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Learning to Grasp

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Technische Aspekte Multimodaler Systeme

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Gliederung

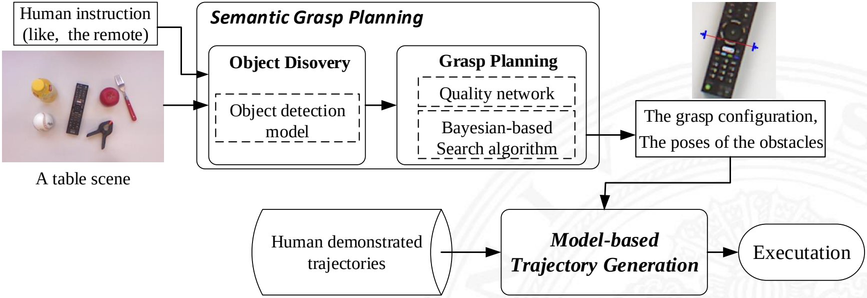
Requirements of the implementation of semantic reach-to-grasp tasks:

1. Detecting the preferred object on a table (Object dicovery or detection)
2. Finding a feasible grasp configuration to grasp it.(Grasp planning)
3. Generating a constraint-satisfied trajectory to reach it. (Trajectory generation)

Motivations:

1. Grasping unkown objects (without mesh models) is difficults, espically in a unstructure environment.
2. Generating a constraint-satisfied trajectory is important for the reaching movement.
3. The implementation of semantic reach-to-grasp (RTG) task.

A unified learning framework



Grasp Planning

Grasp planning aims to find a grasp configuration with highest quality.

$$g^* = \operatorname*{argmax}_{g \in G} Q(I, g) \tag{1}$$

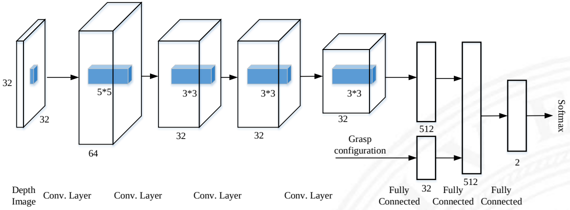
where g is candidate grasp. I is the segmented image. $Q(I, g)$ is quality function.

Two key problems:

- How to define a quality function to evaluate the performance of candidate grasps.
- How to search the optimal grasp in a large grasp space.

Grasp Planning

Learning a quality function with Neural Network(NN).



Details of the quality network:

- dataset: Dex-Net2.0 presented by Mahler et al [5]. $samlpe = \langle image, grasp, quality \rangle$.
- grasp representation: $g = \{x, y, z, \theta\}$
- learning params: 20 epochs, batch size=64, learning rate=0.005(exponential decay), Stochastic Gradient Descent (SGD) method with a momentum rate(0.9)

Bayesian-based search algorithm

Bayesian Optimization (BO) is a global optimization technique for black-box function.

- A surrogate model: used to represent the distribution of the quality function and representated by a Gaussian Process(GP).

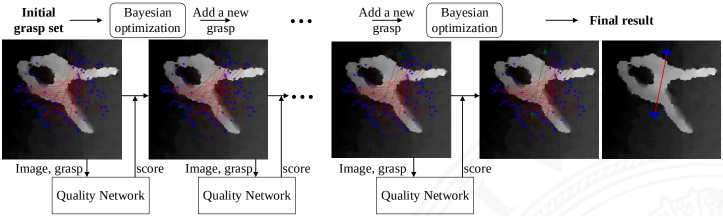
$$q_{gp}(g) \sim \mathcal{GP}(m(g), k(g, g')) \tag{2}$$

- A acquisition function: used to find the optimal query point(candidate grasp) and representated by the Upper Confidence Bound (UCB) policy.

$$a_{UCB}(g_{n+1}|D^n_{grasp}) = \mu(g_{n+1}|D^n_{grasp}) + \beta\sigma^2(g_{n+1}|D^n_{grasp}) \tag{3}$$

Bayesian-based search algorithm

Bayesian-based search algorithm is used to find the optimal grasp.



1. Sample an initial set of candidate grasps to form a dataset D_{grasp}
2. Fit the GP model with D_{grasp}.
3. Search a local optimum:$\hat{g} = \text{argmax}_g \, a_{UCB}(g|D_{grasp})$.
4. Compute the quality:$\hat{q} = Q(I, \hat{g})$ and $D_{grasp} \leftarrow D_{grasp} \cup (\hat{g}, \hat{q})$
5. Repeat 2-4, until a optimal grasp g^*

Results:

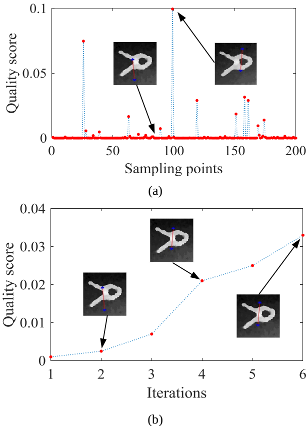


Abbildung: A comparison of the results from two different search algorithms. a) The MC-based search algorithm, b) the Bayesian-based search algorithm.

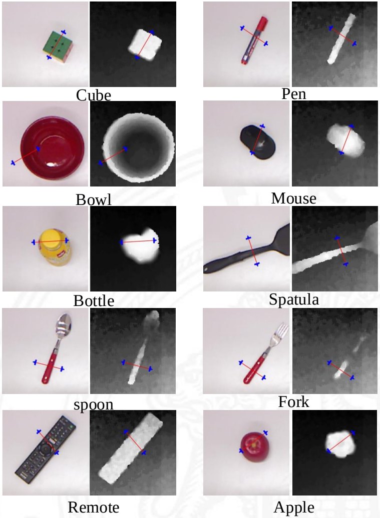


Abbildung: Examples of the grasp planning.

Model-based trajectory Generation

Trajectory generation based on optimal control.

$$\begin{aligned} J(\overline{Z}_t, \overline{U}_t) &= \min_{\overline{U}_t} \sum_{i=t}^{t+H} l(x_i, u_i) \\ \text{s.t.} \quad z_{i+1} &= f(z_i, u_i, f_i), \forall i \in t, \cdots, t+H \end{aligned} \tag{4}$$

where $l(x_i, u_i)$ is a user-defined cost function. The forward dynamic model $z_{i+1} = f(z_i, u_i, f_i)$ governs the state transition given the robot control u_i and the state z_i.

Two key problems:

- How to build a accuracy dyanmic model to predict the state transition of the robot.
- How to adapt the reaching movement according to the changing environment.

1. Learning a forward dynamical model from human demonstrations

$$M\ddot{x}(t) + C\dot{x}(t) + K(x - x_g) = f_t + u_t \tag{5}$$

where $u \in \mathbb{R}^3$ is the virtual robot control input in the Cartesian space and $f \in \mathbb{R}^3$ is the virtual human control that forces the impedance model to match the human expectation.

$$f(x) = \frac{\sum_{i=1}^{k} \omega_i \psi_i(x)}{\sum_{i=1}^{k} \psi_i(x)} \tag{6}$$

2. Iteration Linear-Quadratic-Regulator (iLQR) method is used to perform trajectory optimization.

$$p(u_t|x_t) = \mathcal{N}(K_t(x_t - \overline{x}_t) + k_t + \overline{u}_t, \Sigma_t) \tag{7}$$

Results:

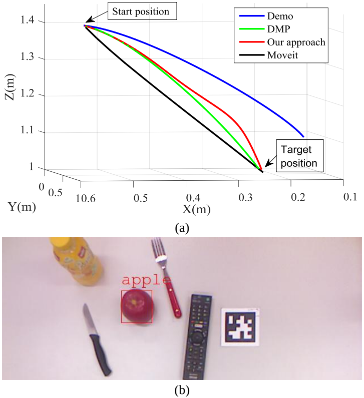


Abbildung: Comparison of the three different trajectory generation methods.

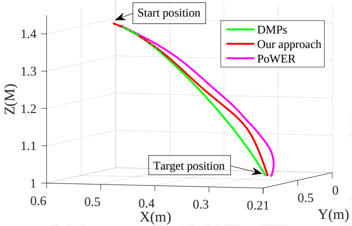
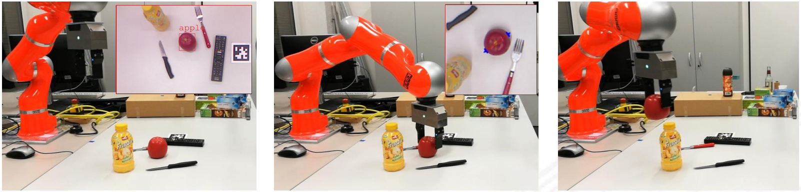


Abbildung: Comparison of two different trajectory optimization approaches.

1. reproduce human natural movement.
2. Fast adaptability.

Robotic experiments



(a) (b) (c)

Tabelle: The overall performance of the proposed unified learning framework.

Component	Accuracy
Object discovery	46/48
Robot grasping operation	39/48
Robot reaching movement	48/48

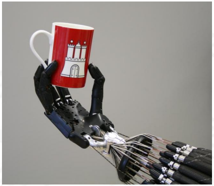
Disscusion

- Object detection helps to improve the success of grasp planning.
- Learning grasp quality from datasets (collected by human or simulation).
- The Bayesian-based search algorithm is robust to the uncertainty of object shape.
- The planned grasp may fail due to the slippage or the irregular shape of the objects, like the bowl. It is preferred to employ tactile sensors for grasp adaptation.
- Trajectory generation has a form of conventional impedance control. It is preferred to learn the robot control and the impedance parameters simultaneously.
- Multi-finger grasping will be more complex.

Future work: Multi-finger grasping

Grasp planning is a optimization problem.

$$
\begin{array}{lll}
\underset{\boldsymbol{\theta},\mathbf{H},\mathbf{p},\mathbf{n}}{\arg\min} & f(\boldsymbol{\theta},\mathbf{H},\mathbf{p},\mathbf{n}) & \text{objective function} \\
\text{subject to:} & h_i(\theta_i,\mathbf{H}) - \mathbf{p}_i = 0 & \text{hand constraints} \\
 & l_i(\theta_i,\mathbf{H}) - \mathbf{n}_i = 0 & \\
 & g(\mathbf{p}_i) = 0 & \\
 & \nabla g(\mathbf{p}_i) \times \mathbf{n}_i = 0 & \text{object constraints} \\
 & \nabla g(\mathbf{p}_i) \cdot \mathbf{n}_i < 0 & \\
 & Q_{\text{task}}(\boldsymbol{\theta},\mathbf{H},\mathbf{p},\mathbf{n}) \in \mathcal{G}_{\text{task}} & \text{task constraints}
\end{array}
$$



... but it is difficult to be solved. Most of the existing works focus on data-driven method [1]:

- Heuristic-based
- Learning from human demonstration
- Learning from Labeled training data
- Reinforcement learning.

Future work: Multi-finger grasping

Assumptions 1

One explanation for human efficiency in selecting appropriate grasp assumes that human unconsciously simplifies the large search space through learning and experience.

Our basic idea: first detect grasp type and then determine the optimal contact points.

- How to detect grasp type.
- How to use the detected grasp type to define a initial grasp.
- How to optimize multi-finger grasping.

Some relative search topics:

1. Semantic (affordance) detection, human action recognition.
2. Grasp taxonomy.
3. Grasp by component, task-specific grasp.
4. Analysis-base grasp planning.

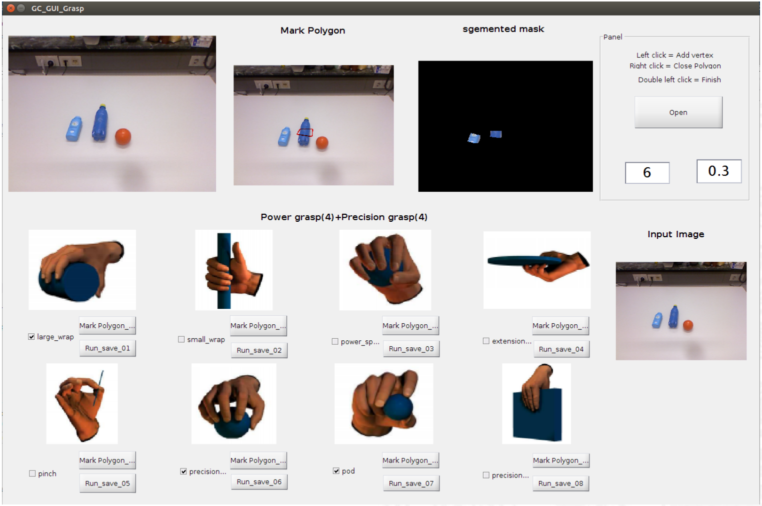
Grasp type detection

Three popular networks (FCN, SegNet/DeconvNet, **DeepLab v2**[2]) can be used to perform Pixel-level semantic detection. No public dataset. We have to build a multi-finger grasping dataset.

- 8 grasp types are selected from Feix's grasp taxonomy [4].
- 12 objects with different attribute are contained.

Shape attribute: prismatic, round, flat.
Task attribute: tool, container, food box.

Grasp type detection



...based on OpenCV GrabCut.

Grasp type detection

Assumptions 2

Grasp type g is largely depended on object$o$ and task$t$.

5 tasks: Pick-and-place, Hand-over, pouring, tool-use, opening.
Bayesian rule:

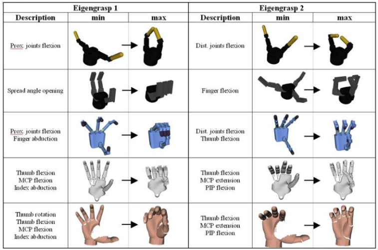
$$
\begin{aligned}
p(g|o,t) &= \frac{p(o|g,t)p(t|g)p(g)}{p(o)p(t)} \\
&= \frac{p(o|g)p(g)p(t|g)p(g)}{p(o)p(t)p(g)} \\
&= \frac{p(g|o)p(g|t)}{p(g)} \\
&\propto p(g|o)p(g|t)
\end{aligned}
\tag{8}
$$

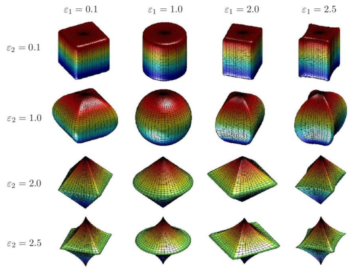
$p(g|o) = \frac{1}{n*m}\sum_{i=1}^{n}\sum_{j=1}^{m} p(g|r_{i,j})$ (Pixel-level grasp type detection).
$p(g|t)$ (data statistic).

Grasp optimization

After determining grasp type and region, we need to find the contact points between object and fingers.

- Grasp representation: a low-dimentional representation, e.g., Eigengrasps [3].
- Shape representation: e.g., superquarics.
- Grasp optimization.





... still not clear with this part. I will do it later.

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Future work

Thanks for your attention! Any questions?