Context Dependent Action Affordances and their Execution using an Ontology of Actions and 3D Geometric Reasoning

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Abstract:
When looking at an object humans can quickly and efficiently assess which actions are possible given the scene context. This task remains hard for machines. Here we focus on manipulation actions and in the first part of this study define an object-action linked ontology for such context dependent affordance analysis. We break down every action into three hierarchical pre-condition layers starting on top with abstract object relations (which need to be fulfilled) and in three steps arriving at the movement primitives required to execute the action. This ontology will then, in the second part of this work, be linked to actual scenes. First the system looks at the scene and for any selected object suggests some actions. One will be chosen and, we use now a simple geometrical reasoning scheme by which this action's movement primitives will be filled with the specific parameter values, which are then executed by the robot. The viability of this approach will be demonstrated by analysing several scenes and a large number of manipulations.

1 INTRODUCTION

From every day life we know that different scenes suggest different actions, e.g. a plate, an apple, and a knife – as shown in Fig. 1 – suggests a "cutting the apple" action. However, assessing whether or not a robot could actually do this, whether it should/could do rather something else or whether not much can be done at all given such scenes remains a difficult problem. It amounts to estimating the affordance of certain actions given the context provided by the scene. One approach to solving this problem is to analyse a scene and derive from it a symbolic representation, which can then be used to find possible actions and/or to do planning.

To achieve this, in (Rosman and Ramamoorthy, 2011) a complex network of geometrical relations in the spatial and temporal domains is used. Via Support-Vector-Machines (SVMs) topological features and symbolic meanings are learned. In (Sjoo and Jensfelt, 2011) patterns of functional relationships are defined, e.g. the object "work surface" with the action "manipulate". Similar, in (Liang et al., 2009) posture templates are applied to the input data of each frame. The resulting series of templates eventually forms a library of actions. The authors use variable-length Markov models for learning. In (Paul et al., 2016) a common representation for abstract spatial relations and natural language is investigated. However, (Konidaris et al., 2014) state that there cannot be one perfect representation, but rather that

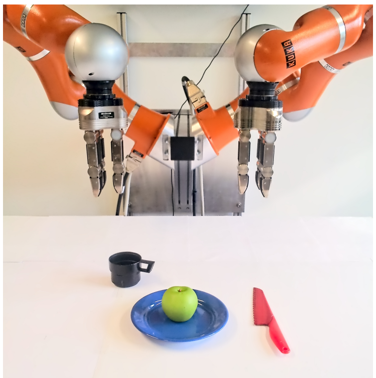


Figure 1: This scene contains a simple snack scenario. We ask: what actions can be performed by the robot?

"actions must play a central role in determining the representational requirements of an intelligent agent: a suitable symbolic description of a domain depends on the actions available to the agent."

Staying closer to the actual motion patterns one can also break down actions into segments, using – for example – principal component analysis (PCA) as in (Yamane et al., 2011). A motion sequence is here projected into a state space, which is then mapped to the first n principal components. In that reduced state space a threshold is applied and the action is divided into two parts. The same is iteratively applied to each subspace until some exit criteria is met. The resulting segments could then be interpreted as meaningful action parts.

There are also non-vision based methods available, for example in (Jamali et al., 2015) and (Jamali et al., 2014), but these methods will not be discussed any further, as we are focusing on vision here.

All these approaches are problematic, because it remains difficult to smoothly link sensor signals (e.g. from scene analysis) to symbolic action concepts and then back to the signal domain for creating the trajectories needed for the execution of an action by a robot. There is a danger of too strongly focusing on the symbolic side or of remaining too close to the signal domain.

Here we focus on manipulation actions and one goal of the current study is to improve on this by introducing a deeper hierarchy of several layers between signals and symbols for analysing a scene in a given action context. We ask: What is needed to push (or pick, or cut, etc.) a certain object? Which are the *general preconditions* required for this regardless of the actual objects in the scene? And – if those hold – are also the *specific conditions* met to actually do it?

We build on the Semantic Event Chains (SECs) framework (Aksoy et al., 2011) but we extend them in several ways. SECs are matrices that show how touching relations between pairs of objects change during an action. The entries of the SEC matrix are ("T") for Touching, ("N") for Not touching and ("A") for Absent relation. A manipulation action is segmented at keyframes which are moments that a touching relation changes. The original SEC framework did not much care about objects. Here, based on an older study (Wörgötter et al., 2012), we will now incorporate (still abstract) object roles to build an object-action-linked ontology of manipulations, where these object roles define the general preconditions that need to be met to perform a certain action *at all*. On top of this, we introduce a simple framework for geometric reasoning, which allows the machine to check specific preconditions, too, to finally execute an action.

In this study the robot selects one object in a scene and asks – like a child during play – what could I do with it? The framework will then analyse the situation and suggest possible manipulation actions, thereby addressing the problem of context dependent affordances.

2 Method

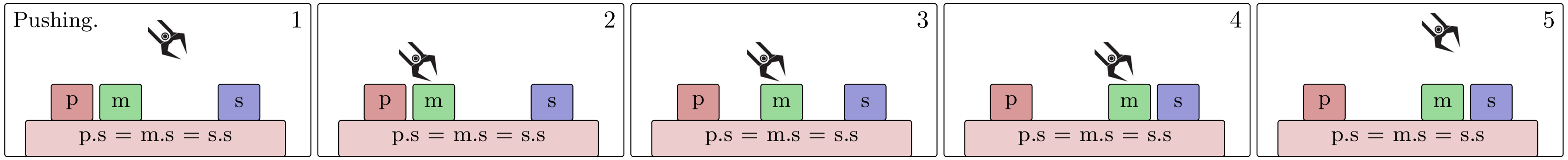
This section divides into two parts: 1) definition of the ontology and 2) algorithm to arrive at robotic execution of manipulation actions using the ontology given an observed scene. We start with the first aspect.

2.1 Ontology of Manipulation Actions

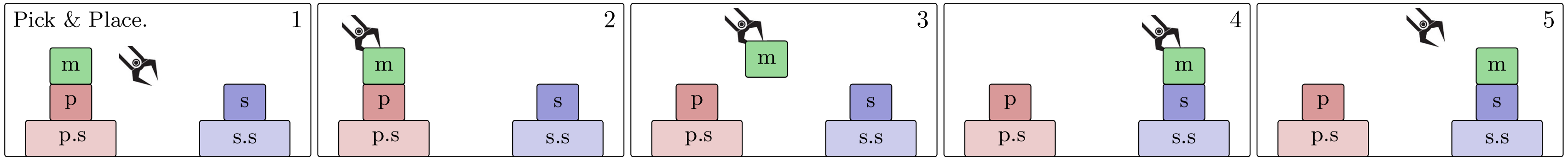
We use all manipulation actions defined in (Wörgötter et al., 2012) and create a new ontology by incorporating three layers: 1) abstract object relations (SEC), 2) object topologies and also 3) action primitives. Before doing this we need to define the roles of an object in a more general way.

Defining Object Roles: Those are determined by the changes that occur following an action in the relation of an object to other objects. An action involves at least two objects: a *hand* and a *main* object. Resulting object categories (hand, main, primary, secondary, etc.) and their abstract roles are defined as follows:

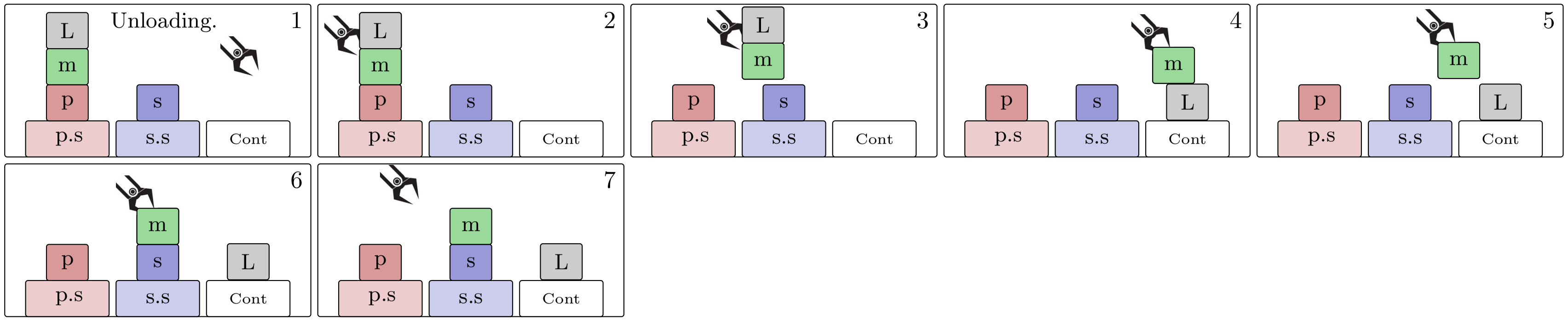
- *Hand* (The object that performs the action): not touching anything at the beginning and the end of action. It touches at least one object.
- *Main* (The object which is directly in contact with the hand): not touching the hand at the beginning and the end of action. It touches the hand at least once.
- *Primary* (The object from which the main object separates): initially touches the main object. Changes its relation to not-touching during the action.
- *Secondary* (The object to which the main object joins): initially does not touch the main



(a) Action 1: Pushing.



(b) Action 2: Pick and place.



(c) Action 3: Unloading.

Figure 2: Schematic of actions in the ontology are shown for the three categories. From each category only one action is shown. The objects are marked using the following convention: h = hand, m = main m.s = main support, p = primary, p.s = primary support, s = secondary, s.s = secondary support, L = Load, and Cont = Container.

Table 1: Summary of ontology of actions. Actions are divided into three categories and further into sub-categories. There can be more than one action in each sub-category.

Category	Sub-Category	Example Actions
Actions with main support	Actions with hand, main and main support	push, punch, flick
	Actions with hand, main, main support and primary	push apart, cut, chop
	Actions with hand, main, main support and secondary	push together
	Actions with hand, main, main support, primary and secondary	push from a to b
Actions without main support. (These action have primary, secondary and their supports)	primary $\neq$ secondary and primary support $\neq$ secondary support	pick and place, break off
	primary $\neq$ secondary and primary support = secondary support	pick and place, break off
	primary $\neq$ secondary and primary = secondary support	put on top
	primary $\neq$ secondary and primary support = secondary	pick apart
	primary = secondary	pick and place, break off
Actions with load and container	The relation of load and main changes from N to T (loading)	Pipetting
	The relation of load and main changes from T to N (unloading)	Pour, Drop

object. Changes its relation to touching during the action.

- *Load* (The object which is indirectly manipulated): does not touch the hand. During the action either touches/untouches the main and untouches/touches container.
- *Container* (The object whose relation with load changes and it is not the main object): touches or untouches the load object.
- *Main support* (The object on which the main object is located): touching the main object all the time.
- *Primary support* (The object on which the primary object is located): touching the primary object all the time.
- *Secondary support* (The object on which the secondary object is located): touching the secondary object all the time.
- *Tool* (The object which is used by the hand to enhance the quality of some actions): touching the hand all the time.

Action categories are based upon the objects, which the hand interacts with. These fall into three categories:

1. Actions with main support: In this category the main object is always in touch with the main support; An example is shown in Fig. 2a.
2. Actions without main support: In this category the main object is lifted from the main support; Nn example is shown in Fig. 2b.
3. Actions with load and container: In this category a container with load, e.g. a glass filled with water, is used; An example is shown in Fig. 2c.

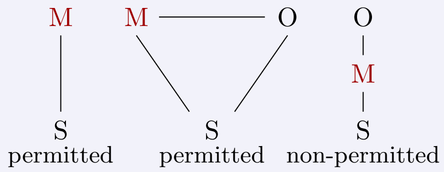
and several actions usually exist for each group. A more detailed list of actions is shown in Tab. 1. The full definition of the ontology is shown elsewhere[1]. Now we can define the layers of the ontology.

Layer 1) SEC based object relations at start: The individual graphical panels in Fig. 2 represent the columns of a Semantic Event Chain (which reflect the transition of object relations and are the necessary conditions for successful execution). Fig. 2b shows a *pick and place* action; its corresponding SEC is shown in the upper part of Fig. 3. The first column shows the SEC-defined

[1] http://www.dpi.physik.uni-goettingen.de/cns/index.php?page=ontology-of-manipulation-actions

Ontology Repository

State	1	2	3	4	5
hand, main	N	T	T	T	N
main, primary	T	T	N	N	N
main, secondary	N	N	N	T	T
main, p.s	N	N	N	N	N
main, s.s	N	N	N	N	N



Primitive 1	move (main)	move (prim.)	move (sec.)	ungrasp	
Primitive 2	grasp			move (free)	

Figure 3: This figure shows one example action, pick and place, in the proposed ontology repository, which is also shown in Fig. 2b. It consists of three parts: the SECs (top), including the SEC precondition (top with green bar), topological preconditions (middle), and primitives (bottom). "M" is the main object; "O" depicts other objects in the scene, and "S" stands for support.

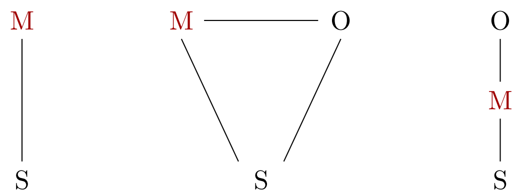


Figure 4: All complex graph structures can be reduced to one of these three graphs. "M" is the main object; "O" depicts other objects in the scene on which there are no further information. The support is "S".

pre-conditions. If and only if these touching relations are not violated, the action could commence. But this is not yet sufficient.

Layer 2) Object Topologies: All actions are always performed at the main object and this will only be possible if the SEC-pre-condition hold *and if* the main object appears in the scene with certain topological connections to other objects. The middle part of Fig. 3 shows which topologies are permitted for *pick and place*.

Remarkably there are only three possible topological relations to which all scenes that include the main object can be reduced. To achieve this the complete connectivity graph of who-touches-whom will be reduced into those subgraphs that contain the main object. Each subgraph consists of at least the *main* object and the *support*, and, if directly touching neighbors exist, only one directly touching neighbor (Fig. 4). There are three cases:

1. The main object has only one touching relation. The touched object is a support, e.g. a table (see Fig. 4, left). A real world example is shown in Fig. 7b; the blue plate is on top of the board and the board becomes the support.
2. The main object has two touching relations. One is a support, the second one is another object, which is also touching the support (see Fig. 4, middle). In Fig. 7b, the apple touches its support (green plate) and the yellow pedestal which is on the same support.
3. The main object has two touching relations. It touches its support and another object, which does not touch the support (see Fig. 4, right). In Fig. 7b, the pedestal is on top the green plate and the jar is on top of the pedestal (but does not touch the green plate).

These subgraphs determine the remaining preconditions. For example, a tower structure as

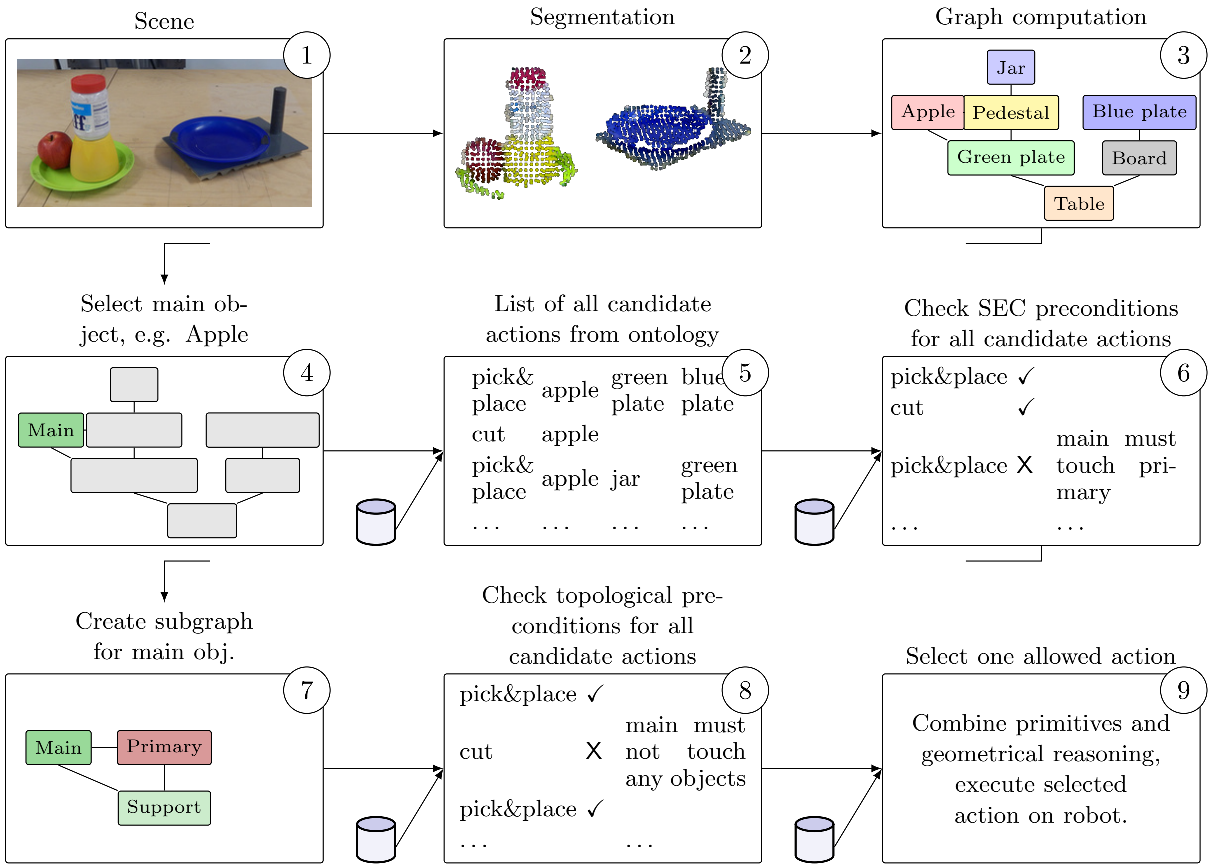


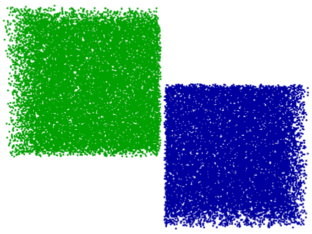
Figure 5: The steps of our proposed framework for scene affordances and execution are summarized here. Starting with a real world scene (1), we perform object segmentation (2), object recognition, and graph calculation (3). The user selects a main object, for example the apple (4). Afterwards, a list of candidate actions based on the ontology is produced (5). The possibility of performing these actions is investigated in two steps by using the preconditions inside the ontology. First, we check preconditions based on the SEC domain; in the example "pick&place the apple from green plate to blue plate is allowed", also cutting. However, "pick&place the apple from the jar to the green plate" is not, since the apple does not touch the jar (6). We create the subgraphs around the main object, as shown in Fig. 4 (7). Afterwards, we check for topological restrictions (8). Here, the action "cut the apple" fails, as the main object must not touch any other objects. This results in a list of allowed actions. One action is selected (either by algorithm, or human), the primitives are read from the ontology and sent to the execution engine. In case of $move(object)$ primitives, we perform the proposed geometric reasoning to get the parameters.

shown in Fig. 4 (right graph) is not allowed for pick and place and pushing actions.

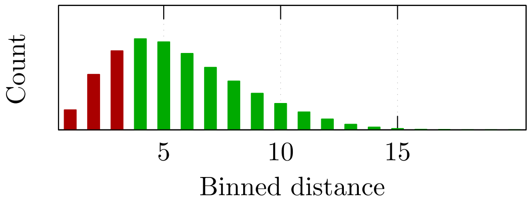
Layer 3) Movement Primitives: SEC pre-conditions and topological pre-conditions define the first two layers of the ontology. The third and last layer is a set of movement primitives, which are needed to execute the action.

For the pick and place action, the primitives are shown at the bottom of Fig. 3. The complete list of primitives for all actions is shown on the web page. How to fill these abstract primitives with execution relevant parameters will be described later and the process of execution of actions is then the same as in (Aein et al., 2013).

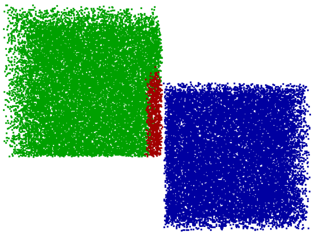
One primitive shall be explained in more detail: The $move(object,\ T)$ primitive sends a command to the robot to move to a pose which is determined by applying transform T to the pose of *object*. The transform T has two parts, a vector p which shows the translation, and a matrix R which shows the rotation. For example, when we want to grasp the *main* object, we perform a $move(main,\ T)$ primitive to move the robot arm end effector to a proper pose for grasping. Since we want the end effector to reach the *main* object, the vector p in this case is equal to zero.



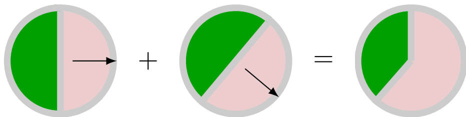
(a) Two blocks serve as an example for geometric reasoning. The possible movement direction of the green cube without touching the blue one is of interest.



(b) The distances from all voxels of the green block to all voxels from the blue block are binned. In the next step all voxels of the green block, which are below the maximum, are used. They are marked in red in the above histogram.



(c) The points found voxels found in Fig. 6b are marked in red. The normals of these voxels are computed and clustered using k-means..



(d) A half sphere around each of the k resulting vectors is spawned (here: half circle for visualization) and the union of all spheres computed. The union, above marked in red, marks the “forbidden” directions.

Figure 6: Step-by-step explanation of the geometric reasoning algorithm.

However, the rotation part R needs to be set such that the robot approaches the *main* object from a proper angle. This is necessary to avoid possible collisions with other objects near the *main*.

2.2 Algorithm for Execution-Preparation

Fig. 5 shows an overview of the algorithm used for robotic execution of the above defined actions. Most components rely on existing methods and will not be described in detail.

We start with (1) an RGB-D recorded scene which is (2) segmented using the LCCP algorithm (Stein et al., 2014) into different objects from which (3) a graph is created with edges between objects that touch each other. (4) Then we randomly choose one object as main. (5) The complete list of all considered manipulation actions, of which there are 29 (see Tab. 2), is derived from (Wörgötter et al., 2012) (only 3 are indicated in Fig. 5) and (6) for all of them we use the first layer of the ontology to check whether the main object in this scene fulfills their SEC pre-conditions. This leads to (7) computation of all possible subgraphs for main and for those we check (8) with the second layer of the ontology the topological pre-conditions by which the list gets reduced. Now we can (9) use the third layer and extract from the ontology the required action primitives. This concludes the preparation stage and this information is sent to the execution engine.

2.3 Execution-Parameterization: Geometric Reasoning

In order to execute any of the in-principle-possible actions we need to parameterize them. In general we use our action library from (Aein et al., 2013) where the required parameters are all defined. They directly map to the action primitives from stage (9) of the above described algorithm. Thus, we need to now consider the actual scene layout to find possible parameter ranges for these movement primitives. For this we employ geometric reasoning. The goal of this is that given an action and its main object we want to find the directions which are free to manipulate this object. These directions are directly used to define parameter ranges of the action primitives (e.g. $move(object,\ T)$) for action execution.

A step-by step explanation of the geometric reasoning algorithm is shown in Fig. 6. For visualization purposes we will analyze the relative position of two cubes to each other: one green and one blue. In a very simple approach, one could reduce the objects to one point in space, for exam-

(a) Scene 1. (b) Scene 2. (c) Scene 3.

Figure 7: These three scenes are used to test the algorithms.

ple the mean or average position. This however will ignore object sizes as well as shapes. Instead, we want a more general solution, which does not depend on object size, shape, or distance.

First, we compute the distance from each voxel from one cube to each voxel in the other cube and bin the distance as shown in Fig. 6b. For two symmetrical objects we expect a poisson shaped distribution. We will use all voxels, which are below the first maximum and belong to the green cube; these points are marked red in the histogram. The corresponding voxels are marked in Fig. 6c in red, too. Next, we compute the normals of these voxels. They will, as per definition, point away from the green cube. These normals are clusterd using a k-means clustering algorithms. While undersegmentation will be harmful – as not all directions are found – but oversegmentation is not, a k that is greater than the expected number of directions is used. We found $k \approx 8$ leads to good results for most real-world examples. Lastly, we spawn a half sphere around each resulting cluster (half circle in 2d as shown in the example in Fig. 6d). The union of all spheres points to the blocked directions, which is marked in red in the example – the direction where the blue cube is located at. This computation is performed for each object, which is in a certain radius around the main object. The radius is hardware dependent and defined by how much space the robot hand needs to safely grasp or push an object.

The results of this type of reasoning on real scenes will be shown in Section 3.

3 EXPERIMENTS

3.1 Setup and Experiments

We tested the algorithm in a ROS based system. A Microsoft Kinect collects image and depth information, in addition a high resolution Nikon DSLR camera is used for image refinement. We use (Schoeler et al., 2014) for object recognition and pose estimation. For model tracking (Papon et al., 2013) is used. Our robot is a Kuka LWR arm which executes actions as described in (Aein et al., 2013). Fig. 7 shows three scenes that are used for testing:

1. A cup is next to a box and an apple is on top of a pedestal.
2. The scene that we used in previous sections: a plate on top of a cutting board, and an apple on a plate. Touching the apple there is a pedestal with a jar on top
3. A cluttered kitchen scene with many objects.

3.2 Results

Using these scenes, we analyse first the effect of the top two layers of the ontology asking: Given a main object, which actions are in principle permitted. Next, we will consider the third ontology layer and perform geometric reasoning on some examples to show how actual action parameterization can be performed and finally we will perform some actions with the robot.

3.2.1 Action Affordances

The results of action affordances for the three scenes are calculated by using the preconditions of the ontology and analysis of subgraph structures. The results are summarized in Tab. 2. Each column shows the possibility of performing different actions in the ontology for a specific selection of *main*, *primary* and *secondary* objects.

Here, we can see some limitations of the SEC domain. Some actions require additional high level object knowledge (e.g. stirring or levering) and are marked with “n”; for example stirring is always denied as it requires a liquid and a container shaped object (non-permanent objects

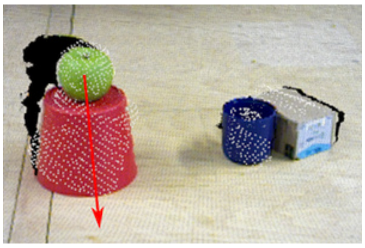


Figure 8: Qualitative results for the geometrical reasoning method. The algorithm is applied to the object pair apple and red pedestal. For graphical purposes only the largest cluster is shown with a red arrow. The computational steps for the arrow are detailed in Fig. 6d. Here, the arrow points from the apple downwards to the pedestal, which is the "forbidden" direction.

pose a big problem for SECs or planning in general). These properties cannot be measured in the SECs domain. One could argue that also cutting, kneading, or scooping needs additional high level object knowledge, but on the touching relations level these preconditions can be ensured.

3.2.2 3D Geometrical Reasoning

Qualitative results of geometric reasoning are shown in Fig. 8, Fig. 9, and Fig. 10. These results show that by processing the low level point clouds one can detect the blocked and free directions of a given object. Some limitations can be found in Fig. 9a, which shows the spatial relation between an apple and a green plate. We expect that we can compute the normals of the point cloud, but at corners, e.g. at the border of object point clouds, this assumption is not always met and the resulting access angles are off. In Fig. 9a, the apple is captured with only few points into the direction downwards to the green plates and the resulting vector goes off to the side and barely through the plate.

Another problem can be seen in scene 3. In Fig. 10c, the relations between the orange spoon and the black spoon in the spoon holder (black spoon and spoon holder are recognized as one object) form one unexpected cluster downwards, all others point towards the spoon. Careful examinations show that there actually are some points belonging to the spoon base below the orange spoon and that the arrow downward is justified. However, the resulting access angle is very small.

3.2.3 Action Execution

The results of action execution are presented in the video attachment of the paper (please see aforementioned web page). The execution of three different actions is shown: "pushing", "pick and place", and "put on top". Selected frames of these experiments are shown in Fig. 11. Shown are the actions "pushing" (left), "pick and place" (middle), and "put on top" (right).

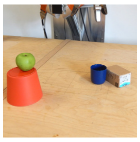
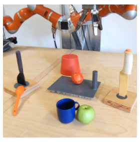
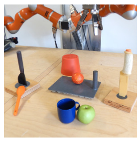
4 CONCLUSION

The goal of this study was to address the problem of affordances given the scene context. We specifically wanted to create a system that can look at objects in a scene and suggest actions which are very likely possible. For this we first defined a novel and hopefully quite complete ontology of manipulation actions which considers objects, too, but still from a rather abstract viewpoint. The main point here is that this allows generalizing the same action across quite different scenes. Combined with geometrical reasoning this system can analyse scenes and suggest and perform many actions.

Thus, essentially the proposed system acts like a multi-layered planner with several levels of pre- and post-conditions. This may indeed ease robotic planning problems by allowing the system to check all conditions in a hierarchy and to finally profit from the geometrical link to the actual scene layout.

Of course, situations may exist that cannot be correctly disentangled this way. The resulting permitted movement directions are always based on parts of the 3D space that had been derived from straight direction vectors. Hence if there is a complex shaped object that hooks-around some other object this type of geometric reasoning will fail. Also, if objects are topologically linked (physically connected) in complex ways to other objects the approach will fail. Our system does not attempt to solve all these problems. Rather, like a child after some experience, here we have arrived at a system that produces *very reasonable* suggestions about how to modify its world using different manipulations. This is the main strength of this approach. We have here a quite powerful bottom-up decision framework, which does not rely on high-level knowledge but could be extended by this (for example using learned models of some aspects of the world) without problems.

Table 2: Results of the action affordances for different scenes and objects. The different scenes are also depicted in Fig. 7. Objects corresponding to the computed affordances are listed below the table heading. Please note that we cannot check the preconditions for some actions, e.g. stirring, knead which are related to the material of objects. These actions are denoted with "n"; they require high level object knowledge. For example you need a liquid and a container object for stirring. This knowledge is not provided in the SEC domain. A "✓" denotes the successful execution of the action; the actions "-" were correctly computed as not possible to execute.

		Scene 1	Scene 2	Scene 2	Scene 3	Scene 3
						
Main Object		cup	apple	yellow pedestal	orange	apple
Primary Object		box	yellow pedestal	green plate	board	cup
Secondary Object		red pedestal	blue plate	blue plate	cup	board
1	punch	✓	✓	✓	✓	✓
2	flick	✓	✓	✓	✓	✓
3	poke	✓	✓	✓	✓	✓
4	chop	-	-	-	✓	-
5	bore	✓	✓	✓	✓	✓
6	cut	-	-	-	✓	-
7	scratch	✓	✓	✓	✓	✓
8	scissor-cut	-	-	-	✓	-
9	squash	✓	✓	-	✓	✓
10	draw	✓	✓	✓	✓	✓
11	push	✓	✓	-	✓	✓
12	stir	n	n	n	n	n
13	knead	✓	✓	-	✓	✓
14	rub	✓	✓	✓	✓	✓
15	lever	n	n	n	n	n
16	scoop	✓	✓	-	✓	✓
17	take down	-	-	-	✓	-
18	push down	-	-	-	✓	-
19	rip off	-	-	-	✓	-
20	break off	n	n	n	n	n
21	uncover by pick&place	n	n	n	n	n
22	uncover by pushing	n	n	n	n	n
23	put on top	-	✓	-	✓	-
24	push on top	-	-	-	-	-
25	put over	n	n	n	n	n
26	push over	n	n	n	n	n
27	grasp	✓	✓	-	✓	✓
28	push apart	✓	✓	-	-	✓
29	push together	-	-	-	-	-

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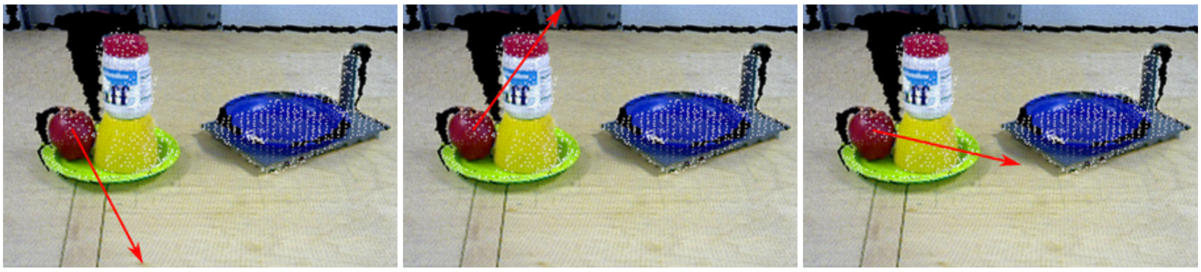
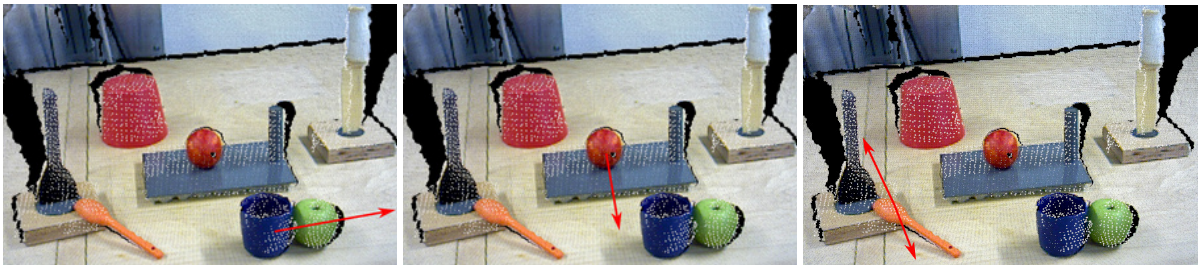


(a) Scene 2: Apple and green plate. (b) Scene 2: Apple and jar. (c) Scene 2: Apple and pedestal.

Figure 9: Qualitative results for the geometrical reasoning method. For graphical purposes only the largest cluster is shown with a red arrow.



(a) Scene 3: Blue cup and apple. (b) Scene 3: Orange and board. (c) Scene 3: Orange and black spoon.

Figure 10: Qualitative results for the geometrical reasoning method for a cluttered scene. For graphical purposes only the largest cluster is shown with a red arrow. In (c) the two largest clusters are depicted using red arrows.

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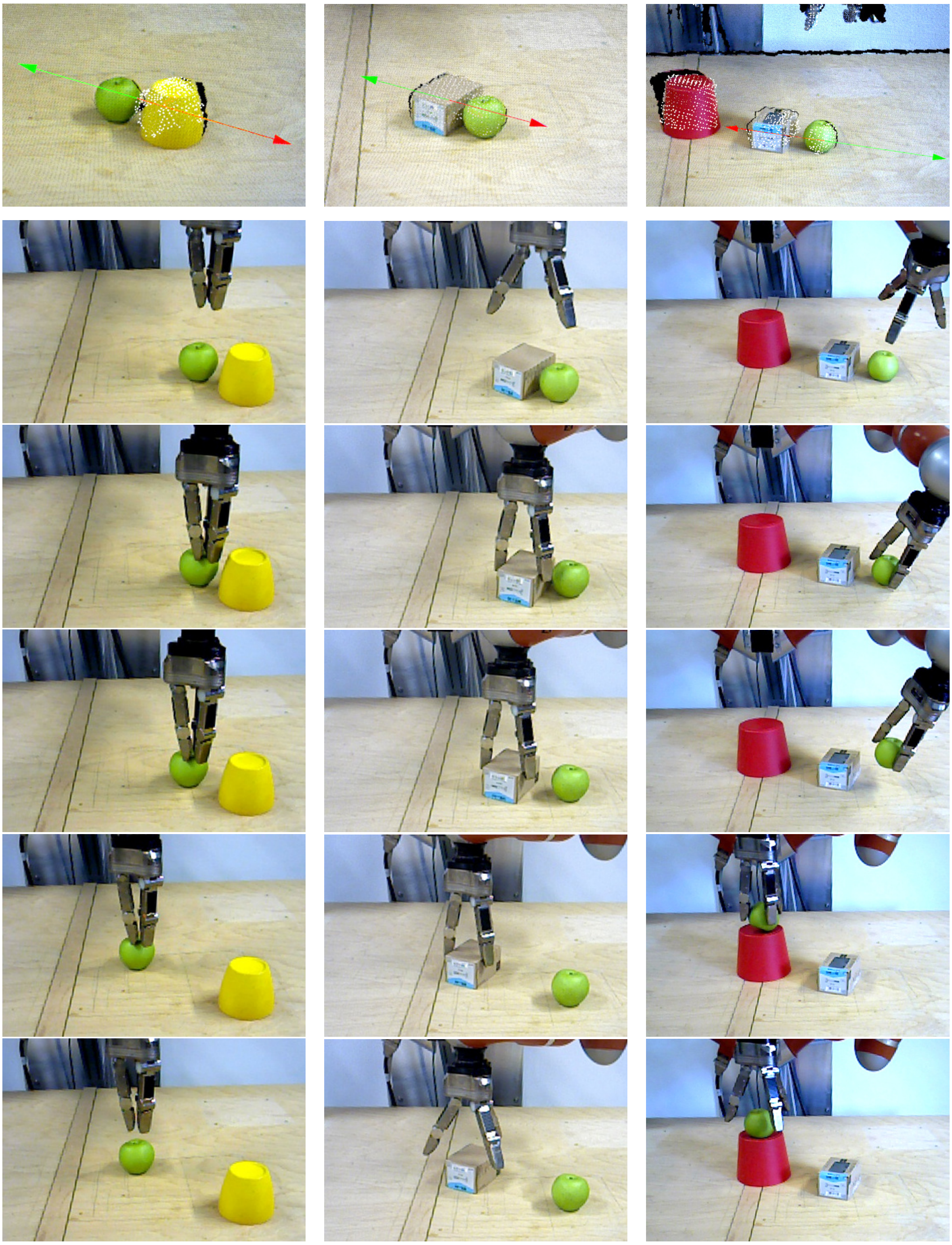

Figure 11: Execution results of three different scenarios: “pushing” (left), “pick and place” (middle), and “put on top” (right). The top row shows the results of the geometrical reasoning. The allowed direction is marked with a green arrow, the forbidden one with a red arrow. The full scene is also shown in the video attachment of the paper.