Grasp Intention Interpretation in Object Handover for Human-Robot Teaming

Hui Li, Akhlak Uz Zaman, and Hongsheng He*

The University of Alabama, Tuscaloosa AL 35487, USA
{hli98, azaman2}@crimson.ua.edu, hongsheng.he@ua.edu

Abstract. Effective human-robot collaboration requires social robots to adapt to individual human grasping habits to ensure smooth and safe object handovers. However, many current robotic systems struggle to interpret diverse grasping behaviors, since individual habits can introduce variations even within the same grasp topology. This limitation affects their effectiveness in social contexts. This paper presents a grasp adaptation algorithm that enables robots to recognize and adjust to human grasping habits. The system recognizes human grasping poses from RGB images and maps them to abstract representations consisting of 21 3D points each. These representations are then classified into one of six standard grasp topologies. Based on the identified topology, key points are selected from the abstract grasp to estimate the object's pose. A reinforcement learning model is subsequently employed to optimize the object handover process. Experimental results demonstrate that this approach significantly enhances both the fluidity and safety of human-robot object handovers.

Keywords: grasping habits adaption · dexterous grasping · grasp topology · deep learning, reinforcement learning

1 Introduction

Human-robot collaboration, particularly in the context of object handovers, is essential for ensuring smooth and effective interactions in both structured and unstructured environments like healthcare and industrial settings [1, 2, 18]. For example, a robot handing tools to a nurse or parts to a factory worker must adapt to the human's grasping habits and workspace, improving safety and efficiency. Extensive research has been conducted to address the handover task in human-robot collaboration. Studies have analyzed the trajectory and velocity of approach movements to ensure smooth transitions [9, 13]. Additionally, object orientation and affordances have been optimized to make it easier for the receiver to grasp the object [4, 15]. Some approaches also involve learning from human behavior to improve the naturalness and effectiveness of handovers [4]. However, less work has been done to adapt to the habits of the receiver,

* Correspondence should be addressed to Hongsheng He. This research was funded by NSF grant #2420355 and #2402466.

particularly the variability in human grasping behaviors, which are influenced by individual preferences and situational factors. Developing systems that can accurately recognize and adapt to these diverse human behaviors is crucial for making robots more intuitive and practical in real-world applications.

Grasp topology and taxonomy are key to understanding human grasping behaviors and robotic adaptation. Grasp topology describes the geometric configuration of the fingers or contact points with an object, such as pinching or cupping. Grasp taxonomy categorizes these topologies into structured classes based on factors like contact points and object shape. This classification aids in designing robots that can effectively recognize and adapt to human grasping behaviors in various tasks and environments. Previous research has shown that human grasp choices tend to cluster over a large set of objects, leading to the development of grasp taxonomies to simplify grasping choices. For example, Cutkosky's taxonomy identified 16 grasp types used by machinists [6], and Feix's taxonomy expanded this to 33 different grasp types [3, 7].

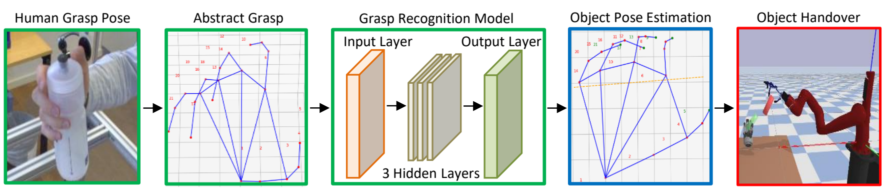

Fig. 1. Structure of the grasp adaptation system.

The FreiHAND dataset provides a large collection of annotated 3D hand poses, high-resolution RGB images, and key points annotations, making it highly valuable for hand tracking and grasp recognition research [20]. In this paper, we extend the FreiHAND dataset to map individual grasping habits to a standard set of grasp topologies.

Reinforcement learning (RL) is a powerful approach for robot control, where robots learn to perform tasks through trial and error [19, 16, 8]. By receiving feedback in the form of rewards or penalties based on their actions, robots improve their behavior over time [17]. This method enables robots to develop adaptive and optimized control strategies for complex and dynamic environments, enhancing their ability to perform a wide range of tasks autonomously. In this paper, a RL model is designed to conduct the object handover task in a simulation environment which is identical to the MagicHand system [11, 10].

We propose a grasp adaptation algorithm, as illustrated in Fig. 1, that processes an RGB image of a human grasping pose, converts it into an abstract grasp representation, and classifies it into one of six standard grasp topologies. Key points are then selected from the abstract grasp based in the identified grasp topology to estimate the appropriate object pose, and a reinforcement learning model is used to optimize the object handover task. The contributions of this research include:

- We designed and developed a deep learning network to classify grasp poses into six standard topologies, enabling the robot to determine the appropriate object pose.
- We created a reinforcement learning model to optimize the object-handover task.

2 Human Grasping Habit Adaption

The proposed system comprises three models: grasp recognition, object pose estimation, and a reinforcement learning model for object handover tasks. This section provides detailed descriptions of each model.

2.1 Recognition of Human Grasp Pose

Standard Grasp Topology In this paper, we classify grasp poses into six distinct grasp topologies [14], as illustrated in Fig. 2. The figure categorizes grasps into two main types: power grasps and precision grasps, based on object shapes and the involvement of virtual fingers (VF). Power grasps, such as those for circular and prismatic objects, prioritize security and stability, utilizing more virtual fingers and 3D wrapping. In contrast, precision grasps focus on dexterity and sensitivity, typically involving fewer virtual fingers and 2D wrapping.

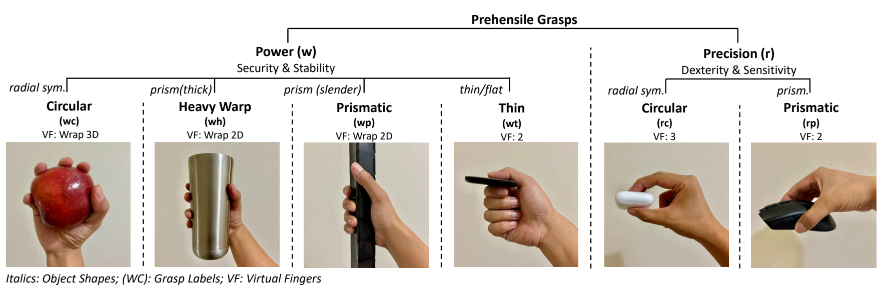

Fig. 2. The predefined grasp topology.

After establishing the grasp taxonomy, a standard grasp pose was selected for each topology by evaluating grasp poses from the FreiHAND dataset. The evaluation was based on how well each pose matched the defined topologies, and the pose that best fit each topology was chosen as the standard grasp pose. The final results are shown in Fig. 3, which displays both the RGB image of the standard grasp pose and the corresponding grasping information. The grasping information includes the abstract grasp and the key points (highlighted in green) of that specific grasp topology. These key points are used to estimate the object pose. The orange dotted axis in the figure represents the estimated object pose, derived from the selected key points.

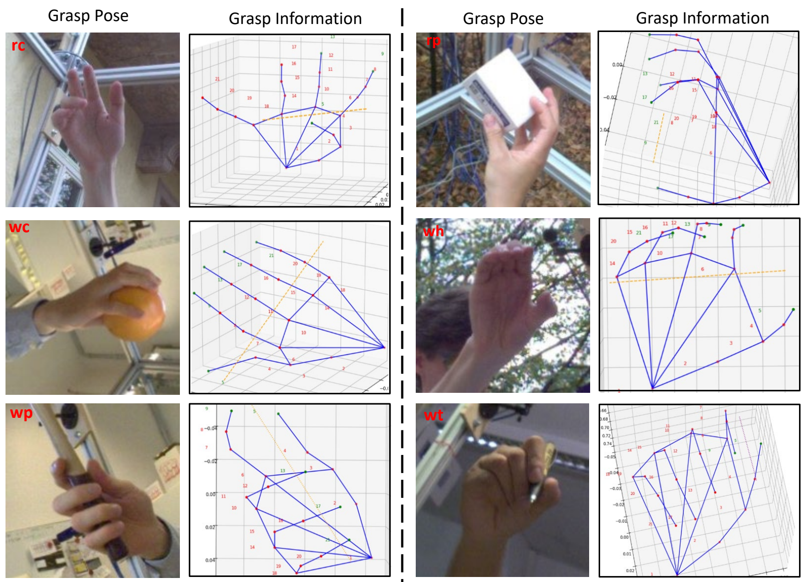

Fig. 3. Standard grasp topology: This figure displays images of the grasp topology, including the skeletons of each standard grasp topology and their corresponding key points, highlighted in green.

Grasp Topology Recognition A multi-layer perceptron (MLP) deep neural network was developed to map abstract grasps to standard grasp topologies. Rectified Linear Units (ReLU) were used as activation functions in the input and hidden layers. The input layer has 63 neurons, corresponding to the 21 3D points in each abstract grasp. The network features three hidden layers with 1,024, 256, and 32 nodes, respectively, to refine the model. The output layer consists of six neurons with Softmax activation functions to classify the grasps. The model was trained on a dataset refined from the FreiHAND dataset.

2.2 Object Pose Estimation

The pose of the object, including both position and orientation, is determined based on the key points associated with the standard grasp topology. For grasp topologies such as "wc", "wh", "wp", "rc", and "rp", the object should be positioned within the grasp's aperture, which is the space between the fingertips of the thumb and the fingers. The object position is defined as the midpoint between p_t, the point representing the tip of the thumb, and p_c, the closest fingertip to p_t. The object position is expressed as $p_m = 0.5\,(x_t + x_c, y_t + y_c, z_t + z_c)$. Since the orientation is typically aligned with the palm or fingers, two key points, p_s and p_e, are pre-selected from the abstract grasp to define the object's orientation. These points are usually located on the palm. The orientation of the object is expressed as

$$\mathbf{L}(t) = (x_m, y_m, z_m) + t \cdot (x_e - x_s, y_e - y_s, z_e - z_s) \tag{1}$$

where x, y, and z are coordinates of the point and t is a scalar parameter. The points p_s, p_e, p_c, and p_t, are specific to each grasp topology and serve as key points provided for analysis.

For the grasp topology "wt" the object should be positioned between the fingertip of the thumb and the side of the index finger, specifically at the key point p_{pip}, which corresponds to the PIP joint (Proximal Interphalangeal Joint) of the index finger. The object's position for this grasp topology is expressed as $p_m = 0.5\,(x_t + x_{pip}, y_t + y_{pip}, z_t + z_{pip})$. The orientation of the object should be roughly parallel to the index finger. In this case, the key points p_s and p_e in (1) represent the PIP and MCP (Metacarpophalangeal) joints of the index finger, respectively.

2.3 Object Handover Using Reinforcement Learning

Once the object's pose is determined, the robot must adjust the object to the specified position and orientation. We designed and developed an reinforcement learning model to achieve this goal. A simulation environment mirroring the MagicHand platform, which supports a variety of manipulation tasks, has been established [10, 12].

The task is to handover the object to a human hand, simulated by a Schunk anthropomorphic robotic hand in a simulation environment, and positioning it at the target pose, represented by a green area. The action space of the proposed model is a six-dimensional vector, including movements and rotations of the robotic hand along the x, y, and z axes. The observation space consists of seven dimensions: the relative position and orientation between the object and the target, as well as the distance between them.

In the task, our goal is to position the object as close to the target as possible, rewarding smaller distances between the object and the target. Additionally, we aim to align the object's orientation with the target's orientation, rewarding smaller differences in orientation along the x, y, and z axes. To ensure safe interaction, we impose penalties for collisions with the human hand. The reward function is expressed as

$$r = e^{-|d|} + e^{-|h|} + e^{-|l|} + e^{-|k|} - \alpha n_{\mathrm{c}} \tag{2}$$

where d is the distance between the object and the target location, and h, l, and k represent the differences in orientation between the object and the target along the x, y, and z axes, respectively. The coefficient α is a constant, and n_c represents the number of contact points with the human hand. We chose an exponential function because its value changes more rapidly when the exponent is large and more slowly when the exponent is small. This approach encourages the robot to make larger adjustments when the current pose is far from the target, while allowing for more precise, gradual adjustments as the pose approaches the target.

The proximal policy optimization (PPO) algorithm is employed to train the model. PPO is a reinforcement learning algorithm designed to improve policy stability by limiting the size of policy updates. It uses a clipped objective function to ensure that the new policy does not deviate excessively from the old policy. The objective function is given by

$$J(\theta) = \mathbb{E}\left[\min\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}\hat{A}(s,a), \text{clip}\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}, 1-\epsilon, 1+\epsilon\right)\hat{A}(s,a)\right)\right]$$

where $\pi_\theta(a|s)$ and $\pi_{\theta_{\text{old}}}(a|s)$ are the probabilities of taking action a in state s under the new and old policies, respectively, and $\hat{A}(s,a)$ is the advantage function. The clipping function clip restricts the ratio of the new to old policy probabilities, with ϵ controlling the extent of the allowed change, thereby balancing exploration with stability.

3 Experiments

The proposed system was evaluated under different thresholds. The simulation environment was set up using PyBullet and Gym, and task simulations were conducted to test the final performance of the system.

3.1 Data Preparation

The FreiHAND dataset provides high-resolution RGB images with detailed 3D hand poses and key points, supporting research in hand tracking and grasp recognition. Its comprehensive annotations are valuable for developing and evaluating hand tracking algorithms and applications in robotics and augmented reality. We revised the dataset by labeling each grasp with a specific topology. A sample of the revised dataset is shown in Fig. 4. Each grasp pose has been meticulously reviewed and classified into one of six predefined topologies or marked as "other." The updated dataset now includes 100 grasp poses for each of the six topologies, totaling 600 annotated grasp poses.

3.2 Grasp Recognition

The revised dataset is divided into two parts: 540 grasp poses for training and validation, and 60 new grasp poses for testing. The proposed algorithm was evaluated using 4-fold cross-validation with hyperparameters of a batch size of

Fig. 4. The revised dataset consists of 600 grasp poses, each paired with a corresponding abstract grasp representation for each grasp topology.

64, 500 epochs, and the Adam optimizer with a learning rate of 0.001. The training accuracy achieved 93.3% while the accuracy on testing set achieved 87.2%. The testing accuracy is relatively low because some of the grasp topologies are difficult to distinguish. For example, the "wh" and "rc" grasps have similar configurations, making them harder to recognize accurately.

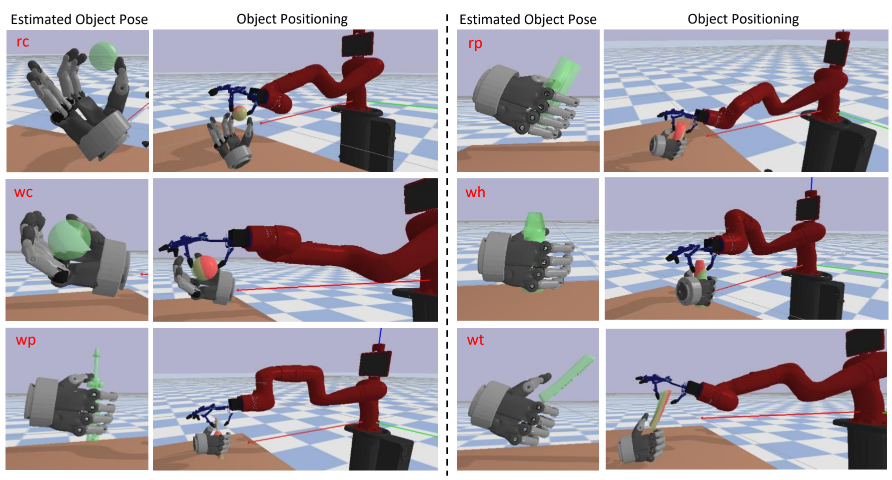

Fig. 5. Handover task for each grasp topology: In each task, the system first estimates the object pose based on the grasp pose of the simulated human hand. The model then attempts to place the object at the target pose.

3.3 Object Pose Estimation and Handover

Determining the effectiveness and accuracy of an object pose can be challenging, so we evaluate it through an object-handover task in a simulation environment. An object pose is considered effective if the robot can successfully pass the object to the human hand, which should then be able to securely grasp it. For this evaluation, we used PyBullet [5] to simulate an AR10 robotic hand mounted on a Sawyer robot holding the object. The human hand, simulated by a Schunk robotic hand, positioned in front of the robot, performs a variant of one of the six grasp topologies. The system estimates the object pose based on the grasp pose of the simulated human hand and highlights the estimated pose as a green area. The handover task for each grasp topology is illustrated in Fig. 5, where the robot's goal is to position the object to align with the green area while avoiding collisions with the human hand.

The model was trained for 20,000 episodes with a learning rate of 1.6×10^{-6} and a batch size of 32, with varying target positions and orientations in each episode. Each grasp topology was tested 100 times achieving an overall success rate of 83%.

4 Conclusions

In conclusion, this paper presents a robust approach to enhancing human-robot cooperation through the development of a grasp adaptation system. By accurately recognizing diverse human grasping habits and classifying them into standard grasp topologies, the system determines optimal object handover strategies for smooth handovers. The use of deep learning for grasp pose recognition and reinforcement learning for strategy optimization demonstrated strong performance in experimental settings. Although challenges remain in distinguishing similar grasp configurations, the results underscore the potential of the proposed system to improve human-robot interaction by making robots more adaptable to varied human behaviors.

References

1. Ajoudani, A., Zanchettin, A.M., Ivaldi, S., Albu-Schäffer, A., Kosuge, K., Khatib, O.: Progress and prospects of the human–robot collaboration. Autonomous robots **42**, 957–975 (2018)
2. Billard, A., Kragic, D.: Trends and challenges in robot manipulation. Science **364**(6446), eaat8414 (2019)
3. Bullock, I.M., Feix, T., Dollar, A.M.: The yale human grasping dataset: Grasp, object, and task data in household and machine shop environments. The International Journal of Robotics Research **34**(3), 251–255 (2015)
4. Cakmak, M., Srinivasa, S.S., Lee, M.K., Forlizzi, J., Kiesler, S.: Human preferences for robot-human hand-over configurations. In: 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 1986–1993. IEEE (2011)

5. Coumans, E., Bai, Y.: Pybullet, a python module for physics simulation for games, robotics and machine learning. http://pybullet.org (2016–2019)
6. Cutkosky, M.R., et al.: On grasp choice, grasp models, and the design of hands for manufacturing tasks. IEEE Transactions on robotics and automation **5**(3), 269–279 (1989)
7. Feix, T., Romero, J., Schmiedmayer, H.B., Dollar, A.M., Kragic, D.: The grasp taxonomy of human grasp types. IEEE Transactions on Human-Machine Systems **46**(1), 66–77 (2015)
8. He, W., Gao, H., Zhou, C., Yang, C., Li, Z.: Reinforcement learning control of a flexible two-link manipulator: An experimental investigation. IEEE Transactions on Systems, Man, and Cybernetics: Systems **51**(12), 7326–7336 (2020)
9. Huber, M., Rickert, M., Knoll, A., Brandt, T., Glasauer, S.: Human-robot interaction in handing-over tasks. In: RO-MAN 2008-the 17th IEEE international symposium on robot and human interactive communication. pp. 107–112. IEEE (2008)
10. Li, H., Tan, J., He, H.: Magichand: Context-aware dexterous grasping using an anthropomorphic robotic hand. In: 2020 IEEE International Conference on Robotics and Automation (ICRA). pp. 9895–9901. IEEE (2020)
11. Li, H., Yihun, Y., He, H.: Magichand: In-hand perception of object characteristics for dexterous manipulation. In: International Conference on Social Robotics. pp. 523–532. Springer (2018)
12. Li, H., Zhang, Y., Li, Y., He, H.: Learning task-oriented dexterous grasping from human knowledge. In: 2021 IEEE International Conference on Robotics and Automation (ICRA). pp. 6192–6198. IEEE (2021)
13. Mason, A.H., MacKenzie, C.L.: Grip forces when passing an object to a partner. Experimental brain research **163**, 173–187 (2005)
14. Rao, B.: Learning robotic grasping strategy based on natural-language object descriptions (2018)
15. Strabala, K., Lee, M.K., Dragan, A., Forlizzi, J., Srinivasa, S.S., Cakmak, M., Micelli, V.: Toward seamless human-robot handovers. Journal of Human-Robot Interaction **2**(1), 112–132 (2013)
16. Stulp, F., Theodorou, E.A., Schaal, S.: Reinforcement learning with sequences of motion primitives for robust manipulation. IEEE Transactions on robotics **28**(6), 1360–1370 (2012)
17. Sutton, R.S.: Reinforcement learning: An introduction (2018)
18. Tavakoli, M., Carriere, J., Torabi, A.: Robotics, smart wearable technologies, and autonomous intelligent systems for healthcare during the covid-19 pandemic: An analysis of the state of the art and future vision. Advanced intelligent systems **2**(7), 2000071 (2020)
19. Thuruthel, T.G., Falotico, E., Renda, F., Laschi, C.: Model-based reinforcement learning for closed-loop dynamic control of soft robotic manipulators. IEEE Transactions on Robotics **35**(1), 124–134 (2018)
20. Zimmermann, C., Ceylan, D., Yang, J., Russell, B., Argus, M., Brox, T.: Freihand: A dataset for markerless capture of hand pose and shape from single rgb images. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 813–822 (2019)