TransCG: A Large-Scale Real-World Dataset for Transparent Object Depth Completion and Grasping

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Abstract—Transparent objects are common in our daily life and frequently handled in the automated production line. Robust vision-based robotic grasping and manipulation for these objects would be beneficial for automation. However, the majority of current grasping algorithms would fail in this case since they heavily rely on the depth image, while ordinary depth sensors usually fail to produce accurate depth information for transparent objects owing to the reflection and refraction of light. In this work, we address this issue by contributing a large-scale real-world dataset for transparent object depth completion, which contains 57,715 RGB-D images from 130 different scenes. Our dataset is the first large-scale real-world dataset and provides the most comprehensive annotation. Cross-domain experiments show that our dataset has a great generalization ability. Moreover, we propose an end-to-end depth completion network, which takes the RGB image and the inaccurate depth map as inputs and outputs a refined depth map. Experiments demonstrate superior efficacy, efficiency and robustness of our method over previous works, and it is able to process images of high resolutions under limited hardware resources. Real robot experiment shows that our method can also be applied to novel object grasping robustly. The full dataset and our method are publicly available at www.graspnet.net/transcg

I. INTRODUCTION

Transparent materials are widely used in modern industry, and robots inevitably need to process transparent objects no matter in manufacturing, logistics, or household services. Recently, many progresses have been made in the field of robot grasping and manipulation [6][26]. However, these advances are not directly applicable in scenes with transparent objects since most of these methods heavily rely on the depth information collected by the RGB-D cameras, yet ordinary depth sensors usually fail to construct a complete depth image in scenes that include transparent objects. The physical properties of transparent objects would lead to the distortion of light path by reflection and refraction, resulting in noisy depth maps. Therefore, many depth-based algorithms are incapable to handle transparent objects such as plastic bottles and glass containers which can be found everywhere in our daily life.

The geometry estimation of transparent objects remains a challenging task in the computer vision field, though progress has been made by many researchers. Ba et al. [2] utilized a special polarization camera to leverage polarization cues for shape estimation and reached satisfactory results, while Li et al. [19] proposed a two-stage physical-based network to reconstruct the shape of the transparent objects using multi-view images and material prior. However, both methods require specialized hardware, which is not a general setting for robotic manipulation. A more common setting is a robot arm with a monocular RGB-D camera, which is the setting that we mainly focus on.

Under this circumstance, Sajjan et al. [34] adapt the depth completion pipeline [40] to scenes that contain transparent objects and then propose ClearGrasp, which predicts the surface normal and the transparent boundary, followed by the global optimization to solve the depth estimation. A synthetic dataset and a small real-world dataset are also proposed along with the method. Zhu et al. [41] present an end-to-end framework for depth completion using the local implicit depth function, along with a synthetic Omniverse Object dataset. Both synthetic datasets provide images containing transparent objects and their ground-truth depth maps, but the lack of real depth maps degrade the performance of those methods in real-world applications inevitably.

To close the syn-to-real gap in the field of grasping concerning transparent objects, we propose TransCG, the first large-scale real-world dataset for transparent object depth completion and grasping. A novel semi-automatic pipeline is proposed to accelerate the data collection and annotation

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process. In total, our dataset contains 57,715 RGB-D images of 51 transparent objects and many opaque objects captured from different perspectives of 130 scenes under real-world settings. The 3D mesh model of the transparent objects are also provided in our dataset. The methodology for building our dataset is shown in Fig. 1.

Furthermore, we propose a robust, efficient and effective network Depth Filler Net (DFNet) for depth completion based on our dataset, which allows it to assist 6-DoF grasping methods on transparent object grasping. The quantitative results show that our proposed DFNet (1) generalizes better across different scenes compared to existing methods; (2) improves most of the metrics to a great extent; (3) yields the highest inference speed and consumes the least computation overhead. We also apply our network to real-world object grasping for novel transparent objects, and a promising performance is witnessed. The full dataset, source code and pretrained models are released at www.graspnet.net/transcg.

II. RELATED WORKS

A. Depth Completion and Estimation

Depth completion and estimation has been studied by many researchers for a long time, which can be categorized into three classes: estimating depth directly from an RGB image [8, 24, 25, 30, 35, 38] and depth completion from an RGB image with sparse depth information [3, 4, 9, 13, 17, 18, 21, 39], estimating depth from an RGB image with inaccurate depth information [8, 34, 40, 41].

Our method falls into the last category since depth information concerning transparent objects is usually noisy and inaccurate. Zhang et al. [40] propose a two-stage depth completion pipeline, which predicts the surface normal and occlusion boundary according to the RGB image, followed by the global optimization to complete the depth map. ClearGrasp [34] makes a few critical modifications to the pipeline and adapts it in depth completion concerning transparent object, but its inference speed is unacceptable in real-time grasping scenarios. Zhu et al. [41] propose a two-stage system consisting of local implicit depth function prediction and depth refinement. Though it outperforms previous works on speed and accuracy, its generalization ability is very limited according to our cross-domain tests in Sec. V-B, which makes it difficult to fit into real-world robotic manipulation settings.

To achieve a better generalization and applicability in real-world environment, a tiny but robust model is needed, which requires a large amount of real-world data as support.

B. Transparent Datasets

Due to the special optical properties of transparent objects which leads to undetermined and inaccurate results of optical sensors, the datasets concerning of transparent objects is usually difficult to build.

For tasks that do not need the depth information, e.g., transparent object classification and segmentation, there are large-scale datasets such as Trans10K-V2 [37] and Stanford2D-3D [1]. For datasets that needs accurate sensor information as ground-truth, the common solutions are synthetic datasets, such as ClearGrasp synthetic dataset [34] and Omniverse object dataset [41]. Built by tools like SuperCausitics [27], the greatest shortcoming to those datasets is that the raw information collected by sensors is unlikely to obtain in simulation. Liu et al. [22] build a real-world keypoint estimation dataset for transparent objects, which consists of the ground-truth depth map generated by substituting the transparent object with the identical opaque objects. But the large amount of real-world samples are all captured alone under certain environments, which is rare in real-world applications. Moreover, the dataset is incomplete for depth completion since transparent mask and surface normals information are missing. The dataset collection approach is also used in ClearGrasp real-world dataset [34] which only has 286 samples since generating the missing information is both time-consuming and labor-consuming.

To overcome the difficulties of building datasets concerning transparent objects, we propose a novel pipeline for transparenet dataset construction. Using the pipeline, we build TransCG, the first complete large-scale real-world dataset for transparent object depth completion and grasping. Details will be introduced in Section III.

C. 6-DoF Grasping

6-DoF grasping refers to those methods that predict the position and rotation of the gripper in 3D domain. Enabling the robots to grasp objects from various angles, it is the basis of robotic manipulation. Due to the versatility and effectiveness of 6-DoF grasping, it is currently the main stream in the grasping field.

GPD [31] propose a two-stage 6-DoF grasping method, which estimates grasp candidates sampled under empirical constraints. PointNetGPD [20] improves GPD by adapting PointNet [22] in evaluation. Mousavian et al. [28] leverage variational auto-encoder to sample grasp poses, and add refinement process after evaluation for better performance. Ni et al. [29] regress the grasp pose from features extracted by PointNet++. Fang et al. [6] propose the GraspNet-1 Billion dataset for general object grasping and an end-to-end grasp pose prediction network. Gou et al. [11] incorporate RGB and depth information to improve the performance of 6-DoF grasping.

All these methods rely heavily on depth image, which makes them unsuitable for transparent object grasping. Thus, utilizing color information to generate high-quality depth map and point cloud to aid the grasping deserves further exploration.

III. DATASET

A. Overview

As introduced before, the previous transparent datasets that need accurate ground-truth depth usually use simulation platforms to generate synthetic data, and real-world datasets are usually small in scale due to the workload of annotations. To overcome the difficulties, we propose a novel pipeline to
TABLE I  
COMPARISONS OF TRANSPARENT DEPTH COMPLETION DATASETS

| Type | Dataset            | Dataset Completeness | #Cam. | #Obj. | #Img. |
|------|--------------------|----------------------|-------|-------|-------|
| Syn  | Clear-Syn [34]     | ✓                    | 1     | 9     | 50K   |
|      | OOD [41]           | ✓                    | 1     | 9     | 60K   |
| Real | Clear-Real [34]    | ✓                    | 2     | 10    | 286   |
|      | TOD [22]           | ✓                    | 1     | 15    | 48K   |
|      | TransCG (ours)     | ✓                    | 2     | 51    | 58K   |

Note. Clear refers to ClearGrasp Dataset (Synthetic/Real-world), OOD refers to Omniverse Object Dataset, OOD refers to Transparent Object Dataset. "#Cam." denotes types of RGB-D cameras, "#Obj." stands for the number of target objects and "#Img." represents the amount of samples.

In brief, we aim to collect a dataset that contains RGBD images with real-world sensors, binding with detail annotations for the transparent objects include their depth, mask, 6D pose, normal, etc. To reduce the annotation effort, our methodology for building the dataset is to automatically localize the transparent objects during data collection. To achieve that, we resort to an optical tracker that can accurately localize a target’s 6D pose in real-time from several IR markers attached to it. Besides, we manage to obtain the 3D model of each transparent object in the training set by wrapping them with opaque materials and scanning with a 3D scanner. With these two preliminaries, we can easily obtain the transparent objects’ 6D pose during data collection. The geometry of transparent objects can be restored by leveraging the tracker results and their 3D models during data annotation. Our pipeline is able to build large-scale real-world dataset conveniently and reduce the human workload by a large extent.

Using the pipeline, we build our TransCG dataset, which contains 57,715 RGB-D images captured by two different cameras, along with the refined ground-truth depth images, transparent ground-truth mask and the surface normals, from 130 scenes under various background settings, within a week. We collect 51 common objects in daily life that can lead to inaccurate depth map, including transparent objects, translucent objects, reflective objects and objects with dense tiny holes. Apart from 65 simple isolated scenes that are similar to the scenes in the previous datasets, we also provide 65 challenging cluttered scenes that are closer to the real-world grasping environment, as shown in Fig. 2. More details are presented in supplementary video. The comparisons between our dataset and existing datasets are summarised in Tab. I.

B. System Setup

To support fast and accurate data collection process, we build a transparent object tracking system, which is the only part that requires human efforts in our dataset building pipeline. The system setup process is illustrated in Fig. 3.

Given a transparent object, we firstly attach a fixer with IR markers to it. A commercial optical tracker is used to record the IR markers and tracks them afterwards. Although we can directly attach IR markers to the object, we found that using a flat fixer can make the tracking more robust. Next, we temporarily wrap the transparent object with some opaque materials and obtain its 3D model with a commercial 3D scanner. With these two steps, we can obtain the transparent object’s 6D pose during data collection, where the details is further explained.

The core of our data collection system consists of a PST tracker, an Intel RealSense D435 camera and an Intel RealSense L515 camera. The tracker outputs the 6D pose of the markers in real-time and the two cameras provide RGBD images with different quality. The 6D pose of the i-th object w.r.t the j-th camera $T_{cam}^{obj}$ can be calculated as follows:

$$T_{cam}^{obj} = T_{cam}^{marker} \cdot T_{cam}^{obj} \cdot T_{marker}^{obj},$$  \hspace{1cm} (1)

where $T_{cam}^{marker}$ denotes the transformation matrix of the tracker origin w.r.t the j-th camera, $T_{cam}^{marker}$ denotes the 6D pose of the markers attached on the i-th object w.r.t the tracker, and $T_{marker}^{obj}$ denotes the transformation matrix of the i-th object’s origin w.r.t the markers.

To obtain $T_{cam}^{obj}$, we perform tracker-camera calibration using a calibration board with both Aruco marker and IR markers. $T_{cam}^{marker}$ is the output of the optical tracker, and $T_{marker}^{obj}$ are annotated by human. We develop a GUI application for the annotation process and evaluate the results in real time by rendering the objects in the corresponding RGB image.

In statistics, the overall human efforts to process an object is around 1 hour. With our built transparent object tracking system, we can easily recover the ground-truth depth information of the transparent objects afterwards.

C. Data Collection

To collect a large amount of data automatically, we attach our tracking system to a robot arm that moves along a fixed
transparent object with fixer

tracker – marker configuration

scanning the object (with fixer)

6D pose: \( T_{\text{camera-object}} = T_{\text{camera-tracker}} T_{\text{tracker-marker}} T_{\text{marker-object}} \)

(a) transparent object with fixer
(b) tracker – marker configuration
(c) scanning the object (with fixer)
(d) 3D model
(e) tracker – object annotation
(f) 6D pose tracking system
(g) PST tracker
(h) Intel RealSense D435 camera
(i) Intel RealSense L515 camera

Fig. 3. System setup process. Given a transparent object (a), we attach a fixer with IR markers to it (b) and record its pattern with an optical tracker (c), which can enable tracking afterwards. Then we scan the object (d) and get its 3D model (e). After that, we manually perform tracker-object annotation to get the transformation matrix from marker to object (f), where an GUI is developed for real-time evaluation (h). The whole annotation and tracking process is assisted by our 6D pose tracking system (g), which consists of a PST tracker, an Intel RealSense D435 camera and an Intel RealSense L515 camera.

IV. METHOD

A. Overview

In this section, we detail our method for depth completion and grasping. For depth completion, we propose an end-to-end network which is illustrated in Fig. 4. Given an RGB image \( \mathcal{C} \in \mathbb{R}^{H \times W \times 3} \) and an inaccurate partial depth image \( \mathcal{D} \in \mathbb{R}^{H \times W} \), our network completes the depth information and predicts the full depth map \( \mathcal{\hat{D}} \in \mathbb{R}^{H \times W} \), where \( H \times W \) is the size of an image. The details of the network will be introduced in Sec. IV-B. In Sec. IV-C we apply our depth completion to a grasp pose detection network [6] which takes point cloud as inputs and outputs the grasping poses. We demonstrate that our network can generate high quality depth for transparent objects that can enable depth-based grasping.

B. Depth Completion

Inspired by previous literature [3] about depth estimation from sparse sensing, we propose our end-to-end depth completion network **Depth Filler Net (DFNet)** that predicts full depth map according to RGB information and inaccurate partial depth. Adapting a U-Net architecture with depth of four layers, our network takes dense blocks [12] as backbones and formulates **Conv-Dense-Conv-Downsampling** (CDCD) blocks, **Conv-Dense-Conv** (CDC) blocks and **Conv-Dense-Conv-Upsampling** (CDCU) blocks. Empirical statistics about depth estimations and completions show that original depth information is critical throughout the networks. Hence we provide the original depth information as an input to every CDCD, CDC and CDCU block. Skip paths are added to retain information in high resolutions. Inspired by AlphaPose [7], we adapt dense up-sampling convolution (DUC) [50] instead of ordinary deconvolution layers in CDCU blocks.

Our network is trained using the following loss function:

\[
\mathcal{L} = \mathcal{L}_d + \beta \mathcal{L}_s, \tag{3}
\]

where \( \mathcal{L}_d \) penalizes depth inaccuracy, \( \mathcal{L}_s \) penalizes unsmoothness and \( \beta \) is the weight parameter. Formally,

\[
\mathcal{L}_d = \left\| \mathcal{D} - \mathcal{D}^* \right\|^2, \tag{4}
\]

\[
\mathcal{L}_s = 1 - \cos \left\langle \mathcal{\hat{D}}_h \times \mathcal{\hat{D}}_w, \mathcal{D}^*_h \times \mathcal{D}^*_w \right\rangle,
\]

where \( \mathcal{\hat{D}}_h \) and \( \mathcal{\hat{D}}_w \) are the horizontal and vertical 1D convolution kernels respectively.
where $\hat{D}$ and $D^*$ denotes the predicted depth and the ground-truth depth, $D_w$ and $D_h$ are gradient vectors along width-axis and height-axis of depth map $D$ respectively. For both losses, we regard depths out of range $[0.3, 1.5]$ as invalid pixels and remove them from losses to reduce the impact of outliers.

C. Object Grasping

To verify the depth completion results in robotic manipulation, we select the fundamental object grasping as the downstream task of our network.

Given an RGB image along with a depth image collected by an RGB-D camera, we first scale the images to an appropriate size and feed into our depth completion model DFNet, which outputs the refined depth in the same resolution as the input. Then, the refined depth is scaled back to the original size, which can be used to construct the scene point cloud using camera intrinsics. After that, the scene point cloud is sent to GraspNet-baseline [6] as the input to the end-to-end grasp pose detection network. Finally, the grasp pose detection network outputs the grasp candidates, and the grasp will be executed by a parallel-jaw robot.

V. EXPERIMENTS

A. Depth Completion Experiments

We compare our method with several representative approaches on our TransCG dataset. ClearGrasp [34] is the first algorithm which leverages deep learning with synthetic training data to estimate depth information concerning transparent objects, and LIDF-Refine [41] is the state-of-the-art model for transparent object depth completion. All baselines are trained in our TransCG dataset using their released source codes and optimal hyper-parameters for fair comparisons.

For our model, the hidden channels in the network is set to 64. In every dense block, the layers $L$ and the feature channels of each layer $k$ are set to 5, 12 respectively, as suggested in literature [3]. We use AdamW optimizer [23] with initial learning rate of $10^{-3}$ and multi-step learning rate scheduler which decays the learning rate by 5 after 5, 15, 25, 35 epochs. We train the model for 40 epochs with the batch size of 32. Several data augmentation approaches such as random flipping, rotation, noise adding and chromatic transformations in HLS color space are conducted during training. Concerning loss, we set $\beta = 0.001$.

For all methods, we scale the images to $320 \times 240$ during training and testing. We use 4 NVIDIA GeForce RTX 3090 GPUs for training and one for testing.

The following common metrics of depth completion for transparent objects are used in comparisons. All metrics are calculated on the transparent areas according to transparent masks unless specified.

- RMSE: the rooted mean squared error between depth estimates and ground-truth depths.
- REL: the mean absolute relative difference.
- MAE: the mean absolute error between depth estimates and ground-truth depths.
- Threshold $\delta$: the percentage of pixels with predicted depths satisfying $\max(d/\hat{d}, \hat{d}/d) < \delta$, where $d, \hat{d}$ are corresponding pixels of $D, \hat{D}$, and $\delta$ is set to 1.05, 1.10 and 1.25 following [34, 41].

The quantitative results are reported in Tab. II. In our TransCG dataset, our method achieves the state-of-the-art results compared to previous methods. Moreover, our method has the smallest size, fastest inference time and lowest GPU memory occupation, which allows it to perform depth completion of high quality under limited resources.

B. Cross-Domain Experiments

Cross-domain experiments are performed to verify the robustness of our proposed depth completion method and the generalization ability of our proposed TransCG dataset.

For cross-domain experiments of different methods, two experiments are conducted, namely (1) test the performance on our TransCG dataset after training on ClearGrasp synthetic dataset and Omniverse object dataset; (2) test the...
performance on ClearGrasp real-world dataset after training on our TransCG dataset. Results shown in Tab. III reveal that our method is the most robust one among all methods. Also, it is worth noticing that although LIDF-Refine [41] reaches satisfactory results when training domain is similar to the testing domain, the cross-domain testing decreases its performance a lot since its local implicit depth function is environment-dependent. On the contrary, our method is insensitive to domain changes and is able to achieve satisfactory results under different environment settings.

For cross-domain experiments of different datasets, we select our method as the depth completion model to test the generalizability of the training dataset on a third-party transparent object dataset [22] and the ClearGrasp real-world dataset. Results shown in Tab. IV demonstrate that our dataset has a great generalization ability compared to the previous synthetic datasets, even though ClearGrasp real-world dataset has a similar environment as ClearGrasp synthetic dataset which is used for training. The performance differences also reflect the shortcomings of synthetic datasets compared to real-world datasets.

C. Real Robot Experiments

To verify the performance of our method in real-world settings, we conduct real robot object grasping experiments. The object grasping pipeline incorporated with our method is introduced in Sec. IV-C. The experiments are conducted on a UR-5 robot with an Intel RealSense D435 camera and a Robotiq two-finger gripper, as shown in Fig. 5.

We randomly select 8 transparent objects to perform real-robot experiments, 6 of which are completely novel, and the rest 2 objects are the same objects without fixers and markers from our testing set. For every experiment, we randomly put the objects and repeat grasping until an object fails for 3 times. The success rate is defined as \#successfully-grasped objects \#objects, and the completion rate is defined as \#successfully-grasped objects \#attempts. Table V reports the experiment results, which shows the effectiveness and feasibility of our method. More details are presented in supplementary video.

VI. Conclusion

In this paper, we propose TransCG, the first large-scale real-world dataset for transparent object depth completion and grasping, built by our novel data collecting pipeline. Our dataset fills the syn-to-real gap in the transparent depth completion area and has a great generalization ability in real-world environments. Moreover, we propose an end-to-end depth completion network DFNet, which is more efficient and robust compared to previous methods. Our model reaches the state-of-the-art results on our TransCG dataset. Real robot experiments of grasping also demonstrates that our method is applicable in real-world settings with novel objects.
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