ICRA2018 Report

related work in Robotics and Automation

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- Main Points

  - ICRA Introduction
  - ICRA 2018 Summary
  - Robotic Grasping

- ICRA Introduction

  - ICRA: IEEE International Conference on Robotics and Automation
  - TRO(IEEE Transaction on Robotics, IF 4.264),IJRR(International Journal of Robotics Research, IF 4.047)
  - Deadline: 9.15
  - Conference Date: 20-25 May
  - PaperPlaza: https://ras.papercept.net/conferences/scripts/start.pl

- ICRA Introduction

  - Exhibition: Academics and industry

- ICRA Introduction

  - Exhibition: Academics and industry

- ICRA Introduction

  - Exhibition: Academics and industry

- ICRA Introduction

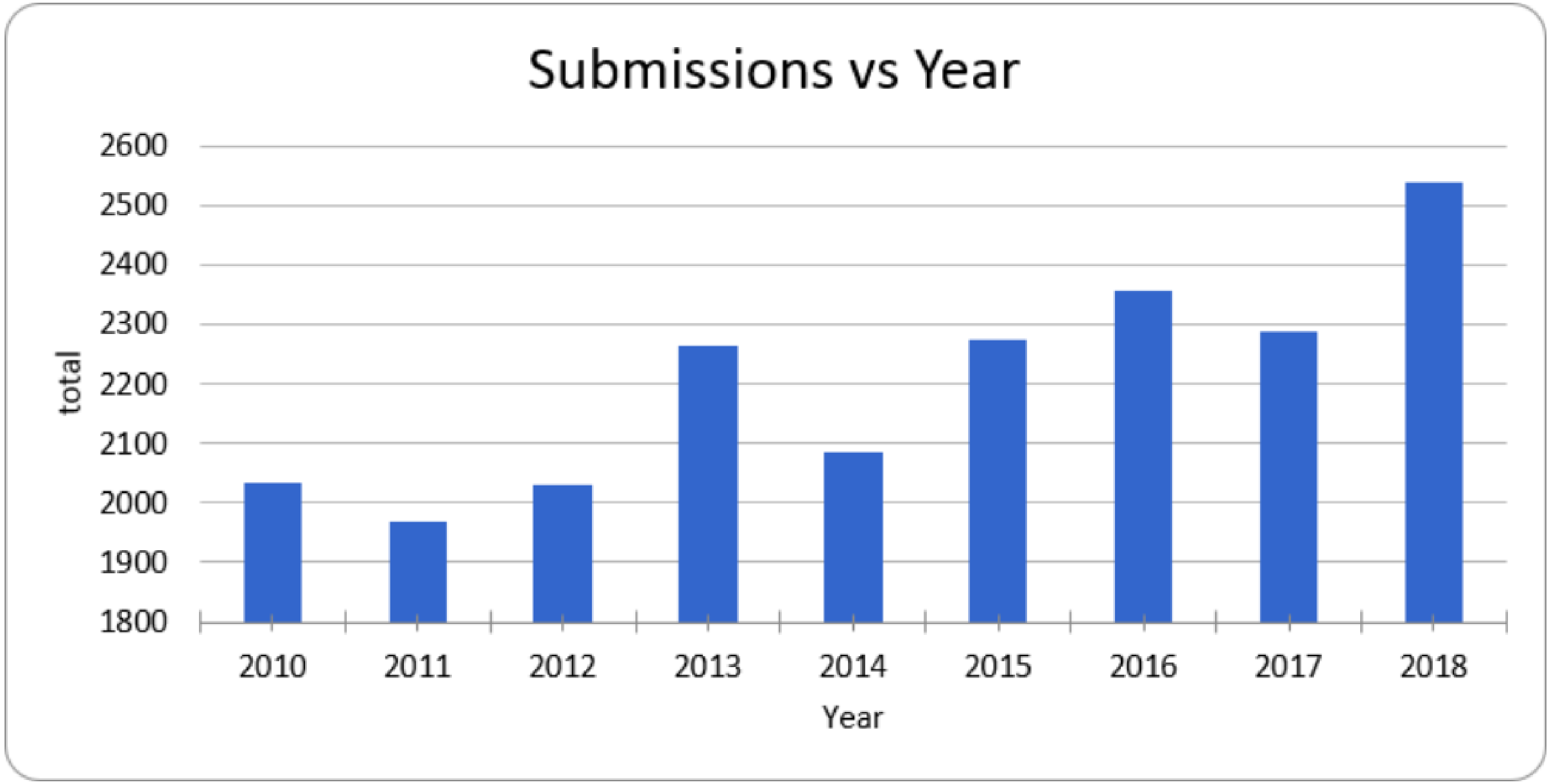
  - Exhibition: Academics and industry

- ICRA2018 Summary
  - Submissions

2586 paper submitted

1981 submitted to ICRA

605 submitted to RAL



- ICRA2018 Summary
  - Submissions

Number	Country
613	USA
230	China
159	Germany
115	Japan
89	France
85	UK
83	Italy
82	South Korea
75	Australia
62	Canada

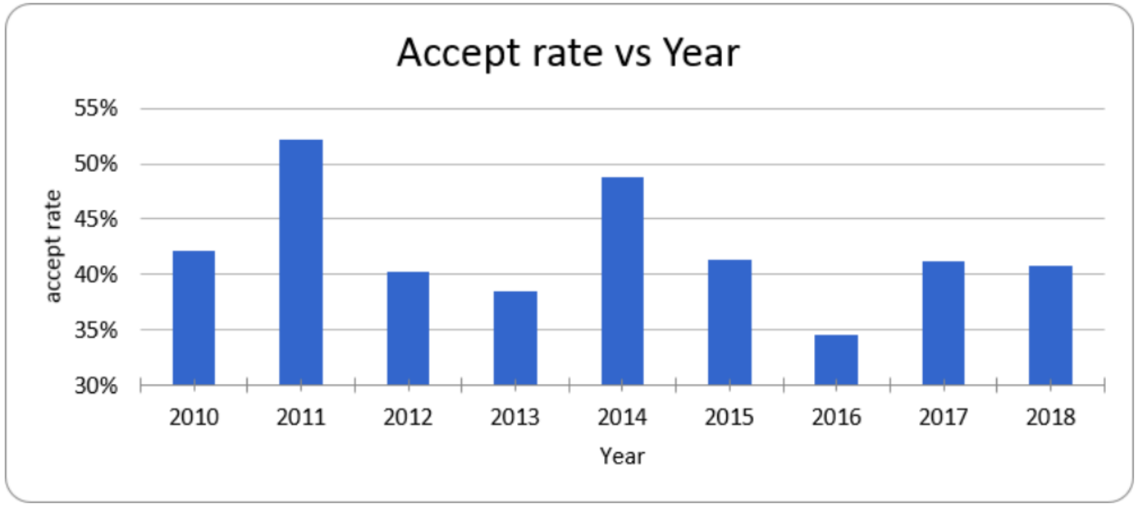
- ICRA2018 Summary
  - Presenting

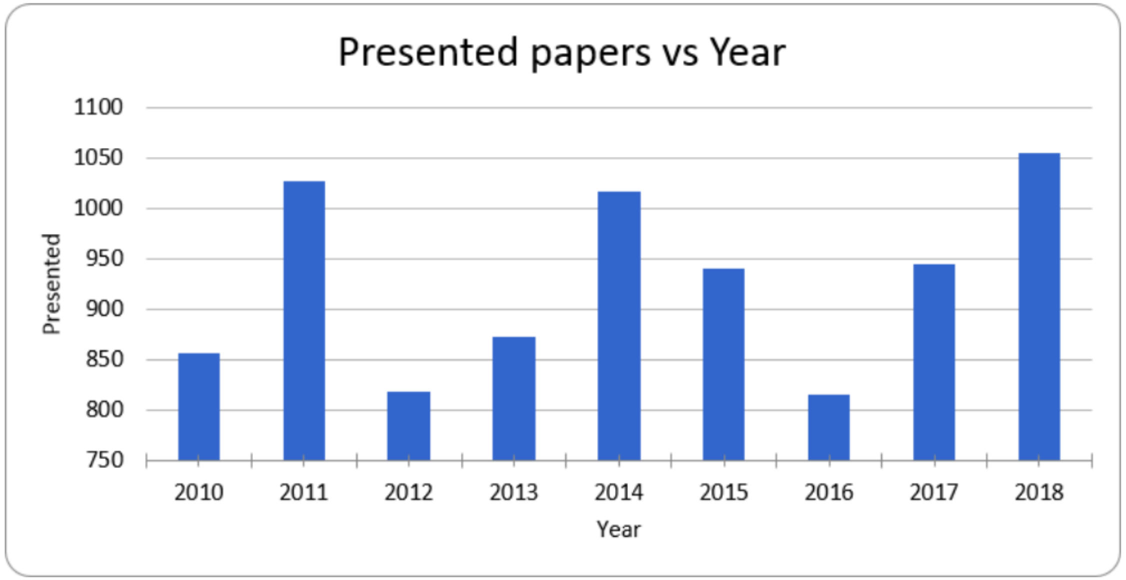
1056 papers presented

40.8% acceptance rate

31 workshops

6 forums





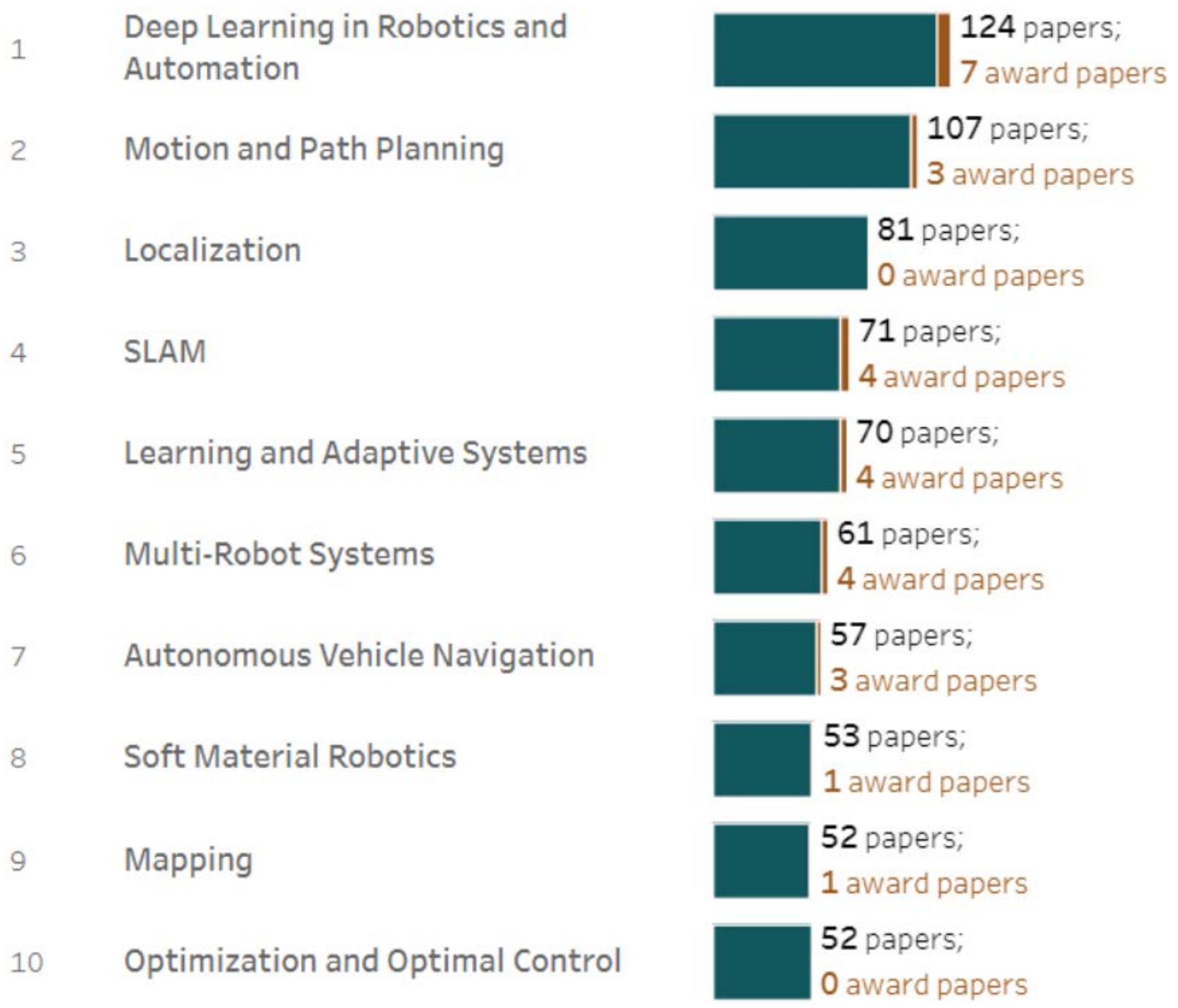
- ICRA2018 Summary
  - Presenting

35 Award Papers (3%)

1. IEEE ICRA Best Conference Paper Award
2. IEEE ICRA Best Student Paper Award
3. IEEE ICRA Best Paper Award in Automation
4. IEEE ICRA Best Paper Award in Cognitive Robotics
5. IEEE ICRA Best Paper Award on Human-Robot Interaction (HRI)
6. IEEE ICRA Best Paper Award in Robot Manipulation
7. IEEE ICRA Best Paper Award in Medical Robotics
8. IEEE ICRA Best Paper Award on Multi-Robot Systems
9. IEEE ICRA Best Paper Award in Service Robotics
10. IEEE ICRA Best Paper Award in Robot Vision
11. IEEE ICRA Best Paper Award on Unmanned Aerial Vehicles
12. IEEE ICRA 2018 Award for the Most Influential Paper

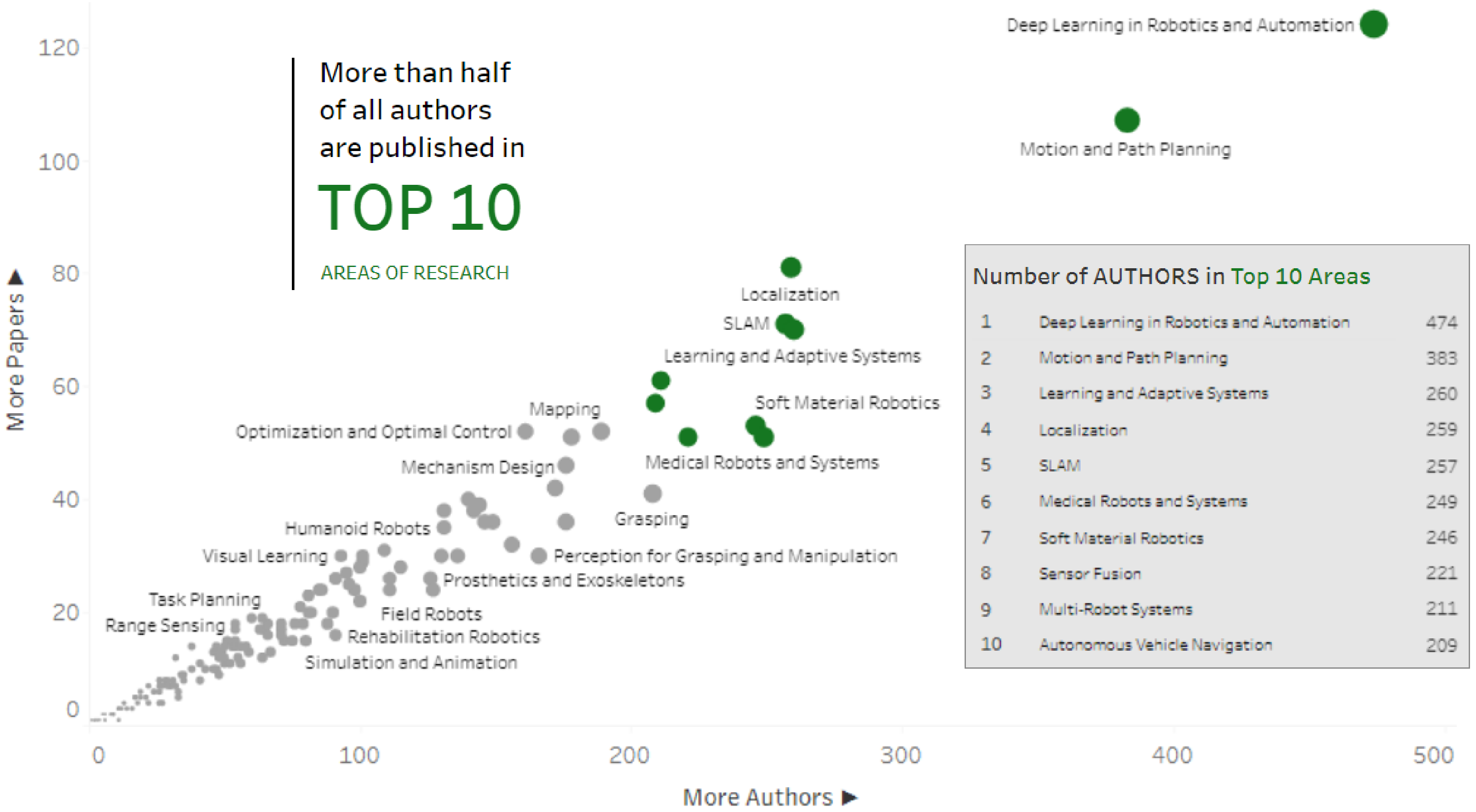
- ICRA2018 Summary
  - Presenting

Top 10 Keywords



- ICRA2018 Summary
  - Presenting

3681 Authors



Number of AUTHORS in Top 10 Areas

1	Deep Learning in Robotics and Automation	474
2	Motion and Path Planning	383
3	Learning and Adaptive Systems	260
4	Localization	259
5	SLAM	257
6	Medical Robots and Systems	249
7	Soft Material Robotics	246
8	Sensor Fusion	221
9	Multi-Robot Systems	211
10	Autonomous Vehicle Navigation	209

Robotic Grasping

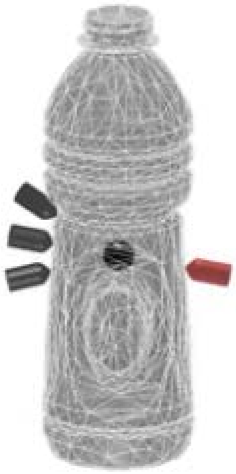
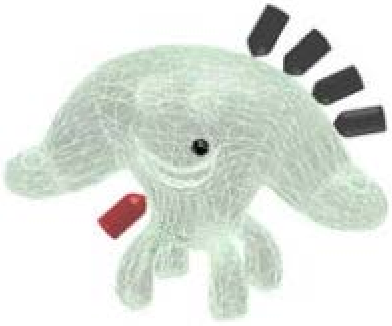
related work in Robotics and Automation

- A good autonomous grasping strategy is able to ensure stability, task compatibility and adaptability to new objects.

- Robotic Grasping

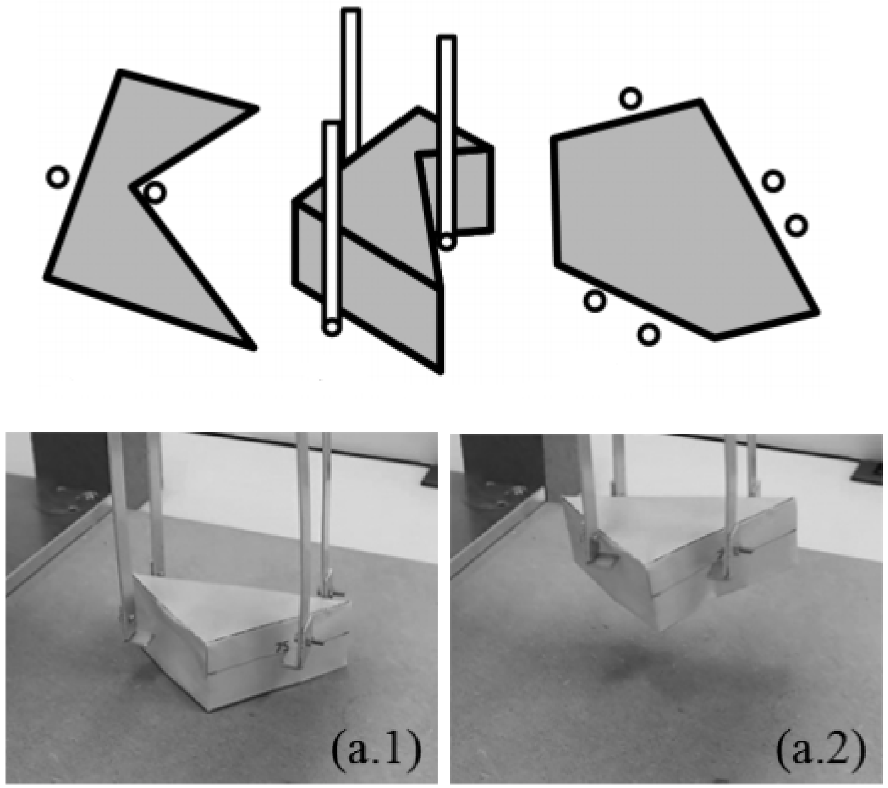
  - Analysis Approach
    - Force closure
    - Precision grasp: contact points computation
    - Known Object: Model, Physical properties (gravity, friction coefficient)
    - Collision-free environment
    - Sensitive to uncertainty (disturbance)



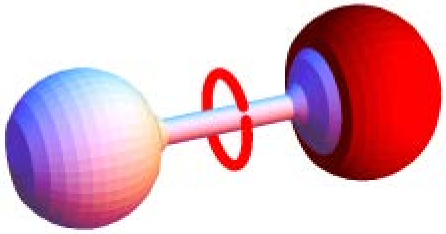



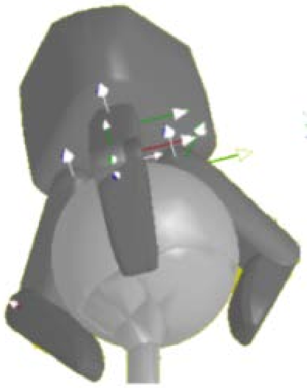
- Robotic Grasping

  - Caging grasp
    - The target object cannot escape from the cage
    - power grasp: contact surface
    - Robust to uncertainty: unknown object
    - 2D caging grasp (planar cage), 3D caging grasp (circle cage, sphere cage)

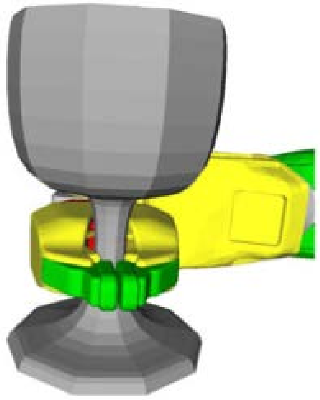


Planar Cage





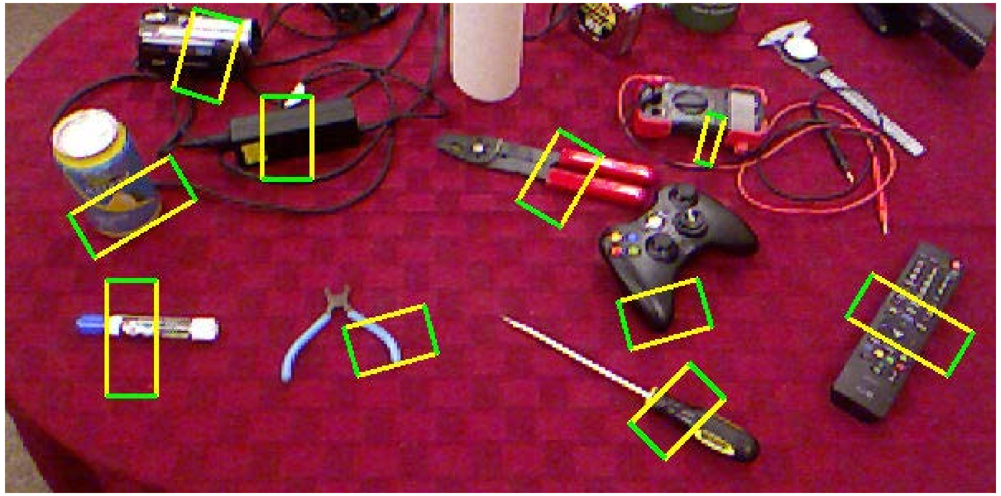
Sphere Cage



Circle Cage

- Robotic Grasping

  - Data-driven approach
    - Robotic grasp of novel object via Deep Learning
    - Grasp representation: grasp rectangle (Manually label)



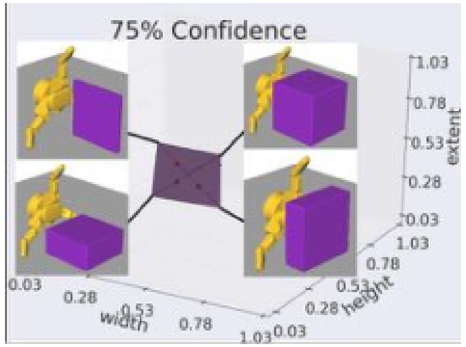
ICRA2018: Robotic Grasping Analysis Approach

- Manipulation – grasping
  - *Analysis approach:*

Grasping Objects Big and Small: Human Heuristics Relating Grasp-type and Object Size

Ammar Kothari, John Morrow, Ravi Balasubramanian, and Cindy Grimm
Robotics, Oregon State University, USA

- **Goal**: Understand human heuristics for mapping object size to grasp pre-shape
- Created a grasp taxonomy for a 3 finger manipulator based on human grasps
- Administered online surveys with training videos to gather shape space ranges for pre-shapes from people
- Used data to build confidence regions based on shape size to guide planners on choosing a grasp pre-shape



Given a pre-shape, largest and smallest objects that people believe can be grasped

- Manipulation – grasping

  - Contribution
  - Online data collection that captures human preference about what grasp types are preferred for different fundamental object shapes and sizes.
  - Motivation
  - Few studies focused on human preference for robotic grasp.
  - Human preferences for grasp type based on object size and shape was previously unavailable to robotic grasp planning algorithms.
  - Reduce the search space.

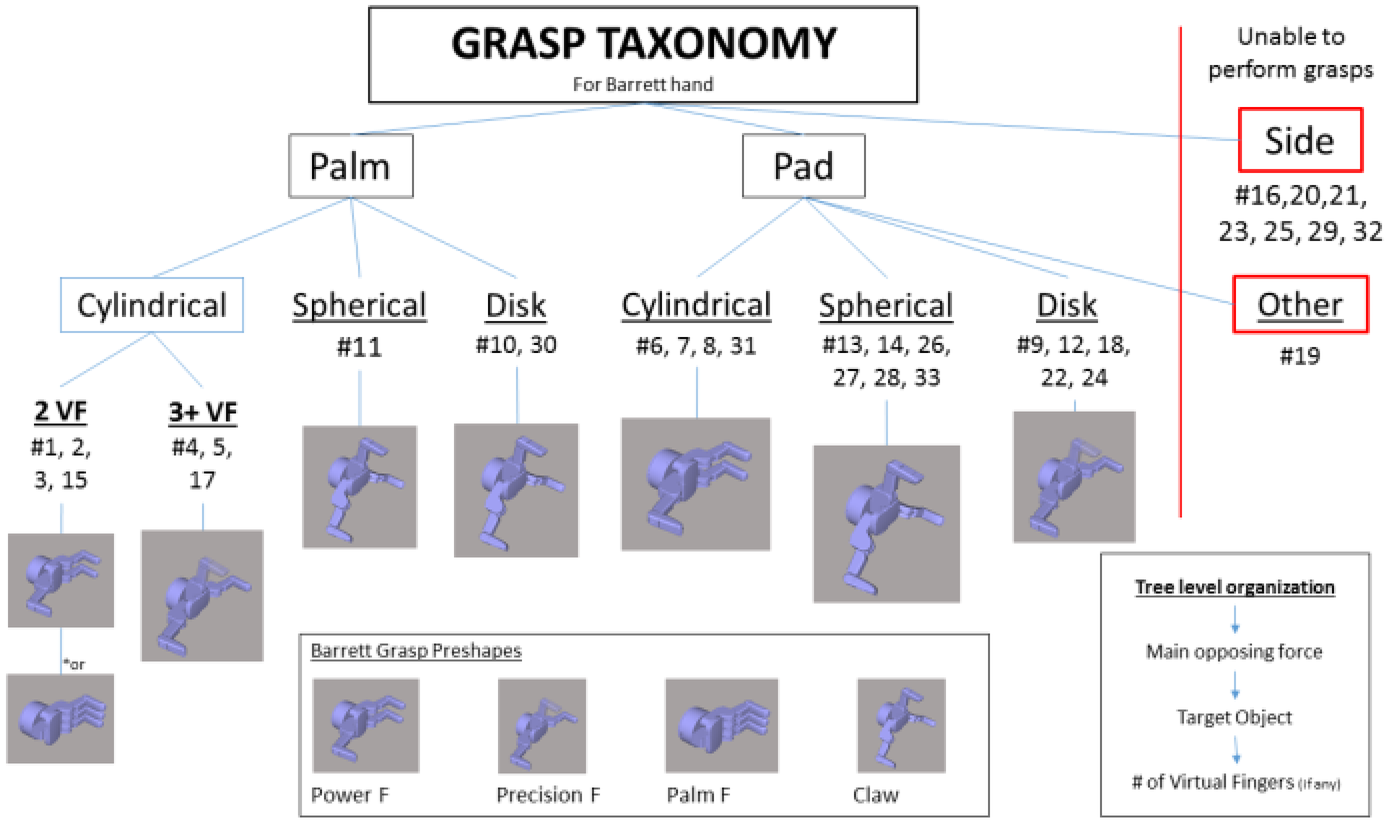


Fig: Grasp taxonomy adapted for Barrett hand, based on GRASP (Human) Taxonomy [5]. Grasps with red boundaries, such as those utilizing the side of the finger as the main opposing force, were not achievable due to limitations with the Barrett hand's kinematics. Four grasp preshapes were identified for the Barrett hand and were applied to all achievable grasp types. These grasp types are named at the bottom of the figure based on the main opposing forces and human inferred intent of each preshape grasp

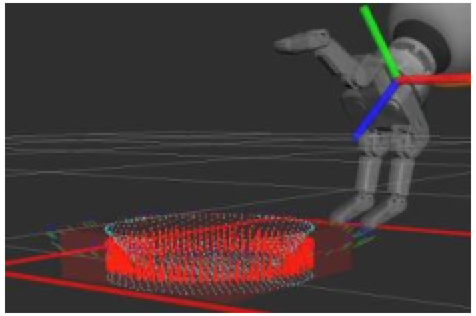
Grasping objects big and small: Human heuristics relating grasp-type and object size

- Manipulation – grasping
  - *Analysis approach:*

Grasping Flat Objects by Exploiting Non-Convexity of the Object and Support Surface

Iason Sarantopoulos, Yannis Koveos and Zoe Doulgeri
Information Technologies Institute, Center of Research and Technology Hellas, Thessaloniki, Greece

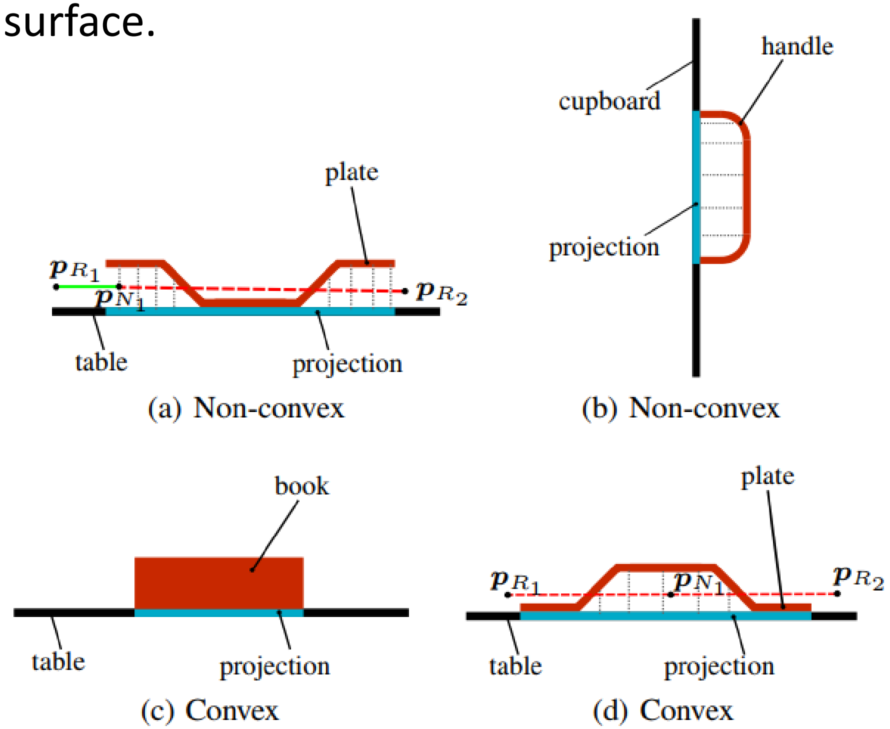
- Proposes a grasp strategy which exploits environmental contact for grasping domestic flat objects on support surfaces, inspired by human strategies.
- Assumes object point cloud availability.
- Considers cases where state-of-the-art grasp planners may not find a solution.
- Uses the non-convex geometry of the object-surface combination like in plates or handles.



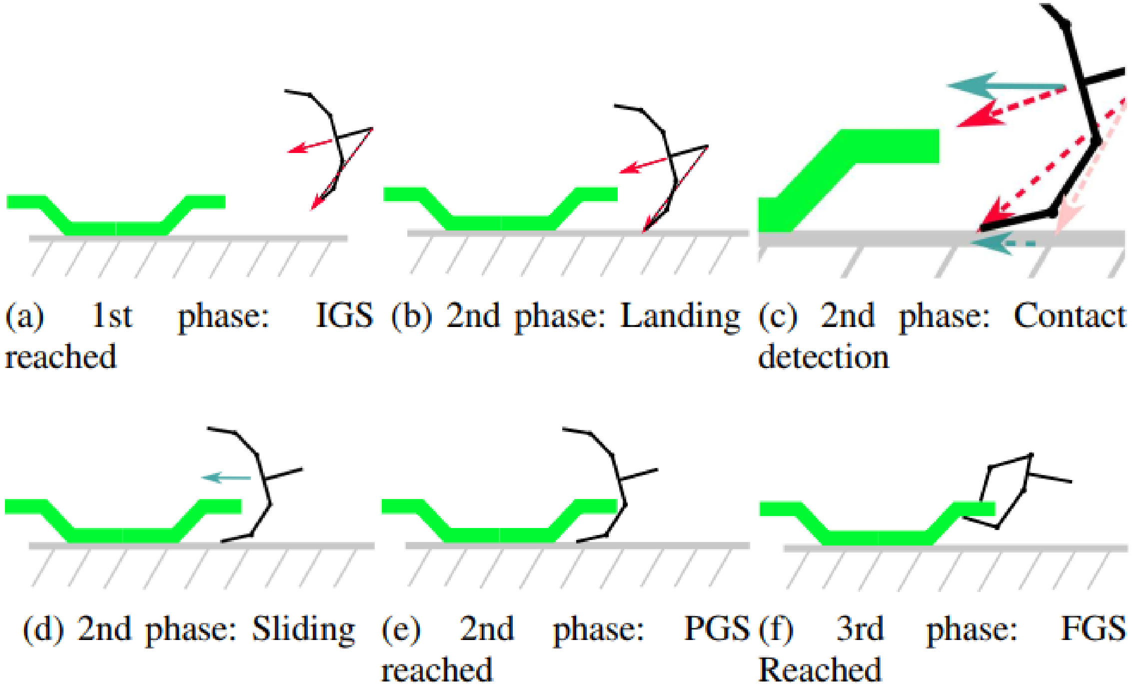
Grasping a plate using the non-convex space (red points)

- Manipulation – grasping

  - Contribution
    - A contact exploiting grasp strategy for domestic flat objects placed or hinged on support surfaces.
    - support surface which are characterized by non-convexity in their object-surface combination
    - opposable grasp
  - Motivation
    - Collision free space around target object.
    - The flatter an object is, the more difficult to grasp it without colliding with the support surface.
    - humans compensated for the uncertainties introduced by impaired vision by using contact with the support surface.



(a) Non-convex (b) Non-convex (c) Convex (d) Convex



(a) 1st phase: IGS reached (b) 2nd phase: Landing (c) 2nd phase: Contact detection (d) 2nd phase: Sliding (e) 2nd phase: PGS reached (f) 3rd phase: FGS Reached

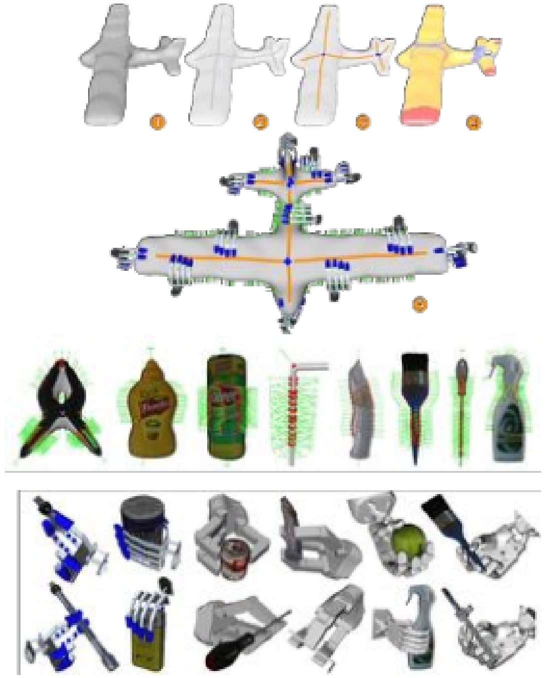
Grasping Flat Objects by Exploiting Non-Convexity of the Object and Support Surface

- Manipulation – grasping
  - *Analysis approach:*

Planning High-Quality Grasps using Mean Curvature Object Skeletons

Nikolaus Vahrenkamp, Eduard Koch,
Mirko Wächter and Tamim Asfour
Institute for Anthropomatics and Robotics
Karlsruhe Institute of Technology (KIT), Germany

- Efficient generation of high-quality grasps in terms of robustness and force-closure rates
- Combined analysis of topological object information and local surface structure
- Different grasping strategies to generate precision and power grasps
- Evaluation with KIT and YCB real-world object model databases and several robotic hands



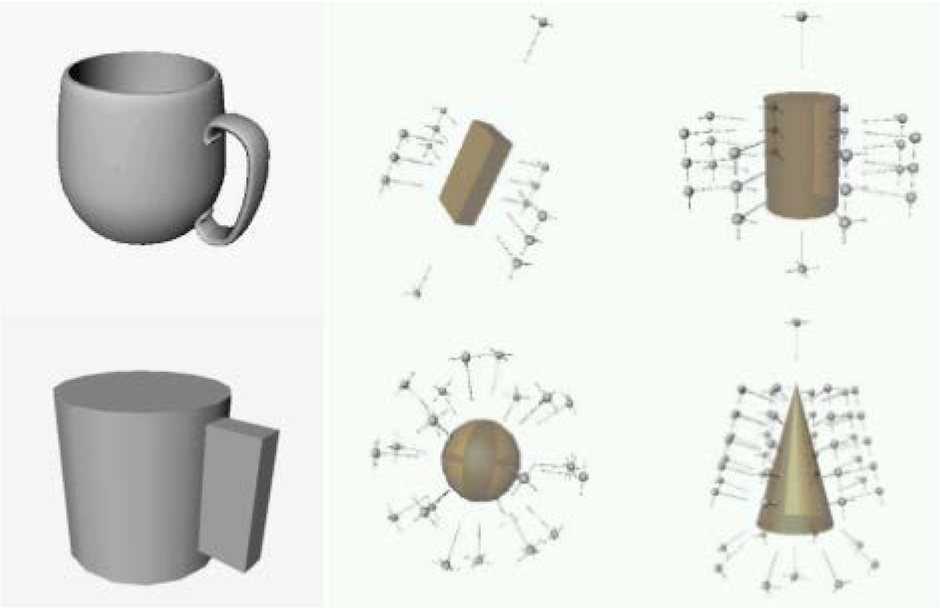
- Manipulation – grasping

  - Part-based approach
  - Generation of grasp candidates through object shape approximation with primitives
  - Performance:

    1.Not overall objects or its parts might be well-represented by primitive shapes

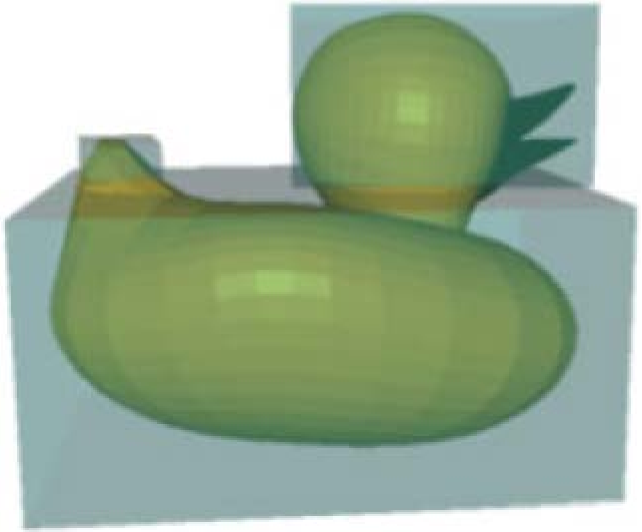
    2.perform poorly when used for grasping applications and propose instead to set a priori a number of elementary shapes, for a instance, SQ(superquadrics) that cannot be further split

    3.simple representation of the object will sacrifice potentially promising candidate grasps to poor geometry approximation



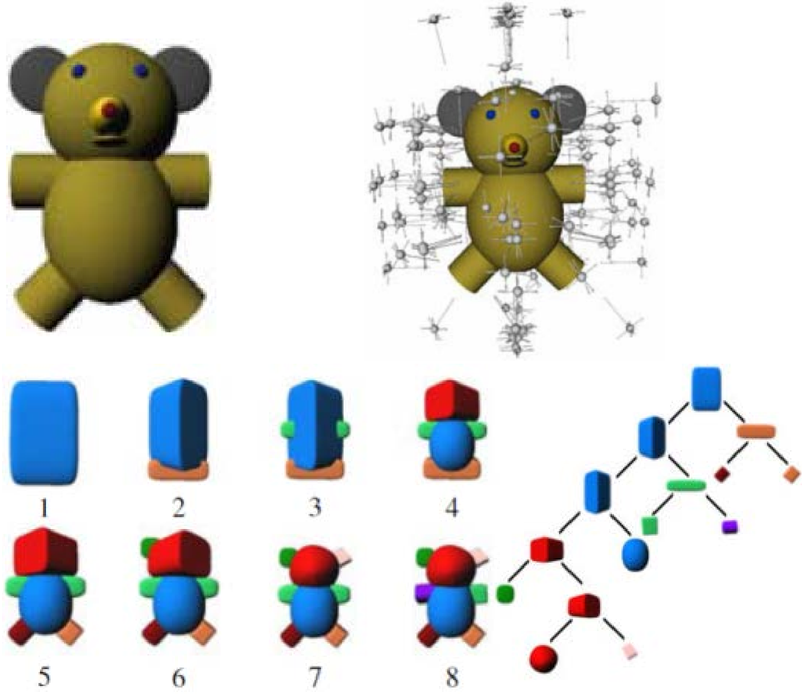
Primitive shape Decomposition

A. T. Miller, S. Knoop, H. I. Christensen, and P. K. Allen, "Automatic grasp planning using shape primitives," in Proc. IEEE Int. Conf. Robot. Autom., 2003, pp. 1824–1829.



Box Decomposition

K.H ¨ ubner and D. Kragic, "Selection of robot pre-grasps using box-based shape approximation," in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., 2008, pp. 1765–1770.



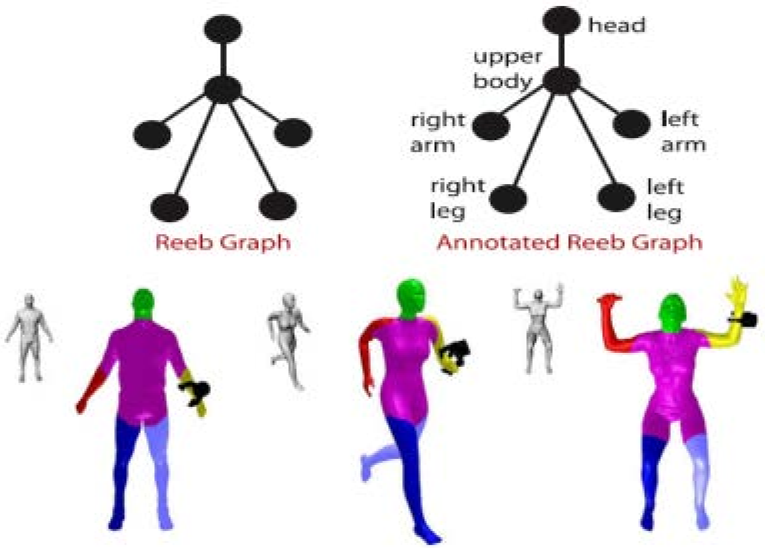
SQ Decomposition

C. Goldfeder, P. K. Allen, C. Lackner, and R. Pelossof, "Grasp planning via decomposition trees," in Proc. IEEE Int. Conf. Robot. Autom., 2007, pp. 4679–4684.

- Manipulation – grasping

  - Part-based approach
  - Generation of grasp candidates through Reeb graph segments
  - Performance:

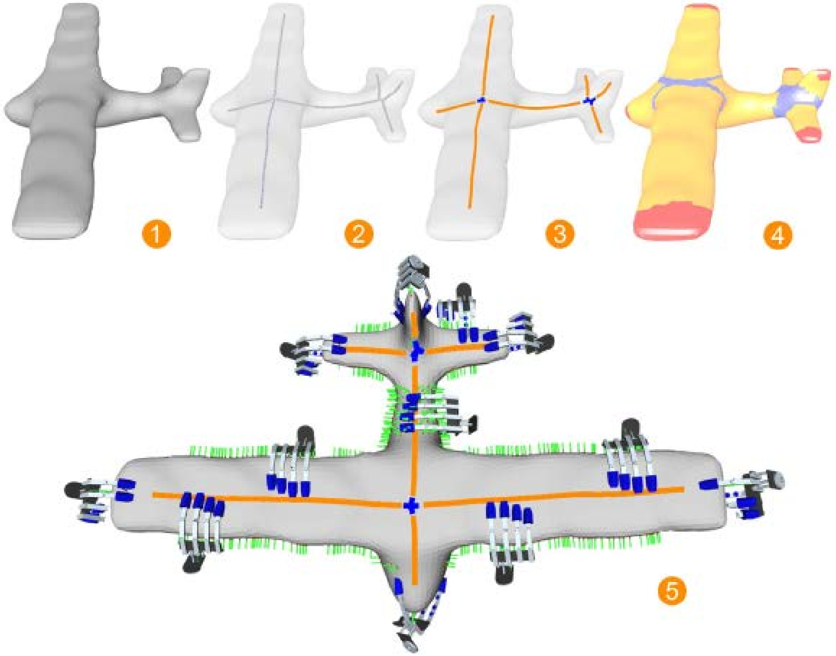
    1. the purely topology-based approaches do not take into account geometry features, is that it is not possible to discriminate between classes of objects that have the same topological structure

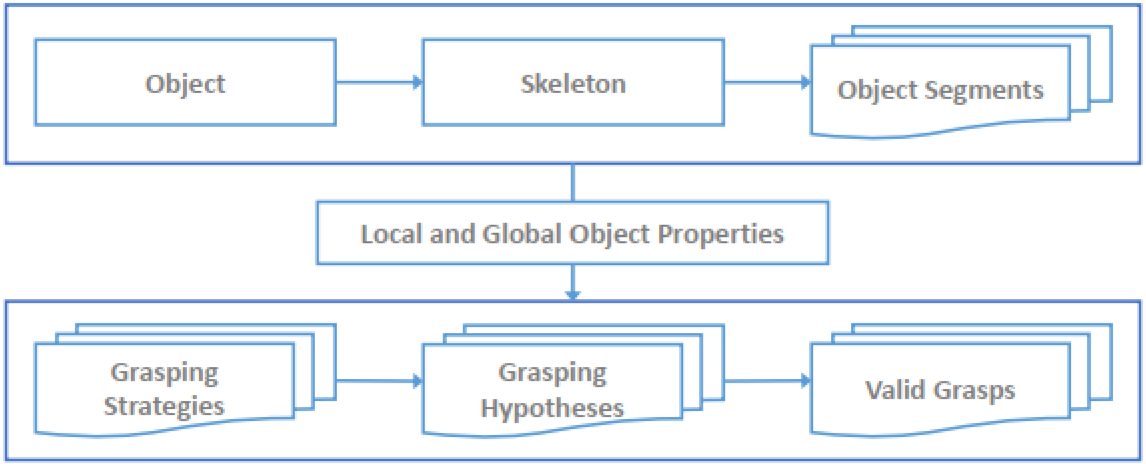


A 3D shape segmentation approach for robot grasping by parts Jacopo Aleotti, Stefano Caselli RAS2012

- Manipulation – grasping

  - Contribution
    - Skeleton-based grasp planner : Integrating Topological information and local surface structure to generate robust robotic grasp
    - Building mean curvature skeleton and segmenting the object to identify graspable regions
    - Grasp strategies: precision and power grasps
  - Motivation
    - Force-closure approach: small disturbances lead to unstable grasping configuration.
    - Part-based approach(primitive shapes, superquadrics, Reeb graph segments, voxelized object presentation):randomized grasp generation





The grasp planning process

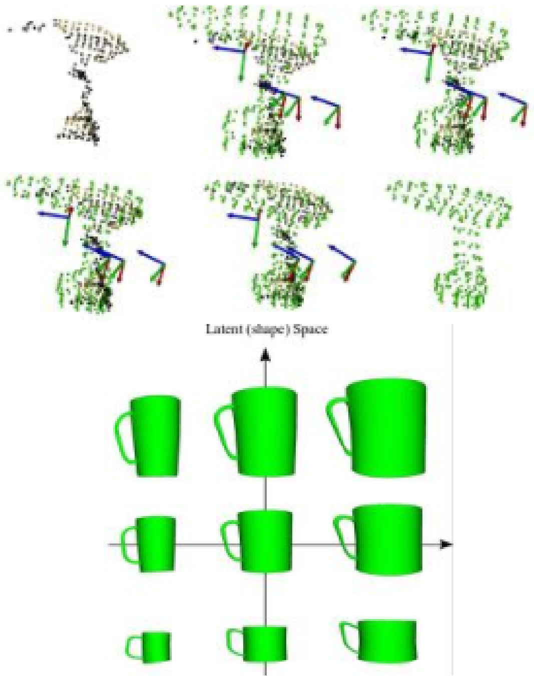
Planning High-Quality Grasps using Mean Curvature Object Skeletons

- Manipulation – grasping
  - *Analysis approach:*

Transferring Grasping Skills to Novel Instances by Latent Space Non-Rigid Registration

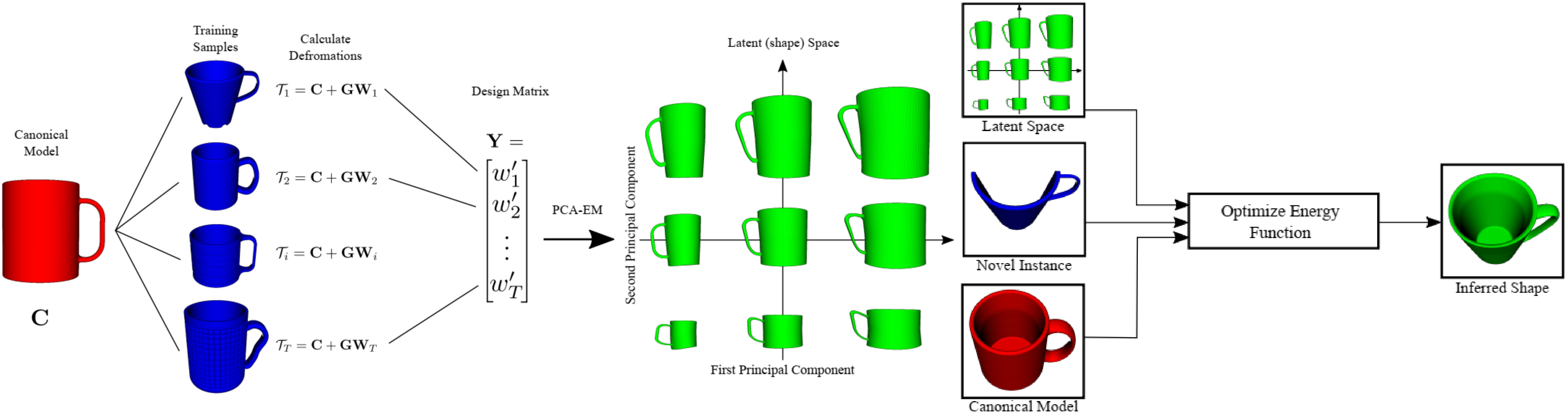
Diego Rodriguez, Corbin Cogswell, Seongyong Koo and Sven Behnke
Autonomous Intelligent Systems, University of Bonn, Germany

- Transfer of grasping poses of novel objects by learning a latent shape space of the category of the object.
- The shape space is built registering training samples with CPD and subspace methods.
- Reconstruction of partially observed instances due to learned category-level information
- New instances can be generated through interpolation and extrapolation in the shape space



- Manipulation – grasping

  - Contribution
  - Propose an approach for transferring grasping skill from known objects to novel instances of an object category.
  - Latent space non-rigid registration (Coherent Point Drift (CPD) 连贯点集漂移)
  - Generate novel instances through interpolation and extrapolation in this shape space
  - Novel shapes from partial views



Learning of the latent space

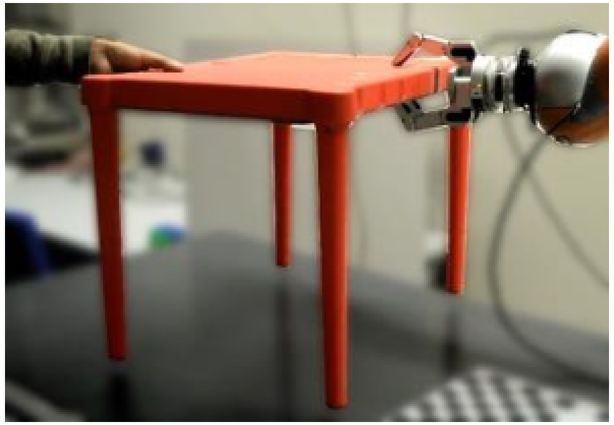
Transferring Grasping Skills to Novel Instances by Latent Space Non-Rigid Registration

- Manipulation – grasping
  - *Analysis approach:*

Grasp Planning for Load Sharing in Collaborative Manipulation

Usama Tariq, Rajkumar Muthusamy and Ville Kyrki
Department of Electrical Engineering and Automaion,
Aalto University, Finland

- Decentralized grasp planning for collaborative manipulation of unknown objects.
- Grasp analysis based on task specific minimization of grasp wrenches.
- On-line system for human-robot collaborative lifting proposed.
- Demonstrated optimal load sharing between agents during manipulation.

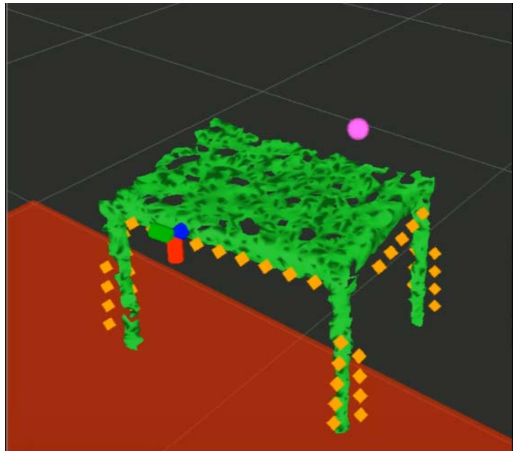


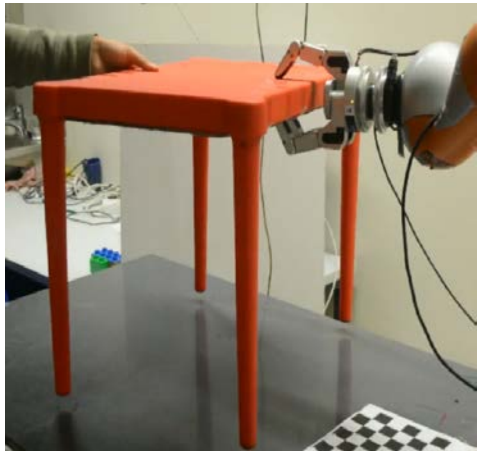
Human-robot collaborative lift up

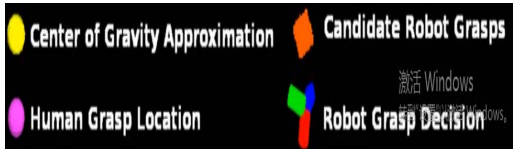
- Manipulation – grasping
  - Contribution
    - Robot grasp planning for load sharing
  - Motivation
    - the load sharing has not been addressed from the perspective of planning cooperative grasps

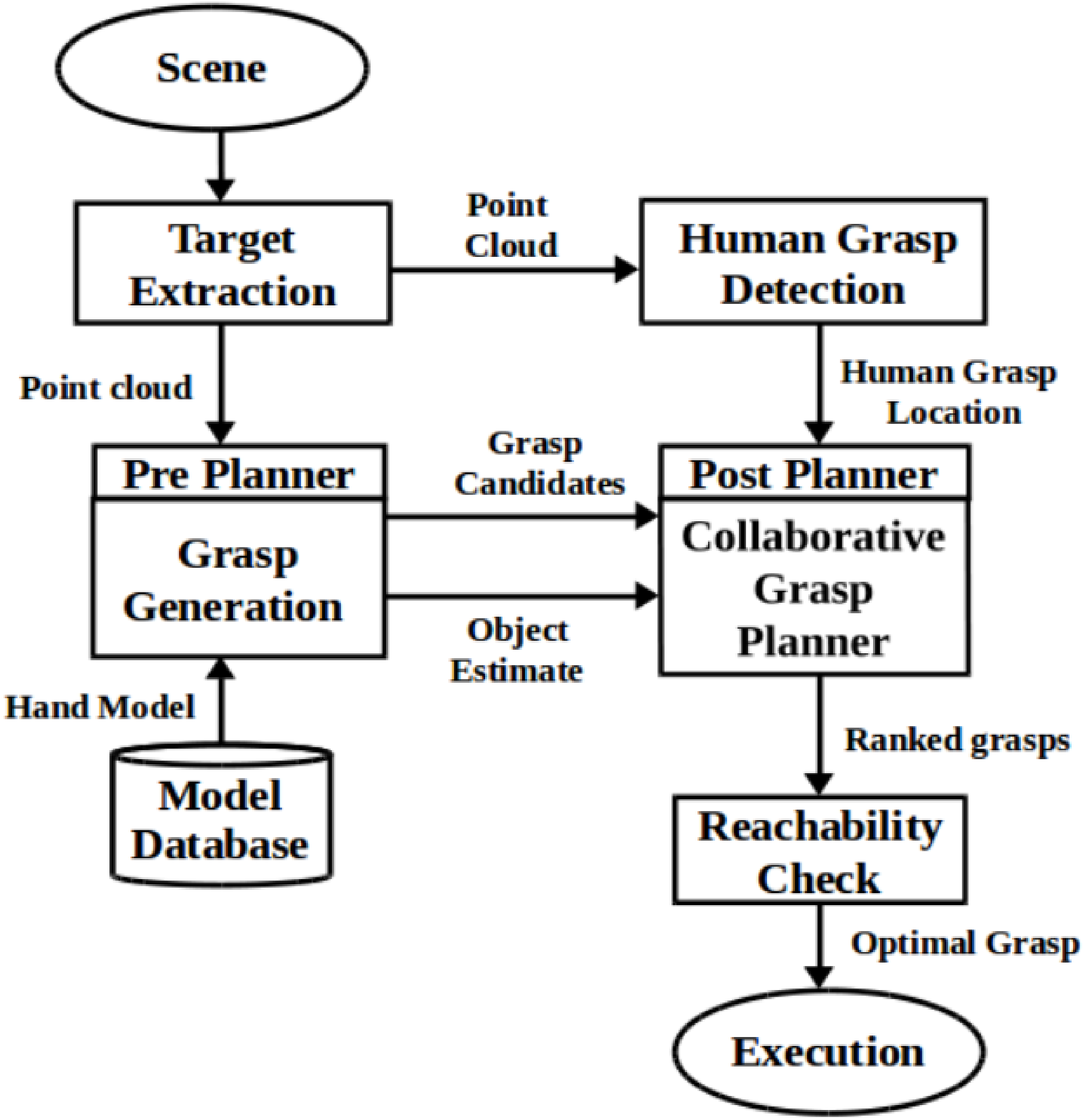
Grasp Planning for Load Sharing in Collaborative Manipulation

- Manipulation – grasping
  - Human Grasp Detection and Decision Making









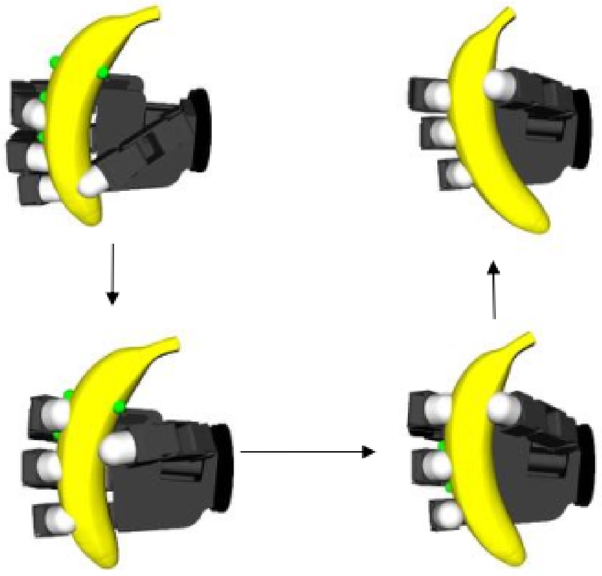
Grasp Planning for Load Sharing in Collaborative Manipulation

- Manipulation – grasping
    - *Analysis approach:*

Geometric In-Hand Regrasp Planning: Alternating Optimization of Finger Gaits and In-Grasp Manipulation

Balakumar Sundaralingam and Tucker Hermans,
School of Computing, University of Utah, USA

- We generate plans for moving from an initial fingertip grasp to desired fingertip grasp.
- We can generate plans on any arbitrary object, given the object's mesh.
- Our method performs alternating optimization of fingertip relocation (finger-gaiting) and object reposing (in-grasp manipulation).
- We solve the alternating optimizations through sequential quadratic programming.



Example sequence generated from our planner

https://robot-learning.cs.utah.edu/project/in_hand_manipulation

- Manipulation – grasping

  - ■ Problem Definition
  - In-hand regrasping, the problem of moving from an initial grasp to a desired grasp on an object using the dexterity of a robot’s fingers for precision grasps
  - ■ Motivation
  - Cluttered spaces limit grasp configurations

Initial Grasp

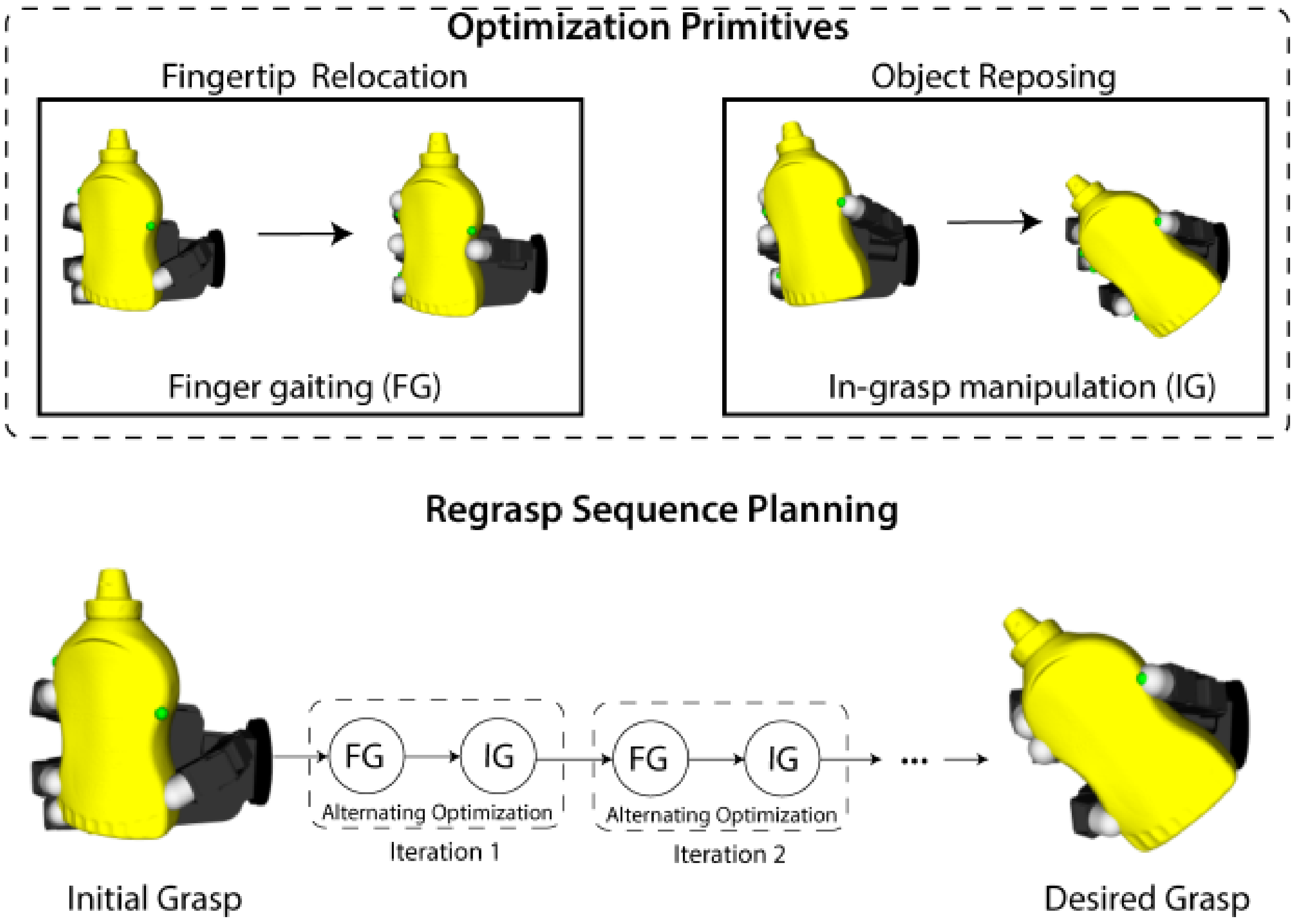
Desired Grasp

Geometric In-Hand Regrasp Planning: Alternating Optimization of Finger Gaits and In-Grasp Manipulation

- Manipulation – grasping

  - Problem Definition
  - Find a sequence of hand joint configurations to move to the desired grasp keeping the object in-hand

  - OPT1:Optimization for finger gaits
    - Force-closure
  - OPt2:Optimization for object reposing
    - In-grasp manipulation
  - Alternating Optimization



Geometric In-Hand Regrasp Planning: Alternating Optimization of Finger Gaits and In-Grasp Manipulation

- Manipulation – grasping

  - Contribution
  - An optimization based planner for relocating fingertips on an object surface
  - A sequence planner to regrasp an object in-hand from an initial fingertip grasp to a desired fingertip grasp.
  - Solution is collision-free and guarantees kinematic feasibility
  - Work on arbitrary object mesh

Geometric In-Hand Regrasp Planning: Alternating Optimization of Finger Gaits and In-Grasp Manipulation

- Manipulation – grasping
  - *Analysis approach:*

Caging Loops in Shape Embedding Space: Theory and Computation

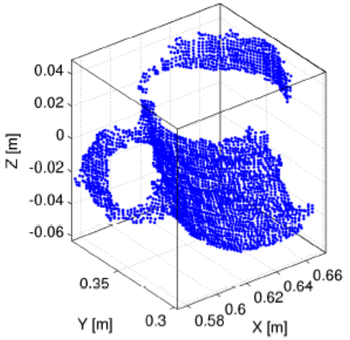
Jian Liu[1], Shiqing Xin[1], Zengfu Gao[1], Kai Xu[2], Changhe Tu[1] and Baoquan Chen[1]

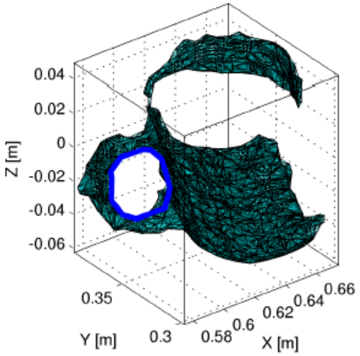
[1]Shandong University, [2]National University of Defense Technology, China

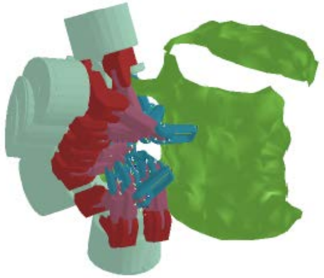
- A novel method for synthesizing **multi-scale** caging grasps, based on topological analysis of shape-aware distance field in shape embedding space.
- A rigorous study on the relation between field topology and caging loops, based on Morse theory.
- A grasping system implemented with robot gripper, along with thorough evaluations and comparisons on both 3D printed and real-world objects.

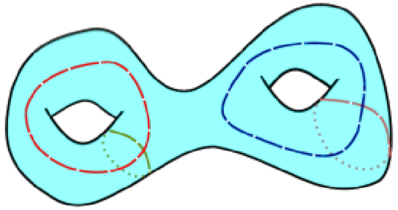
- Manipulation – grasping
  - Geometry or topology based 3D caging grasp

This paper presented a topology-based approach that is applicable to objects with holes. It used non-trivial first homology group to identify graspable loops and measure the linking between the robot fingers and object with Gauss linking integrals.

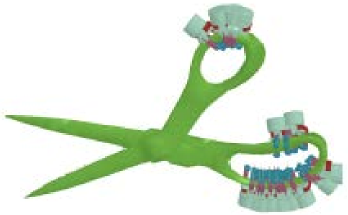








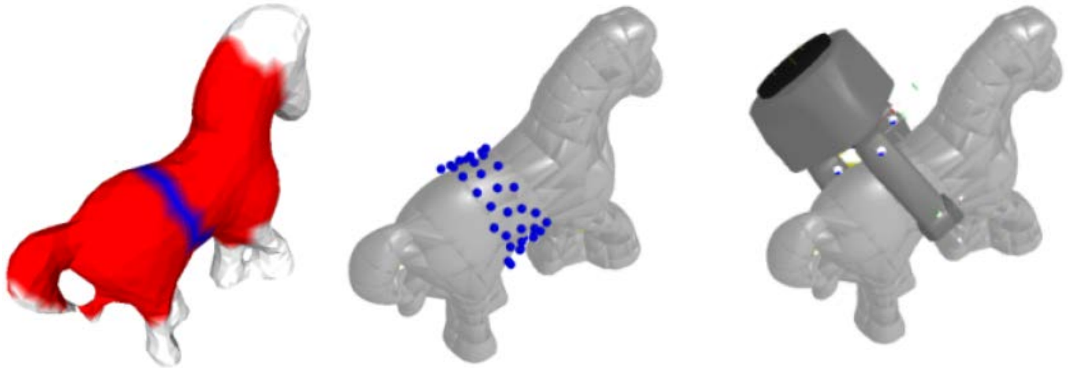
Analysis:
1.The topological loop is non-trivial
2. It is too dependent on the topological information of a 3D object, but it ignores the geometric feature.
3. It is sensitive to quality of point cloud.

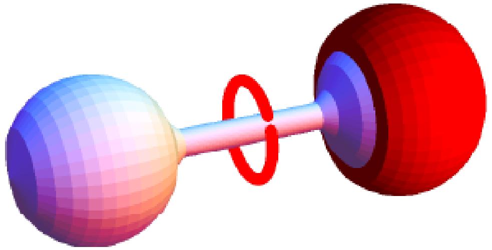


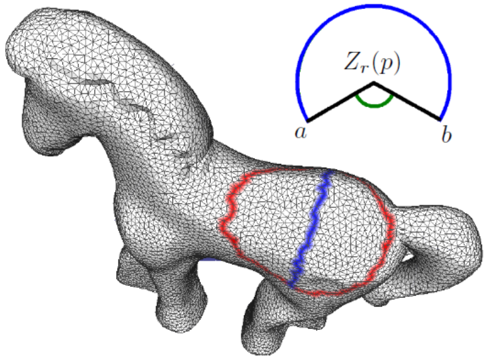
Pokorny, Florian T., Johannes A. Stork and Danica Kragic. “Grasping objects with holes: A topological approach.” 2013 IEEE International Conference on Robotics and Automation (2013): 1100-1107.

- Manipulation – grasping
  - Geometry or topology based 3D caging grasp

This paper proposed an idea of using geodesic balls on the object's surface in order to approximated the maximal contact surface between a grasp and an object. Two types of caging grasps are developed: circle caging and sphere caging, where circle caging means wrap almost completely around an elongated part of an object.



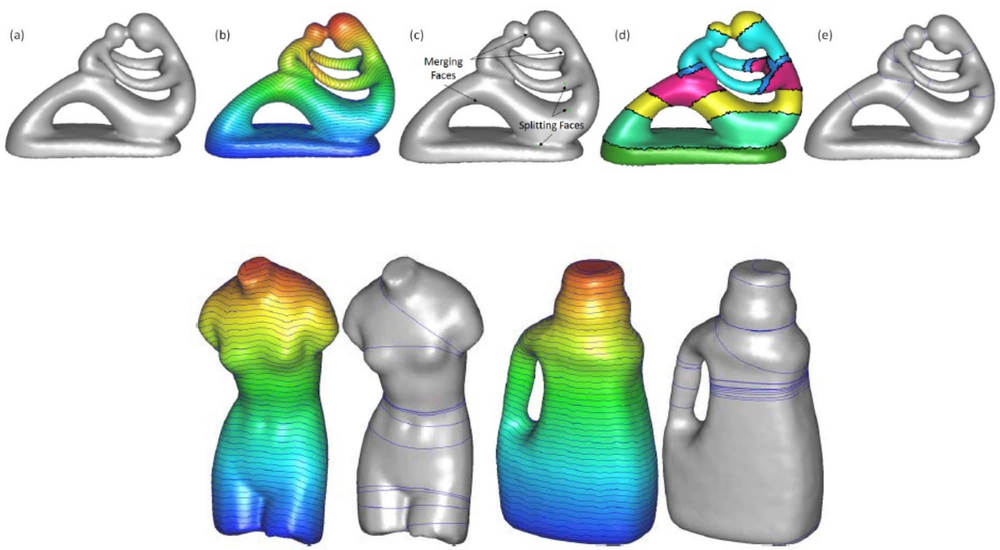


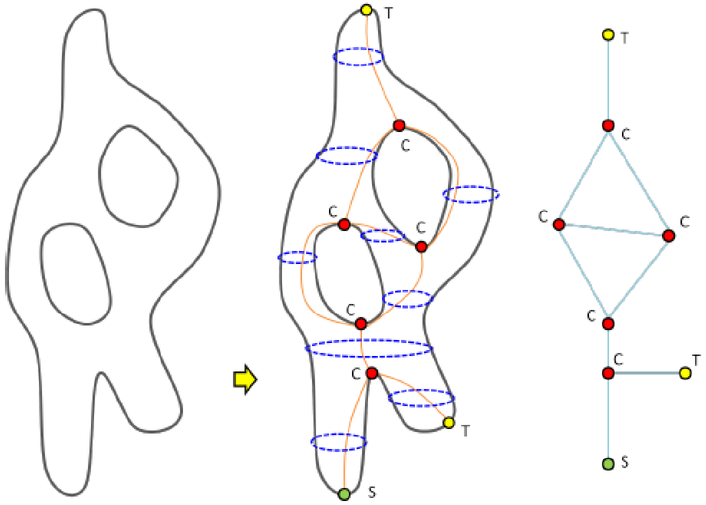


Zarubin, Dmitry, Florian T. Pokorny, Marc Toussaint and Danica Kragic. "Caging complex objects with geodesic balls." 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (2013): 2999-3006.

- Manipulation – grasping
    - Geometry or topology based 3D caging grasp

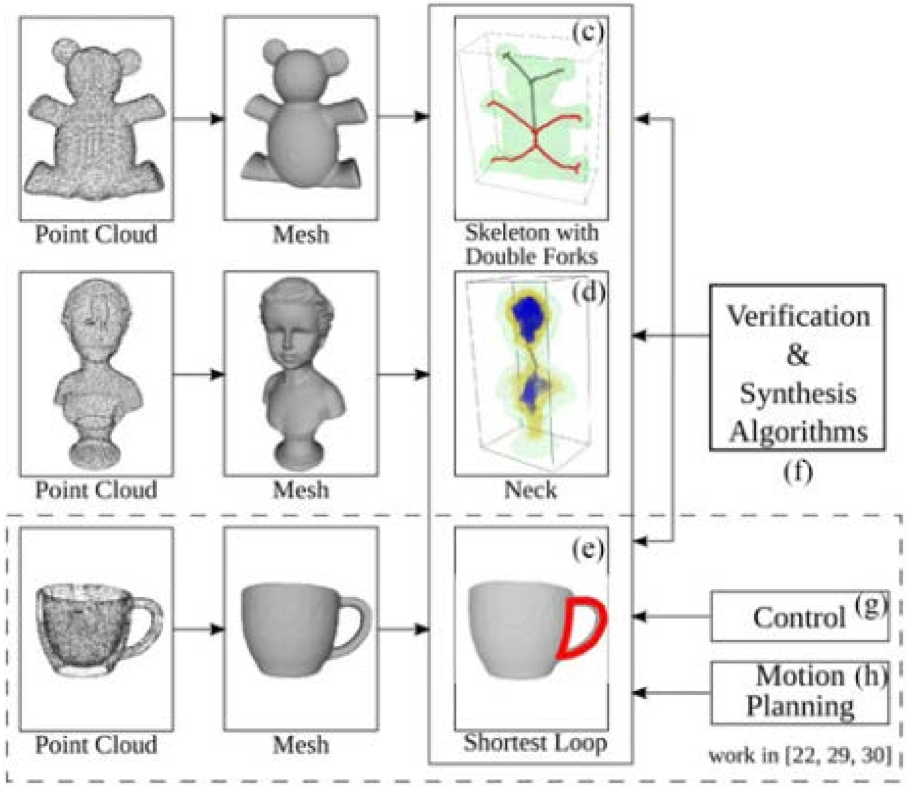
With the help of a Reeb graph and geodesic distance field ,this paper considers geometry information and topology analysis to compute local minimal rings. Isocurves generated by geodesic distance field are used as initial rings. Then the initial rings are stretched for local minimal rings by topological branches based on the Reeb graph.





Kwok, Tsz-Ho, Weiwei Wan, Jia Pan, Charlie C. L. Wang, Jianjun Yuan, Kensuke Harada and Yong Chen. “Rope caging and grasping.” 2016 IEEE International Conference on Robotics and Automation (ICRA) (2016): 1980-1986.

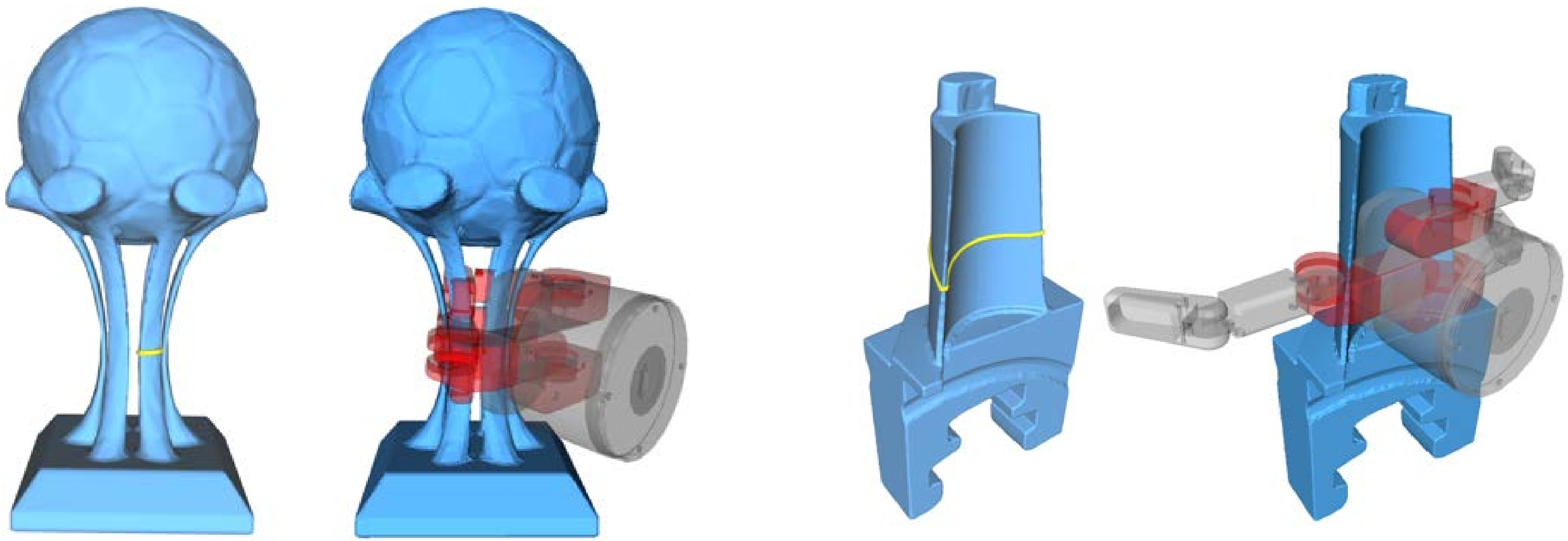
- Manipulation – grasping
  - Geometry or topology based 3D caging grasp



Varava, Anastasiia, Danica Kragic and Florian T. Pokorny. “Caging Grasps of Rigid and Partially Deformable 3-D Objects With Double Fork and Neck Features.” *IEEE Transactions on Robotics* 32 (2016): 1479-1497.

- Manipulation – grasping
  - Challenge

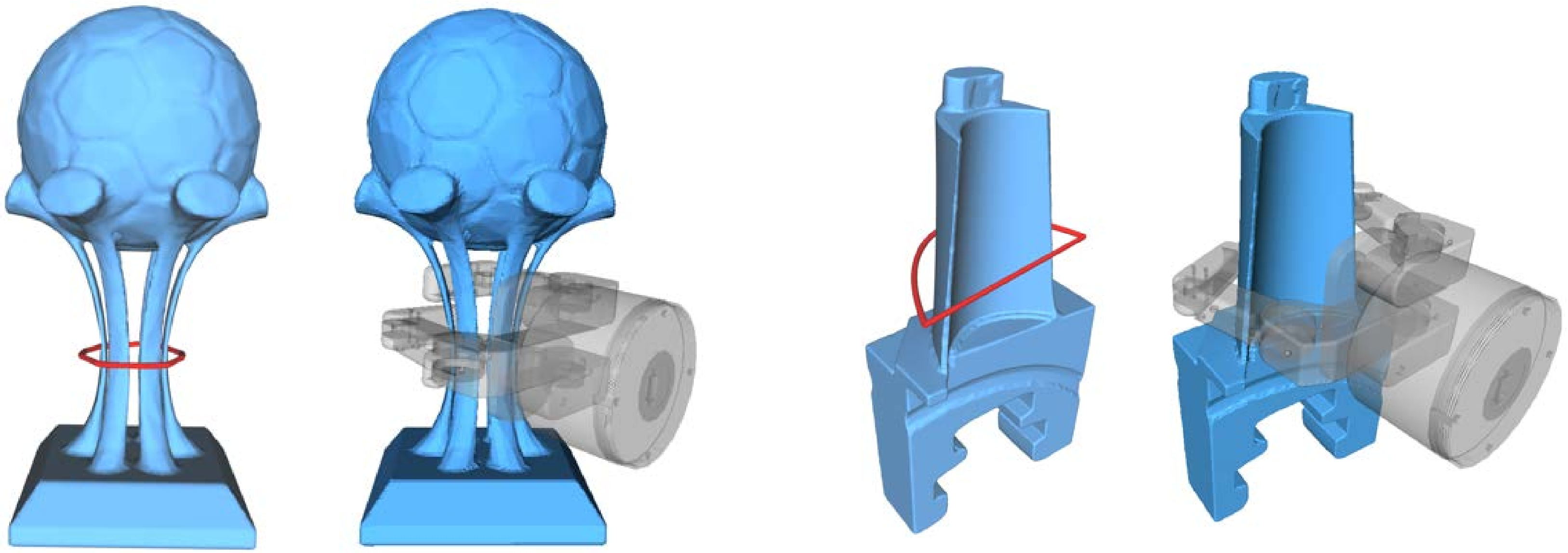
- Caging loops constrained on the target surfaces.
- Model or holes may be too small for the fingers to pass through.
- Non-convexity of the caging loop will lead to Gripper-object collision.



Jian Liu, Shiqing Xin, Zengfu Gao, Kai Xu, Changhe Tu and Baoquan Chen, “Caging Loops in Shape Embedding Space: Theory and Computation”, IEEE International Conference on Robotics and Automation (ICRA 2018), Brisbane, Australia, May 21-25, 2018.

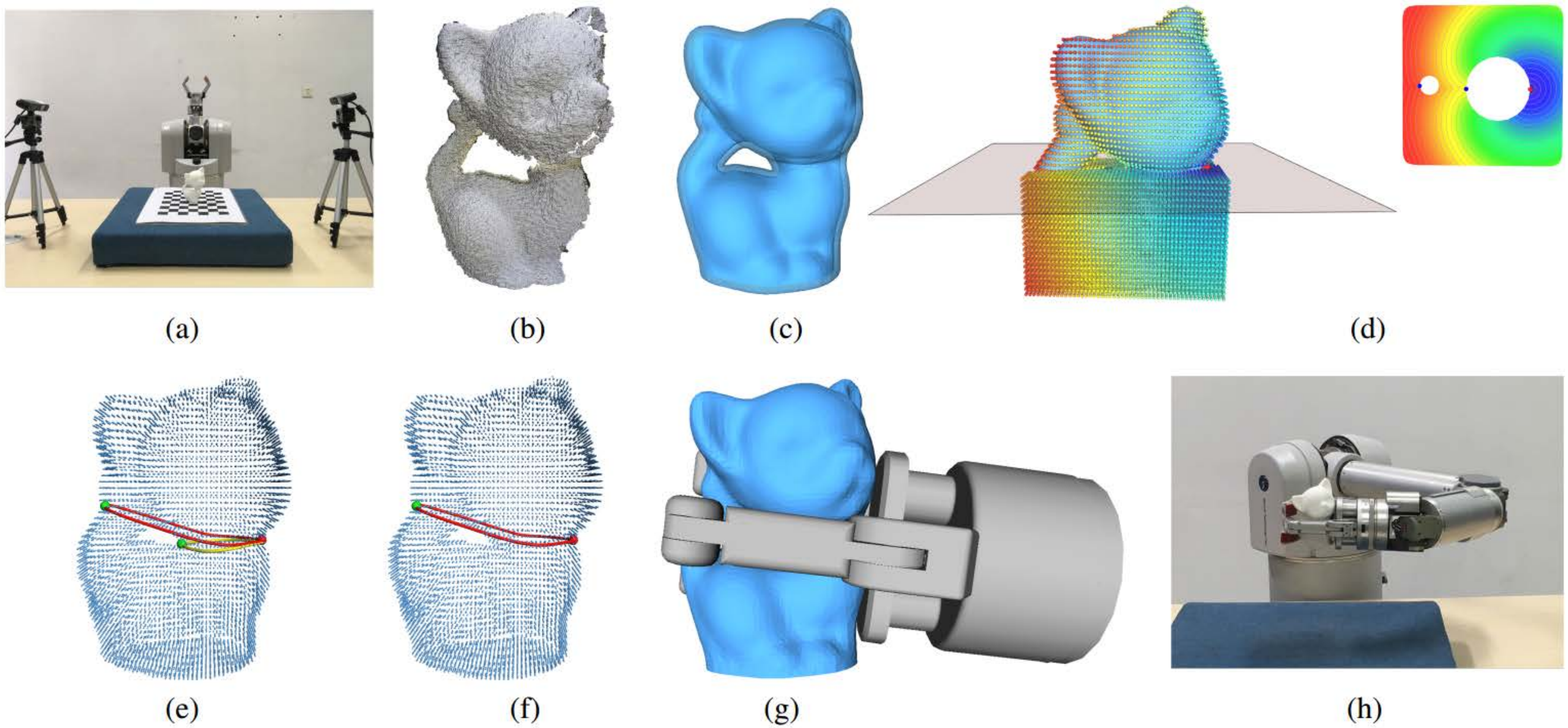
- Manipulation – grasping
  - Challenge

- Caging loops should be defined in shape embedding space.
- Feasible grasp would be enclosing the object with a loop encompassing multiple handles.



Jian Liu, Shiqing Xin, Zengfu Gao, Kai Xu, Changhe Tu and Baoquan Chen, "Caging Loops in Shape Embedding Space: Theory and Computation", IEEE International Conference on Robotics and Automation (ICRA 2018), Brisbane, Australia, May 21-25, 2018.

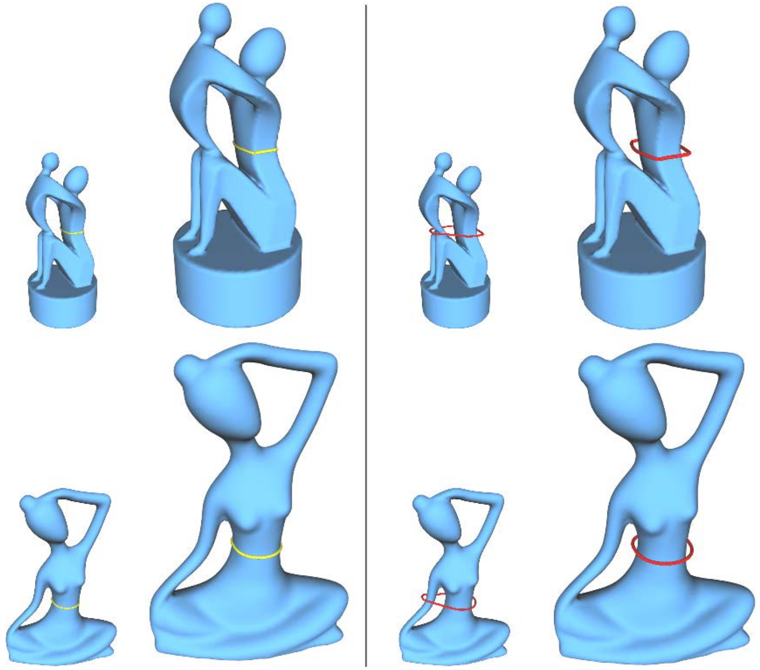
- Manipulation – grasping
  - Overview



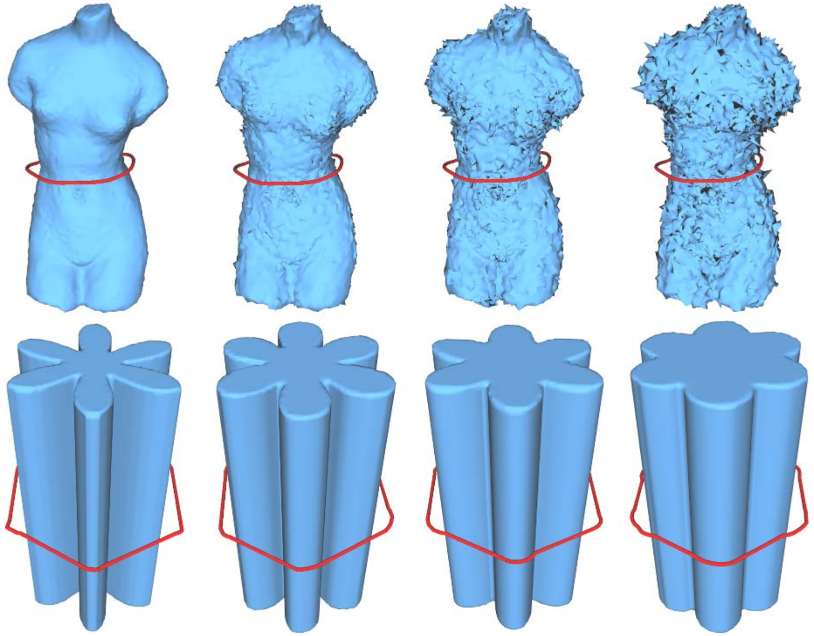
An overview of our caging loop based grasping system. (a) Our system setup, composed of one robotic arm and two depth cameras. (b) The incomplete point cloud scanned by the two depth cameras. (c) The *r*-offset surface of the reconstructed target object that defines the grasping space. (d) A *p*-based distance field and two Morse saddle points (blue). (e) Two caging loop candidates induced by the two Morse saddle points. (f) The yellow loop is filtered since it is far from being locally shortest at the base point (red). (g) A simulation of grasping. (h) Real grasping conducted by our system.

Jian Liu, Shiqing Xin, Zengfu Gao, Kai Xu, Changhe Tu and Baoquan Chen, "Caging Loops in Shape Embedding Space: Theory and Computation", IEEE International Conference on Robotics and Automation (ICRA 2018), Brisbane, Australia, May 21-25, 2018.

- Manipulation – grasping
  - Results



Test on High-genus Models in Various Sizes



Test on Models with Various Levels of Noise and Geometric Feature

Test on Real Objects

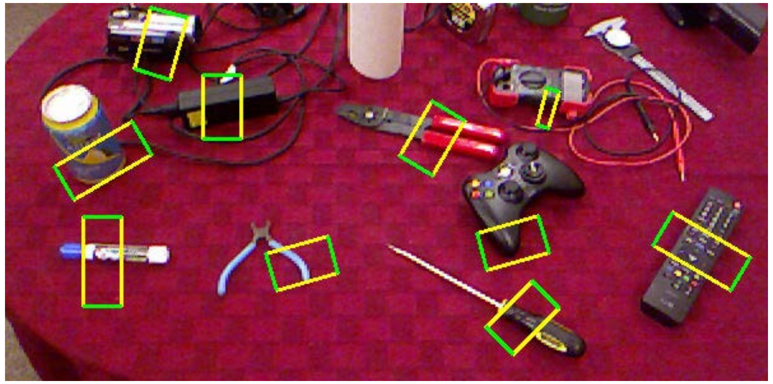
Jian Liu, Shiqing Xin, Zengfu Gao, Kai Xu, Changhe Tu and Baoquan Chen, "Caging Loops in Shape Embedding Space: Theory and Computation", IEEE International Conference on Robotics and Automation (ICRA 2018), Brisbane, Australia, May 21-25, 2018.

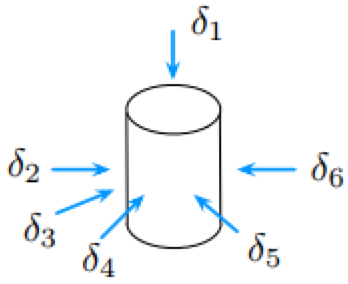
- Manipulation – grasping
  - Summary
    - Special tasks, target object
    - Dynamic grasp (human, shape-aware)

ICRA2018: Robotic Grasping
Data-driven Approach

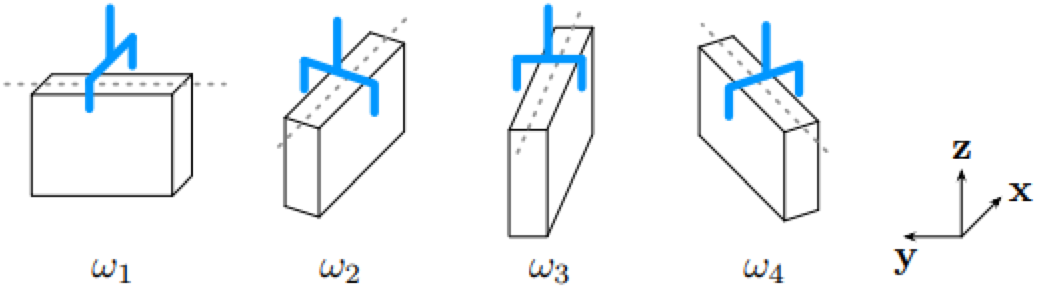
- Manipulation – perception, learning

  - ■ Contribution
  - Deep learning approach to robotic grasping of unknown objects
  - Suitable grasp pose from multiple grasping/approach direction and wrist orientation.
  - ■ Motivation
  - Limitation of Data-driven approach:
    1) They neither account for stability nor feasibility of the grasp
    2) Grasping/approach direction and wrist orientation
    3) Design types of end-effectors





(a) Grasping directions



(b) Wrist orientations

Learning Object Grasping for Soft Robot Hands - MIT

Learning 6-DOF Grasping Interaction via Deep Geometry-aware 3D Representations – Google Brain

Dex-Net 3.0: Computing Robust Vacuum Suction Grasp Targets in Point Clouds using a New Analytic Model and Deep Learning

Grasping of Unknown Objects using Deep Convolutional Neural Networks based on Depth Images - KIT

- Manipulation –perception, learning
  - *Learning & perception*

Grasping of Unknown Objects using DCNNs based on Depth Images

Philipp Schmidt, Nikolaus Vahrenkamp,
Mirko Wächter and Tamim Asfour
Institute for Anthropomatics and Robotics
Karlsruhe Institute of Technology (KIT), Germany

- Deep learning approach for grasping unknown objects based only on depth image as input
- Output: Full end-effector poses with arbitrary approach directions
- Training data generated using analytical grasp planner – scalable!
- Evaluation using the KIT, YCB object model datasets and a big data grasping database in simulation and in robot experiments

- Manipulation – perception, learning

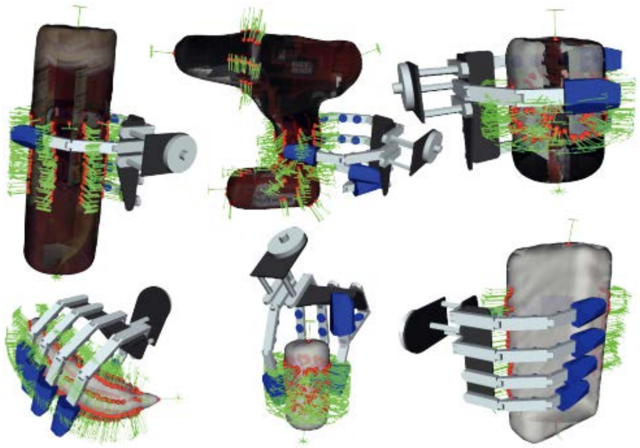
■ Problem Identify

- Estimating suitable grasp configuration of unknown objects with partial view using Deep learning approach

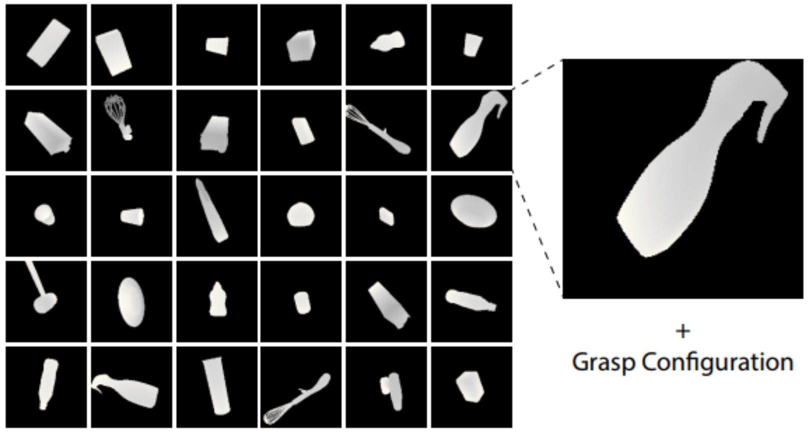
■ Strategy

1. Training : Closure grasps by analytic grasp planners + simulation

Known objects



Grasp planner



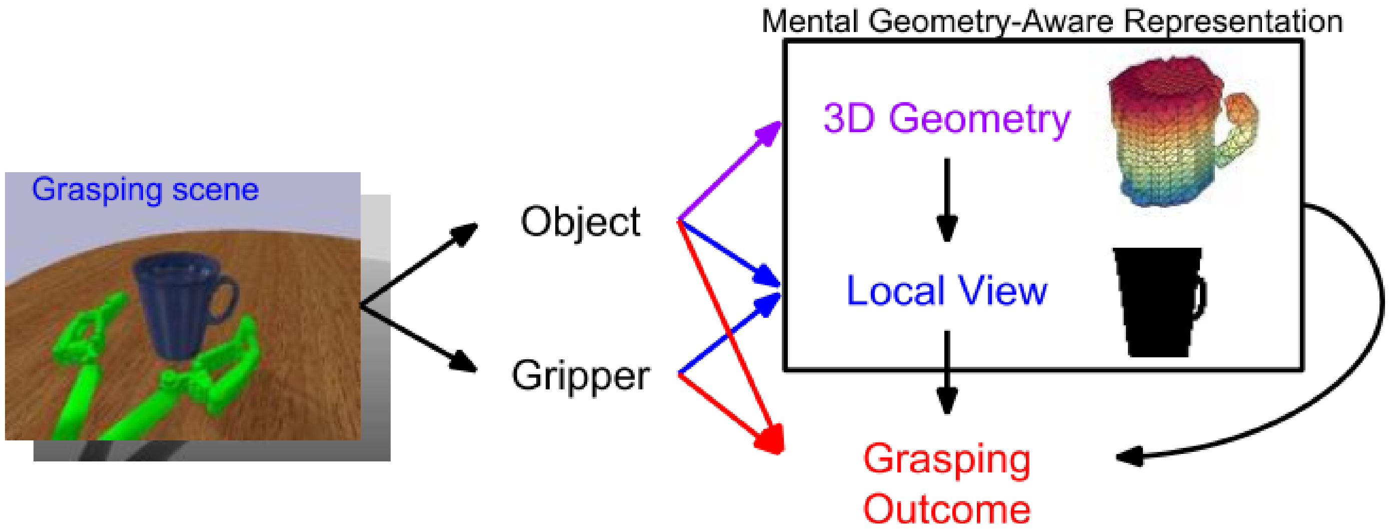
Multi-view + grasp pose

Grasping of Unknown Objects using Deep Convolutional Neural Networks based on Depth Images - KIT

- Manipulation –perception, learning
    - *Learning & perception*

Learning 6-DOF Grasping Interaction via Deep Geometry-aware 3D Representations

Xinchen Yan[*], Jasmine Hsu[1], Mohi Khansari[2], Yunfei Bai[2], Arkanath Pathak[1], Abhinav Gupta[1], James Davidson[1], Honglak Lee[1]
[1]Google, [2]X Inc, *University of Michigan

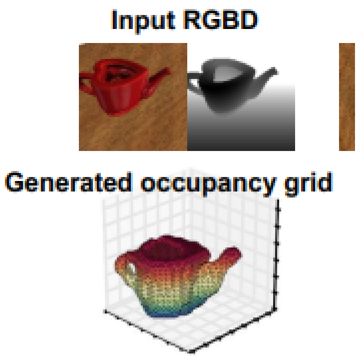


Learning grasping interactions from demonstrations with deep geometry-aware representations. First, we learn to build mental representation by reconstructing the 3D scene with 2.5D training data. Second, we learn to predict grasping outcome with its internal representation.

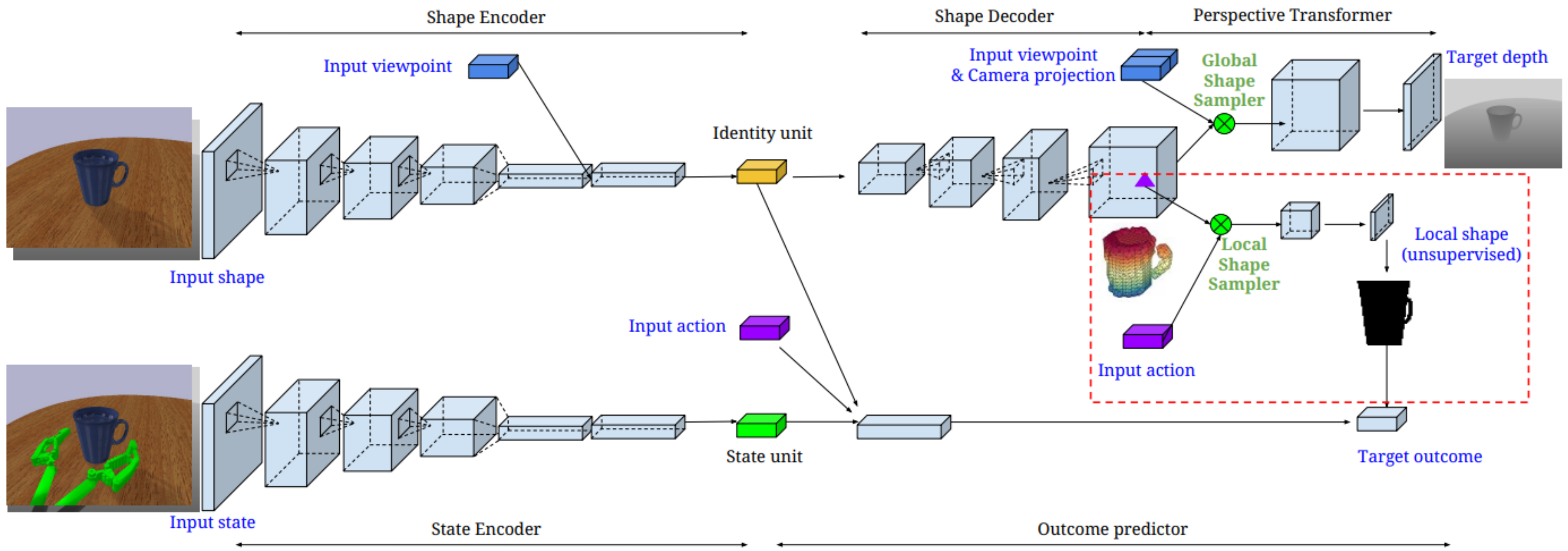
- Manipulation – perception, learning

  - Problem Identify
  - Estimating suitable grasp configuration of unknown objects with partial view using Deep learning approach

  - Strategy
  1. Training : Closure grasps by grasp physical engine + simulation



3D shape generation from single-view RGBD input



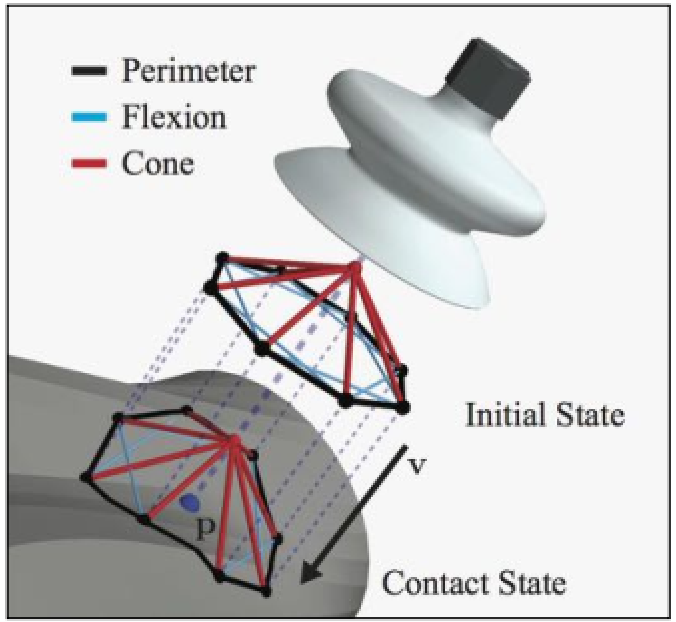
Learning 6-DOF Grasping Interaction via Deep Geometry-aware 3D Representations – Google Brain

- Manipulation –perception, learning
  - *Learning & perception*

Dex-Net 3.0: Computing Robust Vacuum Suction Grasp Targets in Point Clouds using a New Analytic Model and Deep Learning

Jeffrey Mahler[1], Matthew Matl[1], Xinyu Liu[1], Albert Li[1], David Gealy[1], and Ken Goldberg[1,2]
[1]Dept. of EECS, UC Berkeley [2]Dept. of IEOR, UC Berkeley

- We propose a compliant suction contact model for (1) the formation of a vacuum seal and (2) the ability to resist external wrenches
- We use the model to generate Dex-Net 3.0, a dataset of 2.8 million point clouds, suction grasps, and grasp robustness labels
- We train a deep Grasp Quality Convolutional Neural Network (GQ-CNN) on Dex-Net 3.0 to classify robust suction targets in point clouds
- Grasps planned with the GQ-CNN achieve up to 98% success on novel objects in experiments with an ABB YuMi



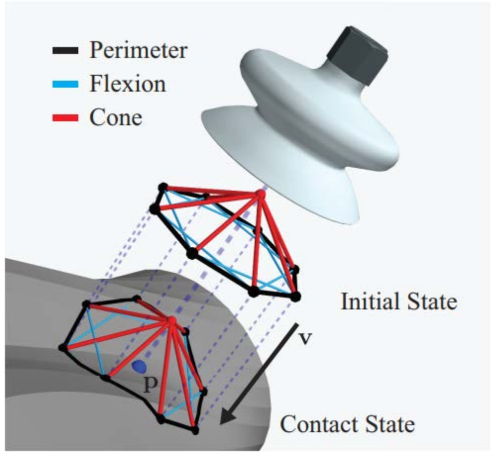
Our Seal Formation Model

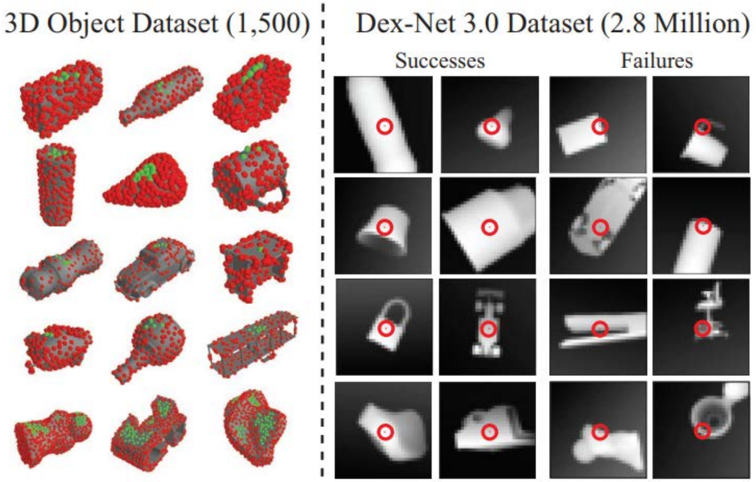
- Manipulation – perception, learning

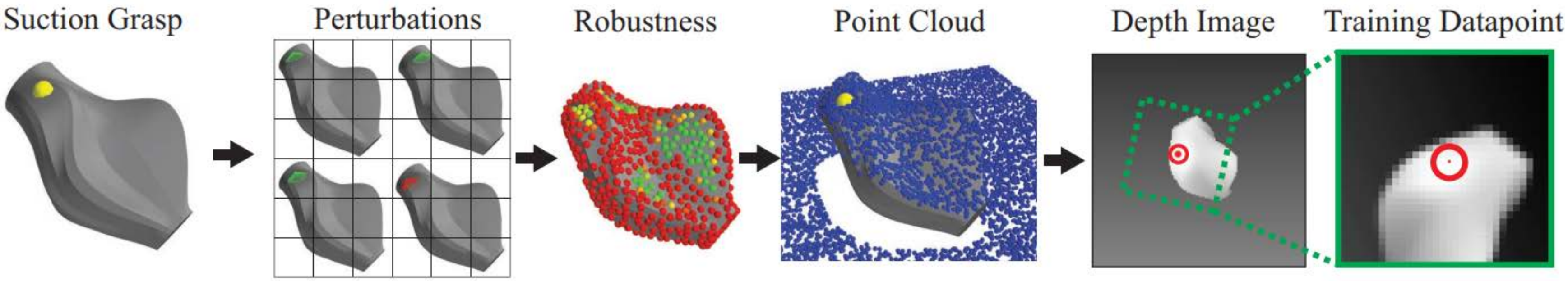
  - Problem Identify
  - Estimating suitable grasp configuration of unknown objects with partial view using Deep learning approach

  - Strategy

1. Training : robust suction grasps by physical analysis (seal formation & resist gravity) + simulation







Dex-Net 3.0: Computing Robust Vacuum Suction Grasp Targets in Point Clouds using a New Analytic Model and Deep Learning

- Manipulation –perception, learning
    - *Learning & perception*

Learning Object Grasping for Soft Robot Hands

Changhyun Choi, Wilko Schwarting, Joseph DelPreto, and Daniela Rus

Computer Science & Artificial Intelligence Lab
Massachusetts Institute of Technology, USA

- A **3D deep convolutional neural network (3D CNN)** approach for grasping **unknown objects** with **soft hands**.
- Our soft hands guided by the 3D CNN algorithm show **87% successful grasping** on previously unseen objects.
- Comparative experiments show the **robustness** of our approach with respect to **noise** and **occlusions**.

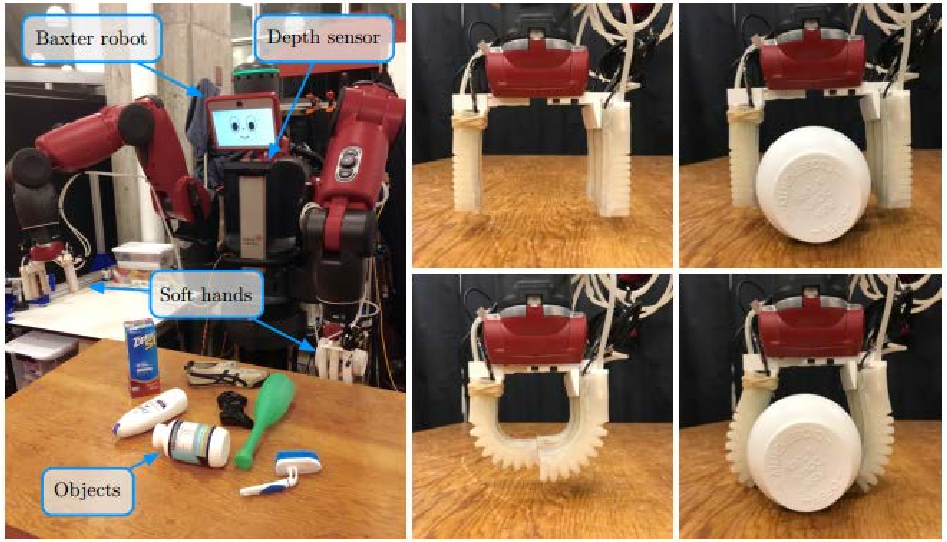
Successful example grasps of our 3DCNN approach

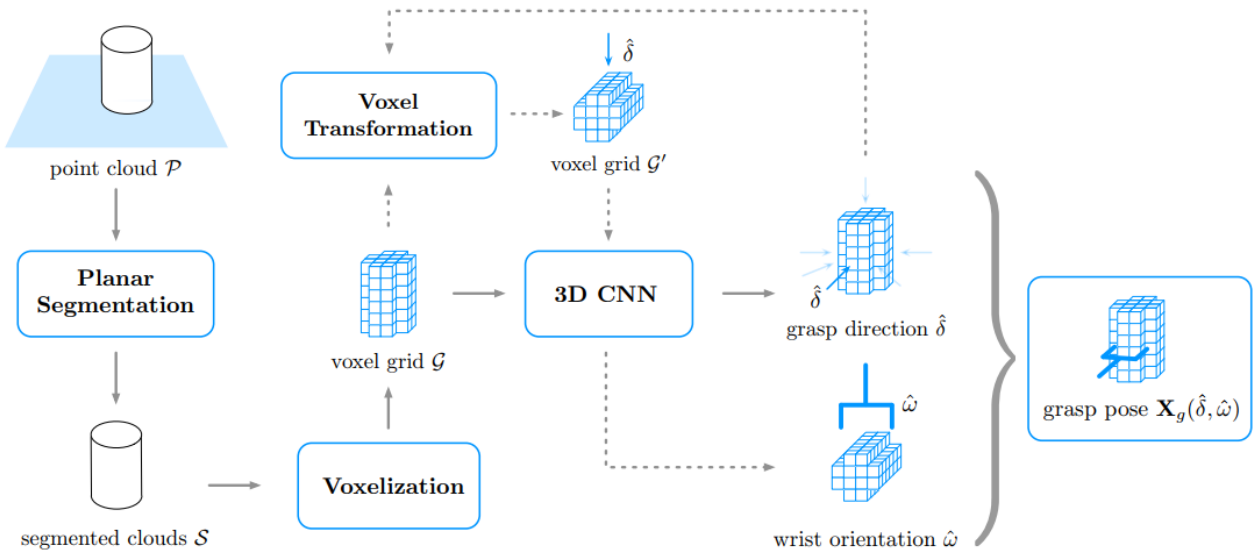
- Manipulation – perception, learning

  - Problem Identify
  - Estimating suitable grasp configuration of unknown objects with partial view using Deep Learning approach

  - Strategy

2. Training : trial-and-error scheme (point cloud + physical grasp pose)





Learning Object Grasping for Soft Robot Hands - MIT

- Manipulation – grasping
  - Summary
    - Robust/feasible grasp configuration
    - New types of robot hand

Thank you!