RPRG: Toward Real-time Robotic Perception, Reasoning and Grasping with One Multi-task Convolutional Neural Network

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Abstract—Autonomous robotic grasp plays an important role in intelligent robotics. However, it is challenging due to: (1) robotic grasp is a comprehensive task involving perception, planning and control; (2) autonomous robotic grasp in complex scenarios requires reasoning ability. In this paper, we propose a multi-task convolutional neural network for Robotic Perception, Reasoning and Grasping (RPRG), which can help robot find the target, make the plan for grasping and finally grasp the target step by step in object stacking scenes. We integrate vision-based robotic grasp detection and visual manipulation relationship reasoning in one single deep network and build the autonomous robotic grasp system. The proposed network has state-of-the-art performance in both tasks. Experiments demonstrate that with our model, Baxter robot can autonomously grasp the target with a success rate of 94.2%, 77.1% and 62.5% in object cluttered scenes, familiar stacking scenes and complex stacking scenes respectively at a speed of 6.5 FPS for each detection.

I. INTRODUCTION

The development of service robots can make people’s lives more convenient. However, in the research of intelligent robotics, autonomous robotic grasp is a very challenging task [1]. For use in daily life scenes, autonomous robotic grasp should satisfy the following conditions:

- Grasp should be robust and efficiency.
- The desired object can be grasped in a multi-object scene without possible damages to other objects.
- The right decision can be made when the target is not visible or the target is covered by other things.

For human beings, grasp can be completed naturally with high efficiency even when the target is unseen or strange. However, robotic grasp involves many difficult aspects including perception, planning and control. For more complex scenes (e.g. the target is hidden or covered by other objects), robots also need the ability to reason. For example, as shown in Fig. 1, in order to prevent damage to other objects, the robot must plan the order of the grasping through reasoning, perform multiple grasps in sequence to execute the task and finally get the target. These difficulties make the autonomous robotic grasp challenging.

Therefore, in this paper, we propose a new vision-based multi-task convolutional neural network (CNN) to solve the mentioned problems for autonomous robotic grasp, which can help robot complete grasp task in more complex scenes (e.g. grasp hidden target or target below other things without damage to other things). Our proposed algorithm includes three parts: Perception, Reasoning and Grasping. To tackle perception problem, we combine RoI based robotic grasp detection into our multi-task network, which can handle a wide variety of objects and simultaneously detect objects and grasps with the affiliation between them. In order to give the robot the ability to reason, visual manipulation relationship reasoning is integrated in our multi-task CNN to enable the robot to predict the correct order for grasping, preventing damages to objects. Though the perception and reasoning process takes RGB images as input, in grasping execution, we use depth information for grasp location and coordinate transformation.

Though there are some previous works that try to complete grasping in dense clutter scenes [2]–[4], as we know, our proposed algorithm is the first to combine perception, reasoning, and grasp planning simultaneously, and attempts to realize autonomous robotic grasp in complex scenarios. To evaluate our proposed algorithm, we validate the performance of our model in VMRD dataset [5]. For robotic experiment, Baxter robot is used as the executor to complete grasping task, in which the robot is required to find the target, make the plan for grasping and grasp the target step by step.

The rest of this paper is organized as following: Related work is reviewed in Section II; Our proposed algorithm is detailed in Section III; Experimental results including validation on VMRD dataset and robotic experiment are shown in Section IV, and finally the conclusion and discussion are described in Section V.
II. RELATED WORK

A. Robotic Grasp Detection

As development of deep learning, robotic grasp based on convolutional neural network (CNN) achieves state-of-the-art performance on several dataset such as Cornell dataset [6]–[11], Dex-net [12] and CMU grasp dataset [13]. However, the existing works for robotic grasp can not deal with complex grasping tasks (e.g. grasping a specific target in multi-object scenes). Our previous work [14] detects grasps on Regions of Interest with the affiliation between detected grasps and objects, enabling the robot to grasp specific target in object cluttering scenes. However, the target is required to be visible and graspable. When the target is hidden or placed below other things, grasping process will be invalid.

There are some works that try to complete grasp in dense clutter scenes [2]–[4]. A deep network is used to simultaneously detect fruit and grasp by Guo et al. [2], which is trained on a fruit dataset including 352 RGB images. However, the model can only output the grasp belonging to the most exposed fruit without perception and understanding of the overall environment and reasoning of the relationship between objects, which limits the use of the algorithm. Algorithms proposed in Levine et al. [3] and Gualtieri et al. [4] only focus on the detection of grasps in scenes where objects are densely cluttered, rather than what the grasped objects are. Therefore, this sort of algorithms will no longer apply when the robot is requested to get an specified object in the scene.

B. Visual Manipulation Relationship Reasoning

Recent works prove that deep network achieves advanced performance on visual relationship reasoning [15]–[17]. Different from visual relationship, visual manipulation relationship [5] is proposed to solve the problem of grasp order in object stacking scenes with consideration of the safety and stability of objects. In this work, features of object pairs are feed into relationship prediction network to classify the correct manipulation relationship between each object pair. However, when this algorithm is directly cascaded with the grasp detection network to solve grasping problem in object stacking scenes, there are two main shortcomings: 1) it is difficult to correctly match the detected grasps and the detected objects in object stacking scenes; 2) the cascade structure causes a lot of redundant calculations (e.g. the extraction of scene features), which makes the speed slow.

Therefore, in this paper, we build a robotic autonomous grasp system combining the advantages of the previous works [5], [14], which implements robotic perception, reasoning and grasping in one multi-task deep network. The robot is enabled to simultaneously detect objects and grasp with the affiliation between them and make correct decisions in object stacking scenes to find and grasp the target.

III. TASK DEFINITION

In this paper, we focus on grasping task in scenes where the target and several other objects are cluttered or piled up, which means there can be occlusion and overlap between objects, or the target is hidden under other objects and cannot be observed by the robot. Therefore, we set up an environment with several different objects each time. In each experiment, we test whether the robot can find out and grasp the specific target. The target of the task is input by humans. The desired robot behavior is that following the correct manipulation relationship predicted by the network, the final target input by human can be grasped step by step.

We focus on grasping task in realistic and challenging scenes as following:

1) Object Cluttered Scenes: Object cluttered scenes include more objects than scenes in training dataset where objects are scattered. It is used to test the ability of grasping one specific target of our proposed approach in common multi-object scenes. Under this condition, the robot should grasp the target directly because the target is exposed to the robot and graspable, which is still a challenging task.

2) Familiar Stacking Scenes: Familiar stacking scenes include 2-5 objects, where objects are stacked together and there are occlusions and overlaps between objects. These scenes are similar with those appearing in VMRD dataset, and there is at least one object on the target. In most situations, the target is visible. The robot needs to plan the grasping order and executes grasps one by one until the target is successfully grasped.

3) Complex Stacking Scenes: Complex stacking scenes include 6-10 objects. Objects are piled up and there are more severe occlusions and overlaps than familiar stacking scenes. In the beginning, the target is difficult to detect in most cases. Therefore, it can test whether the robot can make correct decision to find the target and successfully grasp it. This is the most challenging task in this paper.

IV. PROPOSED APPROACH

A. Architecture

The architecture of our proposed approach is shown in Fig. 3. The input of our network is RGB images of working scenes. First, we use CNN (e.g. ResNet-101 [18]) to extract image features. Region proposal network (RPN) [19] follows the feature extractor to output regions of interest. The main-body of our approach includes 3 parts: Perception, Reasoning and Grasping. “Perception” is used to obtain the object and
grasp detection results with the affiliation between them. “Reasoning” takes object bounding boxes output by “Perception” and image features as input to predict manipulation relationship between each pair of objects. “Grasping” uses perception result to transform grasp rectangles into robotic grasp configuration executed by the robot. Each detection produces one robotic grasp configuration, and the iteration is terminated until the desired target is grasped.

1) Feature Extractor: As shown in Fig. 3 convolutional features are shared among RPN, object detection, grasp detection and visual manipulation relationship prediction. The shared feature extractor used in our work is ResNet-101 layers before conv4 including 30 ResBlocks. Therefore, the stride of shared features is 16.

2) Region Proposal Network: RPN includes three $3 \times 3$ convolutional layers: a intermediate convolutional layer, a RoI regressor and a RoI classifier. The RoI regressor and classifier are both cascaded after the intermediate convolutional layer to output locations of RoIs and whether each RoI is candidate of object bounding box.

Details about Object Detector, Grasp Detector and Manipulation Relationship Predictor will be discussed in following subsections.

B. Perception

Referring to our previous work [14], in “Perception” part, we simultaneously detect objects and grasps with the affiliation between them. The convolutional features and RoIs output by RPN are first feed into RoI pooling layer, where the features are cropped by RoIs and pooled using adaptive pooling into same size $W \times H$ (in our work, the size is $7 \times 7$). The purpose of RoI pooling is to enable the corresponding features of all regions of interest to form a batch for network training.

1) Object Detector: Object detector takes a mini-batch of RoI pooled features as input. As in [18], a ResNet’s conv5 layer including 9 convolutional layers are adopted as the head on top of all RoI pooled features for final regression and classification. The header’s output is then be averaged on each feature map. The regressor and classifier are both fully connected layers with 2048-d input and no hidden layer, outputting locations of refined object bounding boxes and classification results respectively.

2) Grasp Detector: Grasp detector also takes RoI pooled features as input to detect grasps on each RoI. Each RoI is first divided into $W \times H$ grid cells. Each grid cell corresponds to one pixel on RoI pooled feature maps. The grasp detector outputs $k$ (in this paper, $k = 4$) grasp candidates on each grid cell with oriented anchor boxes as priors. Different oriented anchor size is explored during experiments including $12 \times 12$ and $24 \times 24$. Similar to object detector, a header including 3 ResBlocks is cascaded after RoI pooling in order to enlarge receptive field of features used for grasp detection. The reason is that a large receptive field can prevent grasp detector from being confused by grasps that belongs to different RoIs. Otherwise, the outputs in overlap on two different object bounding boxes will be exactly the same, making it impossible to distinguish the owner of the detected grasps.

Then the grasp regressor and grasp classifier follow the grasp header and output $5k$ and $2k$ values for grasp rectangles and graspable confidence scores respectively. Therefore, the output for each grasp candidate is a 7-dimension vector, 5 for the location of the grasp $(\delta x_a, \delta y_a, \delta w_g, \delta h_g, \delta \theta_g)$ and 2 for graspable and ungraspable confidence scores $(c_g, c_{ug})$.

Therefore, the output of “Perception” part for each object contains two parts: object detection result $O$ and grasp detection result $G$. $O$ is a 5-dimension vector $(x_{min}, y_{min}, x_{max}, y_{max}, cls)$ representing the location and category of an object and $G$ is a 5-dimension vector $(x_g, y_g, w_g, h_g, \theta_g)$ representing the best grasp. $(x_g, y_g, w_g, h_g, \theta_g)$ is computed by Eq. (1):

$$
\begin{align*}
x_g &= \delta x_g \times w_a + x_a \\
y_g &= \delta y_g \times h_a + y_a \\
w_g &= \exp(\delta w_g) \times w_a \\
h_g &= \exp(\delta h_g) \times h_a \\
\theta_g &= \delta \theta_g \times (90/k) + \theta_a
\end{align*}
$$

where $(x_a, y_a, w_a, h_a, \theta_a)$ is the corresponding oriented anchor.

C. Reasoning

Inspired by our previous work [5], we combine visual manipulation relationship reasoning in our network to help
robot predict the grasping order without potential damages to other objects.

**Manipulation Relationship Predictor:** To predict manipulation relationships of object pairs, we adopt Object Pairing Pooling Layer (OP2L) to obtain features of object pairs. Similar to object detector and grasp detector, features of objects are also adaptively pooled into size of $W \times H$. The difference is that the convolutional features are cropped by object bounding boxes instead of RoIs. Features of each object pair $(O_1, O_2)$ include the features of two objects and the union bounding box. Note that $(O_1, O_2)$ is different from $(O_2, O_1)$ because manipulation relationship does not conform to the exchange law. If there are $n$ detected objects, the number of object pairs will be $n \times (n - 1)$, and there will be $n \times (n - 1)$ manipulation relationships predicted. In manipulation relationship predictor, the features of the two objects and the union bounding box first pass four convolutional layers respectively, and finally manipulation relationships are obtained by a fully connected network containing two 2048-d hidden layers.

After getting all manipulation relationships, we can build a manipulation relationship tree to describe the correct grasping order in the whole scene. Leaf nodes of the manipulation relationship tree should be grasped before the other nodes.

**D. Grasping**

"Grasping" part is used to do inference on outputs of the network. In other words, the input of this part is object and grasp detection results and the output is the corresponding robotic configuration to grasp each object. Note that there is no trainable weights in "Grasping" part.

1) **Grasp Selection:** As described above, the grasp detector outputs a large set of grasp candidates for each RoI. Therefore, the best grasp candidate should be selected first for each object. According to experience, there are two methods to find the best grasp: (1) choose the grasp with highest graspable score; (2) choose the one closest to the object center in Top-N candidates. The second one is proved to be a better way in [10], which is used to get the grasp of each object in our paper. In the experiment, $N$ is set to 3.

2) **Coordinate Transformation:** The purpose of the coordinate transformation is to map the detected grasps in the scene image to the grasp vector and grasp point in the robot coordinate system. In this paper, an affine transformation is used approximately for this mapping. The affine transformation is obtained through four reference points with their coordinates in the image and robot coordinate system. The grasp point is defined as the point in grasp rectangle with minimum depth while the grasp vector is the average surface normal around the grasp point. The grasp point and grasp vector will be mapped into robot coordinate system for location of the robot gripper in grasp execution.

**E. Training**

Our networks are trained end-to-end with one multi-task loss function. The loss function includes three parts: object detection loss $L_O$, grasp detection loss $L_G$ and visual manipulation relationship reasoning loss $L_R$, where $L_O$ is same with [19] and $L_R$ is a multi-class Negative Log-Likelihood classification loss. $L_G$ is designed to simultaneously minimize the grasp rectangle regression loss and classification loss. As described above, each oriented anchor $(x_a, y_a, w_a, h_a, \theta_a)$ will be corresponding to 5-dimension offsets $(\delta x_a, \delta y_a, \delta w_a, \delta h_a, \delta \theta_a)$ and 2-dimension of confidence scores $(c_{ug}, c_{ag})$. Therefore, grasp detection loss is defined as following:

$$L_G = L_{Greg} + \alpha L_{Gcls}$$

where $\alpha$ is 1 in this paper. The whole loss for our network is defined as follow:

$$loss = L_O + \lambda L_G + \beta L_R$$

where $\lambda$ and $\alpha$ are all set to 1 in our experiments.

**V. Experiment**

**A. Dataset**

Dataset used to train our model is VMRD dataset with grasps [5], [14]. There are 4683 images with grasps totally, which are divided into training set and testing set with 4233 and 450 images respectively. More than 100k grasps are labeled on these images with object index that indicates the owner of these grasps. In each image, there are 2-5 objects stacked together with overlaps and occlusions. Manipulation relationships are also labeled as manipulation relationship tree, where the leaf nodes should be grasped before the other ones.

During training, we take advantages of online data augmentation including random brightness, random hue, random contrast, color space conversion, vertical rotation and horizontal flip. That is to say, in each iteration, images feed into network are different from all the previous, which can prevent overfitting and enhance the generalization ability of our model in different workspace. Note that the image preprocessing does not change the image size including reshape and crop. Before the images are feed into the network, we approximately subtract 144 on each pixel to mean-center all the inputs.

**B. Training Details**

Our networks are trained end-to-end on GTX 1080Ti with 11GB memory using PyTorch as the deep learning platform. Learning rate is set to 0.001 according to experience, which
TABLE I
VALIDATION RESULTS OF PERCEPTION

| Algorithm   | Setting                  | MR₀ (%) | LAMR (%) | mAP (%) | mAP with grasp (%) | Speed (FPS) |
|-------------|--------------------------|---------|----------|---------|---------------------|-------------|
|             |                          |         |          |         |                    |             |
|            |                          | Lower is Better | Higher is Better |
| RoI-GD [14]| 12 × 12 Anchor, k=4     | 24.9    | 76.9     | 94.5    | 68.2               | 9.1         |
| Ours       | 12 × 12 Anchor, k=4     | 24.1    | 74.9     | 96.2    | 68.0               | 7.6         |
|            | 24 × 24 Anchor, k=4     | 26.5    | 77.6     | 96.3    | 65.0               |             |
|            | 12 × 12 Anchor, k=4, Hi-res | 23.2  | 74.7     | 95.6    | 69.1               | 6.5         |
|            | 24 × 24 Anchor, k=4, Hi-res | 24.4  | 75.9     | 96.0    | 70.5               |             |

* Best results from RoI-GD [14] are selected as the baseline.

TABLE II
VALIDATION RESULTS OF REASONING

| Algorithm | Setting                  | Obj. Rec. (%) | Obj. Prec. (%) | Total Image Acc. (%) | Object Number per Image |
|-----------|--------------------------|--------------|---------------|----------------------|-------------------------|
|           |                          |              |               |                      |                         |
| VMRN [5]  | -                        | 82.3         | 78.0          | 63.1                 | -                       |
| Ours      | 12 × 12 Anchor, k=4     | 85.7         | 87.2          | 66.4                 | 61/65/130/209/55/106/53/70 |
|           | 24 × 24 Anchor, k=4     | 86.0         | 88.8          | 67.1                 | 57/65/134/209/60/106/51/70 |
|           | 12 × 12 Anchor, k=4, Hi-res | 85.9  | 85.8          | 65.3                 | 61/65/132/209/51/106/49/70 |
|           | 24 × 24 Anchor, k=4, Hi-res | 84.7  | 86.5          | 65.1                 | 60/65/133/209/55/106/45/70 |

Fig. 4. Examples of perception and reasoning results on VMRD test set. Perception: (a) True positive examples. (b) Images with incorrect detections. The top row is object detection results and the second row is grasp detection results. Reasoning: (c) examples of manipulation relationship reasoning.

C. Result

1) Perception: Perception results include object detection results and grasp detection results, which are shown in Table I. Like our previous work [14], an object is considered as a true positive detection when the bounding box and best grasp are all correctly detected. In detail, the detection \((O,G)\) should satisfy following conditions:

- The bounding box from \(O\) should have an IoU larger than 0.5 with the ground truth and be classified correctly
- The best grasp from \(G\) should has a Jaccard Index larger than 0.25 and angle difference less than 30° with at least one ground truth grasp

In Table I MR₀ is the miss rate when \(log(FPPT)\) is equal to 0. LAMR is the abbreviation of Log-Average Miss Rate [20]. mAP is used to measure object detection results while mAP with grasp combines object detection \(O\) and grasp detection \(G\) together to measure the performance of the perception. Compared with our previous work, improvements on object detection and grasp detection are 1.8% (94.5% to 96.3%) and 2.3% (68.2% to 70.5%) respectively. We assume that it is because of regularization in learning [21] in multi-task training.

2) Reasoning: Reasoning results are shown in Table II and Fig. 5. We can see that our model improves the performance of visual manipulation relationship reasoning compared with our previous work [5]. We assume that the improvements are achieved following these changes: (1) Different from our previous work, in this paper, we use ResNet-101 as the feature extractor, or called “backbone” instead of ResNet-50 and VGG-16 in [5]; (2) the object detector is Faster-RCNN from [19] instead of SSD in [22]; (3) the backbone is updated using multi-task loss function.
including grasp detection loss.

Two examples in Fig. 4(c) demonstrate the output of visual manipulation relationship reasoning. We can see that our model can efficiently build the manipulation relationship tree for grasping task in object stacking scenes. Note that for scenes where there are more than 1 objects belonging to the same category (like shown in the first example of Fig. 4(c), there are two screwdrivers), our model can also work well by giving each object a unique ID (called “index” in VMRD) to distinguish them.

3) Grasping: In this part, robotic grasping experimental results are explored using model with $12 \times 12$ anchor and Hi-res input. As described in Section III, Robotic experiments include three parts: (1) Object Cluttered Scenes where objects are scattered and the target should be directly grasped by the robot; (2) Familiar Stacking Scenes where there are 2-5 objects stacked like in VMRD dataset; (3) Complex Stacking Scenes where there are 6-10 objects stacked together and the target should be found first and grasped then following the correct grasping order. The most challenging task is grasping in Complex Stacking Scenes.

We use Baxter robot as the executor and Kinect v2 as the camera. Though RGB images are used to do perception and reasoning, when grasping, depth information should be combined for computing the grasp point and grasp vector in robot coordinate system. Robotic environment is shown in left of Fig. 5(a).

Experimental results are shown in Table III and Fig. 6. From the table, we can see that our model works well under all three conditions and achieves a success rate of 94.2%, 77.1% and 62.5% respectively. Complex conditions will have negative affects on the overall success rate. Some failures are demonstrated in Fig. 7. In the first picture, target detection failure is caused by the low confidence score of the glasses. As described in the previous section, if the robot cannot see the target, it will move visible things away to find it. Therefore, the box is selected. The second picture demonstrates incorrect grasp detection, which is caused by the confusion of grasps belonging to two different objects due to excessive object overlap. The third picture shows an oversized grasps for our robot. The incorrect order is came across occasionally like shown in the last picture.

VI. CONCLUSIONS

In this paper, we propose a multi-task deep network for robotic perception, reasoning and grasping, which can help robot find the target, make the plan for grasping and finally grasp the target step by step in object stacking scenes. The proposed network has the state-of-the-art performance in both multi-object grasp detection and visual manipulation relationship reasoning. Experiments demonstrate that with our model, Baxter robot can autonomously grasp the target with a success rate of 94.2%, 77.1% and 62.5% in object cluttered scenes, familiar stacking scenes and complex stacking scenes respectively at a speed of 6.5 FPS for each detection. In future work, we will try to overcome object and grasp detection difficulty in excessive overlap scenes for better performance of our model.

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