

An Intelligent Grasping Platform Based on Point Clouds

Zijie Zhang^{1,2}, Jing Zeng^{1,2}

¹School of Automation and Information Engineering, Sichuan University of Science & Engineering, Yibin, China

²Artificial Intelligence Key Laboratory of Sichuan Province, Yibin, China

Abstract

An intelligent grasping platform based on point clouds is designed to execute effective manipulator grasping for clustered objects. For the software, ROS(Robot Operating System) is used as the programming framework to achieve the trajectory planning and control, and PCL(Point Cloud Library) is used to process point cloud data. For the hardware, X-Arm6 6-DOF manipulator and DAHUAN AG-95 gripper are combined to construct a robot arm, and Intel RealSense D435i is fixed at the end of the arm to collect point cloud data in real time. Several algorithms are verified on the proposed platform. Experiment results show that all the selected methods can be well applied to the designed platform, and the algorithm combining improved GPD and point cloud registration trick performs best.

Keywords

Grasping; Point clouds; ROS; Clustered objects.

1. INTRODUCTION

Autonomous grasping, as an important means for various robots to interact with the outside world, has always been a research hotspot in the field of robotics[1]. Early grasping systems generally completed the grasping task by robot teaching[2]. During the teaching process, engineers will record several working poses of the manipulator and write them into the control program. Then, the arm and end effector can complete the grasping task mechanically according to the predetermined trajectory and grasping poses. The intelligent level of the this grasping system is low, and a slight change in the class or position of the target object will lead to grasping failure.

With the improvement of sensor technology, a large number of high-quality and cheap visual sensors have been popularized, and the introduction of visual information has made robots have the potential to work in unstructured environments[3]. Among the numerous visual data, point cloud can better describe the three-dimensional structure features of the target object, which is very beneficial to grasp pose detection. On the one hand, directly searching grasp poses from the point cloud can take the three-dimensional structure of the target object and the end effector into consideration at the same time, and obtain a more reliable grasp pose through geometric analysis[4]; On the other hand, the grasp poses detected in the 2D image can only guide the manipulator to grasp the object from the direction perpendicular to the camera plane[5], which greatly limits the flexibility of grasping, while the grasp poses detected in the point cloud can be dispersed in various positions on the object surface[6].For the latter, manipulator can complete the grasping task from multiple directions, while improving the success rate of inverse kinematics solution, it provides preconditions for grasping planning under constraint conditions (such as obstacle-avoidance grasping).

To sum up, taking point cloud as input to intelligent grasping algorithm has high research value. This paper builds a reliable grasping platform according to this strategy. First, X-Arm6, a 6-degree-freedom manipulator, is combined with DAHUAN AG-95 gripper to constitute integrate arm. Then, depth sensor, Intel RealSense D435i, is attached on the end link to get point clouds of target objects. Finally, above hardware and necessary software are combined using ROS which can easily plan manipulator moving trajectory and generate control command for grasping. Several grasp pose detection algorithms are verified on the designed platform. The experiment results show that the proposed platform has good engineering effect, and the grasp pose detection algorithm using the improved ICP(Iterative Closest Point) method[7] and the improved GPD[8] performs best.

2. INTELLIGENT GRASPING PLATFORM BASED ON POINT CLOUDS

2.1. Software module

In this experiment, the operating system of the host computer of the grasping system is Ubuntu 18.04, and the ROS(Melodic version) and the PCL(V1.9.0) are used for complement development. ROS is an open source meta-operating system that relies on the Ubuntu operating system. Its essence is a series of software libraries and toolkits, which can provide simple and efficient programming interfaces. The host control module can directly control the hardware through the programming interfaces provided by ROS, so users can quickly start the robot development project without understanding the complicated internal structure of the robot. Benefiting from the above advantages, ROS has been widely used in scientific research and practical production.

In ROS, multiple nodes often cooperate to deal with one task. The set of these nodes is called function package. ROS comes with a large number of function packages about the development of manipulator, which are all part of MoveIt! function package group. MoveIt! It can solve three core problems in the development of manipulator, including kinematics solution, arm trajectory planning and collision detection. Move_group, the core node of MoveIt!, is the bridge connecting the host computer and the robot hardware system. Users can send control commands to Move_group through programming interface, graphical interactive interface or other interfaces. Move_group will execute a series of actions to guide manipulator to work position, including reading the robot's URDF model file, call the appropriate planning algorithm to generate the trajectory of manipulator, sending the trajectory information to the robot's controller, and process the received feedback real-time information of the robot collected from the sensor.

PCL is a completely open source point cloud processing algorithm library, which is jointly developed and maintained by researchers from Stanford University and Munich University of Technology. PCL supports Linux, Windows, MAC OS and other mainstream operating systems. The library provides a large number of modern C++ templates, which can fulfill lots of point cloud processing tasks such as feature extraction, filtering, tree indexing, classification, segmentation and visualization.

2.2. Hardware module

The hardware of the designed platform, as shown in Figure 1, is mainly composed of three parts, including depth sensor Intel RealSense D435i, 6-DOF manipulator X-Arm6 and end effector AG-95.

The combination of lens of D435i is shown in Figure 2. D435i can not only collect the RGB and depth information of the target object at the same time, but also align them to render the colorful point cloud, which is widely used in grasp pose detection, SLAM(Simultaneous Localization and Mapping)[9] and 3D reconstruction[10]. D435i includes three cameras and one auxiliary light source. In Figure 2, from left to right, it is left infrared camera, infrared dot matrix

projector, right infrared camera and RGB camera. The infrared dot matrix projector can emit infrared laser to the surrounding, and generate more feature points in the environment. These feature points will be captured by the infrared camera, which can improve the calculation accuracy of depth measurement. RGB cameras can acquire up to 30 frames of image data per second.

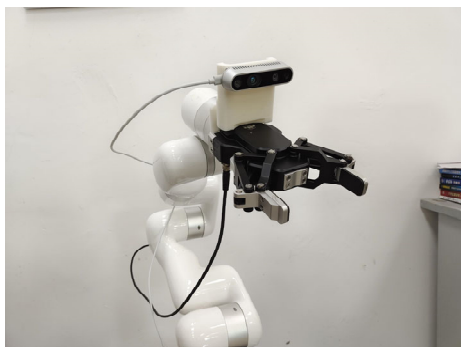


Figure 1. Hardware system

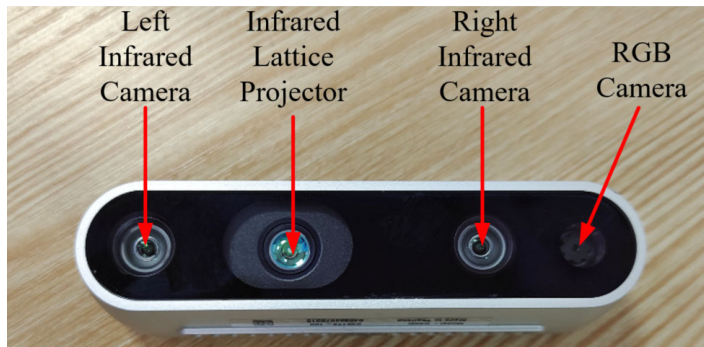


Figure 2. Structure of D435i

DAHUAN AG-95 gripper and X-Arm6 manipulator are combined to accomplish grasping task. DAHUAN AG-95 is a joint type adaptive parallel two-finger gripper. Its main geometric parameters are shown in Figure 3-a; X-Arm6 is a series manipulator with six degrees of freedom. Its main geometric parameters and the position of link frame are shown in Figure 3-b and Figure 3-c. Table 1 records the D-H parameters of X-Arm6.

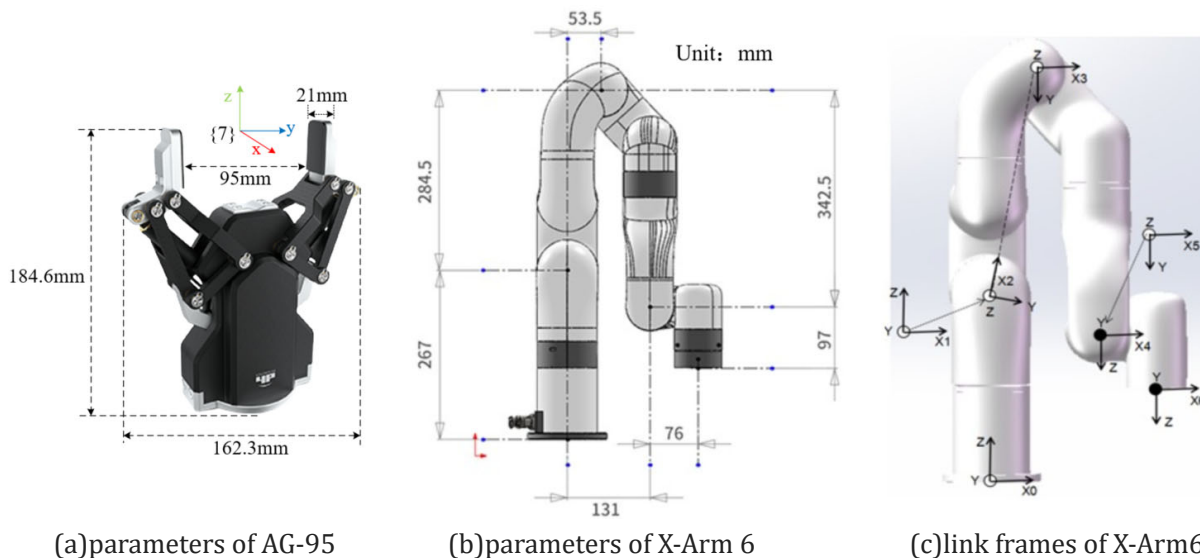


Figure 3. Parameters of robot arm

3. EXPERIMENT AND ANALYSIS

3.1. Experiment process and evaluation metrics

A total of 16 common objects O_1-O_{16} of different categories are selected in the grasping experiment. Among them, O_1-O_{10} is the objects that exist in the YCB grasping data set, and $O_{11}-O_{16}$ is the object that does not exist in the data set. We combine these objects into three groups, each group contains five known objects and three unknown objects. For each group of objects, the grasping experiment is carried out according to the steps given in Figure 4 (Figure 4 shows

the grasping algorithm using improved GPD and improved ICP. Detailed grasping process of other methods can be found in references).

First, all the objects are placed randomly in the workspace, control the manipulator to move to two preset observation points, and start the camera installed at the end of the link to collect two frames of point cloud from right and left perspectives; Then, two point clouds are fine registered to reconstruct the 3D shape of objects using improved ICP, and reliable grasp poses are detected from the processed point cloud by improved GPD. Then, with the help of MoveIt!, moving trajectory manipulator is planned and inverse solution to detected grasp poses are solved. Finally, above information is sent to the controller of robot to command it to grasp target object. It should be noted that, in this experiment, the robot needs to try to grasp all objects within a limited number of grasping times, and transfer them to the specified position to clear the work space. If the time of grasping reaches the limitation(in our experiment, the limitation of grasping time is 10), or all objects are successfully transferred, then this round of experiment is done, the experiment results will be recorded, and the next set of object need to be put into the work space.

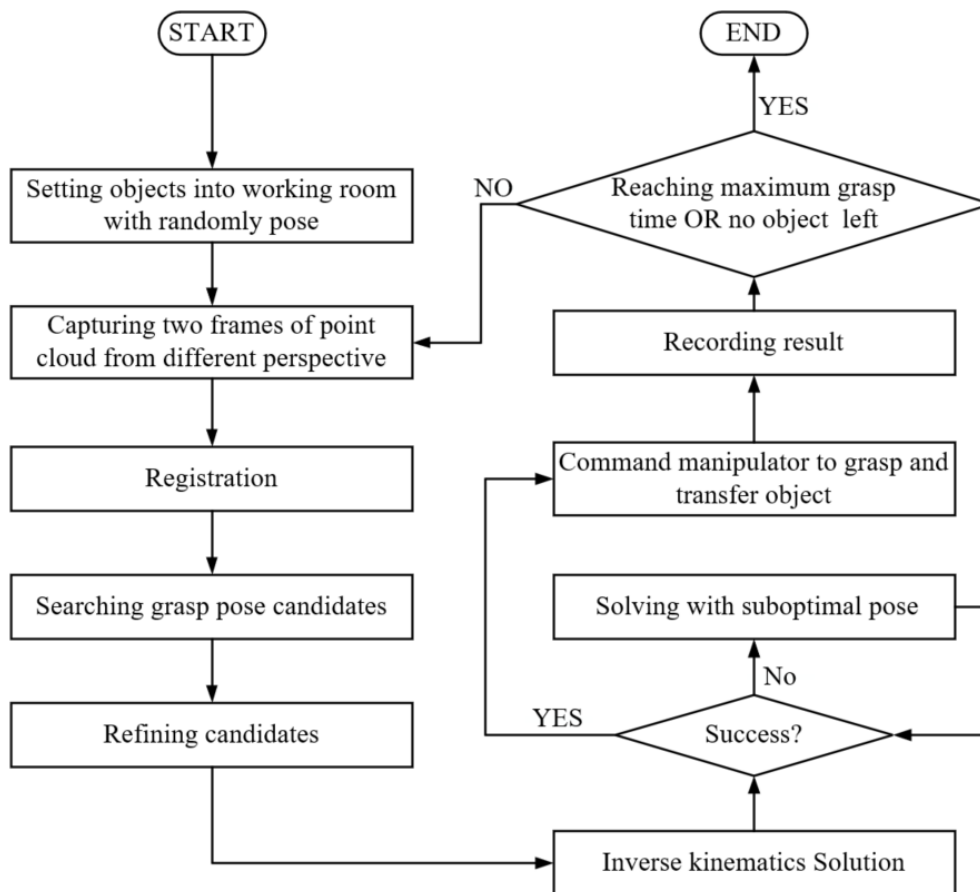


Figure 4. Experiment process

Grasping completion degree is used to evaluate the performance of the used grasp detection algorithm. The calculation formula of this index is as follows:

$$cr_i = \frac{N_i}{8} \times 100\% \tag{1}$$

In formula (1), cr_i is the grasp completion rate of the i -th group of objects, and N_i is the total number of objects successfully transferred in the i -th group of objects. Given cr_i , the average grasping completion rate can be further calculated:

$$cr = \frac{1}{3} \sum_{i=1}^3 cr_i \times 100\% \tag{2}$$

In formula (2), cr is the average grasping completion rate of the tested algorithm for three groups of object. cr_i and cr are used to evaluate the performance of different algorithms facing clustered scene.

3.2. Result analysis

Figure 5-a and Figure 5-b are the point clouds of the first group of object captured from different perspectives. It can be seen intuitively that when there is occlusion or overlap between objects, the object point cloud collected from one perspective is more incomplete than the single object scene. For example, the right point cloud shown in Figure 5-b can hardly describe the three-dimensional structure of the headset and the dome. At this time, point cloud registration is especially crucial for grasp pose detection.

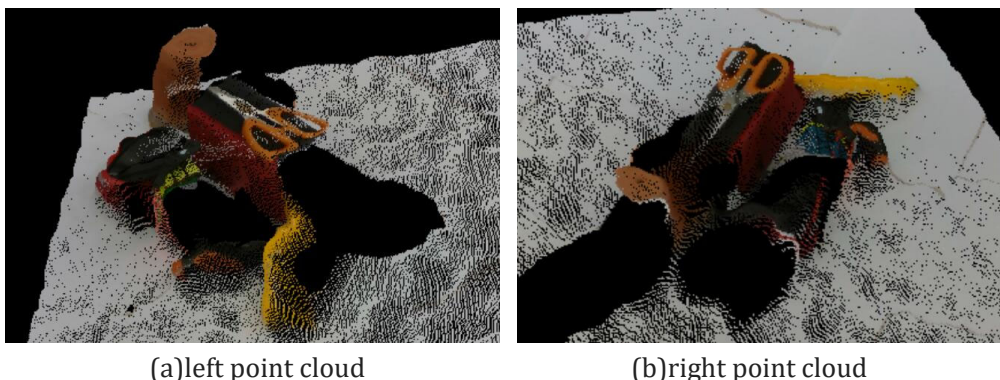


Figure 5. Cluttered object point clouds captured from different two perspectives

Figure 6 shows the grasp pose detection process of the improved GPD algorithm. As can be seen from Figure 6-a, compared with the single-view point cloud, the registered point cloud not only improves the contour of the object, but also fill up some ground structure that is not perceived due to occlusion, both of which are conducive to improving the reliability of grasp pose detection. Figures 6-b and 6-c respectively visualize the grasp candidates and the selected high-quality grasp pose.

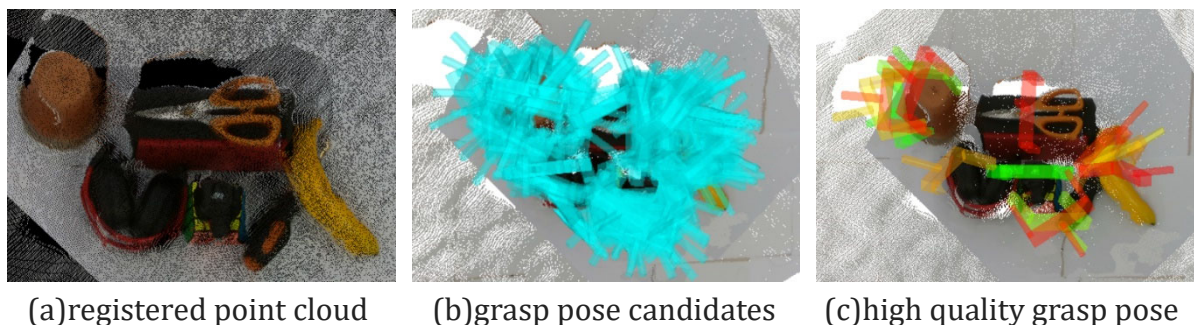


Figure 6 The process of grasp pose detection



(a) moving to the object (b) closing the gripper (c) picking the object

Figure 7. Grasping process

Figure 7 records the grasping process of real robot. First, as shown in Figure 7-a, the gripper will move to the detected grasp pose; Then, the gripper closes and the robot tries to pick up the target object, as shown in Figure 7-b and Figure 7-c. It should be pointed out that, in order to avoid collision, if the kinematics conditions allow, the manipulator will first move to a transitional pose, and then the gripper will move in a straight line along the approaching direction to reach the object.

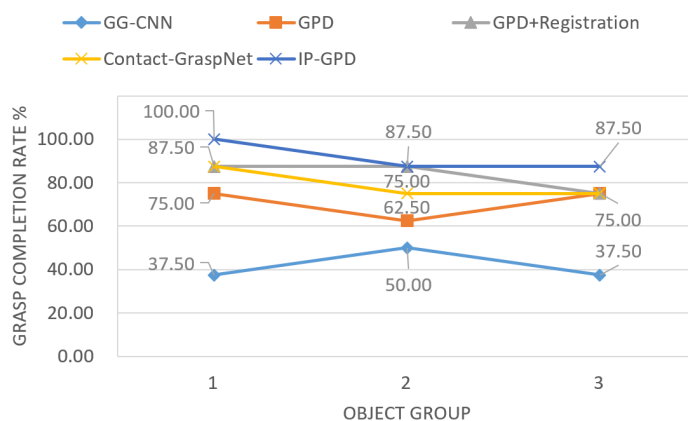


Figure 8. Completion rate of each object group

In addition to the grasp pose detection method combining improved GPD and improved ICP(hereinafter referred to as “IC-GPD”), we also test GG-CNN[11], original GPD[12], GPD with point cloud registration, and Contact-GraspNet[13] algorithms. Figure 8 detailed records the grasping completion rate using different algorithms for each group of object, and Figure 9 records the average grasping completion rate.

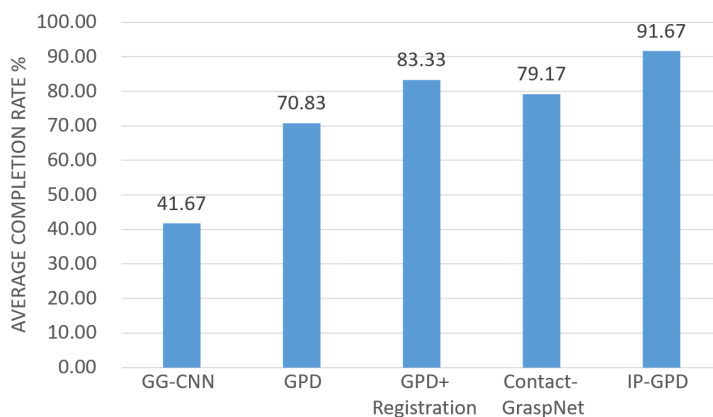


Figure 9. Average completion rate of each object group

It can be summarized from Figure 8 that, on the one hand, for the first group and the third group of object, IC-GPD has achieved completion rates of 100.00% and 87.50% respectively, which is superior to all the other methods, while for the second group of object, it is still not inferior to other methods. On the other hand, GG-CNN performs pretty bad in the experiment, and more than half of the objects could not be successfully grasped for each group. The essential reason for this phenomenon is that as a 2D planar grasp detection algorithm, the detected 2D grasping anchor box from GG-CNN does not fully consider the 3D geometry of the object. Under the guidance of this algorithm, the manipulator is very easy to collide with dense objects. On the contrary, 3D grasp pose detection algorithm based on point cloud can efficiently make collision detection and eliminate bad poses. So, richer geometric information of the input point cloud means lower probability of failure grasping, which also explains why the registration strategy brings better performance.

As can be seen from Figure 9, except for the GG-CNN algorithm, the average grasping completion rate of other methods is pretty high. There are two reasons for this phenomenon: one is that the permitted grasping time is greater than the total number of objects, and the other is that there are obstacle and overlap between objects in the work space, which may lead gripper to grasp two objects in one time. For example, in Figure 7-a, the robot simultaneously grasps the packing box and the scissors on the top of it. This phenomenon of trying to grasp two or more objects at one time can sometimes cause unexpected result. For example, in the third group of object, IC-GPD attempts to guide the robot to grasp the mouse and the nearby aluminum bottle simultaneously. When the gripper was closed, the two objects seemed to be stable, but when the manipulator was lifted, due to the small friction between them and the influence of gravity, relative movement occurred, causing inevitable sliding.

4. CONCLUSION

An intelligent grasping platform based on ROS is designed. X-Arm6 manipulator, DAHUAN AG-95 gripper, and Intel RealSense D435i are combined to construct a vision-guided robot arm. PCL and MoveIt! are used to process raw point clouds and generate control message respectively. Several grasp pose detection algorithms are verified on our platform. The results show that presented platform can adapt to all the tested methods, and the IC-GPD performs best in grasping experiment.

REFERENCES

- [1] Cai J, Cen J, Wang H, et al. Real-time collision-free grasp pose detection with geometry-aware refinement using high-resolution volume[J]. *IEEE Robotics and Automation Letters*, 2022, 7(2): 1888-1895.
- [2] Pan Y, Chen C, Zhao Z, et al. Robot teaching system based on hand-robot contact state detection and motion intention recognition[J]. *Robotics and Computer-Integrated Manufacturing*, 2023, 81(1): 102492-102500.
- [3] Liang H, Ma X, Li S, et al. Pointnetgpd: Detecting grasp configurations from point sets[C]//2019 International Conference on Robotics and Automation. IEEE, 2019: 3629-3635.
- [4] Nguyen V D. Constructing force-closure grasps[J]. *The International Journal of Robotics Research*, 1988, 7(3): 3-16.
- [5] Du G, Wang K, Lian S, et al. Vision-based robotic grasping from object localization, object pose estimation to grasp estimation for parallel grippers: a review[J]. *Artificial Intelligence Review*, 2021, 54(3): 1677-1734.

- [6] Fang H S, Wang C, Gou M, et al. Graspnet-1billion: A large-scale benchmark for general object grasping[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. IEEE, 2020: 11444-11453.
- [7] Zhang Z Z, Zhang G L, Zeng J. et al. Grasping method for manipulator based on two registered point clouds[J]. Foreign Electronic Measurement technology, 2022, 41(11): 102-108.
- [8] Information on <http://www.jcyyy.com.cn/tg/jcyyy/home>.
- [9] Yang Z, Li Y, Lin J, et al. Tightly-coupled fusion of iGPS measurements in optimization-based visual SLAM[J]. Optics Express, 2023, 31(4): 5910-5926.
- [10] Zhao L, Wang H, Zhu Y, et al. A review of 3D reconstruction from high-resolution urban satellite images[J]. International Journal of Remote Sensing, 2023, 44(2): 713-748.
- [11] Morrison D, Corke P, Leitner J. Learning robust, real-time, reactive robotic grasping[J]. The International journal of robotics research, 2020, 39(2-3): 183-201.
- [12] Ten Pas A, Gualtieri M, Saenko K, et al. Grasp pose detection in point clouds[J]. The International Journal of Robotics Research, 2017, 36(13-14): 1455-1473.
- [13] Sundermeyer M, Mousavian A, Triebel R, et al. Contact-graspnet: Efficient 6-dof grasp generation in cluttered scenes[C]//2021 IEEE International Conference on Robotics and Automation. IEEE, 2021: 13438-13444.