Knowledge-Enabled Robotic Agents for Shelf Replenishment in Cluttered Retail Environments

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May 16, 2016

Abstract

Autonomous robots in unstructured and dynamically changing retail environments have to master complex perception, knowledge processing, and manipulation tasks. To enable them to act competently, we propose a framework based on three core components:

1. A background knowledge enabled perception system, which is capable of combining diverse information sources to cope with challenging conditions, such as occlusions and stacked objects with a variety of textures and shapes,
2. Knowledge processing methods that identify the current scene, and produce strategies for tidying up supermarket racks, and
3. The necessary careful manipulation skills in confined spaces to arrange objects in semi-accessible rack shelves.

We show that our approach yields feasible, situation aware manipulation strategies. We demonstrate our framework in an idealistic simulated environment, as well as on a real shopping rack using a PR2 robot. Typical supermarket products are detected and rearranged in the retail rack, tidying up what was left after customer interaction, or while restocking sold items.

1 Introduction

Robotics has become a disruptive technology, in which autonomous mobile manipulation platforms become more broadly available. This poses a challenging research problem for the field of autonomous agents and multi-agent systems where the question of how we can design and realize robotic agents that are embodied and can manipulate the physical world in order to accomplish human-scale manipulation tasks in open and realistic environments is still largely unanswered.

The application domains where we can expect robotic agents that manipulate their environments first are mobile fetch-and-place tasks in semi-structured environments. Take for example a supermarket: Common tasks include refilling product shelves, and putting misplaced products back to where they belong. In contrast to factory-based tasks for robots, where predefined sequences are executed over and over again, retail scenarios are semi-structured, but unpredictable in details. Products might be missing, requirements of where to place which item change, or products and shelves are partially obstructed. Another example are warehouses in which robots will have to fetch items on an order list, place them into a box, and close the box for shipping.

These tasks offer a lot of useful structure that can be exploited by the robotic agents. In a supermarket the items are placed such that they can be easily seen, the items usually have sizes and shapes that fit well in the human hand, the front side is typically visually distinctive and contains valuable information such as the weight of the content, etc. They also constitute challenges as identical items are placed directly...
next to each other, complicating object segmentation as well as manipulating objects without causing side effects on the neighboring items.

The tasks that the robotic agents are to accomplish include loading an empty rack, restocking sold items, cleaning up unordered shelves, rearranging product configurations, etc. Moreover, we can cater for all kinds of dynamic scenarios with little to no predefined constraints, but different settings, including tasks like warehouse commissioning. It requires the adequate handling of a large variety of objects where each of them might have to be handled in its own specific way. The tasks have to be performed robustly and flexibly over long extended periods of time providing robotic agents with the opportunities for lifelong learning.

Manipulation tasks that fall into this category are seeing increasing interest. 2015’s Amazon Picking Challenge [26] recently raised the bar towards an integrated system for pick and place in industrial environments where the contributing systems had to perform perception and manipulation on a warehouse rack. Some of the presented solutions were quite promising in their performance, however, certain aspects in the provided challenge were simplified mainly concerning the degree of environment clutter and reasoning about high-level plans.

In this paper, we design, realize, and investigate a robotic agent that performs a limited kind of shelf reordering. The robotic agent takes a qualitative spatial description of how the items in a shelf should be re-ordered, such as the cereal should be placed to the right of the coffee. The robotic agent then tessellates the target region of the items into variable size grid cells that are allocated for the individual product groups. The items are to be placed in the respective grid cell, next to each others and facing the front.

In detail, the solution presented herein supersedes the setting of the Amazon Picking Challenge firstly in the way that objects can be recognized and grasped even if they are subject to heavy occlusion, or similar objects are stacked or aligned with each other. Multiple instances per object are not a limitation either. Typically, upon customer interaction, the shelves in retail environments quickly become unordered, cluttered and arranged in a way that it is hard to restore a particular order using existing solutions.

Secondly, the Challenge’s entries were required to only drop off the picked objects into a basket. Our approach, instead of simply dropping the retrieved objects somewhere, focuses on reasoning about their semantics which is crucial for everyday scenarios like ours which require to achieve a certain final object configuration. Additionally, since we want to avoid to accidentally clear up the whole shelf, awareness and avoidance of clutter objects are a central requirement in such a scenario.

In summary, recapitulating the specific constraints imposed on our scenario, the contribution of our work is:
• **Perception**: a cluttered everyday scenario with no object location and orientation priors, heavy occlusion, multiple instances of the same object, repetitive textures or shapes, and stacked and aligned objects with no free space

• **Knowledge-based Reasoning**: object occlusion resolution by implicit secondary manipulation actions, a solver for autonomously tidying up retail shelves, and vague action descriptions

• **Manipulation**: knowledge-based autonomous object manipulation with implicit failure recovery

## 2 Related Work

### 2.1 Robotic Assistants in Retail Environments

As a predecessor of the tedious task of cleaning up shelves in a retail environment, shopping assistant robots have been developed recently [9] [10] which provide a variety of customer assistance, but most times do not interact with the store items directly. Usually, such systems have been operating semi-autonomously to a certain degree, that means, for instance, that the user is only guided to a selected product in the respective aisle, but has to pick it up himself. Fully-autonomous systems recently have been starting to emerge especially for the use in warehouse environments, however, retail environments provide a research area still to be explored.

In the course of the existing solutions, self-localization methods have been specialized to cope with extensive indoor environments like a supermarket [19]. However, only localizing the rack’s location is not sufficient for efficient interaction with the contained objects. In order to interact with items stored in a rack, a robot additionally has to gain semantic knowledge about the items as well as their exact pose.

A new shelf auditing robot has recently been introduced by Simbe Robotics [24]. This solution provides inventory keeping of perceived store items while moving through the aisles, alerting staff to perform re-stocking wherever necessary. Rather than dedicating the reasoning and manipulation tasks to human operators we implement a fully autonomous solution.

### 2.2 Perception in Cluttered Retail Environments

Perception of object candidates turns out as challenging in cluttered scenes like in our scenario where the arrangement of the retail items changes over time due to customer interactions. Moreover, the products can be observed only partially due to occlusions, additionally, they may be neatly stacked and can feature varying poses and appearances. Due to the diverse nature of products sold in retail stores, a robust perception must be able to deal with different shapes, physical extents, and levels of texturness.

To overcome these challenging conditions, the items could be RFID-tagged which allows for an easy identification and localization [6]. On the other hand, invasive approaches [11] attempt to detect objects in unstructured scenes through manipulation and tracking changes in the scene. Nevertheless, we follow a vision-based detection approach which does not require to modify or manipulate objects. A monolithic perception system may fail to cope under these diverse conditions. On the contrary, fusing specialized object detection approaches leads to enhanced perception capabilities which can cope with the conditions present in our target application scenario.

### 2.3 Knowledge-Based Reasoning and Mobile Manipulation

In order to manipulate objects which are placed currently unreachable behind others, Stilman et al. [18] use a sampling-based planner to move away the blocking objects first, although they show their results in simulation only.

Okada et al.’s method [16] follows a similar idea, but deploys their planner on humanoid robots manipulating doors and other obstacles on the way to their objective. Their goal, as well as ours, is to enable robots to implicitly perform necessary manipulation actions, although these actions were not part of the original task plan. Robots having this ability can act according to the current situation without being told so explicitly.
3 System Overview

Addressing the problems stated in this paper would not be possible without a tight integration between specific modules that are needed by an autonomous robotic agent. Figure 2 shows the overall system architecture, highlighting the specific results/tasks of each component. Three main components were used to build up the system, each of them introduced recently, mainly because they are open-source software, freely available for anyone to use, and because they meet the required needs of being modular and easy to extend:

- CRAM [2] – high level robot planning and reasoning
- KNOWROB [20] – centralized knowledge processing and inference framework
- ROBOSherLOCK [1] – knowledge-enabled robotic perception framework

Furthermore, in the following sections, we will highlight the two essential perception components used by ROBOSherLOCK and tasked with the gist of the recognition process: a texture [22] and a shape-based [15] recognition system.

The entry point to the system is a generalized plan for rearranging the shelf, generated by CRAM. As a first step, ROBOSherLOCK is queried for the detected items. At this point, using knowledge about the environment stored in the semantic map of KNOWROB, the raw data is filtered in order to contain only the regions of interest for the current task, that is, the respective shelf.

Based on the filtered images, the instance and shape recognition then hypothesize about possible products and their locations, and transmit these back to CRAM through ROBOSherLOCK. Internally, the plan generation evaluates different strategies for executing the rearrangement task, which are ranked based on their intrinsic cost as calculated by an A*-based planner implemented in CRAM.

The best ranked strategy is then chosen to be executed. Once the best strategy has been chosen, the actual manipulation plan is generated and executed by the robot. In case of failures that occur during the manipulation (e.g. unable to grasp object, dropped object, unable to plan manipulation trajectory, etc.), control is handed back to CRAM where the contingency is resolved and an alternative plan is generated.

Details on these components will be presented in the next sections as well as in Figure 2 which additionally shows some example results from the different perception and knowledge-processing modules.

4 Perception in Cluttered Retail Environments

As discussed earlier, perception in retail environments faces many challenges due to the variety of object appearances, shapes and their arrangements in confined spaces. On the other hand these environments allow to infer semantical knowledge which can be exploited to enhance the performance of the perceptual tasks.

Therefore, we follow a top-down and bottom-up approach. We use top-down knowledge such as the location of shelves or what objects are expected to be on a concrete shelf. Being aware of such
top-down knowledge, in a bottom-up manner perceptual capabilities are required to detect and recognize individual object instances on the shelves under dynamic conditions with respect to object location, poses or appearance.

Due to the nature of such dynamic conditions, perceptual capabilities are needed which can cope with the detection of objects which are not distinctly recognizable or unknown. Moreover, it may be not feasible to train a perception system with the variety of object instances beforehand.

Nevertheless, detecting instances which are unknown or known to the system still represent a challenging task due to the appearances which can feature contacts to other objects, transparency, deformability or occlusions. Hence, it is required to consider multiple cues with respect to color, texture or geometry to achieve capabilities that can cope with such scenarios.

4.1 Perception Framework

In this paper we make use of the recently introduced and freely available ROBOHERLOCK framework \[1\], a knowledge-enabled perception system that has its roots in Unstructured Information Management \[8\] and takes advantage of the ensembles-of-experts approach.

In ROBOHERLOCK, perception tasks are considered as being queries that need answering. These queries are answered in a three-step process: (1) hypothesizing about regions in the image that could be of interest, (2) annotating the generated hypotheses with semantical labels, and (3) testing, ranking and merging the resulting hypotheses and annotations.

This is made possible through two defining concepts of the framework: firstly, the use of background knowledge about a robot’s environment operating in a retail scenario that can simplify perception tasks (e.g. localization in a semantic map). This information is valuable for filtering the incoming images so that only semantically meaningful regions are further processed by the experts. Having this background knowledge about where the robotic agent is located also enables the system to formulate expectations about which categories of objects it is supposed to perceive in the environment, enabling the detection of misplaced items.

Secondly, the perceptual capabilities of the framework are modeled so that it can autonomously make decisions about which perception algorithm to run in order to successfully accomplish the given task, and how to fuse the results from several, often contradictory sources.

In order to assure consistency of the perceived objects in the environment it is desirable to have a consistent labeling of the objects in the environment. Consistency in the ROBOHERLOCK framework is assured by maintaining a perceptual memory of objects \[23\].

ROBOHERLOCK is capable of incorporating more or less any kind of perception module, thus, for the purpose of this work, the functionalities of a shape and a textured object recognizer are wrapped into annotators. Additionally, ROBOHERLOCK handles the consistency of the results by merging the different hypotheses and assures the interface to the knowledge-based reasoning module. A detailed description of the perception modules is presented in the following.

4.2 Object Recognition Modules

Two recognition modules were embedded into the ROBOHERLOCK framework to handle different modalities present in our target scenario. The texture-based recognition module (Sec. 4.2.1) is used to generate hypotheses about objects from the knowledge base. Hence it serves as an object instance recognizer and enables higher-level processes to use the associated knowledge to perform well-informed planning and actions.

On the other hand, objects not present in the database are handled by the shape-based object recognition module (Sec. 4.2.2), which, in addition to segmenting object candidates, provides shape category information. An unsupervised approach not only allows to improve the perception system’s confidence via hypotheses fusion, but also provides the means to handle unknown objects and enables the acquisition of new knowledge.

Both object recognition modules used in this work have been extensively tested by their original authors and proven to be successful in the unloading of heterogeneous goods \[12\] \[15\] as well as in handling the cargo of coffee sacks \[21\]. While perception in retail environments and perception in shipping containers differ in certain aspects, both cases have to cope with similar challenges – big occlusions,
clutter, large variety of object types and ambiguous boundaries between objects. A detailed discussion of the internals of the recognition pipeline falls out of the scope of this paper, thus only a short summary with a focus on the main components can be provided here.

After some optional RGBD data smoothing operations, like median-based filtering or virtual scans rendered from a Signed Distance Function [4] map aggregating multiple views, the data is processed by two types of segmentation algorithms:

- **Type I: model-unaware**, in the sense that they do not utilize prior information about the known objects present in the knowledge base. A segmenter of this type over-segments the scene and the resultant atomic patches form the basis for downstream segmenters and object recognition modules. A robust over-segmentation can be achieved, like Mueller et al. [15] and Vaskevicius et al. [21] described in their original work, using the Mean Shift [7] algorithm extended to operate in RGBD space or a clustering approach based on Super Voxels [17].

- **Type II: model-aware** segmenters may combine neighboring atomic patches from the Type I segmenters according to some application-dependent heuristics, such as convexity.

It is important to emphasize the over-segmentation step. While this step is not designed for providing object candidates, it forms segments which respect the boundaries of objects even in very challenging scenes. At the same time these segments divide the RGBD raster into contiguous clusters, which are homogeneous with respect to certain geometric and/or color-based criteria. This higher level (patch-based) representation of data enables more efficient and robust analysis of the scene structure.

Finally, the patches obtained during segmentation are passed through a rough filtering step based on geometric characteristics and are further analyzed by the specific recognition modules, as described in the following.

### 4.2.1 Texture-based Object Recognition

The texture-based recognition module used in the proposed system was introduced by Vaskevicius et al. [22]. Here we only provide a short overview of the system and its extensions we implemented for the publication at hand.

The recognition consists of bottom-up and top-down perception steps and is done by combining texture information obtained from a color image with geometric properties of the scene observed in a depth image. To this end, an object database of 3D models is built and is augmented with visual and shape cues. A digital 3D representation of real-world objects can be acquired using, for example, an infrastructure-free approach like the one proposed in [13], a fully autonomous robot-based method or commercial off-the-shelf modeling tools which can create high-fidelity meshes. The cues extracted from the database are then used in the online stage to generate hypotheses about the objects in the observed environment.

First, the filtered valid atomic patches obtained by the segmentation module are used to define a region of interest in the RGB image for which to extract visual features. Next, a RANSAC step is used to generate hypothesis for the most likely positions of database objects, while respecting 3D geometrical constraints between feature keypoints. The candidate object poses computed by the matching algorithm are then used to reproject the models of the objects into the RGBD image plane. Patches from the over-segmentation, color and range information are then used to test the hypothesis consistency and to filter out false positives. Objects with high consistency scores are considered to be recognized and their corresponding patches are removed from the scene. Detection is then reiterated on the remaining segments to handle multiple object instances.

### 4.2.2 Shape-based Object Recognition

The shape-based recognition module focuses on object class learning using the hierarchical part-based shape categorization method for RGB-augmented 3D point clouds proposed by Mueller et al. in [15].

An unsupervised hierarchical learning procedure is applied, which allows to classify shape parts to a set of symbols. These symbols reflect the surface-structural appearance of parts on different specificity levels of detail. Based on this symbolic representation, a hierarchical graph-based model is learned that encodes the constellation of classified parts from the set of specificity levels learned in the previous step.
Given the learned constellation of parts for certain shape categories, an energy minimization inference procedure is applied on the hierarchical graph-model to obtain the corresponding shape category of an object instance which consists of a set of shape parts.

As Mueller et al. demonstrated in [15], the additional evidence on different levels of shape detail contained in the proposed hierarchical graph constellation model is a major factor that leads to a more robust and accurate categorization compared to their former flat approach [14].

5 Knowledge-Based Reasoning and Mobile Manipulation in Retail Environments

Competently tidying up a shopping rack requires a number of knowledge-intensive skills. A robot has to autonomously generate a strategy on how to achieve its goal, such as where to place which object in what order. When applying this strategy, it has to perform a number of pick-and-place actions in a possibly cluttered, heavily constrained environment. A static model of the rack including its dimensions as well as grasping configurations for the objects are used to dynamically populate a collision scene and compute how objects need to be approached.

These processes are dominated by decisions made based on strongly volatile information (object poses, robot pose, current and target rack arrangement). A sophisticated memory collection system is used to record episodic robot experiences that can then be used to store and evaluate the effects of individually generated strategies.

5.1 Knowledge-based Strategy Planning

When rearranging products in a shopping rack, an autonomous robot needs an idea of which action sequence \( A(S_i) \rightarrow S_j \) brings the rack from its current state \( S_0 \) into the desired one \( S_g \). To find such an action sequence, we equipped an off-the-shelf A* planning algorithm with additional capabilities, being:

1. **Generation of action sequences, such that** \( A(S_0) = S_g \)
   The generated sequences consist of parameterized atomic actions that the robot can execute. The supported actions are **pick**, **place**, **handover**, **move-torso**, and **move-base**. While **pick** and **place** are self-explanatory, **handover** describes handing over a held object into the other (free) hand of the robot to prevent unnecessary, lengthy base movement. **move-torso** lifts or lowers the torso of the robot to reach the upper and lower parts of a rack, and **move-base** repositions the robot in front of the rack to better reach the outer extents.

2. **Generation of multiple solutions** \( A_i \) in descending quality
   After the modified A* algorithm has found a solution, it is stored and then artificially charged with an infinite cost, preventing the algorithm to converge onto that solution. It then generates the next, potentially less optimal one, until either all feasible, or a defined maximum number of solutions are generated. An autonomous robot then has a number of solutions at its disposal to evaluate using external criteria if necessary.

3. **Matching of generic goal states** \( S_G = \{ S_{g0}, S_{g1}, S_{g2}, \ldots \} \)
   The modified planner can plan towards an explicit goal (the original A* behavior), such that it is required to place specific product instances onto defined positions in the rack:
   \[
   \begin{bmatrix}
   Cornflakes_1 & Cornflakes_2 & Cornflakes_3
   \end{bmatrix}
   \]
   Instead, generic goals allow the planner to converge to any solution that satisfies class-based matching of objects:
   \[
   \begin{bmatrix}
   Cornflakes & Cornflakes & Cornflakes
   \end{bmatrix}
   \]
   This leads to faster convergence and to a larger search space when producing multiple solutions. We achieve this by modifying the state comparison function whenever the algorithm checks whether it reached the goal state.
A* does not possess any of these capabilities by default. When extending the algorithm, we found these enhancements suitable for the shopping rack scenario at hand, although they are highly applicable outside of this domain.

In order to perform an A* search, we require a distance measure and a heuristic cost function between states. When a state \( S_0 \) differs from \( S_1 \), i.e. their distance measure or heuristic cost is non-zero, we call \( S_0 \) entropic. We define the heuristic cost function \( H \) between them as

\[
H(S_0, S_1) = \frac{\text{No. of misplaced objects in } S_0 \text{ rel. to } S_1}{\text{Total no. of objects in } S_0}
\]

(1)

In general it holds that \( H(S_0, S_1) \neq H(S_1, S_0) \). This is due to the dominance of the first factor’s object count in \( H \)’s denominator. In practice, this is justified by \( S_0 \) holding the amount of available objects, and \( S_1 \) holding the possible object places. There might be less objects than could be placed in a rack. The opposite situation never comes up in a valid scenario.

The distance measure \( D \) between two states \( S_0 \) and \( S_1 \) is defined as the their transition cost, i.e. the cost of getting from one state to the other according to a sequence of actions. The transition cost \( T_c \) of \( A_i(S_0) \rightarrow S_1 \) is therefore defined as the sum of \( n \) actions in \( A_i \). The individual atomic action types are weighted with \( w \):

\[
D(S_0, S_1) = T_{i}^{S_0 \rightarrow S_1} = \sum_{k=1}^{n} w(A_{i,k}) + T_c
\]

(2)

A state \( S_i \) also reflects the current base and torso position of the robot, as well as which objects currently reside in its hands. When differing, each of these elements adds a cost of 1 to \( T_c \). It always holds that \( D(S_0, S_1) = D(S_1, S_0) \).

Since \( w \geq 1 \), \( H(S_0, S_1) \) never overestimates \( D(S_0, S_1) \), as required for \( A^* \):

\[
D(S_0, S_1) \geq H(S_0, S_1)
\]

(3)

The generated action sequence \( A_i \) is performed step by step. Local failures are taken care of, such as replanning of trajectories when no valid solution could be found. Due to its purely symbolic nature, the planner fails to capture reality’s uncertainty. Therefore if the local failures surpass a given frustration limit (rendering the action sequence invalid), new action sequences are planned based on the current state of the rack.

### 5.2 Motion Planning

Our high-level plans are designed and executed using the robot plan system CRAM [2]. Within CRAM, motion planning tasks are performed every time when the feasibility of a manipulation action is verified, or when said action is actually performed. To execute motion planning and to control robot actuators, we use the MoveIt! framework by Chitta et al. [5]. MoveIt! supports free-space motion planning, but unfolds its full potential when its planning scene, the environment defining motion constraints, is populated with collision objects. To make semantic knowledge about the collision environment accessible to cognition-enabled robots controlled by CRAM, we use the KNOWRob knowledge processing system [20].

In our scenario, collision objects are the individual parts of the rack, the walls of the surrounding room, and the objects to manipulate. Figure [3] shows a visualization of our populated manipulation scene, featuring supermarket furniture. When manipulatable objects are positioned on the rack, the robot knows about the rack geometry and avoids unwanted contacts during manipulation.

The planning scene needs to be administered from outside MoveIt! to be useful for manipulation actions. While static collision objects are asserted from a static knowledge base, such as the rack and the surrounding walls, objects in the scene are not known during design time of that knowledge base. Also, during the course of action of reordering objects in the real world, the changes need to be adapted in the planning scene to reflect which areas not to touch when moving the robot’s arms.

In CRAM, the planning scene is synchronized with the robot’s internal belief state of its environment whenever a significant event is registered. These events include, but are not limited to, actions in manipulation, navigation, and perception.
5.3 Grasp Planning and Execution

After detecting objects and determining their symbolic destination positions, an underspecified fetch-and-place task needs to determine all details necessary for actual execution. Specifying this task as vague as possible leaves an autonomous robot space for choosing execution relevant parameters:

```
(fetch-and-place
  (an object
    (type box)
    (label "Cornflakes")
    (color yellow))
  (a location
    (on rack-1)
    (near (an object
      (category "Cereals")))))
```

Assuming that the robot perceived a yellow, box-like object with the label “Cornflakes”, it now has to decide

- how to get hold of it, and
- where exactly to place it in 6D space.

CRAM now asserts an object resembling the cornflakes box in size in its belief state and pose, and thus in the MoveIt! planning scene. A manipulation action is instantiated that first moves the gripper close to the object and then, allowing explicit contact with the box, grasps it. A motion path is then calculated by MoveIt! that lets the robot safely transport the box out of the rack.

While from a motion path point of view placing is performed similarly, the final position needs to be determined first. The internal representation of the rack contains, besides dimensions, meta data describing the rack shelves as surfaces, able to hold objects. In CRAM, an underspecified location description like the one above is resolved, under consideration of such model knowledge, using the `(reference ?loc)` call. `?loc` is a location description such as `((on rack) (shelf 2))`, and `reference` jointly matches all knowledge fitting `?loc`, resulting in a 6-DOF pose on one of the rack shelves.

5.4 Memory Collection and Data Analysis

Autonomous decision-making requires a combination of static knowledge with characteristics of the current situation. While the former is manually designed, the latter is generally not easily accessible
6 Experimental Evaluation

We evaluate the system, based on the quality of the plans that get generated from the real perception data. Furthermore, we showcase two execution sequences on a PR2 robot, highlighting the rearrangement of objects, and reasoning about which object to manipulate in occluded scenes.

6.1 Setup

In order to show the feasibility of our general integrated perception and knowledge-based manipulation approach, we exemplarily apply it to a PR2 robot working in a retail environment. This environment, like shown in Figure 3, consists of a rack similar to the ones found in typical stores and supermarkets, containing products of different size, shape, texture and weight, selected from various grocery categories.

The strength of our approach lies in equipping an autonomous robot with knowledge-backed strategies for re-ordering products found in such racks. Given a current arrangement, and a desired target arrangement, a robot must make a number of decisions for the appropriate manipulation. Using CRAM, we offer such a robot a set of ways to achieve its goals:

- Perceiving the current occupancy of the rack, extracting symbolic representations of the contained objects and their poses
- Generating an action sequence representing a strategy to bring the rack into an arbitrary desired arrangement
- Executing this strategy by moving the base of the robot, its torso, and performing various pick and place actions
- Properly reacting to failures by unwinding the current situation, replanning, and continuing the execution

In our experiments, we present a shopping rack with a number of misplaced objects to a PR2 robot that then, after generating the appropriate action sequence, moves all objects to the places where they belong.
Figure 5: Ten different experiment arrangements of objects in a shopping rack. The left images show the source camera data. The right images depict the processed object instances recognized by the perception system.

| Series 1 | Series 2 |
|----------|----------|
| Camera   | Processed| Camera   | Processed |
| a        |          |          |          |
| b        |          |          |          |
| c        |          |          |          |
| d        |          |          |          |
| e        |          |          |          |
| f        |          |          |          |
| g        |          |          |          |
| h        |          |          |          |
| i        |          |          |          |
| j        |          |          |          |

Table 1: Heuristic cost weight values used by the modified A* planner, and while determining an action sequence’s overall cost.

| Action $A_{i,k}$ | Pick | Place | Move Torso | Move Base |
|------------------|------|-------|------------|-----------|
| Weight $w$       | 1.2  | 1.2   | 2.0        | 1.0       |

6.2 Planning Experiments

To evaluate the importance of harmonizing the different system components of our approach when dealing with complex shopping rack scenarios, we present a series of example cases. In these, we demonstrate the effects of slight variations in perception data on the output of the planning algorithm, and thus, in the manipulation phase.

Figure 5 depicts 20 shopping rack situations, separated into two qualitatively different series. Each situation is shown as the camera input for the perception system, as well as the data as it was actually processed. The number of objects, as well as their pose in the rack are slightly changed in each case, resulting in obstructed objects (cases 1.b-c, f-j), inclusion of irregular objects (cases 1.f, h-j), and stacking of similar (cases 2.a, e-f) and different objects (case 2.b-c, i-j). In some cases, objects were not or wrongly detected (cases 2.c, e). Table 1 shows details of the planned action sequences based on these 20 situations. The planner’s goal was to group the available objects and evenly distribute them over two of the rack’s shelves. Initially, no object was at its goal pose.

The cost shown in Table 1 represents the accumulated cost of all individual actions inside of a planned sequence as used by A*. The action cost values are shown in Table 1. Picking and placing are rather simple actions, while moving the robot’s torso takes quite some time. As execution time is a quality criterion while tidying up shopping racks, it is more expensive. Moving the robot’s base is rather fast, and
| Time | Pick | Place | Move | Move | Cost | Anomalies |
|------|------|-------|------|------|------|-----------|
|      |      |       |      |      |      |           |
| 1.a  | 1.2s | 4     | 4    | 7    | 0    | 23.6      | -         |
| 1.b  | 0.9s | 4     | 4    | 5    | 0    | 19.6      | Obstruction |
| 1.c  | 2.6s | 4     | 4    | 7    | 2    | 25.6      | Obstruction |
| 1.d  | 0.8s | 4     | 4    | 7    | 0    | 23.6      | -         |
| 1.e  | 10.9s| 4     | 4    | 6    | 2    | 23.6      | -         |
| 1.f  | 16.1s| 5     | 5    | 3    | 2    | 20.0      | Obstruction, irregular object |
| 1.g  | 1.9s | 4     | 4    | 5    | 2    | 21.6      | Obstruction |
| 1.h  | 124.4s| 5   | 5    | 7    | 2    | 28.0      | Multiple obstructions, irregular object |
| 1.i  | 8.1s | 5     | 5    | 6    | 0    | 24.0      | Multiple obstructions, irregular object |
| 1.j  | 18.9s| 5     | 5    | 3    | 2    | 20.0      | Multiple obstructions, irregular object |
| 2.a  | 101.8s| 5   | 5    | 5    | 2    | 24.0      | Stacking (same) |
| 2.b  | 5.5s | 5     | 5    | 5    | 0    | 22.0      | Stacking (different), obstruction |
| 2.c  | 21.2s| 4     | 4    | 6    | 2    | 23.6      | Stacking (different), obstruction |
| 2.d  | 50.4s| 6     | 6    | 8    | 2    | 32.4      | Multiple obstructions, irregular object |
| 2.e  | 0.5s | 3     | 3    | 5    | 0    | 17.2      | Stacking (same) |
| 2.f  | 9.9s | 5     | 5    | 3    | 2    | 20.0      | Stacking (same) |
| 2.g  | 3.1s | 4     | 4    | 5    | 2    | 21.6      | Obstruction |
| 2.h  | 2.0s | 4     | 4    | 5    | 2    | 21.6      | -         |
| 2.i  | 3.0s | 4     | 4    | 6    | 2    | 23.6      | Stacking (different) |
| 2.j  | 2.2s | 5     | 5    | 5    | 0    | 22.0      | Stacking (different) |

Table 2: Details from action sequences as generated based on the data from Figure 5. “Time” is the time taken to plan the action sequence, “Cost” is the accumulated cost of all individual actions. Several situations feature anomalies, such as obstruction, irregular, or stacked objects.

handing over an object from one hand to the other takes longer than picking and placing.

As Table 2 suggests, the cost does not exceedingly increase when meeting difficulties, such as obstructions, or stacked objects. Instead, the planning time increases by factors of up to 100 while rearranging the same amount of objects. Only case 2.d was especially taxing, requiring 50s for planning and scoring a cost of 32.4.

Failures in perception are therefore not directly reflected in the planner’s output. In case 2.c, two stacked objects are identified as only one object, leading to a simpler, and wrong plan. In 2.e, both lower objects on the stacks are not detected at all, also resulting in a wrong final configuration, and ultimately in a very “cheap”, fast to plan action sequence. In these cases, we rely on the failure detection and recovery mechanisms which are implemented in CRAM. After every manipulation action, the performing robot re-perceived and validated the current scene, and re-plans its strategy if inconsistencies are detected.

### 6.3 Robot Experiments

In order to assess the feasibility of the proposed system we run several scenarios on a PR2 robot. The experiments presented are shown in Figure 6. We chose these scenarios in order to highlight the reasoning capabilities of the robotic agent with respect to the arrangement of objects found. The video we created in the course of this work shows the system being executed on the PR2 robot.

The first experiment (Figure 6, upper row) showcases our implementation of rearranging objects on the shelf based on similarity of objects. The initial arrangements of objects, as well the respective results from the perception system are shown in Figure 4. The robotic agent, once having perceived the objects, plans the necessary steps in order to create an arrangement where similar objects are placed next to each other. In the case of this scenario, it plans manipulation steps such that two of the objects get exchanged (the pancake mix and the tomato sauce).

In the second experiment we highlight the knowledge-enabled reasoning capabilities of the system, in the case where objects that need to be manipulated are occluded by other objects. This is achieved through

https://youtu.be/xFwinZAHrnA
7 Conclusion

We have shown a novel application of knowledge-based manipulation in an everyday scenario which requires extended perception and reasoning capabilities.

We demonstrated a working, well integrated system consisting of a knowledge-enabled perception system, a novel planner for rearrangement strategies, and the necessary manipulation skills on a robotic agent. The most prominent challenges in the addressed scenario cover a large amount of robotics subfields, from perceiving objects in complex scenarios to generating goal-driven plans for competent robot behavior. We have shown the feasibility of our framework on a robot operating in a scenario similar to typical retail environments. In the current state of the art it is hard to measure the competence of full robotic systems other than evaluating individual components. In our experiments we show how the results of the real perception system reflect in the generation of manipulation plans for robotic agents. Having a quantifiable connection between beliefs about the real world and the quality of the plans for the robotic agents allows us to further investigate other modalities for improving the robot behavior.

In summary, this paper shows the importance of both advanced perception systems as well as cognition-enabled planning techniques in order to succeed on performing autonomous manipulation in a challenging real-life scenario under dynamic conditions.

References

[1] M. Beetz, F. Balint-Benczedi, N. Blodow, D. Nyga, T. Wiedemeyer, and Z.-C. Marton. RoboSherlock: Unstructured Information Processing for Robot Perception. In International Conference on Robotics and Automation, 2015.

[2] M. Beetz, L. Moesenlechner, and M. Tenorth. CRAM – A Cognitive Robot Abstract Machine for Everyday Manipulation in Human Environments. In International Conference on Intelligent Robots and Systems, 2010.

[3] M. Beetz, M. Tenorth, and J. Winkler. Open-EASE – A Knowledge Processing Service for Robots and Robotics/AI Researchers. In International Conference on Robotics and Automation, 2015.

[4] D. Canelhas, T. Stoyanov, and A. Lilienthal. Improved local shape feature stability through dense model tracking. In International Conference on Intelligent Robots and Systems, 2013.
[5] S. Chitta, I. Sucan, and S. Cousins. MoveIt! [ROS topics]. *Robotics & Automation Magazine*, 1(19):18–19, 2012.

[6] L. Chuan, A. Johari, M. Wahab, D. Nor, N. Taujuddin, and M. Ayob. An RFID warehouse robot. In *International Conference on Intelligent and Advanced Systems*, 2007.

[7] D. Comaniciu and P. Meer. Mean shift: a robust approach toward feature space analysis. *Transactions on Pattern Analysis and Machine Intelligence*, 24(5):603–619, May 2002.

[8] D. Ferrucci and A. Lally. UIMA: An Architectural Approach to Unstructured Information Processing in the Corporate Research Environment. *Natural Language Engineering*, 10(3-4):327–348, 2004.

[9] C. Gharpure and V. Kulyukin. Robot-assisted shopping for the blind: Issues in spatial cognition and product selection. *Intelligent Service Robotics*, 1(3):237–251, 2008.

[10] T. Kanda, M. Shiomi, Z. Miyashita, H. Ishiguro, and N. Hagita. An Affective Guide Robot in a Shopping Mall. In *International Conference on Human Robot Interaction*, 2009.

[11] S. Koo, D. Lee, and D.-S. Kwon. Unsupervised object individuation from RGB-D image sequences. In *International Conference on Intelligent Robots and Systems*, 2014.

[12] R. Krug, T. Stoyanov, M. Bonilla, V. Tincani, N. Vaskevicius, G. Fantoni, A. Birk, A. Lilienthal, and A. Bicchi. Improving Grasp Robustness via In-Hand Manipulation with Active Surfaces. In *International Conference on Robotics and Automation – Workshop on Autonomous Grasping and Manipulation: An Open Challenge*, 2014.

[13] R.-G. Mihalyi, K. Pathak, N. Vaskevicius, T. Fromm, and A. Birk. Robust 3D Object Modeling with a Low-Cost RGBD-Sensor and AR-Markers for Applications with Untrained End-Users. *Robotics and Autonomous Systems*, 66, April 2015.

[14] C. Mueller, K. Pathak, and A. Birk. Object recognition in RGBD images of cluttered environments using graph-based categorization with unsupervised learning of shape parts. In *International Conference on Intelligent Robots and Systems*, 2013.

[15] C. Mueller, K. Pathak, and A. Birk. Object shape categorization in RGBD images using hierarchical graph constellation models based on unsupervisedly learned shape parts described by a set of shape specificity levels. In *International Conference on Intelligent Robots and Systems*, 2014.

[16] K. Okada, A. Haneda, H. Nakai, M. Inaba, and H. Inoue. Environment manipulation planner for humanoid robots using task graph that generates action sequence. In *International Conference on Intelligent Robots and Systems*, 2004.

[17] J. Papon, A. Abramov, M. Schoeler, and F. Wörgötter. Voxel Cloud Connectivity Segmentation – Supervoxels for Point Clouds. In *Computer Vision and Pattern Recognition*, 2013.

[18] M. Stilman, J.-U. Schamburek, J. Kuffner, and T. Asfour. Manipulation planning among movable obstacles. In *International Conference on Robotics and Automation*, 2007.

[19] T. Tasaki, S. Tokura, T. Sonoura, F. Ozaki, and N. Matsuura. Mobile robot self-localization based on tracked scale and rotation invariant feature points by using an omnidirectional camera. In *International Conference on Intelligent Robots and Systems*, 2010.

[20] M. Tenorth and M. Beetz. KnowRob: A knowledge processing infrastructure for cognition-enabled robots. *International Journal of Robotics Research*, 32(5):566–590, 2013.

[21] N. Vaskevicius, K. Pathak, and A. Birk. Fitting superquadrics in noisy, partial views from a low-cost RGBD sensor for recognition and localization of sacks in autonomous unloading of shipping containers. In *International Conference on Automation Science and Engineering*, 2014.

[22] N. Vaskevicius, K. Pathak, A. Ichim, and A. Birk. The Jacobs robotics approach to object recognition and localization in the context of the ICRA’11 Solutions in Perception Challenge. In *International Conference on Robotics and Automation*, 2012.
[23] T. Wiedemeyer, F. Balint-Benczedi, and M. Beetz. Pervasive 'Calm' Perception for Autonomous Robotic Agents. In *International Conference on Autonomous Agents and Multiagent Systems*, 2015.

[24] Will Knight, Technology Review. Robot Makes Sure Stores Don’t Run Out of Doritos. http://www.technologyreview.com/news/543281/robot-makes-sure-stores-dont-run-out-of-doritos. Accessed: 2015-11-16.

[25] J. Winkler, M. Tenorth, A. K. Bozcuoglu, and M. Beetz. CRAMm – Memories for Robots Performing Everyday Manipulation Activities. In *Second Annual Conference on Advances in Cognitive Systems*, 2013.

[26] P. Wurman and J. Romano. The Amazon Picking Challenge 2015 [Competitions]. *Robotics & Automation Magazine*, 22(3):10–12, Sept 2015.