Manipulation Planning and Grasping

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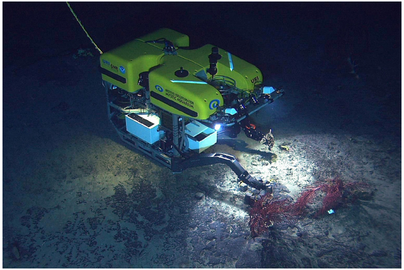
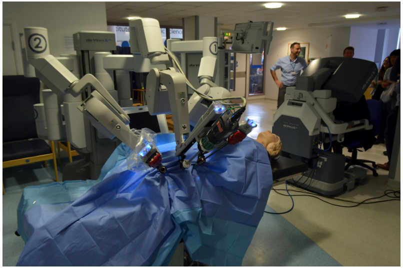
Different Applications

Actemium Industrial Robots [1]



NOAA Remote Operated Vehicle [8]



Da Vinci Surgical System [4]

Canadarm2 at ISS [13]

Manipulation: Goals

Manipulation consists of two separable tasks:

- Endeffector Positioning (manipulation planning)
- Endeffector Application (e.g. grasping)

In general manipulators look like this:

KUKA LWR 4+ [7]

Manipulation: Goal

Computing a movement for a manipulator's initial configuration so that its endeffector reaches a required target position.

How can that problem be computed?

More Difficulties

Additionally many factors need to be considered:

- Obstacle detection & collision avoidance
- Cost reduction $\leftrightarrow$ efficient manipulation
- Moving manipulator or object (or both)
- Physical constraints: weight, speed, momentum, range
- Technical constraints: power, latency, accuracy, singularities

For now we focus on the first two...

Configuration Space

The position (and orientation) of the Endeffector regarding to the base depends on:

- Constant Device Features (≈distances & angles between links and joints)
- Variable Joint Configuration (≈motor settings of the joints)

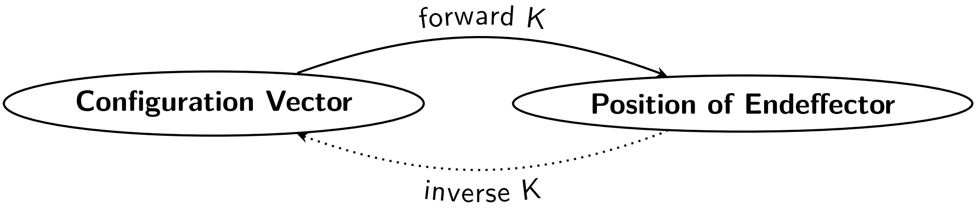
→If constant device features are known, the manipulation problem corresponds to a path search in configuration space.

Configuration Space

- The Configuration Space C_{space} defines all configurations of a manipulator.
- For a N-DOF-Manipulator C_{space} has N dimensions, each dimension representing a joint.
- A configuration vector q contains all joint settings of the manipulator.
- The reachable configuration space (in regards to range, obstacles, singularities...) is called C_{free}

Kinematics

- Kinematics is the mathematical field of the description of mechanical motion.
- Kinematics is used to compute positions and motions of the endeffector into C_{space} and back.



Manipulation Planning in a Nutshell

1. Determine the current configuration vector A of the manipulator.
2. Find a configuration vector B for the Endeffector's target position.
3. Find a feasible path between configuration vectors A and B in C_{space}.
4. Move the manipulator's joints according to that path, which results in a continuous motion in topological space.

But:

- A perfect solution can not be computed - C_{space} is too big and there might be no or infinite optimal paths.

Approaches

1. Roadmap Techniques
2. Cell-Decomposition Techniques
3. Artificial Potential Methods
4. Probabilistic Roadmaps

All approaches aim to create a searchable representation of C_{free}.

In general C_{free} is best to be described as a **graph**.

→ Manipulation planning can be performed by a shortest path graph search like Dijkstra or A*.

Graph creation and search algorithms can be tuned for:

- distance
- safety
- speed
- accuracy
- *completeness*

Roadmap Techniques

Idea:

Describe the N-Dimensional configuration space C_{free} as a connectivity graph and perform a search for a feasible path between two configurations.

Roadmap Techniques: Visibility Graph

All obstacles are represented by vertices, edges are the visible connections between them.

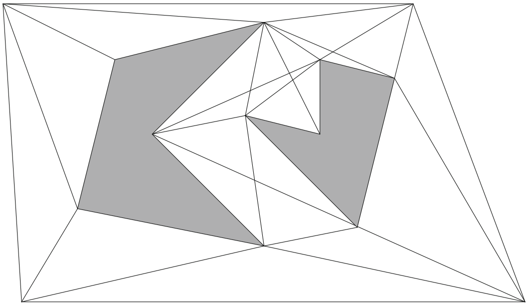


Figure: Example Visibility Graph Gasparetto et al. [16], p. 8

→ All paths are close to obstacles.

Roadmap Techniques: Voronoi Diagrams

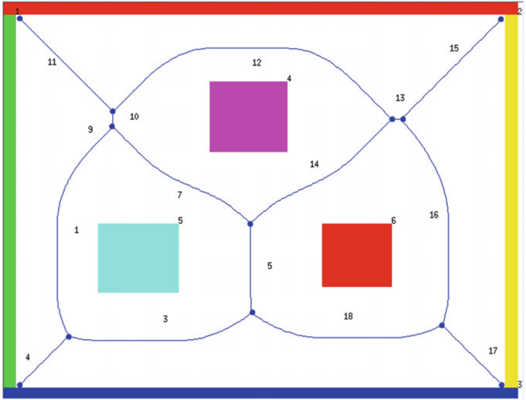


Figure: Example of a Voronoi Diagram Gasparetto et al. [16], p. 9

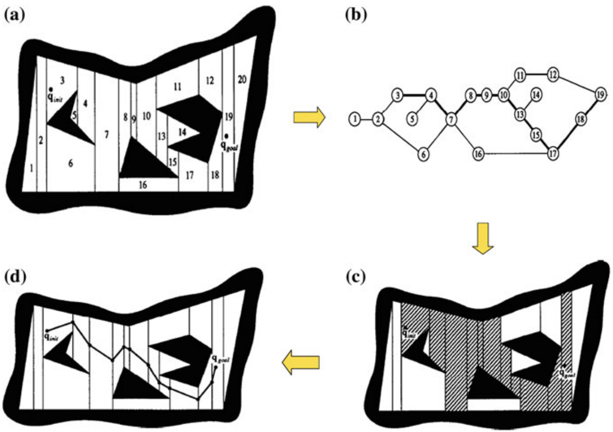
→ Paths are as far away from obstacles as possible.

Cell-Decomposition

Idea:

Compute a tree of paths in C_{free} by disabling all obstacles from a graph representation of C_{space}.

Exact Cell-Decomposition



- **a** subdivision of space into numbered polygons
- **b** connectivity graph
- **c** regions to be crossed
- **d** path

Figure: Exact Cell-Decomposition Gasparetto et al. [16], p. 10

Approximate Cell-Decomposition

To generate a connectivity graph for a required accuracy:

1. Divide C_{space} into 2^n equal sized cells.
2. Check if cells are free or blocked by obstacles.
3. If a cell is only partially blocked by an obstacle, decompose recursively.

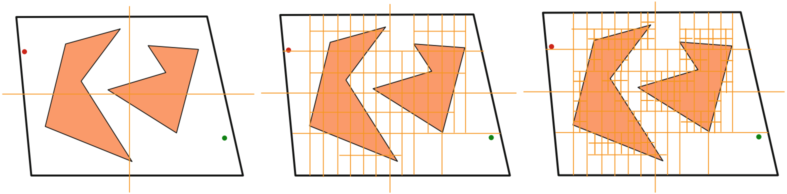


Figure: 2-Dimensional Cell-Decomposition Gasparetto et al. [16], p. 10

Cell-Decomposition: Tree-Representation

- The corresponding graph of the cell decomposition is a tree of adjacent configuration vectors.
- The motion is therefore specified as a path in that tree and can be computed by graph search techniques.

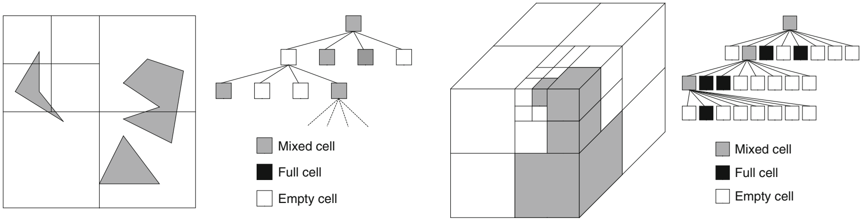
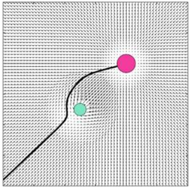


Figure: Approximate Cell-Decomposition Gasparetto et al. [16], p. 11

Artificial Potential Methods

Idea:
C_{space} is defined as a potential field.

- The target configuration is the attracting force
- Obstacles are producing a repulsive force.


Artificial Potential Field [3]

$\rightarrow$ The motion is lead by the path of the highest potential along the field.

Probabilistic Roadmaps

Idea:

(Drastically) reduce complexity of Roadmap computation by probabilistic algorithms.

Probabilistic Roadmap

1. Find obstacles and surround with connected nodes.
2. Add random nodes to C_{free} and connect to closest existing nodes.
3. Repeat step 2 until a density criterion is reached.
4. Perform graph search algorithm on created roadmap.

This process can be optimized, e.g. by adding more nodes at areas with coarse connectivity.

Probabilistic Roadmap Planner

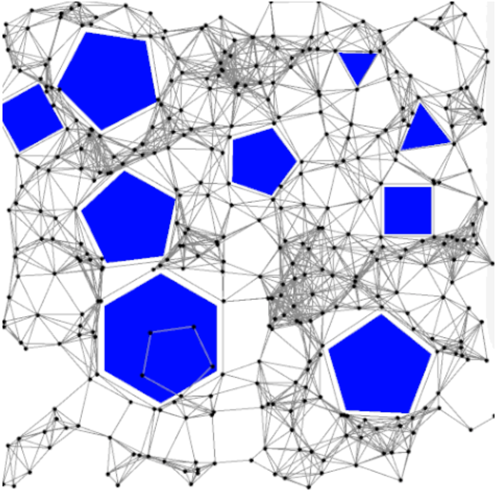


Figure: Probabilistic Roadmap Visualization [9]

Grasping

Shadowhand [12]

Often motion planning and grasping goes hand in hand.

The two main problems are:

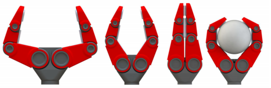
- Where to grasp?
- How to grasp?

Gripper

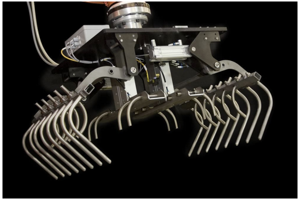
Robotiq 2/3-Finger Gripper [10][11]

The problem of grasping is always highly dependant on the used gripper.

Empire Robotics - VERSABALL [6]



Domenica 2-Finger Gripper [5]



Applied Robotics Heavy Load Gripper [2]

Basic Grasping

Simplest approach:

1. Create a 3D-model of object and define grasping point/area
2. Position gripper (e.g. two finger) ahead of grasping point via Inverse Kinematics
3. Perform grasp either by known thickness of object or by pressure sensor.

...of course there are more robust and dynamic approaches

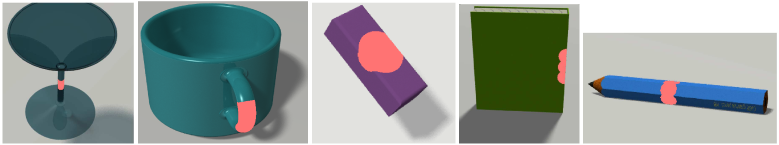
Supervised Learned Grasping

Goal:
Grasping objects without environmental knowledge (e.g. 3D-Models, objects position/orientation)

Supervised Learned Grasping

[14] Saxena et al. - *"Robotic Grasping of Novel Objects using Vision"*

1. Supervised learning on labeled grasping points for different objects.

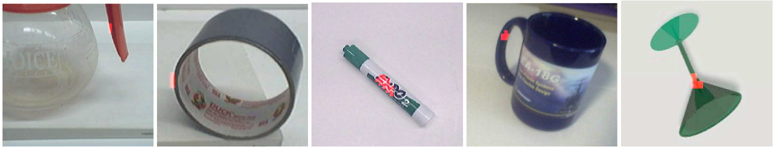


[14] Saxena et al.,p. 3

Therefore local image features (e.g. edges, textures, color, etc. . .) are processed.

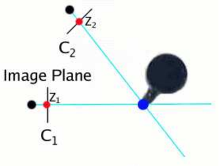
Supervised Learned Grasping

2. Recording 2D-images of target objects from different angles.
3. Classification of grasping points at the images.



[14] Saxena et al.,p. 6

4. Triangulation of grasping points by image and camera locations.



[14] Saxena et al.,p. 6

Supervised Learned Grasping

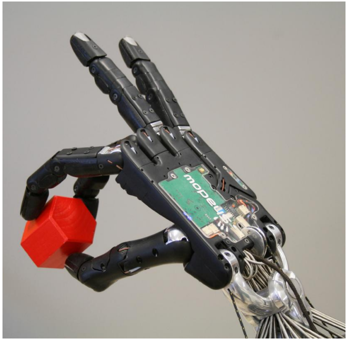
5. Manipulation Planning for adjusted target configuration via Inverse Kinematics.

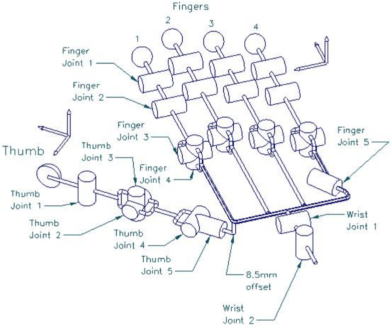
[14]

Saxena et al.,p. 12

Humanoid Hands

- 24 DOF (20 controllable) - the human hand has ≈ 22 DOF
- powered by air-muscles





[15]Bernadino et al., p. 3

Figure: Shadowhand at University of Hamburg

Grasping Approaches

- **Analytical Approach:**
  Determine grasping points on the object and compute finger motions via Inverse Kinematics (manipulation planning).
- **Empirical Classification:**
  Analyze and classify human grasping behaviour and map (primitive sequences of) motions to robotic hands.

Eigengrasps

- About 80% of human grasps (22 DOF) can be approximated by only a view dimensions.
- All grasps can be described by a couple of different hand poses.

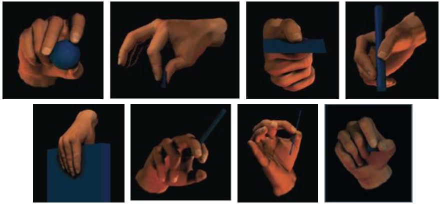
Idea: Formalize suitable hand poses as *eigengrasps* and compute appropriate grasp behavior for different 3D-Shapes (and hands).

Postural Grasp Synergies

[15] Bernadino et al. - *"Precision Grasp Synergies for Dexterous Robotic Hands"*

- Grasp Synergies are correlating configurations of hand joints.

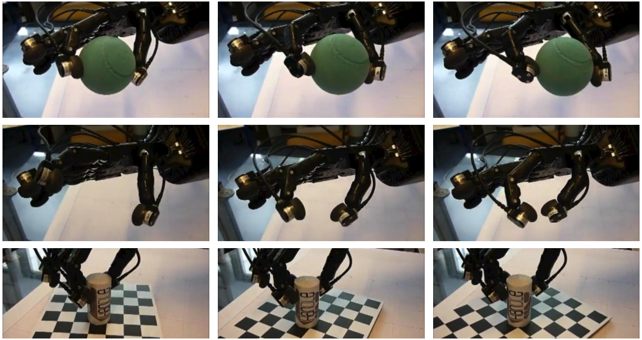
[15]Bernadino et al., p. 4



[15]Bernadino et al., p. 4

- They are computed by the most significant correlations of joint configurations in the eigengrasps via PCA.

Postural Grasp Synergies



[15] Bernadino et al., p. 6

90% of the grasps can be described by only 6 principal components.

(≈ dimensions)

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[11] Robotiq 3-Finger Gripper. http://support.robotiq.com/display/IMB/Home. 11.06.2016.
[12] Shadowhand with Bulb. https://commons.wikimedia.org/wiki/File:Shadow_Hand_Bulb_large_Alpha.png. 11.06.2016.
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[16] G. Carbone and F. Gomez-Bravo, editors. Motion and Operation Planning of Robotic Systems - Background and Practical Approaches, volume 29 of Mechanisms and Machine Science. Springer International Publishing, 2015.