Real-Time, Highly Accurate Robotic Grasp Detection using Fully Convolutional Neural Networks with High-Resolution Images

Dongwon Park, Yonghyeok Seo, and Se Young Chun

Abstract—Robotic grasp detection for novel objects is a challenging task, but for the last few years, deep learning based approaches have achieved remarkable performance improvements, up to 96.1% accuracy, with RGB-D data. In this paper, we propose fully convolutional neural network (FCNN) based methods for robotic grasp detection. Our methods also achieved state-of-the-art detection accuracy (up to 96.6%) with state-ofthe-art real-time computation time for high-resolution images (6-20ms per 360×360 image) on Cornell dataset. Due to FCNN, our proposed method can be applied to images with any size for detecting multigrasps on multiobjects. Proposed methods were evaluated using 4-axis robot arm with small parallel gripper and RGB-D camera for grasping challenging small, novel objects. With accurate vision-robot coordinate calibration through our proposed learning-based, fully automatic approach, our proposed method yielded 90% success rate.

I. INTRODUCTION

Robot grasping of novel objects has been investigated extensively, but it is still a challenging, open problem in robotics. Humans instantly identify multiple grasping areas of novel objects (perception) and almost instantly plan how to pick them up (planning), and then actually grasp it reliably (control). However, accurate robotic grasp detection, trajectory planning, and reliable execution are quite challenging for robots. As the first step, detecting robotic grasps accurately and quickly from imaging sensors (e.g., RGB-D camera) is an important task for successful robotic grasping.

Robotic grasp detection or synthesis has been widely investigated for many years. Grasp synthesis is divided into analytical and empirical (or data-driven) methods [1] for known, familiar objects and novel objects [2]. In particular, machine learning (non-deep learning) based approaches for robotic grasp detection have utilized data to learn discriminative features for a suitable grasp configuration and to yield excellent performance on generating grasp locations [3], [4], [5]. A typical approach for them is to use a sliding window to select local image patches and to evaluate graspability so that the best image patch with the highest graspability score is chosen for robotic grasp detection result. In 2011, one of the state-of-the-art graspability prediction accuracies without deep learning was 60.5% and its computation time per image was very slow due to sliding windows (50 sec per image) [5].

Deep learning has been successful in computer vision applications such as image classification [6], [7] and object detection [8], [9]. Deep learning has also been utilized for

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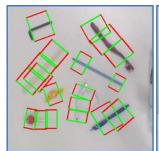




Fig. 1: (Left) an example of detecting multiple robotic grasps (5D grasp representations) for multiple objects in one image using our proposed method. (Right) an example of our real robotic grasp experiment picking up a toothbrush.

robotic grasp detection and has achieved significant improvements over conventional methods. Lenz et al. proposed deep learning classifier based robotic grasp detection methods that achieved up to 73.9% (image-wise) and 75.6% (object-wise) prediction accuracy [10], [11]. However, its computation time per image was still slow (13.5 sec per image) due to sliding windows. Redmon et al. proposed deep learning regressor based grasp detection methods that yielded up to 88.0% (image-wise) and 87.1% (object-wise) with remarkably fast computation time (76 ms per image) [12]. Recently, Chu et al. proposed two-stage neural networks with grasp region proposal network and robotic grasp detection networks and have achieved up to 96.0% (image-wise) and 96.1% (objectwise) prediction accuracies [13]. However, its computation time has slightly increased due to region proposal network (120 ms per image). Real-time robotic grasp detection can be critical for some applications with dynamic environment or dynamic objects. Thus, reducing computation time while maintaining high prediction accuracy seems desirable.

In this paper, we proposed novel fully convolutional neural network (FCNN) based methods for robotic grasp detection. Our proposed methods yielded state-of-the-art performance comparable to the work of Chu *et al.* [13] while their computation time is much faster for high resolution image (360×360 image). Note that most deep learning based robotic grasp detection works used 227×227 resized image including [13]. Our proposed methods can perform multi-object, multigrasp detection as shown in Fig. 1 (Left). Our proposed methods were evaluated with a 4-axis robot as shown in Fig. 1 (Right) and achieved 90% success rate for real grasping tasks with novel objects. Since this small robot has a gripper with the maximum range of 27.5 mm, it was critical to accurately calibrate robotic grasp information

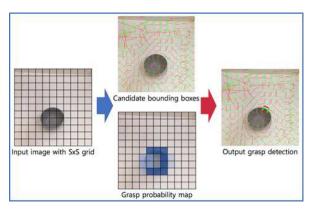


Fig. 2: A typical multibox approach for robotic grasp detection. An input image is divided into $S \times S$ grid and regression based robotic grasp detection is performed on each grid box. Then, the output with the highest grasp probability is selected as the final result. This approach can be applied to multiobject, multigrasp detection tasks.

and our vision system information. We proposed a simple learning-based vision-robot calibration method and achieved accurate calibration and robot grasping performance. Here is the summary of the contributions of this paper:

- 1) Newly proposed real-time, single-stage FCNN based robotic grasp detection methods that yielded state-of-the-art computation time for high resolution image (360×360 image) while achieving comparable state-of-the-art prediction accuracies, especially for more strict performance metrics. For example, our method achieved 96.6% image-wise, 95.1% object-wise with 10 ms per high-resolution image while the work of Chu et al. [13] achieved 96.0% image-wise, 96.1% object-wise with 120 ms per low-resolution image. In other words, our method yielded comparable accuracies with 12× faster computation than Chu et al. [13]. Our FCNN based methods can be applied to multigrasp, multiobject detection.
- 2) Our proposed methods were evaluated for real grasping tasks and yielded 90.0% success rate with challenging small, novel objects and with a small parallel gripper (max open width 27.5 mm). This was possible due to our proposed simple, full automatic learning-based approach for vision-robot calibration. Our method achieved less than 1.5 mm error for calibration, which is close to vision resolution.

II. RELATED WORK

Pre-deep learning era. Data-driven robotic grasp detection for novel object has been investigated extensively [2]. Saxena *et al.* proposed a machine learning based method to rank the best graspable location for all candidate image patches from different locations [3]. Jiang *et al.* proposed a 5D robotic grasp representation and further improved the work of Saxena *et al.* by proposing a machine learning method to rank the best graspable image patch whose representation includes orientation and gripper distance among

all candidates [5]. The work of Jiang *et al.* achieved the prediction accuracy of 60.5% (image-wise) and 58.3% (object-wise) with computing time of 50 sec (50,000 ms) per image.

Two-stage, classification based approach. Lenz et al. proposed to use a sparse auto-encoder (SAE), an early deep learning model, to rank the best graspable candidate image patch from sliding window with multi-modal information (color, depth and surface norm) [10], [11]. Their methods achieved up to 73.9% (image-wise) and 75.6% (object-wise) prediction accuracy, but its computation time per image was still slow (13.5 sec or 13,500 ms per image) due to timeconsuming sliding windows. Wang et al. proposed a realtime classification based grasp detection method using a stacked SAE for classification, which is similar to the work of Lenz et al., but with remarkably efficient grasp candidates generation [14]. This method utilized prior information and pre-processing to reduce the search space of grasp candidates such as object recognition result and the graspability of previously evaluated image patches. It also reduced the number of grasp representation parameters such as height (h) for known gripper and orientation (θ) that could be analytically obtained from surface norm. Mahler et al. proposed Dex-Net 2.0 for point clouds based on two-stage approach with GQ-CNN and reported that 93.0% (image-wise) prediction accuracy was achieved [15]. Note that this approach is similar to those of R-CNN [16] or fast R-CNN [17] in object detection.

Single-stage, regression based approach. Redmon *et al.* proposed a deep learning regressor based robotic grasp detection method based on the AlexNet [6] that that yielded 84.4% (image-wise) and 84.9% (object-wise) with fast computation time (76 ms per image) [12]. When performing robotic grasp regression and object classification together, image-wise prediction accuracy of 85.5% was able to be achieved without increasing computation time. Kumra *et al.* also proposed a real-time regression based grasp detection method using ResNet [7] especially for multimodal information (RGB-D). Their method yielded up to 89.2% (image-wise) and 88.9% (object-wise) prediction accuracies with fast computation time (103 ms per image) [18].

Multibox based approach. Redmon et al. also proposed a multibox based robotic grasp detection method (called MultiGrasp) by dividing the whole input image into $S \times S$ grid and applying regression based robotic grasp detection to each grid box [12]. This approach did not increase computation time (76 ms per image), but did increase prediction accuracy up to 88.0% (image-wise) and 87.1% (object-wise). The pipeline of multibox based approach is illustrated in Fig. 2. Note that the last step (red arrow) is a simple selection on the highest grasp probability. Simply modifying this last step to select more than one result could result in multiobject, multigrasp detection. Guo et al. proposed a hybrid multibox based approach with visual and tactile data based on ZFnet [19] by classifying graspability, orientations (θ), and by regressing locations and graspable width (w), height (h) [20]. The work of Guo et al. achieved 93.2% (image-wise) and 89.1% (object-wise) prediction accuracies.

Note that MultiGrasp by Redmon et al. has influenced sev-

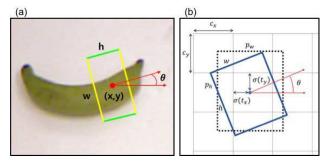


Fig. 3: (a) A 5D grasp representation with location (x, y), orientation θ , gripper opening width w and plate size h. (b) For the (2,2) grid cell, all parameters for 5D grasp representation are illustrated including a pre-defined anchor box (black dotted box), a 5D grasp representation (blue box).

eral object detection methods such as YOLO [21], SSD [22], and recently YOLO9000 [9]. YOLO is based on AlexNet [6] to estimate the location and class of multiple objects [21]. SSD further developed regression based object detection by incorporating intermediate CNN features [22]. Recently, YOLO9000 extended the original YOLO significantly with fast computation and high accuracy [9]. Our proposed robotic grasp detection methods are inspired by YOLO9000 [9].

Hybrid approach. Recently, Asif *et al.* proposed Grasp-Net that predicts graspability and then estimates robotic grasp parameters based on high-resolution grasp probability map [23]. This approach achieved 90.6% (image-wise) and 90.2% (object-wise) with state-of-the-art computation time (24 ms per image). Chu *et al.* proposed two-stage neural networks combining grasp region proposal network and robotic grasp detection network [13] based on Faster R-CNN for object detection tasks [8]. This approach has yielded state-of-the-art prediction accuracies, 96.0% (image-wise) and 96.1% (object-wise), with slightly increased computation time due to region proposal network (120 ms per image).

III. PROPOSED METHODS FOR ROBOTIC GRASPS

A. Problem Description

The goal of the problem is to predict 5D robotic grasp representations [5], [11] for multiple objects from a given color image (RGB) and possibly depth image (RGB-D) where a 5D robotic grasp representation consists of location (x,y), orientation θ , gripper opening width w, and parallel gripper plate size h, as illustrated in Fig. 3 (a). Then, the 5D robotic grasp representation

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

in camera based vision coordinate system should be transformed into a new 5D grasp representation $\{\tilde{x}, \tilde{y}, \tilde{\theta}, \tilde{w}, \tilde{h}\}$ in actual robot coordinate system so that they can be used for actual robot grasping task.

B. Reparametrization of 5D Grasp Representation and Grasp Probability

MultiGrasp estimates 5D grasp representation $\{x, y, \theta, w, h\}$ as well as grasp probability (confidence)

z for each grid cell by reparameterizing θ to be $c=\cos\theta,\ s=\sin\theta$ [12]. In other words, 7 parameters $\{x,y,c,s,w,h,z\}$ are directly estimated using deep learning based regressors in MultiGrasp. This approach has also been used in YOLO, object detection deep network [21]. Inspired by YOLO9000, a better and faster deep network for object detection than YOLO [9], we propose the following reparametrization of 5D grasp representation and grasp probability for robotic grasp detection as follows:

$$\{t^x, t^y, \theta, t^w, t^h, t^z\}$$

where $x = \sigma(t^x) + c_x$, $y = \sigma(t^y) + c_y$, $w = p_w \exp(t^w)$, $h = p_h \exp(t^h)$, and $z = \sigma(t^z)$. Note that $\sigma(\cdot)$ is a sigmoid function, $\exp(\cdot)$ is an exponential function, p_h , p_w are the pre-defined height and width of an anchor box, respectively, and (c_x, c_y) are the location of the top left corner of each grid cell (known). Thus, deep neural network for robotic grasp detection of our proposed methods will estimate $\{t^x, t^y, \theta, t^w, t^h, t^z\}$ instead of $\{x, y, \theta, w, h, z\}$. These parameters are illustrated in Fig. 3 (b). Note that x, y, w, h are properly normalized so that the size of each grid cell is 1×1 . Lastly, the angle θ will be modeled as a discrete value instead of a continuous value, which is different from MultiGrasp. This discretization of the angle in robotic grasp detection was also used in [20].

(x, y) coordinates in each grid cell (offset). Instead of predicting (x, y) in the image coordinate, our proposed methods will predicting the location of robotic grasp by estimating the (x, y) offset from the top left corner of each grid cell (c_x, c_y) . For $S \times S$ grid cells,

$$(c_x, c_y) \in \{(c_x, c_y) | c_x, c_y \in \{0, 1, \dots, S - 1\}\}$$

Thus, for a given (c_x, c_y) , the range of (x, y) will be

$$c_x < x < c_x + 1, \quad c_y < y < c_y + 1$$

due to the re-parametrization using sigmoid functions.

w, h coordinates in each cell (anchor box). Anchor box approach has also been useful for object detection [9], so we adopt it to our robotic grasp detection. Due to the re-parametrization using anchor box, estimating w, h is converted into estimating t^w, t^h , which are related to the expected values of various sizes of w, h, and then classifying the best grasp representation among all anchor box candidates. In other words, this re-parametrization changes regression problems for w, h into regression + classification problems. We propose to use the following 7 anchor boxes:

$$(p_w, p_h) \in \{(0.76, 1.99), (0.76, 3.20), (1.99, 0.76), (1.99, 1.99), (1.99, 3.20), (3.20, 3.20), (3.20, 0.76)\}.$$

C. Loss Function for Robotic Grasp Detection

We proposed a novel loss function for robotic grasp detection considering the following items.

Angle in each cell (discretization). MultiGrasp reparameterized the angle θ with $c = \cos \theta$ and $s = \sin \theta$ so that estimating c, s yields the estimated $\theta = \arctan(s/c)$.

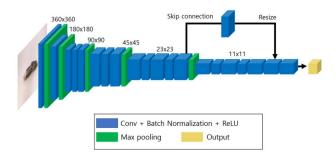


Fig. 4: Proposed FCNN architecture based on Darknet-19.

Thus, MultiGrasp took regression approach for θ . We proposed to convert this regression problem for estimating θ into the classification problem for θ among finite number of angle candidates in $[0,\pi]$. Specifically, we model that $\theta \in \{0,\pi/18,\ldots,\pi\}$. Along with data augmentation for different angles every epoch, we were able to observe substantial performance improvement. Similar angle discretization for robotic grasp detection was also used in [20].

Grasp probability (new ground truth). Predicting grasp probability is crucial for multibox approaches such as Multi-Grasp. Conventional ground truth for grasp probability was 1 (graspable) or 0 (not graspable) as used in [12]. Inspired by YOLO9000, we proposed to use IOU (Intersection Over Union, Jaccard index) as the ground truth for grasp probability: the ground truth for grasp probability is

$$z^g = \frac{|P \cap G|}{|P \cup G|} \tag{1}$$

where P is the predicted grasp rectangle, G is the ground truth grasp rectangle, and $|\cdot|$ is the area of the inner set.

Proposed loss function. We propose to use the follow cost function to train robotic grasp detection networks that we will describe in the next subsection: For the output vector of the deep neural network $(t^x, t^y, \theta, t^w, t^h, t^z)$ and the ground truth $\{x^g, y^g, \theta^g, w^g, h^g, z^g\}$,

$$\begin{split} &L(t^{x}, t^{y}, \theta, t^{w}, t^{h}, t^{z}) = \\ &\lambda_{\text{coord}} \sum_{i=1}^{S^{2}} \sum_{j=1}^{A} m_{ij}^{obj} [(x_{i}^{g} - x_{i})^{2} + (y_{i}^{g} - y_{i})^{2}] + \\ &\lambda_{\text{coord}} \sum_{i=1}^{S^{2}} \sum_{j=1}^{A} m_{ij}^{obj} [(w_{ij}^{g} - w_{ij})^{2} + (h_{ij}^{g} - h_{ij})^{2}] + \\ &\lambda_{\text{prob}} \sum_{i=1}^{S^{2}} \sum_{j=1}^{A} m_{ij}^{obj} [(z_{i}^{g} - z_{i})^{2}] + \\ &\lambda_{\text{class}} \sum_{i=1}^{S^{2}} \sum_{j=1}^{A} m_{ij}^{obj} \text{CrossEntropy}(\theta_{i}^{g}, \theta_{i}) \end{split}$$

where $x_i, y_i, w_{ij}, h_{ij}, z_i$ are functions of $(t^x, t^y, t^w, t^h, t^z)$, respectively, S^2 is the number of grid cells and A is the number of anchor boxes (7 in our case). We set $\lambda_{\rm coord} = 1$, $\lambda_{\rm prob} = 5$ and $\lambda_{\rm class} = 1$. We set $m_{ij} = 1$ if the ground truth (x^g, y^g) is in the ith cell and $m_{ij} = 0$ otherwise.

D. Proposed FCNN Architecture

We chose three well-known deep neural networks for image classification tasks Alexnet [6] (base network for Multi-Grasp [12]), Darknet-19 (similar to VGG-16 [24] that was used in [13], but with much smaller memory requirement for similar performance) [9], and Resnet-50 [7] (base network for [20], [13]). These pre-trained networks were modified to yield robotic grasp parameters and their fully connected (FC) layers were replaced by 1×1 convolution layers to make FCNN architecture so that images with any size (e.g., high resolution images) can be processed. Most previous robotic grasp detection methods use 227×227 resized images as input, but our proposed FCNN based methods can process higher resolution images. We chose to process 360×360 images for grasp detection without resizing. Skin connection layer was also added so that fine grain features can be used. For example, a passthrough layer was added in between the final $3 \times 3 \times 512$ layer and the second to last convolutional layer for Darknet-19 as illustrated in Fig. 4 [9]. Similarly. we added similar skip connection for Resnet-50 in between the convolutional layer right before the last max pooling layer and detection layer. Unfortunately, we did not add skip connection for Alexnet since the pre-trained network did not provide access to inner layers.

E. Learning-based Vision-Robot Calibration

For a successful robot grasping, accurately predicted 5D grasp representation $\{x,y,\theta,w,h\}$ in vision coordinate system must be converted into 5D grasp representation $\{\tilde{x},\tilde{y},\tilde{\theta},\tilde{w},\tilde{h}\}$ in actual robot coordinate system considering gripper configuration. Thus, accurate calibration between vision and robot coordinate systems is critical for robotic grasping. Our robot is equipped with a gripper whose maximum open distance w is 27.5 mm. In order to grasp small objects whose widths are 10-20 mm, the calibration error between vision and robot coordinates should be less than or equal to 1-2 mm.

We proposed a learning-based, fully automatic vision-robot calibration method as illustrated in Fig. 5: (1) a small known object (round shape in our case) is placed in a known location, (2) the robot moves the object to a random

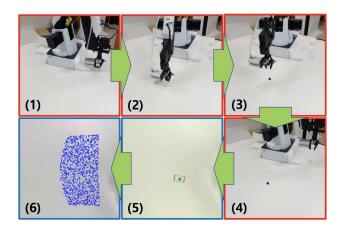


Fig. 5: Proposed learning-based vision-robot calibration.

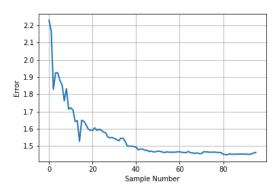


Fig. 6: Calibration error (in mm) for x, y in robot coordinate system over increasing number of learning samples.

location, (3) the robot places the object, (4) the robot is away from field of view, (5) vision system predicts 5D grasp representation, and (6) the procedure is repeated to collect many samples. Then, 5D grasp representations in both vision coordinate and robot coordinate can be mapped using linear or nonlinear regressions or using simple nonlinear neural networks. For simplicity, we calibrated only x, y with affine transformation using LASSO [25] assuming known w (maximum open width of the gripper), known h (fixed gripper), and relatively good tolerance for θ . The ranges of x, y in our robot coordinate are 150 to 326 mm, -150 to 150 mm, respectively, and the ranges of x, y in our vision coordinate are 160 to 290 pixel, 50 to 315 pixel, respectively. One pixel corresponds to about $1.35 \times 1.13 \text{ mm}^2$.

Fig. 6 shows that calibration error (in mm) is in general decreasing as the number of samples is increasing and the error is below 1.5 mm which is close to one pixel in vision if there are more than 40 samples. Note that since there are 6 LASSO coefficients for mapping x, y's, theoretically only 3 points should be enough to determine all 6 coefficients. However, in practice, much more samples are necessary to ensure good calibration accuracy. This result implies that using high resolution images seem important for successful grasping due to potential high accuracy of calibration.

IV. EXPERIMENTS AND EVALUATION

A. Evaluation with Cornell Dataset

We performed benchmarks using the Cornell grasp detection dataset [10], [11] as shown in Fig. 7. This dataset consists of 855 images (RGB color and depth) of 240



Fig. 7: Images from Cornell grasp detection dataset.



Fig. 8: Novel objects for real robot grasping tasks.

different objects with the ground truth labels of a few graspable rectangles and a few not-graspable rectangles. Note that we cropped images with 360×360 , but did not resize it to 224×224 . Five-fold cross validation was performed and average prediction accuracy was reported for image-wise and object-wise splits. When the difference between the output orientation θ and the ground truth orientation θ^g is less than 30° , then IOU or Jaccard index in Eq. (1) that is larger than a certain threshold (e.g., 0.25, 0.3) will be considered as a success grasp detection. The same metric for accuracy has been used in other previous works [11], [12], [18].

All proposed methods were implemented using pyTorch and trained with 500 epochs and data augmentation that took about 4 hours of training. For fair comparison, we implemented the work of Lenz *et al.* [10], [11] and Multi-Grasp [12] using MATLAB or Tenforflow. They achieved similar performance and computation time that were reported in their original papers. All algorithms were tested on the platform with a single GPU (NVIDIA GeForce GTX1080Ti), a single CPU (Intel i7-7700K 4.20GHz) and 32GB memory.

B. Evaluation with 4-axis Robot Arm and RGB-D

We also evaluated our proposed methods with a small 4-axis robot arm (Dobot Magician, Shenzhen YueJiang Tech Co., Ltd, China, Fig. 1 (Right)) and a RGB-D camera (Intel RealSense D435, Intel, USA) attached to have the field-of-view including the robot and its workspace from the top. The following 6 novel objects (toothbrush, candy, earphone cap, cable, styrofoam bowl, L-wrench were used for real grasp tasks as shown in Fig. 8. After our learning-based vision-robot calibration, for each object, 5 repetition were performed. If the robot arm is holding an object for more than 3 sec, it is counted as a success grasp.

V. RESULTS

A. Evaluation Results on Cornell Dataset

Table I summarizes all evaluation results on the Cornell robotic grasp dataset for all our proposed methods. Our proposed methods yielded state-of-the-art performance, up to 96.6% prediction accuracy for image-wise split with any metric with state-of-the-art computation time of 3-20 ms. For object-wise split, our proposed methods yielded comparable results for less tolerant metrics (25%, 30%), but yielded state-of-the-art performance for more strict metrics (35%, 40%), demonstrating that our methods yielded highly accurate grasp detection information with true real-time computation. The results of Table I also indicate the importance of good deep network (Darknet, Resnet over Alexnet), of using reparametrization (Offset), and of using high resolution images as input for better performance. Fig. 9 qualitatively illustrates some of these points. Using low resolution image and/or

TABLE I: Performance summary on the Cornell dataset with IOU metric. Our proposed methods yielded state-of-the-art prediction accuracy in both image-wise and object-wise splits with state-of-the-art computation time. Note that Resnet-50, Darknet-19, Alexnet require 82.6, 48.5, and 6.0MB memory, respectively. Performance unit is in % unless specified.

Image size	Offset	Deep network	Data type	Image-wise				Object-wise				Time / image (ms)
image size				25%	30%	35%	40%	25%	30%	35%	40%	Time / image (ms)
360	О	Resnet-50	RG-D	96.6	94.6	91.5	86.7	95.4	92.5	88.5	82.5	20
360	О	Resnet-50	RGB	96.6	93.7	91.0	85.7	95.1	92.5	88.7	82.9	10
360	О	Darknet-19	RG-D	96.6	95.4	92.4	87.4	94.7	92.0	89.0	83.2	15
360	О	Darknet-19	RGB	96.4	93.6	90.7	86.5	94.0	91.3	86.5	80.3	6
360	-	Darknet-19	RGB	89.8	87.6	84.9	80.1	87.7	85.4	81.6	72.5	6
224	О	Darknet-19	RGB	93.5	89.7	85.4	77.7	91.5	88.0	81.9	75.6	8
360	О	Alexnet	RGB	93.6	90.3	86.5	80.2	91.1	86.8	81.0	73.5	4
224	-	Alexnet	RGB	89.1	79.5	69.0	57.3	86.7	76.6	64.6	51.1	3
227	Chu [13]			96.0	94.9	92.1	84.7	96.1	92.7	87.6	82.6	120
227	Guo [20]#a			93.2	91.0	85.3	-	82.8	79.3	74.1	-	-
227	Guo [20]#c			86.4	83.6	76.8	-	89.1	85.1	80.5	-	-
227	Kumra [18]			89.2	-	-	-	88.9	-	-	-	10
227	Redmon [12]			88.0	-	-	-	87.1	-	-	-	76
227	Lenz [10]			73.9	-	-	-	75.6	-	-	-	13500
227	Jiang [5]			60.5	-	-	-	58.3	-	-	-	50000

simple network architecture seems to result in missing small graspable candidates as indicated with missing small graspable areas around shoe neck.

B. Evaluation Results with 4-Axis Robot Arm

Fig. 10 illustrates our robot grasp experiment with "candy" object. While previous methods or our method with low image resolution tend to grasp candy part, our proposed method yielded grasp areas around stick part of the candy and our robot actually grasped it as shown in the figure. Table II summarizes our robot experiments showing that our proposed method with high resolution yielded 90% grasp success rate while other methods yielded 53% or less.

VI. CONCLUSIONS

We proposed real-time, highly accurate robotic grasp detection methods that yielded state-of-the-art prediction accuracies with state-of-the-art computation times. We also demonstrated that high accuracy of our proposed methods

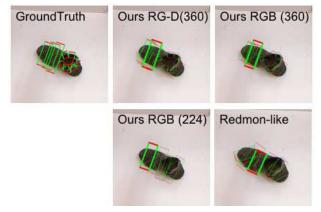


Fig. 9: One grasp detection results with different image resolution, data type, and with different deep network. All methods were able to detect large grasp areas, but the methods with small deep network and/or low image resolution missed some small grasp areas.

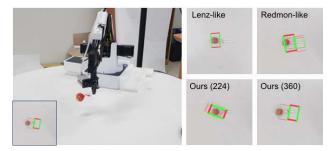


Fig. 10: An illustration of our robot grasp experiment with "candy" (Left) and multigrasp detection results for "candy" using 4 different methods. Ours (360) successfully detect stick part of the candy.

with our proposed learning-based, fully automatic vision-robot calibration method yielded 90% success rate in robotic grasping tasks with challenging small objects.

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TABLE II: Performance summary of real robotic grasping for 6 novel, small objects with 5 repetitions. For Lenz and Redmon, our in-house implementations (modifications) were used after validating their performance with the Cornell dataset. Darknet implementation was used for Ours with resized image (224) and with high resolution image (360).

Object	Lenz*	Redmon*	Ours(224)	Ours(360)
toothbrush	80%	80%	60%	100%
candy	0%	60%	20%	100%
earphone cap	40%	20%	80%	80%
cable	0%	0%	40%	100%
styrofoam bowl	0%	20%	80%	60%
L-wrench	80%	100%	40%	100%
Average	33%	47%	53%	90%

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