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Haptic Object Identification for Advanced Manipulation Skills

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LIVING MACHINES 2020

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Motivation

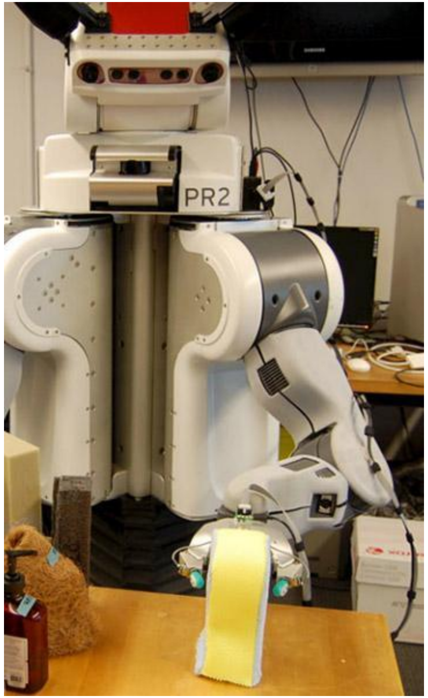
Allow robots to manipulate unknown objects

Object Identification using Computer Vision

- ✓ Extract shapes and geometries
- ✗ Extract structural information
- ✗ Estimate physical parameters

Object Identification through Haptic Exploration

- ✓ Extract shapes and geometries
- ✓ Extract structural information
- ✓ Estimate physical parameters



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Outline

- Problem Formulation
- Background
- Haptic Exploration
- Haptic Object Identification
- Experimental Results
- Outlook and Summary

Problem Formulation

Iteratively Refine Estimated Object Properties

Given:

- robot pose $\boldsymbol{x}_{0:t}$
- control inputs $\boldsymbol{u}_{0:t}$
- and measurements $\boldsymbol{r}_{0:t}$

from start to time t, refine object knowledge given as the belief of

(object geometry) $$\boldsymbol{M} \leftarrow \mathcal{F}_m(\boldsymbol{x}_{0:t}, \boldsymbol{u}_{0:t}, \boldsymbol{r}_{0:t}, \Theta),$$

(material parameters) $$\Theta \leftarrow \mathcal{F}_p(\boldsymbol{x}_{0:t}, \boldsymbol{u}_{0:t}, \boldsymbol{r}_{0:t}, \boldsymbol{M}).$$

⇨ Identification is directly coupled

⇨ Mainly solved individually in literature

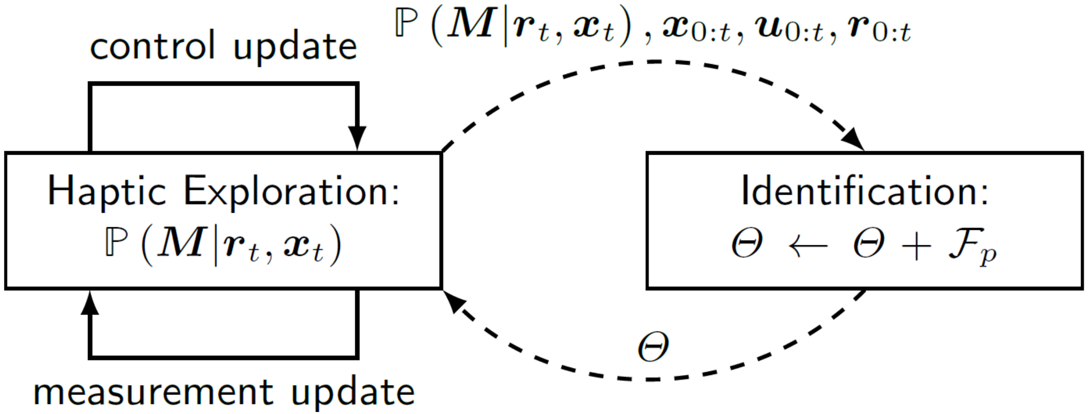
Related Work

Haptic Exploration

- Haptic SLAM [Behbahani+ 2015]
- SLAM with known shapes [Schaeffer+ 2004]
- Bayesian exploration framework [Julian+ 2012]

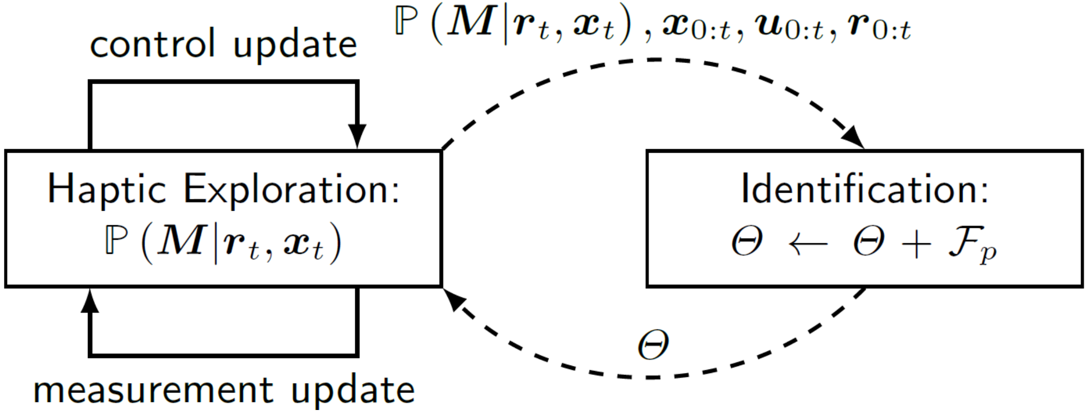
Haptic Identification

- Tactile object recognition [Pezzementi+ 2011, Friedl+ 2016]
- Object classification [Decherchi+ 2011]
- Material classification [Xu+ 2013]



Outline a combined object estimation framework

Framework Overview



Outline a combined object estimation framework

Grid-based

Shape-based

Background

Simultaneous Localization and Mapping (SLAM)

- Estimate pose of robot while simultaneously estimate map of environment
- Joint distribution: $\mathbb{P}\left[\boldsymbol{x}_t, \boldsymbol{M} | \boldsymbol{x}_{0:t-1}, \boldsymbol{u}_{0:t}, \boldsymbol{r}_{0:t}\right]$
- Most common solutions use Extended Kalman Filter and Particle Filters

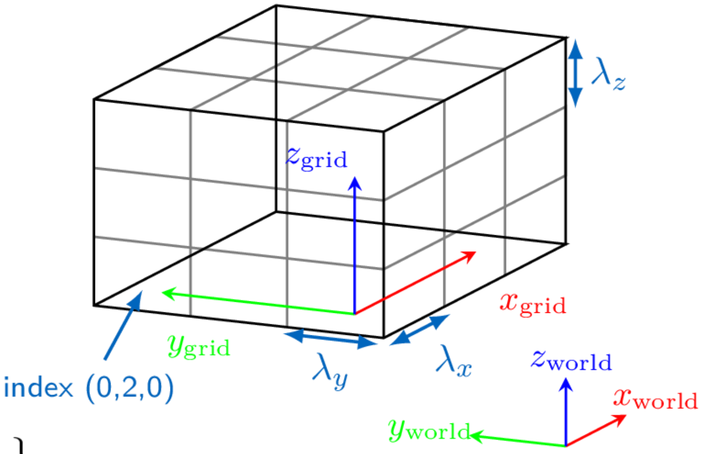
Haptic SLAM [Behbahani+ 2015]

- Estimate robot pose while constructing a map of object based on haptic feedback
- Particle Filter approach using an occupancy grid

Background – Inference Grids

Occupancy Grid $\boldsymbol{M}$

- State of cell: $m_t \in \{\texttt{occ}, \texttt{empty}\}$
- Content of cell: $\mathbb{P}\left[m_t = \texttt{occ} | \boldsymbol{r}_t\right]$
- Iterative update: $m_t = m_{t-1} + \log \frac{\mathbb{P}[\boldsymbol{r}_t|\boldsymbol{f}]}{1-\mathbb{P}[\boldsymbol{r}_t|\boldsymbol{f}]}$



Inference Grid $\boldsymbol{\mathcal{M}}$ [Elfes1989; Korthals2017]

- Multi-layer occupancy grid: $\boldsymbol{\mathcal{M}} := \{\boldsymbol{M}_0, \boldsymbol{M}_1, \ldots \boldsymbol{M}_n\}$
- Encodes 2^n states

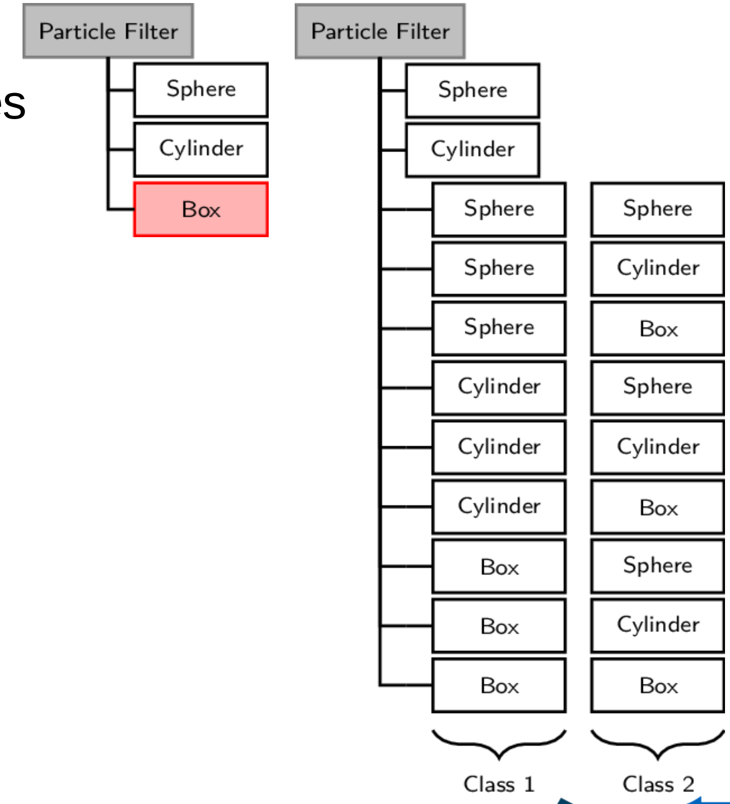
Background – Geometric Shape Representation

Representing Objects Using Geometric Primitives

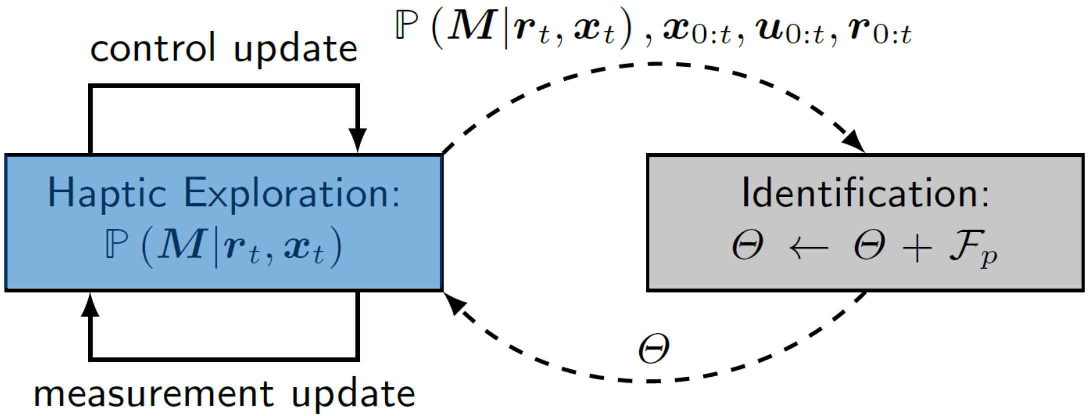
- Data efficient
- Can represent structure by arbitrary combinations
- Allows to directly regress model-parameters from data

Incorporated Models

- Spheres $\Phi := (r, \boldsymbol{c})$
- Cylinders $\Phi := (r, h, \boldsymbol{c}, \boldsymbol{a})$
- Boxes $\Phi := (\boldsymbol{c}_1, \boldsymbol{c}_2, \ldots, \boldsymbol{c}_8)$
- Planes $\Phi := (\boldsymbol{n}, \boldsymbol{c}_1, \boldsymbol{c}_2, \boldsymbol{c}_3, \boldsymbol{c}_4)$



Haptic Exploration



Grid-based

Shape-based

Collected Sensor Data

Sensor

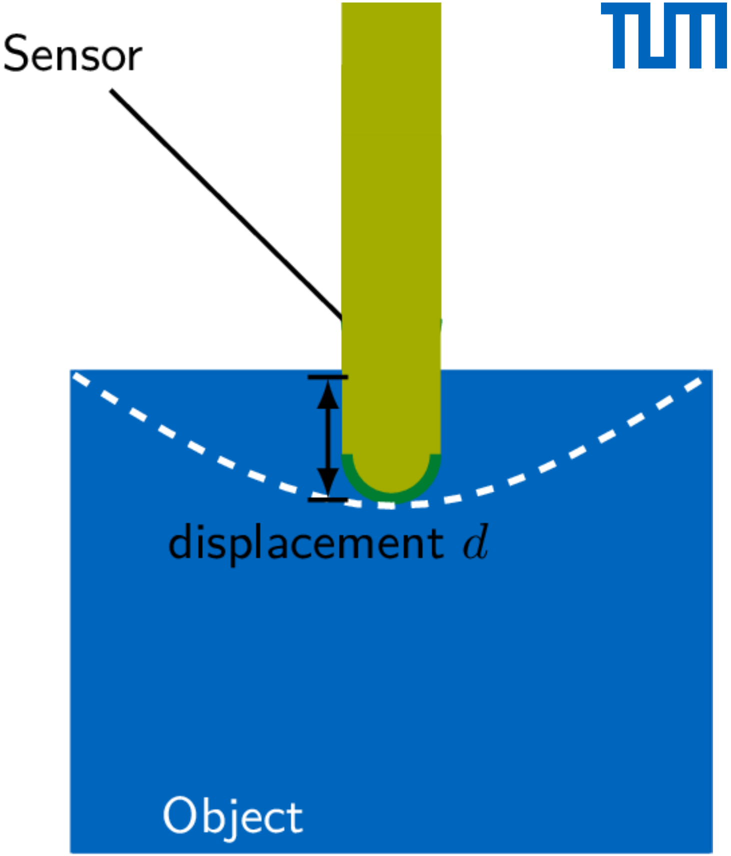
normal contact force

Measurement Procedure

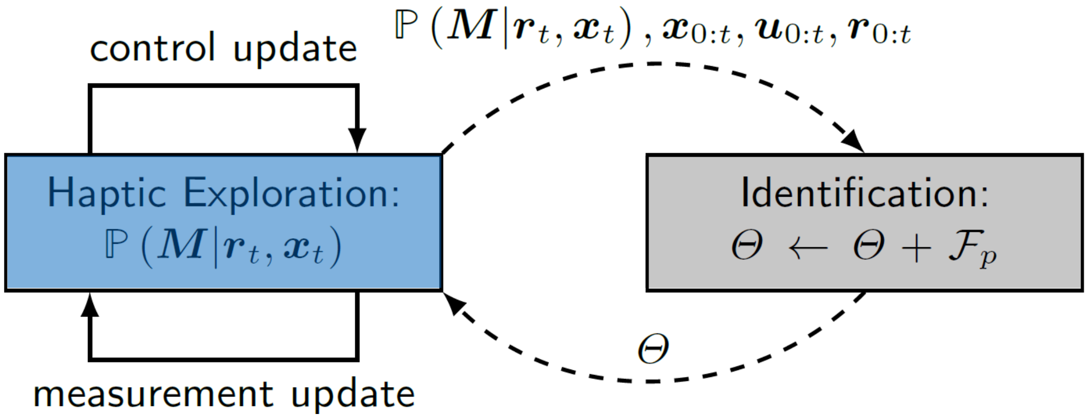
increase force F_t until $F_t > F_{\max}$ or $d_t > d_{\max}$

Measurement Data

$$\boldsymbol{r}_t = (\boldsymbol{x}_t, d_t, F_t)$$



Haptic Exploration – Grid-Based



Grid-based

Shape-based

Haptic Exploration – Grid-Based

1. Select Next Exploration Goal

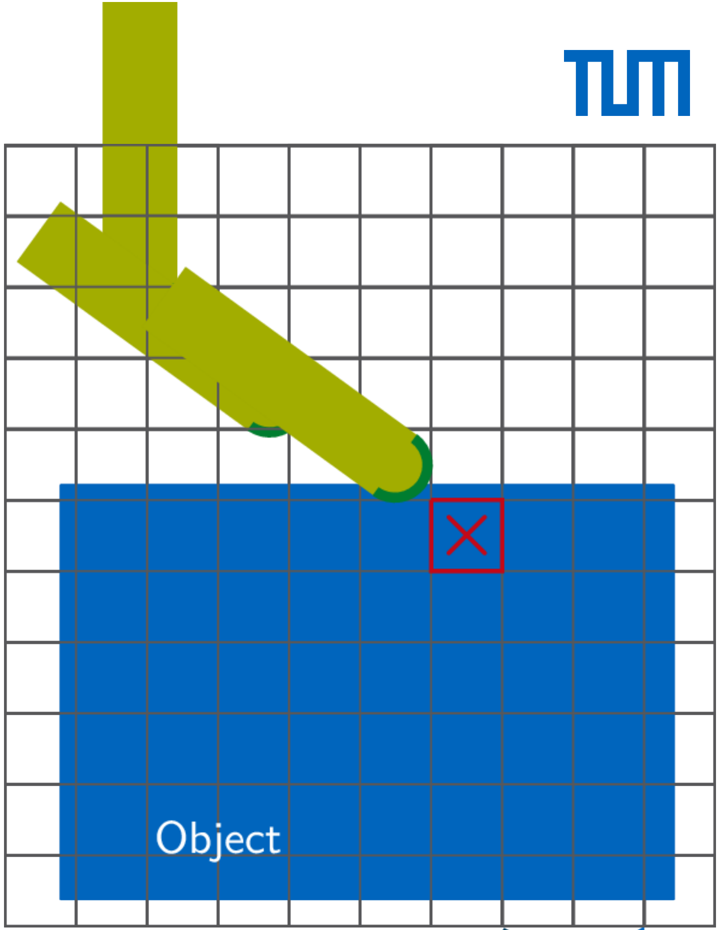
- utility $\boldsymbol{U}(m_t)$: expected information gain
- accessibility $\boldsymbol{\alpha}(m_t)$: cell reachability

⇨ select next cell as $\operatorname{argmax}_{m_t} \{\boldsymbol{U}(m_t)\boldsymbol{\alpha}(m_t)\}$

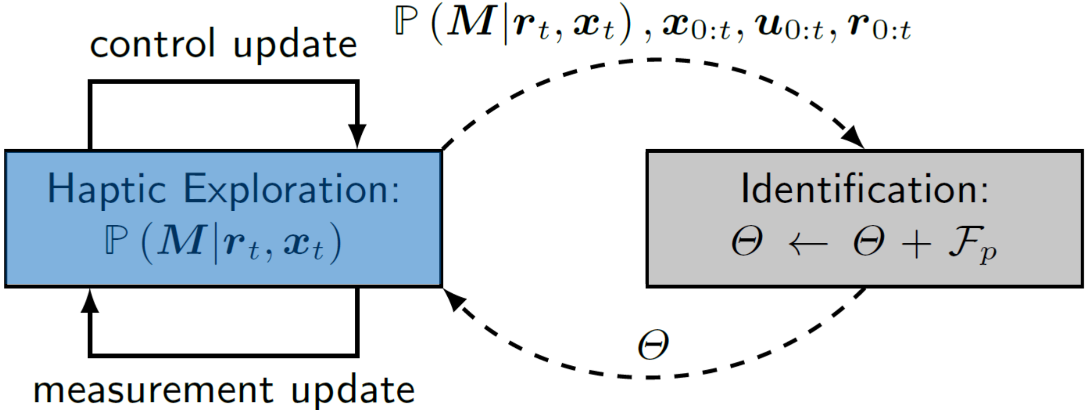
2. Take New Measurement

3. Process Data

- Update belief of explored cells
- Store measured data in buffer



Haptic Exploration – Shape-Based



Grid-based

Shape-based

Haptic Exploration – Shape-Based

1. Select Next Exploration Goal

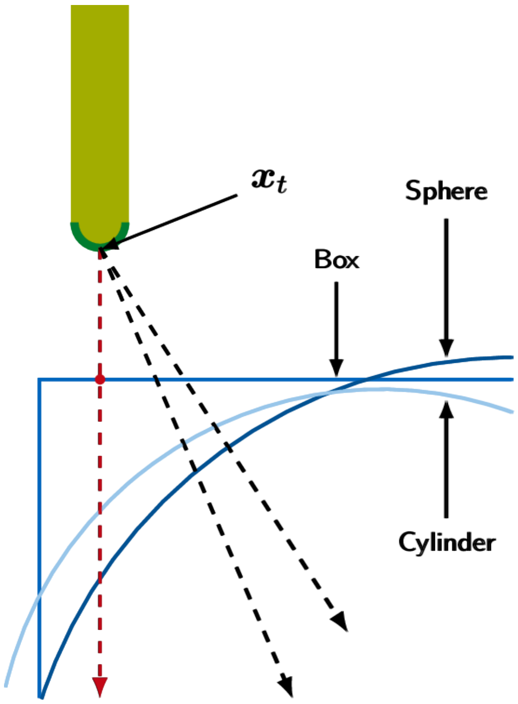
utility $U(\boldsymbol{x}_t)$: evaluates the deviation of shape-types for current particle samples

⇨ select next cell as $\operatorname{argmax}_{\boldsymbol{x}_t} \{U(\boldsymbol{x}_t)\}$

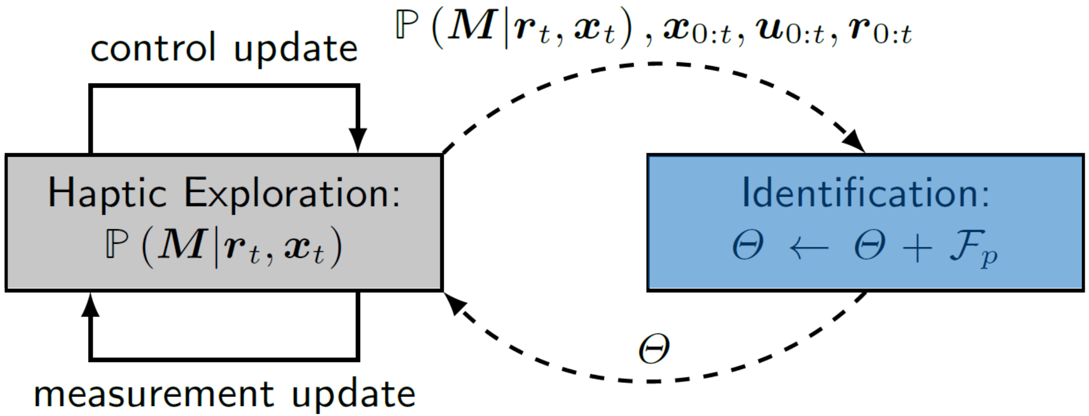
2. Take New Measurement

3. Process Data

- Update belief of current shape particles
- Store measured data in buffer



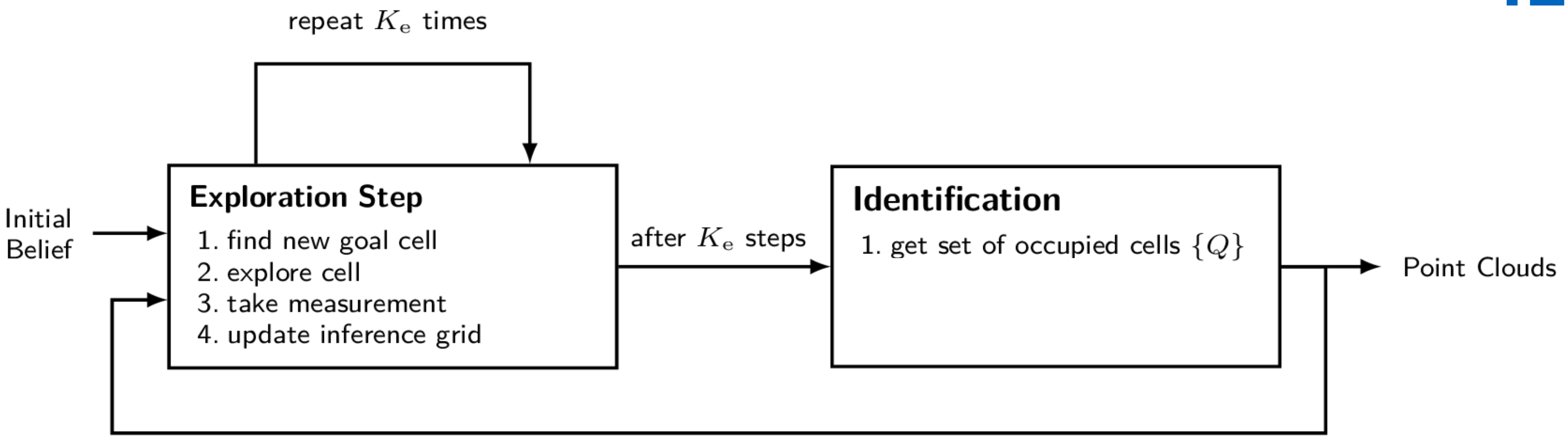
Haptic Identification – Grid-Based



Grid-based

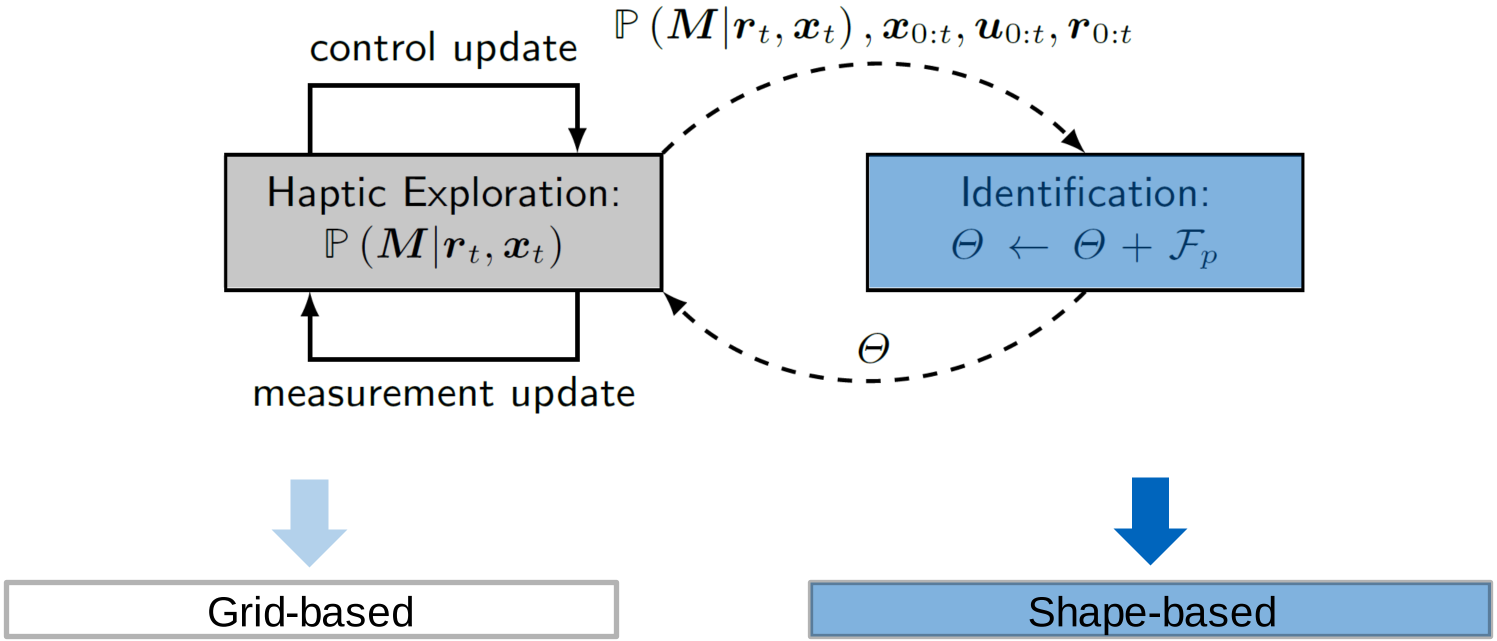
Shape-based

Haptic Identification – Grid-Based

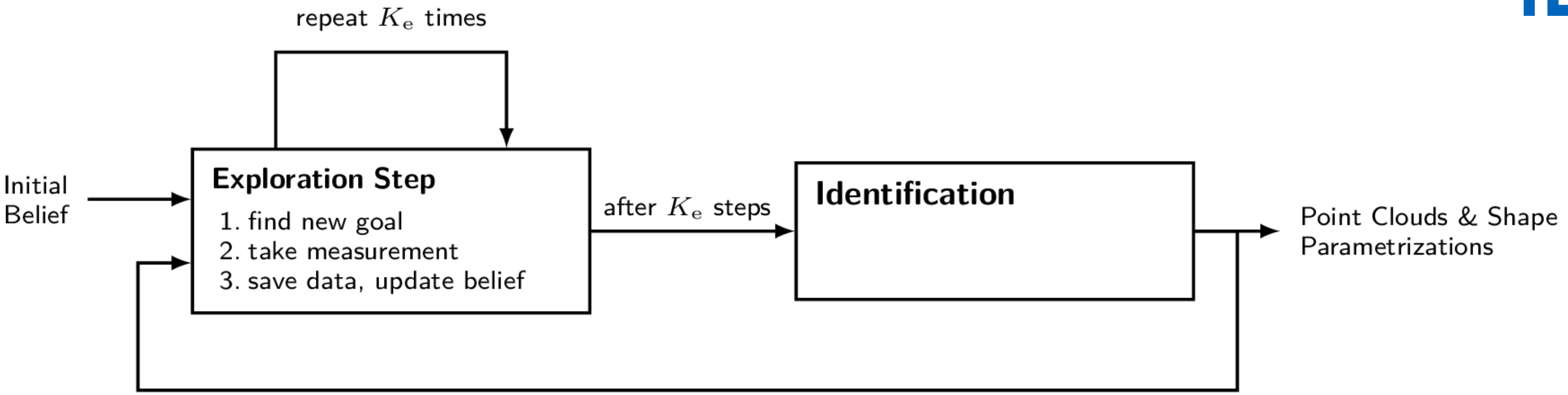


- Run data-clustering given the new measurements
- Use clusters to refine decision / class boundaries in inference grid
- Re-calculate belief of class membership in inference grid

Haptic Identification – Shape-Based

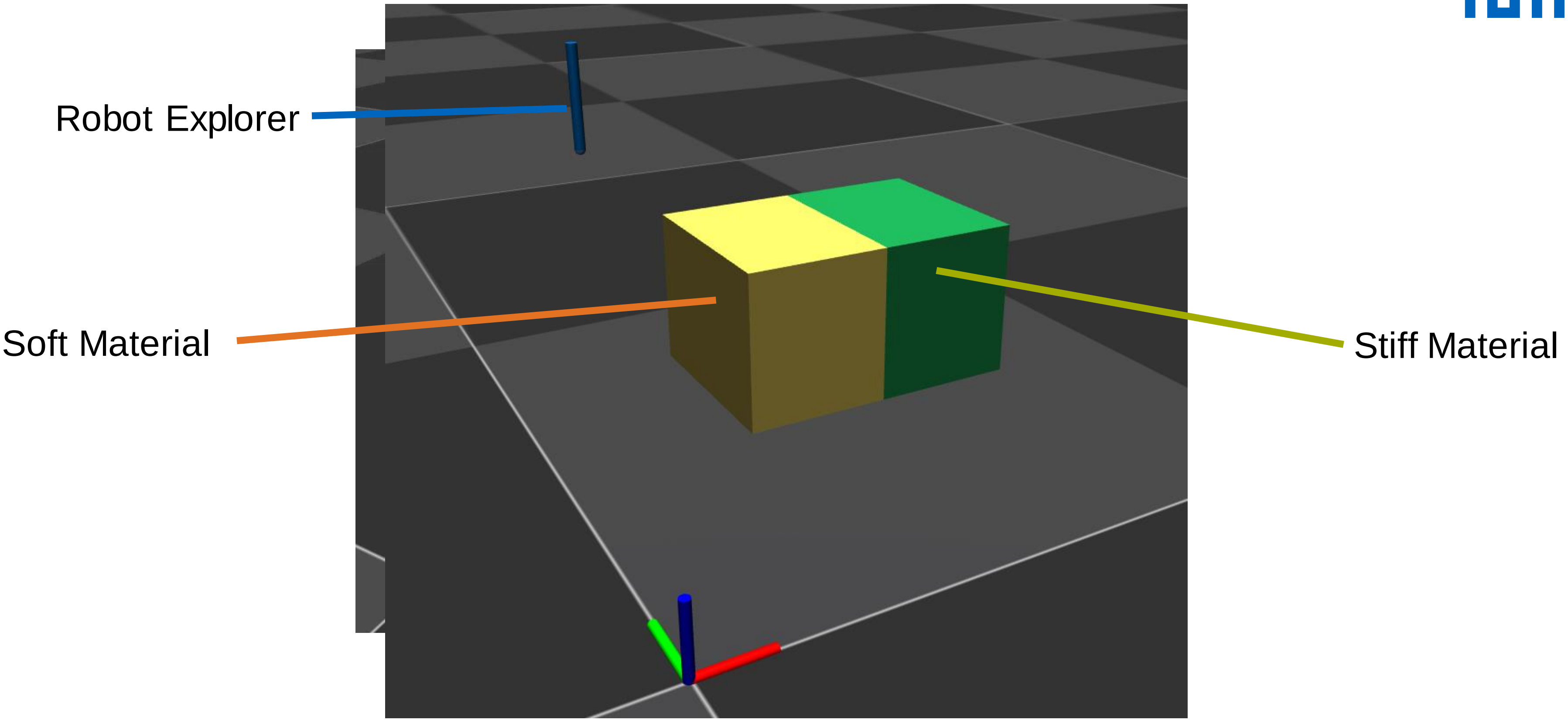


Haptic Identification – Shape-Based



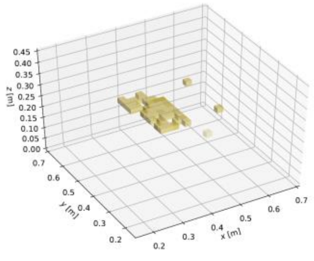
- Delete particles with lowest belief
- Randomly generate new particles:
  - Update clusters with new measure batch
  - Sample new geometric primitive shape-combinations
- Update belief of all particles for new classification metric

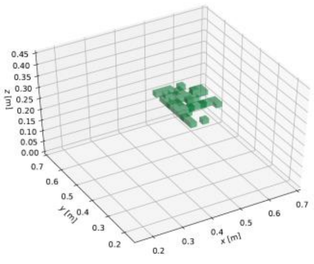
Experimental Results

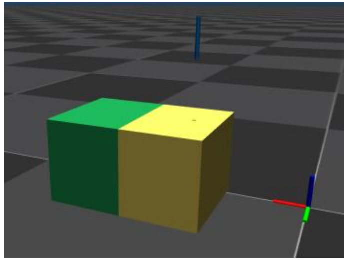


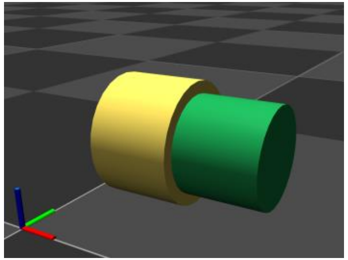
Simulation Environment in ©MuJoCo

Experimental Results – Grid Based

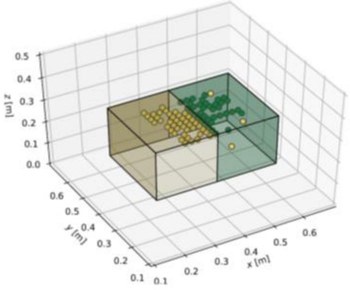


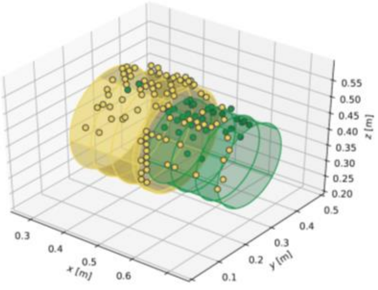






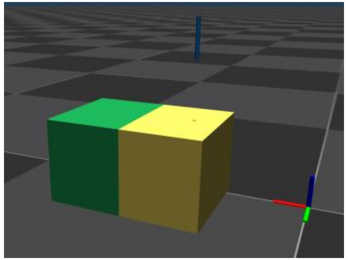
	$k[\mathrm{N/m}]$	$\hat{k}[\mathrm{N/m}]$	F_1
Yellow Box	165	107.81	0.966
Green Box	1452	615.11	0.962
Yellow Cyl.	282	164.75	0.834
Green Cyl.	1192	397.34	0.667

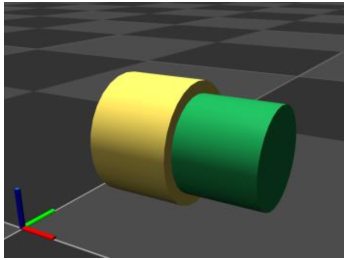


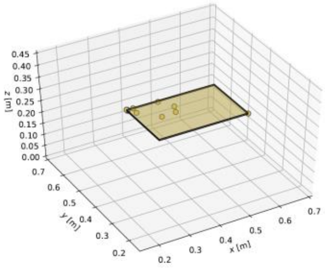


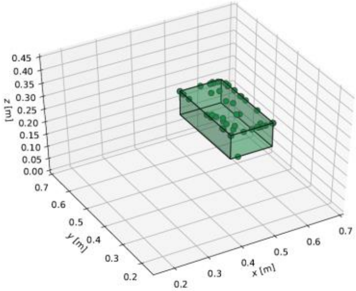
Experimental Results – Shape-Based

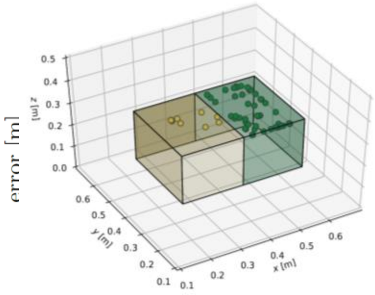
	$k[\mathrm{N/m}]$	$\hat{k}[\mathrm{N/m}]$	F_1
Yellow Box	165	113.85	0.952
Green Box	1452	717.02	0.987
Yellow Cyl.	282	104.54	0.963
Green Cyl.	1192	947.15	0.987

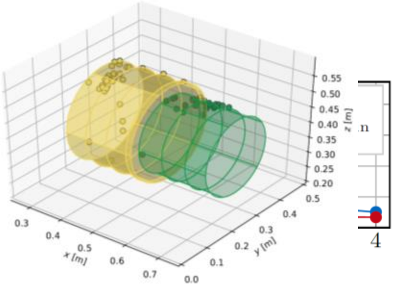












Conclusion and Outlook

Developed Haptic Exploration and Identification Frameworks

Grid-based

- Minimize cell uncertainty
- Cluster cells
- Output:
  - clustered point clouds

Shape-based

- Minimize shape uncertainty
- Cluster measurements
- Output:
  - clustered point clouds
  - parametrized shape representations

Future Work

- Further improve classification and estimation methods
- Combine frameworks into a hybrid mechanism
- Evaluate performance on robot platform

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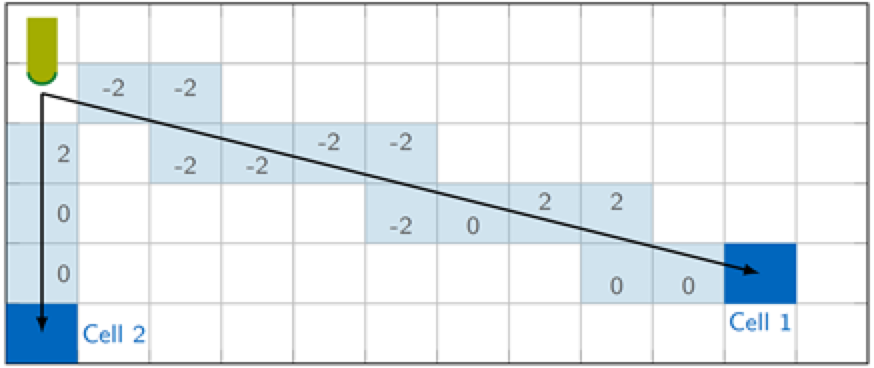
Robotic Simulation

Appendix – Grid Utility

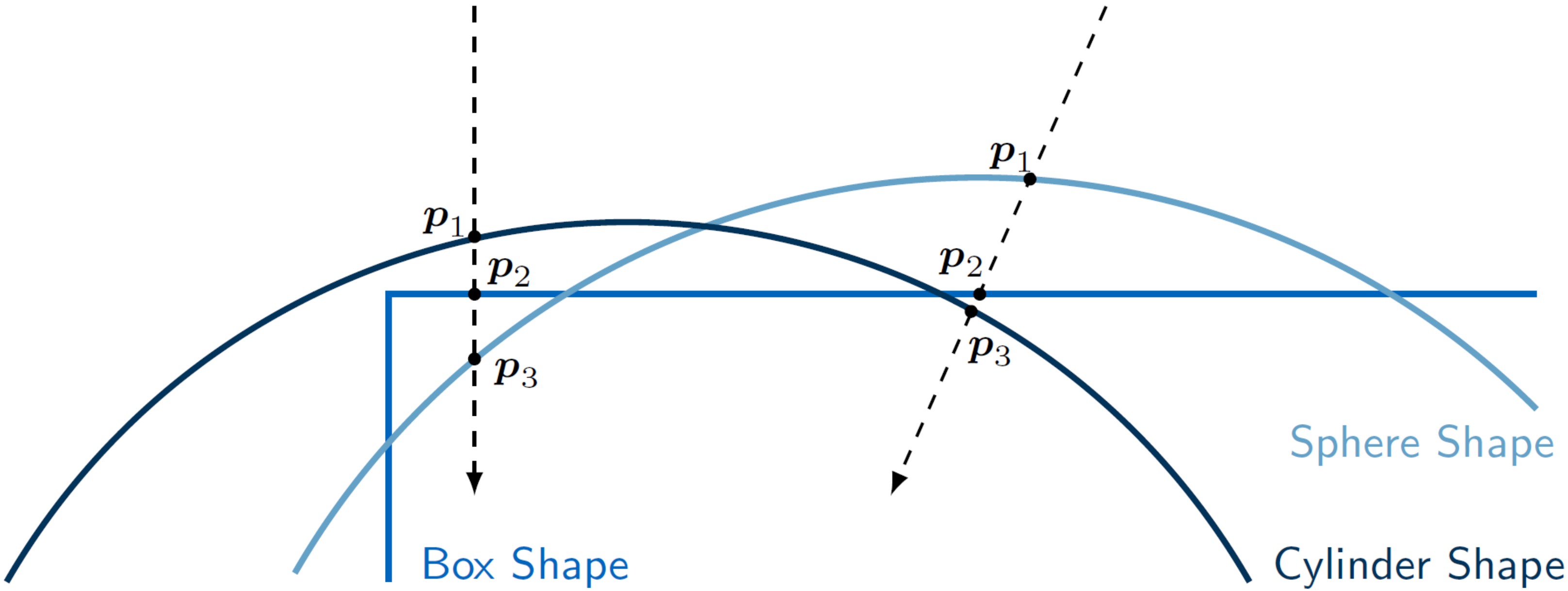


$$U(c) = \frac{1}{K_m} \sum_{i=1}^{K_m} \sum_{r \in \mathcal{X}} \sum_{\xi^i \in \mathcal{X}} \mathbb{P}\left[r_+ = r | \xi^i\right] \mathbb{P}\left[\xi^i\right] \ln\left(\frac{\mathbb{P}\left[\xi^i | r_+ = r\right]}{\mathbb{P}\left[\xi^i\right]}\right),$$

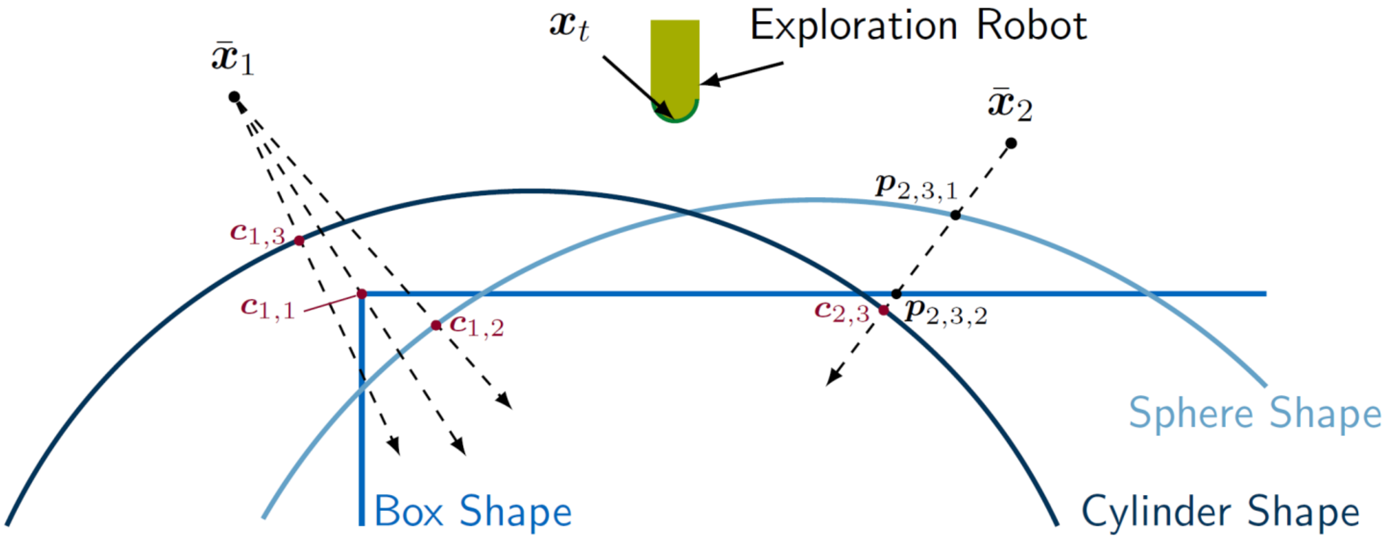
Accessibility: $\alpha(\mathcal{D}_{x,c}) = \begin{cases} \frac{1}{D} & \text{if } \boldsymbol{M}_t^0(c_i) = 0 \; \forall c_i \in \mathcal{D}_{x,c}, \\ \left| \frac{1}{D} \sum_{c_i \in \mathcal{D}_{x,c}} -\mathrm{sign}(\boldsymbol{M}_t^0(c_i)) \right| & \text{otherwise,} \end{cases}$

Rank: $\mathrm{rank}(\boldsymbol{c}_t, \mathcal{D}_{x,c}) = \alpha(\mathcal{D}_{x,c}) \boldsymbol{U}(c)$

Appendix – Shape-Based Utility 1



Appendix – Shape-Based Utility 2



$$U(\mathcal{P}, \mathcal{S}_t) = \sum_{S^j \in \mathcal{S}_t} \sum_{\boldsymbol{p}_i \in \mathcal{P}} \mathcal{N}(\boldsymbol{p}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma}) \mathbb{P}\left[S^j | \boldsymbol{x}_t, \boldsymbol{r}_t\right] \ln\left(\frac{\mathcal{N}(\boldsymbol{p}_i | \boldsymbol{\mu}_j, \boldsymbol{\Sigma})}{\mathbb{P}\left[S^j | \boldsymbol{x}_t, \boldsymbol{r}_t\right]}\right)$$

Verification of Stiffness Model in Mujoco