

Task-oriented grasping for dexterous robots using postural synergies and reinforcement learning

Dimitris Dimou

*Institute for Systems and Robotics
Instituto Superior Técnico
Lisboa, Portugal
mijuomij@gmail.com*

José Santos Victor

*Institute for Systems and Robotics
Instituto Superior Técnico
Lisboa, Portugal
jasv@isr.tecnico.ulisboa.pt*

Plinio Moreno

*Institute for Systems and Robotics
Instituto Superior Técnico
Lisboa, Portugal
plinio@isr.tecnico.ulisboa.pt*

Abstract—In this paper, we address the problem of task-oriented grasping for humanoid robots, emphasizing the need to align with human social norms and task-specific objectives. Existing methods, employ a variety of open-loop and closed-loop approaches but lack an end-to-end solution that can grasp several objects while taking into account the downstream task’s constraints. Our proposed approach employs reinforcement learning to enhance task-oriented grasping, prioritizing the post-grasp intention of the agent. We extract human grasp preferences from the ContactPose [1] dataset, and train a hand synergy model based on the Variational Autoencoder (VAE) to imitate the participant’s grasping actions. Based on this data, we train an agent able to grasp multiple objects while taking into account distinct post-grasp intentions that are task-specific. By combining data-driven insights from human grasping behavior with learning by exploration provided by reinforcement learning, we can develop humanoid robots capable of context-aware manipulation actions, facilitating collaboration in human-centered environments.

Index Terms—component, formatting, style, styling, insert.

I. INTRODUCTION

Human grasping behavior is influenced by the broader context of the manipulation action to be performed. One important factor that humans take into account for grasping an object is the reason behind grasping it in the first place. A common example is when we want to grasp something in order to use it or to hand it over to another person. In this case we tend to grasp the object from its functional part when we intend to use it, while we leave that part free when we want to hand it over, this way the other person can grasp it from its functional part and use it directly without needing to perform a regrasp.

Having humanoid robots that follow human social norms is important to accelerate human-robot collaboration and facilitate the introduction of humanoids to human centered environments. To achieve this we need to develop grasping methods that can imitate the human grasping behavior. This means that the robot must take into account task-specific factors, enabling more sophisticated and context-aware manipulation actions.

Work partially supported by the H2020 FET-Open project *Reconstructing the Past: Artificial Intelligence and Robotics Meet Cultural Heritage* (RePAIR) under EU grant agreement 964854, by the Lisbon Ellis Unit (LUMLIS), by the FCT PhD grant [PD/BD/09714/2020], by LARSyS FCT funding (DOI: 10.54499/LA/P/0083/2020, 10.54499/UIDP/50009/2020, and 10.54499/UIDB/50009/2020) and by the Portuguese Recovery and Resilience Plan (RRP), project number 62, Center for Responsible AI.

The primary challenge of this problem lies in its inherent connection with human behavior, preferences, and social norms. Therefore, any proposed solutions must be derived from real-world data that encapsulate these characteristics.

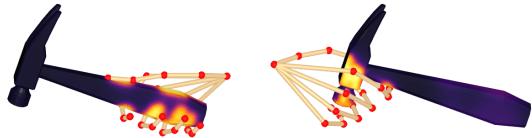


Fig. 1: Example of different execution of a grasp according to the post-grasp intention as captured in the dataset presented in [1]. In the left figure, the person grasps the hammer in order to use it, in the right it grasps it in order to hand it over to another person.

Previous works have employed open-loop grasp generation methods, where a grasp sampling method produces a static grasp pose, considering task constraints to ensure alignment with the task’s function. Subsequently, a motion planning algorithm devises a trajectory to execute the proposed grasp. Conversely, in closed-loop approaches, a policy utilizes observations and task constraints as inputs, generating actions that result in suitable object grasping. Open-loop methods often depend on extensive labeled datasets for training the grasp generation modules. However, their inherent nature prevents them from adjusting trajectories based on real-time observations or accommodating measurement uncertainties. In contrast, closed-loop methods typically leverage reinforcement learning algorithms to train grasping policies through exploration, necessitating numerous training samples and complex reward shaping to incorporate human priors.

In this work, we explore task-oriented grasping using reinforcement learning based on the intended post-grasp manipulation action. We develop an agent that can grasp objects in a way that is well-suited for the particular task that wants to accomplish. To achieve this, we start by extracting the grasp preferences from the ContactPose [1] data, which contains human grasps on various objects with the intention to use them or to hand them over. We retarget the human grasps postures to the robotic hand and use them to train a synergy model,

based on the VAE model, to generate new hand postures in a low-dimensional space. We, then, train an agent (i.e. a single policy), using reinforcement learning, that uses the synergy model as action space, to grasp multiple objects conditioned on a specified post-grasp intention.

To sum up our main contributions are the following:

- We train one policy to grasp multiple objects while taking into account the post-grasp intention of the agent.
- We utilize a hand synergy model trained on grasps performed by humans to improve the quantitative and qualitative performance of the agent.
- We demonstrate that the agent is able to grasp objects based on its post-grasp intention similarly to how humans grasped them.

II. RELATED WORK

Previous works on task-oriented grasping can be categorized into open-loop grasp pose generation methods and closed-loop grasping approaches. Typically, open-loop approaches divide the grasping behavior into two stages: first, a grasp pose is generated, usually represented by a 6DoF pose for the hand and finger configuration and then the target grasp pose is passed to a motion planning algorithm to find a feasible trajectory for execution. In this case, the our interest lies in the grasp pose generation phase. In [2], they use a classic geometric grasp sampling method from the GraspIt! simulator to generate grasps for several household objects. They then label the grasp-object pairs with task descriptions, such as hand-over, pouring, or tool-use. Finally, they train a Bayesian Neural Network, to model the relationships between the recorded features. During runtime, they query the network to output grasp poses given the task label and object properties. In [3], they train a Gaussian Mixture Model to model the correlations between task-specific grasps and object properties. New grasps are then predicted using Gaussian Mixture Regression based on the learned model. In a more recent study [4], they develop a Graph Convolutional Neural Network (GCN) to encode grasp, object, and task relationships. When presented with a new object, multiple grasp poses were sampled using a geometric heuristic, and the grasp-object pair was encoded into the GCN alongside the task description. The grasp evaluator then predicted a grasp score, and the grasp with the highest score was selected.

Another line of work involves visually detecting affordances on the objects, i.e. parts of the object that are compatible with a specific task and then using a grasp sampling method to estimate suitable grasps for that part. For example, in [5], they use a Convolutional Neural Network to detect task affordance regions on objects from point clouds. Given a task and a voxelized point cloud of an object, the network predicts which voxels of the object are compatible with the given task. Given the graspable part of the object, an optimization-based grasp sampler computes contact points that result in a high-quality grasp. In [6], they develop a discriminative model that predict a label indicating whether a grasp is suitable for a given context. They use a neural network architecture to detect affordances

for each part of the object. A geometric heuristic then samples new grasps predict a score. The grasp with the highest score was finally selected.

Open-loop grasp methods offer a modular approach to grasp sampling and can generate of multiple candidate grasps for a given context. However, a significant drawback is that training such models typically requires large amounts of labeled data, particularly with human-based annotations, which can be challenging to obtain. Additionally, incorporating trajectory planning and collision avoidance adds another layer of complexity. Notably, open-loop grasp generation with task constraints has not yet been widely applied to humanoid hands, possibly due to their increased complexity compared to simpler grippers or robotic hands.

Closed-loop methods offer an alternative to open-loop grasp generation by modeling the entire grasping action. Typically, these methods involve training a policy using reinforcement learning. The key challenge lies in appropriately defining the task and designing a suitable reward function to guide the policy towards desired behavior.

For example, in [7], they used data from [8], which consists of 3D models of everyday objects annotated with contact maps captured from humans performing two tasks (using the object and handing it off). Using this data, they trained a CNN to detect affordance regions on objects from RGB images. The affordance map, along with the state of a humanoid robotic hand, formed the state representation in a reinforcement learning environment. The reward function encouraged the agent to grasp the objects from the same affordance regions that human subjects did. However, the agent's resulting finger configurations were unnatural and did not resemble those of a human hand. To address this limitation and encourage more human-like grasps, the authors later extended their work in [9]. They introduced an auxiliary reward that measures the distance between the robotic hand's posture and a human hand posture grasping the same object. Human hand poses were extracted from internet videos using a hand pose estimation algorithm. This addition led the new agent to learn more natural hand movements, resulting in an increased grasp success rate. However both approaches focus on grasping the objects from their functional part, i.e. in order to use it, without taking into account other post-grasp intentions of the agent.

Reinforcement learning approaches offer certain advantages, as they do not require successful grasp examples for training, relying instead on learning from experience. Additionally, these policies can perform the entire grasping task, eliminating the need for separate trajectory planning or collision avoidance steps. Their closed-loop nature also makes them more robust in the face of external perturbations or measurement uncertainties. However, a crucial limitation lies in their dependency on specific reward functions, potentially restricting their applicability to only the tasks defined by these rewards. Consequently, using the grasping behavior in a new task may require retraining the agent with a different reward function. On the other hand, these algorithms demand vast amounts of samples, making simulation-based training more feasible than

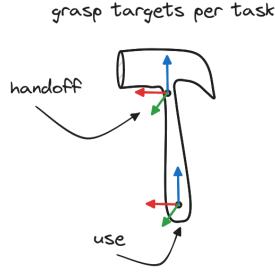


Fig. 2: Example grasping targets for hammer extracted from the ContactPose dataset [1].

real-world applications. Additionally, effective training often requires careful reward shaping to achieve desirable behavior.

III. METHODS

The goal of this work is to develop an agent that can grasp several objects based on the post-grasp intention that will be given as a conditional variable to the policy. We assume that the policy has access to the global pose of the object and the robot's state. The goal of the agent is to lift the corresponding object from the table in front of it while taking into account its post-grasp intention. To achieve this we extract grasp data from a dataset of human grasp with different post-grasp intentions and then train a policy with reinforcement learning to exhibit the desired behaviour.

A. Dataset pre-processing

We rely on the dataset introduced in [1] which consists of 3D models of everyday objects annotated with contact maps captured from humans operators grasping the objects with two different post grasp intentions: 1) using the object and 2) handing the object off to another person. The dataset also contains the hand posture, i.e. the 3D position of keypoints on the fingers of each subject, which was estimated through a 3D vision pipeline. We use two types of data in our work: 1) the grasp postures of the human subjects and 2) the grasp locations that they chose.

Hand postures. Firstly, we retarget the grasp postures executed on the objects by the participants to the robotic hand by designing a fixed mapping function between the two kinematic chains. More specifically, for each joint we compute the angle defined by the adjacent points (red points in Figure 1) and we remap this angle to the joint limits of the robotic hand. We perform this procedure for all grasps and all objects in the ContactPose dataset, resulting in 2596 grasps. Using this dataset we train a VAE model to extract the synergy space following the method presented in [10]. This model allows us to sample new grasps by providing new latent points.

Grasp targets. Subsequently, we determine target grasp points on each object that correspond to each post-grasp intention. Example grasp target points on the hammer, according to Figure 1, can be seen in Figure 2. To automate this process, for each grasp we compute a 3D point that is the average position of the fingertips of the thumb, the index,

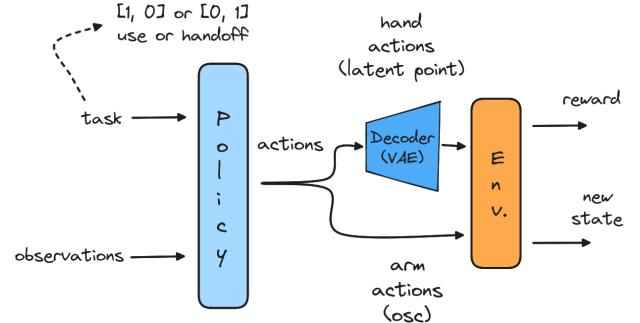


Fig. 3: Proposed agent structure for task-oriented grasping.

and the middle finger. Each object was grasped by multiple participants, so for each object we have multiple 3D points indicating the location where each participant grasped it from. Since the dataset includes two post-grasp intentions, we cluster the contact points into two clusters. For each cluster then we check if there were more handoff grasps or use grasps and assign the corresponding label to it. The center of the cluster is then defined as the grasp target for that object and that post-grasp intention. These target grasp points are used to guide the reinforcement learning policy to grasp the object close to it. Given the synergy grasp model and the grasp targets for each object and post-grasp intention we can move on to train our policy.

B. Dexterous task-oriented grasping

Our goal is to develop an agent that can grasp multiple objects based on the post-grasp intention that it is conditioned on. To this end, we train a policy using reinforcement learning to generate the required actions to perform the task. We assume that the policy has access to the pose of the objects, the target object, and proprioceptive information, which are joined together in the observation variable. We also assume that the post-grasp intention is given as a conditional variable to the policy.

Policy. A graphical representation of the policy structure can be seen in Figure 3. The policy is modeled with a neural network that takes as input the current observations and the post-grasp intention and outputs two actions, one for the hand and one for the arm. The hand action is a low-dimensional point in the synergy space which is then decoded by the synergy model into the finger joint values. The arm action is the end-effector displacement in Cartesian space which is used by an Operational Space Controller (OSC) [11] to compute the desired joint angles. To optimize the policy we use the Proximal Policy Optimization (PPO) [12] algorithm which is a popular online reinforcement learning algorithm. Note that we train one policy that can handle all objects and post-grasp intentions.

Action and state space. The policy takes as observations the robot's state, i.e. the joint angle values, the object's state, i.e. its 6DoF pose, and its category, which is an one-hot encoded variable. In addition, it is given a task-conditional

variable, that indicates the post-grasp intent, which is also one-hot encoded. Consequently, the policy generates actions for the robot to execute. The actions are a 6 DoF pose for the end-effector that is commanded to the robotic arm using an inverse kinematics controller, and a latent point that is used by the VAE model to generate the grasp posture of the robotic hand.

Reward function. The policy is trained to lift the specified object from the table by taking into account the post-grasp intent. To achieve this, we design the reward function such that the reward is high when the object is lifted and the grasp location is close to the desired grasp target. Our reward function depends only on the current state and is formulated as follows:

$$r = w_1 * r_{hand_obj_dist} + w_2 * r_{lift} + w_3 * r_{rotation}$$

$$r_{hand_obj_dist} = r_{fingertips_object_dist} + r_{palm_object_dist}$$

$$r_{lift} = r_{object_height} + r_{object_grasped}$$

The reward is the sum of three terms that are used to achieve specific outcomes. Firstly, the reward measures the proximity of the grasp location associated with the desired grasp target. The $r_{hand_obj_dist}$ function measures the distance from the fingertips to the target grasp location, $fingertips_object_dist$, and the distance from the palm to the target grasp location on the object, $r_{palm_object_dist}$. As the distance get smaller the reward increases. This encourages the policy to place the hand on the target grasp location and close the fingers. By reinforcing a high reward for a close alignment between the chosen grasp location and the specified target, the learning process is fine-tuned to prioritize precision in object manipulation. Secondly, the reward is structured to attain a high value upon successful lifting of the targeted object. This encourages the agent to converge towards actions that lead to the successful execution of the lifting task. The r_{lift} function consists of two terms one that measures the height of the object, r_{object_height} and increases as the object height increases, and a binary term, $r_{object_grasped}$ that gives a positive reward if the object is lifted above a specific height. Finally, we include a rotation reward, $r_{rotation}$, for the hand that encourages the hand to keep its orientation towards the floor, and facilitate the exploration phase.

IV. EXPERIMENTS

A. Experimental set-up

Implementation details. For all our experiments we use the 7 DoF Kinova Gen3 robotic arm with the Seed Robotics hand, which in simulation has 19 DoFs. For simulation we use Nvidia’s IsaacGym physics based simulator that allows to train multiple environments in parallel. From the ContactPose database we choose the following objects: hammer, flashlight, and light bulb. We chose these objects due to the fact that the post-grasp intentions were clearly separated on the object’s surface. For example, the hammer all grasps associated with the *use* post-grasp intention were on the handle and most of

the grasps associated with the *use* post-grasp intention were on the head. In contrast, the grasps on the other objects were more randomly placed on the objects making it hard to separate the use cases.

The policy network consists of an RNN network with 768 hidden units and 1 layer followed by an MLP network with 3 layers with 768, 512, 256 units respectively and ELU activation functions. Each policy was trained with 2048 parallel environments, for 20k epochs and for 2 different seeds. In our simulated environment the robot is placed on the floor and all the available objects on a table in front of it (Figure 5). The object’s position and rotation are randomized using additive Gaussian noise.

Evaluation. We evaluated our approach by comparing it to a reinforcement learning (RL) policy that directly outputs finger joint values to control the hand. The baseline policy was designed with identical observations, reward functions, and action space for the arm, and utilized the same network architecture as our model. Additionally, we compared against a policy that utilizes a synergy model based on the principal component analysis (PCA) method. PCA is a popular approach to model the synergy space of robotic hands and has been used in several works [13], [14]. For the evaluation, we conducted 5000 environment simulations to calculate the average grasp success rate. Additionally, we documented the rewards achieved during training and the final distances from the hand to the grasp targets for each task. We further examined the impact of increasing the number of latent dimensions in the synergy model on policy performance. Lastly, we performed an ablation study by excluding the object category from the policy’s observations to assess its influence.

B. Results

Quantitative. Figure 4 shows the accumulated rewards that each policy achieved during training. The policy that uses the joint action space achieves higher average rewards in general which is probably because it learns to grasp the object faster and has lower variance across the different seeds. On the other hand, the policy with the PCA action space achieves the highest final rewards. The accumulated reward though is not binary, i.e. if the object was grasped or not, but depends on how fast the object is grasped and how high the object is lifted, so it is not a good proxy for the grasping performance of the agent. Since the reward alone does not guarantee better performance in the task at hand, we compared the best policy from each method using the grasp success rate as a metric. More specifically, we run 5000 test environments using the best policies and computed the average grasp success rate, measured by the times the object was lifted from the table in each episode. The results, shown in Table I, indicate that the policy with the VAE action space perform better in terms of grasp success, which is the objective of the agent. Moreover, in Figure 7, we confirm the correct behavior of the policy according to the task. To determine that, we show the distance of the robot’s hand to each grasp target (which was defined for each object as described in III-A) for the two post-grasp

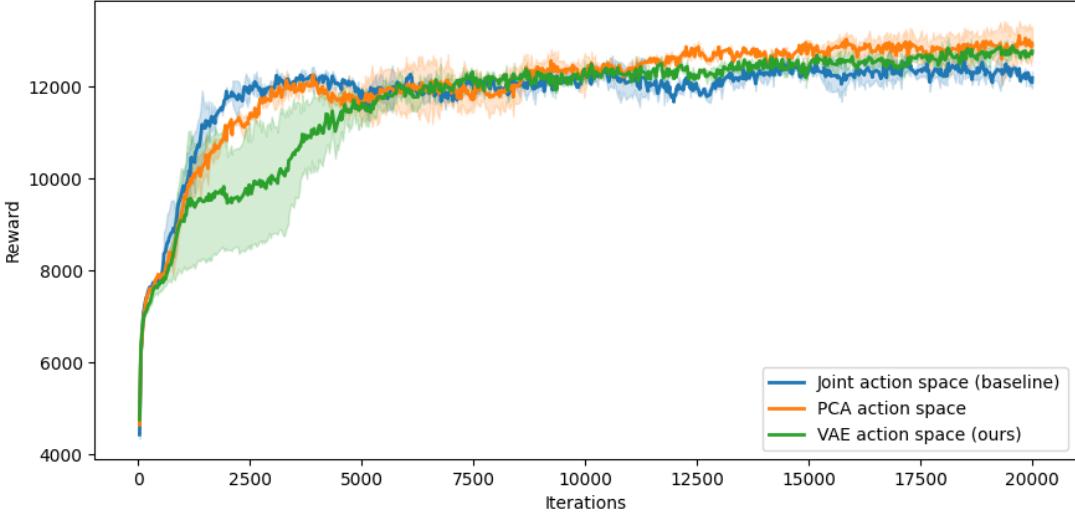


Fig. 4: Rewards for training policies with 1) full joint control, 2) PCA synergy space, and 3) VAE synergy space. The thick line is the average among the two seeds and the shaded part denotes the standard deviation.

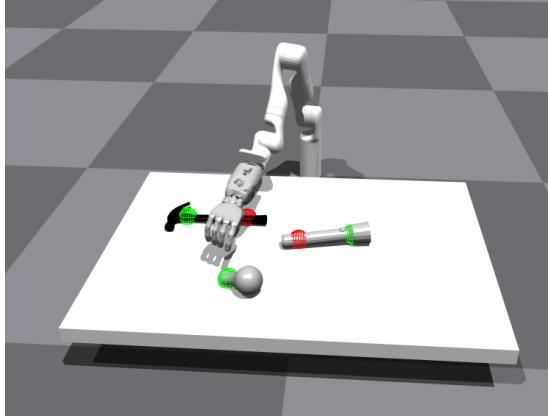


Fig. 5: Training environment.

intentions. This distance was computed at the end of each episode, so at the final position of the hand with respect to the object. We performed 1000 trials for each object and each post-grasp intention and kept the results of the trials where the grasp was successful. For example, the right column of figures, which correspond to trials with the handoff post-grasp intention, shows that in every successful trial the distance of the hand to the handoff target (green dots) defined on the object was lower than the distance of the hand to use grasp target. On the other hand, on the left figures, which correspond to the use post-grasp intention, the distances are the opposite. This demonstrates that the policy actually learns to associate each grasp position on the object to a different post-grasp intention.

Figure 6, shows the rewards of policy with synergy models with increasing number of latent dimensions from 1 to 5, while Table II shows the corresponding success rates. Using one latent dimension achieves a lower grasp success rate, probably

due to the reduced synergy space that is unable to represent successful grasps. Larger than two dimensions achieve similar grasp success rates, except the model with 3 latent dimensions which is probably an experimental artifact. Finally, in Table III, we see the success rate of the policy with and without the object category as an observation. While the removal object category does not affect the average grasp success rate, in Figure 9 we see that the agent does not learn to grasp the object from the correct location according to its post-grasp intention. This is evident by the fact that for both post-grasp intentions the robot grasps the object closer to the handoff grasp target instead of grasping it from the corresponding target according to the task, as shown in Figure 7.

TABLE I: Average success rate for each policy for 5000 trials.

Method	Success Rate
Joint action space	66%
PCA action space	71%
VAE action space (ours)	83%

TABLE II: Average success rate for policies with synergy models of different latent dimensions.

Number of latent dimensions	Success Rate
1	59%
2	83%
3	68%
4	84%
5	81%

Qualitative. A qualitative advantage of using the synergy space learned by the VAE model as action space for the policy, is that the resulting grasps, i.e. the final finger configurations of the hand, resemble the ones executed by the human subjects.

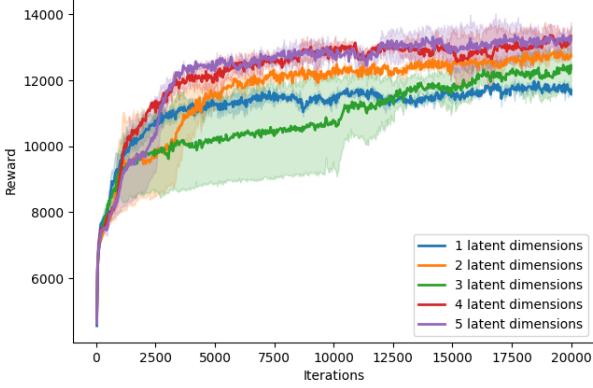


Fig. 6: Rewards for policies that use synergy models of different latent dimensions.

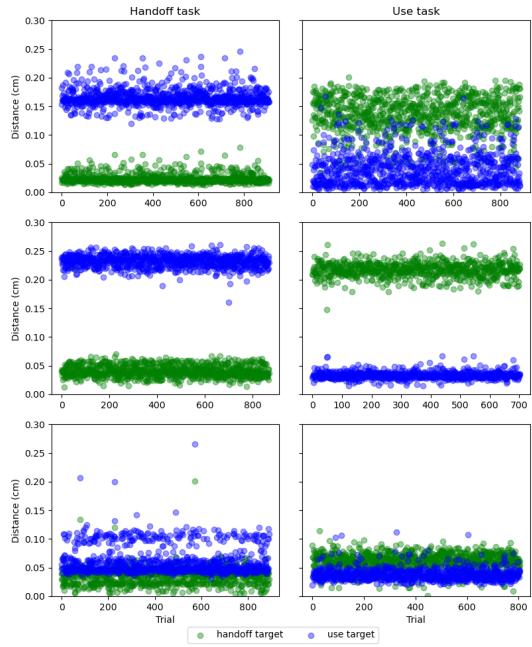


Fig. 7: Distances of the robot's hand to each grasp target for each task. The results are for a 1000 grasp trials performed for each object and each post-grasp intention performed using our proposed approach.

The first row of Figure 10 depicts grasps using the joint angles as action space, while the second row depicts grasps from the policy that uses the synergy space as action space. In the first case, the grasp postures are unnatural, not all fingers are used and might become unstable for subsequent tasks. On the other hand, the grasps from the synergy space are typical power grasps, similar to the ones the human subjects performed.

V. CONCLUSION

In summary, we have presented an agent that is able to grasp several objects while taking into account a post grasp intention. The agent is trained on data collected from humans

TABLE III: Average success rate for each policy for 5000 trials.

Method	Success Rate
Policy without object category observation	82%
Policy with object category observation	83%

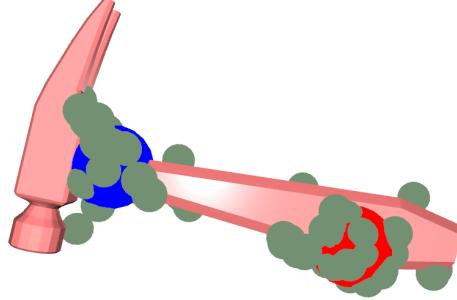


Fig. 8: Clustering results for grasp points on hammer object.

grasping objects in order to use them and hand them off. The agent is trained using online reinforcement learning in a simulated environment. We use the framework of postural synergies to reduce the action space in the reinforcement learning environment and generate human like grasps. Our results demonstrate that the agent learns to grasp objects in a similar way that humans prefer to grasp them according to the dataset. In addition, using a synergistic approach we are able to improve the grasping success rate of the agent compared to using directly the joint action space. Our work, though still presents some limitations, such as that the agent uses only the position of the grasping targets and not the orientation of the object so in future work it would be useful to try to use the functional characteristics of the object. Finally, we assume that the objects of a class, i.e. hammers, have similar sizes, and the policy might fail on objects with very different size. Relying on vision data for the observations, i.e. point clouds, might alleviate this limitation.

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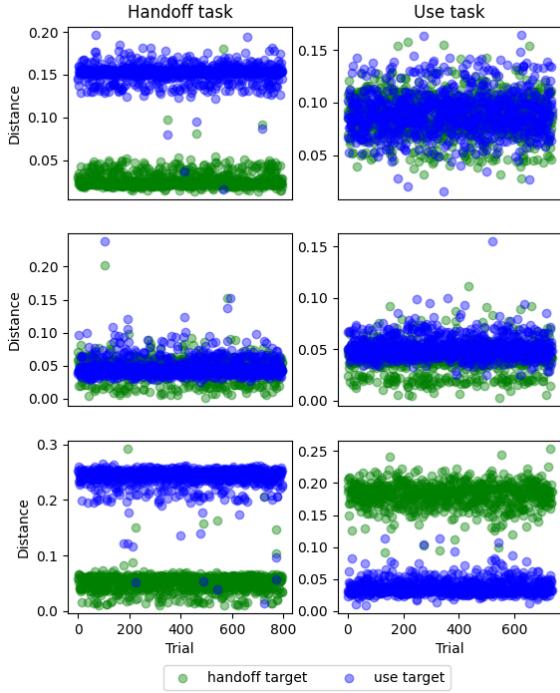


Fig. 9: Distances of the robot’s hand to each grasp target for each task. The results are for a 1000 grasp trials performed for each object and each post-grasp intention performed using a model that does not take as observation the object’s category.

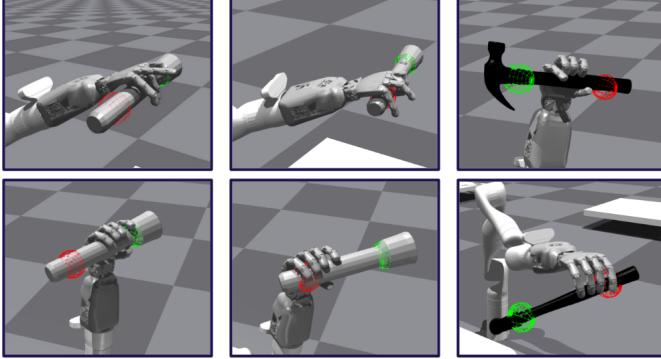


Fig. 10: The first row of depicts grasps using the joint angles as action space, while the second row depicts grasps from the policy that uses the synergy space as action space

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