Abstract— Reducing the scope of grasping detection according to the semantic information of the target is significant to improve the accuracy of the grasping detection model and expand its application. Researchers have been trying to combine these capabilities in an end-to-end network to grasp specific objects in a cluttered scene efficiently. In this paper, we propose an end-to-end semantic grasping detection model, which can accomplish both semantic recognition and grasping detection. And we also design a target feature filtering mechanism, which only maintains the features of a single object according to the semantic information for grasping detection. This method effectively reduces the background features that are weakly correlated to the target object, thus making the features more unique and guaranteeing the accuracy and efficiency of grasping detection. Experimental results show that the proposed method can achieve 98.38% accuracy in Cornell grasping dataset. Furthermore, our results on different datasets or evaluation metrics show the domain adaptability of our method over the state-of-the-art.

Keywords: Grasp detection, semantic, clutter background, image segmentation

I. INTRODUCTION

Semantic grasping detection is the key ability of the robot to interact with the environment. Robotic semantic grasping aims to find the target object in a cluttered environment and predict the grasping configuration according to its features. Traditionally, robotic grasping detection is commonly achieved by traversing the features of the whole image [1-8] without distinguishing the target features and background features. Therefore, humans can easily grasp a specified object in a cluttering scene, but it is far from an easy problem for a robot to solve.

Recognition and location of the target and selecting the features of the target area are the key steps to realizing the semantic grasping of the robot. With the development of deep learning technology, object detection models based on deep learning have achieved satisfactory results [9]. On this background, [10] proposed a multi-task model that simultaneously implements object detection and grasp detection. This multi-task model [11] [12] realizes grasping the specified object in the final form, but the model still adopts the features of the whole image for grasping detection. This method is unreasonable because the grasp detector processes a large number of background features that have limited contribution to the object grasp. Besides, the grasping detection branch and target detection branch is wholly separated in the multi-task mode. The object detection branch can not guide the operating range of the grasp detector. Therefore, the grasp detection branch does not independently use the characteristics of the target object to estimate the grasp configuration. This model is susceptible to local ambiguity features in a cluttering background to predict the wrong grasping configuration. As shown in Fig. 1 Feature Map, there are many features similar to the target object in the image, which will lead the model to provide wrong prediction results.

Recently, [13] proposed identifying the target object’s category and ROI (Region of Interest) region through the object detection method and only using the features of the ROI region to predict the grasp pose. This method reduces the area of grasping detection, and the model pays more attention to the features of the target object. However, due to the axial symmetry of ROI, there will still be background features and local features of other objects in the ROI region, thus affecting the model’s performance. To solve the above problems, some learning-based algorithms further reduce the background features that contribute little to the detection by using semantic segmentation [14]. However, the redundant feature extraction structure of this method requires huge computing power and time.

In this paper, we discard redundant structures in the network and use an end-to-end model to generate grasp predictions for specified objects with quality scores. Our model implements semantic segmentation and grasp detection simultaneously via sharing one single backbone. In order to improve the representation ability of feature maps, we adopt a feature fusion network that merges low-level features with rich semantic and structural information. Moreover, we design a
feature filtering mechanism, which only preserves the features of the target region in the feature map according to the result of semantic segmentation to predict grasping configuration. Compared with the existing methods, our model is a dense end-to-end model, which predicts the grasping configuration according to the ontology characteristics of the target object. Our approach is closer to the human object-oriented grasping detection method and has higher accuracy than the ROI-based [13] method and state-of-the-art method [2].

The main contributions of this paper are concluded as follows:

This paper proposes a dense end-to-end grasp detection model focusing on object features. The model uses the result of semantic segmentation to calibrate the region of the target object and predicts the grasping position of the target with the features of the region. This method makes the model focus more on learning the geometric and texture features of the object itself rather than the whole image's features without discriminating. Therefore, the model is more sensitive to the target object and still performs well even when the working scenario changes.

Pointing at the characteristics of robot semantic grasping, we propose a target feature filtering mechanism. This mechanism only preserves the regions with single semantic features in the feature graph and deletes the features of unrelated regions. We design ablation experiments to verify the contribution of this mechanism to grasp detection.

In this paper, we propose a grasp dataset containing both multi-object and single-object. The dataset includes 46 categories of ordinary things in daily life, including 512 single-object images and 300 multi-object images. In addition, we marked multiple grasping positions for each object in the image. At the same time, we use this dataset to verify the performance of our model in single-object scenarios and multi-object scenarios, respectively.

II. RELATED WORK

At present, researchers mainly adopt the analytic approach [15], model-based approach [16], and learning-based approach for grasping detection. The analytic approach [17], [18] refers to finding the region in the point cloud that satisfies the specific predefined grasping requirements. This method can efficiently predict reliable robot grasping posture but requires a lot of hand-engineered features. Model-based approach [19], [20] takes the object's 3D model as input to predict the grasp pose. People predefined special grasping posture according to different object shapes. Therefore, such approaches have shortcomings in predicting the novel object's grasp pose. The learning-based grasping detection method becomes possible with the popularization of deep learning technology and the pretraining model. And features extracted through deep learning models proved to be better than hand-engineered ones. Hence, the learning-based approach has attracted great attention from researchers. This section will focus on the learning-based approach and the direction that researchers have taken to improve it.

[21] first proposed to represent the grasping position of the target object in RGB or RGB-D image with an orientation rectangle. This method transforms the complex grasping configuration detection into a problem similar to object detection and lays a foundation for later grasping detection research. Based on this method, [1] sped up the grasp detection by local constrained prediction mechanism to divide the image into multiple regions and then use the direct regression method to predict the possible grasping positions in each region. This method addresses the issue that the direct regression algorithm can only predict one grasping position in the input image and improves the accuracy of the grasping detection model. [4] further improves the grasping accuracy of the model by using ResNet-50 as the backbone network to directly regression the grasping configuration in RGB-D images. This method demonstrates that the deeper the network, the better the performance of the grasping detection model. The above methods are based on the scene features to direct regression the grasp configuration. However, due to the complexity of the robot working scene, the training of the direct regression algorithm is complicated and requires a quantity of time and computing resources.

In order to alleviate the issues of difficult training and limited accuracy of the direct regression model, researchers optimize the model's performance by reducing the scope of the detection region and adding prior knowledge of grasping position.

A. Based on prior knowledge

Inspired by Faster-RCNN [9], [5], [6], [8] proposed to generate multiple groups of anchors with specific sizes in the image as grasping position priors. According to the confidence score, the model selects the anchor that matches the standard as the candidate and predicts the offset between the candidate anchors and ground-truth to generate the grasp configuration. The method converts the angle data of the grasp rectangle into discrete category data and predicts the angle information by the classification method. [7], [22] proposed to replace the traditional horizontal anchor with an orientation anchor to enrich further the prior knowledge of grasping position. The performance of the method achieves state-of-the-art results at that time.

Using the grasping detection algorithm [5], [6], [8] based on prior knowledge can efficiently indicate potential graspable candidates in the image. Besides, the encoded angle information [7], [12] makes the training and testing of the grasping detection model more efficient compared with the direct regression method. However, these methods do not distinguish between objects and background when detecting grasping positions, which is an indiscriminate global grasping detection. In the whole image, the target only accounts for a tiny part of the image, and most of the rest is the background information that contributes limited to the grasp detection. Therefore, indiscriminately grasping detection will cause the consumption of computing resources due to a large amount of background information, and there are ambiguous features similar to grasping position in complex background features that affect the accuracy of the grasping detection model.

B. Region reduction approach

As opposed to finding grasp positions throughout the scene, [13] proposed a ROIs-based grasping detection model inspired by the target detection algorithm to narrow the scope of grasping detection and distinguish objects in the working
scene. The model first detects the objects in the scene and their ROI [9] regions and then uses the features in the ROI region of the target object to predict the grasping configuration rather than the features of the whole scene. Therefore, the model can distinguish different kinds of objects through an object detection algorithm, reduce the scope of grasping detection, and endowed the predicted grasping position with object category information so that the model achieves a more intelligent performance. However, due to the axial symmetry of ROI and the irregularity of the target object, it cannot avoid the influence of local information of other objects and background information on the grasping detection model.

[14] proposed a grasping detection model based on semantic segmentation. The model uses the method of semantic segmentation to determine the pixel regions of different categories of objects and only uses the pixels information in the target object region for grasping detection. This method decreases the interference of background information to the performance of grasping detection. However, the redundant model structure reduces the efficiency of grasping detection.

Inspired by [13] and [14], we propose a dense end-to-end semantic grasping detection model. In the mode, we reduce the superfluous redundancies structures in scene perception and propose a feature filtering mechanism to refine the features areas for grasp detection. The simplified design reduces the training cost and computing resource consumption of the model. Meanwhile, the feature filtering mechanism makes the model more sensitive to different objects’ structure and texture information and reduces the dependence on background features. Therefore, it is more robust to unstructured environments.

III. PROBLEM FORMULATION

In this section, we will describe in detail how our model represents the grasping configuration and how the model predicts grasping configurations of different objects in the multi-object work workspace.

A. Grasp descriptors

Given the features of a target object, the purpose is to identify the target’s potential grasp configurations. In this paper, we use the widely used 5-dimensional grasp representation [1], [3], [4], [23], [24] to represent the object grasp configuration. This grasp representation ultimately gives the grasping position of the target object and the opening size and closing orientation of the parallel plate gripper. The 5-dimensional grasp is represented as follow:

$$g = \{x, y, \theta, w, h\}$$

(1)

Where \(\{x, y\}\) represents the center point of the grasp configuration, that is, the center point of the parallel gripper, \(\theta\) is the angle between the closing direction of the parallel gripper and the horizontal direction, \(h\) is the opening size, \(w\) is the width. An example of grasp representation is shown in Fig. 2.

B. Grasp detection

As mentioned in Section 2, to avoid the model using the global features of the image for grasp detection, we use a semantic segmentation algorithm to distinguish different feature regions of the input image. Thus guidance the model detects grasp configuration in a specific region. In order to train the model’s perception of different object features, we labeled the objects in each picture in the dataset with mask labels containing category information.

For the multi-object scene, our model predicts the grasp configuration for each object in the image one by one. Only the grasp configuration with the highest confidence of each object is reserved for generating the final prediction result of the image.

IV. METHOD

A. Architecture

The structure of our model is shown in Fig. 3. It is composed of four parts, backbone unit, feature fusion unit, feature filtering unit and grasp detector unit.

The backbone network is a feature extractor that learns the features of different dimensions of input RGB/RGD images through five down-sample processes. The lower layers of the feature extractor learn edge information or contour information in the input image, while the higher layers learn abstract semantic information, as shown in Fig. 4. The features learned by different task backbone networks are comparable, so we can utilize transfer learning to speed up the model's training process. Therefore, in this paper, we choose the pre-trained VGG16 network as the backbone of the model to extract the features of the input image.

The feature fusion unit is used to fuse features of different dimensions generated by the feature extractor. For the deep convolutional neural network, with the depth increasing, the receptive field of the model becomes more extensive, and the resolution of the feature map decreases and contains more abstract information, as shown in Fig. 4. Therefore, for small size objects in the input image, the deep feature map provides little information. In grasp detection and semantic segmentation, shallow features are more suitable for small objects, and depth features are ideal for large objects. We consider the characteristics of these two size feature maps and propose a feature fusion method, which doubles the size of the feature map and concatenates it with the upper feature map so that the final feature map contains rich semantic information and structural information. The feature maps generated after feature fusion are represented by C1, C2, C3, and C4, which are called common feature maps, as shown in Fig. 3. C1

![Figure 2. A 5-dimensional grasp representation with location \((x, y)\), rotation \(\theta\), gripper opening width \(h\) and plate size \(w\).](image-url)
Therefore, we named this mechanism a feature filtering unit, and other irrelevant feature elements will leak out. Like a sizer, it only keeps the qualified feature elements, and the target object area and trowelling the background features, the feature map after down-sampling to highlight the features of the Hadamard Product of the weight vector with the common other background areas are set to 0. After binarization, the feature map generated by the semantic segmentation algorithm contains abundant features used for semantic segmentation to distinguish pixel regions of different objects in the input image. C2-C4 are used to estimate grasp configurations.

After feature filtering, the fused feature map is finally used to predict the grasp configuration. We will explain the feature fusion unit and grasp detector unit in detail in the following two sections.

### B. Feature filtering unit

The feature filtering unit plays an important role in our work. In this unit, we utilize the C1 feature map to semantic segmentation process based on the multi-classification principle. We divide the result of the semantic segmentation algorithm into multiple feature maps according to object category; each feature map contains only one object's category information and location information. Then, we binarized the feature map generated by the semantic segmentation algorithm. The pixel value of the target object areas is set to 1, and the other background areas are set to 0. After binarization, the feature map is similar to a binarization weight vector. We do the Hadamard Product of the weight vector with the common feature map after down-sampling to highlight the features of the target object area and trowelling the background features, as shown in Fig. 1.

After binarization, the feature map only contains 0 and 1 elements. Like a sizer, it only keeps the qualified feature elements, and other irrelevant feature elements will leak out. Therefore, we named this mechanism a feature filtering mechanism.

Figure 3. The complete structure of our grasp detection model. This model consists of four components, backbone feature extractor, feature fusion unit, feature filtering unit, and grasp detector. The binarization module is a feature encoding module based on target position and category.

Figure 4. The feature maps are output by each convolution layer. The shallow feature map (F1) mainly contains specific contour features, while the deep feature map (F5) contains more abstract semantic features.

C. Grasp Detector

This module uses the feature of a single target after feature filtering to predict the grasp configuration of the target. Inspired by [8], we transform the continuous angle data into discrete category data and use the classification method to predict the angle of the grasp rectangle. Eq. 2 describes the mapping relationship between angle data and category data.

$$\text{class}_\theta = \text{round}(\theta + \frac{90}{10}) + 1$$ (2)

This method maps the angle data in the range of 0°-180° into 19 categories, and the category distribution is shown in Fig. 5. At the same time, in order to predict the graspable of different grasping positions, we add another dimension on the basis of 19 categories to predict the score of grasping positions.

D. Loss function

We propose a multi-task model, which can realize instance segmentation and grasping detection simultaneously. Therefore, the model's loss function consists of segmentation loss to supervised segmentation branch training and regression loss and classification loss to supervised grasp detection branch training.

We use the cross-entropy function as the loss function of segmentation. We define the segmentation loss as:

$$L_{\text{Seg-Loss}}(p_i) = -\sum_{i} p_{i} \log(\hat{p}_{i})$$ (3)

Where $N$ is the number of item categories in the dataset. $p_i = [p_{i,0}, ..., p_{i,N-1}]$ is the one-hot encoding of the sample truth value. When the sample belongs to class $i$, $p_{i} = 1$; otherwise, $p_{i} = 0$. $\hat{p}_{i} = [\hat{p}_{i,0}, ..., \hat{p}_{i,N-1}]$ is a probability distribution resulting from the model predicted value calculated by softmax and is used to represent the probability that the sample belongs to the $i$'th category.

We use smooth L1 [9] as regression loss of grasping rectangle prediction. For the multi-object scene, our model predicts the grasp configuration of objects one by one according to the result of instance segmentation. Therefore, the regression loss in the model training process is composed of the different target loss values. The ground-truth corresponding to different targets will be selected according to the different target loss values.
the center point's position of the image's annotations. We regard the image annotations contained in the pixel region of the target object as ground-truth; otherwise, it is not. We define the regression loss as follow:

\[ L_{\text{reg-los}}(\{t\}) = \frac{1}{n} \sum_{n=0}^{n} \sum_{(x,y,w,h)} \text{smooth}_{L}(t_n - \hat{t}_n) \]  

(4)

Where \( t_n \) is the predicted value of the network, \( \hat{t}_n \) is the ground truth of the corresponding grasp configuration. \( t \) is a vector representing the four parameters of the grasp rectangle. \( n \) represents the number of objects to be grasped in the image.

We use cross-entropy as the classification loss (\( L_{\text{cls-los}} \)) to supervise the prediction of angle class and graspable. The classification loss is consistent with the description of \( L_{\text{seg-los}} \) and will not be described here. Therefore, we can define the loss function of the grasping detection branch as follows:

\[ L_{\text{Grasp-los}}(\{t\},\{p\}) = L_{\text{reg-los}} + L_{\text{cls-los}} \]  

(5)

Finally, the total loss function of our model is defined as:

\[ L_{\text{total}} = L_{\text{seg-los}} + \alpha L_{\text{Grasp-los}} \]  

(6)

In our work, the instance segmentation branch plays an important role in the model. In order to achieve the best performance of the model, we set \( \alpha \) to 0.5.

V. EXPERIMENTS SET

A. Dataset

In order to verify the effectiveness of our proposed architecture. A BUPT grasp dataset is firstly collected. Then, we apply our proposed grasp detection model on a public grasp dataset and the collected dataset. Both datasets contain color and depth images to multiple modes.

a) BUPT Dataset: The dataset collected platform consists of an AUBO robotic arm, a parallel gripper, and the Kinect2, as shown in Fig. 6. We placed a Kinect2 depth camera in front of the experimental platform to collect the visual information. The BUPT grasp dataset we collected contains 46 categories of everyday objects in life, including cups, screwdrivers, bananas, etc., with 812 images in total. There are 512 single-object images and 300 images with 3-5 different objects. Meanwhile, in order to enable the BUPT dataset to be used for model testing and training, we annotate multiple ground truth grasps and one contour for each object in each image in the dataset.

b) Cornell Dataset: The Cornell Dataset consists of 885 images containing a single object, and each object has annotated multiple ground-truth grasps. In addition, in order to facilitate training the model, we adopt the same standard as the BUPT Dataset to label the contour of the object in the Cornell Dataset.

For data preparation, we perform extensive data augmentation to prevent over-fitting during model training. In this paper, we first crop the image to a fixed size of 480*480 according to the center crop, left-crop, and right-crop methods. Then we rotate the image with angle [0, 20, 40, ... ,340] in degree.

B. Metrics

To demonstrate the performance of our model, we also use a rectangular metric similar to [2], [3], [8] and [11]. This metric considers not only the position, but also the rotation angle, width and height of the predictions. A grasp is considered to meet the metric if it satisfies the following two conditions.

a) The difference between the predicted grasp angle and the ground truth is within 30 degrees.

b) The Jaquard index of the predicted grasping rectangle and ground-truth is greater than 25%.

The Jaquard index is defined as follow:

\[ J(G, \hat{G}) = \frac{G \cap \hat{G}}{G \cup \hat{G}} \]  

(7)

Where \( G \) and \( \hat{G} \) are ground truth and predicted grasp rectangle, respectively. \( G \cap \hat{G} \) is the overlap area between the predicted grasp rectangle and the ground-truth, and \( G \cup \hat{G} \) is the union area between the these two rectangles.

C. Implementation details

In our work, the backbone network is pre-trained on the ImageNet dataset to speed up model training and prevent overfitting. In the experiment, we fused the output of the Backbone network, C1 feature map after fusion was used for semantic segmentation, and C2-C4 was used for grasp detection experiment, respectively.

Our models are implemented with the PyTorch deep learning framework. For training and testing our model, we use a single NVIDIA GTX2080Ti with 11GB memory. The batch size is set as 1. Our model is trained end-to-end for 100 epochs. We used Adam as the optimizer for model training, and the learning rate was set to 0.0001. We set the learning rate decay of 0.00008 for each epoch.

VI. RESULTS AND ANALYSIS

A. Ablation Study

In this part, we demonstrate the contribution of each component to the model performance through a series of self-comparison experiments. Table 1 shows the detailed comparative experimental results. In the first two experiments, the model uses the F3 features to predict grasp configuration, and in the second experiment, we introduce feature filtering units. The performance of the RGB image changes slightly.
The reason is that the background of the center-cropped Cornell grasp dataset is clean, so the F3 features generated by the model can easily determine the location of objects, as shown in Fig. 4. We use the first and third sets of experiments to explore the effectiveness of the feature fusion mechanism on model performance. We can see that the model’s accuracy with the feature fusion mechanism outperforms the Baseline by 2.65% when RGB images are used as input. This is because the C3 features after feature fusion contain both detailed information and semantic information. As described in Fig. 4, object information in the C3 features is more affluent than that in the F3 features. At the same time, by comparing the experimental results of No. 2 and No. 3, we can see that the feature fusion mechanism has a more significant contribution to grasping detection in the case of a simple background. We believe that this result will improve when the environment becomes complex. In the last experiment, the model included feature fusion and feature filtering mechanisms, and the model performance was 3.88% higher than the Baseline when RGB images were input into the model. This demonstrates that the method and contribution we proposed effectively improve the performance of the grasping detection model.

During the entire ablation experiment, we only used C3 and F3 features to predict the grasp configuration. The input image size in our model is 480^2×480, and the object occupies only a small part of pixels in the image. After 16 times downsampling, there are few features of the object left, as shown in Fig. 4, F5. Moreover, F5 features almost contain no structural information but more semantic information, which is not reasonable for grasping prediction. In addition, it is difficult to filter the diminished and distorted feature information. In contrast, C3 and F3 features are more suitable for grasp detection because C3 and C4 provide finer features containing more detailed image information with little loss of network depth.

### B. Results for Single-object Grasp

Table II summarizes the results of our method and the state-of-the-art methods on the single-object Cornell grasp dataset. In the case of the VGG-16 backbone network, the comparison with Zhang et al. [25] shows that our approach improves the performance of the grasp detection model. At the same time, compared with the state-of-the-art method, our model’s accuracy has the lowest variability under different Jacquard thresholds. The reason may be that our model learns and predicts grasp configurations from the overall features of the object rather than the local features of the object. Therefore, the model is not disturbed by local features, and it is easier for the model to find grasping positions that match human grasping habits.

Table III summarizes the results of the previous methods and our proposed method. We can see that our algorithms achieve the highest accuracy. Compared with the method of using anchor with position prior submitted by Guo et al. [5], our method achieves a 5.18% gain of the final performance. This demonstrates that the feature filtering mechanism proposed by us can effectively guide the model to focus on the features of the object itself and minimize the influence of irrelevant features on the model performance. Compared with the ROI-based grasp detection algorithm proposed by Zhang et al. [13], our algorithm using lightweight Backbone has achieved a 4.78% improvement in performance. The reason may be that the more detailed feature extraction method of our algorithm provides excellent aid to the improvement of model performance.

Table IV summarizes the accuracy of our algorithm and Zhang’s algorithm [25] under different angle thresholds. We can see that our algorithm can still maintain satisfactory performance even when the angle threshold is under the harsh condition of 10°. At the same time, our model has good robustness to the change of angle threshold from the perspective of accuracy variation amplitude. This also proves that the object-centric grasping detection method can obtain better performance.

In Fig. 7, we visualized semantic grasping results and the corresponding ground-truth of our model in the test set of the Cornell Grasp dataset. Our model uses the results of semantic segmentation to filter the features entering the grasp detector, so the semantic segmentation branch provides semantic information for the grasp detector, making the generated grasp configuration with semantic information. As shown in Fig. 7, the first and third rows are the predicted results of the model, containing the grasp configuration and corresponding semantic information, confidence score. The second and fourth rows are ground truth.

Some detection results judged to be incorrect by the model are shown in Fig. 8. We can see that the grasping positions predicted by the model are all correct, but the predicted angles are biased. This is the main reason to be judged as an unsuccessful grasp. On the other hand, even though there is a significant deviation between the predicted grasping

| TABLE I  | SELF-COMPARISON EXPERIMENTS ON CORNELL GRASP DATASET UNDER DIFFERENT CONDITIONS |
|---|---|---|
| No. | Method | Setting | Accuracy (%) |
| 1 | Baseline | RGB, F3 | 94.5 |
| 2 | Baseline | RGB, F3 | 94.5 |
| 3 | Baseline | RGB, C3 | 98.0 |
| 4 | Baseline, Feature filtering | RGB, C4 | 95.76 |

| TABLE II  | ACCURACY OF DIFFERENT METHODS |
|---|---|---|---|
| Author | Backbone | Input | Accuracy (%) |
| Guo et al. [5] | ResNet-50 | RGB | 93.2 |
| Zhang H. et al. [13] | - | RGB | 93.6 |
| Fu-Jen. et al. [6] | RGB-D | 96.0 |
| Ours | VGG-16 | RGB | 98.38 |

In Table II, we summarize the results of different methods. We can see that our algorithm achieves the highest accuracy, indicating that our method is effective in improving the performance of the grasp detection model.
TABLE III  ACCURACY UNDER DIFFERENT JACCARD THRESHOLDS

| Author         | Backbone | Input | 20%  | 25%  | 30%  | 35%  | Variability (%) |
|----------------|----------|-------|------|------|------|------|-----------------|
| Guo et al. [5] | -        | RGD   | 93.8 | 93.2 | 91.0 | 85.3 | 9               |
| Chu et al. [6] | ResNet-50 | RGD   | -    | 96.0 | 94.9 | 92.1 | 4               |
| Zhang et al. [25] | VGG-16 | RGD   | 98.0 | 97.5 | 93.8 | 87.5 | 10.7            |
|                 | ResNet-101 | RGD  | 98.88| 98.88| 96.4 | 93.7 | 5.2             |
| Ours            | VGG-16   | RGB   | 99.46| 98.38| 98.03| 96.39| 3.1             |

TABLE IV  ACCURACY UNDER DIFFERENT ANGLE THRESHOLDS

| Author           | Backbone | Input | 10º  | 20º  | 30º  | Accuracy (%) |
|------------------|----------|-------|------|------|------|---------------|
| Zhang et al [25] | VGG-16   | RGD   | 79.0 | 95.1 | 97.5 | 91.93         |
| Ours             | VGG-16   | RGB   | 91.93| 97.24| 98.38| 98.38         |

Figure 7. The results of semantic grasp detection. The first and third rows are the predicted results of the model, containing the grasp configuration and corresponding semantic information. The second and fourth rows are ground truth.

Figure 8. Unsuccessful grasp detection from our model. The first row is the detection result. The second row is the corresponding ground truth.

configuration and the ground-truth in angle, there are still some predicted grasp configurations that the robotic can successfully grasp in practice, such as the situation in the second and fourth images. Therefore, incomplete annotated datasets are also a factor that affects the performance of the model.

VII. CONCLUSION

In this paper, we propose a novel semantic grasping detection model. Inspired by human grasping habits, we propose a feature filtering mechanism in this model to reduce the influence of irrelevant features on grasping detection, which effectively improves the performance of grasp detection. Moreover, based on this mechanism, our algorithm realizes object-centric semantic grasping detection. Besides, the feature fusion mechanism is used for robotic grasping detection, which enriches the semantic and fine-grained information of object features. The results of ablation experiments also demonstrate the effectiveness of our proposed methods. The final experimental results show that the proposed grasping detection algorithm based on VGG-16 achieves an accuracy of 98.38%, which means our method is comparable with the current state-of-the-art grasp detection algorithms on the Cornell grasp dataset.

REFERENCES

[1] Joseph Redmon and Anelia Angelova, “Real-time grasp detection using convolutional neural networks”, IEEE International Conference on Robotics and Automation, pp. 1316-1322, 2015.
[2] Shao Z, Qu Y, Ren G, et al. Batch Normalization Masked Sparse Autoencoder for Robotic Grasping Detection[C]//2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2020: 9614-9619
[3] Cheng H, Ho D, Meng M Q H. High Accuracy and Efficiency Grasp Pose Detection Scheme with Dense Predictions[C]//2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020: 3604-3610.
[4] Sulabh Kumra and Christopher Kanan, “Robotic grasp detection using deep convolutional neural networks”, Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems, 2017.
[5] Guo D, Sun F, Liu H, et al. A hybrid deep architecture for robotic grasp detection[C]//2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017: 1609-1614.
[6] Fu-Jen Chu, Raimian Xu and Patricio Vela, "Real-world multi-object multi-grasp detection", IEEE Robotics and Automation Letters, 2018.
[7] Xinwen Zhou, Xuguang Lan, Hanbo Zhang, Zhiqiang Tian, Yang Zhang and Nanning Zheng, "Fully convolutional grasp detection
network with oriented anchor box", IEEE/RSJ International Conference on Intelligent Robots and Systems, 2018.

[8] D. Park, Y. Seo and S. Y. Chun, "Real-Time, Highly Accurate Robotic Grasp Detection using Fully Convolutional Neural Network with Rotation Ensemble Module," IEEE International Conference on Robotics and Automation, Paris, France, pp. 9397-9403, 2020.

[9] Ren S, He K, Girshick R, et al. Faster r-cnn: Towards real-time object detection with region proposal networks[J]. Advances in neural information processing systems, 2015, 28: 91-99.

[10] Jia Q, Cao Z, Zhao X, et al. Object Recognition, Localization and Grasp Detection Using a Unified Deep Convolutional Neural Network with Multi-task Loss[C]/2018 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, 2018: 1557-1562.

[11] Zhang H, Lan X, Bai S, et al. A multi-task convolutional neural network for autonomous robotic grasping in object stacking scenes[C]/2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2019: 6435-6442.

[12] Park D, Seo Y, Shin D, et al. A single multi-task deep neural network with post-processing for object detection with reasoning and robotic grasp detection[C]/2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020: 7300-7306.

[13] Zhang H, Lan X, Bai S, et al. Roi-based robotic grasp detection for object overlapping scenes[C]/2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2019: 4768-4775.

[14] Dong M, Wei S, Yu X, et al. Mask-GD segmentation based robotic grasp detection[J]. arXiv preprint arXiv:2101.08183, 2021.

[15] Morrison D, Corke P, Leitner J. Closing the loop for robotic grasping: A real-time, generative grasp synthesis approach[J]. arXiv preprint arXiv:1804.05172, 2018.

[16] Caldera S, Rassau A, Chai D. Review of deep learning methods in robotic grasp detection[J]. Multimodal Technologies and Interaction, 2018, 2(3): 37.

[17] 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.

[18] Bohg J, Morales A, Asfour T, et al. Data-driven grasp synthesis—a survey[J]. IEEE Transactions on Robotics, 2013, 30(2): 289-309.

[19] Sahbani A, El-Khoury S, Bidaud P. An overview of 3D object grasp synthesis algorithms[J]. Robotics and Autonomous Systems, 2012, 60(3): 326-336.

[20] Bicchi A, Kumar V. Robotic grasping and contact: A review[C]/Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065). IEEE, 2000, 1: 348-353.

[21] Jiang Y, Moseson S, Saxena A. Efficient grasping from rgbd images: Learning using a new rectangle representation[C]/2011 IEEE International conference on robotics and automation. IEEE, 2011: 3304-3311.

[22] Song Y, Gao L, Li X, et al. A novel robotic grasp detection method based on region proposal networks[J]. Robotics and Computer-Integrated Manufacturing, 2020, 65: 101963.

[23] Jang E, Vijayanarasimhan S, Pastor P, et al. End-to-end learning of semantic grasping[J]. arXiv preprint arXiv:1707.01932, 2017.

[24] Cai J, Tao X, Cheng H, et al. CCAN: Constraint Co-Attention Network for Instance Grasping[C]/2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020: 8353-8359.

[25] Zhang H, Zhou X, Lan X, et al. A real-time robotic grasping approach with oriented anchor box[J]. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2019.