

# Intro to Robotic Grasping

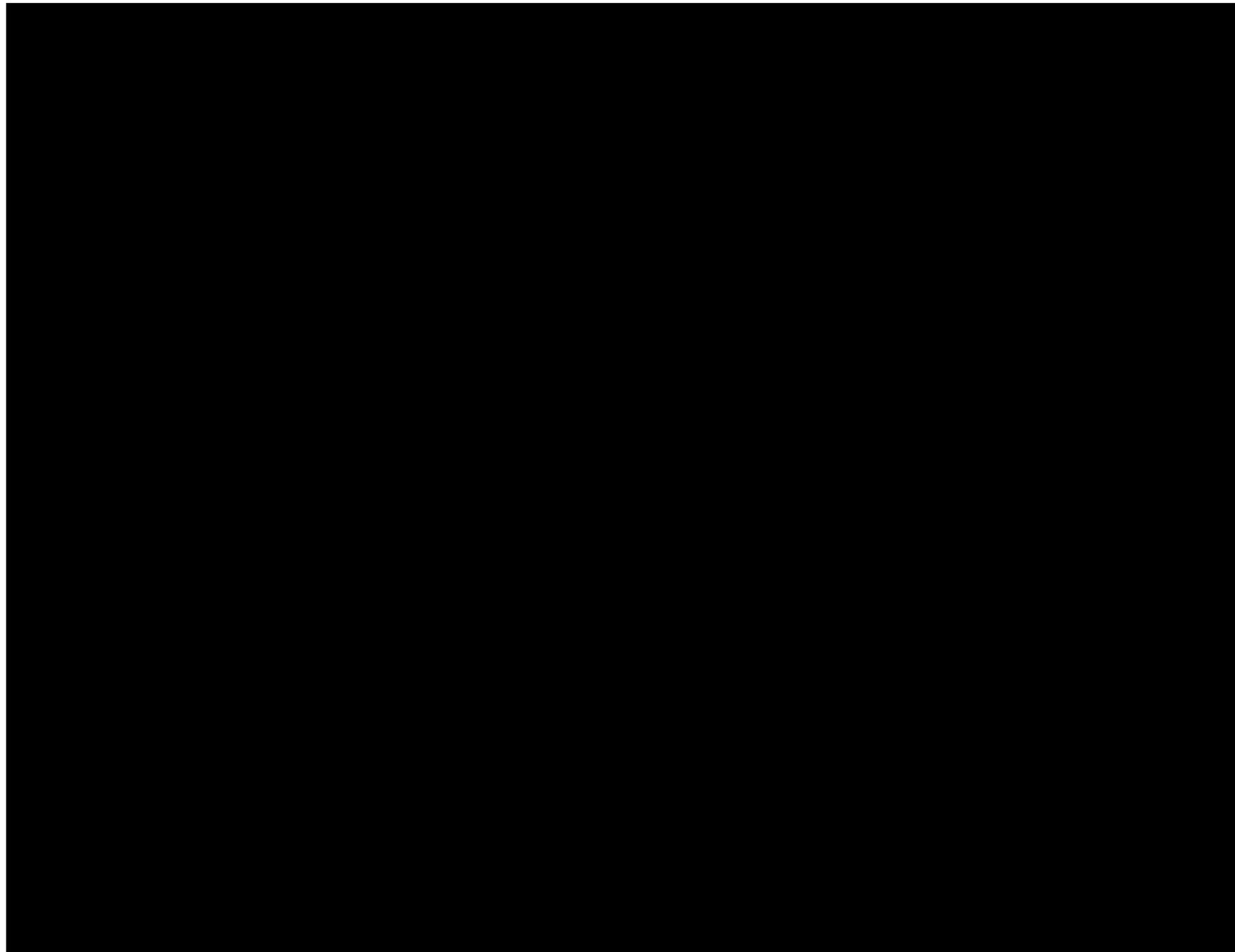
Instructor: Chris Mavrogiannis

TAs: Kay Ke, Gilwoo Lee, Matt Schmittel

# Logistics

- Lab 3
  - Deadline Friday **March 6th**
  - Demo Thursday **March 5th** (recitation slots)
  - **Extra Credit important for final project**
- Final Project
  - Released
  - Demo Thursday **March 12th** (recitation slots)
  - Short writeup due **Monday 16th**

# Manipulation



**Julia Child slicing potato – example from Matt Mason's 16-741 class at CMU**

# Manipulation



<https://www.youtube.com/watch?v=l9U8X6I1vow>

<https://sites.google.com/view/kpam>

Lucas Manuelli\*, Wei Gao\*, Peter Florence, Russ Tedrake. kPAM: KeyPoint Affordances for Category-Level Robotic Manipulation. In International Symposium on Robotics Research (ISRR), Hanoi, Vietnam, October 2019

# Manipulation

**Definition 1.** Manipulation refers to the activities performed by hands.

**Definition 2.** Manipulation is when an agent moves things other than itself.

**Definition 3.** Manipulation is when an agent moves things other than itself through selective contact.

**Definition 4.** Manipulation is pick-and-place manipulation plus in-hand manipulation plus mechanical assembly plus. . . .

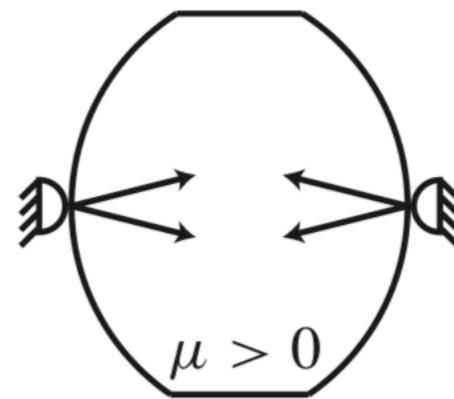
**Definition 5.** Manipulation refers to an agent's control of its environment through selective contact.

# Special Case: Grasping

- Special class of manipulation (others include caging, nonprehensile manipulation, etc)
- Exerting force/moment on object via a set of **contacts** to keep it in stable equilibrium or rearrange it
- Often quasistatic



Form closure  
does not imply  
force closure



Force closure  
does not imply  
form closure

# Special Case: Caging

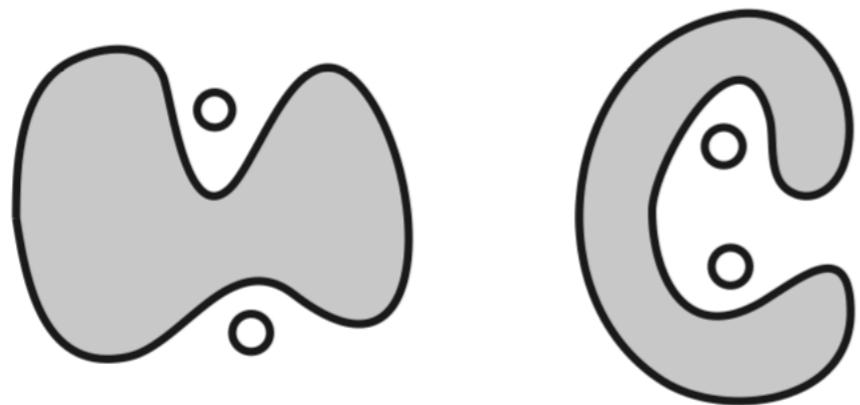


Fig. 2. Examples of squeezing (left) and stretching (right) caging configurations.

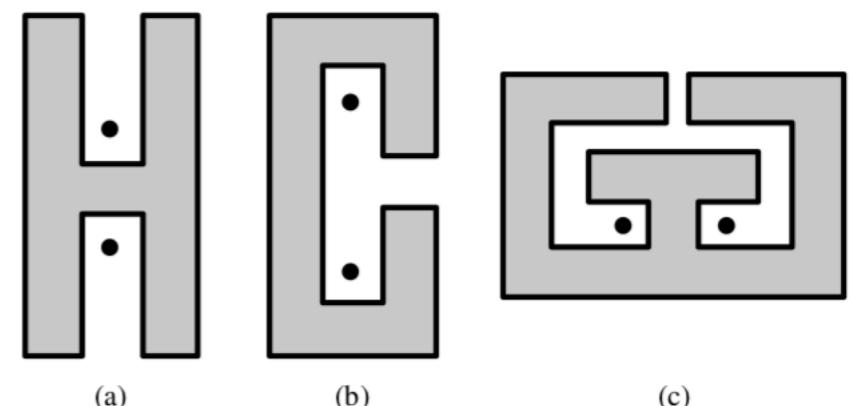


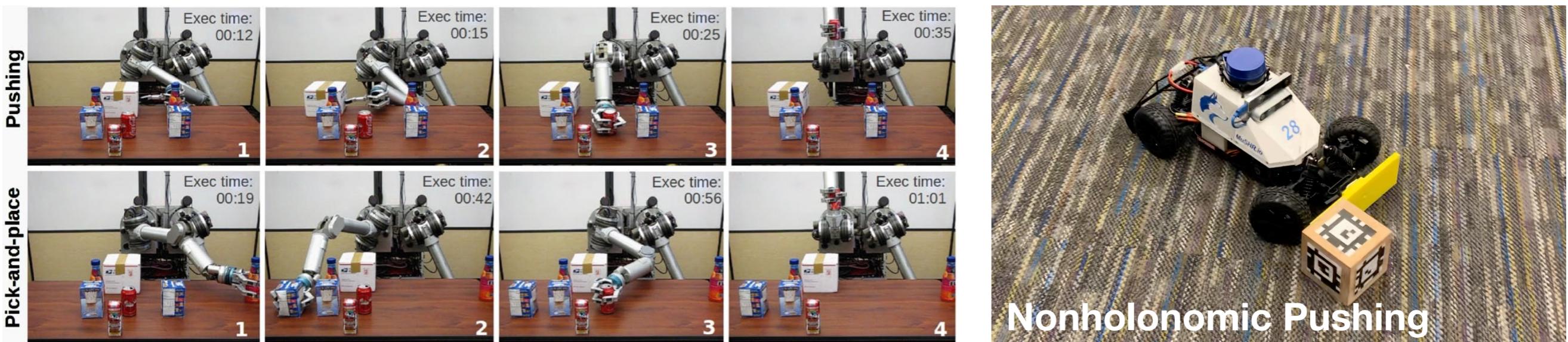
Fig. 1. Examples of (a) squeezing caging, (b) stretching caging (c), both.

- To cage an object is to arrange obstacles so that all motions of the mobile body are bounded.
- An object is caged if and only if the manipulator is unable to escape from the object while preserving its shape.

Rodriguez, A., Mason, M. T., & Ferry, S. (2012). From caging to grasping. *The International Journal of Robotics Research*, 31(7), 886–900. <https://doi.org/10.1177/0278364912442972>

# Special Case: Nonprehensile Manipulation

“The environment is your friend”



<https://youtu.be/QLvgEDFE68Y>

<https://youtu.be/tVDO8QMvYhc>

Chavan-Dafle, N., Holladay, R., & Rodriguez, A. (2020). Planar in-hand manipulation via motion cones. *The International Journal of Robotics Research*, 39(2–3), 163–182. <https://doi.org/10.1177/0278364919880257>

A Planning Framework for Non-Prehensile Manipulation under Clutter and Uncertainty. M.R. Dogar and S.S. Srinivasa. *Autonomous Robots*, 33(3), 2012.

# The Cutkosky Grasp Taxonomy

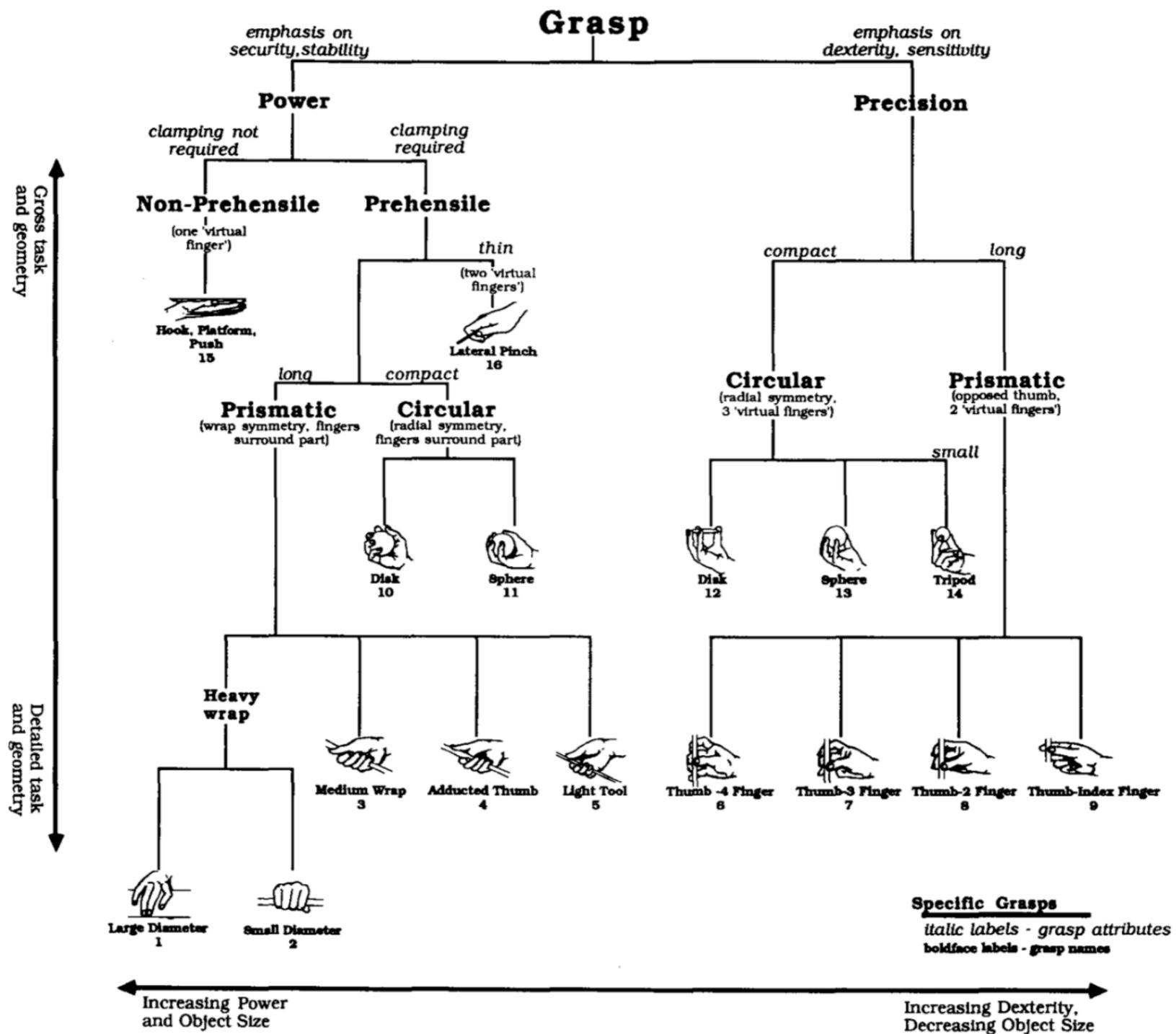


Fig. 4. A partial taxonomy of manufacturing grasps, modified from a taxonomy presented in [4]. The drawings of hands were provided by M. J. Dowling and are reprinted with permission of the Robotics Institute, Carnegie-Mellon University.

# Robotic Grasping

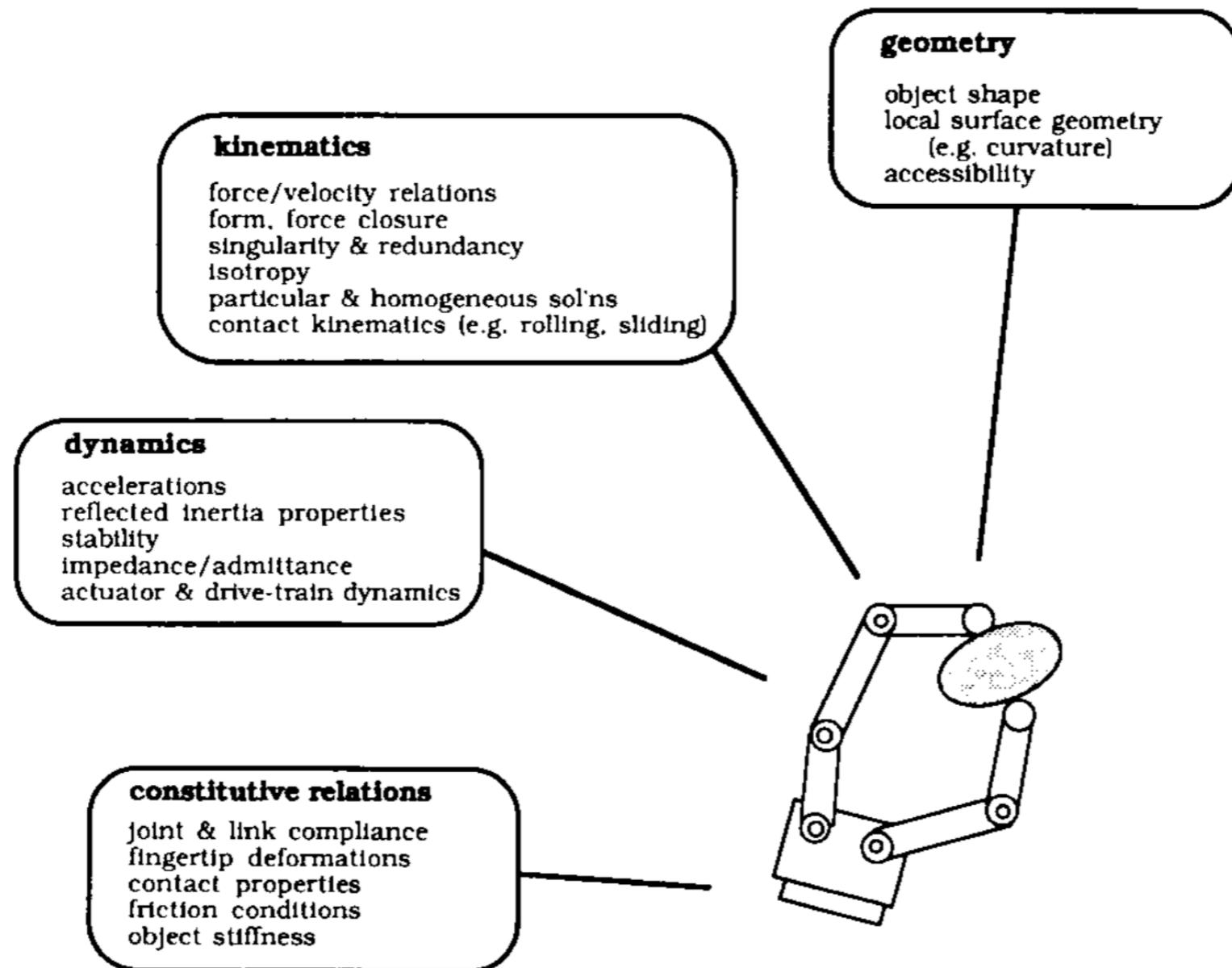
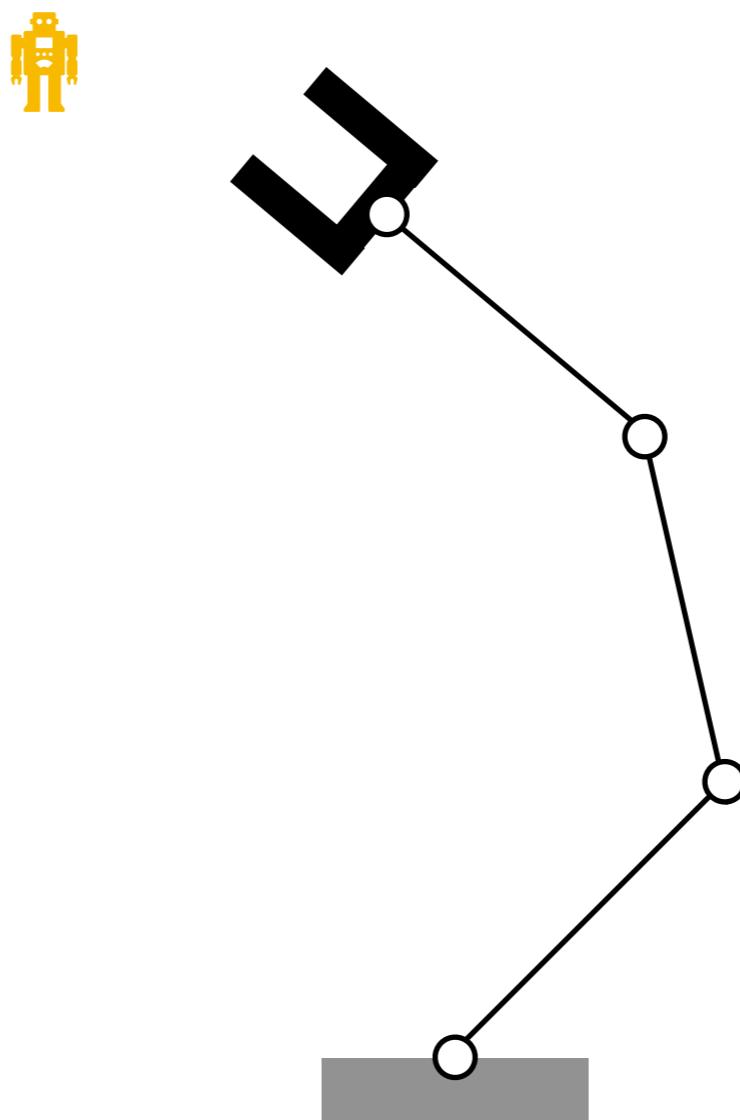


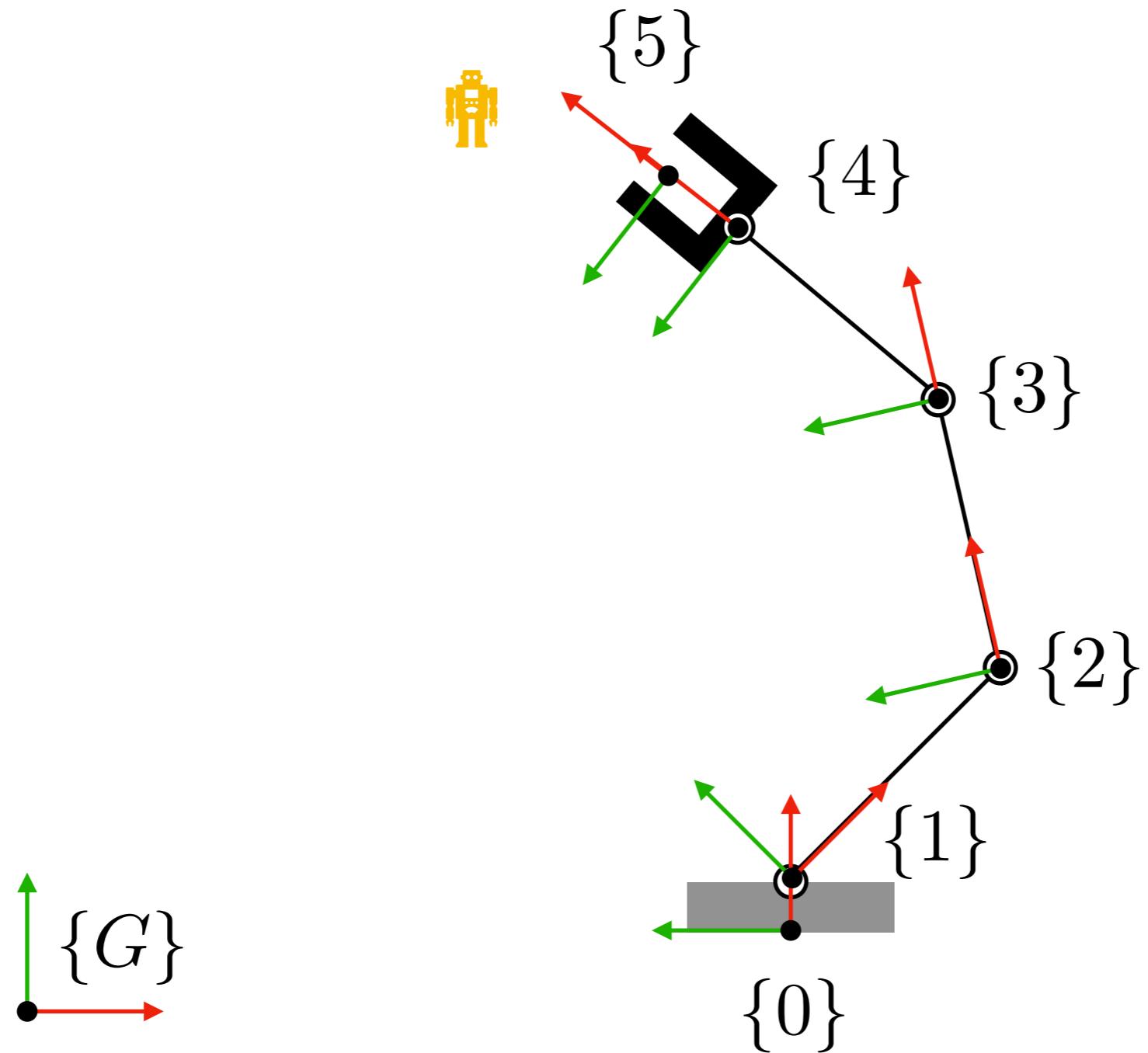
Fig. 1. Issues in analytic modeling of grasping and manipulation.

# Serial Manipulators

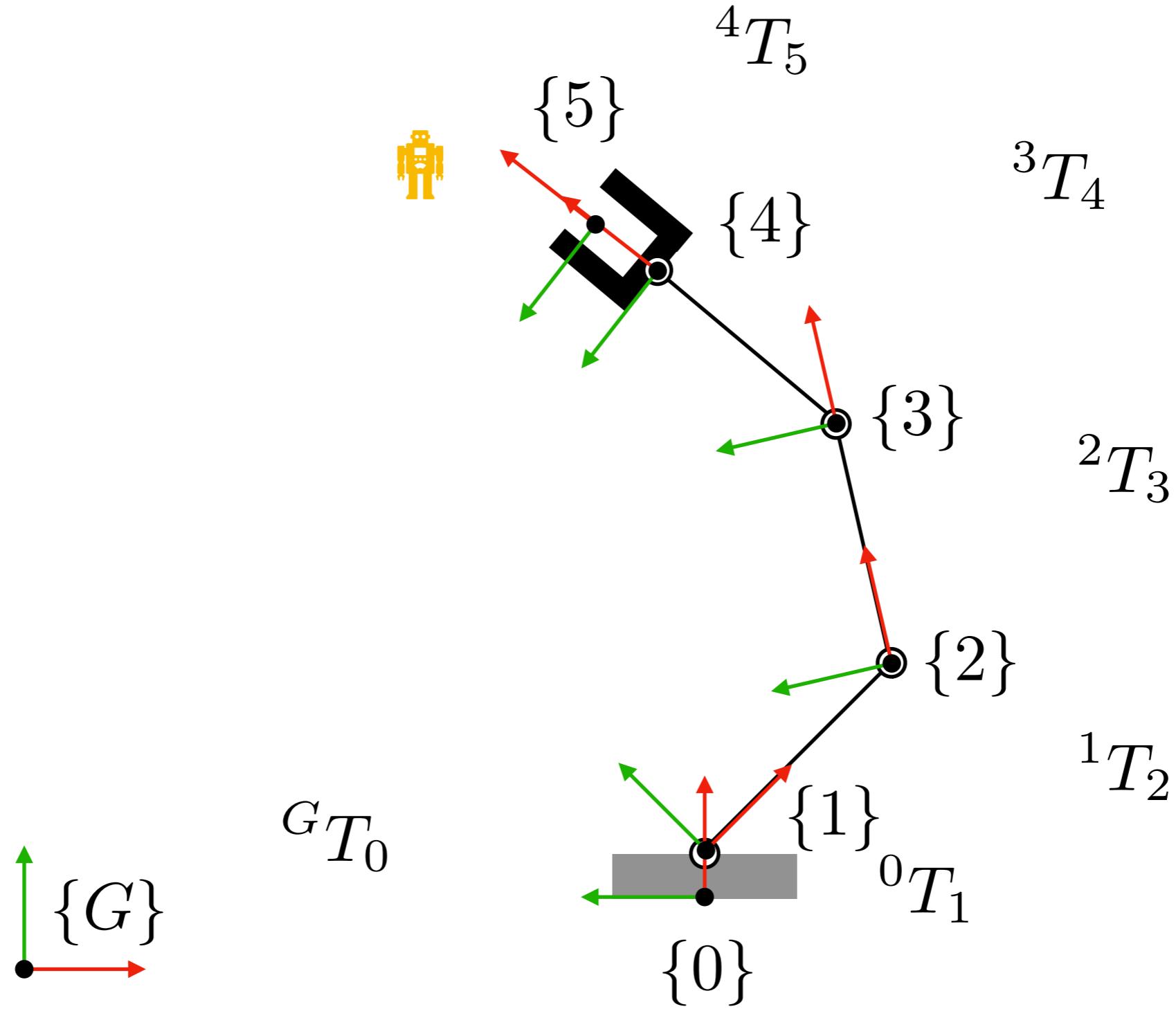
# Serial-Manipulator Kinematics



# Kinematics



# Homogeneous Transform

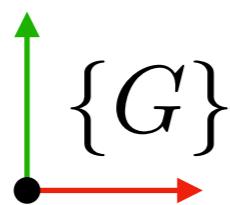


# Homogeneous Transform

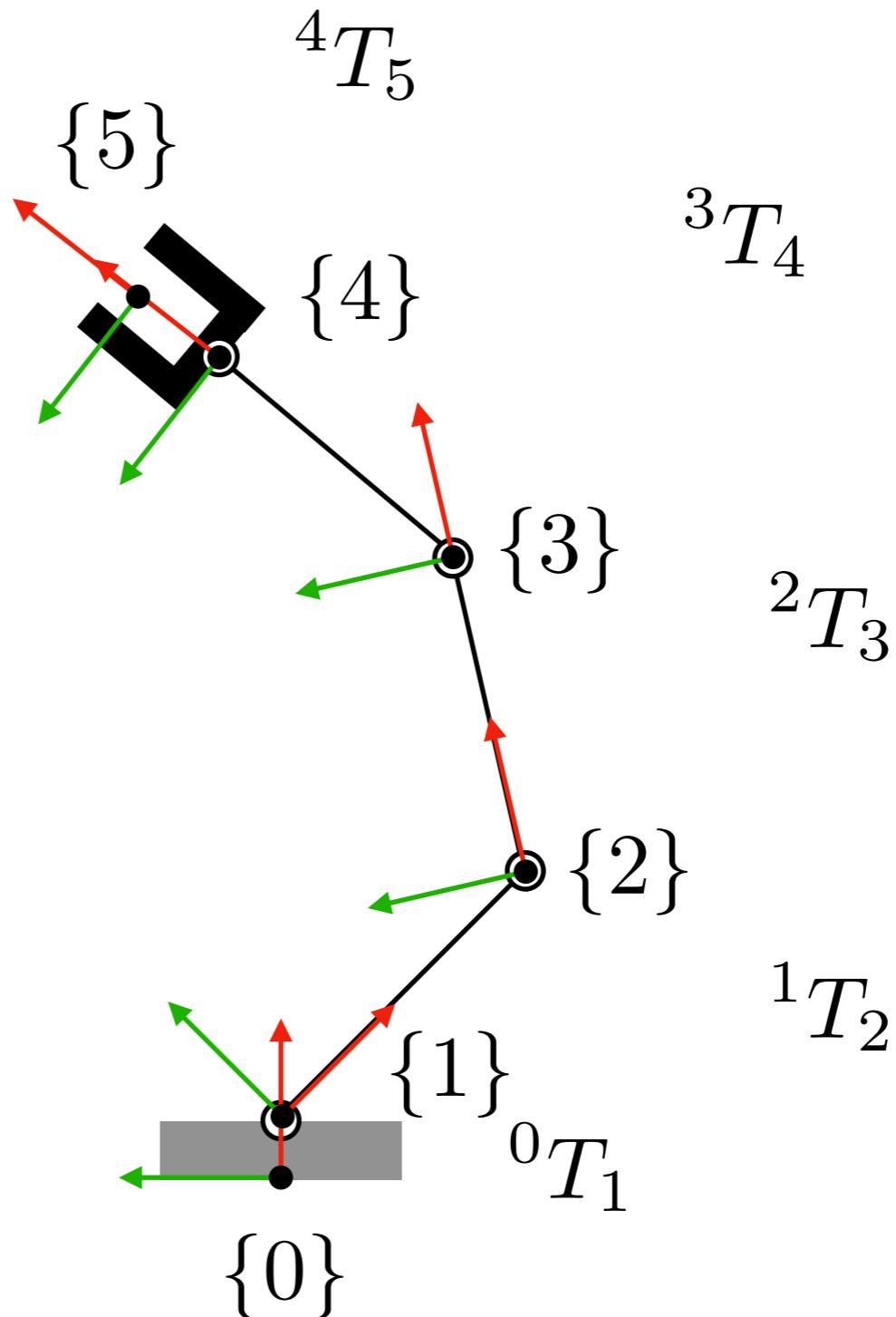
**Rotation**    **Translation**

$${}^i T_{i+1} = \begin{bmatrix} {}^i R_{i+1} & {}^i d_{i+1} \\ 0 & 1 \end{bmatrix}$$

2D, 3D, same formulation



$${}^G T_0$$



# Synthesis of Transforms

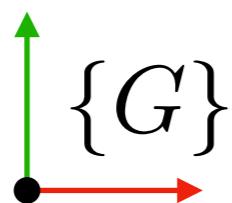
**Rotation      Translation**

$${}^i T_{i+1} = \begin{bmatrix} {}^i R_{i+1} & {}^i d_{i+1} \\ 0 & 1 \end{bmatrix}$$

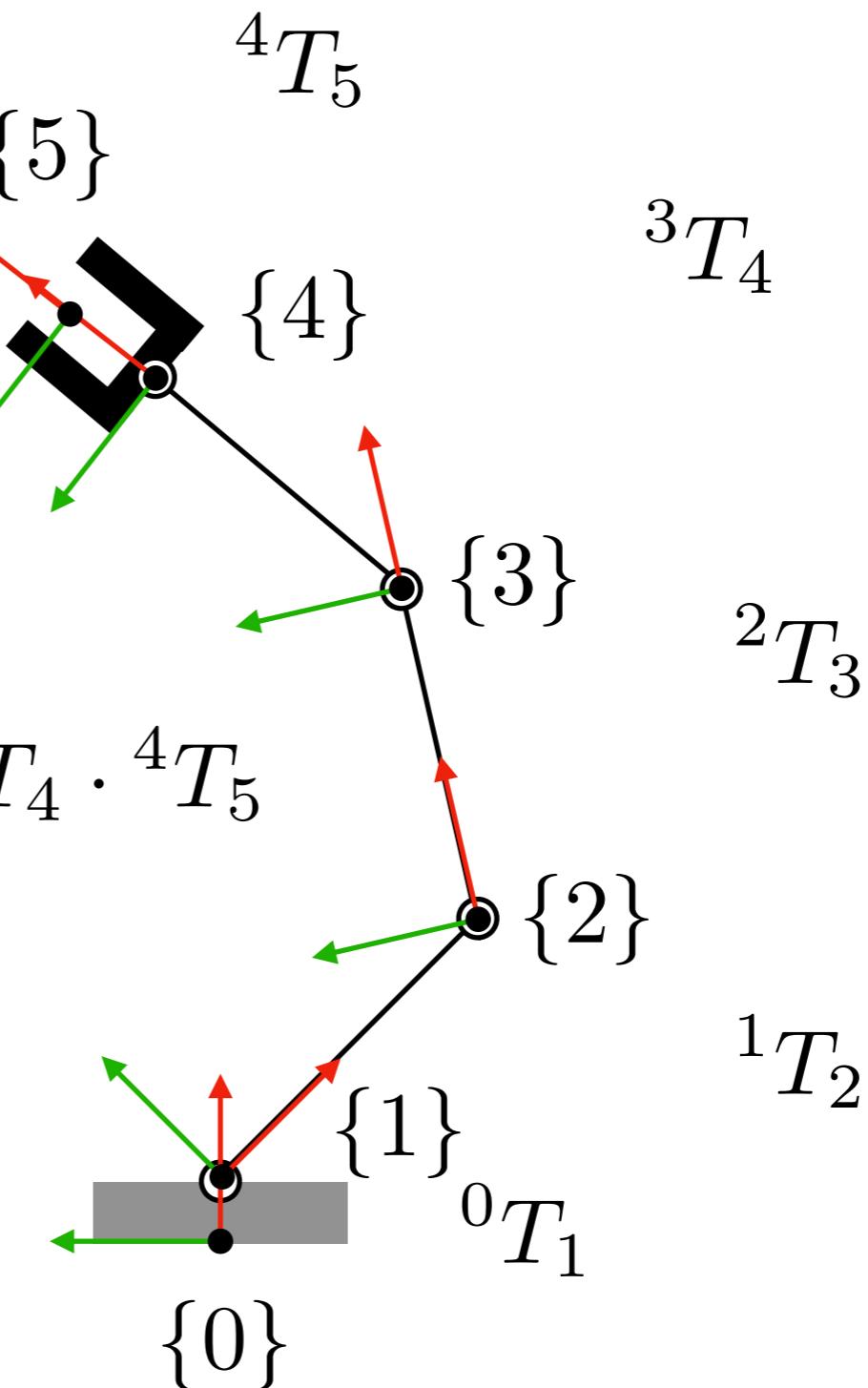
**2D, 3D, same formulation**

$${}^G T_5 = {}^G T_0 \cdot {}^0 T_1 \cdot {}^1 T_2 \cdot {}^2 T_3 {}^3 T_4 \cdot {}^4 T_5$$

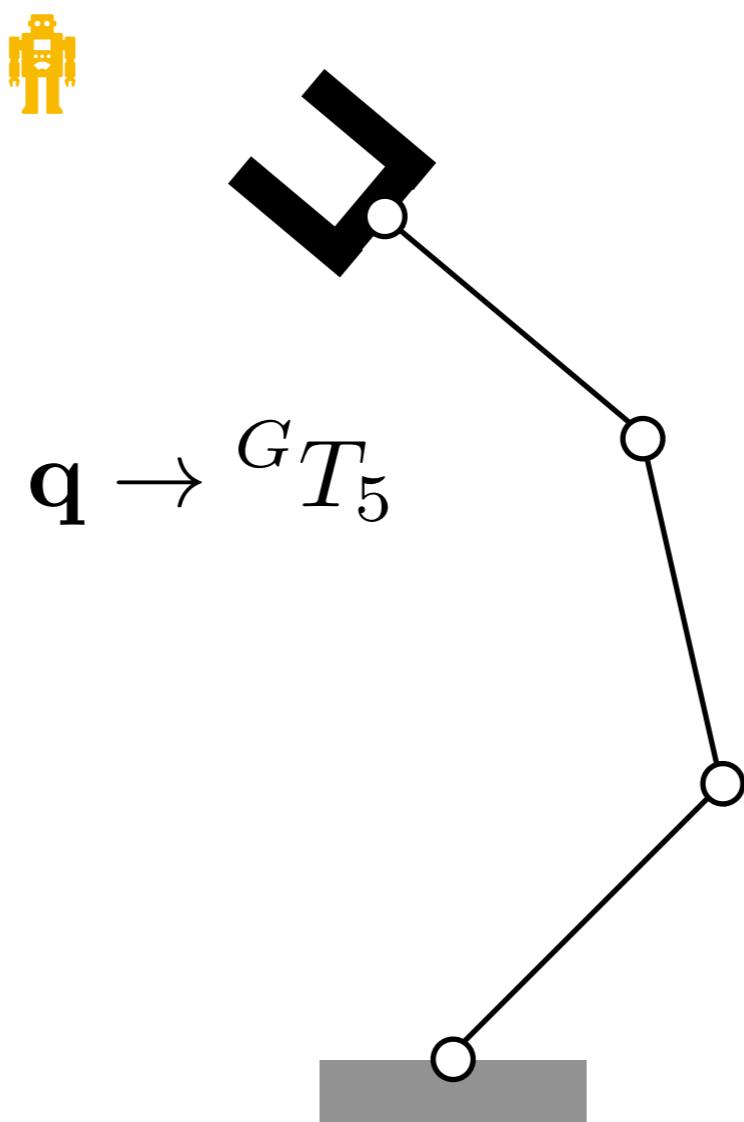
**Forward kinematics**



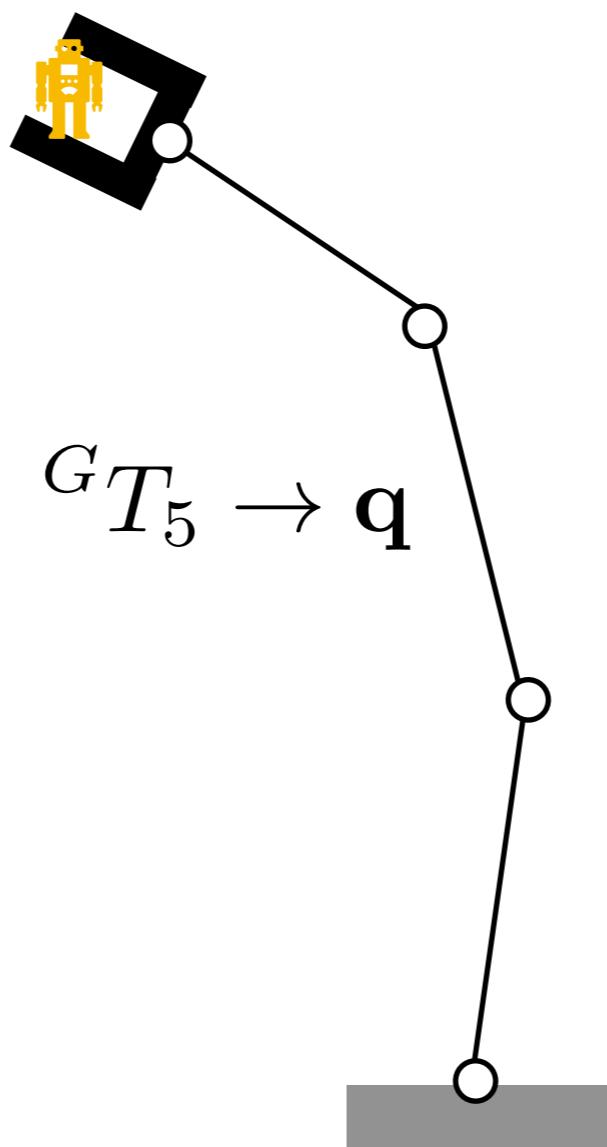
$${}^G T_0$$



# Forward Kinematics

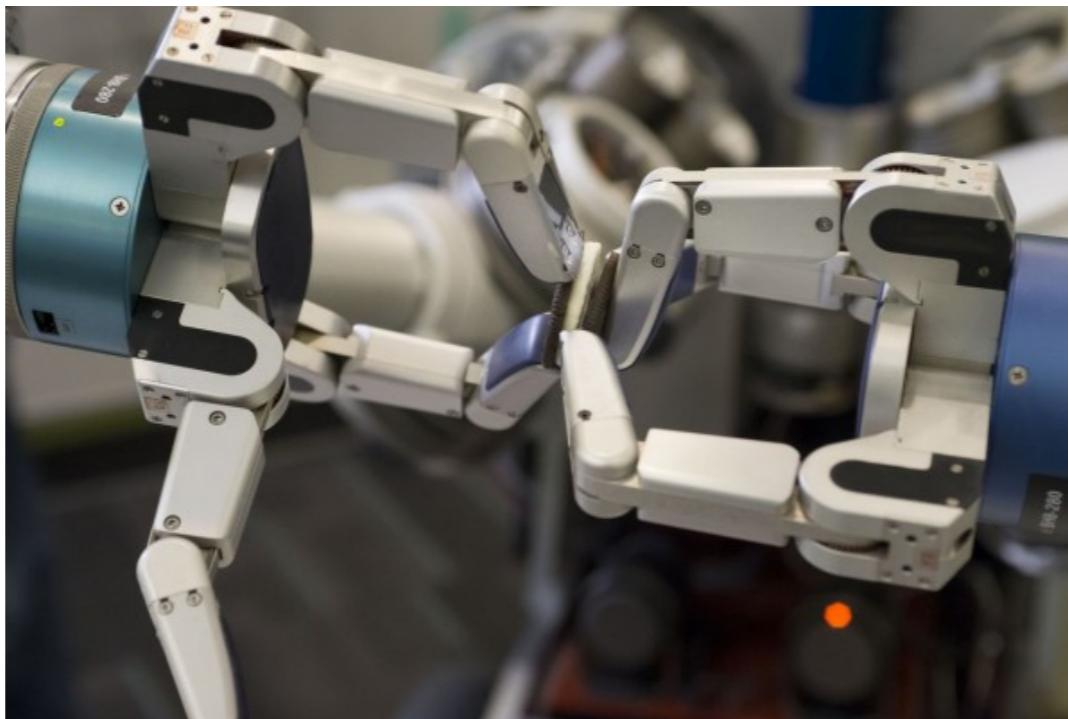


# Inverse Kinematics



# Robot Hands

# Multifingered Rigid Hands



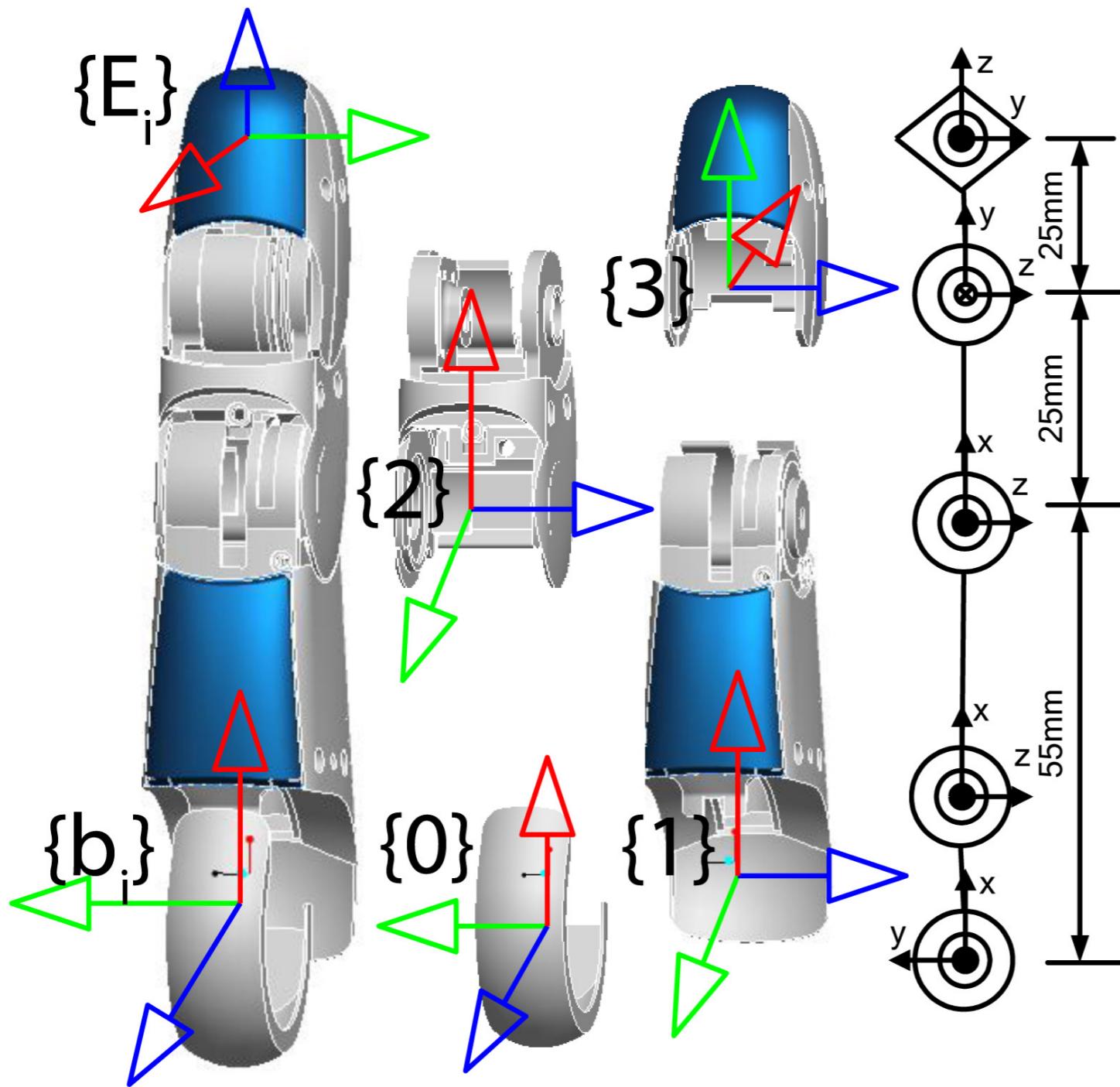
(Barrett Hand) HERB



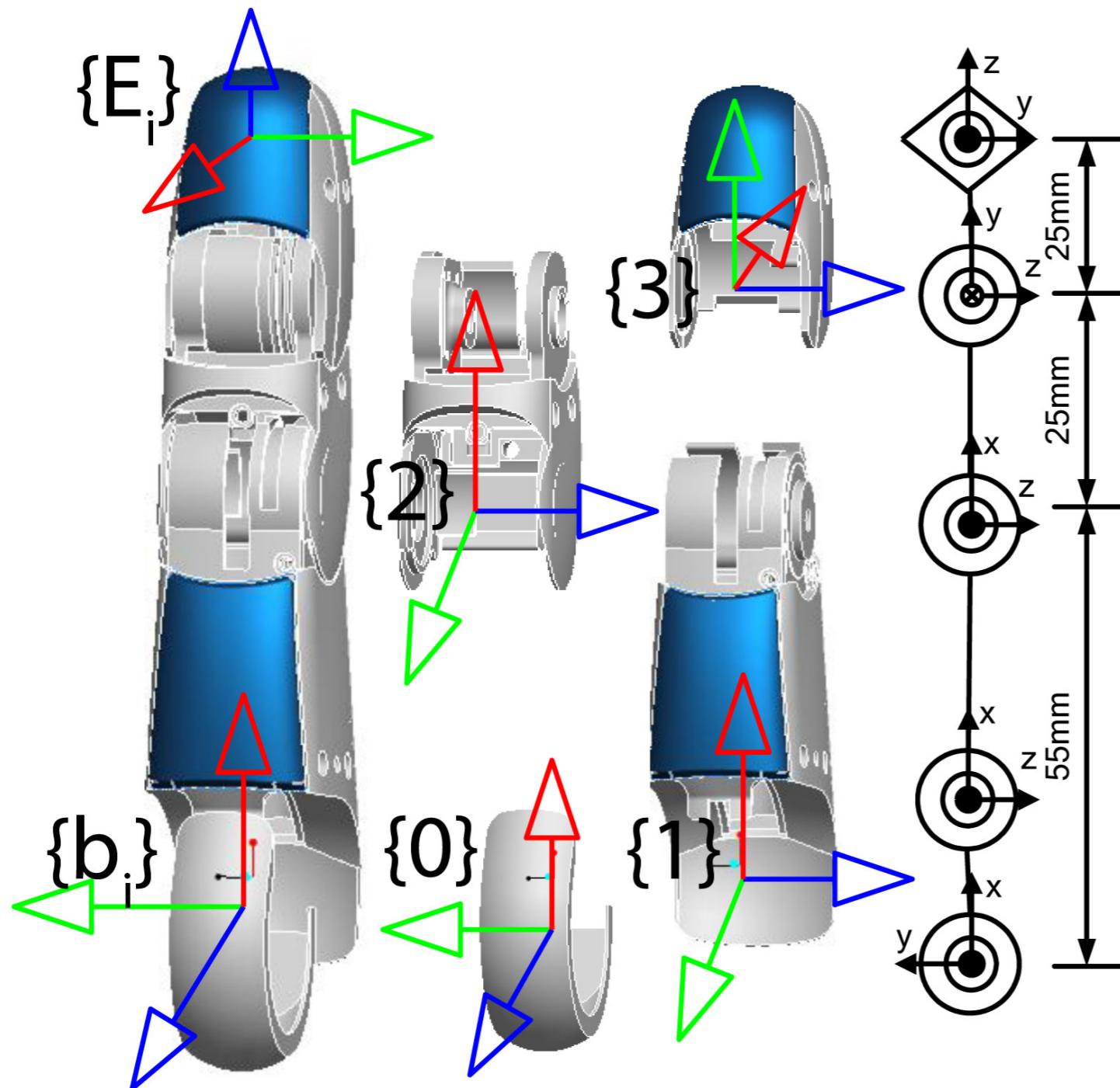
DLR/HIT II

Shadow Dexterous Hand,  
Shadow Robot Company

# Example: DLR/HIT II

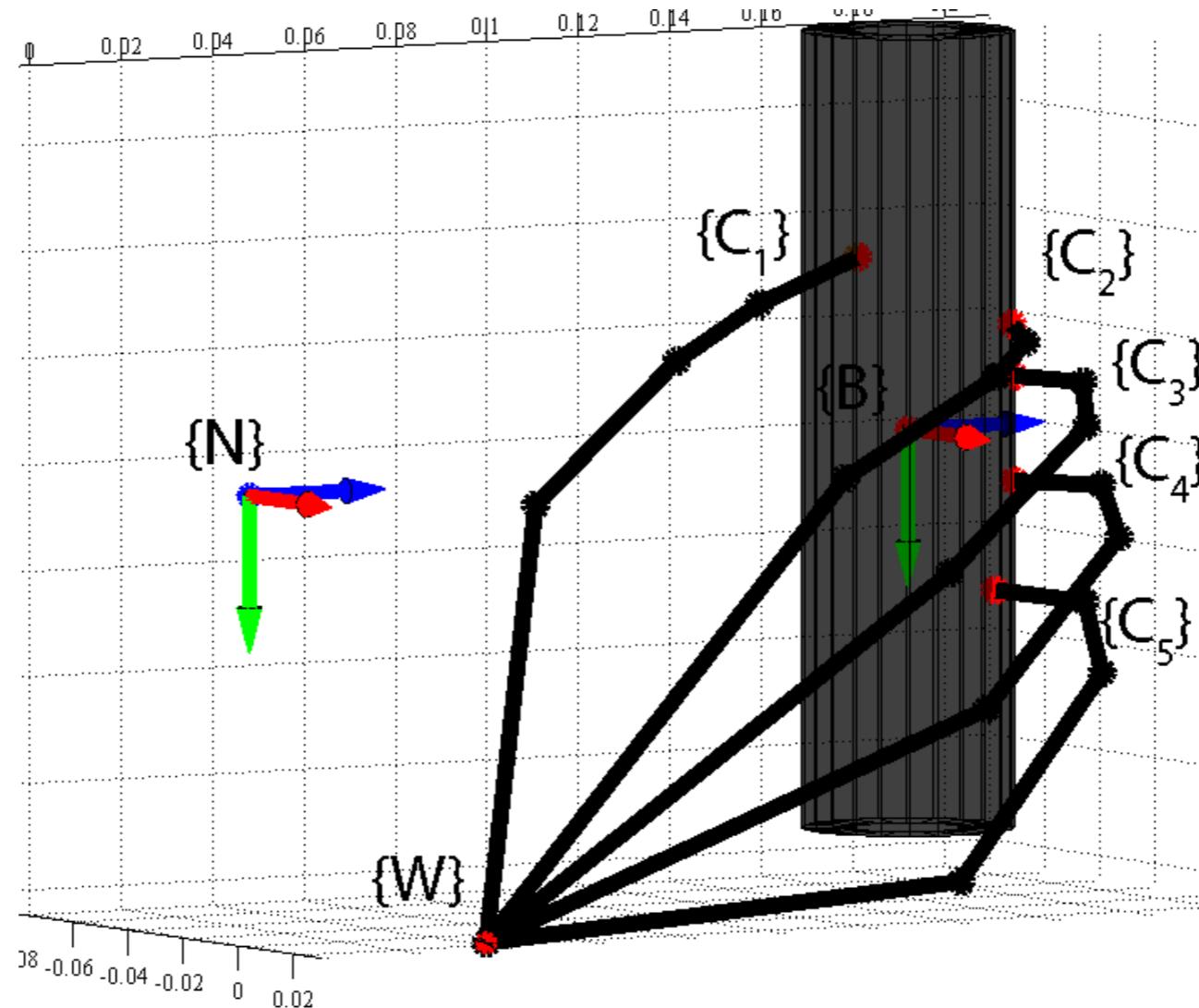


# (Modified) Denavit-Hartenberg Notation



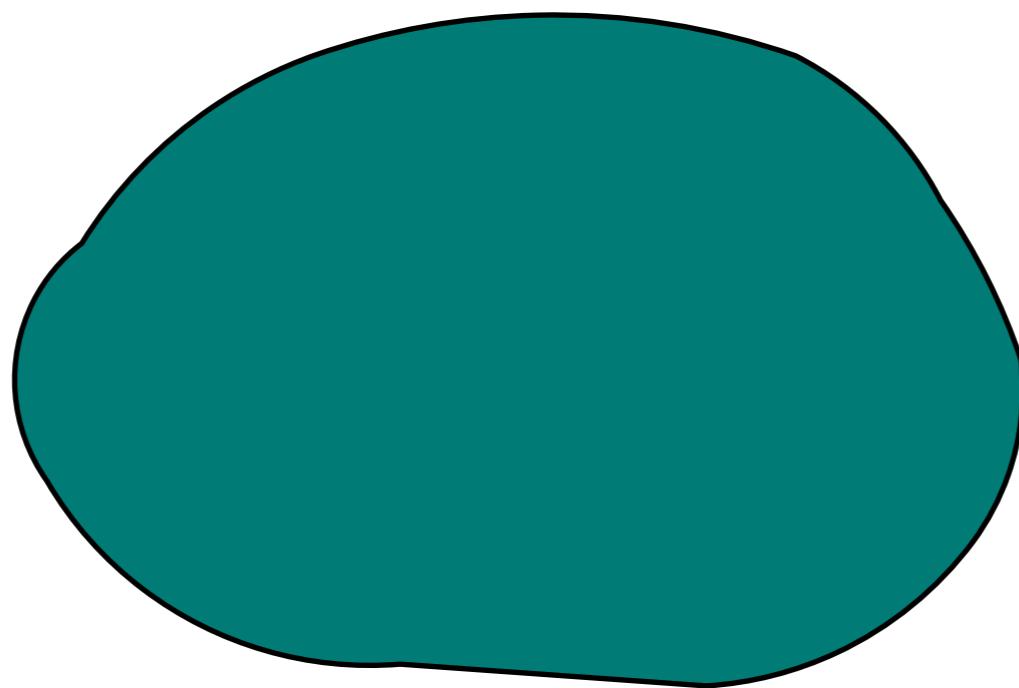
j	$\alpha_{j-1}$	$a_{j-1}$	$d_j$	$\theta_j$
0	0	0	0	$q_0$
1	$90^\circ$	0	0	$q_1$
2	0	55	0	$q_2$
3	0	25	0	$q_3 - 90^\circ$
$E_i$	$-90^\circ$	0	25	$180^\circ$

# DLR/HIT II Forward Kinematics



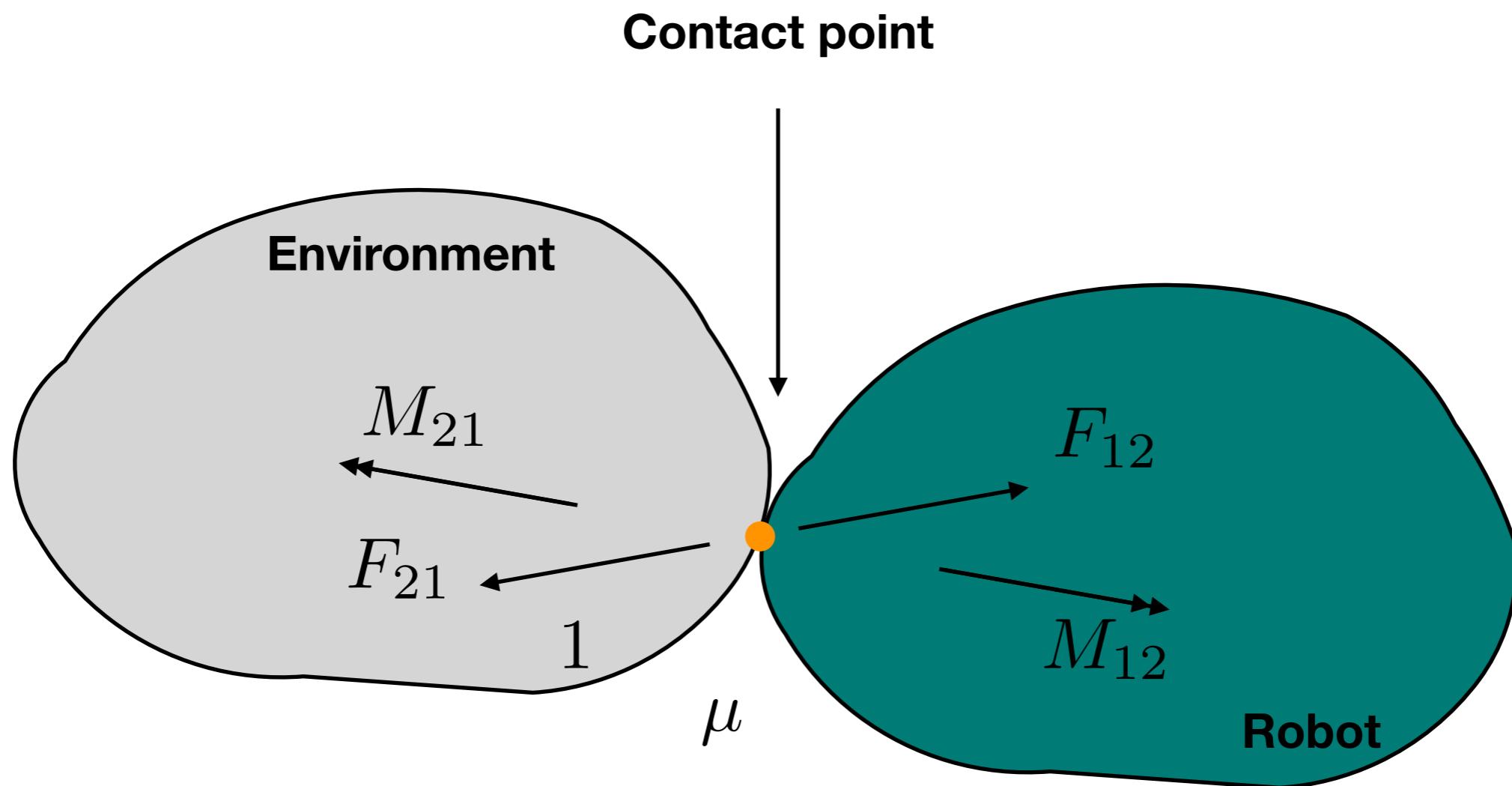
# Contact

# Rigid Body Assumption

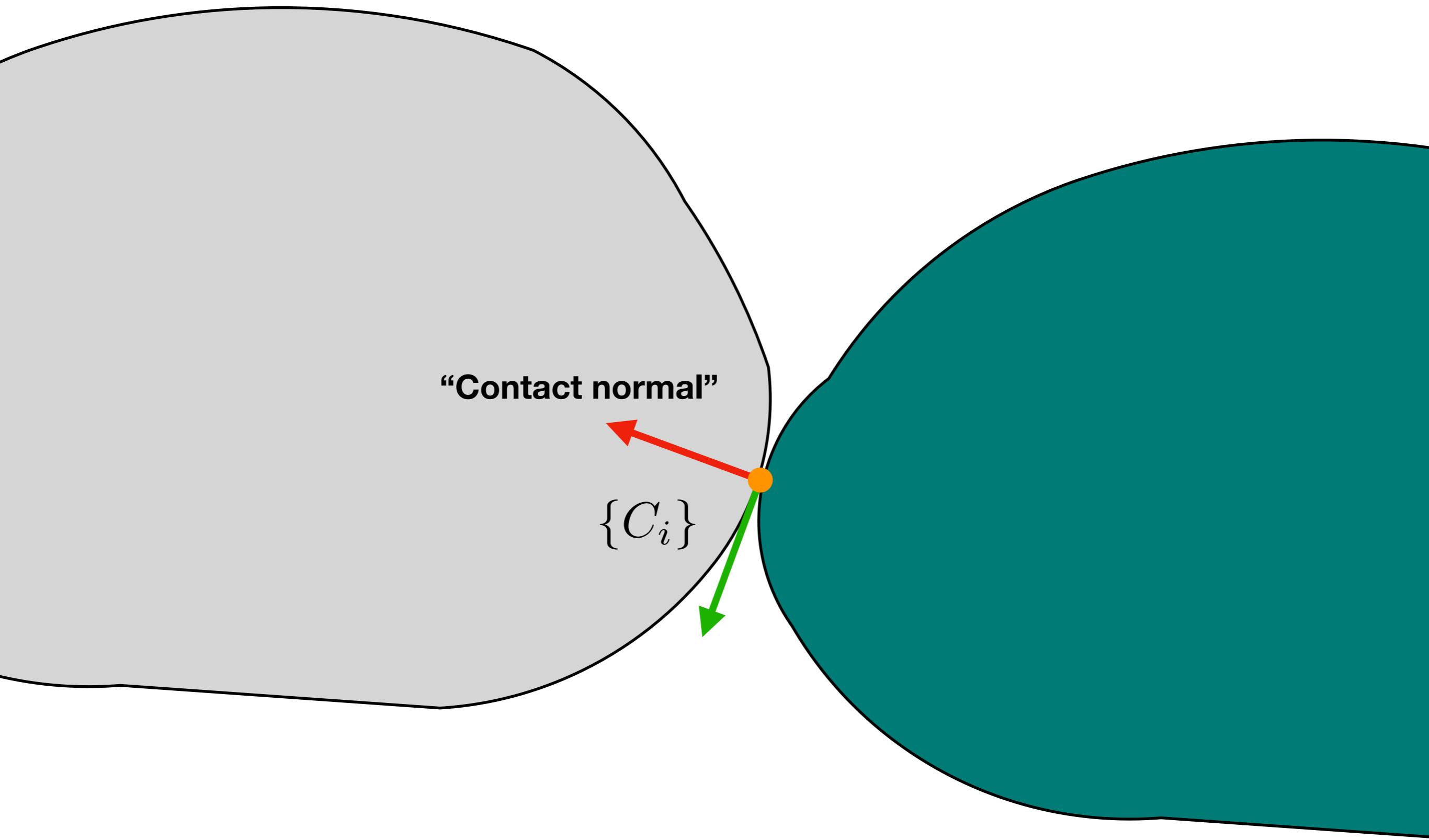


- Neglect deformations.
- Distance between any points of body constant.
- Simplifies analysis, practically valid for a number of problems.

# Contact



# Zoom In



# Contact Modeling

## Point Contact without Friction

- Transmission: Only normal velocity/force.
- Frictional forces/moments negligible; contact patch small, surfaces slippery.

## Hard Finger

- Transmission: Only translational velocity/force.
- Useful: Significant friction at contact but contact patch small.

## *Soft Finger*

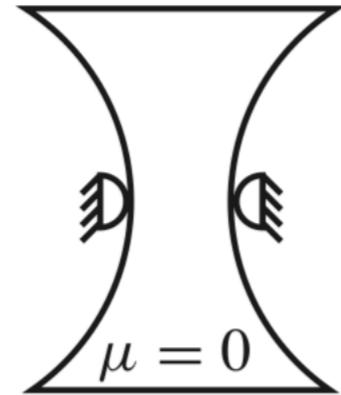
- Transmission: translational velocity/force + rotational velocity/moment around contact normal.
- Useful: when contact patch is large and friction significant.

# Closure Grasps

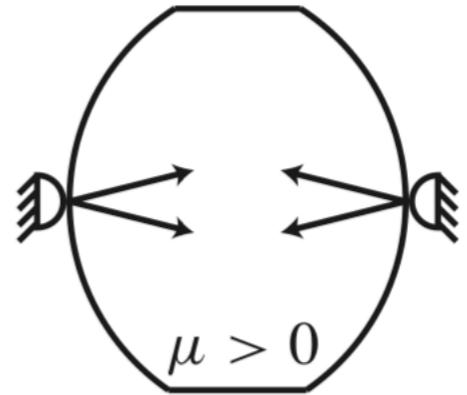


Figures from Bruno Siciliano and Oussama Khatib. 2016. Springer Handbook of Robotics (2nd. ed.). Springer Publishing Company, Incorporated.

# Closure Grasps



Form closure  
does not imply  
force closure



Force closure  
does not imply  
form closure

**Figure from Matt Mason**

## Form Closure

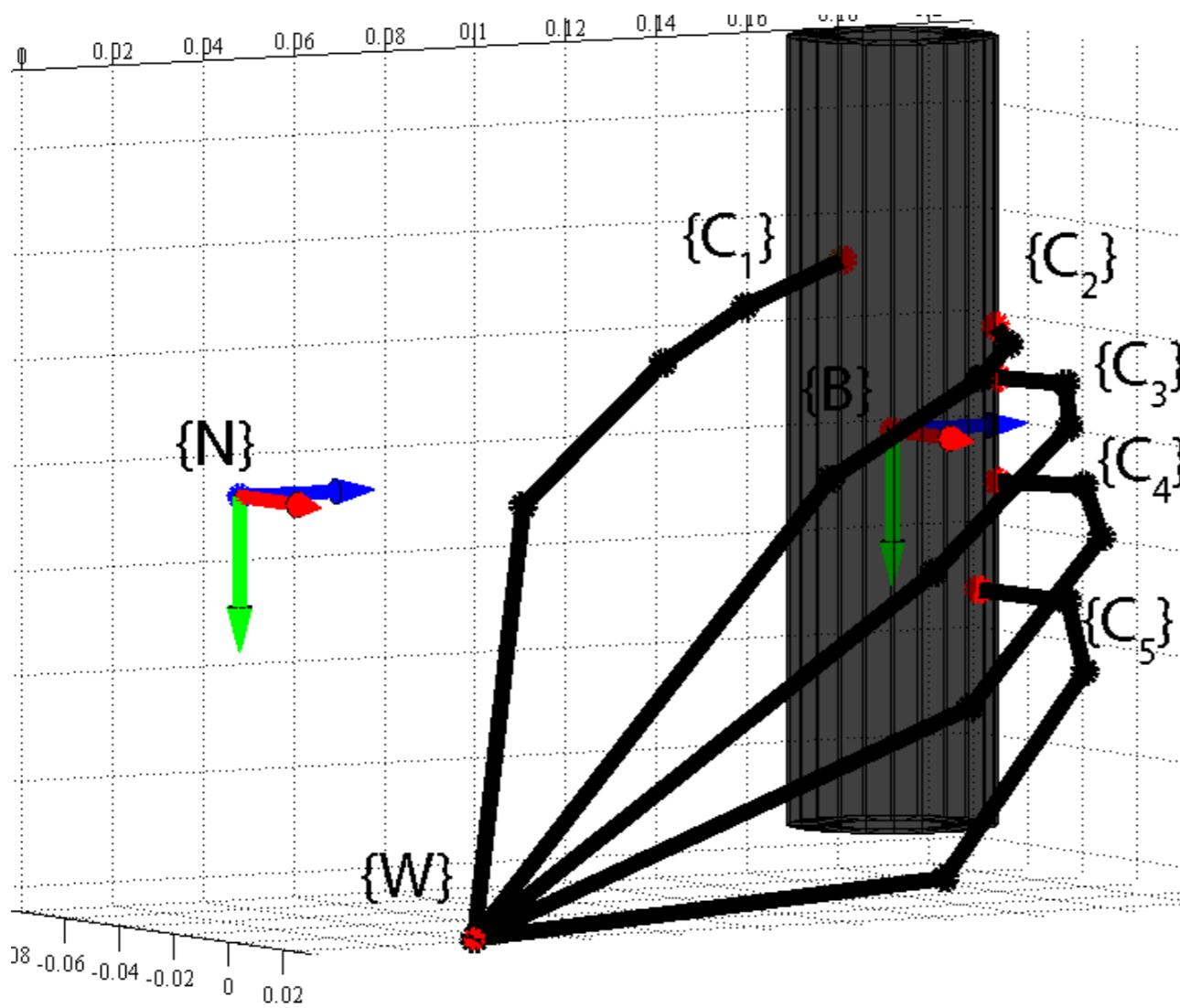
- Fingers and palm wrap around object forming a *cage*.
- Impossible to move the object, even infinitesimally.
- *Power Grasp*.
- Guarantees maintenance of contact (links rigid, joint actuators strong)

## Force Closure

- Under any external wrench, contact forces exist that satisfy object equilibrium conditions.
- Hand to squeeze arbitrarily tight to compensate for external wrenches, through friction.
- *Precision Grasp*.

# Analysis

# Grasp Analysis



**Kinematics**

$${}^G T_{C_i}$$

**Force at contact (HF)**

$$C_i f_i$$

**Wrench to object's CoM**

$$\mathbf{g} = \mathbf{G}^C \mathbf{f}$$

$6 \times 1 \quad 6 \times 15 \quad 15 \times 1$

↑

**Grasp Matrix**

# Force Closure

## 2 Conditions

- Object at equilibrium
- No sliding at contacts

$$\mathbf{g} = -\mathbf{w}$$

**External wrench**

$$\sqrt{{}^C f_{t,i}^2 + {}^C f_{o,i}^2} \leq \mu {}^C f_{n,i}$$



$$\mathcal{F}_i = \{{}^C \mathbf{f}_i = [{}^C f_{n,i} \quad {}^C f_{t,i} \quad {}^C f_{o,i}]^T \in \mathbb{R}^3 \mid \sqrt{{}^C f_{t,i}^2 + {}^C f_{o,i}^2} \leq \mu {}^C f_{n,i}\}$$

**Friction cone**

# Synthesis

# Grasp Synthesis

$$\mathbf{f}^* = \arg \min_{\mathbf{f}} Q(\mathbf{f}, \mathbf{q})$$

s.t.     $\mathbf{g} + \mathbf{w} = 0$     (**equilibrium**)

$$C_i \mathbf{f}_i \in \mathcal{F}_i \quad (\textbf{friction cone})$$

$$NT_{C_i} - NT_{O_i} = 0 \quad (\textbf{kinematics})$$

$$\mathbf{f}_i \in \mathcal{F}_i^{motor} \quad (\textbf{force constraints})$$

$$q_i \in \mathcal{Q}_i \quad (\textbf{joint limits})$$

# Grasp Quality Measures

## Categories

- Contact forces
- Hand configuration
- Grasp Robustness

...

## Examples

- Normal force magnitudes
- Manipulability
- Task-specificity

...

# Recent trends: End-to-end Manipulation

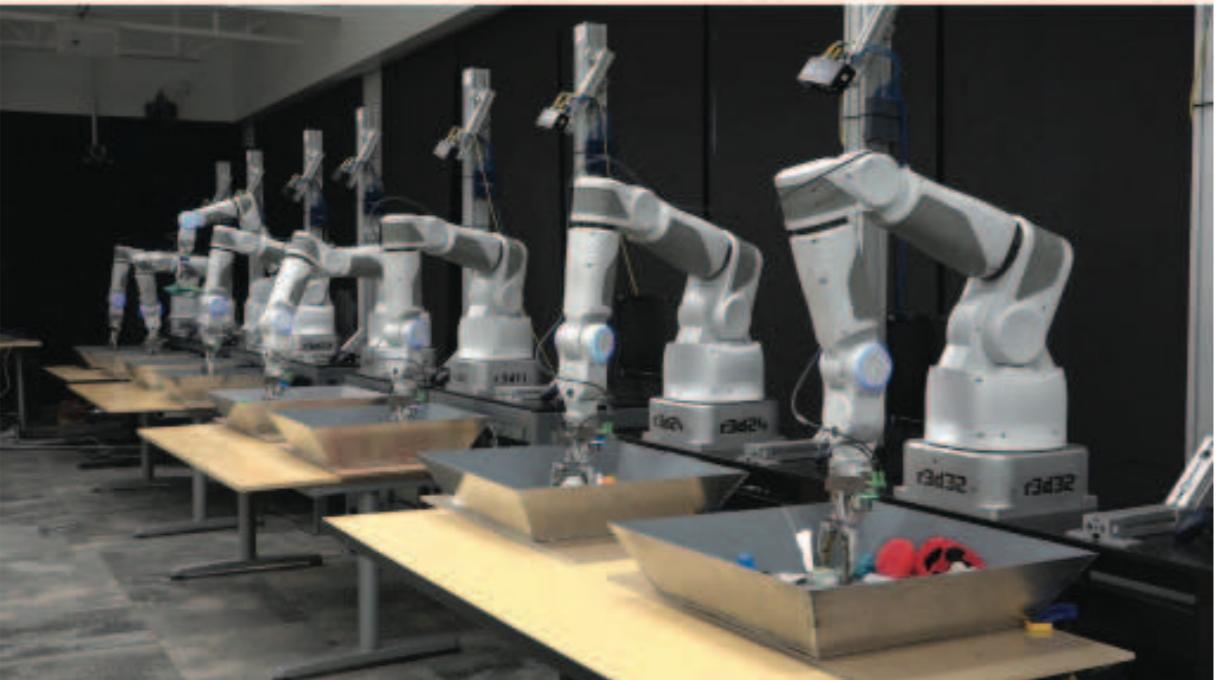
# Deep Learning for Detecting Robotic Grasps



[\*\*https://youtu.be/f9Cuzql1SkE\*\*](https://youtu.be/f9Cuzql1SkE)

Lenz, I., Lee, H., & Saxena, A. (2015). Deep learning for detecting robotic grasps. *The International Journal of Robotics Research*, 34(4–5), 705–724. <https://doi.org/10.1177/0278364914549607>

# Learning Hand-Eye Coordination for Robotic Grasping



The Google “arm farm”

[https://youtu.be/cXaic\\_k80uM](https://youtu.be/cXaic_k80uM)

Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International Journal of Robotics Research*, 37(4–5), 421–436. <https://doi.org/10.1177/0278364917710318>

# Dex-Net



<https://youtu.be/GBiAxoWBh0>

<https://berkeleyautomation.github.io/dex-net>

The Dexterity Network (Dex-Net) is a research project including code, datasets, and algorithms for generating datasets of synthetic point clouds, robot parallel-jaw grasps and metrics of grasp robustness based on physics for thousands of 3D object models to train machine learning-based methods to plan robot grasps. The broader goal of the Dex-Net project is to develop highly reliable robot grasping across a wide variety of rigid objects such as tools, household items, packaged goods, and industrial parts.

# Assistive Feeding



[\*\*https://www.youtube.com/watch?v=t2eO4CD-0WY\*\*](https://www.youtube.com/watch?v=t2eO4CD-0WY)

(Dr. Tapo Bhattacharjee will talk about ADA next week)

# Next: Social Robot Navigation

