An Interactive Perception Method for Warehouse Automation in Smart Cities

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***Abstract*—The smart city is an integrated environment that heavily relies on intelligent robots, which provides the basis for the warehouse automation. However, a warehouse is a typical unstructured environment, and robotic grasp and manipulation are extremely important for the package, transfer, search, and so on. Currently, the most usual method is to detect the picking or grasping points for some specific end-effector including suction cup, gripper, or robotic hand. The manipulation performance is, therefore, strongly influenced by the visual detector. To tackle this problem, the affordance map has recently been developed. It characterizes the operation possibilities afforded by the operation scene and has been used for several grasp tasks. Nevertheless, the conventional affordance method often fails in complicated environments due to the mistake calculation results. In this article, we develop a novel framework to integrate the interactive exploration with a composite robotic hand for robotic grasping in a complicated environment. The exploration strategy is obtained by a deep reinforcement learning procedure. The developed new composite hand, which integrates the suction cup and grippers, is used to test the merits of the proposed interactive perception method. Experimental results show the proposed method significantly increases the manipulation efficiency and may bring great economic and social and benefits for smart cities.**

***Index Terms*—Affordance map, interactive perception, reinforcement learning, robotic grasp, smart city, warehouse automation.**

I. Introduction

THE SMART city is an integrated hyperconnected environment that strongly relies on intelligent robots, which can be used for fully automated trash removal, surveillance, logistics, and so on. They can also improve the city services by providing higher quality services at a lower cost [1]. Therefore, robots are now becoming critical enablers especially for countries facing labor shortages and aging populations [2], [3].

Among the various components of smart city, warehouse automation, which is widely recognized as one of the most effective ways to reduce labor demands and improve efficiency, is certainly an important feature of a smart city's network [4]–[6]. Warehouse automation will play a critical role in all sorts of delivery systems and is already being used for e-commerce, supermarket, etc. It forms the basic infrastructure for smart cities.

The autonomous guided vehicles have been extensively deployed for warehouse automation [7]. However, they can only be used for the delivery of storage racks, but not specified objects. The picking, grasping, and sorting of objects are still great challenging for warehouse automation [8], [9]. Those problems have attracted extensive attention of scholars from the communities of robotics, mechanics, and machine intelligence [10].

Even though robotic grasping and manipulation are vital in smart cities, most of the current industrial equipment work in the well-known structured scenes, where naive picking strategies are sufficient. Indeed, many industrial robots working in the manufactory can be classified into this case. For challenging unstructured environments, the visual detection of the grasp region recently attracts many efforts. The mainstreaming work usually uses an off-the-shelf visual detector and pose estimator to determine the graspable point for off-the-shelf end-effectors [11].

Very recently, the grasp affordance has become promising in clutter environments. It is used to characterize the action space afforded by true objects without needing to either create a detailed three-dimensional mental model of the world or perform logical reasoning about rule-based behavior [12]. The authors of [13] developed an object-agnostic grasping method to obtain the grasp operations and obtain pixel-level probability maps of the grasp affordance for four operation primitives from visual observations. This article achieves great success in Amazon Robotics Challenge. In spite of this point, the complex and unstructured environment prevents the single-shot affordance map from performing robust grasp or picking. In addition, in many cases, where the affordance map may be obtained easily, the practical action is not easy to be performed. Fig. 1 shows two typical cases for the failure cases. In such a scenario, the affordance always outputs misleading results.

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Fig. 1. Some failure affordance cases: The top panel shows the original images captured by the global camera and the bottom panel shows the affordance maps. In the case of clutter (left) or occlusion (right), using the conventional affordance calculation may result in mistake proposals.

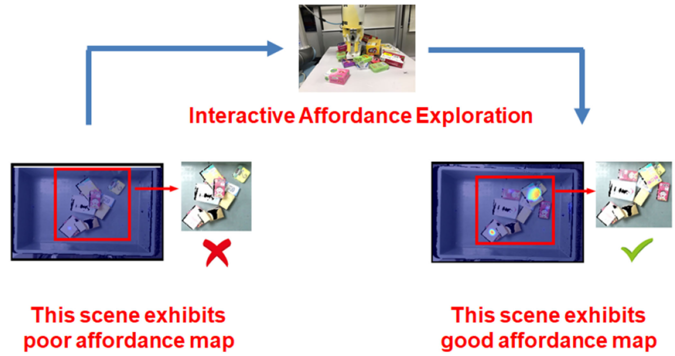

Fig. 2. Motivation of the proposed interactive affordance exploration strategy: When the obtained affordance map is not suitable for performing grasp, the manipulator is used to push some objects away and achieve a better affordance map, which indicates better grasp quality.

The above problem can be dealt with by the interactive perception method [14]–[18]. This method attempts to conduct physical interactions to produce new sensory information to change the environment and, therefore, simplifies the grasp tasks [19]. Thereby, it enables robust perceptually guided manipulation behaviors [20]. Such strategies have been used in [21], in which the manipulator smartly interacts with the environment and optimizes the layout of the objects for better grasp conditions. The pushing strategy can be further performed to rearrange the objects and improve the recognition performance. Nevertheless, it has not been found in applications of grasp tasks.

In this article, we introduce the grasp affordance map into the interactive exploration and establish a new interactive affordance exploration framework. This new strategy follows the natural behavior: When a subject hopes to pick some object, he usually pushes away the objects, which prevent the target from being grasped. Such an exploration strategy makes it possible to achieve better grasp quality. In Fig. 2 we show the main idea. To summary, we list the main contributions as follows.

1) We establish a new framework to integrate the interactive exploration with a composite hand for robust grasping in complicated scenes.
2) We design a novel composite hand, which consists of one suction cup and grippers. It is used to test the performance of the proposed interactive affordance exploration strategy.
3) We develop a deep reinforcement learning algorithm to perform the interactive affordance search in a practical environment.

The rest of this article is organized as follows. Section II is related to the proposed interactive affordance exploration framework. In Section III, we discuss the detailed reinforcement learning algorithm. The designed novel manipulation hand is presented in Section IV. The experimental setup and results are provided in Section V. Finally, Section VI concludes this article.

II. Framework

To improve the grasp quality, we resort to the affordance map, which is defined as an image indicating the confidence of each pixel for grasping [13], to provide pixel-level grasping points. This formulates the well-known *recognition before grasping* problem in classical manipulation scenarios. Nevertheless, in many practical complicated scenarios, it is very difficult to evaluate the quality of the grasping point just from the calculated affordance map. To this end, we develop the interactive exploration method, which encourages the robot to purposely push some objects to adjust the scene, until a suitable affordance map is achieved.

In Fig. 3, we show the whole pipeline of the developed robotic manipulation platform, in which the RGB-D images of the manipulation scenario are captured, and then, the convolutionary neural network [13] is utilized to obtain the affordance map. If the obtained affordance map is judged to be inappropriate for manipulation, the obtained RGB-D images are sent into a deep Q network (DQN) to encourage the robot to interact with the scene by pushing other objects away. Such a procedure is repeated till some suitable object in the environment can be successfully grasped. Furthermore, we develop a reinforcement learning algorithm to design the DQN, which produces smart actions given the affordance map for the current images. Compared with the architecture of [22] and [23], tactile sensing is introduced to increase the grasp performance, and more experimental results are presented in this article.

Note that in [21], the authors proposed an active perception method for grasp. In their notation, the term active perception means using a grasp-first-then-recognize paradigm, where they leveraged object-agnostic grasping to isolate each object from the clutter in order to significantly improve recognition accuracy for novel objects, while in our article, the interactive perception exhibits a significant difference because the manipulator always changes the scene to achieve a better affordance map.

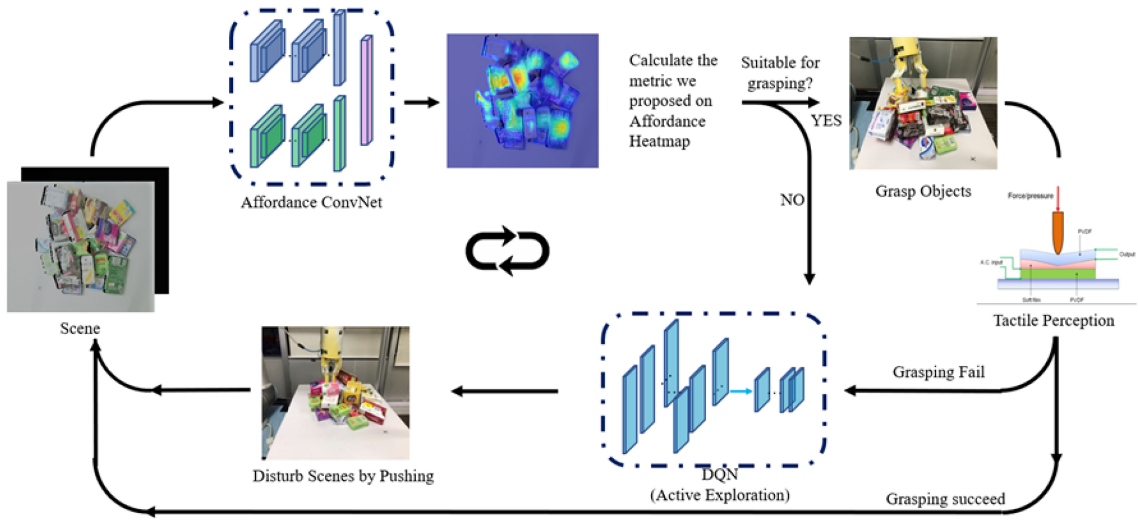

Fig. 3. Whole working pipeline: The robot uses a global camera to capture the RGB and depth images of the operation environment and feed those images to the ConvNet, which provides the grasp affordance image. Based on the obtained affordance map, the robot evaluates the reliability of the suction position extracted from the affordance image. If it is not satisfactory, the robot feeds the RGB and depth images to a DQN network, which provide an appropriate action for the robot to change the environment, such a procedure is repeated until the object can be grasped successfully.

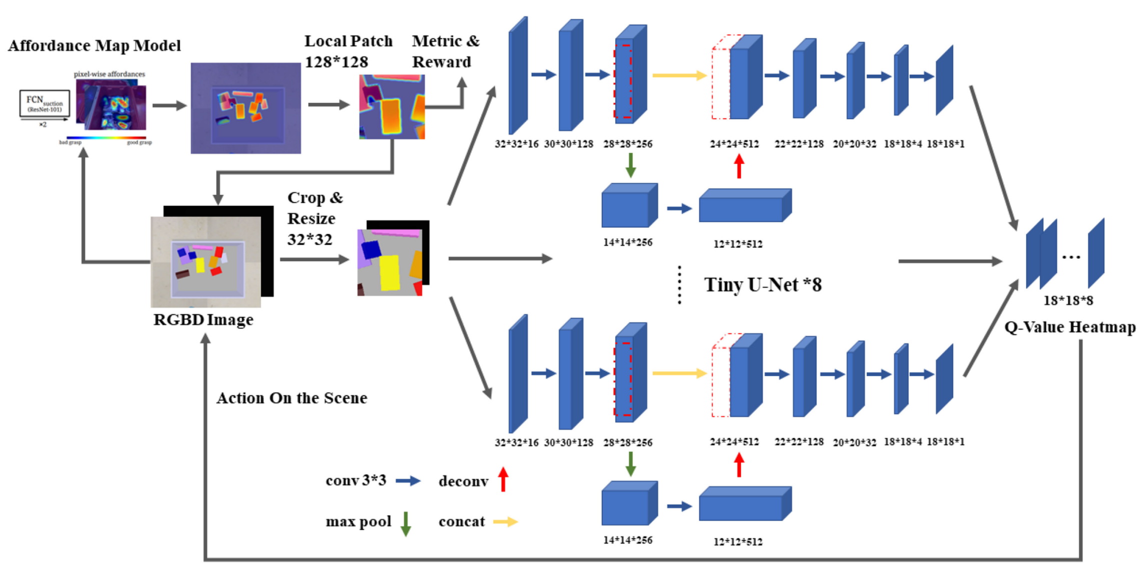

Fig. 4. Deep reinforcement learning architecture. The red-dashed box represents the part, which is extracted to be concatenated to the next layer. For the obtained RGB and depth images, we calculate the corresponding affordance image and crop the center patch around the point with the largest confidence. Furthermore, we feed this local patch into eight paralleled small U-Net and obtain eight different operation directions on subpixel-level locations.

III. Learning for Interactive Exploration

To develop an optimal action policy for the interactive affordance exploration, we design a DQN, which encourages the robot to search a better affordance map for reliable picking or grasping. The network architecture is shown in Fig. 4.

For notational simplicity, the concerned state and action at time instant t are denoted as s_t and a_t, respectively. During the exploration period, the robot could obtain the reward $r_t = r(s_{t-1}, a_t)$, and the accumulated reward is denoted as $R_t = \sum_{i=t}^{\infty} \gamma^{i-t} r_i$, where γ is the forgetting factor. For grasp policy π, we use $Q^\pi(s_{t-1}) = \mathbb{E}[R_t | s_{t-1}, \pi]$ to denote the action-value mapping and Q^π as the estimated one. We resort to the Bellman equation to calculate the optimal action policy.

The DQN utilizes multilayer neural network as the function approximator to estimate the action-value mapping $Q(w) \to Q^*$. We use w to denote all of the parameters of the network. They can be iteratively estimated by minimizing the following temporal difference objective:

$$\hat{w} = \arg\min_{w} \mathbb{E}\Bigg[\Big(r_t + \gamma \max_{a_{t+1}} Q(s_t, a_{t+1}; w) - Q(s_{t-1}, a_t; w)\Big)^2\Bigg]. \tag{1}$$

By formulating the temporal difference error as the following objective:

$$\mathcal{L}(w) = [r_t + \gamma \max_{a_{t+1}} Q(s_t, a_{t+1}; w) - Q(s_{t-1}, a_t; w)]^2 \quad (2)$$

we transform the optimization problem as standard regression estimation problem.

A. State Representation

The state vector s_t is obtained using the Affordance ConvNet developed in [13], which is trained using manually annotated images. It utilizes the RGB-D images as the input and produces the grasp affordance image, in which the higher values exhibit more preferable picking locations.

Since the goal is just to interact with the environment to achieve a better affordance map, it is not necessary to investigate the whole scene. To this end, we design a local-patch-based U-Net architecture, which can get a better affordance map with smaller numbers of action steps and significantly reduce the network size for efficient inference. That is to say, the most promising grasping point should be the one with the largest value in the affordance image, and therefore, we crop the 128×128 patch near this pixel. Furthermore, we downsample it into 32×32 patch before feeding to the U-Net-based network. After that, we obtain the 1024-dimensional state vector s_t.

B. Action Representation

To reduce the reaction space, we determine eight robotic operations to help the robot to push the objects from eight different directions, with prescribed distance. We still utilize the U-Net [24] to produce the pixelwise action (see Fig. 4). To reduce the network size, we perform downsampling and upsampling for only once and resize RGB-D input to quarter resolution. For each one operation, the network produces an action possibility for each location. The movement distance is defined as one half of the size of the local patch, and the direction is defined as $O_i = i * \pi/4$ for $i = 0, \ldots, 7$, respectively. Therefore, the whole architecture contains eight U-Net networks, and the action a_t can be selected from this set. So, we have

$$a_t \in \{O_i | i = 0, 1, \ldots, 7\}. \quad (3)$$

C. Reward Function

We design the reward function $r(s_{t-1}, a_t)$ to encourage effective actions according to

$$r(s_{t-1}, a_t) = \begin{cases} 1, & \text{success} \\ -1, & \text{failure} \end{cases} \quad (4)$$

where the status *success* is claimed when the robot picks the object successfully. Otherwise, the status *failure* is claimed.

IV. Development of the Composite Hand

To realize the developed interactive perception strategy, we invent a novel composite hand, which contains a pair of parallel pinching fingers with one suction cup. The main details can be found in Fig. 5. The parallelogram mechanism driven by the motor is used for each finger. This mechanism ensures both fingers are parallel during the grasp period. In addition, the developed novel hand system has a tactile sensor. We choose FSR-32 as the tactile sensor, which is a single point thin-film pressure-sensitive resister [25]. The tactile sensor is fixed around the middle of the surface of one finger. A bump is also designed on the surface of the robotic finger for the sensor to perceive the pressure.

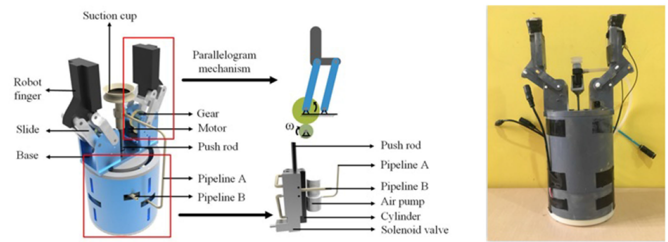

Fig. 5. Designed composite robotic hand, which consists of one suction cup and two parallel pinching fingers.

One important feature of this composite hand is the combination of fingers and a suction cup, which is simple and robust to many different scenarios. In fact, we can find a lot of applications of the suction cup, including the self-sealing suction cup arrays [26], the stretchable suction cup with electroadhesion [27], and so on. In addition, the authors of [28]–[32] developed many bioinspired suction cups. In spite of this point, there exist lots of limitations on the working surface. In addition, the difference between the direction of the force and the moving direction of the suction cup may degrade the grasp quality [33]. Therefore, it is vital for the robot to discover appropriate grasping or picking points in a difficult scene if the suction cup is used.

When the picking point is discovered and validated, the hand popped the suction cup out to contact the object. Then, the air pump produces the negative pressure to pick the object. After that, the push rod retracts to bring the object between the two fingers and the fingers close to grasp the object to improve the grasp stability.

Furthermore, during the grasping process, the tactile sensor is used for detecting whether the robotic hand has successfully grasped the object or not as well as helping the robotic hand grasping the object adaptively. First, since the robotic hand is a hard structure, the tactile sensor can help the robotic hand to perceive the size of the object for applying the proper force to the object during the grasping process. In addition, considering the human's perception way, it is simple and possible to use the tactile sensor to detect whether the hand grasps objects successfully by checking whether there is pressure on the sensor after the pinching in the grasping process.

In Fig. 6, we show an action cycle, during which the hand utilizes both fingers to hold the object once the suction cup successfully lifts the object. This strategy significantly improves the grasp quality. Furthermore, when the hand moves, the force produced by the grippers and the suction cup can jointly ensure the object to be reliably held.

In spite of the advantages of the suction cup, we still encounter great challenges in practical scenarios. The main reason for

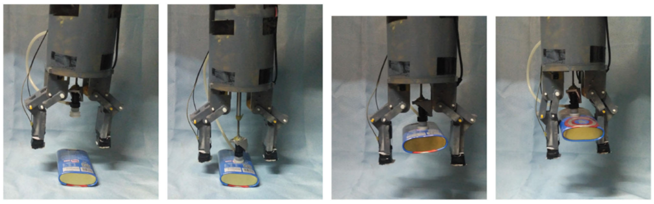

Fig. 6. From left to right: the robotic hand moves toward the object, the suction cup is released to pick the object, the suction cup draws back, and the fingers close to reliably grasp the object.

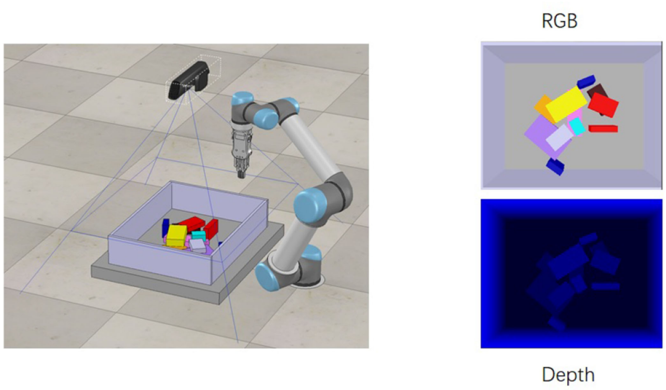

Fig. 7. Simulated operation environment, which is used for the reinforcement learning training. It is developed using the V-REP tools.

failure is that the suction cup is always guided to pick the object, which exhibits the highest affordance value. However, as we have shown, the affordance map is not always reliable, and therefore, the failure case is unavoidable. This should be solved using our proposed interactive perception method.

V. Experimental Results

In this validation, we first train the DQN using reinforcement learning in the simulation environment. Then, we transfer the learned strategy to the physical environment to perform the practical grasp experiments.

A. Reinforcement Learning Training

The simulation scenes are developed using V-REP [34]. We use a UR5 manipulator with a robotic hand to perform interactive exploration and fix a Kinect RGB-D camera to capture the global scene (see Fig. 7). The cluttered scenes are simulated using randomly placed 11 object blocks.

The DQN network is trained by RMSPropOtimizer. We progressively change the learning rate from 10^{-3} to 2.5×10^{-4} and fix the momentum value to be 0.9. To pay more attention on the recent epoch, we set the forgetting factor $\gamma = 0.6$. We further utilize the ϵ-greedy strategy to present allowance for more attempts on new actions and disclose novel actions. Fig. 8 presents the evolutionary curve of the loss function. The training period lasts 25 h on a conventional computer with GPU. Finally,

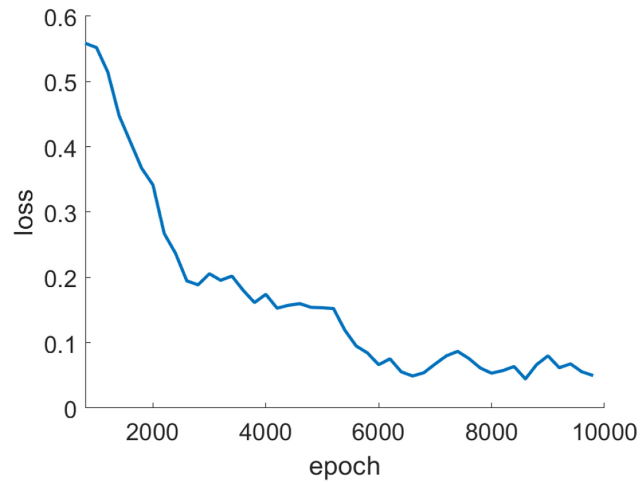

Fig. 8. Evolution curve of the loss function in the reinforcement learning.

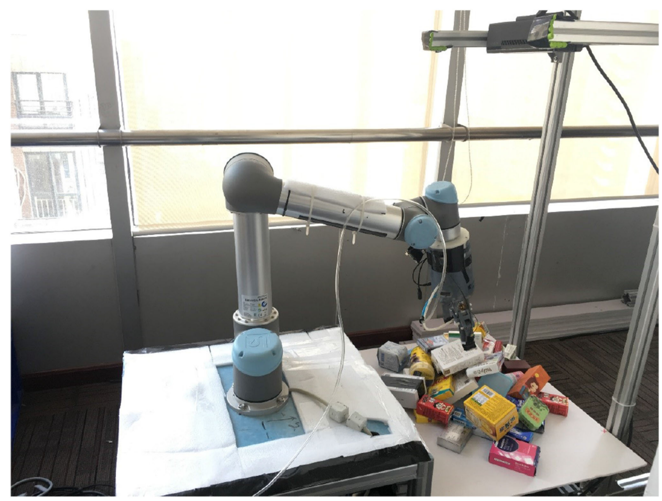

Fig. 9. Physical experimental platform, which contains a Kinect camera as a vision sensor, a UR5 manipulator with the developed composite robotic hand.

we transfer the obtained model to the physical environment for practical manipulation and grasp.

B. Robotic Experiments

In Fig. 9, we show the real physical experimental platform. The grasp operation scenes are formed with 40 objects. For comparison, we denote the conventional grasp method presented in [13] as the *Passive Method* and the proposed one as the *Interactive Method*. The difference between them is the former uses the static affordance map, and the latter uses the interactive affordance map.

For the *Passive Method*, when the object with the maximum affordance score cannot be picked, the robotic hand will continue to perform this mistaken picking action, since the operation scene and the resulting affordance image are not updated at all.

Fig. 10. Three typical scenes. The first row corresponds to the *Difficult* category. The left and right panels in the second row correspond to the *Moderate* and *Easy* categories, respectively.

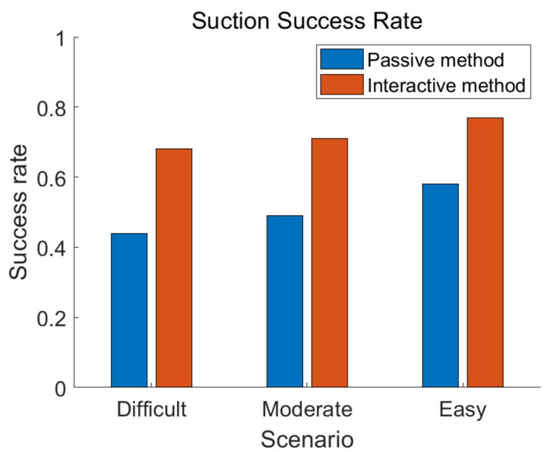

Fig. 11. Suction success rate comparison between passive and interactive methods.

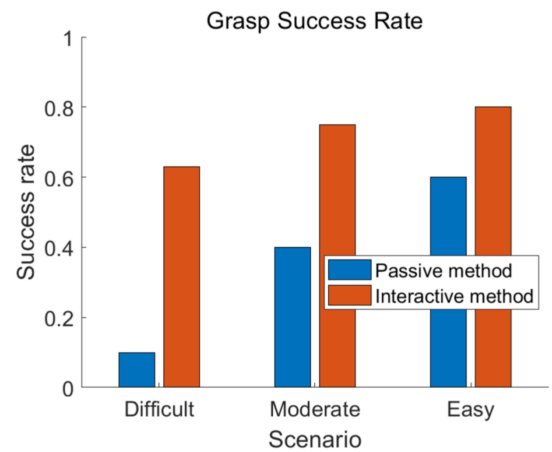

Fig. 12. Grasp success rate comparison between passive and interactive methods.

Therefore, a trial is regarded as a failure if the picking action fails on one object for consecutive three times. On the other hand, the trial is regarded as a success if the first ten objects are picked successfully. Using this protocol, we may present the following three evaluation metrics:

1) the average number of successfully picked objects;
2) the suction success rate, which is defined as the number of successfully picked objects divided by the number of operations;
3) the scene success rate, which is defined as the number of successful tests divided by the number of tests.

We perform the validation on 20 different scenes with the *Passive Method* and the *Interactive Method*. Following the setting in [35], the test scenes can be clustered into three classes, which are shown in Fig. 10. In Figs. 11–13, we show the detailed results, which can be summarized as follows.

1) *Difficult:* The first class contains 11 scenes, in which the objects are nearly clustered and concentrated. For such scenes, the developed interactive exploration method achieves good performance. The scene success rate is increased from 44% to 68%, while the average number of pushing operation is 8.3. More importantly, the developed system increases the possibility of successfully grasping picking more than ten instances from 10% to 63%.
2) *Moderate:* The second class includes four scenes, in which the objects are not so clustered. For such scenes, the developed method increases the success rate of picking from 49% to 71% and increases the possibility of picking more than ten instances from 40% to 75%. Since those scenes are more simple than the first class, the mean number of pushing actions decreases to 4.5.

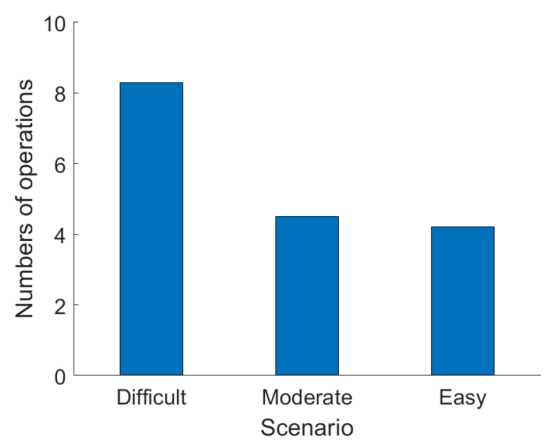

Fig. 13. Number of operations using the interactive method.

TABLE I
EXPERIMENTAL RESULTS

Method	Passive Method	Interactive Method
♯Grasped Objects	5.35	8.80
Suction Success Rate	50.5%	70.7%
Scene Success Rate	28%	68.9%

3) *Easy:* The third class includes five scenes, in which the objects are more scattered, and some isolated objects can be found. For such scenes, the straightforward affordance method can be utilized to obtain the success rate of 58%, while the developed interactive perception method increases the success rate to 77%. Due to the simplicity of scenes, the mean number of pushing actions is decreased to 4.2, while the possibility of picking more than ten instances is increased from 60% to 80%.

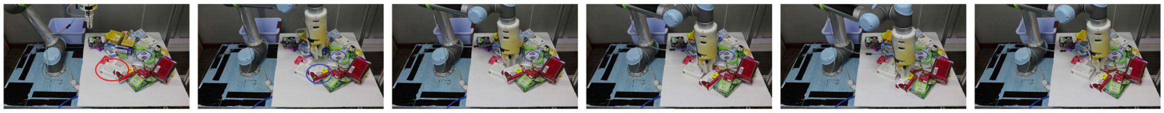

Fig. 14. In the left image, the robotic manipulator begins to select the box (marked with red eclipse), which is partially occluded by another box. The second image shows that the robotic manipulator approaches the occluding box (marked with blue eclipse). The third image shows that the robotic manipulator contacts the upper box. The second stage: The fourth to sixth images show that the robotic manipulator pushes the occluding box away and isolate the target box for better grasp condition.

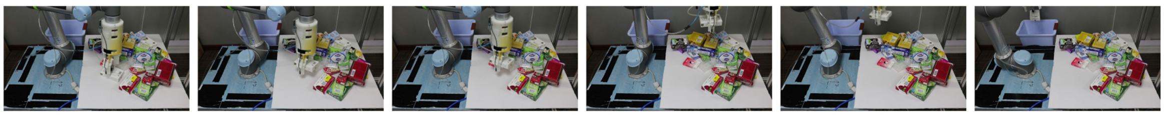

Fig. 15. First image shows that the robotic manipulator releases the suction cup to pick the target box. The second image shows that when the object is picked, the suction cup is withdrawn, and the robotic fingers are utilized to grasp the target object. The third image shows that the robotic manipulator grasps the target object to move to another position. The fourth to sixth images show that the robotic manipulator takes the grasp object to the preselected location.

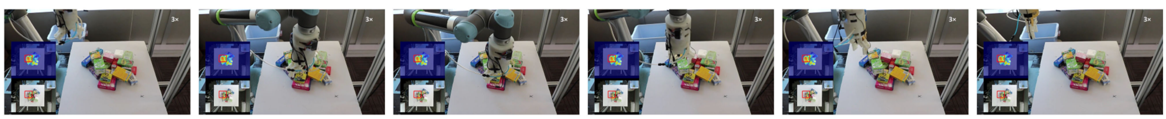

Fig. 16. Typical results using a passive affordance method. A sequence of a failure grasp procedure, during which the affordance map provides unliable results and the corresponding object cannot be picked.

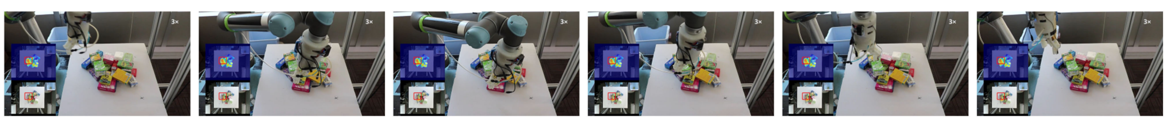

Fig. 17. Manipulator will repetitively try to pick the objects, which is indicated by the affordance map, and therefore, nothing can be picked. The affordance maps on the RGB and depth images are shown in the bottom-left corner of each figure.

The above results validate that for the difficult scenes, the developed interactive perception approach shows significant improvement because more pushing actions are required to interact with the environment.

Table I presents the statistical results of all of the experimental scenes. It is apparent that the developed system performs better in the suction success rate and the scene success rate when the interactive exploration is utilized. The applications of the interactive perception strategy significantly reduce the possibility of repeating mistaken lifting actions and improve the adaptability, which cannot be achieved with a static affordance map. In fact, if the robot only depends on the static affordance map, it often fails in cluttered scenes. On the contrary, if the robot depends on the affordance map produced by the interactive exploration method, it may ensure that the surrounding of the lifting object is empty. Therefore, the robot may obtain more reliable decisions. In Figs. 14 and 15, we show some consecutive frames of the manipulation.

As a comparison, we show a sequence of operations using a passive affordance method in Figs. 16 and 17. Since the affordance map returns unreliable results, the manipulator cannot successfully pick and grasp the object. What is worse, since the scene is unchanged, the manipulator will persistently lock the specific object and grasp nothing in the next trial.

Fig. 18. Some failure cases of the proposed interactive perception method. *Left:* DQN produces useless pushing action (the dashed arrow), which does not change the operation scene. *Right:* Object to be picked lacks sufficient support.

The main time cost during one execution lies in two aspects: the affordance map calculation, which takes 1 s, and the action generated by the DQN, which takes no more than 0.5 s. Therefore, the whole decision period is about 1.5 s. This time cost can be further reduced with algorithm optimization.

Before closing this article, we provide some failure cases of the proposed interactive perception method in Fig. 18, which shows the limitation of the proposed method. In very few cases, the DQN may produce useless pushing action, which does not change the operation scene (see the left panel of Fig. 18). This is partially due to scarce training cases. Generally speaking, such a problem can be automatically solved by adding more steps. Another failure case occurs when the object to be picked lacks sufficient support (see the right panel of Fig. 18).

VI. Conclusion

In this article, we integrated the interactive perception with a new composite hand and developed a deep reinforcement learning algorithm to improve the grasp affordance map. The experimental results on robotic grasp tasks showed the potentials of the interactive perception approach. Very recently, the developed interactive perception system has won the First Prize in a university-level invention competition. We believe such a new novel method will bring great economic and social and benefits to smart cities.

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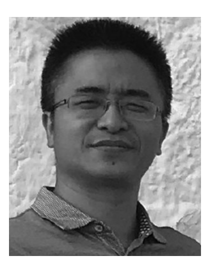

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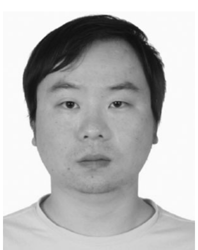

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