Karlsruhe Institute of Technology

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Humanoid Grasping and Manipulation in the Real World

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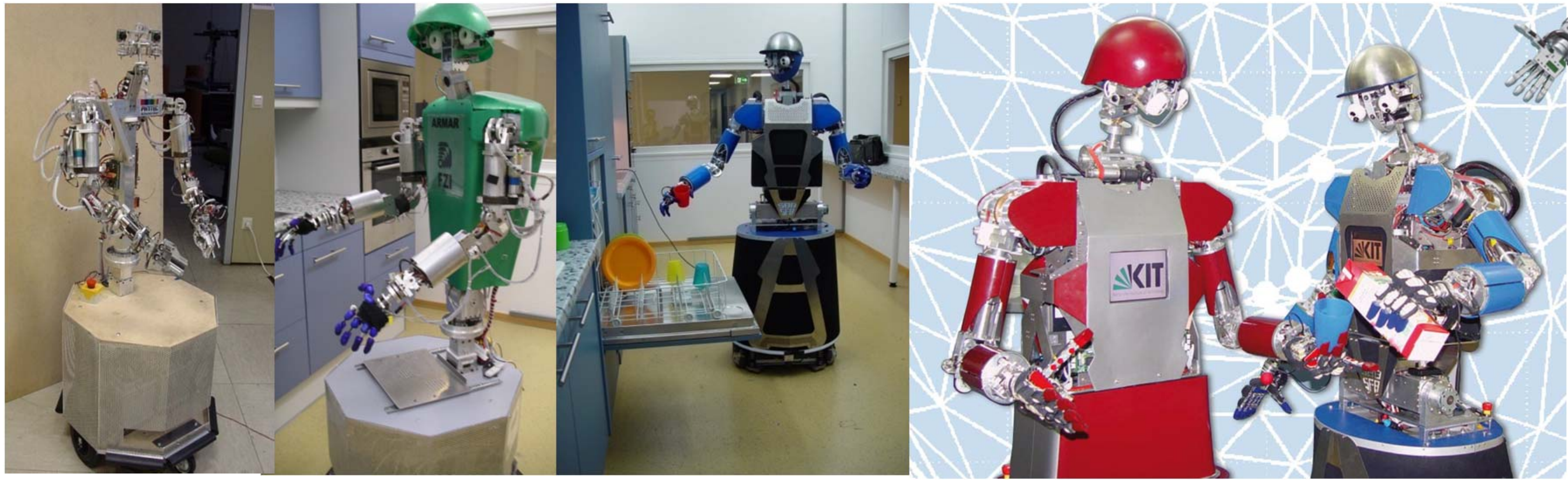

http://his.anthropomatik.kit.edu http://his.anthropomatik.kit.edu/english/65.php

Three key questions

- Grasping and manipulation in human-centered and open-ended environments
- Learning through observation of humans and imitation of human actions
- Interaction and natural communication

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Interactive tasks in the Robo-KITchen

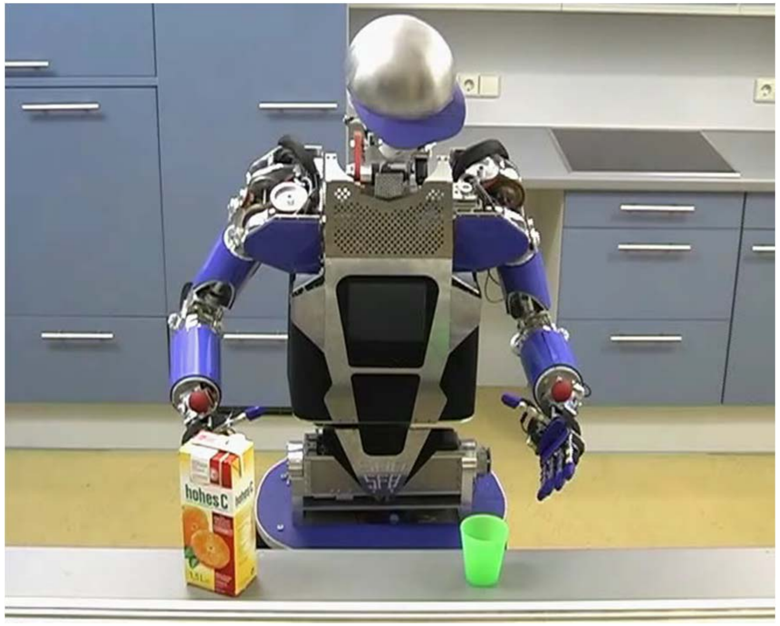
- Object recognition and localization
- Vision-based grasping
- Hybrid position/force control
- Vision-based self-localisation
- Collision-free navigation
- Combining force and vision for opening and closing door tasks
- Learning new objects, persons and words
- Audio-visual user tracking and localization
- Multimodal human-robot dialogs
- Speech recognition for continuous speech

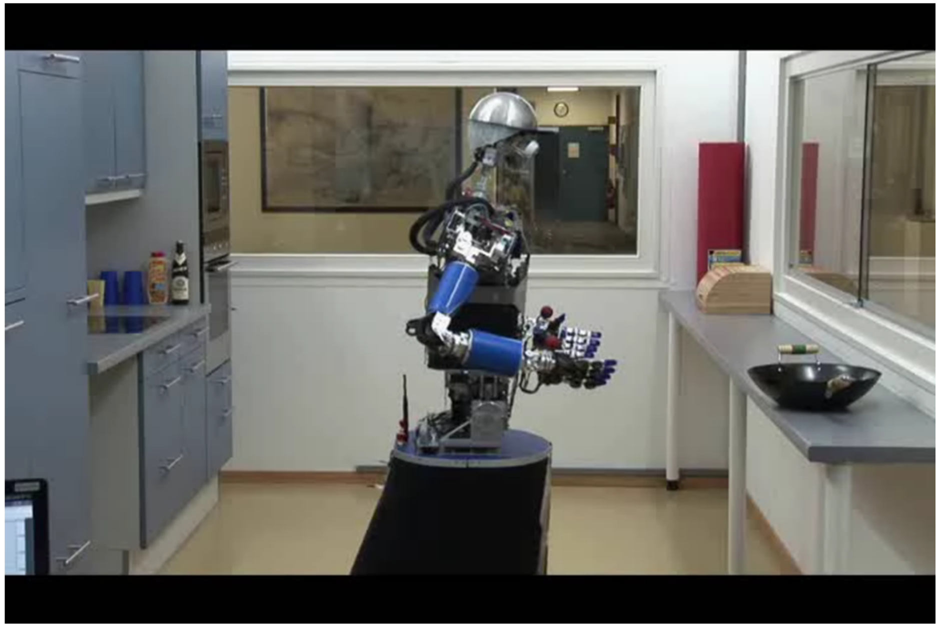
[Humanoids 2006, IROS 2006, IROS 2007, RAS 2008, Humanoids 2008, Humanoids 2009]

Bimanual grasping and manipulation

- Stereovision for object recognition and localization
- Visual Servoing for dual-hand grasping
- Zero-force control for teaching of grasp poses

Humanoids 2009





Loosely coupled dual-arm tasks

Tightly coupled dual-arm tasks

Humanoid grasping and manipulation in the real world

- **In this workshop:**

  Given world knowledge for grasp and motion planning

- **Mobile manipulation workshop on Friday:**

  Autonomous knowledge acquisition

Outline of the talk

- Motion planning
  - IK-RRT: Integrated IK-solving and motion planning
  - Grasp-RRT: Integrated grasp and motion planning
  - Execution using visual Servoing on humanoid robot

- Grasp planning
  - Medial axis planner
  - Grid of medial planner

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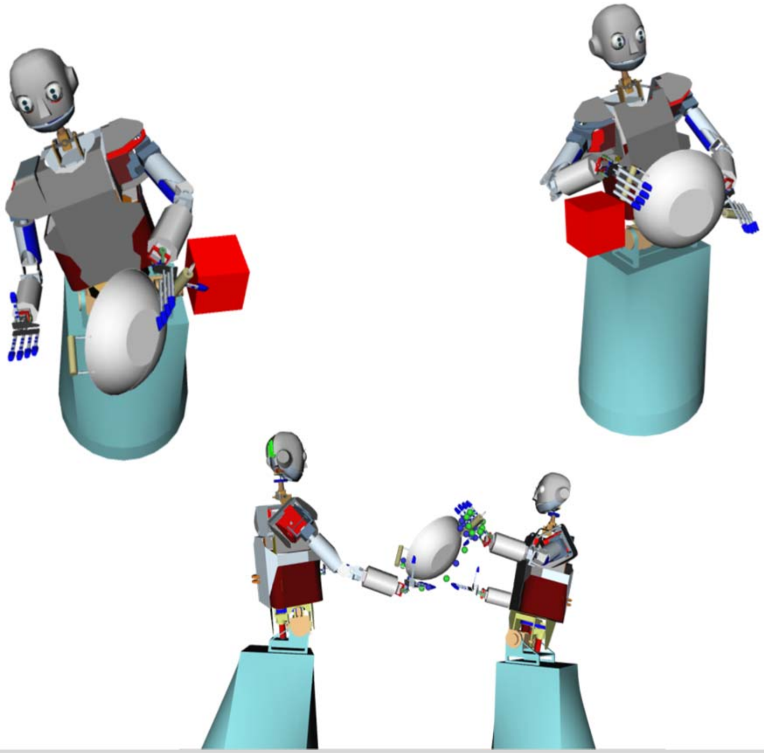
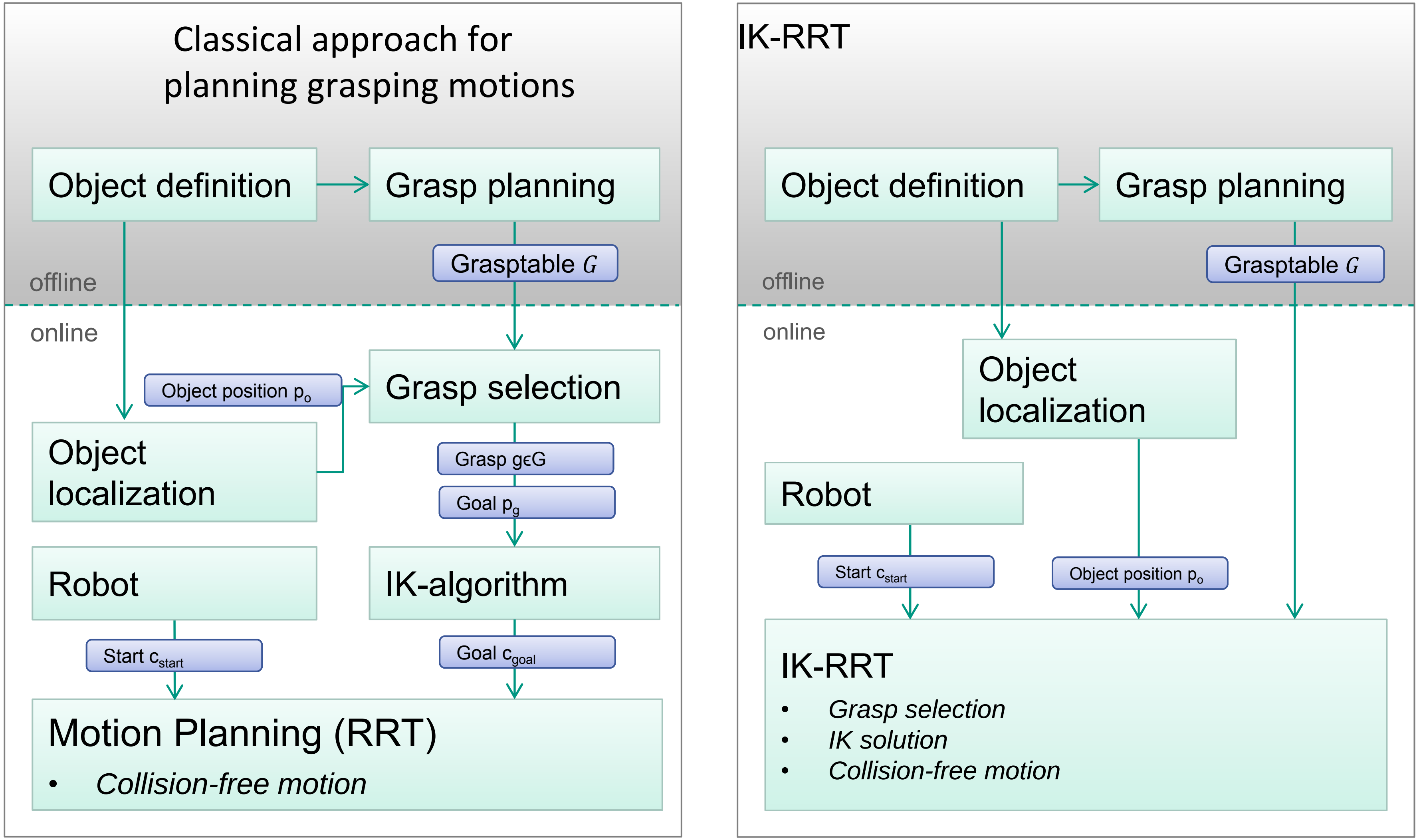
IK-RRT: Integrated IK-Solving and Motion Planning

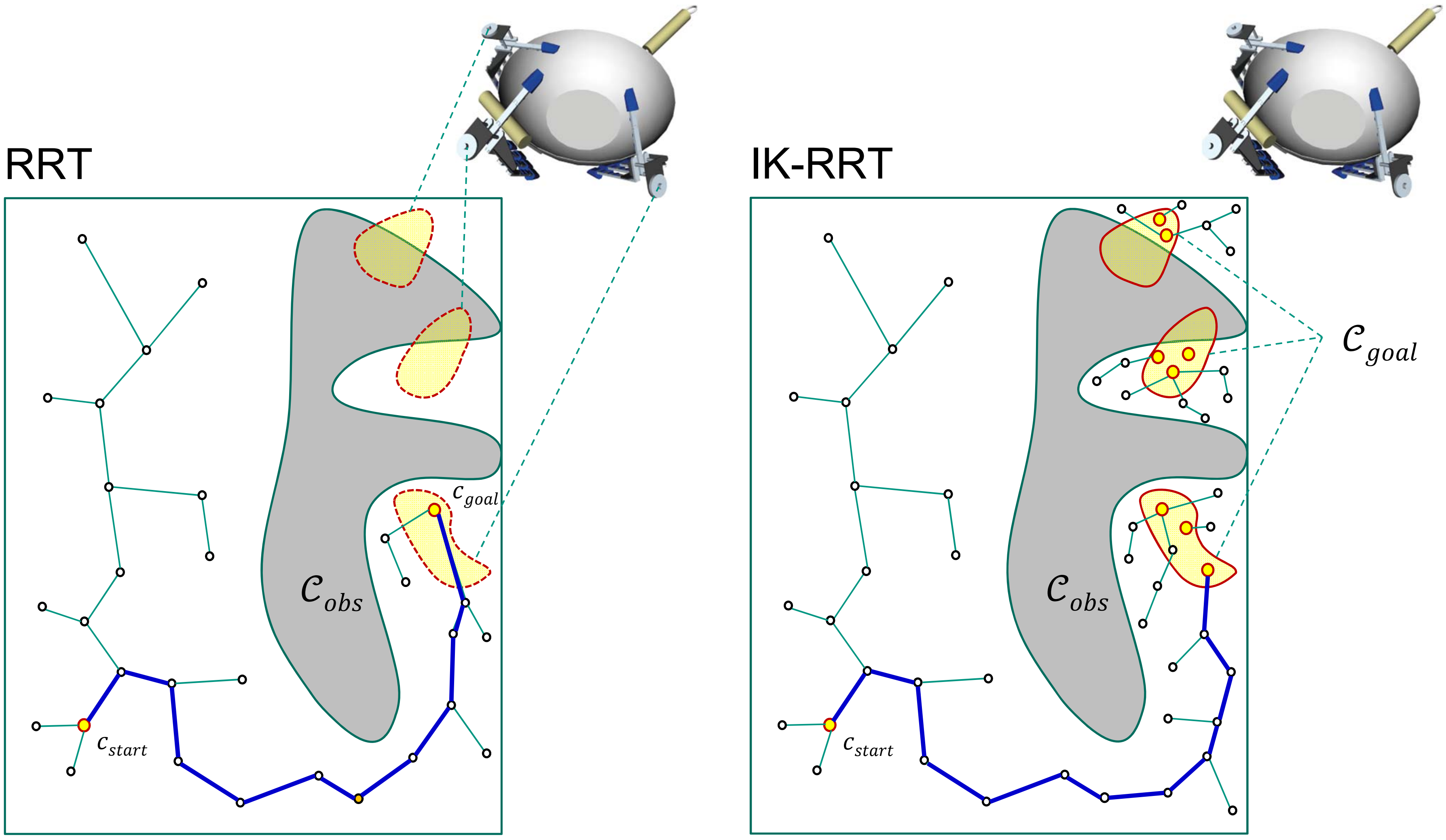
- RRT-based algorithm
- Integrates the three main tasks needed to grasp an object:
  - Select a feasible grasp
  - Solve the IK-problem
  - Create a collision-free motion
- Can be used for high-dimensional planning problems
  - Single arm or bimanual tasks: grasping, re-grasping, hand over
  - Efficient IK-solvers needed



IK-RRT: Overview



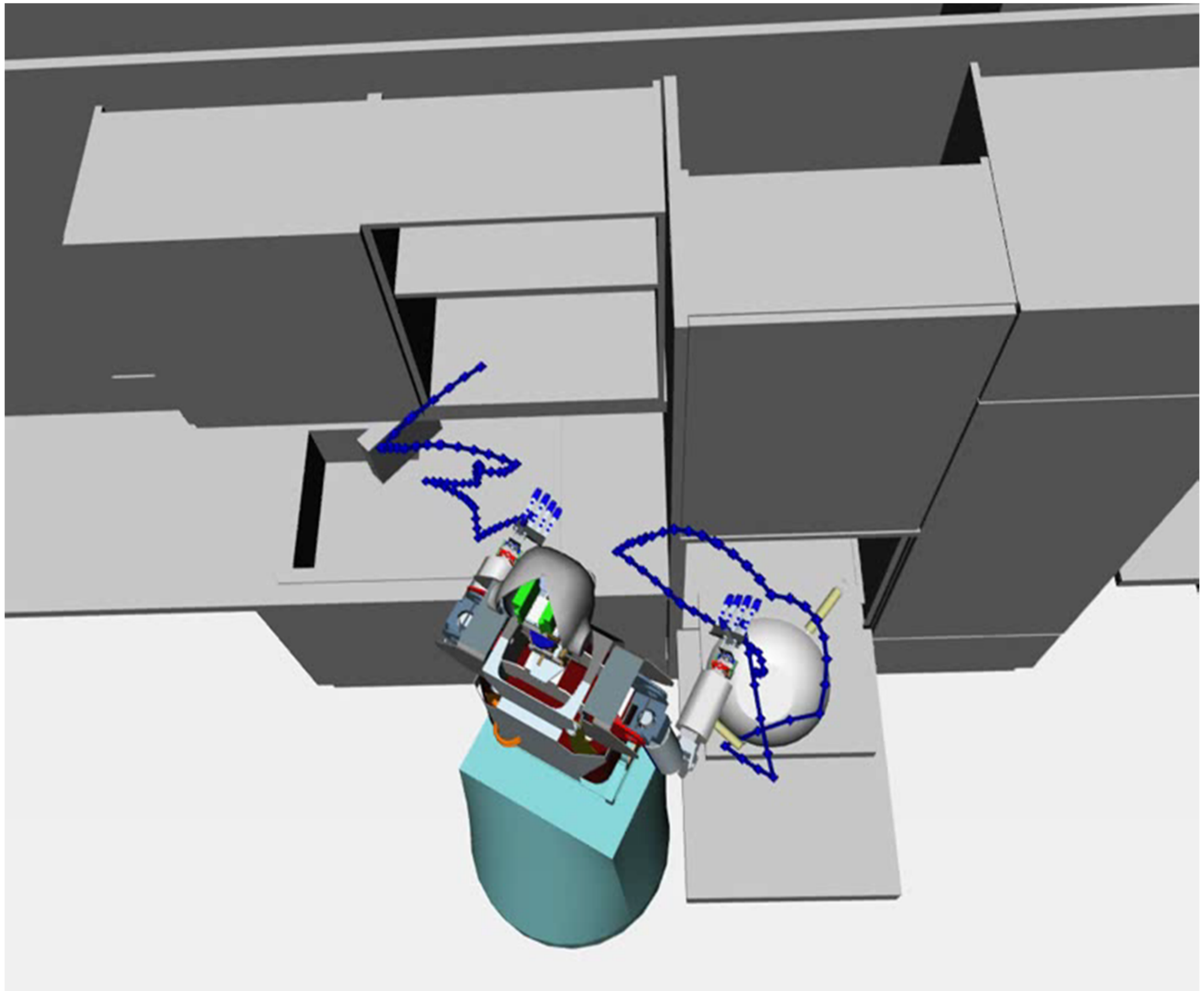
IK-RRT: Example in 2D



IK-RRT: Example – Re-grasping

- 17 Degrees of Freedom (DoF) of AMRAR-III
- Input:
  - Startconfiguration of the robot
  - Start- and goal position of the object
- Average planning time: ~7 seconds

Motion	Planning time
Grasping	365 ms
Re-grasp motion	5463 ms
Placing	1286 ms
Total	7113 ms

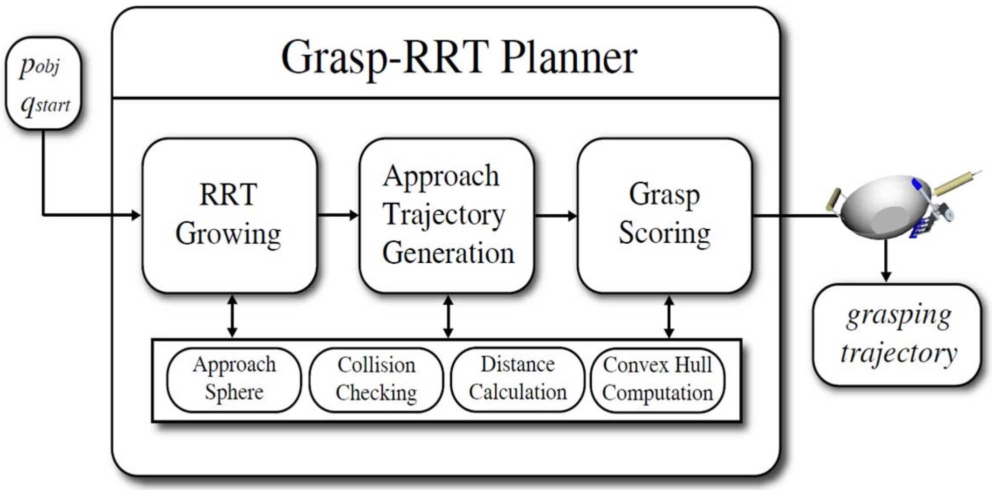


Grasp-RRT: Integrated Grasp and Motion Planning

- Uni-directional RRT-based algorithm
- Initialization:
  - object pose: p_{obj}
  - start configuration: q_{start}
- Algorithm:
  - Build up RRT from q_{start}
  - Find a feasible grasp:
    1. Select a RRT node
    2. Store workspace position p_i
    3. Move hand toward object
    4. Evaluate grasp quality

Algorithm 1: $GraspRRT(q_{start}, p_{obj})$

```
RRT.AddConfiguration(q_start);
while (!TimeOut()) do
    ExtendRandomly(RRT);
    if (rand() < p_SearchGraspPose) then
        n_grasp ← ApproachTrajectory(RRT, p_obj);
        if (ScoreGrasp(n_grasp) > score_min) then
            return BuildSolution(Grasp);
    end
end
```



Grasp-RRT: Integrated Grasp and Motion Planning

- Uni-directional RRT-based algorithm

- Initialization:
  - object pose: p_{obj}
  - start configuration: q_{start}

- Algorithm:
  - Build up RRT from q_{start}
  - Find a feasible grasp:
    1. Select a RRT node
    2. Store workspace position p_i for every q_i
    3. Move hand toward object
    4. Evaluate grasp quality

Algorithm 1: $GraspRRT(q_{start}, p_{obj})$

$RRT.AddConfiguration(q_{start})$;
while (*!TimeOut()*) **do**
    ExtendRandomly(RRT);
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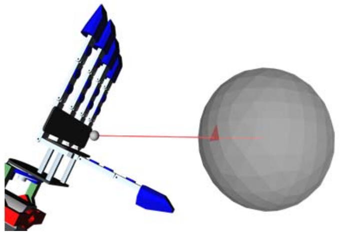
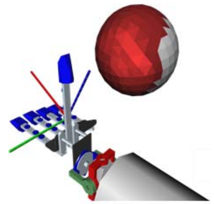
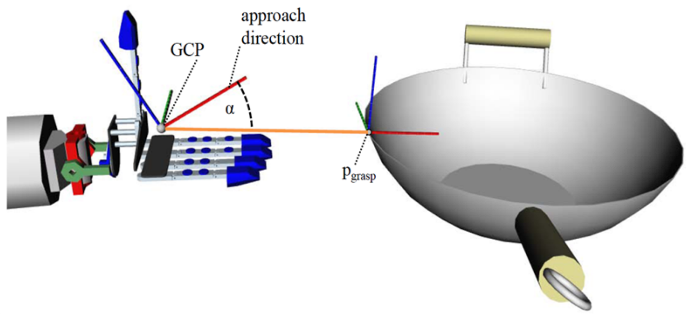
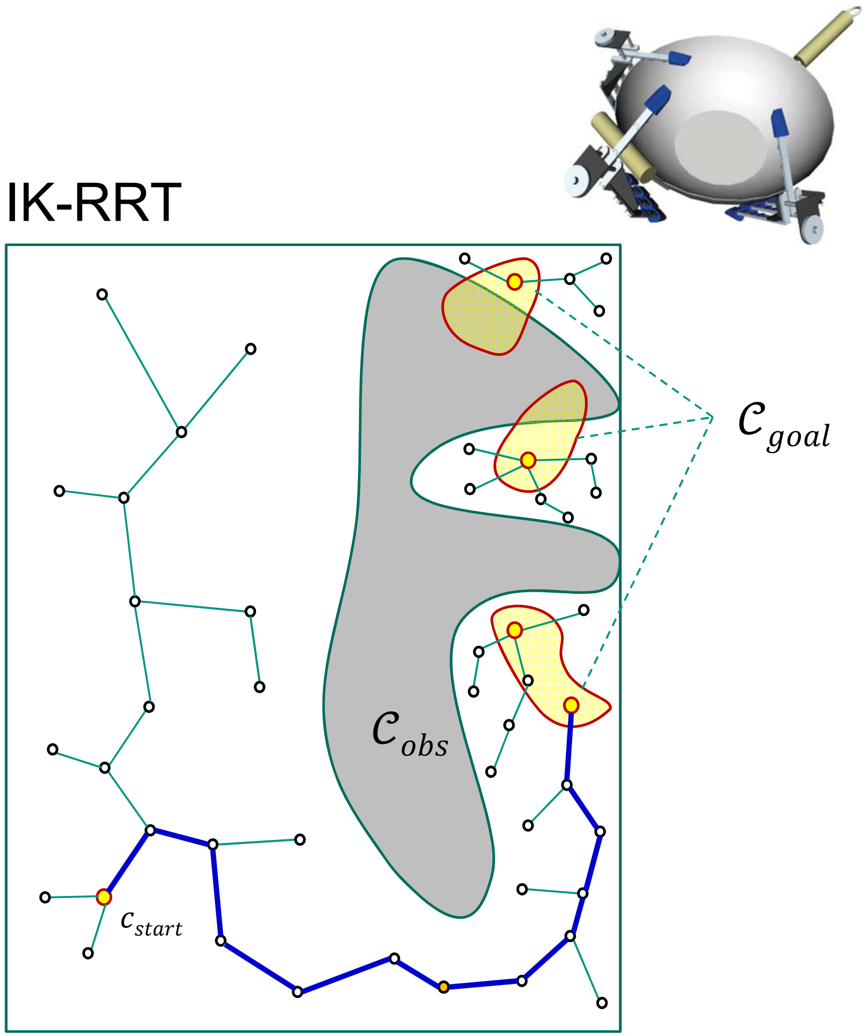
    end
end

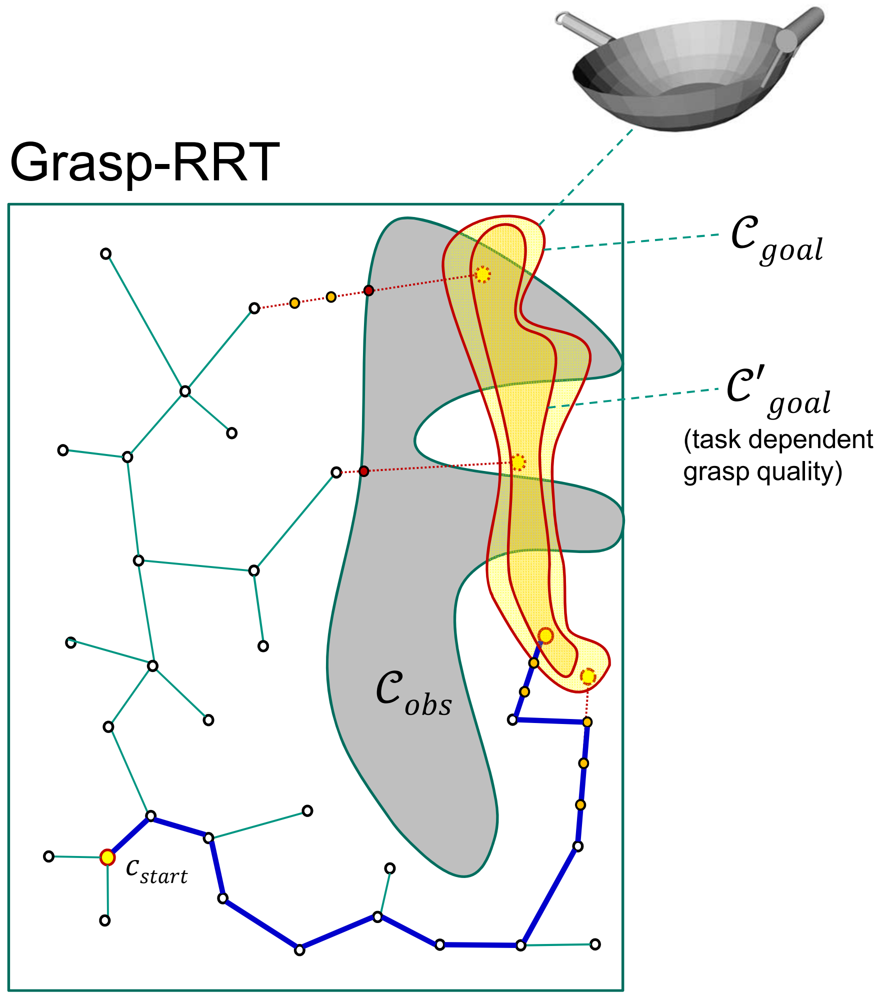




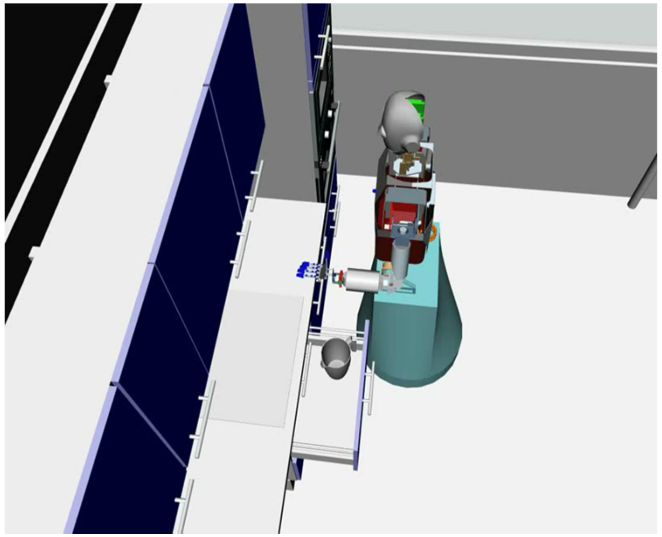


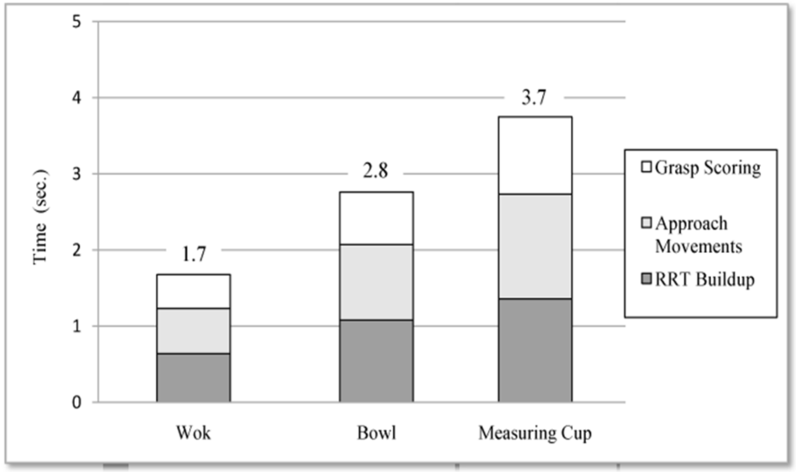
Grasp-RRT: Example in 2D

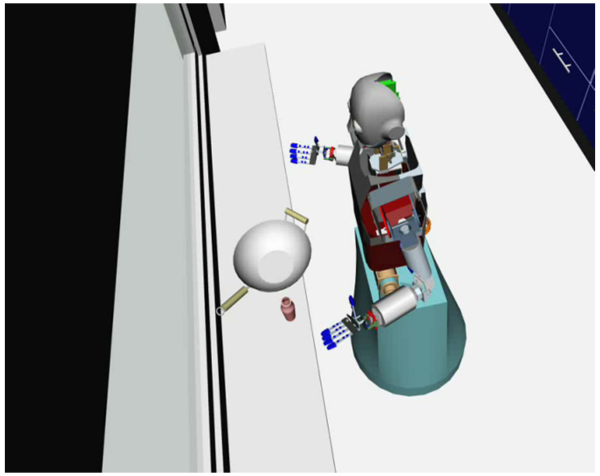


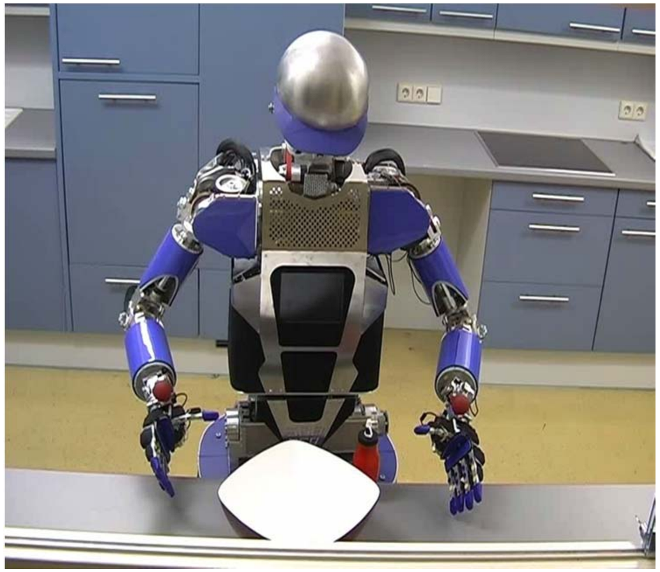


Grasp-RRT: Evaluation

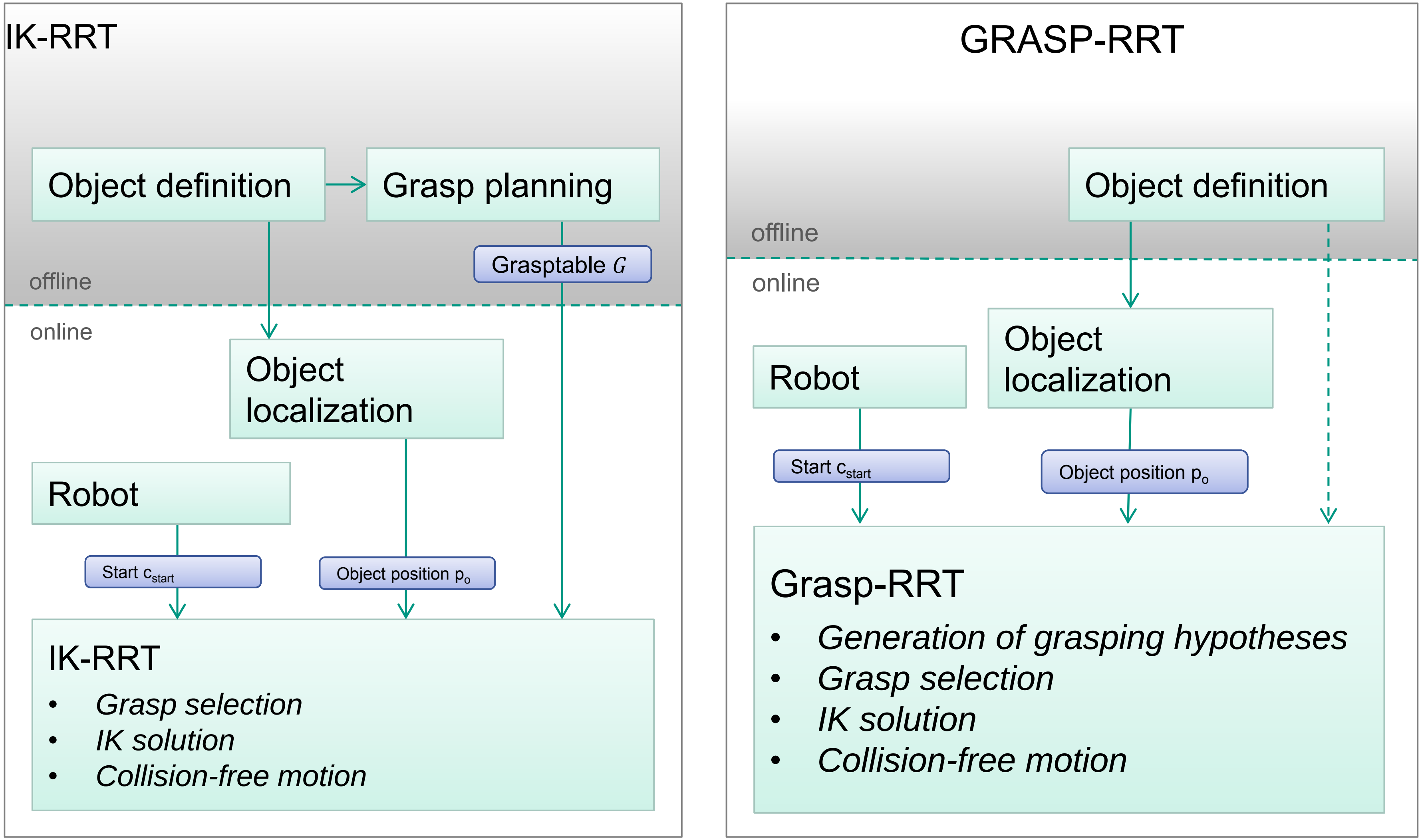






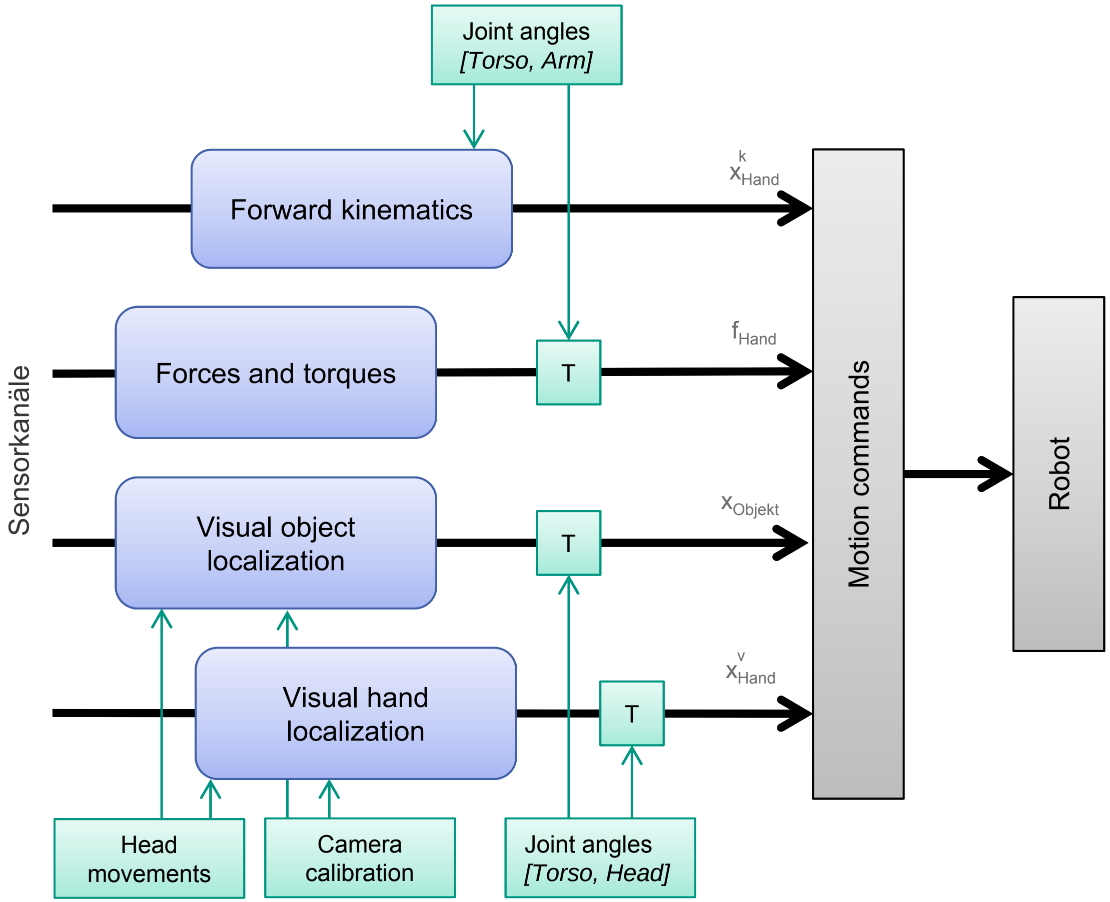


Comparison: IK-RRT <-> Grasp-RRT

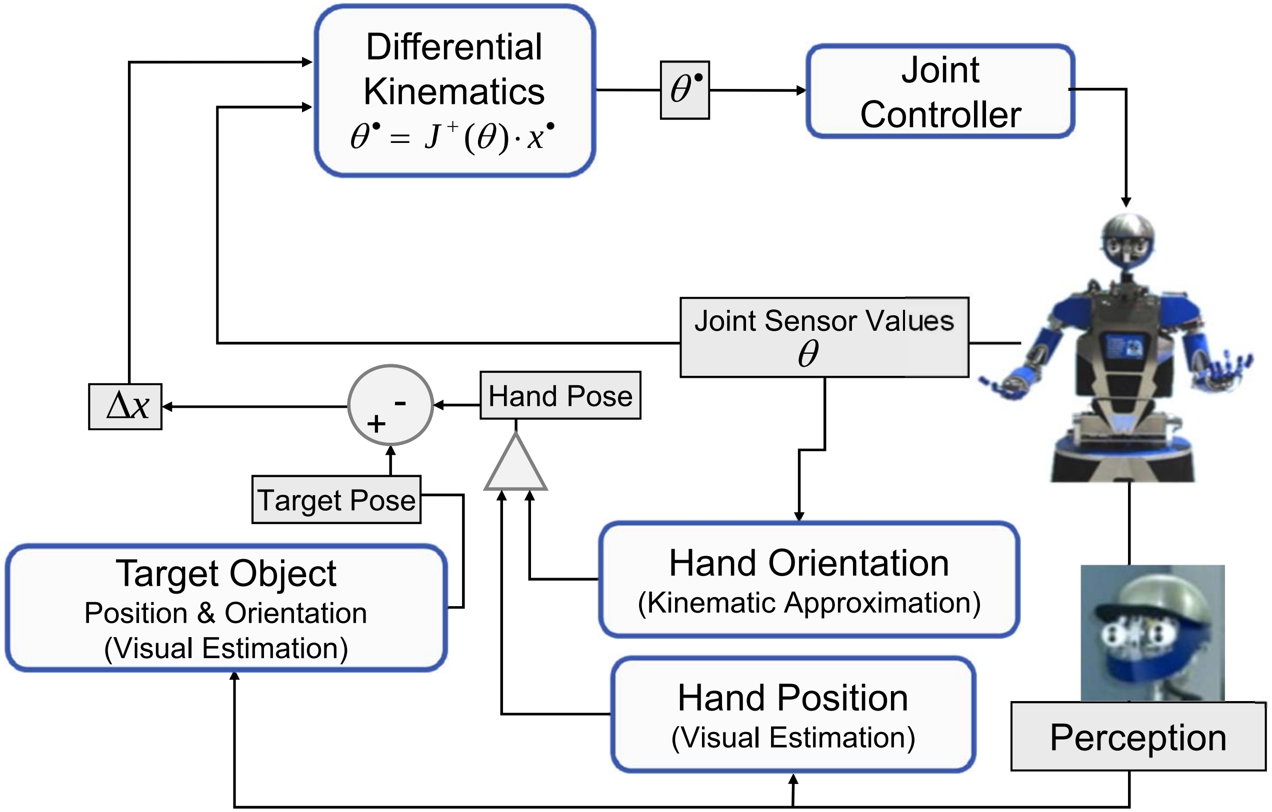


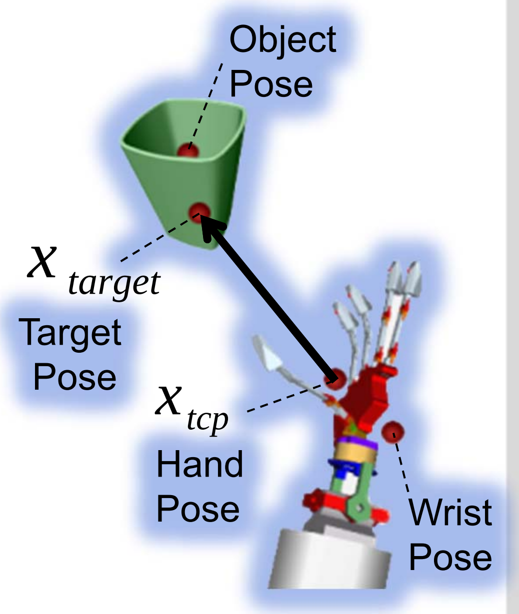
Sensor-based execution of grasping motions

- Vision-based execution
  - Model knowledge
  - Without external sensors
- Sensor channles
  - Force / Contact
  - Vision
  - Exploiting redundant sensor information



Execution: Position-based Visual Servoing





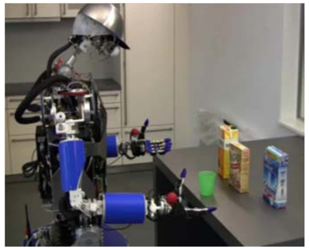
$$\theta^{\bullet} = J^{+}(\theta) \cdot x^{\bullet}$$

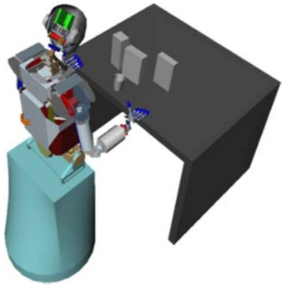
$$\partial^{t} = x^{t}_{vision} - x^{t}_{kinematic}$$

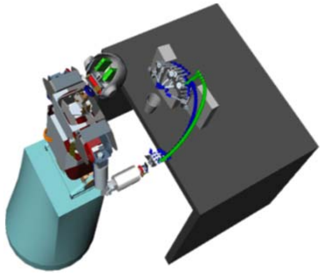
$$x^{t+1}_{tcp} = x^{t+1}_{kinematic} + \partial^{t}_{tcp}$$

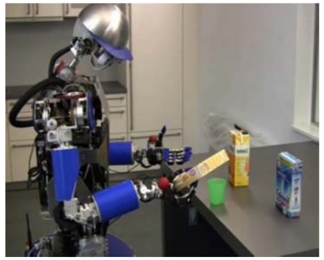
Complete execution of a grasping task

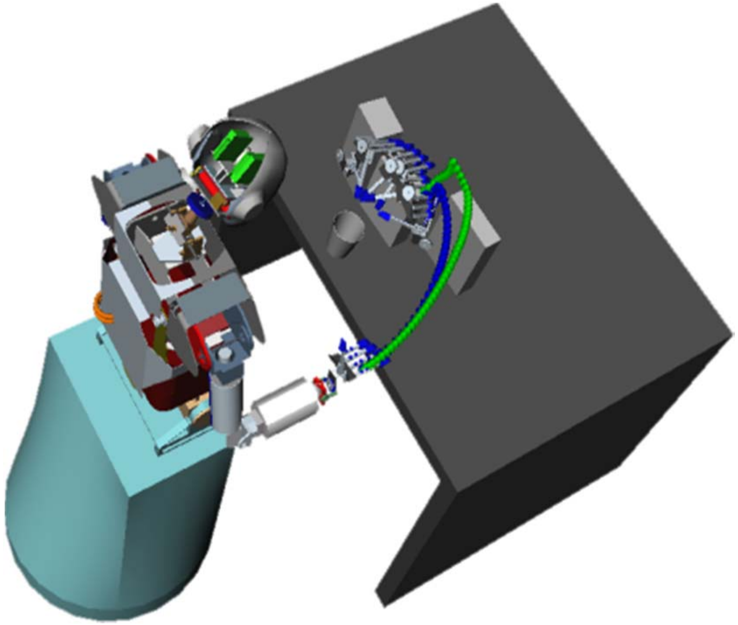
Grasping Task → Scene Representation → **Motion Planning** → **Sensor-based Execution**

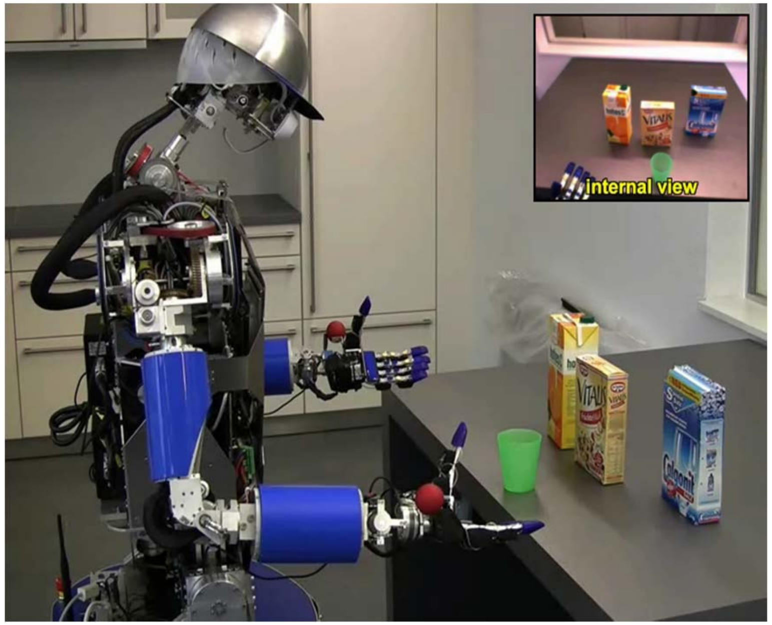












A Parameter-free Algorithm for Exact Motion Planning

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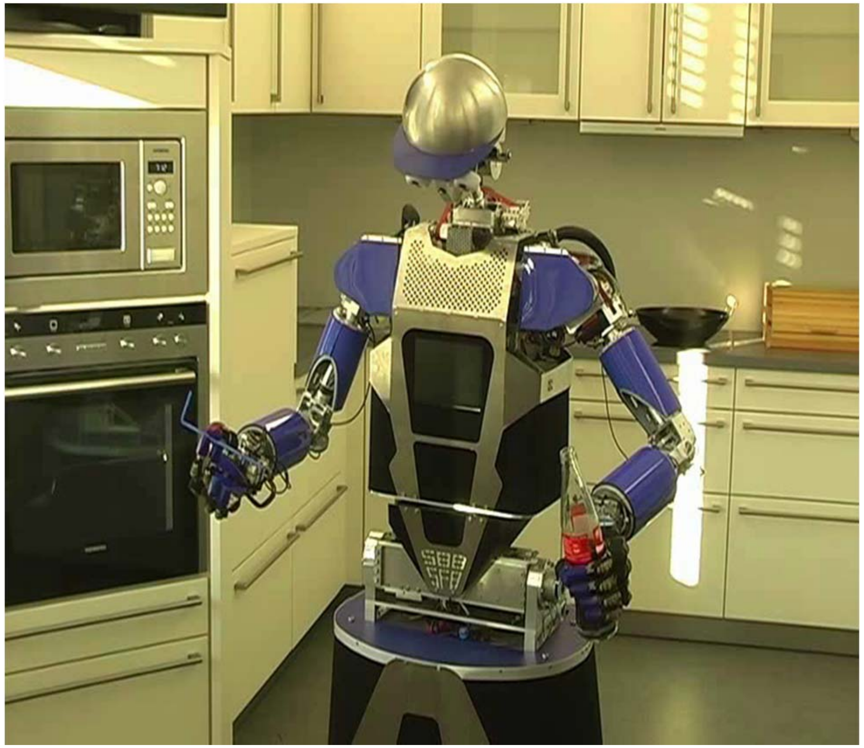
- Based on Rapidly-exploring Dense Trees (BiRDT)
- Discrete collision detection (DCD) for efficient planning
- Guaranteeing collision-free results with Continuous Collision Detection
- Probabilistically complete



[Vahrenkamp, Kaiser, Asfour, Dillmann, ICRA 2011]

Session: TuA1

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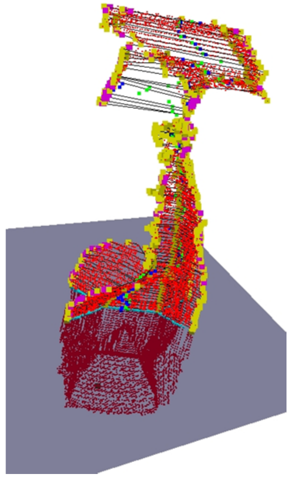
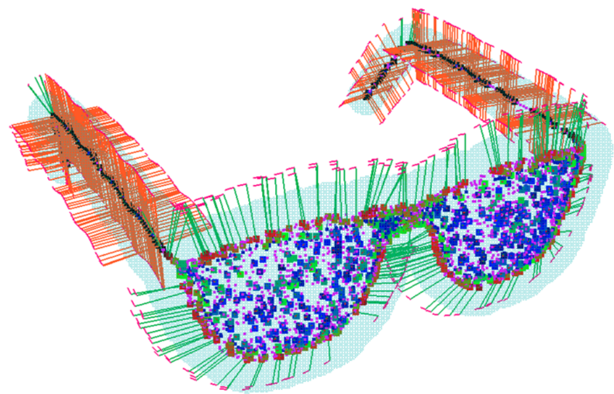
Grasp planning

- Object representation is very important!

- Two new methods for grasp planning
  - based on Medial Axis
    (IROS 2010)
  - based on grid of medial spheres
    (submitted to IROS 2011)





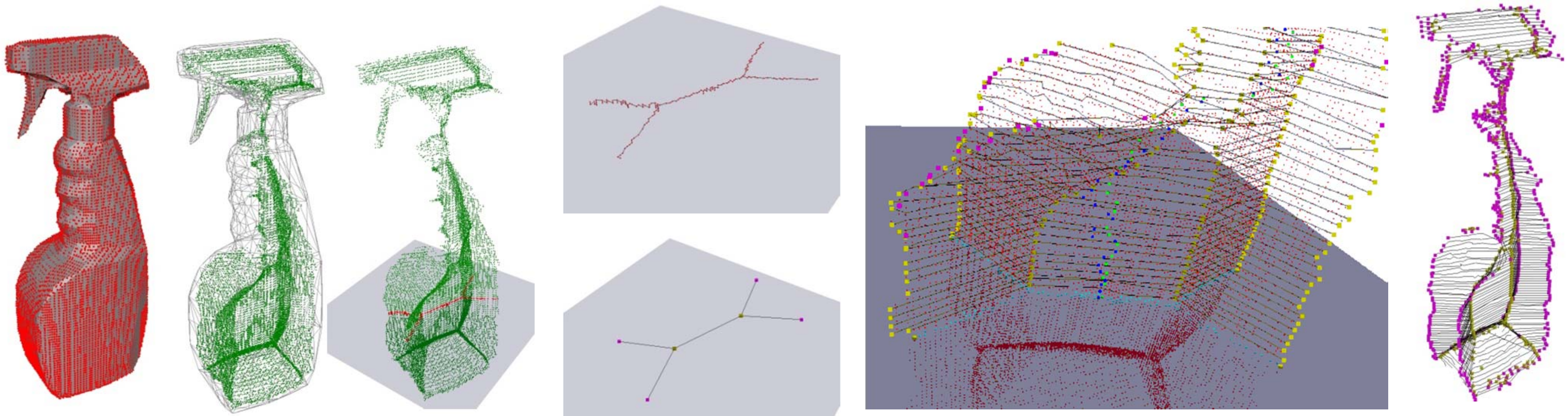
Grasp planning based on Medial Axis

- How to increase efficiency of grasp planning by testing only geometrically meaningful “natural looking” grasps?
- Solution:
  - Exploit local symmetries of object geometry
  - Medial axis as object representation
- Medial axis [Blum67]
  - Shape approximation by inscribing spheres of maximal diameter
  - Inscribed spheres have to touch the geometric shape from the inside at two or more points
- Medial axis = Union of all inscribed spheres‘ centers
- Medial axis = topological skeleton of an object

H. Blum, Models for the Perception of Speech and Visual Form. Cambridge, Massachusetts: MIT Press, 1967, A transformation for extracting new descriptors of shape, pp. 362–380.

Algorithm

1. Sample of the object‘s surface
2. Compute the medial axis
3. Analysis of slices of the medial axis
    - Minimum Spanning Tree (MST)
    - Clustering
    - Convex hull
4. Generate candidate grasps using a set of heuristics
5. Test grasp stability



Heuristics for Candidate Grasp Generation (1)

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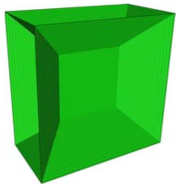
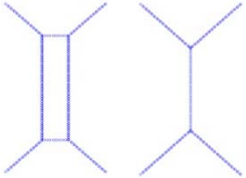
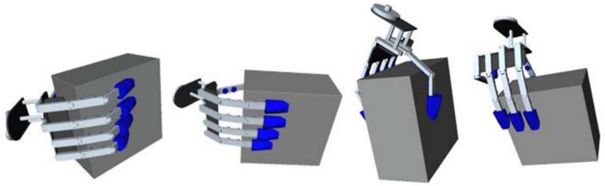
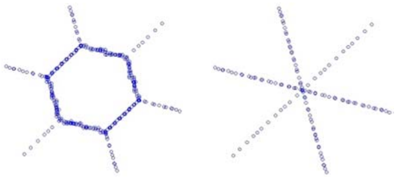
Medial axis | **Slice structure** | **Heuristics and resulting grasps**

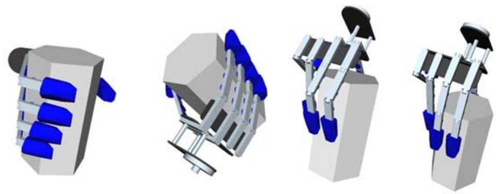



- Approach branching vertices of Minimum Spanning Tree (MST)
- Align hand's roll angle to symmetry planes



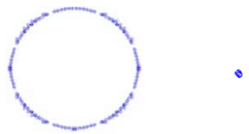



- Approach spikes of a star
- Align hand's roll angle to symmetry planes

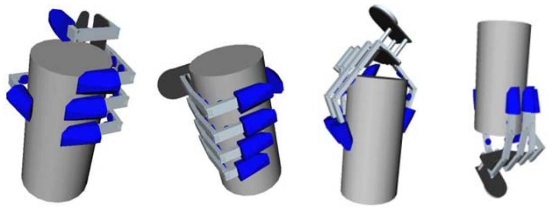


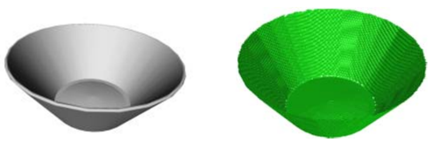
Heuristics for Candidate Grasp Generation (2)

Medial axis | **Slice structure** | **Heuristics and resulting grasps**



- Approach circle/symmetry axis from various directions
- Align hand‘s roll angle to symmetry axis





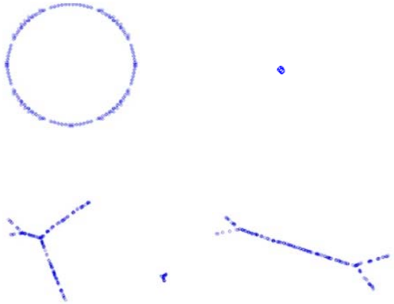
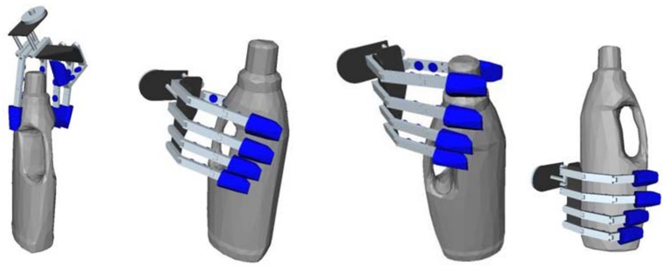
- Objects with opening: Approach rim of the object

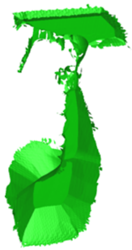
Heuristics for Candidate Grasp Generation (3)

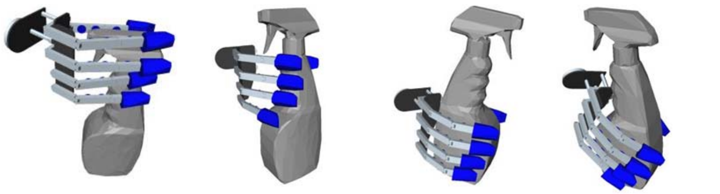
Medial axis | **Slice structure** | **Heuristics and resulting grasps**

- Complex objects: Combine heuristics presented before



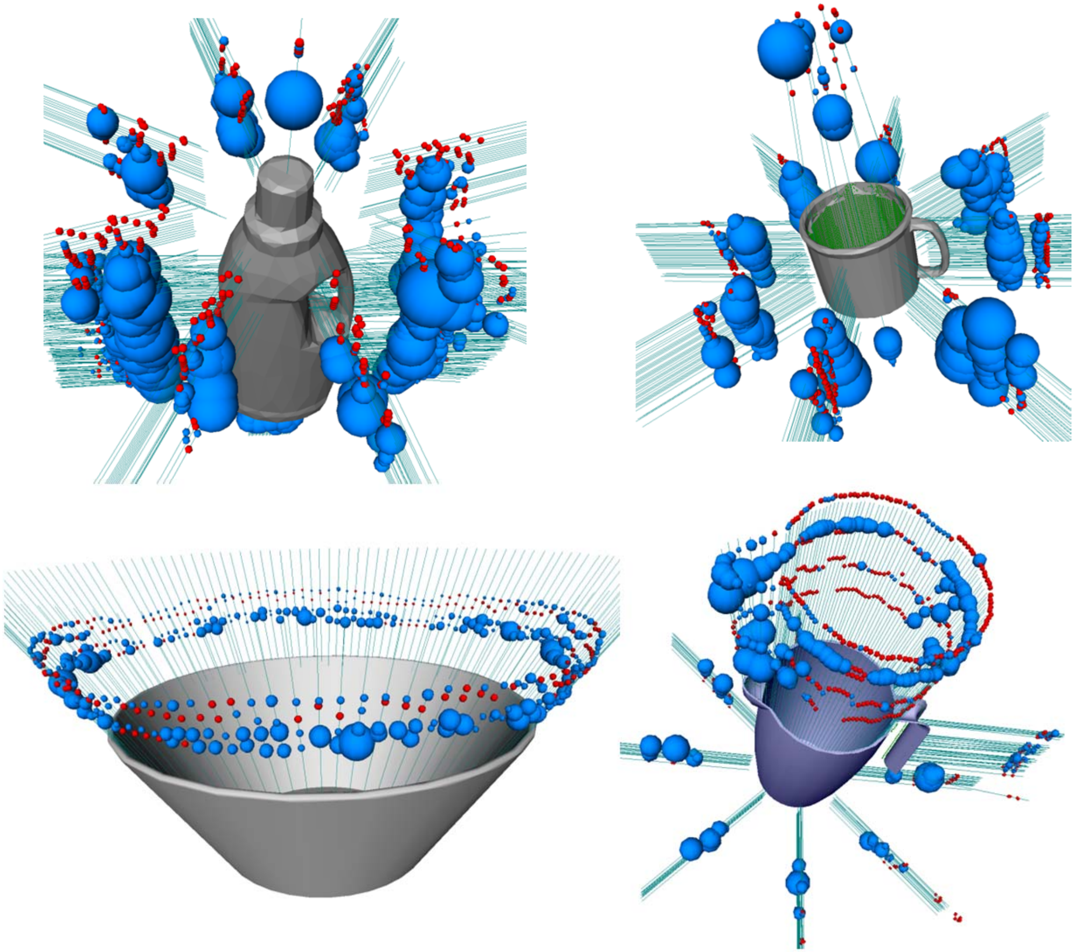





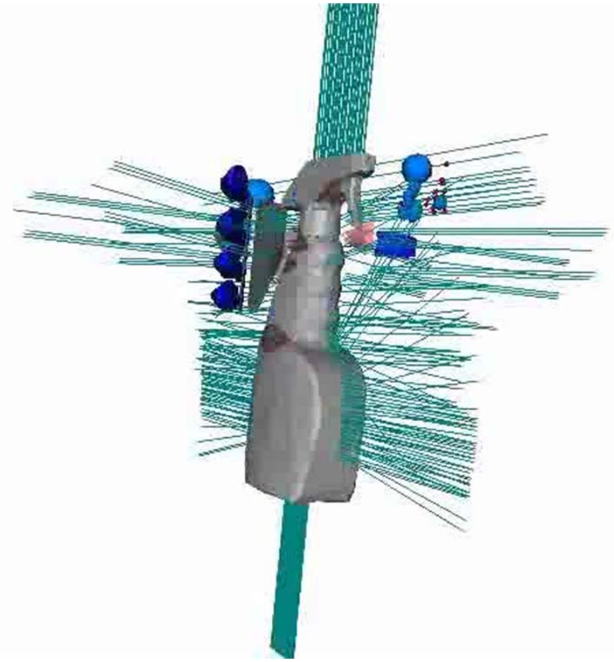
Results: Grasp Quality (Force Closure)

- Blue spheres: stable grasps
- Red spheres: unstable grasps
- Sphere position: Wrist position of hand during grasp
- Sphere diameter: measure for stability (Biggest spheres = most stable grasps)



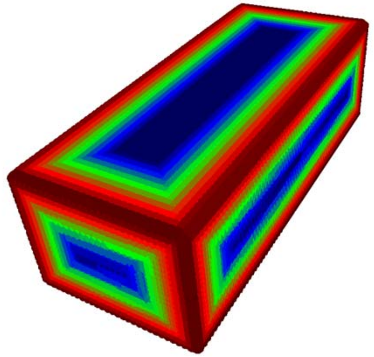
Efficiency of the grasp planner

- Comparison with planner based on surface normals [Berenson07]
  - Number of generated grasp candidates
  - Percentage of stable grasps
- Medial axis-based planner is more efficient
  - Notable: results for relatively big objects (bread box, salad bowl)



Objects	MA-based planner Candidates	MA-based planner Stable	Surface normals planner Candidates	Surface normals planner Stable
Bread box	632	86.2%	13440	15.5%
Prismatic box	1344	90.7%	8512	36.0%
Salt can	2144	96.9%	7904	45.7%
Detergent	1996	65.9%	12672	26.2%
Spray	1304	55.1%	11200	21.2%
Cup	1428	59.5%	6688	37.0%
Pitcher	1124	47.0%	15504	25.9%
Salad bowl	504	68.5%	13648	4.5%

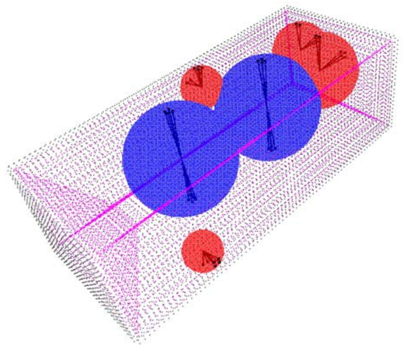
Grid of medial spheres grasp planner



- Based on the medial axis transform
- In addition: efficient access to spheres in local neighborhood (via grid index computation):

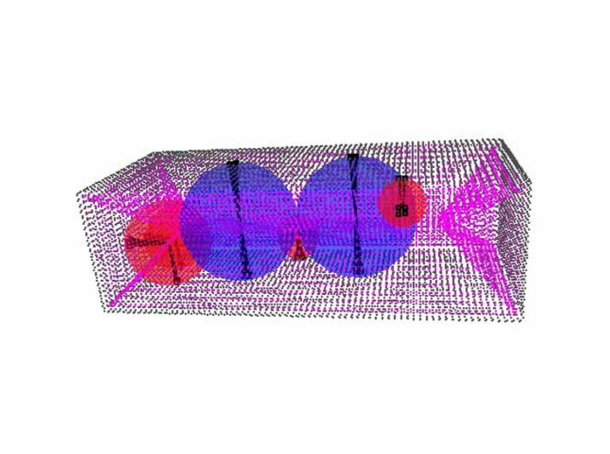
$$\begin{pmatrix} i_x \\ i_y \\ i_z \end{pmatrix} = \begin{pmatrix} \lfloor n_x(x - x_{min})/(x_{max} - x_{min}) \rfloor \\ \lfloor n_y(y - y_{min})/(y_{max} - y_{min}) \rfloor \\ \lfloor n_z(z - z_{min})/(z_{max} - z_{min}) \rfloor \end{pmatrix}$$

- Attributes of each sphere:
  - Center
  - Radius
  - Points where the sphere touches the object‘s surface
  - Object angle: maximum angle included by the sphere‘s center and two surface points touched by the sphere.
  - Example:
    - Blue spheres: object angle ~180°
    - Red spheres: object angle ~90°



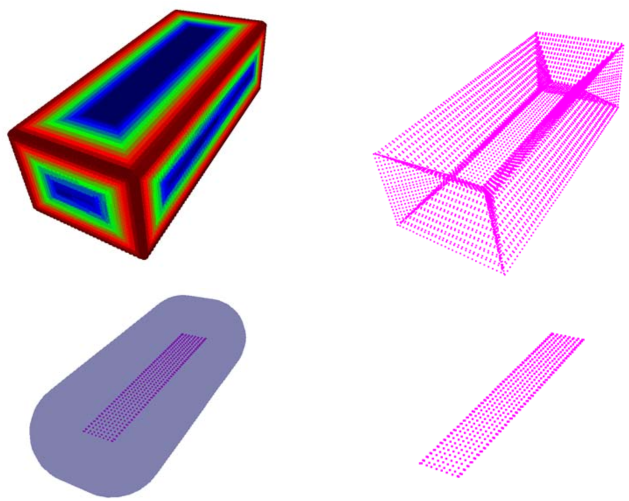
Selecting spheres for grasp planning

- Which spheres are important for grasp planning?
- Rough structure (occupied volume) vs. surface details of the object
- Goals:
  - Exploit local symmetry planes / axes for grasp planning
  - Generate grasps with two opposed virtual fingers
- Main parameters:
  - Object angle
  - Sphere radius
- Grasp planning:
  - Consider only spheres with object angle >= 120°
  - This removes edges and corners of the object
  - Symmetry planes and axes are preserved



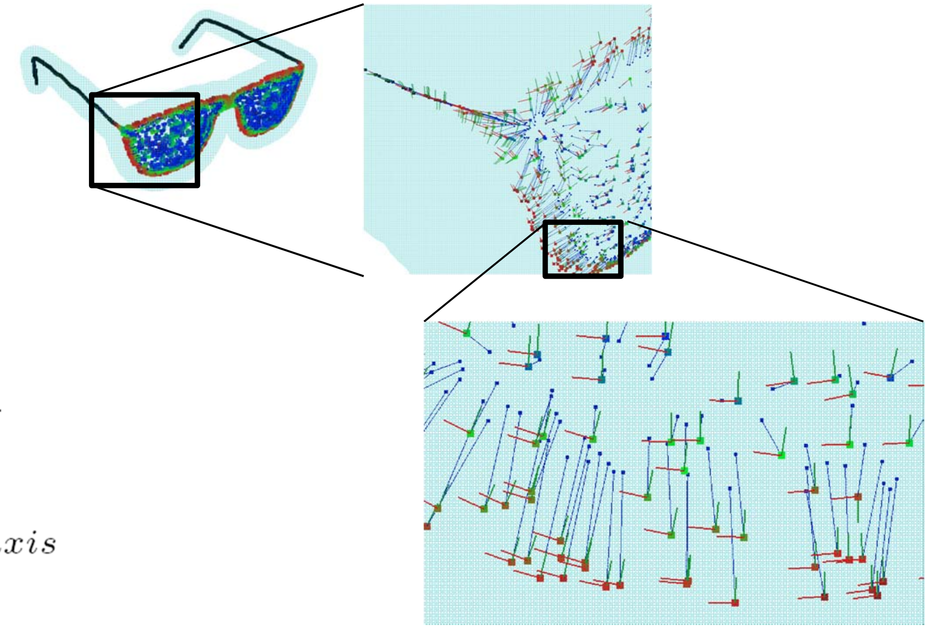
Grid of medial spheres

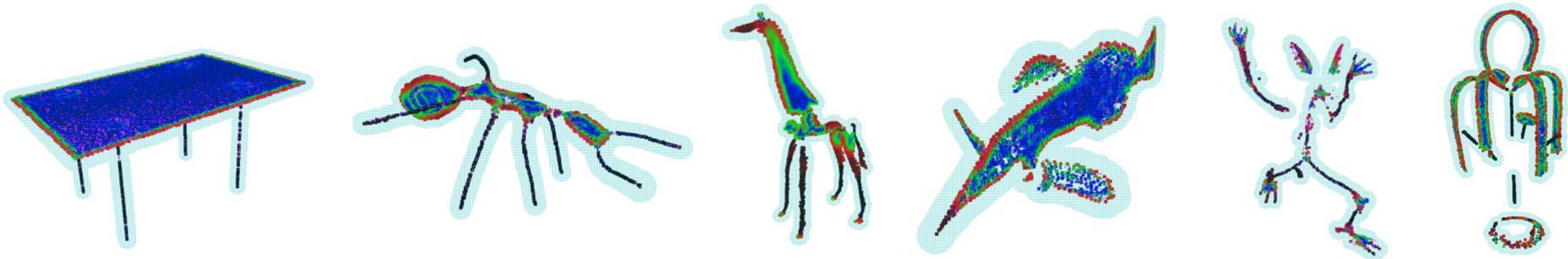
Medial Axis



Analyzing an object‘s symmetry properties

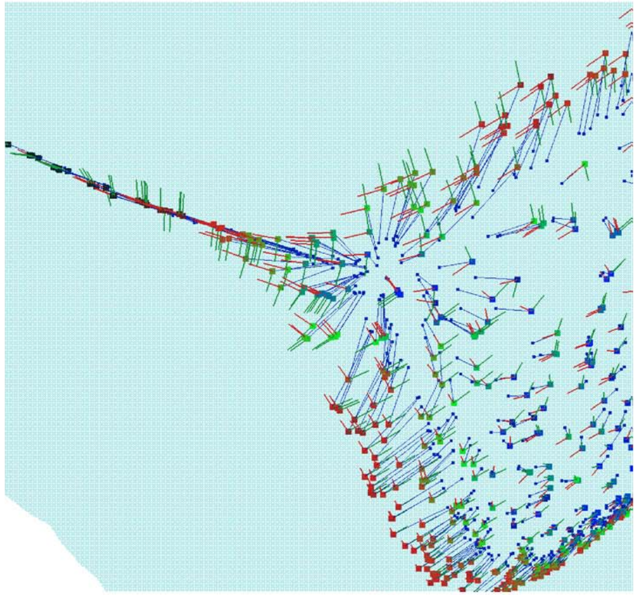
- Estimate symmetry properties of sphere centers in each sphere‘s local neighborhood
- Principal Component Analysis:
  - Directions of eigenvectors
  - Ratio of eigenvalues $\rho_{ev} = \frac{\lambda_2}{\lambda_1}$
- Classification of spheres:
  - On local symmetry axis $\rho_{ev} \leq \rho_{axis}$
  - On local symmetry plane
    - At the rim $\rho_{axis} \leq \rho_{ev} \leq \rho_{plane}$
    - Inside the plane $\rho_{ev} > \rho_{plane}$

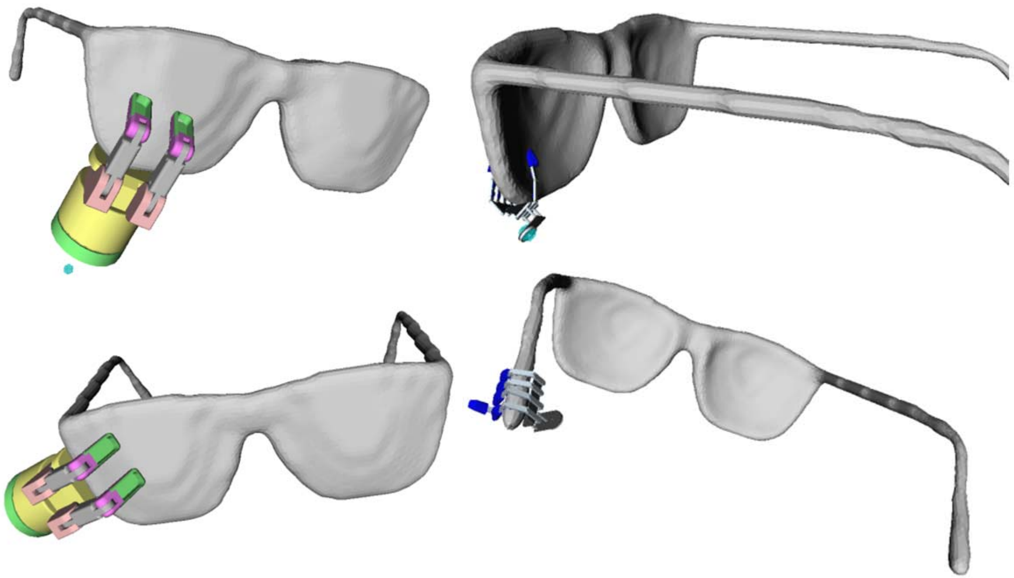


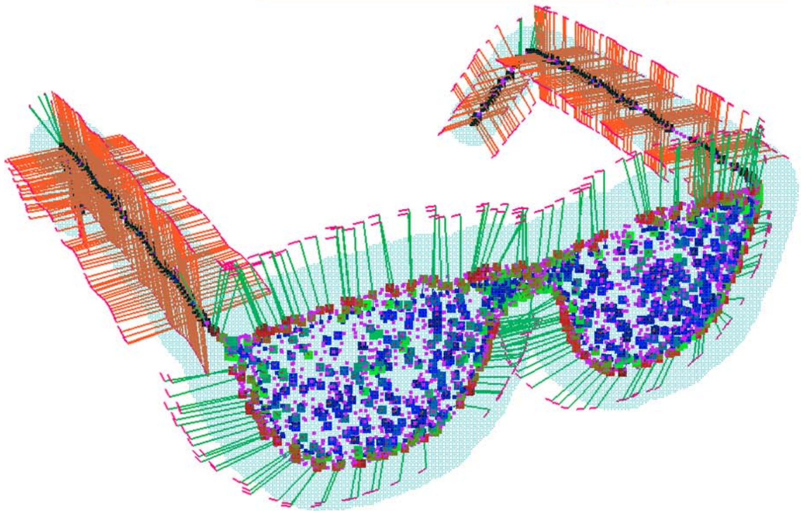


Generating candidate grasps

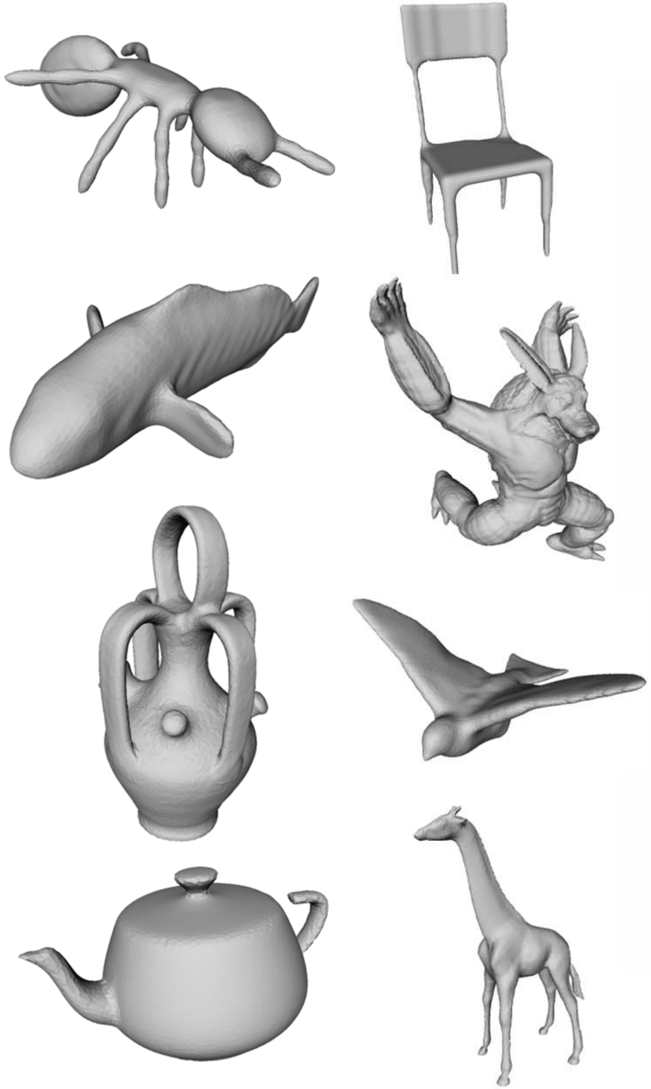
- Symmetry axis
  - Hand approach directions perpendicular to local symmetry axes
- Rim of symmetry plane
  - Hand approach directions perpendicular to local symmetry planes





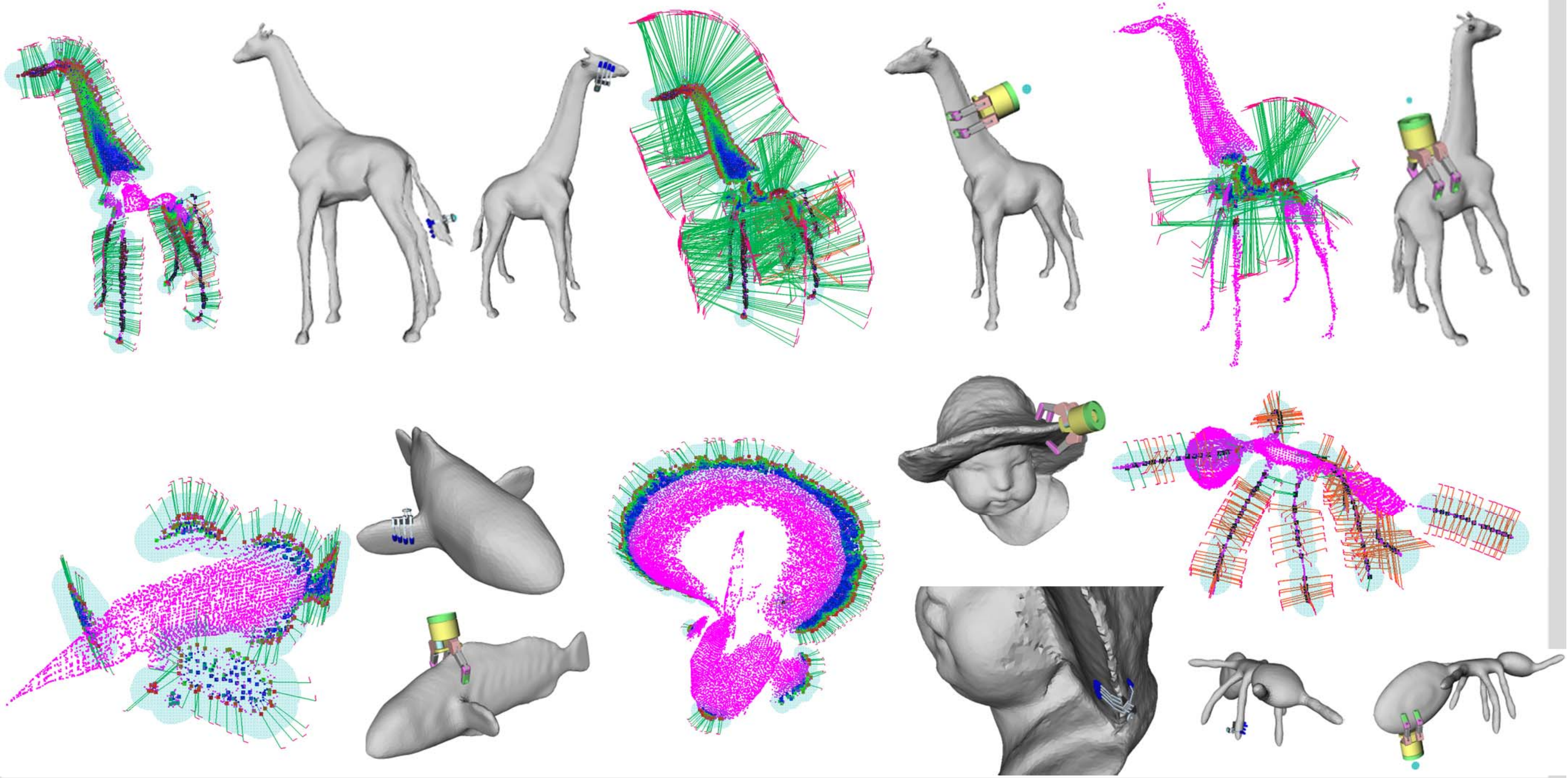


Candidate grasps: some examples

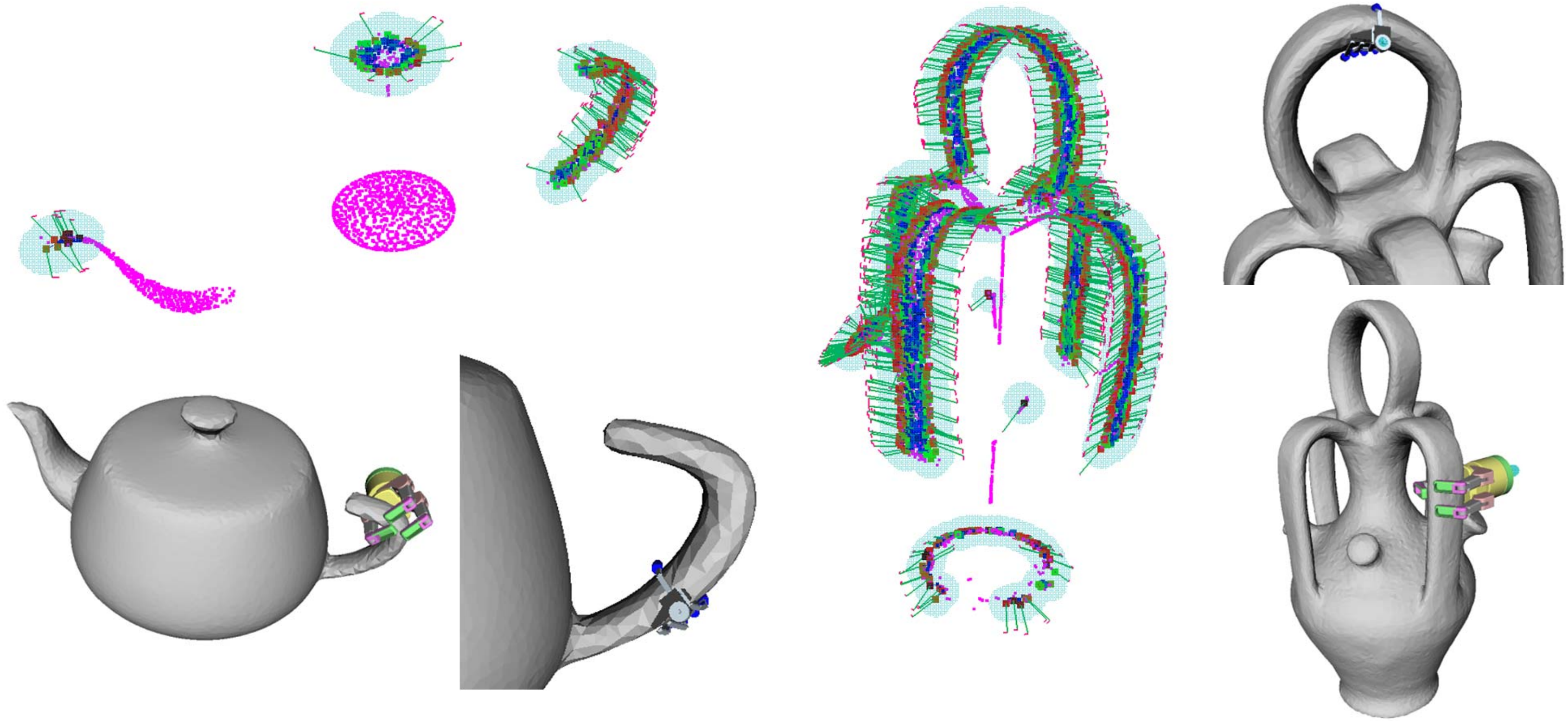


Advantages: Hand size vs. Object size

- Respect maximum sphere diameter graspable by the robot hand
- Optional: do not generate grasps for „small“ spheres



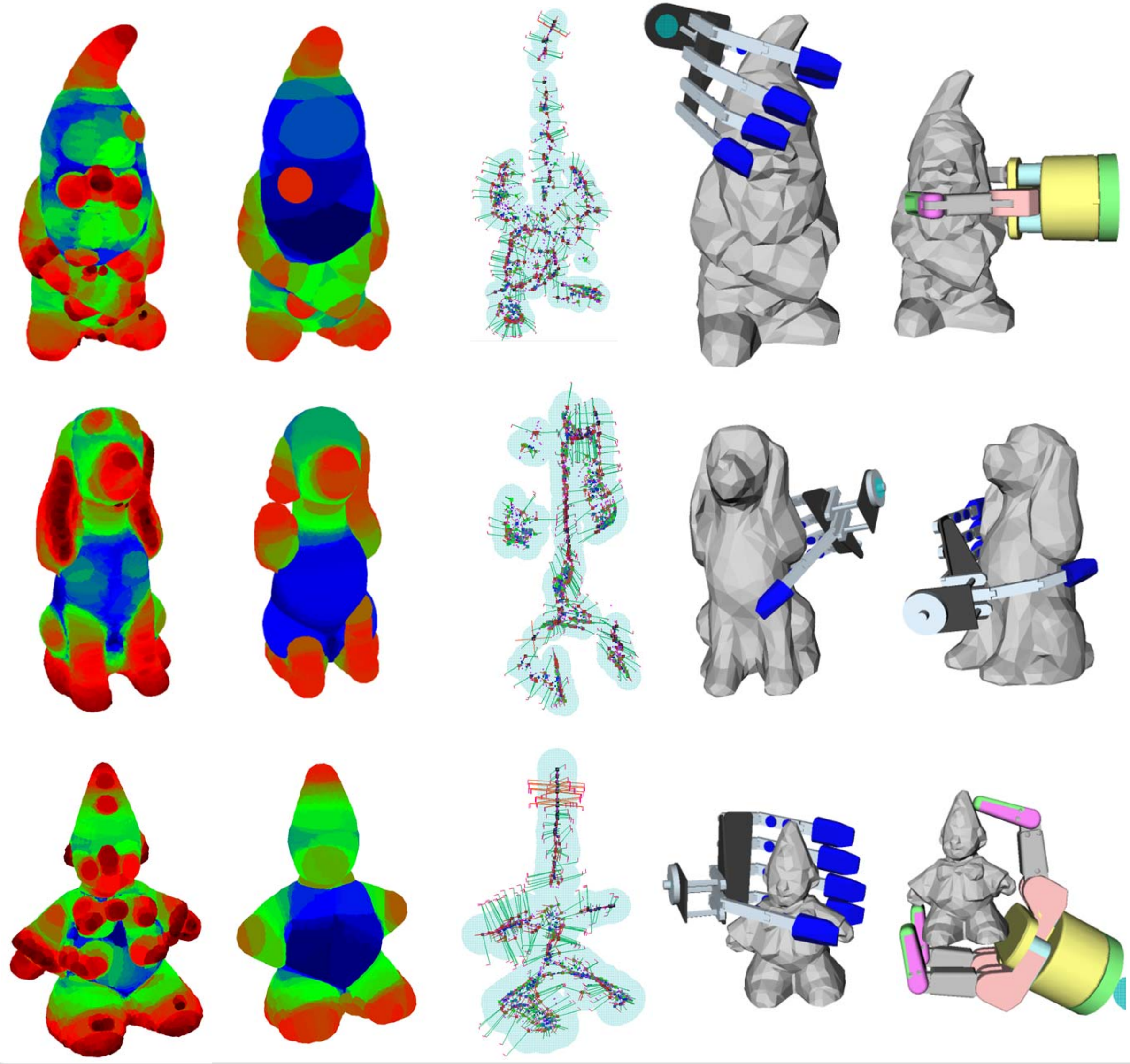
Advantages: Grasps on handles



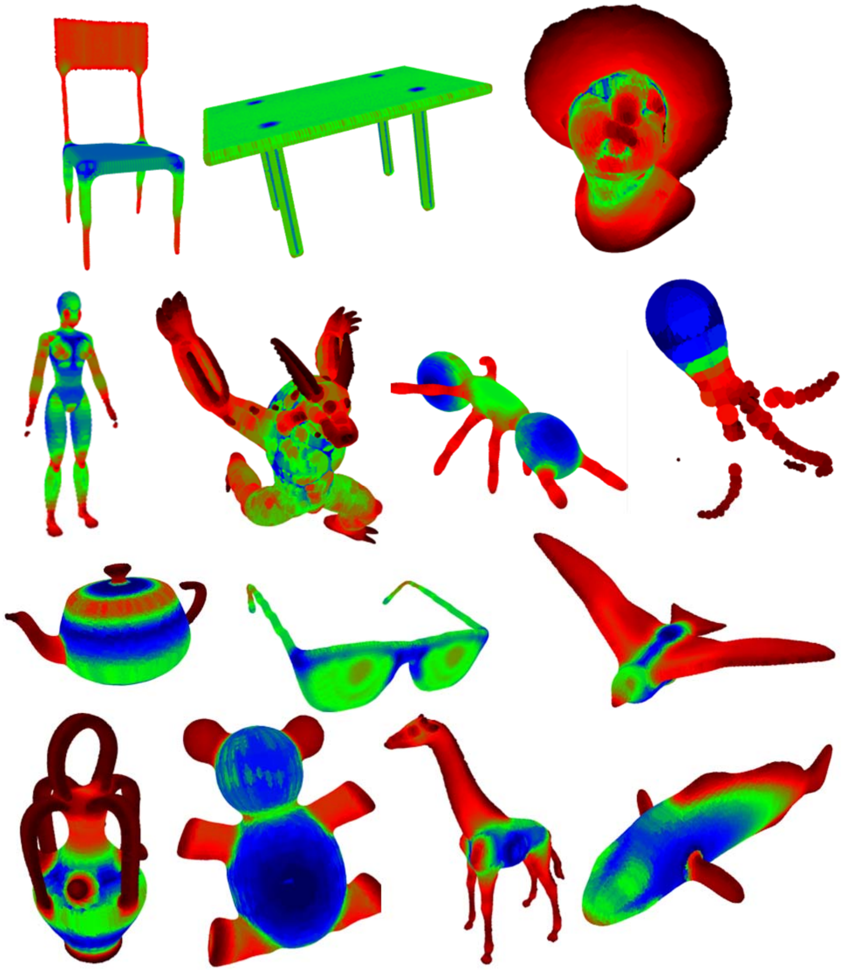
- For big objects, the algorithm finds many grasps at the handles
  - Simply due to geometric considerations, as the hollow bodies are too big to grasp
  - No semantic knowledge (task dependency) necessary

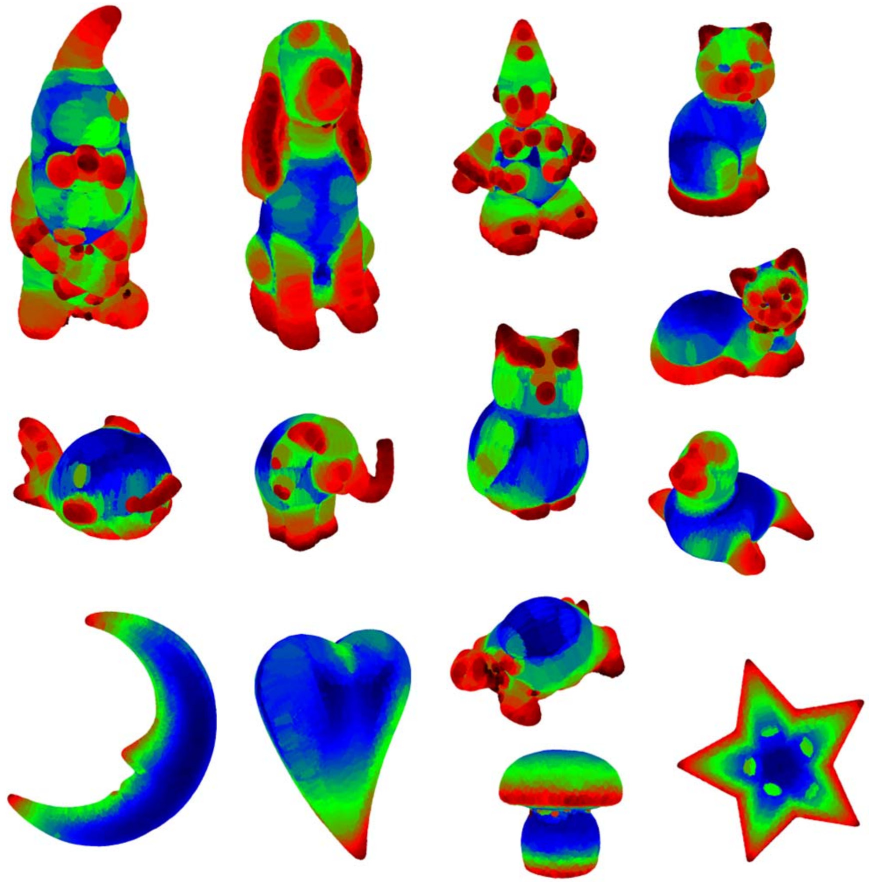
Advantages: Surface details

- How to deal with surface details?
- Solution: discard „small“ spheres
- Planner considers only rough geometry of the object.



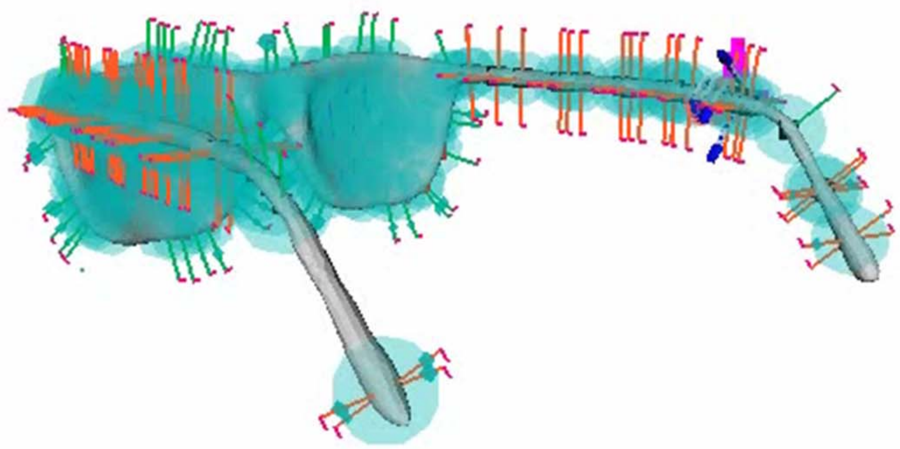
Object sets for testing





- Chen Mesh Segmentation Benchmark [Chen2009]
- Real objects

Force-closure testing



Results

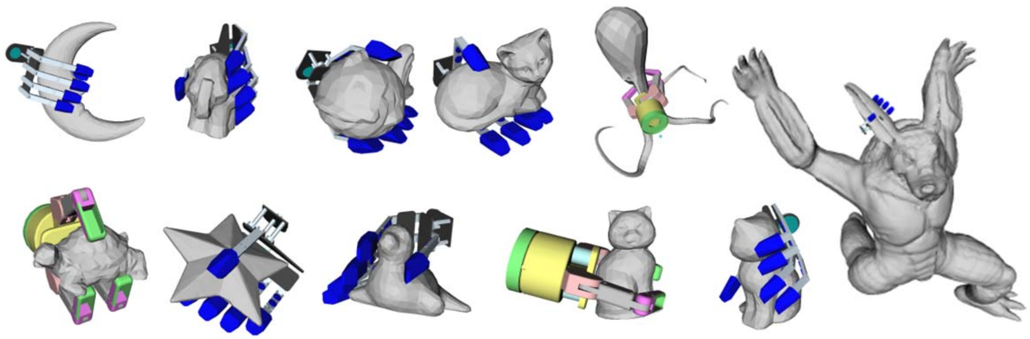
Chen benchmark

Objects	ARMAR-III hand scale 1.0	ARMAR-III hand scale 0.5	Barrett hand scale 1.0	Barrett hand scale 0.5
1 Female doll	71.3%	54.6%	53.13%	37.9%
41 Glasses	93.9%	7.8%	73.7%	10.7%
81 Ant	94.4%	71.1%	61.3%	45.7%
101 Chair	89.6%	49.2%	73.9%	72.2%
125 Octopus	53.7%	55.2%	26.9%	44.7%
141 Table	91.9%	92.5%	94.6%	85.0%
161 Teddy	100.0%	83.3%	86.7%	51.2%
225 Fish	76.5%	83.3%	68.4%	81.1%
245 Bird	75.0%	68.3%	75.0%	65.6%
290 Monster	70.5%	64.7%	67.8%	38.2%
305 Bust	50.0%	70.0%	100.0%	92.9%
361 Vase	76.8%	65.3%	69.6%	55.1%
379 Tea kettle	78.9%	63.2%	75.7%	31.3%
390 Giraffe	85.5%	68.3%	71.4%	56.0%

Real objects

Objects	ARMAR-III hand	Barrett hand
1001 Clown	63.5%	61.2%
1002 Elefant	75.3%	76.0%
1003 Owl	78.0%	68.2%
1004 Spheric fish	59.0%	78.3%
1005 Lawn gnome	53.1%	57.7%
1006 Heart	89.0%	77.0%
1008 Dog	63.7%	69.2%
1009 Sitting cat	64.9%	59.5%
1010 Lying cat	80.7%	80.7%
1012 Moon	58.9%	64.4%
1013 Mushroom	80.0%	55.5%
1014 Turtle	57.1%	70.3%
1015 Seal (Seehund)	73.5%	59.2%
1016 Star	44.4%	66.7%

- Experiments:
  - Hand models:
    - ARMAR-III
    - Barrett
  - Object models:
    - Chen benchmark
      - 100% scaled objects
      - 50% scaled objects
    - Real objects
- Results:
  - Mostly >50% of the generated candidates are force-closure grasps



Summary

- *Grid of medial spheres* object representation:
  - Based on the medial axis transform
  - Volumetric approximation
  - Arbitary level of detail
  - Symmetry properties as part of the object representation

- Grasp planning algorithm:
  - For arbitrarily shaped objects
  - Generates geometrically meaningful candidate grasps
  - Further advantages:
    - Hand size and object size considered
    - Grasps on handles simply due to geometric considerations
    - Surface details can be ignored, if necessary
  - High yield of force-closure grasps

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Thank you ...

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