Grasping Known Objects with Humanoid Robots: A Box-Based Approach

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Abstract— **Autonomous grasping of household objects is one of the major skills that an intelligent service robot necessarily has to provide in order to interact with the environment. In this paper, we propose a grasping strategy for known objects, comprising an off-line, box-based grasp generation technique on 3D shape representations. The complete system is able to robustly detect an object and estimate its pose, flexibly generate grasp hypotheses from the assigned model and perform such hypotheses using visual servoing. We will present experiments implemented on the humanoid platform ARMAR-III.**

I. INTRODUCTION

Future applications of service robots require advanced object grasping and manipulation capabilities. According to Gibson [1], one of the main properties that characterizes an object is how it can be acted upon, namely what kind of actions it *affords*. In the work presented here, we deal with the problem of object grasping on a humanoid robot.

The development of humanoid robots for human daily environments is an emerging research field of robotics and challenging tasks. Recently, considerable results in this field have been achieved and several humanoid robots have been realized with various capabilities and skills. Integrated humanoid robots for daily-life environment tasks have been successfully presented with various complex behaviors (see e.g. [2], [3]). However, in order for humanoid robots to enter daily environments, it is indispensable to equip them with fundamental capabilities of grasping. This includes manipulating objects encountered in the environment and dealing with kitchen appliances and furniture such as fridges, dishwashers and doors. Research on humanoid grasping and manipulation has been done on humanoid platforms such as the HRP2 [4], ARMAR [3], the NASA Robonaut [5], Justin [6], or Dexter [7], where the problem of grasping has been approached from different perspectives.

The work to be presented in this paper is part of the EU PACO-PLUS project (www.paco-plus.org) and follows the concept of Object-Action Complexes [8], [9], [10]. Although humans master object grasping easily, few suitable representations of the entire process have yet been proposed in the neuroscientific literature. Thus, the development of robotic systems that can mimic human grasping behavior is still a challenging field of research. In addition, the robot embodiment usually does not resemble that of a human, i.e. grasps suitable for a human may not be suitable for a robot, and vice versa.

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In our earlier work, we proposed and motivated a flexible framework for object grasping [11]. In this framework, we took advantage of closely connecting grasps to an efficient shape approximation technique based on box primitives and various dependencies that have to be considered in the field of grasping. However, this work was done in simulation only, using the grasp simulator GraspIt! [12].

For real experiments, object grasping with mobile manipulators requires several additional modules to be at place. Our early work demonstrated that it is possible to perform tasks through a careful design and implementation of individual modules [13]. The work presented here will also take into account the system integration aspects and demonstrate object grasping tasks on a humanoid robot. It is an extension of our previous work [3], [14] toward the realization of complexes humanoid manipulation and grasping tasks in a kitchen environment. Another main contribution of this paper will be the transfer of the above mentioned grasping approach from simulated environments to a real-world application.

This paper is organized as follows: in Section II, we will describe the central modules of our system. In Section III, the robot platform will be sketched, before we present experimental grasping results in Section IV.

II. OUR APPROACH

We will now present a strategy for grasping known objects, comprising an off-line, box-based grasp generation technique on 3D shape representations. Since the focus of this paper is the presentation of an integrated system, the applied sub-modules will be described very briefly. We provide references to our related work in which details on technical implementations and algorithms can be found. The subtasks of our system are:

A. An *Object Database*, representing 3D models of known objects,
B. a visual *Object Identification and Pose Estimation* module to recognize such an object in a real scene,
C. a *Shape Approximation* module to transform offline models into primitive shape representations,
D. a *Grasp Generation* module to dynamically generate grasp hypotheses from such representations, and
E. a *Grasp Execution* module, based on visual servoing, to execute such hypotheses on a humanoid robot.

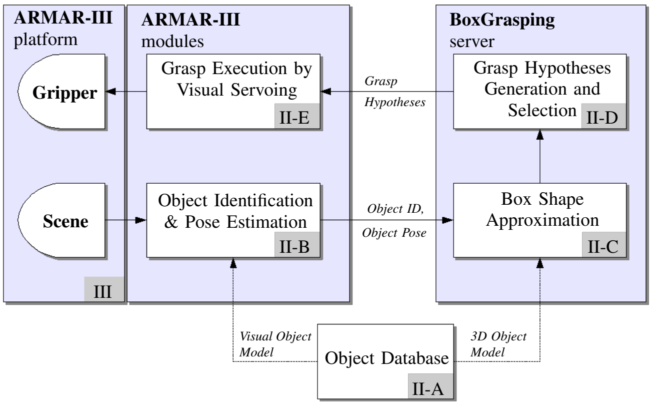


Fig. 1. System architecture for the proposed grasp generation approach.

The architecture of these modules and their interaction, as also links to the following subsections describing each single module, is presented in Fig. 1.

A. An Object Model Database

The grasping experiments we will present in this paper are performed on household objects with known geometry. The respective object models are part of the public available KIT ObjectModels Web Database [15]. In order to obtain such models, we use the interactive object modeling system introduced in [16],[17]. To acquire a 3D model, the respective object is placed on a rotation plate which is situated in front of a Minolta VI-9OO laser scanner. The scanner uses an active triangulation measurement method, providing a resolution of 640×480 measurement points and an accuracy of less than 0.2mm. Different aspects of the object are generated using different rotation angles of the plate. The measurement process results in a registered and triangulated mesh which is available in OpenInventor, VRML and Wavefront OBJ formats. In addititon, an Allied Vision Marlin stereo camera pair mounted on a rotating rig takes images of the object during the process described above. These images are used to generate texture information for the object model. The meshes from the database are registered with the recognition system (see Section II-B) and made available for box decomposition (see Section II-C).

B. Object Identification and Pose Estimation

A two-step approach using local features is applied in order to identify and localize textured objects in a scene, as presented in [18]. First, the object is recognized including 2D localization, which is accomplished using 2D feature correspondences between the image of the scene and images in the database. 2D localization is computed from a homography based on SIFT descriptor correspondences. Based on the 2D localization result, a 6D pose estimate of the object is computed by making use of the stereo camera system. For 6D pose estimation, interest points within the localized 2D area of the object are collected and correlated with the second camera image, yielding a sparse depth map. The resulting point cloud is registered with the object model.

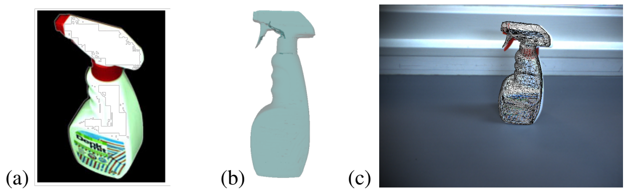


Fig. 2. Visual representations and 3D models, like (a-b), are used to describe objects in the database. (c) Result of the final pose estimate for an example scene, after application of the calibrated rigid body transformation.

To later associate object-centered grasps with objects on the basis of 3D meshes generated in the object modeling step, the fixed rigid body transformation between the object mesh and the estimated object pose has to be determined. For this purpose, we developed a tool which computes the pose of the object of interest by using the recognition module for one given scene. In parallel, the scanned model is mapped into the stereo image pair of this scene, and its pose is adjusted manually so that the model projection matches the stereo views. The desired rigid body transformation is then given by the transformation between the automatically computed pose estimate and the manually adjusted pose. An exemplary result of a final pose estimate, as also corresponding samples from the database, are shown in Fig. 2.

C. Shape Approximation through Box Decomposition

We base the generation of grasp hypotheses on a box-based 3D shape approximation technique that we presented in [19] and recently optimized in [20]. Originating from an arbitrary 3D point set and the computation of its oriented minimum volume bounding box (MVBB) [21], our method recursively splits a set of boxes to tightly envelop the point set by a set of MVBBs. By this split-and-fit strategy we aim at approximating the object shape with a minimum number of tight fitting MVBBs. The main parameter for a decomposition is a volume gain value. In case a box split will not result in a sufficient cutting-off of unoccupied space, it will not be split any further. For more details on the algorithm, we refer to [19], [20]. It is important to note that we can approximate a set of points by a box constellation. In the application here, we first decompose all 3D models (like the one in Fig. 2b) by extracting the point data from the meshes in the database in an offline step and store their respective box constellations.

D. Grasp Hypotheses Generation and Selection

Grasp hypotheses directly emerge from each face of the final box decomposition, where the approach of the gripper is aligned to the face's normal, and orientations aligned to the face's edges. The set of valid faces is reduced by mainly applying geometrical heuristics that decribe various dependencies, e.g. like spatial constellation, visibility or task at hand, as presented in [11]. To include grasp quality learning, we earlier presented two approaches based on supervised neural networks that use the grasp simulator GraspIt! [12] for learning stable grasps from 2.5D representations of object parts. Applying boxes as shape primitives efficiently allows us to generate such part-based 2.5D 'depth maps' from the

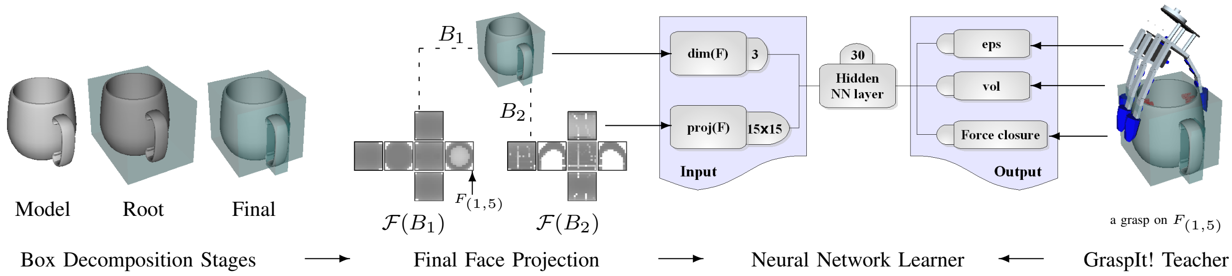


Fig. 3. The applied neural network structure holds 228 input, 30 hidden and 3 output neurons. As an input, a face projection F plus its box dimensions *dim(F)* are fed into the network, since faces are normalized to 15×15. *eps* and *vol* are the grasp quality measures that GraspIt! delivers. The force closure is also learned separately even if it equals ($eps > 0$). From this model, off-line learning of grasp qualities from face representations is possible.

3D data and the box constellation (see Fig. 3). In this paper, we will use only one specific grasp pre-shape, namely a power-grasp with a model of the robot hand that we will use. How an additional dependency concerning the gripper kinematics can be introduced in order to control finger fine-positioning was presented in [20].

E. Grasp Execution

The grasp execution on ARMAR-III [22] (see also Section III) comprises three different stages: the first two stages describe the approach of the end-effector to the final grasp pose, while in the third stage the object is grasped by closing the five-fingered hand. For approaching, two sequential poses are generated for the end-effector: (i) a pre-grasp pose which assures a collision free approach towards the grasp pose, and (ii) the grasp pose itself, which determines the final position and orientation of the end-effector before closing the fingers. While reaching for the grasp pose requires high accuracy in order to guarantee a stable grasp execution, the approach of the pre-grasp pose does not demand high accuracy. Consequently, the approach of the pre-grasp pose is realized by solving the inverse kinematics (IK) problem, while reaching for the final grasp pose is accomplished using a visual servoing approach. For both stages, the 7 joints of either the left or the right arm and the torso yaw of ARMAR-III (around the body axis) are considered.

In order to find a solution to the IK problem, we use a probabilistic approach which randomly samples start configurations. Using a Jacobian pseudoinverse method, the end-effector is moved from the sampled configurations towards the desired target pose. Thus local minima resulting from the numerical approach can be overcome and invalid postures resulting from joint limits and self-collisions can be handled. For providing natural postures as solutions for the IK problem, the resulting configuration is rated using the distance from a pre-defined grasp posture in joint space, e.g. grasping an object from the right hand side when using the right arm. The generated rating together with the ability to find a solution for the IK problem is used to rate grasp hypotheses with respect to the embodiment.

In order to execute a grasp, the torso and arm have to be moved from the pre-grasp pose to the final grasping pose. Since there are inaccuracies both in the perception of the object pose and in the execution of arm movements, we make use of a visual servoing approach to achieve exact alignment of the end effector and the object [14]. With this approach it is possible to track the hand in a robust manner and thus to adjust the pose of the hand to the feasible grasping pose.

III. EXPERIMENTAL PLATFORM

As already mentioned, we integrated the system presented in the last section on a humanoid platform, ARMAR-III. The humanoid robot ARMAR-III (see Fig. 4) was designed under a comprehensive view so that a wide range of tasks can be performed. From the kinematics control point of view, the robot consists of seven subsystems: head, left arm, right arm, left hand, right hand, torso, and a mobile platform.

The head has seven degrees-of-freedom (DoF) and is equipped with two eyes. The eyes have a common tilt and can pan independently. Each eye is equipped with two color cameras, one with a wide-angle lens for peripheral vision and one with a narrow-angle lens for foveal vision. The visual system is mounted on a four DoF neck mechanism (lower pitch, roll, yaw, upper pitch). For the acoustic localization, the head is equipped with a microphone array consisting of six microphones (two in the ears, two in the front and two in back of the head). Furthermore, an inertial sensor is installed in the head for stabilization control of the camera images.

The upper body of the robot provides 33 DoF: 14 for the arms, 16 for the hands and 3 for the torso. The arms are designed in an anthropomorphic way: 3 DoF in the shoulder, 2 DoF in the elbow and 2 DoF in the wrist. Each arm is equipped with a five-fingered hand with 8 DoF (see [23]). Each joint of the arms is equipped with a motor encoder, an axis sensor and a joint torque sensor to allow for position, velocity and torque control. In the wrists, 6D force/torque sensors are used for hybrid position and force control. Four planar skin pads (see [24]) are mounted to the front and back side of each shoulder, thus also serving as a protective cover

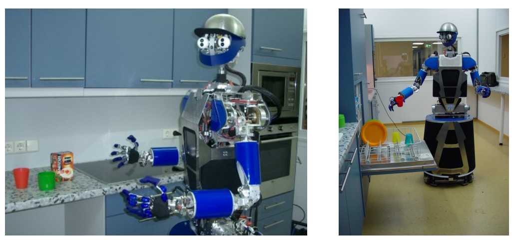


Fig. 4. ARMAR-III in the experimental kitchen environment. The robot is equipped with an active head including peripheral and foveated vision, two arms, two five-fingered hands and a holonomic mobile platform.

for the shoulder joints. Similarly, cylindrical skin pads are mounted to the upper and lower arms respectively.

The locomotion of the robot is realized using a wheel-based holonomic platform, where the wheels are equipped with passive rolls at the circumference (Mecanum wheels or Omniwheels). In addition, a spring-damper combination is used to reduce vibrations. The sensor system of the platform consists of a combination of three laser range finders and optical encoders to localize the platform. The platform hosts the power supply of the robot and the main part of the robot computer system.

For detailed information the reader is referred to [3], as also to [25] for a detailed description of the mechanics.

IV. GRASPING EXPERIMENTS

In this section, we will demonstrate the proposed method using the ARMAR-III humanoid platform in a kitchen environment, grasping common household objects.

A. Experimental Setup

For the experiments, meshes for all database objects were generated using the interactive modeling center. We will present results for three of those objects: a zwieback box, a cylindrical salt container and a complex shaped detergent sprayer bottle (see Fig. 5). In the end, the process steps for the experiment resemble the architecture modeled in Fig. 1.

In the offline preparation, all objects were registered with the recognition system as described in II-B. In order to generate a set of grasp hypotheses on each object, the decomposition of the high quality meshes (generated in the modeling step) into boxes was performed. These hypotheses are reduced using constellation and gripper embodiment dependencies, i.e. grasp hypotheses on blocked or too large surfaces will be removed. In order to rate the hypotheses related to grasp stability, grasp quality learning from a different set of training objects was performed for the left and the right hand of ARMAR-III using the GraspIt! simulator.

For the online experiments, each object is placed on the kitchen sideboard, in the field of view of the robot, and localized using the recognition system. The resulting object pose is used to transform the object-centered grasp hypotheses to the current scene. The resulting grasp hypotheses comprise approach direction, pre-grasp pose and grasp pose. The inverse kinematics solver is deployed in order to derive a rating for the reachability of the generated hypotheses. Reachable grasp hypotheses are then executable using the configuration resulting from the solver in order to align with the pre-grasp position. Finally, we manually select three of those valid grasps for each object. To perform each of them, the final poses are approached using visual servoing with a red colored ball at the wrists of both hands. Once the final grasp pose has been reached, the robot closes the hand in order to lift the object.

Fig. 5. Objects used in the experiment: zwieback, salt, sprayer bottle.

B. Experimental Results

The experimental results are depicted in Tab. I. In the first column, the corresponding models and their box approximations are shown, along with some statistics about the decomposition. The database point meshes were generated as described in Section II-A. Since both the zwieback and the salt are compact shapes, only one box was found to be necessary to suit the shape. In the case of the detergent bottle, the decomposition procedure yielded an approximation consisting of five boxes. The recursive fitting-and-splitting strategy is also reason for the higher effort in offline computation time for this object. Also note that here, though 6 boxes originally yield 30 facets, 9 of them were automatically removed because of occlusion in the constellation.

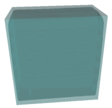
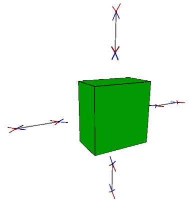
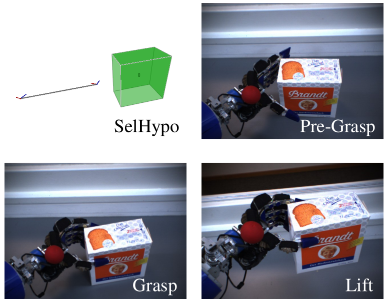
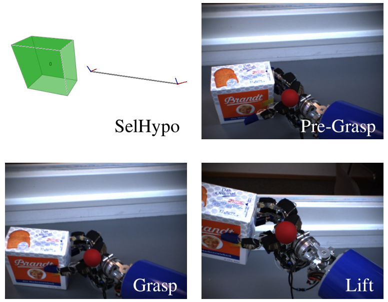
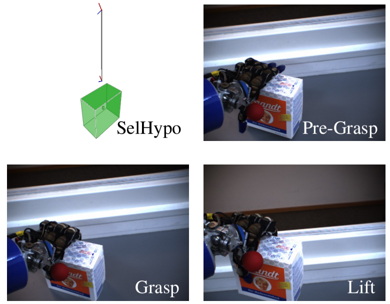
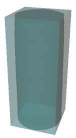
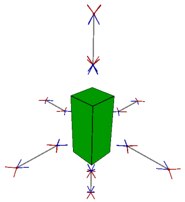
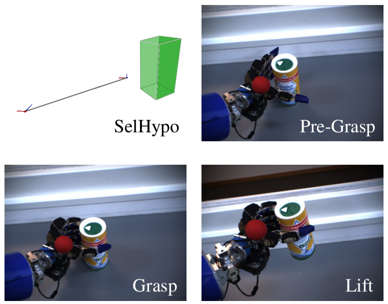
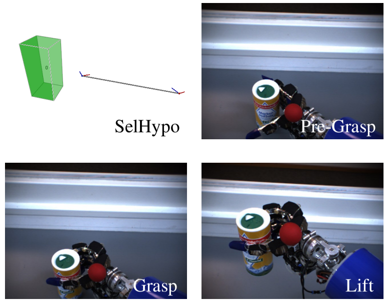
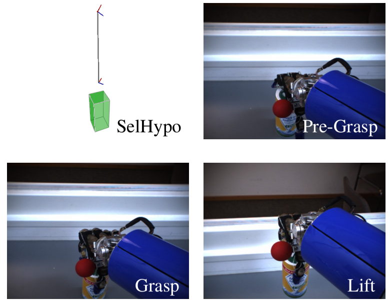
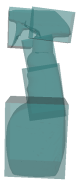
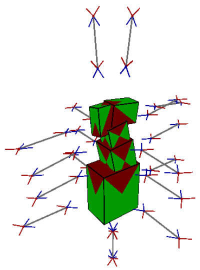
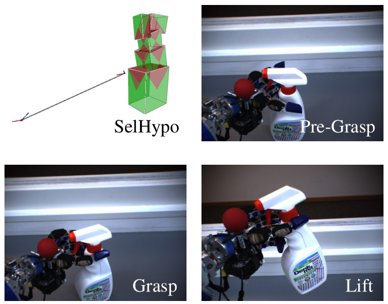
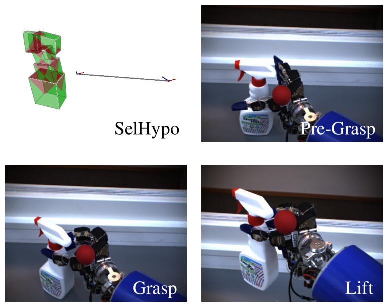
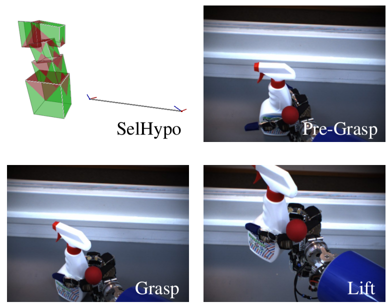
In the second column, the complete sets of generated hypotheses are depicted. The visual representations also include the grasp hypotheses removed from constellation (dark triangles). While 4 hypothesis (orientation-aligned to the four edges) emerge from each of the valid facets, some of them are removed by further constellation or gripper dependencies. Note, for example, that the zwieback box provides no grasp hypotheses from the back or front side, since the dimensions of these facets exceed the gripper aperture.

As one can see from the selected grasps in the third column, the zwieback box was successfully grasped from the left hand side, the right hand side and from the top. Similar grasps were performed on the salt can. It should be noted that it is a more difficult task to grasp the salt can from the top because of its circular lid. The box approximation of the object yielded a successful grasp even for this difficult case. It also has to be mentioned that grasps are selected manually since representations of the supporting table or other distracting objects have not been considered in this experiment, i.e. grasp hypotheses from the bottom of the object would theoretically be valid, too. Grasps on the detergent bottle were performed on two different boxes of the set: the bottom and the central box, approaching the object from the left hand side as well as from the right hand side, also resulting in stable grasps.

Despite the fact that no haptic sensor feedback is used, and that all objects turn more or less when force is applied to them during the gripping phase, all grasps are stable even during the lifting, as also they look quite intuitive and natural. It is also emphasized how grasp hypotheses selection and grasp planning can point to task-dependent grasping. For example, a power-grasp on a large box (e.g. sprayer, bottom) is suitable one for a ‘transport’ action, while a pinch-grasp on a small box (e.g. sprayer, middle) is suitable for a ‘show’ or ‘hand-over’. However, the current hand model does not support a lot of such grasp pre-shapes.

TABLE I

EXPERIMENTAL GRASPING RESULTS, INCLUDING (A) 3D DATABASE MODEL AND DECOMPOSITION, (B) GRASP HYPOTHESES AND (C) THREE SELECTED GRASPS FOR THREE OBJECTS.

Offline Generation of Grasp Hypotheses		Online Grasp Generation by Hypotheses Selection		
		(C) Grasps		
(A) Model and Decomposition	(B) Grasp Hypotheses	#1	#2	#3
 209,003 points Leaf Boxes: 1 Valid Faces: 6 Time: 4.43 sec	 8 Final Hypotheses			
 188,460 points Leaf Boxes: 1 Valid Faces: 6 Time: 4.26 sec	 16 Final Hypotheses			
 123,191 points Leaf Boxes: 5 Valid Faces: 21 Time: 26.43 sec	 36 Final Hypotheses			

V. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a grasping strategy for known objects, comprising an off-line, box-based grasp generation technique on 3D shape representations. The complete system is able to robustly detect an object and estimate its pose, flexibly generate grasp hypotheses from the assigned model and perform such hypotheses using visual servoing. Through the presented systems integration approach, we showed for the first time that grasp hypotheses delivered from box approximations of object models are well applicable on a real robot system. Throughout the presented experiments, object pose changes dependent on the force applied to it. Though grasps are generally stable and look human-like, we keep in mind the issue of what one can call the grip component. For the sake of efficiency and intuitive motivation, we are aware that our approach is a pre-grip component on very robust shape information. A sophisticated grip component would greatly contribute in terms of corrective movements by analyzing haptic feedback.

The box representation of an object is simple. However, the projection of an object onto the box faces ignores the real 3D shape of the object in the box, not considering the correct surface normals of the object in the grasp planning. Thus, there is a possibility that planned grasps are infeasible, which addresses the limitation of the grasp planning. In [20], we examined the integration of gripper kinematics using finger positioning estimates on the described projection patterns. However, and as future work, one can imagine higher-level part classification from point sets of the model that have been segmented through decomposition. This topic relates to work on part-based shape representations. Classification of shape is a beneficial, but also complex task, as additionally, the box constellation might be very different and unstable as influenced by noise, perspective view and uncertainties. For the purpose of grasp hypothesis generation, this is not a severe problem, while it will be in part and object classification tasks. Finally, the evaluation of the proposed method on unknown, i.e. unmodeled, objects based on 3D input perceived from a real vision system will be a challenging future work task, due to the same uncertainties.

VI. ACKNOWLEDGMENTS

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