Quillen. Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. The International Journal of Robotics Research. 2018, 37(4-5), pp. 421-436. https://doi.org/10.1177/0278364917710318.
- R. Newbury, M. Gu, L. Chumbley, A. Mousavian, C. Eppner, J. Leitner, J. Bohg, A. Morales, T. Asfour, D. Kragic, D. Fox, A. Cosgun, Deep Learning Approaches to Grasp Synthesis: A Review. 2022, Australian National University Canberra. https://doi.org/10.48550/arXiv.2207.02556.
- L. Pinto and A. Gupta, Supersizing self-supervision: Learning to grasp from 50K tries and 700 robot hours. 2016 IEEE International Conference on Robotics and Automation (ICRA), Stockholm, Sweden, 2016, pp. 3406-3413. https://doi.org/10.1109/ICRA.2016.7487517.



A. Deep Learning Approaches to Grasp Synthesis: A Review

Inclusion/Exclusion Criteria of Papers

- From the papers found in the databases, only publications that met the following criteria are included in this review:
 - Paper considered grasping from a table-top scenario,
 - All 6-DoF were used for the grasp pose,
 - Deep Learning methods were applied in some aspect of the work,
 - Published after Jan 1, 2012, (the year AlexNet was published) and Written in English



B. Hand-Eye coordination

- Cross Entropy Method
 - 64 samples and 3 iterations with the 6 best grasp directions, starting with a normal distribution at the current position.
 - All samples are constrained to the workspace and rotations between
 - All grasp directions are projected to the table height.

