Learning Task-Oriented Grasping from Human Activity Datasets

Abstract—We propose to leverage a real-world, human activity RGB datasets to teach a robot Task-Oriented Grasping (TOG). On the one hand, RGB-D datasets that contain hands and objects in interaction often lack annotations due to the manual effort in obtaining them. On the other hand, RGB datasets are often annotated with labels that do not provide enough information to infer a 6D robotic grasp pose. However, they contain examples of grasps on a variety of objects for many different tasks. Thereby, they provide a much richer source of supervision than RGB-D datasets. We propose a model that takes as input an RGB image and outputs a hand pose and configuration as well as an object pose and a shape. We follow the insight that jointly estimating hand and object poses increases accuracy compared to estimating these quantities independently of each other. Quantitative experiments show that training an object pose predictor with the hand pose information (and vice versa) is better than training without this information. Given the trained model, we process an RGB dataset to automatically obtain training data for a TOG model. This model takes as input an object point cloud and a task and outputs a suitable region for grasping, given the task. Qualitative experiments show that our model can successfully process a real-world dataset. Experiments with a robot demonstrate that this data allows a robot to learn task-oriented grasping on novel objects.

I. INTRODUCTION

Knowing accurate poses and shapes of hands and objects during everyday manipulation tasks can provide cues for teaching robots to grasp objects in a task-oriented manner. For example, humans typically grasp knives at their handle to cut with the blade. There are two main approaches for learning Task-Oriented Grasping (TOG). They involve either manually labeling of suitable contact regions on objects for a certain task [1]–[3] or executing task-relevant motion trajectories and scoring the grasps based on the action outcomes [4]. Both approaches have been demonstrated for a relatively small set of tasks and objects. A major bottleneck is data collection that requires either manual labeling of contact regions or designing task trajectories.

A way to circumvent this is to leverage rich human activity datasets that contain task-labeled images and videos of humans manipulating objects [5]–[7]. The caveat is that these datasets are often 2D and they lack annotations that could facilitate the inference of a 6D grasp pose which is central to robot grasping. A potential solution is to lift this data to 3D which is a challenging problem in itself. While there has been a lot of work on pose and shape estimation of either hands [8]–[11] or objects [12]–[14] from RGB images, research on jointly estimating hands and objects is scarce [15]–[19]. The challenges are: 1) strong occlusions from both hands and objects and 2) tedious annotations of real images with hand and object information. While the first problem has been addressed in the past [15]–[17] by devising algorithms that estimate hands and objects in conjunction, the lack of large real-world, annotated datasets impedes the generalization capacity of these algorithms to novel objects. To address this, [15] generated a large synthetic dataset of a hand grasping objects on which the authors train a model to reconstruct hand-object pairs in 3D. However, the results often lack sufficient detail especially for the object. Furthermore, synthetic datasets suffer from the sim-to-real gap.

In this paper, we present an approach for learning TOG by processing a real-world dataset of RGB images showing humans performing everyday manipulation actions on various objects. This provides us with distributions of task-oriented grasps on objects which can be used to teach a robot how to grasp novel objects in a task-oriented manner (see Fig. 1). For processing the dataset, we develop a method that predicts hand pose and configuration as well as object pose and shape from a single RGB image. We exploit the notion that jointly...
estimating hands and objects can be beneficial and devise a network architecture that internally couples them. In the experiment section, we quantitatively evaluate the proposed model by reporting the effect of using a hand to estimate an object pose and vice versa. Our method shows competitive results in comparison to state-of-the-art [15] while being more detailed in object shape estimation. To transfer this knowledge to a robot, we train a CNN that predicts if a grasp is suitable for a task on a novel object. We demonstrate the applicability of our approach by executing task-oriented grasps with a real robot on objects belonging to either of three categories. In summary, we make the following contributions:

1) A framework for estimating hand pose and configuration as well as object pose and shape from a single RGB image.
2) Competitive results to state-of-the-art [15] and generalization to novel object instances from three categories.
3) TOG models learned from a challenging real-world dataset of humans manipulating objects.
4) Real robot demonstrations of task-oriented grasps of previously unseen object instances from a given category.

II. RELATED WORK

A. Modeling Hand-Object Interactions

Tekin et al. [16] propose a CNN that jointly predicts hand and object poses. The proposed model was trained on a real-world First-Person Hand Action Benchmark (FHB) [20] dataset which contains hand annotations per image. However, only four objects are annotated with poses. To address the lack of object annotations, [15] generate an RGB dataset of synthetic hands and objects on different backgrounds and train a CNN that reconstructs meshes of hand-object pairs from an image. However, reconstruction often requires a strong regularization of the shape due to the large dimensionality of the problem. Thus, the reconstructed objects in [15] often have blob-like shapes. This makes it difficult to discern shape details that may be crucial for learning TOG. For example, when learning to grasp a knife for cutting, it is important to know where the blade is. While [16] and [15] yield promising results for the hand estimation, [16] lacks generalization power over object shapes due to only four objects being annotated and [15] lacks sufficient detail in reconstructed objects and hands.

In this paper, we build upon our previous work on hand-held object pose and shape estimation [17] where we train a CNN that predicts an object pose and a shape from an RGB image. It uses information about the hand as additional input to the CNN which we showed to significantly improve the results of object pose estimation. To obtain the information on the hand, we run an existing hand pose detector [8] on the input RGB image. However, if the hand pose estimate is inaccurate, this can negatively influence the object pose estimate. This is often the case, since the dataset used for training of [8] does not contain a lot of samples with object occlusions. To address this limitation, in this work, we train a CNN that jointly predicts the hand and the object from an RGB image. It is trained on a combination of the real-world FHB dataset and our own synthetic dataset. FHB contains dense hand annotations and the hand is partially occluded by the objects. This ensures generalization over different hand poses. The synthetic dataset contains dense object pose and shape annotations for a wide variety of objects and the objects are partially occluded by the hand. This ensures generalization to novel objects and poses. As in our previous work, our method outputs an object pose and a shape descriptor which is used to retrieve the most similar mesh from a set of training meshes for that category. We extend our previous work by also predicting the hand pose and joint angles. We show in the experiments (Sec. VI-B) that, in contrast to [15], our method yields more precise estimates of hands and object which we can use for TOG.

B. Task-Oriented Grasping

The problem of grasping an object in a manner that allows for a subsequent execution of a certain task is known as Task-Oriented Grasping [1], [4], [21] and is more challenging than simply grasping an object to hold it stably. The first challenge is to find grasps that have the right trade-off between stable and task-compliant. The second challenge pertains to data collection that would enable general, all-purpose algorithms that can deal with variety of objects and tasks. To collect the data, authors often manually label regions on objects that are suitable for TOG.

For example, [1] train a CNN that predicts part affordances, which are used to formulate task constraints on the location and orientation of the gripper. Constraints are given to an optimization-based grasp planner, which executes the grasps. Similarly, [3] train task-oriented CNNs to identify regions a robot is allowed to contact to fulfill a task. Both part affordances and contact regions are manually annotated. Another approach is to learn TOG from self-supervision. Fang et al. [4] generate task-specific motion trajectories with different objects in simulation and used them to score grasps on objects for two tasks. Grasps are scored based on whether the task succeeded or not. The challenge with both of these approaches is to either manually label contact regions or generate the task trajectories which is expensive and time-consuming. We propose a model for processing a real-world dataset of RGB images that, when lifted to 3D allows us to obtain annotations without the manual effort.

III. FROM RGB IMAGES TO TASK-ORIENTED GRASPS

We develop a method that can enable a robot to execute task-oriented grasps on novel object instances of a known category. To this end, we learn a category specific model from examples of task-oriented grasps that are mined from a large-scale, RGB dataset of human manipulation actions. We divide the problem into two subproblems. The first subproblem pertains to processing RGB dataset to obtain hand-object pairs in 3D. The second subproblem pertains to executing task-oriented grasps by using the data generated in the previous stage.

To address the first subproblem (Fig. 2 left), we train a CNN that takes as input an RGB image of a hand and an object and outputs the hand pose and configuration (we use
terms hand configuration and hand shape interchangeably) and the object pose and shape descriptor used to retrieve the most similar looking mesh to the object in the image. To address the second subproblem (Fig. 2, right), executing task-oriented grasps, we run the network on the RGB datasets of human manipulation actions and obtain statistics on the relative hand poses with respect to retrieved object meshes. This data is then used to transfer the task-oriented grasp experience to a robot which is presented with a novel object.

Once we obtain the object pose estimates, position \( \tilde{p}_O \) and orientation \( \tilde{W}_O \), we can in turn use them to improve on initial hand estimates by predicting the hand values with the object information. Formally:

\[
\begin{align*}
   h_{\tilde{p}}^{p} &: (X, \tilde{p}_O) \mapsto \tilde{p}_H^{p} \\
   h_{\tilde{W}, \tilde{\beta}} &: (X_H, W_O) \mapsto (\tilde{W}_H, \tilde{\beta})
\end{align*}
\]

2) Object: We estimate an object position and orientation by learning two functions. The first takes as input an RGB image showing an object segmented from the background \( X_O \) (obtain with Mask R-CNN [22]) and a hand position \( \tilde{p}_H \) and outputs an object position estimate \( \tilde{p}_O \). The second function takes as input an object crop \( X_O^c \) and a hand rotation matrix \( \tilde{W}_H \) and outputs an estimated object rotation matrix \( \tilde{W}_O \). This yields two functions:

\[
\begin{align*}
   o_p &: (X_O, \tilde{p}_H) \mapsto \tilde{p}_O \\
   o_w &: (X_O^c, \tilde{W}_H) \mapsto \tilde{W}_O
\end{align*}
\]

The object pose estimation problem benefits from the knowing the hand pose in several ways. First, the hand provides cues about object position even when the object is occluded by the hand. Second, the hand orientation provides cues about object orientation, e.g., a knife is often grasped at the handle such that the blade is pointing downwards.

We use these quantities to estimate the object pose.

We model the object shape estimation as a retrieval problem. Namely, we aim at finding the most similar mesh (among all meshes in a category) to the object in the image. We do this by generating a joint embedding space for shape and image data points (same as in our previous work [17]). It ensures that an object shape and image features are mapped close together in the embedding space if they belong to the same object and distant otherwise. During inference, this allows us to retrieve the most similar mesh to the object in the image by querying the nearest neighbor in the embedding space.

Formally, the third function takes as input the crop \( X_O^c \) and outputs a shape feature vector \( \delta(X_O^c) \) which is used to retrieve the most similar looking mesh during inference.

\[
o_M &: X_O^c \mapsto \delta(X_O^c)
\]

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**A. Hand-Object Pose and Shape Estimation**

Given an RGB image \( X \) of a human hand holding an object, our goal is to predict a 6D pose and a configuration of the hand \( H = (\theta_H, \beta) \) as well as a pose and a shape of the object \( O = (\theta_O, M) \). A pose of a hand or an object is parameterized with a transformation matrix \( \theta \) which describes a position \( p \in \mathbb{R}^3 \) and an orientation \( W \in \mathbb{R}^{3 \times 3} \) of the hand or the object in the camera frame (we use subscripts \( H \) and \( O \) to indicate either hand or object pose). The configuration of the hand contains 21 joint angles \( \beta \in \mathbb{R}^{21} \) and the shape of the object \( M \) is a polygonal mesh.

1) Hand: We estimate the hand pose and configuration in two steps. The first step where we obtain the initial hand predictions does not include an information about an object and the second step uses object pose to refine the initial hand predictions.

We get the initial hand estimates by learning two functions. The first one takes as input an RGB image \( X \) and predicts the hand position \( \tilde{p}_H \) in the camera frame. The second function takes as input a crop, i.e., a minimum bounding box around the hand \( X_H^c \) and predicts the rotation matrix \( \tilde{W}_H \) of the hand’s coordinate frame with respect to the camera as well as the hand configuration \( \tilde{\beta} \). Formally, we learn two mappings:

\[
\begin{align*}
   h_p &: X \mapsto \tilde{p}_H \\
   h_{\tilde{W}, \tilde{\beta}} &: X_H^c \mapsto (\tilde{W}_H, \tilde{\beta})
\end{align*}
\]
we apply the grasp with the human hand model. We store which has a realistic human hand model. Specifically, we can segment the object into suitable/unsuitable regions which we call TOG-T.

To generate images and their labels, we use GraspIt! [25]. To demonstrate this, we run our network for hand-TOG. It consists of: 1) an approaching normal \(X\), 2) a roll rotation around the approaching normal, i.e., a roll \(\omega \in \mathbb{R}\) and 3) an offset from the object surface \(s \in \mathbb{R}\). The approaching normal is parallel to the object surface normal and aligned with the \(z\)-axis of the human hand. For definition of SE(3) see [23].

B. Task-Oriented Grasping

As stated in Sec. [III] we want to mine large datasets of RGB images showing hands interacting with objects to learn TOG. To demonstrate this, we run our network for hand-object pose and shape estimation on a realistic RGB dataset depicting hands in interaction with objects. For each of the three categories: bottles, knives, spoons, we process all the images in the dataset which yields a set of mesh models annotated with human grasps for a certain task. To ensure generalization to previously unseen objects, we train a CNN which we call TOG-T, that takes as input an object in the form of a binary voxel grid \(M_o\), a grasp \(g = (n, \omega, s)\) (which we construct from a human hand pose, see Fig. 3), and a task \(t\). It outputs a binary score; 1 if the grasp is suitable for the task and 0 otherwise. We use this representation of a grasp instead of a full hand pose to make it more object-centric. Then we can segment the object into suitable/unsuitable regions for approaching and grasping. The area that is suitable for grasping reflects the human grasp distribution, however, only a subset of grasps in the area are also stable for specific gripper.

To address the stability issue, we leverage our previous work where we trained a CNN to predict a stability score of a two-finger antipodal grasp, which we call TOG-S network [2]. Similarly to TOG-T network, it takes as input \(M_h\) and \(g\) and outputs a stability score between 0 and 1. We consider those grasps valid that have a stability score \(\geq 0.5\) and are deemed suitable for the task.

IV. DATASETS

We use two datasets for training, one for object pose and shape learning which we call synthetic dataset and another for hand pose and configuration learning, the First-person hand benchmark (FHB) [5]. For testing the model and collecting the task-oriented grasps, we use GUN-71 [24], an egocentric dataset of a variety of real hand-object pairs.

The synthetic dataset consists of approximately 100 meshes per category taken from ShapeNet and ModelNet40. To generate images and their labels, we use GraspIt! [25] which has a realistic human hand model. Specifically, we import an object mesh \(M\) in a random pose. Then, we sample a grasp from a predefined set \(h_o \in H_o\) which we generated off-line per object with the EigenGrasp planner [26]. Finally, we apply the grasp with the human hand model. We store RGB images \(X_o\) and \(X_o'\), both obtained by masking the hand with white pixels. These images are labeled with the hand pose \(\theta_H\) and joint configuration \(\beta\).

During the generation of a grasping set \(H_o\), we reject the grasps that do not reflect a realistic distribution of human grasps for that category, e.g., we discard the grasps on a blade of a knife. Note, that the remaining grasps are not necessarily task-oriented. They simply reflect the most common object part that humans grasp. Making the grasps task-oriented would require manual inspection which we circumvent by automatically processing the rich RGB dataset.

FHB is an egocentric dataset that contains real RGB-D videos of humans manipulating objects. We decided to train the hand predictor on this data instead of ours or [15] synthetic datasets to avoid the sim-to-real gap. Each frame is annotated with 3D joint positions relative to the camera frame. Ground truth meshes and pose labels are provided for only 4 of 26 objects. We pre-process the data for training the hand predictor by first scaling the joint positions to comply with the human hand model in GraspIt!. Then, via inverse kinematics, we obtain \(\theta_H\) and \(\beta\) for each RGB frame. Video sequences yield 105,459 images \(X\). We also crop these to obtain \(X_o\).

GUN-71 is a real-world egocentric dataset which we process to collect the data for TOG. It consists of RGB images of hands manipulating a plethora of different objects from many categories. No annotations, except from the grasp type shown in the image are available.

V. TRAINING AND INFERENCE
A. Hand-Object Pose and Shape Estimation

1) Network Architecture: The network architecture is split into a hand predictor and an object predictor (see Fig. 4). The hand predictor (orange), predicts the hand pose \(\theta_H\) and joint configuration \(\beta\). The object predictor (blue) predicts the object pose \(\theta_O\) and features of the image crop \(\delta(X_o')\).

To train the object pose estimator (Eq. 5 and 6), we use object and hand annotations from our synthetic dataset. To train the hand pose estimator (Eq. 3 and 4), we use only the hand annotations from the FHB dataset since the four annotated objects in the dataset are not useful for our scenario. To obtain the necessary object annotations, we find the most similar hand pose and configuration in the synthetic dataset and query the pose of a held object.

To obtain the initial estimate of the hand position \(p_H\), the hand predictor starts with convolutional layers that operate on a full image \(X\). The output is flattened and fed to a set of fully
connected layers to regress to $\hat{p}_H$. To estimate the rotation matrix $W_H$ and joint configuration $\hat{\beta}$, the hand predictor starts with convolutional layers that operate on a hand crop $X'_O$. The output is flattened and fed to a set of fully connected layers to regress to $\tilde{W}_H$ and $\hat{\beta}$.

To estimate the object position $p_O$, the object predictor starts with convolutional layers that operate on full-size images $X_O$ of object segments. The output is flattened and concatenated with $p_H$. This vector is passed to a set of fully connected layers and the network outputs $\tilde{p}_O$. To estimate the object rotation matrix $W_O$ and a shape vector $\delta(X'_O)$, the object predictor starts with convolutional layers that operate on object segment crops $X'_O$. The output is flattened and generated $\delta(X'_O)$ and an orientation feature vector that is concatenated with $\tilde{W}_H$. To account for potential noisy hand estimates at inference, we add noise to each Euler angle of the hand orientation $W_H$ (max $\pm 30^\circ$). The concatenated vector is fed to a set of fully connected layers to regress to $W_O$.

When training the hand predictor with an object, $p_O$ and $W_O$ are used to refine the initial hand predictions which is achieved by concatenating them with the intermediate hand predictor layers, running them through a set of fully connected layers and outputting the final $\hat{p}_H'$ and $\tilde{W}_H'$.  

2) Loss Functions: To learn the hand pose and configuration we train the network with the mean squared error (MSE) loss between the ground truth and estimated position, rotation matrices and joint angles.

To learn the object position we train the network with the MSE loss between the ground truth and estimated position. Computing the orientation loss over the whole rotation matrix is challenging due to ambiguities in the representation and object symmetry. However, with a representation that is invariant to symmetry we can facilitate the learning process. Following [27], we construct a category-specific representation $R_O$ which consists of columns $u$ of the object rotation matrix and is defined depending on the type of symmetry that an object possesses (see Fig. 5). For each category, we compute the rotation loss by extracting the columns $\tilde{u}$ from the estimated rotation $\tilde{W}_O$ and constructing $\tilde{R}_O$. The orientation loss is then the MSE between $\tilde{R}_O$ and $R_O$. Therefore, estimated rotations $\tilde{W}_O$ that differ from the ground truth rotations $W_O$ are not penalized if they yield the same $R_O$.

For object shape estimation, we take a retrieval approach that requires to learn a suitable embedding space. For training, we use a shape loss that encourages similar data points to be mapped close to each other in the embedding space and distant otherwise. The shape loss is computed between the features of two data points. In our model, the first data point is the image crop $X'_O$ around the object and the second data point is a mesh $M$ which we represent as a binary occupancy grid denoted by $\delta(M)$: $M \in \mathbb{R}^2_{H \times W \times D}$. Specifically, we use a Siamese network that outputs the features $\delta(X'_O)$ and $\delta(M)$. The loss is computed as:

$$\mathcal{L}_{obj} = (1 - y) \frac{1}{2} d^2 + \frac{1}{2} \text{max}(0, m - d)^2,$$

where $d$ is a Euclidean distance between the features $\delta(X'_O)$ and $\delta(M)$, $m$ is a margin (defined in [28]) and $y$ is a binary valued function which is 1 if $X'_O$ and $M$ belong to the same object, and 0 otherwise.

3) Inference: To collect the data for TOG, we run the network on the GUN-71 dataset in which we label each image with a task. The full RGB image $X$ is first pre-processed with Mask R-CNN to get object segments $X'_O$, $X'_H$ and the category $c$. Simultaneously, we run a hand detector on $X$ to get the hand crop $X'_H$. The hand detector is trained on EgoHands [29], a dataset for hands in complex egocentric interactions. This gives us the necessary inputs to the network $\{X, X'_H, X'_O\}$. For each image in the dataset, we first obtain the hand estimates $\hat{\beta}$, then we use them to get object estimates $\hat{\theta}_O, \delta(X'_O)$. These are finally then used to refine the initial hand estimates. We predict the hand without an object first, since the hand predictor trained in such manner already performs well (in contrast to the object predictor without the hand). For mesh retrieval at inference time, we rely on pre-computed $\delta(M)$ for all training set meshes $\tilde{M}$. To retrieve a suitable object mesh $\tilde{M}$ given $\delta(X'_O)$, we compute the pairwise distances between all $\delta(M)$ and $\delta(X'_O)$ and select the nearest neighbor in the embedding space. Finally, we transform the global hand and object poses to the object coordinate frame such that the grasp is encoded with respect to the object. This gives us a set of meshes annotated with human grasps for a certain task.

B. Task-Oriented Grasping

1) Network Architecture: The TOG-T CNN takes as input a volumetric representation $M_V$ of an object and a grasp $g$. It starts with two volumetric convolutional layers to first process the mesh and generate a lower dimensional representation of the object shape. This is then concatenated with the grasp vector and passed to a set of fully connected layers that output either 1 if the grasp is suitable for the task and 0 otherwise. Furthermore, to account for partial and noisy data in the real world, we add a dropout in the first layer that randomly removes 50% of the input points. The network is trained with sigmoid cross entropy loss.

2) Inference: During inference, our goal is to execute grasps that are stable and suitable for a task with a parallel gripper on a novel object from a known category. Concretely, when presented with an object, the robot must reason about what gripper poses with respect to the object ensure stability once the object is lifted and also task suitability in terms
of contact locations. This is a difficult problem which poses several challenges. First, we need to segment the object from the table and the background. Second, we need to obtain the points on the object surface and their corresponding normals. From this, we can generate the object representation \( M_V \) and the grasp representations \( g \) that form the input to the TOG-T network. Finally, we need to plan collision-free grasps and execute them in the robot workspace.

To segment the object point cloud, we place it in its canonical orientation, next to an April tag whose coordinates in the camera frame are known. The segmentation is achieved by filtering the points that are in the proximity to the April tag [30]. This gives us a raw object point cloud. Note that using an April tag to segment an object and estimate its pose is a short-cut and any other method for 3D segmentation or pose estimation could have been used, e.g., [12]. From the point cloud, we generate the object volumetric representation \( M_V \) by scaling the points to fit inside a \( 50 \times 50 \times 50 \) grid. We also compute the normals \( n \) which we use together with randomly sampled rolls \( \omega \) and offsets \( s \) to generate grasps \( g \) to be tested. Finally, we run \( M_V \) and \( g \) through the TOG-T network to obtain the task-suitable regions and TOG-S network to obtain the stability scores. We rank the grasps according to stability scores and execute the grasp with the highest score that is also suitable for the task and kinematically reachable.

VI. EXPERIMENTS

In this section, we present experiments and results that test the following hypotheses:

1) Using a combination of real and synthetic data to train our CNN for hand-object estimation yields more accurate results in terms of relative poses than reconstructing the hand-object pairs. We test this through a qualitative comparison of ours and a state-of-the-art method for hand-object reconstruction [15] on the challenging real-world dataset GUN-71 [24] (Sec. VI-A). A quantitative evaluation would require manually annotating of images in dataset and no other labeled RGB dataset exists that contains such a variety of objects and manipulation tasks.

2) Using a hand helps facilitate object pose learning and vice versa. In Sec. VI-B.1 we test this by quantitatively comparing object pose estimation results with and without a hand on the synthetic dataset as well as hand pose estimation results with and without an object on the FHB dataset.

3) Representing the hand with a pose and joint configuration instead of 3D joint positions is favorable when requiring precise estimation of object poses. In Sec. VI-B.2, we test this hypothesis by comparing object pose estimation results when using either of the two aforementioned hand representations.

In Sec. VI-C we demonstrate that our method can be used to enable a robot to grasp novel objects instances from a known category in a task-oriented manner.

A. Qualitative Evaluation On a Real-World Dataset

We show a qualitative comparison between our method and [15] on the GUN-71 dataset in Fig. 6. For each category, we show three examples consisting of an input image, results of hand and object estimation using our method and the results of reconstructing hand-object pairs. Note that our method operates on full images and outputs global poses in the camera frame while [15] is trained on a crop around the hand-object pair and a hand which is relatively centered. It outputs hand-object reconstructions that are relative to the hand wrist.

Qualitative results show that our method yields more precise object poses and shapes. In comparison, their method sometimes reconstructs the wrong object, i.e., instead of the tool in the hand it reconstructs the object that the tool is used on, both of which are in the cropped region. For example, for the knife in first row of Fig. 6 their method reconstructs an apple instead of the knife. The same drawback is evident for spoons and less so for bottles. Furthermore, even when the reconstructed object is correct, it lacks sufficient detail for learning TOG. For example, for knives it is hard to distinguish the blade from the handle or to determine where the sharp side of the blade is. In contrast, our method outputs more precise and plausible object and hand poses and shapes. This is mainly because: 1) [15] need to regularize the hand shape which can sometimes fail (i.e., when the hand is occluded by the object) and generate results that are not physically plausible and 2) due to the higher dimensionality of the problem, reconstructing an object is more difficult than retrieving its shape and estimating its pose.

In the bottom row of Fig. 6 we show the failures on one example per category which illustrate the limitations of our
method. For example, in knives, it is sometimes difficult to discern the angle of a blade w.r.t. camera.

| Position | Orientation |
|----------|-------------|
| bottle   | 19.49 58.89 11.56 17.10 |
| knife    | 16.00 57.98 43.92 53.79 |
| spoon    | 18.28 62.25 51.23 56.44 |

Similarly for spoons, it is difficult to discern if the concave or the convex side is facing the camera. Wrong estimates of the orientation in this case yield high errors, although the visual appearance is quite similar. However, [15] suffers from similar limitations as the exact orientation is almost impossible to detect from their results.

B. Quantitative Evaluation

1) The Effect of Joint Estimation of Objects and Hands:
To evaluate the shape, we compute the F1 score [31] between the ground truth and predicted shapes (see Fig. 5). We obtain the highest score for bottles. To evaluate the object pose, we report Mean Absolute Error (MAE) between the ground truth and estimated orientation in degrees and position MAE in millimeters. To obtain Euler angles in degrees from a rotation matrix, we generate all the possible rotation matrices which have the same orientation representation \( R_D \) (see Sec. III-A.2) convert them to Euler angles, and compute MAEs between all the generated angles and the ground truth angles. We report the minimum over all MAEs in Fig. 7. Namely, due to symmetry around the \( z \)-axis in bottles, all possible rotations around it would yield the same appearance and \( R_D \). Therefore, when we report the final orientation MAE, we do not penalize rotations around the \( z \)-axis that differ from the ground truth. We do similar for knives and spoons.

We report the results of object pose estimation when training with and without a hand pose. The results show that when using the hand we obtain better results than when omitting the hand. This is because the hand pose informs the object pose estimation. Overall, we achieve the smallest errors in orientation for bottles. This is expected since bottles posses axial spherical symmetry which means we are estimating only one column of its rotation matrix. Spoons achieve the highest error. This is because it is often difficult to discern if the concave or the convex part is facing the camera (which is a strong indication of the orientation).

The same applies vice versa, i.e., training the hand pose estimation with an object yields better results. To evaluate this, we report MAEs in position, orientation and joint angles when training with and without an object. We also report mean root-relative end-point error (HP error) (mm) over joint positions and compare our results with [15]. We use the same split for training and testing as [5].

Results in Fig. 9 show that hand pose estimation is better when adding an object. Furthermore, our HP error is comparable to state of the art [15] who achieve the error of 28.82. In their case, the error is calculated over a filtered FHB dataset in which the frames where the manipulating hand is further than 1 cm away from the manipulated object are omitted. Note that our method operates on hand pose and joint angles and to obtain estimates of joint positions we use inverse kinematics which inevitably induces some error. Although estimating hand joint positions instead of pose and configuration would probably reduce this error, in the following section we will show that hand pose and configuration representation yields better results when the goal is to facilitate object pose estimation.

2) The Effect of Different Hand Representations:
We evaluate the effect of two different hand representations on object pose estimation. We report position and orientation MAEs for both cases in Fig. 10. Results show that when using hand pose and joint configuration (H-PC) representation we obtain better results than when using the hand joint positions (H-JP) representation. This is expected when estimating the orientation, since there is a regularity between the hand and the object rotation matrices. This is evident in bottles which are often grasped such that the \( z \)-axis of the human hand is perpendicular to the principal axis of the bottle. On the other hand, high errors in the orientation for H-JP indicate that the network probably considers these values as a noise and can not use them to facilitate object orientation estimation.

C. Task-Oriented Grasping With a Robot

Given a novel object and a task, we want to execute stable and task-oriented grasps with a parallel gripper. We assume that the object is placed on a table in an upright position and that it belongs to one of the three categories: knives, bottles or spoons. To demonstrate the applicability of our method in a real-world setting, we present a robot with a novel object from a known category, then do TOG with the ABB Yumi robot. Fig. 11 shows our experiments. In the first column are the real-world objects, scanned with an RGB-D camera and converted to a volumetric representation \( M_V \) from a point cloud (shown as mesh for better visualization). Second column shows inferred grasping areas (in green) for cutting, stirring and pouring. To ensure stability, we run the grasps that are in the task-suitable region through TOG-S.
network. Third column shows an execution of a grasp with the highest stability score that is also kinematically reachable.

Fig. 11: Left to right: three previously unseen real-world objects (represented as meshes for visualization purposes) from three categories: knives, spoons and bottles, inferred grasping area suitable for cutting with the knife, stirring with the spoon and pouring with the bottle (green); stable, task-oriented grasps on the objects.

VII. CONCLUSION AND FUTURE WORK

We presented an approach for learning TOG by processing a real-world dataset of RGB images GUN-71 showing hands and objects during everyday manipulation scenarios. We devised a CNN that takes as input an RGB image and outputs a hand pose and configuration as well as an object pose and a shape descriptor. To learn TOG, we used this data to train a CNN that predicts task-suitable grasping regions on an object surface. Quantitative experiments showed that adding a hand pose to the training of an object pose yields better results than when training without the hand and vice versa. Qualitative results demonstrated the applicability of our method on GUN-71 and hardware experiments demonstrated that we can use our method to teach a robot how to execute task-oriented grasps on novel objects. In the future, we plan on: i) adding more object categories and ii) estimating hands and objects grasps on novel objects. In the future, we plan on: i) adding our method to teach a robot how to execute task-oriented

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