Action Learning in IRFO

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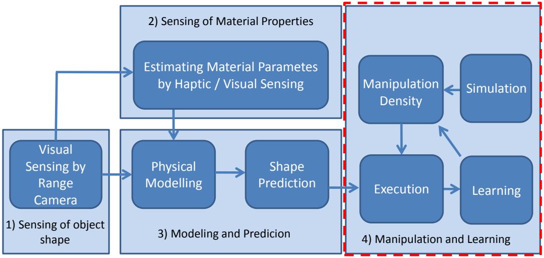
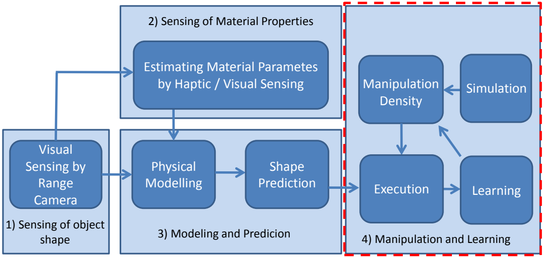
Outline


2) Sensing of Material Properties
Estimating Material Parametes by Haptic / Visual Sensing
Visual Sensing by Range Camera
1) Sensing of object shape
Physical Modelling
Shape Prediction
3) Modeling and Predicion
Manipulation Density
Simulation
Execution
Learning
4) Manipulation and Learning

Outline



Outline:

1. Introduction / background
2. Grasping
3. Peg In Hole operations
4. Laying down operations

Introduction

Grasp learning: association of actions to an object:

- Object relative gripper poses

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- Grasp Density [1]

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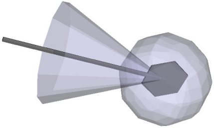
Full 6D Representation:

$$d(x) = \sum_{i=0}^{n} w_i K_{\mu_i,\sigma}(x) \text{ for } x \in SE(3)$$

General, but high-dimensional



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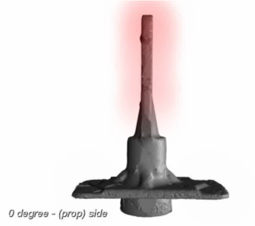

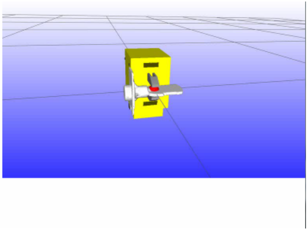

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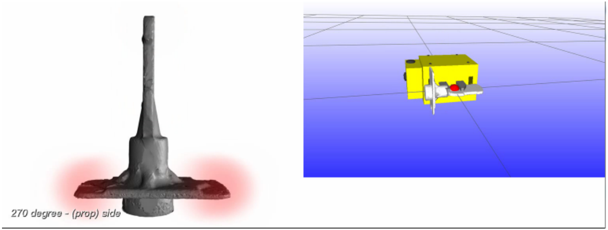

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Within IRFO:

- Grasping of flexible objects
- Apply density-concept to other actions

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Grasping flexible objects

Objective: Grasp learning

- E.g. by learning promising object relative gripper poses with KDE

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Requirements:

1. Define a reference frame

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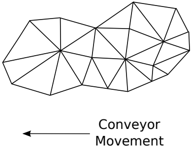
Requirements:

1. Define a reference frame
2. Parametrization of grasps

Definition of reference frame

Objects are:

- similar, not identical
- defined by a 3D mesh



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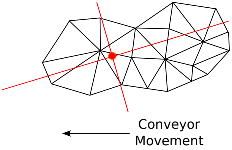

- Let *CM* be their center of mass
- Main axes are found using PCA

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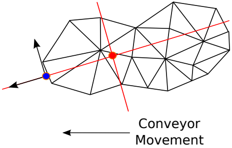
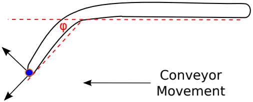


- Let CM be their center of mass
- Main axes are found using PCA

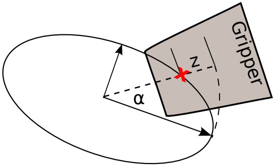
- Outmost point is found
- Object orientation + deflection φ



Concise Parametrization of Grasps

Parametrization using 2 coordinates

- position based on α and z
- orientation based on α or constant



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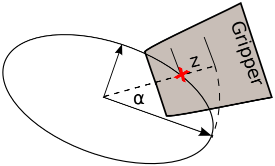
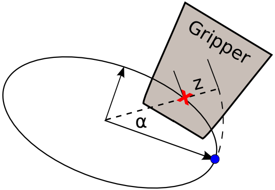


Parametrization using 3 coordinates

- position based on α and z
- orientation based on come angle β



Results

Currently used:

- $\alpha = 0$, $z = constant$

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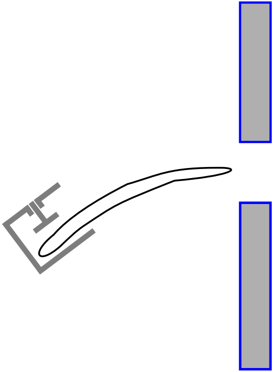
Performance on the real setup:

	Object orientation	
Object	$0° \leq \lvert\theta\rvert \leq 10°$	$10° < \lvert\theta\rvert \leq 45°$
1	100% (10)	100% (7)
⋮	⋮	⋮

Table: Success rates for different objects and orientations.

PegInHole Action



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Prerequisites:

1. 3D-mesh of the object
2. Description of the scene
3. Predicted deflections (static situation)

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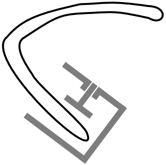
One assumption:

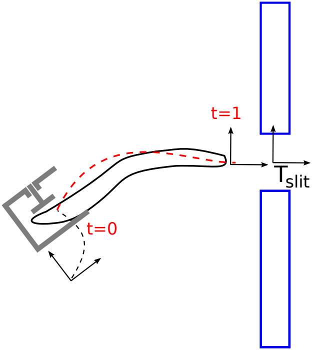
1. deflection is less than 90 degree



PegInHole Curve Approach

Suggestion:

- Define a parameterized curve



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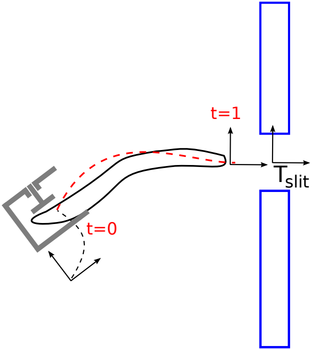

PegInHole Curve Approach

Suggestion:

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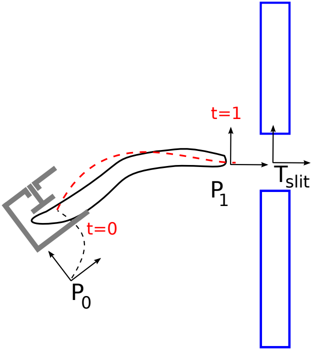
- The path may consist of two dimensions for position and one for orientation.
- Let P_0 and P_1 be the coordinates corresponding to the start and target configuration, both $\in R^2 \times SO(1)$

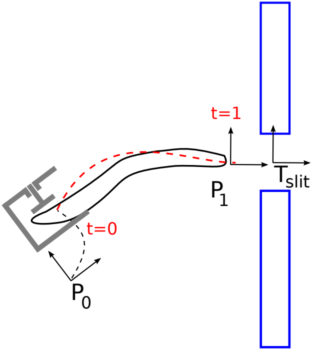


PegInHole Curve Approach

Parametric interpolation:

$$P(t) = P_0 + f(t) \circ (P_1 - P_0)$$

with $t \in [0,1]$, $f(0) = \bar{0}$ and $f(1) = \bar{1}$



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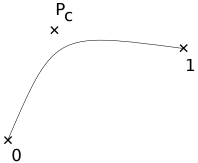
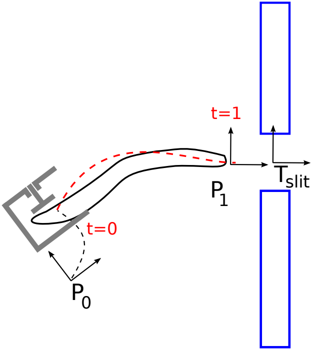
Could be defined by a rational Bézier-curve, so that a control-point P_c and a scalar weight is learned:





PegInHole Curve Approach

Overall system action representation might become

$$K_{\mu,\sigma}(T_G, f, P_c) = K^{G}_{\mu^G,\sigma^G}(T_G)\, K^{O}_{\mu^O,\sigma^O}(f)\, K^{PiH}_{\mu^P,\sigma^P}(P_c)$$

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$$f = F(T_G, 3Dmesh)$$

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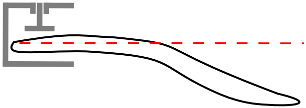

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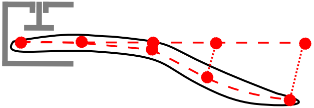

Learning PegInHole actions

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The Peg In Hole action with the highest clearance:

$$\arg\max_{P_c \in R^3} d(P_c, f)$$

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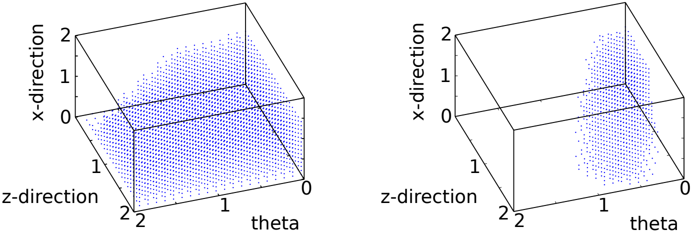
Based on a set of samples from the density, evaluated on the real setup, a refined density can be achieved.

Initial results

Learned controlpoints for two different objects:



Object: $40 \times 15 \times 2mm$ Object: $80 \times 15 \times 2mm$

- Needs additional experiments

Laying Down operation

Objective:

- place object with minimum stress

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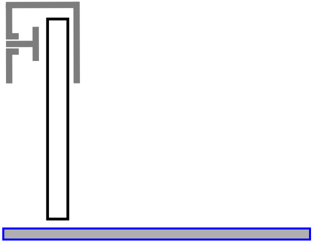

Start: no additional force applied from gripper.

Laying Down operation

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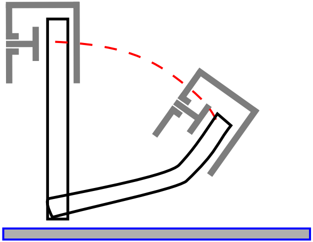

During action: potentially increased force applied by gripper

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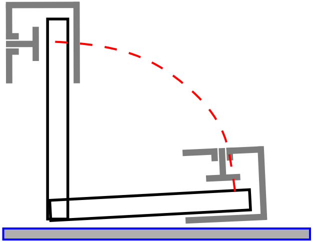

Target: Object is resting on the table.

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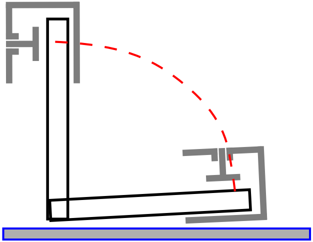

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Concept:

- reuse methodology from PiH-actions

Laying Down experiment

Real setup:

- Outcome is difficult to measure

Laying Down experiment

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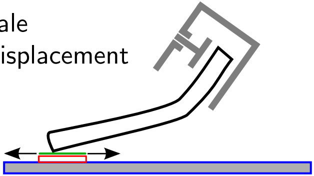
  - Measure vertical forces with scale
  - Estimate horizontal forces by displacement
  - Estimate stress via shape(?)



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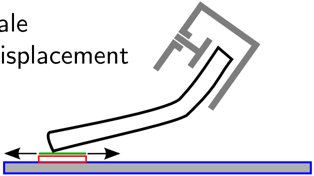

Design of simulated experiments becomes complex:

- Supporting surface from table
- Impact of gripper
- Impact of gravity

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Future task:

- Introduce feedback loop for error correction

Thank you for your attention