KIT-Department of Informatics
Prof. Dr.-Ing. Tamim Asfour

Reference solution for the exam

Robotics II: Humanoid Robotics

am September 17, 2018, 11:00 – 12:00

Family name:	Given name:	Matriculation number:
Tamim	Asfour	123456789

Exercise 1	8 out of 8 points
Exercise 2	11 out of 11 points
Exercise 3	6 out of 6 points
Exercise 4	11 out of 11 points
Exercise 5	9 out of 9 points

Total:	45 out of 45 points

	Grade: **1.0**

Exercise 1 *Grasping*

1. Grasp analysis and grasp synthesis:

   Grasp analysis refers to the study of grasp properties (e.g. stability) for a given set of finger properties that define the grasp (e.g. joint angles). *Grasp synthesis* refers to the opposite problem of determining finger properties for realizing desired grasp properties.

2. Benefits of grasp taxonomies for robotic grasping:

   - Benchmarks for testing capabilities of robotic hands
   - Simplification of the problem of grasp synthesis
   - Inspiration for robotic hand design
   - Guidance for autonomous grasp selection
   - Optimization of grasp synergies

3. Shape completion:

   Shape completion refers to the generation of a complete object model based on incomplete perception (e.g. from a visually perceived point cloud). This process is important for grasp synthesis as many grasp planning approaches require complete meshes of objects including surfaces which are occluded from the robot's current perspective.

4. Online phase vs. offline phase:

   The *online phase* processes information from the current perception and therefore needs to be executed in the moment when grasp synthesis is requested. The *offline phase* performs precomputations which can be executed ahead of time, independent of concrete grasp synthesis problems.

5. Grasp synthesis for known objects (online/offline):

Process	**Online**	**Offline**
Grasp selection	X	
Grasp generation		X
Scene segmentation	X	
Object recognition	X	
Grasp simulation		X

Exercise 2 *Grasp Synergies*

1. Postural synergies:

   Postural synergies are the correlation of degrees of freedom of human or robotic hands in patterns of more frequent use.

2. Soft synergy model:

   The *soft synergy model* approaches the problem of synergies as rigid manifolds by introducing a model of elasticity. The hand is controlled based on the combination of two force fields:

   - One field attracts the hand towards a virtual hand which is shaped on the rigid synergy manifold.
   - The other field is repelling the hand from penetrating the object.

3. Amplitude vector $\mathbf{a}$:

   Approach: $a_1 \cdot \mathbf{e}_1 + a_2 \cdot \mathbf{e}_2 = \mathbf{p}$, with $\mathbf{a} = \begin{bmatrix} a_1 & a_2 \end{bmatrix}^T$.

   Solving for $\mathbf{a}$ yields (one possible way):

$$\begin{aligned}
&\begin{cases} a_1 + \frac{1}{2}a_2 = \frac{4}{5} \;\Rightarrow\; a_1 = \frac{4}{5} - \frac{1}{2}a_2 \\ \frac{1}{4}a_1 + a_2 = \frac{5}{4} \end{cases} \\
&\Rightarrow \frac{1}{5} + \frac{7}{8}a_2 = \frac{5}{4} \Rightarrow a_2 = \frac{6}{5} = 1.2 \\
&\Rightarrow a_1 = \frac{4}{5} - \frac{3}{5} = \frac{1}{5} = 0.2 \\
&\Rightarrow \mathbf{a} = \begin{bmatrix} 0.2 & 1.2 \end{bmatrix}^T.
\end{aligned}$$

4. Realization of $\mathbf{p}_{\text{new}}$:

$$\begin{aligned}
\varepsilon &= \|a_1 \cdot \mathbf{e}_1 + a_2 \cdot \mathbf{e}_2 - \mathbf{p}_{\text{new}}\| \\
&= \|\mathbf{e}_1 + 2\mathbf{e}_2 - \mathbf{p}_{\text{new}}\| \\
&= \left\| \begin{bmatrix} 0 & 0 & -0.2 & 0 \end{bmatrix} \right\| \\
&= 0.2
\end{aligned}$$

5. Exact realization of $\mathbf{p}_{\text{new}}$:

   An exact realization of $\mathbf{p}_{\text{new}}$ requires the addition of a third eigengrasp $\mathbf{e}_3$.

Exercise 3 *Active Perception*

1. In contrast to *active vision*, methods for *active perception* deliberately change the environment for the purpose of goal-oriented data acquisition.

2. ICP is used for determining the transformation between two (sufficiently) overlapping point clouds based on an initial estimation. This process is also called *alignment*.

3. The purpose of pushing actions is to segment unknown textured and non-textured rigid objects.

4. Heuristics for initial object hypotheses:

   (a) Group visual features (SIFT, ...) based on a common regular geometric 3D structure (planes, later cylinders and spheres) as well as spatial proximity. The goal is to detect textured objects.

   (b) Maximally stable extremal regions (MSER) to detect unicolored regions of promising size. The goal is to detect single-colored objects.

   (c) DoG filter to detect visually salient regions. The goal is to detect objects that are neither textured nor unicolored.

5. The original concept of the ICP algorithm was adapted by using a weighted sum of cartesian and color distance in step 1 (closest point search).

Exercise 4 *Haptics*

1. Purpose, attractive and repellent regions:

   The potential field guides the haptic exploration of unknown objects. Unknown regions of the object are attractive, while known regions of the object are repellent.

2. Potential field equation:

$$\Phi(x) = \sum_i \Phi_{a,i}(x) + \sum_j \Phi_{r,j}(x).$$

   The total potential $\Phi(x)$ is the superposition of the attractive potentials $\Phi_{a,i}(x)$ and the repellent potentials $\Phi_{r,j}(x)$.

3. Motion generation:

   The end-effector moves along the negative gradient of the potential field:

$$F = -\nabla\Phi(x).$$

4. Changes of the potential field:

   When the end-effector is moved through unknown regions the regions become known and the attractive potential sources are deleted. When the hand makes contact with the object, repellent potential sources are added.

5. Motion direction:

$$\Phi(\mathbf{x}) = \Phi_{a,1}(\mathbf{x}) + \Phi_{a,2}(\mathbf{x}) = \left\| \mathbf{x} - \begin{bmatrix} 3 \\ 1 \end{bmatrix} \right\|^2 + 3 \left\| \mathbf{x} - \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right\|^2$$

$$\nabla\Phi(\mathbf{x}) = \nabla\Phi_{a,1}(\mathbf{x}) + \nabla\Phi_{a,2}(\mathbf{x}) = 2 \left(\mathbf{x} - \begin{bmatrix} 3 \\ 1 \end{bmatrix} \right) + 6 \left(\mathbf{x} - \begin{bmatrix} 1 \\ 2 \end{bmatrix} \right)$$

$$\Rightarrow -\nabla\Phi \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix} \right) = \begin{bmatrix} 6 \\ 2 \end{bmatrix} + \begin{bmatrix} 6 \\ 12 \end{bmatrix} = \begin{bmatrix} 12 \\ 14 \end{bmatrix}$$

Exercise 5 *Imitation Learning*

1. Parameters for definition of HMMs:

   - Set of states: $S = \{S_1, \dots, S_K\}$
   - Transition probabilities: $A = (a_{ij}) \in [0,1]^{K \times K}$
   - Start probabilities: $\vec{\pi} = (\pi_1, \dots, \pi_K) \in [0,1]^K$
   - Set of discrete observations: $V = \{v_1, \dots, v_N\}$
   - Observation probabilities: $B = (b_j) \in [0,1]^{K \times N}$

2. Training algorithm for HMMs:

   Baum-Welch-Algorithm

3. Principle of semantic segmentation:

   The semantic segmentation uses object/hand contact relation changes as hints for segmenting the demonstration. Object contacts are calculated based on the 6D trajectories and the 3D mesh models.

4. Principle of motion segmentation:

   The motion segmentation analyzes the motion characteristic. It separates the trajectories with a heuristic into most distinctive parts by using an iterative search and recursion until the segments are too small or too similar.

DMP Transformation system:

$$
\begin{aligned}
\tau\dot{v} &= K(g - x) - Dv + (g - x_0)f(u)u \\
\tau\dot{x} &= v
\end{aligned}
$$

DMP Canonical system:

$$\tau\dot{u} = -\alpha u$$

5. Explanation of terms:

Term	**Explanation**
τ	*Temporal factor*
x	Current position
D	Damping constant
K	Spring constant
g	Goal position
x_0	Start position
f	Perturbation force

6. Changeable properties of a DMP-represented motion:
   The start position x_0, the goal position g and the speed τ.