MetaGraspNet: A Large-Scale Benchmark Dataset for Scene-Aware Ambidextrous Bin Picking via Physics-based Metaverse Synthesis

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Abstract—Autonomous bin picking poses significant challenges to vision-driven robotic systems given the complexity of the problem, ranging from various sensor modalities, to highly entangled object layouts, to diverse item properties and gripper types. Existing methods often address the problem from one perspective. Diverse items and complex bin scenes require diverse picking strategies together with advanced reasoning. As such, to build robust and effective machine-learning algorithms for solving this complex task requires significant amounts of comprehensive and high quality data. Collecting such data in real world would be too expensive and time prohibitive and therefore intractable from a scalability perspective. To tackle this big, diverse data problem, we take inspiration from the recent rise in the concept of metaverses, and introduce MetaGraspNet, a large-scale photo-realistic bin picking dataset constructed via physics-based metaverse synthesis. The proposed dataset contains 217k RGBD images across 82 different article types, with full annotations for object detection, amodal perception, keypoint detection, manipulation order and ambidextrous grasp labels for a parallel-jaw and vacuum gripper. We also provide a real dataset consisting of over 2.3k fully annotated high-quality RGB images, divided into 5 levels of difficulties and an unseen object set to evaluate different object and layout properties. Finally, we conduct extensive experiments showing that our proposed vacuum seal model and synthetic dataset achieves state-of-the-art performance and generalizes to real world use-cases.

I. INTRODUCTION

Bin picking with its central role in automation and logistics is an important use-case for autonomous robotic systems in today’s smart warehouses or factories. Many existing commercial systems are able to pick and move objects autonomously by simplifying the task, carefully restricting the item set or structuring the grasp environments. To advance bin picking into the next level, robotic systems must begin to understand the bin scene in order to handle more complex and diverse scenarios, dealing with items differ in shape, color, texture, pose, and dealing with object layouts differ in density and entanglement. In such autonomous systems, vision plays an important role to identify items as well as their poses, grasping points and manipulation order. However, the high complexity of bin scenes as well as the wide range of different articles present great challenges which limit the applicability of today’s robotic systems.

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In this work, we address the vision problem of bin picking in two parts: finding targeted objects, predicting reliable grasp points for the objects. We formulate the object finding as an object detection problem and associate 3 challenges with it in the bin picking context. The first challenge is combining information from multiple modality. Modern robotic grasping systems are equipped with multiple imaging sensors. The most popular ones are RGB and depth. RGB sensor captures the fine details of object’s texture, while depth sensor captures object’s surface location and thus providing excellent geometry information. However, each sensor has its own drawback. RGB sensor is susceptible to shadow, and objects with similar textures are difficult to differentiate. Depth sensor is prone to noise and produces faulty or invalid values for transparent and reflective objects. Leveraging the advantage of both sensor types is a non-trivial problem. The second challenge is scene understanding, namely knowing where objects are and how they are posed and stacked. Objects in cluttered bin scenes are heavily occluded and entangled, which reduces the amount of information that can be used to estimate objects’ pose and their stacking relationship. In addition, it is very common to have multiple instances of the same class randomly stacking in a bin, resulting an object visually breaking into multiple parts, which is prone to being detected as multiple objects. The third challenge is unseen objects, or objects that changes shapes. To detect an unseen object requires the vision system to understand objects at a basic texture and geometry feature.
level. When objects are scattered in the bin, visual features can be separated spatially. When multiple instances of unseen objects stacking together, visual features of the same class entangle at one location, and spatial information is not enough to separate instances.

We formulate grasp points finding as a grasp detection problem. Commercial gripper types includes parallel gripper, suction gripper, variations of both or even 5-finger gripping hands. Each gripper type deals with items with specific shape, and texture. For example, suction gripper can pick box items and bags well, but struggles with complex or filigree objects. With a high diversity of items, there is no single gripper type that is suitable for picking all the items. Highly flexible robotic systems can have multiple gripper types and choosing the right one is non-trivial. A successful grasp is highly dependent on the object’s properties such as local surface property and structure, mass distribution as well as the object’s relationship with other objects in the bin. Finding reliable grasps is therefore not limited to reason about the physical interaction between gripper and object, but also challenges the system to understand the arrangement of objects in the scene and identify an appropriate picking sequence. While many researches have provided excellent datasets on each individual part such as SynPick [1] for pose estimation and gripper-object interaction, REGRAD [2] for relationship reasoning, SuctionNet-1Billion [3] for vacuum grasping or Dex-Net 4.0 [4] for ambidextrous grasping, the problems were only addressed from one side or did not target automation. Because robotic picking is a multi-stage complex problem, solving the problem from one aspect will miss the details of other aspects. Therefore, it is important to have a comprehensive dataset that covers all the aspects of robotic bin picking.

Collecting such comprehensive data from real robot experiments [5], [6] or manually [7] would be too expensive and time prohibitive and as such intractable from a scalability perspective. Motivated by earlier work in the field of synthetic data generation [1], [2] and inspired from the recent rise in the concept of metaverses, we introduce MetaGraspNet: a large-scale photo-realistic physics-based bin picking dataset for ambidextrous grasping and bin scene reasoning. By providing rich semantic scene labels such as amodal segmentation masks or object layout graphs together with heterogeneous grasp labels, object poses, and keypoint labels, MetaGraspNet challenges picking systems to take the next step towards multi-gripper usage and cognitive understanding of bin scenes.

Our contributions can be summarized as following:

- We contribute 36 new objects (including transparent and specular items) suitable for a vacuum or parallel gripper.
- We propose a force-based suction cup model able to predict the vacuum seal for grasp candidates and provide a thorough method for generating parallel-jaw grasps based on physics simulation.
- We contribute a pipeline to generate photo-realistic bin picking scenes together with a large-scale dataset. Besides rich grasp label annotation, it provides segmentation mask, object pose, center of mass heatmaps and propose the concept of semantic object keypoints.
- We present labels to characterize the objects’ layout in the bin: amodal segmentation masks, occlusion rates, object relationship matrix and layout label.
- For evaluation we provide a real dataset consisting of 2.3k pixel-wise annotated RGBD images captured in a logistic setting with an industry-grade camera system.
- We conduct extensive experiments in real world evaluating our proposed vacuum seal model and providing baseline experiments for vacuum grasp point detection and object detection and segmentation.

Our synthetic and real dataset, as well as the complete codebase to generate custom data are publicly available at https://github.com/maximillangilles/MetaGraspNet.

II. RELATED WORK

Datasets for robotic grasping are versatile and differ in many aspects such as scene composition, item diversity, sensor modality, gripper types or labelled properties. Table 1 can be seen as an attempt to give a general overview over existing RGBD datasets and its labelled properties.

Object Sets and Photorealism: Motivated by recent progress in the field of dexterous grasping based on RGBD data [16], we find it beneficial to categorize existing work into depth only or photo-realistic data. While depth only datasets [17], [4], [18], [19], [20], [21] are sufficient for training state-of-the-art grasp detection networks such as [17], [22], [4], they are not applicable to recent multi-modal sensor fusion approaches [16], [3], [23], [24]. Besides this limitation, order picking systems usually depend on an additional upstream object detection. Existing datasets containing textured objects [13], [15], [12] are often limited to the household domain, available in small numbers and represent only a small subset of possible objects in warehouse or industry settings or do not contain real world scans [10].

Parallel-Jaw Grasp Labels and Datasets: Robotic grasping datasets can be categorized by the way its grasp labels are generated. When only considering grasps with four degrees of freedom (DoF), an antipodal grasp can be represented in image space by an oriented bounding box [8], [11] (circle for a suction cup). By transferring the scene and grasp label generation into simulation, [9] was able to increase the dataset size by a factor up to 50 with regard to [8]. With increasing numbers of objects in the scene and complex shape the advantage of 6 DoF grasps becomes more remarkable. Since generating such grasp labels in SE(3) can become very tedious, recent 6 DoF datasets rely on automatic sampling schemes for grasp candidates. The generation of these labels is either based on analytical models such as antipodal-based samplers used in [12], [2] or physics simulation which combines analytical sampling with physics simulators [4], [18]. For an in-depth overview we refer to [25].

Vacuum Grasp Labels and Datasets: Despite the wide deployment of vacuum-based robotic handling systems in
Automation the generation of reliable vacuum grasp labels based on the object’s local shape remains an open field of robotic research, though offering a high potential for energy savings [26]. In [7] appropriate vacuum contact points are sampled by hand. Due to the high-labeling costs their dataset is with 1837 annotated images small in scale. Instead of labelling appropriate areas where vacuum seal can be applied from human experience, Dex-Net 3.0 [19] models the suction cup as a spring system and aims to find suitable suction points on 3D meshes’ surfaces in simulation. The spring model originates from [27], but instead of dynamically simulating the deformation of the suction cup over time as in [28], they simplify the problem by only considering the quasi-static projection of the cup on to the object’s surface and evaluating the geometric deformation of each spring individually. SuctionNet1-Billion [3] simplifies [19] cup model and replaces the original binary scoring by a continuous sealability score. In contrast to [19], their resulting dataset SuctionNet1-Billion has real RGBD data and multiple objects per scene. However, using the semi-automatic annotation process and data from [12] requires manually annotating the objects pose once per scene introducing label inaccuracies, and limiting the items’ arrangement and the overall scene number. In [17] an adaption of [19] model is proposed simulating object-gripper interaction over time. Generating a 3D model for each real-world object is cost-inefficient, and unflexible. Object keypoints is an inexpensive way to describe object shapes and poses in grasping. In fact, many grasping detection and pose estimation works are based on object keypoints [32], [33], but the dataset used in these works are limited in terms of scale and class diversity.

Object Detection and Scene Layout Datasets: Existing object detection datasets in bin picking [29], [30] emphasize scales and number of classes to boost model performance. These datasets do not focus on the unique challenges (described in I) in object detection for bin picking. In highly cluttered scenes items can overlap or are wedged into each other. Simply inferring grasps without considering the underlying scene layout might result in unsuccessful grasp attempts or even damaged objects. Recent work attempts to tackle this problem by trying to learn the manipulation order for a picking system [20], [31]. However, there are currently only a few datasets available providing the required scene layout information [11], [2]. VMRD [11] provides a dataset of over 5k scenes manually annotated. REGRAD [2] uses simulation to increase the dataset size and provides 6 DoF parallel-jaw grasps. UOAIS [30] provides amodal instance segmentation masks to reason about grasp scenes. Despite the high relevance of these works, their datasets do not provide comprehensive modalities, grasping types, object types, as well as layout labels at the same time to address the complex bin picking problem.

Pose Estimation and Keypoint Detection: Although grasping detection methods are model-free, fast and efficient, object pose estimation is still crucial for scene layout understanding or precise placement of picked items. In SynPick [1] a dataset for object pose tracking in dense bin clutter is proposed simulating object-gripper interaction over time. Generating a 3D model for each real-world object is cost-inefficient, and unflexible. Object keypoints is an inexpensive way to describe object shapes and poses in grasping. In fact, many grasping detection and pose estimation works are based on object keypoints [32], [33], but the dataset used in these works are limited in terms of scale and class diversity.

III. Method

The proposed method to generate MetaGraspNet can be divided into three steps: putting together a diverse item set, sampling ambidextrous grasp labels for each object individually, generating bin scenes together with rich annotations in the metaverse (see Fig. 2).

A. Custom Object Dataset and Novel Object Testset

In order to cover a broad area of possible use cases, we extended existing object sets with custom scans regarding the following criteria: parallel and vacuum grasp capability, transparency, reflectiveness, dimensions, industry/warehouse domain, deformability, texture, weight and fragility. The

![Fig. 2. MetaGraspNet data generation pipeline.](image-url)
advancement of affordable consumer-grade and precise 3D scanner hardware (SHINING 3D EinScan-SP) allows to generate custom 3D models for individual use-cases. For our work we chose a subset of 33 high-quality meshes from [3] being part of YCB object set [13], 4 from [15], scanned 36 objects by ourselves and remodeled 9 in CAD software when scanning was not possible.

| TABLE II | NOVEL OBJECT LIST |
|----------|-------------------|
| Class    | Non-Convex | Black | Varying Shape | Transparent |
| Pear     | ✓          |       | ✓             |             |
| Mug      | ✓          |       | ✓             |             |
| Power drill | ✓   |       | ✓             |             |
| Crayon box | ✓   |       | ✓             |             |
| Black clamp | ✓   | ✓     | ✓             |             |
| Black marker | ✓   | ✓     | ✓             |             |
| Wire     | ✓          | ✓     | ✓             |             |
| Wire in a bag | ✓ | ✓ | ✓ |             |
| Ring      | ✓          | ✓     | ✓             |             |
| Eyeglasses | ✓   | ✓     | ✓             |             |

Obtaining accurate 3D models for all objects is challenging and time consuming. Objects with existing 3D models can also be defective or deformed due to physical damage and alter from its rigid model. Therefore, it is crucial to evaluate object and grasping detection models with novel objects (objects that have never been seen before) to ensure the functionality of scene understanding and grasping beyond existing classes. We construct a novel object testset on the following properties: convex/non-convex shape, transparency, varying shape, and black color. Non-convex shaped objects are harder to detect due to center of mass being outside of objects’ body. Objects with varying shape can be challenging to detect in their entirety. Transparency and black color can make the value in depth and point cloud sensor incorrect or invalid. The list of novel objects and their properties are shown in Table II.

B. Parallel-Jaw Grasps Sampling Strategy

In [18], the authors demonstrate the effectiveness of having a combination of antipodal sampling and physics simulation. Our proposed parallel-jaw grasps sampling method is inspired by their approach, however we expand it by a robust sampling strategy and an improved dynamic collision check. For each object in our dataset we generate up to 5k antipodal grasps $G_j$ by sampling finger-object contact points $c_i$ evenly distributed over the mesh’s surface. For each contact point $c_i$ we sample $k=1 \ldots N, N=5$ antipodal [34] grasp attempts $c_{i,k}$ with random deviation in approach direction and translation. The robust antipodal score $s_{antip,i}$ for a contact point $c_i$ is then defined as the number of successful samples divided by the number of total samples $N$. To obtain grasp poses in $SE(3)$ we sample for each successful contact point $s_{antip,i}>0$ up to $l=1 \ldots L$ gripper poses by rotating it around the fingers’ closing direction. A grasp $G_j=G_{i,k,l}$ is considered successful if the gripper does not collide with the object and we assign it $s_{pj,anal,j}=s_{antip,i}$. In the next step, each successful grasp $G_j$ is executed multiple times in a physics simulation in IsaacGym [35]. Again we extend the idea of robust sampling into simulation: Each grasp $G_j$ is simulated with different mass density factors and friction coefficients. Similar to [18] we perform an upward and rotating gripper movement and assume a grasp is successful if the object is still in contact after execution. The robust simulation score $s_{pj,sim,j}$ is then defined as the fraction of successful grasps divided by the total number of attempts.

C. Vacuum Seal Sampling Strategy

In order to minimize the sim-to-real gap for vacuum sealability we propose a new physics-based vacuum suction cup model. Within the model, we adapt the projection idea of [19] due to its universality and efficiency, but introduce a new spring-mass structure (see Fig. 3a). Moreover, in contrast to [3] our proposed model computes the actual forces within the spring-mass model and detects leakages between suction cup and object by analyzing the resulting force vector for each mass point locally.

For the projected spring-mass system, we assume mechanical equilibrium both over all mass points (globally) and at each individual mass point $m_i$ (locally). As forces we consider ring forces $\vec{f}_{r,i}$, obtained from the spring-mass structure, contact forces $\vec{f}_{p,i}$ due to the pressure difference and elastic forces $\vec{f}_{e,i}$ resulting from the compression of the suction cup. While the ring forces $\vec{f}_{r,i}$ can be calculated directly via the deformation of the projected spring structure, we use the global equilibrium in Eq. (1) to calculate the forces $\vec{f}_{e,i}$ introduced by the elastic springs:

$$\sum_{i=0}^{n} \vec{f}_{r,i} + \sum_{i=0}^{n} \vec{f}_{p,i} + \sum_{i=0}^{n} \vec{f}_{e,i} = 0$$

(1)

With $\sum_{i=0}^{n} \vec{f}_{r,i} = 0$ and by assuming that $f_{e,i} = k_e \Delta l_i$ only act in approach direction $\vec{v}$, one can rewrite Eq. (1) as a function of the relative elastic spring deformation $\Delta l_i$:

$$F_p = ||\sum_{i=0}^{n} \vec{f}_{p,i}|| = ||\sum_{i=0}^{n} \vec{f}_{e,i}|| = k_e \sum_{i=0}^{n} \Delta l_i$$

(2)

With $\sum_{i=0}^{n} \vec{f}_{r,i} = 0$ and by assuming that $f_{e,i} = k_e \Delta l_i$ only act in approach direction $\vec{v}$, one can rewrite Eq. (1) as a function of the relative elastic spring deformation $\Delta l_i$:

$$\vec{f}_{e,i} = f_{e,i} \cdot \vec{v} = k_e \cdot \left( \frac{F_p}{n} + \sum_{i=0}^{n} \Delta l_i - l_i \right) \cdot \vec{v}$$

(3)

Knowing the elastic forces $\vec{f}_{e,i}$ and the ring forces $\vec{f}_{r,i}$ for each mass point, we can compute the contact forces $\vec{f}_{p,i}$ using the local equilibrium. The vacuum seal is then checked by analyzing the resulting force direction for each mass point individually. We assume that the seal between cup and object breaks when the resulting force vector for each mass point becomes greater than zero in local normal direction, lifting the cup from the surface.

By assuming that $\Delta l_{max}$ and the ratio between the calculated forces are independent of $n$ and all springs have same
radius, we can reduce the number of parameters in our model from five to two. We perform 145 real world experiments in a robotic cell with a custom 3D printed vacuum seal board (see Fig. 3b) and use Bayesian method [36] to optimize for the resulting two parameters. For every grasp attempt we record the seal by measuring the tear-off-force with the robotic arm Franka Emika Panda and the spring deformation for the same grasp configuration in simulation.

D. Scene Generation and Object Labels

Instead of generating and labeling scenes manually [7], [11] or semi-automatically [12], [3] we take inspiration from the recent rise of metaverse and create bin scenes completely in NVIDIA Isaac Sim [37]. In a digital twin of a real-world bin picking scenario, we let objects drop randomly into the tote. The realistic physics-based interaction between the objects is captured for visibility and collision with other objects or the tote when approaching the scene and performing the grasp. A good grasp not only depends on the local object’s surface conditions. Using path-tracing as rendering setting enables us to capture realistic light and shadow configurations as well as photo-realistic rendering of materials such as glass, plastic or metal. For each viewpoint all the individual objects’ parallel $G_{pj,k,j}$ III-B and vacuum suction grasps $G_{sc,k,j}$ III-C are checked for visibility and collision with other objects or the tote before approaching the scene and performing the grasp. A good grasp not only depends on the local object’s surface (see III-B and III-C), but is also highly affected by the wrenches applied to the gripper contact. For each vacuum grasp the wrench is computed around all three contact axes and scored similar to [3] $s_{sc,sim,j} \in [0, 1]$ while taking into account the object’s orientation and its center of mass. Though being implicitly considered in the $s_{pj,sim}$ (see III-B) we also specify an explicit wrench score $s_{pj,soft,j} \in [0, 1]$ around the finger’s closing direction for each parallel jaw grasp $j$ (soft-finger contact [34]).

Besides grasp labels, we provide extensive object labels for each viewpoint including amodal segmentation masks and occlusion rate, semantic keypoints and center of mass distribution heat maps (see Fig. 4 (a-e)). We define the amodal segmentation mask as a tuple of pixel-wise occlusion masks $M_{occl,k}$ for each object instance $k$ in the scene. The occlusion score $s_{occl,k} \in [0, 1]$ is then defined as the quotient of occluded $M_{occl,k}$ and total object surface area $M_{total,k} = M_{occl,k} \cup M_{vis,k}$. Object keypoints are manually labeled on 3D object models and represent joints or surface centers. We transform them into the scene and perform ray-tracing to check for visibility. A keypoint $x_{key,k} = [id_{sem}, (x, y), id_{class}, id_{instance}]$ is defined as a tuple of image coordinates $(x, y)$, its unique semantic $id_{sem}$, class category $id_{class}$, and instance $id_{instance}$.

E. Scene Layout Label and Scene Difficulties

| Level | Layer Limit | Occlusion Limit (%) | Complete Object | Unique Class |
|-------|-------------|---------------------|-----------------|--------------|
| 1     | 2           | N/A                 | ✓               | ✓            |
| 2     | N/A         | N/A                 | ✓               | ✓            |
| 3     | N/A         | N/A                 | ✓               | ✓            |
| 4     | N/A         | N/A                 | ✓               | ✓            |
| 5     | N/A         | N/A                 | ✓               | ✓            |

We propose two additional labels to characterize the scene layouts. The first label is a matrix storing the relation between each pair of objects, providing a comprehensive layout representation. To construct the relation matrix, we define three types of relationship for a pair of object $A$ and $B$. If $A$ is occluding $B$, we define the relationship between $(A, B)$ as positive, with a numerical value of 1. If $A$ is occluded by $B$, we define the relationship between $(A, B)$ as negative, with a numerical value of -1. If $A$ and $B$ have no direct relationship or $A = B$, we define the relationship between $(A, B)$ as neutral, with a numerical value of 0.
Based on these definitions, for a layout with $N$ objects, we create a relation matrix with $N \times N$ elements, where element $(i, j)$ in the matrix is the relationship between object $i$ and object $j$.

The second label provides a simpler layout description in line with the bin picking task. To better understand the order in which objects must be grasped, we create a directed graph to represent each layout. As robots pick objects sequentially, occluded objects will be revealed entirely once the objects on top of them are picked. Given this, we categorize each object in a layout into 3 different layers. Top layer contains objects that are clear of any obstructions. Secondary layer includes objects that are covered by only a single other object. Others layer includes the rest of the objects. In some cases, there could be groups of interlocked objects. Interlocked objects that are being directly covered by only one object would be considered to be within the secondary layer. An example of a environment of objects from the top down view and the resulting graph can be seen in Fig. 4 (f).

A difficulty rating for each scene would allow us to better understand how the model would perform under different environment conditions. We label images according to 5 different levels of difficulty. Those levels are defined by 4 different characteristics: Number of layers, occlusion percentage, instance completeness, and class uniqueness. Instance completeness refers to if a single object instance is visually crosscut into multiple segments due to occlusion. This often causes object over-detection or over-segmentation in objection detection and segmentation methods. Class uniqueness is if all objects in an image belong to different categories, or are visually distinct from each other. This characteristic evaluates models on distinguishing objects with similar visual features while clustered. The first two difficulty levels will be primarily concerned with understanding how a model deals with different levels of occlusion and layers. The next three levels measures the model’s ability to correctly label object instances. Level 3 includes incomplete objects in an image, and level 4 includes non-unique objects. Level 5 includes both incomplete as well as non-unique objects. The properties of all difficulties levels are shown in Table III.

IV. Dataset Details

The proposed MetaGraspNet benchmark dataset contains 217k RGBD images with 5884 different scenes and 82 different objects from household and logistics domain. Along with the RGBD images, camera parameters are provided for generating point clouds. All labels are provided in the respective camera coordinate system for each viewpoint, arranged in a hemisphere around the bin.

Besides a large-scale synthetic dataset, a smaller real-world evaluation and novel object test set is provided. It contains out of over 580 bin scenes equally distributed over the proposed five layout difficulty levels. Each scene is captured with a high performance 3D vision system based on time-coded structured light (Zivid Two) mounted at the robot’s endeffector from top view and three randomly sampled poses out of the bin hemisphere. Annotations are pixel-wise with semantic and instance segmentation masks, object layout as well as vacuum and parallel-jaw grasp labels. In total, 2.3k RGBD images of real world bin scenes containing over 9.7k items out of 76 classes are provided.

V. Experiments

A. Vacuum Grasp Labels

The proposed physics based sealability model is evaluated with real world grasp experiments. In detail, answering the following questions are of interest: 1) Does the model generalize to different cup materials and dimensions? 2) How accurate does the model perform on real world objects and compared to current state-of-the-art methods?

By performing four times 60 grasps on our custom board on a separate test split with different suction cups, it can be shown that the proposed method generalizes well to common cup materials, sizes and shapes (see Table IV board experiments). To evaluate the performance on real-world objects, experiments on household [13] and 3D printed adversarial objects [19] both used in [3] (see Fig. 5) are performed. For each object its 6D pose in the robotic cell...
is registered by choosing corresponding keypoints between mesh and sensor pointcloud and refining the first estimate with an ICP registration pipeline provided by open3d [38]. In total, by performing 200 grasps (10 positive and 10 negative predicted seal per object) for each cup model it can be shown that the proposed model achieves a very high performance on real-world objects and is able to generalize to different cup sizes as well. (see Table IV real experiments).

In order to benchmark our model against related work in the field, the provided scalability score of SuctionNet-1Billion [3] is compared with our model’s prediction and a reimplemented version of Dex-Net 3.0 [19]. For this experiment only controversial contact points are considered in order to emphasize the difference between these methods (11.0% for [19] and 22.4% for [3] of total amount). A point is considered controversial, if its given seal score is below 0.2 [3] while our method predicts a successful vacuum seal, or respectively if the score is above 0.8 and our methods predicts a failed seal. As shown in Table V our proposed physics based suction cup models outperforms both methods by a large margin. Looking at the results for the experiments with the 30mm diameter suction cup, once again the robustness of our model with regard to cup dimension changes can be confirmed.

### TABLE IV

| Experiment | Material, φ, Conv. | Prec. (PPV) | NPV | Sens. | Spec. | Acc. |
|------------|------------------|------------|-----|-------|-------|------|
| board      | Silicon, 20mm, 3.5^a | 0.98       | 0.87 | 0.96  | 0.95  | 0.95 |
| board      | NBR, 20mm, 3.5^2 | 0.95       | 0.75 | 0.91  | 0.86  | 0.90 |
| board      | Silicon, 20mm, 3.5^3 | 0.90       | 0.92 | 0.94  | 0.90  | 0.90 |
| board      | Silicon, 30mm, 3.5^4 | 0.07       | 0.86 | 0.92  | 0.85  | 0.93 |
| real       | Silicon, 20mm, 3.5^5 | 0.92       | 0.82 | 0.84  | 0.91  | 0.87 |
| real       | Silicon, 30mm, 3.5^6 | 0.87       | 0.92 | 0.91  | 0.88  | 0.89 |

PPV: Positive Predictive Value; NPV: Negative Predictive Value; Conv.: Bellows Convolutions; Sens.: Sensitivity; Prec.: Precision; Acc.: Accuracy

^a 1: ESS-20-CS (used for training); 2: ESS-20-CN; 3: ESS-20-BS; 4: ESS-30-CS

### TABLE V

| Method | Precision (PPV) | NPV | Sensitivity | Specificity | Accuracy |
|--------|----------------|-----|--------------|-------------|----------|
| [19]^1 | 12/20 = 0.60 | 11/20 = 0.55 | 12/20 = 0.60 | 11/20 = 0.55 | 12/20 = 0.60 |
| ours^1 | 49/66 = 0.73 | 49/66 = 0.73 | 6/19 = 0.31 | 49/66 = 0.73 | 57/80 = 0.72 |
| [3]^a | 13/44 = 0.30 | 6/24 = 0.25 | 13/44 = 0.30 | 6/24 = 0.25 | 10/36 = 0.28 |
| ours^a | 10/24 = 0.42 | 10/24 = 0.42 | 10/24 = 0.42 | 10/24 = 0.42 | 49/66 = 0.72 |

PPV: Positive Predictive Value; NPV: Negative Predictive Value

^1 1: ESS-20-CS (φ=20mm); 2: ESS-30-CS (φ=30mm)

### B. Grasp Planning

While previous work such as [4] have shown the potential of synthetic depth data for training picking systems, the performance drop for RGBD based methods [3] from simulation to real world is still significant. Extensive experiments on a physical picking cell equipped with a Franka Emika robot arm and Zivid Two RGBD camera system can demonstrate that the proposed MetaGraspNet dataset is able to close the gap from simulation to real world for cluttered bin scenes. In detail, SuctionNet-1Billion [3] trained on its large-scale real-world dataset is evaluated against a version of [3] trained on the proposed synthetic MetaGraspNet database. In total, 813 grasp attempts distributed over 40 cluttered bin layouts are analyzed. Each scene contains eight randomly sampled items arranged in random poses and partly stacked upon each other (see Fig. 6). In order to avoid human bias, the manual scene creation and recreation for both networks is alternated. For the experiments, background was filtered out and a grasp was considered successful if the object was picked up and moved into another bin. After two failed grasps attempts per object and scene, a human supervisor removed the object. For evaluation the proposed metrics $R_{grasp}$, $R_{object}$ and $R_{mixture}$ from [3] are adapted. As shown in Table VI all, MetaGraspNet outperforms real-world training data in terms of total number of successful grasps $R_{grasp}$ and total number of autonomously cleared objects $R_{object}$. Looking at Table VI, this observation is valid for known as well as unknown objects (see Fig. 6). Only when it comes to successful first grasp attempts on cleared objects $R_{mixture}$, [3] trained on real data outperforms our method on seen objects.

### TABLE VI

| Test Set | $R_{grasp}$ (%) | $R_{object}$ (%) | $R_{mixture}$ (%) |
|----------|----------------|-----------------|-------------------|
| [3]      | ours           | [3]             | ours              |
| complete | 60.7          | 77.6            | 81.0              |
| seen     | 69.5          | 71.2            | 82.8              |
| unseen    | 56.8          | 57.1            | 73.6              |
| unseen^a | 52.8          | 57.1            | 75.0              |

*^a intersecting set of [3] and our object set

### C. Object Detection

Class-agnostic object detection and segmentation is one of the most important yet challenging tasks leading towards robust and reliable understanding of bin scenes. This task ensures the consistent model performance even if there are defective, or unseen objects in the bin. We use classic object detection and segmentation network Mask R-CNN [39] to evaluate the performance gap between our synthetic, real, and unseen datasets on RGB images for this task. We treat all objects as 1 class and exclude the unseen test objects (defined in II) from training. The real dataset is used for either training or testing. The unseen dataset is used for testing only. We train our models on synthetic (Syn) or real (Real) dataset for 37 epochs. We also evaluate a model trained on Syn and fine-tuned on Real (Syn+Real) for 7 epochs. We report our results in Bounding Box Average Precision (Box AP) and Segmentation Average Precision (Seg AP), as shown in VII. From the results, we can see that models trained on synthetic and real dataset have very small performance gap on the unseen object test sets.

### VI. CONCLUSIONS

In this work, we introduced a large-scale comprehensive photo-realistic synthetic train and an extensive real-world evaluation and test dataset for robotic bin picking. Extensive robot experiments could show that the proposed vacuum
TABLE VII

OBJECT DETECTION PERFORMANCE GAP BETWEEN SYNTHETIC, REAL, AND UNSEEN DATA.

| Train set | Test set | Box AP | Seg AP |
|-----------|----------|--------|--------|
| Syn       | Unseen mix | 34.0   | 28.7   |
| Real      | Unseen mix | 34.0   | 32.1   |
| Syn+Real  | Unseen mix | 42.2   | 37.3   |
| Syn       | Unseen only | 12.2   | 9.5    |
| Real      | Unseen only | 9.1    | 10.7   |
| Syn+Real  | Unseen only | 13.2   | 12.4   |

*Unseen mix: contains all the scenes with unseen objects.
Unseen only: contains only unseen objects.

grasp label generation method generalizes to different cup models and together with the proposed synthetic data generation pipeline outperforms real-world data for vacuum based bin picking in clutter. With MetaGraspNet a data generation pipeline is introduced which addresses all vision-related aspects of bin picking and challenges future systems to take the next step towards scene understanding and ambidextrous manipulation.

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