Part-based Grasp Planning for Familiar Objects

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***Abstract*— In this work, we present a part-based grasp planning approach that is capable of generating grasps that are applicable to multiple familiar objects.**

We show how object models can be decomposed according to their shape and local volumetric information. The resulting object parts are labeled with semantic information and used for generating robotic grasping information. We investigate how the transfer of such grasping information to familiar objects can be achieved and how the transferability of grasps can be measured. We show that the grasp transferability measure provides valuable information about how successful planned grasps can be applied to novel object instances of the same object category.

We evaluate the approach in simulation, by applying it to multiple object categories and determine how successful the planned grasps can be transferred to novel, but familiar objects. In addition, we present a use case on the humanoid robot ARMAR-III.

I. INTRODUCTION

Grasping is one of the key capabilities to enable humanoid and service robots operating robustly in human-centered environments. Although reliable grasping in completely known environments is still a challenging topic, real world applications also need to cope with unknown or partially known objects.

Grasp planning in humans is a combination of grasp experience and data processing of the sensor output, as pointed out by [1]. Cognitive cues and previously learned knowledge both play a major role in grasping for humans and for monkeys. Although the use of these concepts in robotic applications is difficult, the general idea of transferring previously learned grasping skills to the current situation is a common approach in robotic grasping. To cope with the wide variety of objects, working with object categories can help to structure the data and allows the transfer of grasping information to objects which are similarly shaped.

Research in the field of neuro-psychology have evidenced that human perception of objects is strongly based on part decomposition. It has been shown in studies on human manipulation [2], [3], that an object is identified by its constituent parts.

Creem et. al. [4] are analyzing the semantic processing of grasps in humans. They show that without semantic processing the human is capable of grasping an object, but not for the intended use. One way humans are able to extract semantic information of novel objects is by the concept of affordance, as introduced by Gibson [5]. For humans the object sensory characteristics intuitively imply it's functionality and usability.

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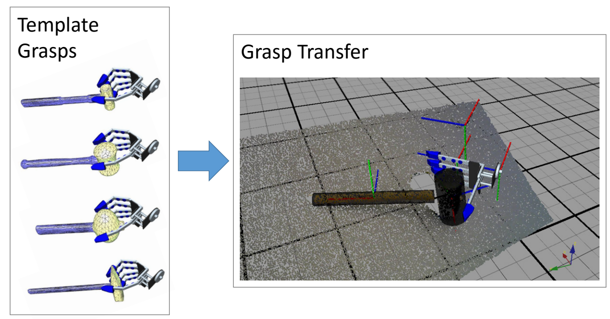

Fig. 1. Template grasps are generated with a part-based grasp planning approach and transferred to a familiar object.

In our approach, the objects are segmented into parts and these parts are labeled with semantic information (e.g. *action*, *handle*, etc) in order to reflect the object affordances. In addition, objects can be categorized depending on their shape, usage, or application. On such object categories grasping information can be generated in order to use this data for online generation of stable grasps, even when no exact shape information is available. Therefore, we extract common grasping information from a set of training data in order to identify promising grasping candidates which generalize over the training samples, i.e. which can be applied to most or even all objects in the category.

In addition we show in this work that a beneficial representation of object categories based on object segments, is particularly useful for determining object categories during online processing when only incomplete shape information is available. These shape segments, which have been annotated with task information, are used to identify stable grasps that have been generated during the training phase.

II. RELATED WORK

A good survey on grasp planning in robotics can be found in [6] and [7]. In the following, we discuss several works that are related to our proposed approach.

A. Part-based grasping

In the past several approaches were presented which segment objects into parts in order to perform grasp planning on these parts. In [8], [9] and [10], objects are represented with simplified data structures in order to reduce the complexity of planning feasible grasps.

Aleotti et al. combine the programming by human demonstration for teaching appropriate grasp with an automatic 3D shape segmentation for object recognition and semantic modeling [11]. The algorithm is trained in a virtual reality environment and applied in a robotics environment. In both environments the object is segmented using a topological method to create a reeb graph. After a training phase, where a human demonstrator is repeatedly demonstrating a specific task, a set of candidate grasps are generated which are applied online by the robot. The work is extended in [12] by the ability of actively exploring the environment of the robot to build a complete 3D model.

B. Grasping of familiar objects

The concept of familiar objects originates from the idea, that objects in the environment can be grouped together into categories with common characteristics. The methods which are reviewed in the following are mostly related to data-driven grasp synthesis, i.e. they make use of an example-based approach. The most similar object is looked up in a database and a preplanned grasp is executed to the novel object.

Rao et al. distinguish in [13] between graspable and non-graspable object parts. A mixture of 2-D and 3-D features are used to train a support vector machine for discrimination. By assuming the symmetry of partially observed objects, its shape is approximated by using the depth information of the sensor. In a last step contact points are found, that are accessible to the robot.

In [14] a comprehensive knowledge base of 3D objects is proposed, where basic shape features are represented by Gaussian distributions. Online grasp planning is performed by searching for the most similar object according to the calculated features.

Detry et al. introduce in [15] a method for generalizing grasping information. The aim is to build a grasp example, that is valid for many similar objects. A grasp example votes for the potential inclusion of a part into the dictionary. Before including a grasp example to the dictionary, dimensionality reduction and unsupervised clustering algorithms are applied.

In [16], [17] and [18] preplanned grasps are adapted to a novel object. In [16] the 3D point cloud of the object is parametrized using a smooth differentiable function via spectral analysis. It is shown, how one can utilize this space of smooth surfaces accompanied with grasping information to continuously deform various surfaces and the corresponding grasping configuration.

In [17] warping techniques are used to preserve the functionality of pre-planned grasps. The transfer is achieved through warping the surface geometry of the source object onto the target object, and along with it the contact points of a grasp.

[18] learns two types of probability densities, one for the contact model and one for the hand configuration model.The contact model describes the relationship of an individual finger part to local surface features at its contact point. The method needs no knowledge of the object category when learning or performing grasp transfer.

[19] demonstrated a category-based approach for task specific grasping. They were able to generalize from a set of example objects and related grasps to novel objects. It is assumed that the object category and several 3-D models belonging to that category are known. The grasps are created offline and optimized on-line. The optimal grasp is defined as the grasp with the maximum expected stability and task compatibility considering shape variability. One advantage of this approach is, that it does not require a construction of a large training data set.

In contrast to the previously discussed works which rely on previously known object categories, there also exist approaches which are able to automatically determine the object categories, see e.g. [20] and [21].

In this work, we combine several existing approaches related to part-based grasping as well as semantic and shape-based grasp transfer to build a system that is capable of generating grasping information on object parts, which can be transferred to similar object shapes even when no accurate object model is available. In addition, we show that the proposed estimation of the grasp transfer success, i.e. the grasp transferability measure, provides valuable information for increasing the grasp transfer success rate.

III. APPROACH

The approach we are following is to leverage high-level shape analysis, like structural shape information from the low-level geometric properties, to grasp planning. One idea of this approach is that in a human environment many parts of objects encode some kind of task affordances. The objects sensory characteristics intuitively imply its functionality and usability. For example, a handle of a cup is always associate with the task pouring, the cap of a bottle is always associate with opening or holding the bottle. Since functional and semantic grasping information is closely connected with object categories, we can assume that each object of one category offers similar functionality. With our approach we are able to transfer grasping information to objects within a category and also on novel objects if their shape is similar to the shapes of a trained category.

Therefore we use a set of training models to generate grasps that can be successfully applied to all objects in a category. In addition, objects are preprocessed in order to build a segmented mesh representation that allows to perform part-based grasp planning and semantic information is connected to each segmented part. With this approach we are also able to identify and to transfer task affordances as they are linked to the object parts.

The whole concept is shown in a descriptive diagram in Fig. 2. The concept is divided into a grasp planning phase and an online phase in which grasping information is transferred to a novel obejct.

A. Offline Grasp Planning

During offline grasp planning, a set of training objects is processed in order to segment them, to attach semantic labels

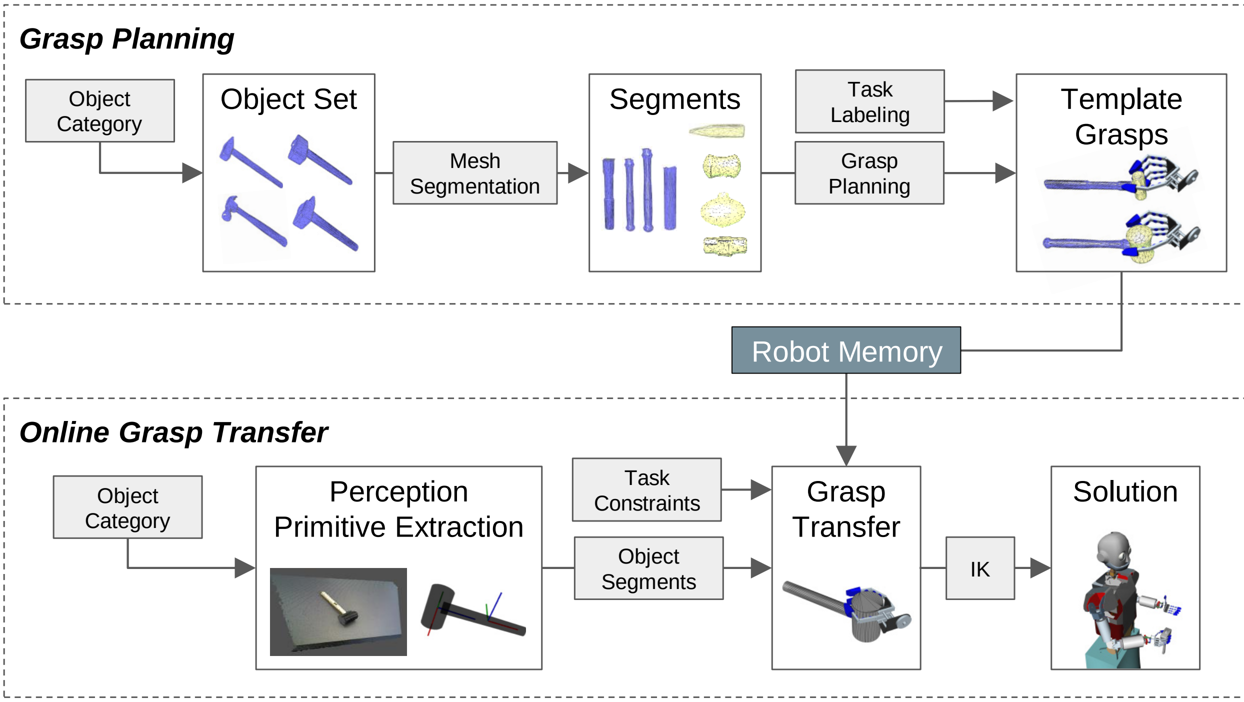

Fig. 2. Part-based grasp planning is performed on multiple objects of an object category. The resulting grasping information is evaluated according to the expected transferability to novel objects. During online processing, grasping information is applied to novel objects which are segmented according to their RGB-D appearance.

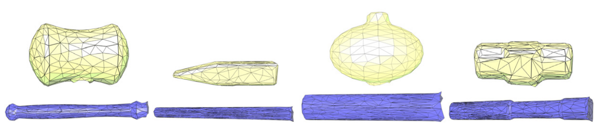

Fig. 3. Segmented parts of several object instances.

and finally to generate grasping information.

1) Mesh Segmentation: For segmenting the objects into parts the method by Shapira et al. [22] is used, where the segmentation is calculated based on shape diameter function (SDF). Before calculating the segmentation several preprocessing steps (refinement, mesh repairing) are applied. The shape diameter function is a volume-based shape-function, which maps volumetric information to the surface boundary mesh. SDF is examining the distance to the opposite side of the 3D object for each point on the surface. The mesh partitioning is then done in two steps, soft clustering and hard clustering.

For soft clustering, k Gaussian distributions are fitted to the histogram of SDF values. In addition, a so called *hard* clustering step is applied in order to smooth the boundaries between the resulting parts. This is achieved with minimizing an energy function using an alpha expansion graph cut algorithm (more details can be found in [22]). Throughout this work, we are making use of the Computational Geometry Algorithms Library [23], which provides a robust implementation of this approach. Some exemplary results can be seen in Fig. 3.

In this work, we used objects from the publicly available object databases [24], [25], [26], and [27].

In the following, we will assume that for a given object category C, all m objects $\{o_0, ..., o_j, ..., o_{m-1}\}$ were segmented successfully. In addition, we assume that every object o_j consists of n parts: $\{s_j^0, ..., s_j^i, ..., s_j^{n-1}\}$. For example a screwdriver always consists of a *shaft* and a *handle*. Since the segmentation fails for some objects due to a big variance in shape, we ensure a consistent set of training objects by manually controlling and if needed adapting the results of the segmentation step.

2) Labeling of Object Parts: When executing a semantic grasp, the intended task is then connected to one or more part descriptions (for the sake of simplicity, we assume that exactly one part is assigned to a description).

The resulting object parts are labeled by a human tutor to add semantic information which can be used during online grasp transfer for task-specific grasping.

For example, for handover tasks, four kinds of functional parts, which are named *action*, *attention*, *handle* and *container* parts, and a *grasping prohibition attribute* have been defined as important factors for good handover motion [28]. Some guidelines have also been presented with the functional parts: action parts should not be pointed at the receiver; attention parts should be clearly visible to the receiver; handle parts should be presented in a way the receiver can easily grasp it; container parts should not be oriented in the direction in which the conditions of the contents cannot be preserved; a part with the grasping prohibition attribute should not be grasped by a robot. Based on these information, we can determine the most appropriate parts to be grasped and better grasp configurations. If the functional part information is connected to the corresponding segmented object part and planned grasps are saved with such object information, we can easily sort the grasps based on the guidelines during online grasp transfer.

Task-specific manipulation knowledge of everyday objects, which would include grasp areas and approach directions, has been presented for various tasks in addition to handover (for example [29]). Similar information can also be considered to select grasps during the online grasp transfer according to the intended task.

3) Grasp Planning: Grasp planning is performed with the Simox Toolbox [30]. The randomized grasp planner of Simox determines stable grasps by aligning an initially specified hand approach direction with a randomly chosen object surface normal. Grasp stability is evaluated by determining the contact points when closing the hand and evaluating the ϵ value of the classical grasp wrench space approach [31]. In this work, we extended the standard grasp planner as follows:

a) Alignment of the Hand: Since grasp planning is performed on segmented object parts, we take advantage of the local shape by evaluating the extends of the part. This is done by applying the principal component analysis (PCA) to all vertices of the actual object part.

If the primary component is significantly larger than the other components, the shape of the object part is suitable for aligning the hand.

The eigenvalues of the PCA are denoted with λ_1, λ_2 and λ_3. Significance is characterized as:

$$\lambda_1 > \frac{2}{3} \sum_i \lambda_i \tag{1}$$

Motivated by [32], this information is used to align the hand's coordinate system with the first eigenvector. [32] identified the wrist orientation as a key human-guided grasp measure and showed that using it along an automated grasp synthesis algorithm improved the automated algorithm's results dramatically. However for objects, where the primary component of the PCA is not significantly larger than the other component, a random wrist orientation offers more flexibility in the grasp execution since more potential orientations are covered. In both cases the rest degrees of freedom of the approach direction are obtained from the surface normal of the selected mesh.

b) Position of the Grasp Center Point: For each surface point of the object part the SDF value provides information related to the local *thickness* of the object since it is approximating the depth of the object at that surface point. This information can be exploited by setting the grasp center point (GCP, see [33]) to the estimated center of the object part, instead of using the surface point for positioning the GCP. Depending on the type of grasp, the appropriate GCP is chosen (see Fig. 4).

For a given (randomly chosen) surface point $\mathbf{x}$ together with its normal $\mathbf{n_x}$ and the local SDF value SDF_x, the target

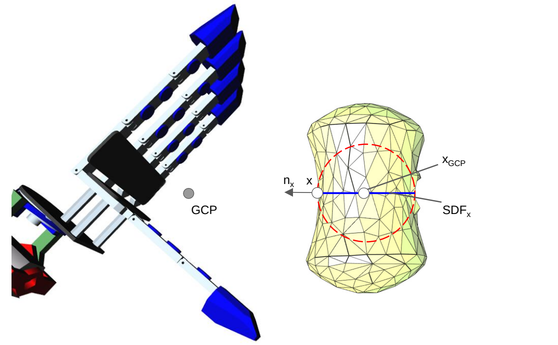

Fig. 4. The approach target $\mathbf{x_{GCP}}$ is computed by shifting the surface point along the inverse direction of the normal towards the estimated center of the object which is determined based on the local SDF_x value.

$\mathbf{x_{GCP}}$ is calculated as follows:

$$\mathbf{x_{GCP}} = \mathbf{x} - \frac{1}{2} SDF_x \mathbf{n_x} \tag{2}$$

The relation between GCP, $\mathbf{x}$, and $\mathbf{x_{GCP}}$ is also depicted in Fig. 4.

Note, that the target pose $\mathbf{x_{GCP}}$ is used to guide the approach movement of the hand until either the GCP reaches $\mathbf{x_{GCP}}$ or a collision between the hand and the object is detected during approaching. Finally, the fingers are closed, the contacts are determined and the grasp stability and quality is computed. If the chosen grasp is stable, the resulting grasping information (i.e. the transformation, the contacts, and the finger joint configuration) is stored in the robot's memory.

4) Generalizing Grasping Information for an Object Category: For generalizing grasping information within an object category at first several grasps are planned for all n object parts.

Therefore, for a given object part i, a randomly chosen instance s_j^i is selected and a grasp g_j is planned as described in Section III-A.3.

For the grasp g_j, we are measuring how successful it can be transferred to the other $m-2$ instances of the selected object part by applying g_j to all instances s_k^i with $k \in \{0, ..., m-1\}, k \neq j$. The grasps g_j is applied by placing the tool center point (TCP) of the opened end effector according to the transformation matrix R_j saved in g_j and by closing the end effector until the actuators are colliding with the instance s_k^i.

To evaluate the success of the grasp transfer, we compute the grasp transfer success rate $sc(g_j)$ which relates the number of successful grasp transfers (collision-free and force closure) with the number of object part instances $(m-1)$.

The results are further analyzed by evaluating the following three transfer quality measures:

- $q_0(g_j)$: The collision rate indicates how often the grasp transfer fails due to a collision.
- $q_1(g_j)$: The average grasp quality over all transferred grasps, calculated with the ϵ metric.
- $q_2(g_j)$: The force closure rate indicates how often the transferred grasp results in a valid force closure grasp.

In order to combine these values, the transferability measure $T(g_j)$ is computed as a weighted sum of the three transfer quality measures:

$$T(g_j) = \sum_{i=0,..,2} w_i q_i(g_j) \tag{3}$$

To determine the weighting factors, a correlation analysis between the three transfer quality measures ($q_0(g_j)$, $q_1(g_j)$, $q_2(g_j)$) and the success rate $sc(g_j)$ is performed. This can be either done for each object category, or, as we did, by computing a single set of weights from a large number of object parts. In our experiments, we determined the weighting factors by evaluating more than 100 objects in five object categories.

The procedure is repeated to generate a list of template grasps. For each generated template grasp g_j the following information is stored:

- S: Meta information including object category, object part, and task information.
- $R_j \in SE(3)$: Transformation between the hand's TCP and the center of the object part.
- $T_j \in \mathbb{R}$: Transferability measure.

a) Local Optimization of the Grasping Pose: So far, the grasp transfer to other object parts within a category is performed by applying the fixed grasp transformation R_j that was computed for a specific grasp g_j to all other object part instances and the results are evaluated by computing T_j.

Since it is obvious that this approach may not produce optimal results, we propose to apply a local optimization strategy by using the local, derivative-free optimization routine of Rowan's [34] "Subplex" algorithm in order to determine a better grasp transformation R'_j. The optimization is performed on the translation vector of R_j and the objective function is the transferability measure T_j.

With this step, we are able to locally optimize the grasping information with the objective to be able to successfully transfer the grasp to other object parts within a category.

We perform this optimization step for all generated grasps and, as shown in the evaluation section, this results in an increased grasp transfer success rate.

B. Online Grasp Transfer

As shown in Fig. 2, grasp transfer is performed online assuming that the system is capable of localizing and segmenting novel objects, e.g. based on RGB-D data. An exemplary approach of these perception tasks is presented in the following section. Since perception and segmentation is beyond the scope of this work, we refer to existing work and focus in the following on the transfer of grasping information.

1) Object Perception and Categorization: The online grasp transfer starts with capturing the point cloud representation of the scene with a depth sensor. Given a noisy scene cloud, the supporting background surface is first removed to extract object clouds only. We then segment the remaining objects into plausible and distinct regions by employing the segmentation method introduced in [35]. This segmentation approach does not consider color or texture cues, but rather relies on the locally connected convex surface regions bounded by concavities. Next, we represent the scene with geometric primitives by fitting geometric models, e.g. plane, cylinder or sphere, to each of the extracted object segments by using the method in [36]. These geometric models can be employed for object categorization as shown in [37], [38], [39].

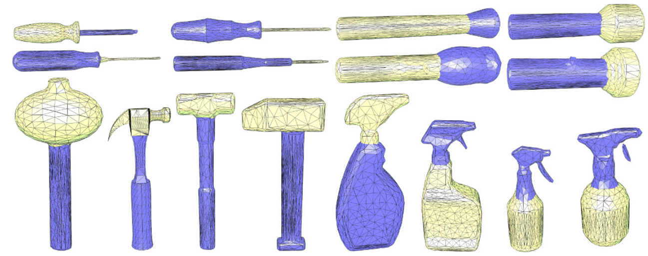

Fig. 5. Example object meshes of the object categories *screwdriver*, *hammer*, *spray bottle*, and *flashlight*

In Section IV-B, we show how this approach is applied in a realistic use case with the humanoid robot ARMAR-III.

2) Grasp Transfer: We assume that a perceived object is segmented into object parts which may be approximated and categorized in order to determine the object category for grasp transfer. In addition, task constraints are considered, e.g. to determine object parts that are available for grasping.

For the selected object part(s), the robot memory is queried to retrieve the list of template grasps. This list of potential grasps is ordered according to the grasp transferability measure T. In order to find a suitable grasp for the current scene, the list is processed until a feasible grasp can be found. Therefore a grasp is evaluated if it is reachable by utilizing the inverse kinematics (IK) solver followed by a collision check that ensures that the resulting configuration is not in collision with the environment.

IV. EVALUATION

A. Grasp Transfer Performance

We evaluated the approach in simulation by performing grasp planning on several object categories. As data set, we used 3D meshes of 18 screwdrivers, five spray bottles, 20 hammers and 15 flash lights. A few example meshes are shown in Fig. 5. In order to evaluate the performance of the grasp transfer to novel familiar objects, we applied the leave-one-out cross validation method, i.e. grasp planning is performed on the objects of a category whereas one object is excluded and the planned grasps are applied to the excluded object. The performance is measured by counting the number of successfully transferred grasps (successful grasps are not in collision with the object parts and result in a force closure finger configuration). Every object of the category is excluded once and the average success rates are computed.

Fig. 6 summarizes the results for different object categories and their different parts.

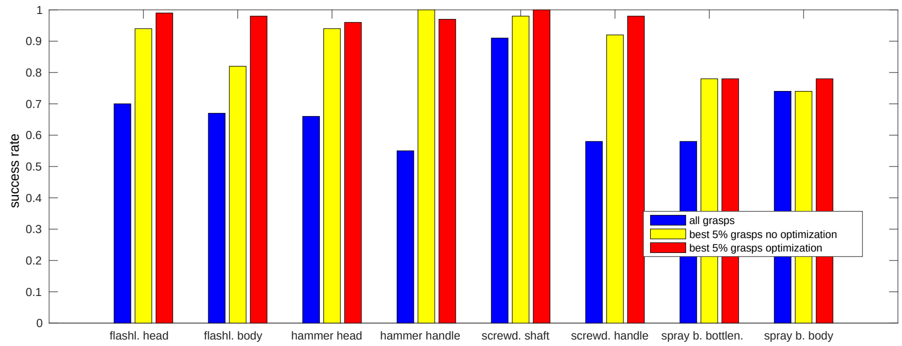

Fig. 6. The grasp transfer success rate for different object categories.

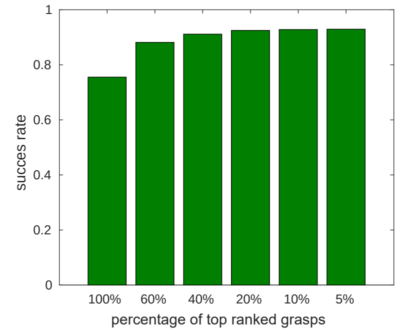

Fig. 7. Average grasp transfer success rates.

The grasp transfer success rate is depicted when considering all planned grasps (blue), when considering the 5% best ranked grasps according to the transferability measure T without the local optimization step (yellow), and when considering the 5% best ranked grasps when applying the local optimization (red).

For the parts of the object categories *flashlight*, *hammer* and *screwdriver*, the success rates are all above 96%. In case of the *spraybottle* category, the success rate of both parts is worse (78%), which is mainly caused by the limited number of object meshes that were available.

The effect of the transferability measure T is evaluated in Fig. 7. Here, the average success rates over the whole object data set is depicted when applying a specific percentage of top ranked grasps according to T. It can be seen that the success rate is noticeable higher for better ranked template grasps.

The results point out that the grasp transfer approach can be successfully applied to familiar objects. In addition, it can be seen that the proposed transferability measure T provides a feasible estimate of the transferability. Finally, the results show that the local optimization step leads to better grasp transfer success rates.

B. Application on the humanoid robot ARMAR-III

In this use case, we show how the complete pipeline as depicted in Fig. 2 is applied to a realistic grasping task with the humanoid robot ARMAR-III [33] (see Fig. 8). The object to be grasped is novel, but familiar, i.e. the object mesh hasn't been used for generating the template grasps during offline grasp planning. In this scenario, we assume that the object category (*hammer*) as well as the environment is known. Nevertheless, the actual shape of the object is not available. As shown in Fig. 8, it is approximated by the perception approaches described in Section III-B.1. The resulting approximation consists of two cylinders which are passed to the grasp transfer component. Note that the robot has no assumption about the detected object parts. Therefore, we apply a naive matching algorithm which returns how each detected object segment in the scene matches with these object parts stored in the known object category. The matching algorithm compares the fitted geometric primitives together with their relative sizes and orientations. This way

Fig. 8. A grasping task for ARMAR-III and the perceived point cloud together with matched shape primitives.

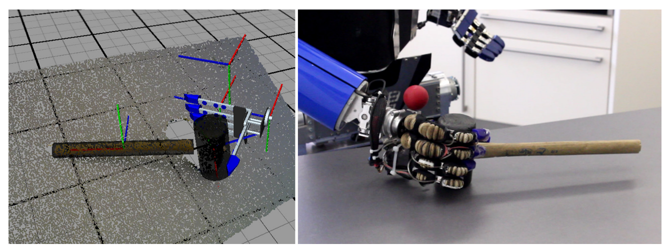

Fig. 9. The transferred grasp and the execution on ARMAR-III.

the robot can estimate which detected object part is the handle or the head of the hammer (see Fig. 8). Fig. 9 shows the transferred grasp and the execution on ARMAR-III.

V. CONCLUSION

We presented an approach for part-based grasp planning that is capable of generating grasps that can be transferred to familiar objects.

Therefore we use multiple object meshes which are segmented according to their shape and volumetric information. Based on the resulting object parts, grasping information is generated with a grasp planning approach that employs a local optimization strategy to improve the transferability between object parts within an object category. We introduced a transferability measure that provides information about the expected success rate of grasp transfer and we showed that this measure correlates with the actual grasp transfer success rate for several object categories.

The approach was evaluated in simulation and employed in a realistic use case, in which grasping information was transferred to a familiar object and the resulting grasping motion was executed with the humanoid robot ARMAR-III.

One key advantage of this approach is its robustness against errors in object recognition and shape estimation because the generated grasping information can deal with shape variations. In addition, we can estimate how good a generated grasp can be applied to familiar objects through the proposed transferability measure.

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