The YCB Object and Model Set:

Towards Common Benchmarks for Manipulation Research

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Abstract— **In this paper we present the Yale-CMU-Berkeley (YCB) Object and Model set, intended to be used for benchmarking in robotic grasping and manipulation research. The objects in the set are designed to cover various aspects of the manipulation problem; it includes objects of daily life with different shapes, sizes, textures, weight and rigidity, as well as some widely used manipulation tests. The associated database provides high-resolution RGBD scans, physical properties and geometric models of the objects for easy incorporation into manipulation and planning software platforms. A comprehensive literature survey on existing benchmarks and object datasets is also presented and their scope and limitations are discussed. The set will be freely distributed to research groups worldwide at a series of tutorials at robotics conferences, and will be otherwise available at a reasonable purchase cost.**

Keywords—benchmarking; manipulation; rehabilitation; prosthetics; grasping.

I. Introduction

Benchmarks are crucial for the progress of a research field, allowing performance to be quantified in order to give insight into the effectiveness of an approach. In robotic manipulation, benchmarking and performance metrics are challenging due largely to the enormous breadth of the application and task space for which researchers are working towards. The majority of research groups have therefore selected for themselves a set of objects and/or tasks that they believe are representative of the functionality that they would like to achieve. Unfortunately such an approach prevents the analysis of experimental results against a common basis, and therefore makes it difficult to quantitatively interpret the performance of the described approach.

Object and model sets are generally the fundamental elements involved in benchmarks for manipulation. Substantial effort has already been put into providing mesh model databases of objects (e.g. [1-4], with a thorough overview provided in section II), generally for object recognition or planning purposes. There have, however, been very few instances of proposed object/task sets for which the physical objects are available to researchers. Access to the objects is crucial to performance benchmarking as many aspects of the grasping and manipulation process cannot be modeled, thereby requiring experiment to demonstrate success or examine failure modes.

In this paper, we present an object set for robotic grasping and manipulation research that is specifically designed to allow for widespread dissemination of the physical objects and manipulation scenarios. The objects and tools provided were selected based on a survey of the most common objects utilized in research in robotics, prosthetics, and rehabilitation, along with a number of additional practical constraints. Along with the physical objects, textured mesh models and high quality images are provided together with their physical properties to

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enable realistic simulations. These models are integrated into the MoveIt motion planning tool [5] and the Gazebo simulation environment. The set will be freely distributed to research groups worldwide at a series of tutorials at robotics conferences, and will be otherwise available at a reasonable purchase cost. Our goal is to do as much as possible to facilitate the widespread usage of a common set of objects and tasks in order to allow easy comparison of results between research groups worldwide.

In choosing the set of objects and data provided, a number of issues were considered. The objects should span a variety of shapes, sizes, weight, rigidity and texture, as well as span a wide range of manipulation applications and challenges. Still, a number of practical constraints must be considered, including the number and size of the objects to allow for easy shipping and storage, keeping the overall cost reasonable, providing objects that are durable so as to not substantially degrade over time or with usage, as well as to choose objects that are likely to be available in a similar form in the future. Preliminary data in the repository includes high-resolution 3D point cloud data with associated meshes and texture (visual) information, object mechanical properties such as major dimensions and mass, as well as models for integration into planning and simulation software, all available at: http://rll.eecs.berkeley.edu/ycb/. We expect to continually expand this to not only include additional data on the objects, but also to propose benchmarking tasks and use protocols to further aid in common performance standards. Furthermore, we will create a web portal for the user community to engage in this effort, proposing changes to the object set and putting forth their own task protocols, among others.

The remainder of this paper is organized as follows: First a comprehensive literature survey on object sets and benchmarks is presented in Section II. Following that our object set is presented and explained in Section III. In Section IV, a use case of the proposed object set is demonstrated. In Section VI, the paper is concluded with discussions and future work.

II. Related Work

The necessity of manipulation benchmarks is highly recognized in the robotics community [6-8] and continues to be an active topic of discussion at workshops on robotic manipulation (e.g. [9]). Prior work on object sets has generally involved large datasets of object scans, which are useful for many simulation and planning applications, as well as for benchmarking in shape retrieval but have limited use in experimental work on grasping and manipulation. One key factor in prior work is that the vast majority of objects in these sets are not easily accessible by other researchers, preventing the use of these objects in the manipulation experiments, with a few exceptions ([10] provides a shopping list, but it is outdated with many dead links, and a commercial kit is available in [11], but provides a very limited set of objects and is not appropriate for many manipulation applications). The current effort is unique in that it both provides a large amount of information about the objects necessary for many simulation and planning approaches, as well as makes the actual objects readily available for researchers to utilize experimentally.

A. Data sets

For benchmarking in robotic manipulation, specifying an object set is essential. Even though there are a large number of efforts (e.g. [1, 2, 4, 12-15]) that provide mesh model datasets of objects, these datasets have limited utility for manipulation benchmarking due to several reasons: First, since most of them are not designed specifically for manipulation benchmarking, the selected objects do not usually cover the shape variety needed for manipulation experiments. Second, in the majority of these datasets, the models are without high-quality texture information (with BigBIRD [1] and KIT [12] datasets standing out as notable exceptions) which is necessary for grasp synthesis algorithms which use feature-based methods (e.g. [16, 17]). Furthermore, none of these databases provide the objects' physical properties which are necessary to conduct realistic simulations.

Several object sets have been proposed targeting the manipulation field: The Columbia Grasp Database [3], the KIT Object Models Database [12] and a household objects list proposed in [10]. The Columbia Grasp Database (CGD) rearranges the object models of the Princeton Shape Benchmark (PSB) [18] for robotic manipulation and provides mesh models of 8000 objects together with assigned successful grasps per model. Such a database is especially useful for implementing machine learning based grasp synthesis algorithms in which large amounts of labeled data are required for training the system. The provided mesh models are without textures and the objects are not physically available to the researchers. A multi-purpose object set which also targets manipulation is the KIT Object Models Database [12] which provides stereo images and textured mesh models of 100 objects. While there are a large number of objects, the shape variety is limited, and like the previously mentioned datasets, the objects are not easily accessible to other researchers. The household objects list [10] provides good shape variety that is appropriate for manipulation benchmarking, as well as a shopping list for making the objects more easily accessible to researchers. Unfortunately, the list is outdated, and most links are not accessible. Also, the 3D models of the objects are not supplied which prevents the use of the object set in simulations.

B. Benchmarks

A number of simulation tools have been presented in the literature for benchmarking in robotic manipulation. The OpenGRASP benchmarking suite [19] presents a simulation framework for robotic manipulation. The suite is based on the OpenGRASP toolkit [20] which supplies an interface to import objects and robot models as well as plugins for actuators and tactile sensors. The benchmarking suite provides test cases and setups, and a standard evaluation scheme for the resultant grasps. So far, a benchmark for grasping known objects has been presented using this suite. The VisGraB [21] provides a benchmark framework for grasping unknown objects. The unique feature of this software is utilizing real stereo images of the target objects for grasp synthesis and executing and evaluating the result in a simulation environment.

Fig. 1: Food items in the YCB Object Set: back row: chips can, coffee can, cracker box, box of sugar, tomato soup can; middle row: mustard container, tuna fish can, chocolate pudding box, gelatin box, potted meat can; front: plastic fruit (lemon, apple, pear, orange, banana, peach, strawberries, plum).

Fig. 2: Kitchen items in the YCB Object Set: back row: pitcher, bleach cleanser, glass cleaner; middle row: plastic wine glass, enamel-coated metal bowl, metal mug, abrasive sponge; front: cooking skillet with glass lid, metal plate, eating utensils (knife, spoon, fork), spatula, white table cloth.

Gripper and hand design is another aspect of robotic manipulation which requires benchmarks for evaluating and comparing the performance of different gripper designs. In [22, 23], benchmark tests are proposed for evaluating the ability of the grippers to hold an object, but only cylindrical objects are used.

In [24], the authors list a large number of objects utilized in the Activities of Daily Living, and evaluate them in terms of their physical properties (mass and dimensions) and frictional properties with a number of common surfaces. Results included a distribution of the amount of force required to displace the objects, providing performance benchmarks for reaching and grasping. The conclusions of this work are considered while designing our object set.

While developed and used primarily for prosthetics and rehabilitation applications, The Southampton Hand Assessment Procedure (SHAP) [11] has been frequently considered by robotics researchers. The test involves a standard set of objects, including some objects of daily living such as a bowl, a drink carton, and a jar, together with some geometrical shapes, for which subjects must do a variety of manipulation tasks, including pouring the drink, opening the jar etc. The test kit is available for purchase, but is pricey and limited to only a small number of objects and tasks.

Fig. 3: Tool items in the YCB Object Set: back: power drill, wood block; middle row: scissors, padlock and keys, markers (two sizes), adjustable wrench, phillips and flat screwdrivers, wood screws, nails (two sizes), plastic bolt and nut, hammer; front: spring clamps (four sizes).

Fig. 4: Shape items in the YCB Object Set: back: Mini soccer ball, softball, baseball, tennis ball, racquetball, golf ball, front: plastic chain, washers (seven sizes), foam brick, dice, marbles, rope, stacking blocks (set of 10), credit card blank.

III. The Object and Data Set

The proposed object set can be seen in Figures 1-7 and listed in Table I. In this section, we describe the object set and the reasoning behind the choices (section III.A), a description of the process and data involved in the scans of the objects (III.B), and the models and integration into simulation and planning packages (III.C).

Table I: Object Set Items and Properties

ID	Class	Object	Mass	Dims. (mm)
1	Food items	Chips Can	205g	75 x 250
2		Master Chef Can	414g	102 x 139
3		Cracker Box	411g	60 x 158 x 210
4		Sugar Box	514g	38 x 89 x 175
5		Tomato Soup Can	349g	66 x 101
6		Mustard Bottle	603g	58 x 95 x 190
7		Tuna fish can	171g	85 x 33
8		Pudding Box	187g	35 x 110 x 89
9		Gelatin Box	97g	28 x 85 x 73
10		Potted Meat Can	370g	50 x 97 x 82
11		Banana	66g	36 x 190
12		Strawberry	18g	43.8 x 55
13		Apple	68g	75
14		Lemon	29g	54 x 68
15		Peach	33g	59
16		Pear	49g	66.2 x 100
17		Orange	47g	73
18		Plum	25g	52
19	Kitchen Items	Pitcher Base	178g	108 x 235
20		Pitcher Lid	66g	123 x 48
21		Bleach Cleanser	1131g	250 x 98 x 65
22		Windex Bottle	1022g	80 x 105 x 270
23		Wine glass	133g	89 x 137
24		Bowl	147g	159 x 53
25		Mug	118g	80 x 82
26		Sponge	6.2g	72 x 114 x 14
27		Skillet	950g	270 x 25 x 30
28		Skillet Lid	652g	270 x 10 x 22
29		Plate	279g	258 x 24
30		Fork	34g	14 x 20 x 198
31		Spoon	30g	14 x 20 x 195
32		Knife	31g	14 x 20 x 215
33		Spatula	51.5g	35 x 83 x 350
34		Table cloth	1315	2286 x 3352
35	Tool Items	Power Drill	895g	35 x 46 x 184
36		Wood Block	729g	85 x 85 x 200
37		Scissors	82g	87 x 200 x 14
38		Padlock	304g	24 x 47 x 65
39		Keys	10.1g	23 x 43 x 2.2
40		Large Marker	15.8g	18 x 121
41		Small Marker	8.2g	8 x 135
42		Adjustable Wrench	252g	5 x 55 x 205
43		Phillips Screwdriver	97g	31 x 215
44		Flat Screwdriver	98.4g	31 x 215
45		Nails	[2,2.7,4.8] g	[4x25, 3x53, 4x63]
46		Plastic bolt	3.6g	43 x 15
47		Plastic nut	1g	15 x 8
48		Hammer	665g	24 x 32 x 135

Table I (cont): Object Set Items and Properties

ID	Class	Object	Mass	Dims. (mm)
49	Tool Items	S Clamp	19.2g	85 x 65 x 10
50		M Clamp	59g	90 x 115 x 27
51		L Clamp	125g	125 x 165 x 32
52		XL Clamp	202g	165 x 213 x 37
53		Mini Soccer Ball	123g	140
54		Soft Ball	191g	96
55		Tennis Ball	58g	64.7
56		Racquetball	41g	55.3
57	Shape Items	Golf Ball	46g	42.7
58		Chain	98g	1149
59		Washers	[0.1,0.7,1.1,3,5.3,19,48] g	[6.4, 10, 13.3, 18.8, 25.4, 37.3, 51]
60		Foam Brick	28g	50 x 75 x 50
61		Dice	5.2g	16.2
62		Marbles	N/A	N/A
63		Rope	18.3g	3000 x 4.7
64		Cups	[13,14,17,19, 21,26,28,31,35,38] g	[55x60, 60x62, 65x64, 70x66, 75x68, 80x70, 85x72, 90x74, 95x76, 100x78]
65		Blank Credit Card	5.2g	54 x 85 x 1
66		Clear Box	302g	292 x 429 x 149
67		Rope		
68		Box Lid	159g	292 x 429 x 20
69		Colored Wood Blocks	10.8g	26
70	Task Items	9-Peg-Hole Test	1435g	1150 x 1200 x 1200
71		Toy Airplane	570g	171 x 266 x 280
72		Lego Duplo	523g	N/A
73		T-shirt	105g	736 x 736
74		Magazine	73g	265 x 200 x 1.6
75		Timer	102g	85 x 80 x 40

A. Objects

We aimed to choose objects that are frequently used in daily life, and went through the literature to take into account the objects that are frequently used in simulations and experiments. In compiling the proposed object and task set, we needed to take a number of additional practical issues into consideration:

- Variety: In order to cover as many aspects of robotic manipulation as possible, we included objects that have a wide variety of shape, size, transparency, deformability, and texture. Grasping and manipulation difficulty was also a criterion: for instance, some objects in the set are well approximated by simple geometric shapes and relatively easy for grasp synthesis and execution, while other objects have higher shape complexity and more challenging for grasp synthesis and execution.
- Use: We included objects that are not only interesting for grasping, but also have a range of manipulation uses. For example, a pitcher and a cup; nails and a hammer; pegs, cloths and rope. We also included

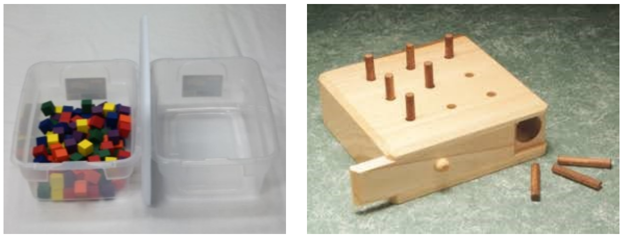

Fig. 5: (left) Box-and-blocks test objects: set of 100 wooden cubes, two containers and height obstacle (container lid) between them. (right) 9-hole peg test: wooden pegs are placed in

(a)

(b)

Fig. 6: Assembly objects: (a) Toy airplane disassembled (left), including toy power screwdriver, and fully assembled (right), (b) LEGO Duplo.

widely used standard manipulation tests in rehabilitation, such as the box and blocks [25] and 9-hole-peg test [26] (Fig. 5). Additionally, "assembly" items/tasks are included: A set of children's stacking cups and a toy airplane that must be assembled and screwed together, and a LEGO Duplo (Fig. 6). As above, these tasks are intended to span a wide range of difficulty, from relatively easy to very difficult. Furthermore, the ability to quantify task performance was also prioritized, including aspects such as level of difficulty, time-to-completion, and success rate, among others.

- Durability: We aimed for objects that can be useful long term, and therefore avoid objects that are fragile or perishable. Also, to increase the longevity of the object set, we chose the objects that are likely to remain in circulation and change relatively little in the near future.

Fig. 7: Task Items: left: Black t-shirt, right: Timer.

- Cost: We aimed to keep the cost of the object set as low as possible to broaden accessibility. We therefore selected standard consumer products, rather than, for instance, custom-fabricated objects and tests. Current cost for the objects is approximately $350.
- Portability: We aimed to have an object set that fits in a large-sized suitcase and be below the normal airline weight limit (22kg) in order to allow easy shipping and storage.

After considering these practical issues and reviewing the literature, the final objects were selected (Table I, Figs. 1-7). The objects in the set can be divided into the following categories: food items, kitchen items, tool items, shape items, task items. Objects from ID 1 to 18 are the food items, containing real boxed and canned items, as well as wooden fruits of complex shapes. The objects from ID 19 to 34 are kitchen items, containing objects for food preparation and serving, as well as glass cleaner and a sponge. The objects from 35 to 56 form the tool category, containing not only common tools, but also items such as nails, screws, and wood to utilize them. The shape items are from ID 57 to 69, which span a range of sizes (spheres, cups, and washers), as well as compliant objects such as foam bricks, rope, and chain.

The manipulation task items are the objects with IDs 70 to 75, and include two widely used tasks in rehabilitation benchmarking (box-and-blocks [25] and 9-hole peg test [26]) as well as assembly objects (children's airplane toy, LEGO), a black t-shirt, a magazine and a timer.

B. Scans

In order to ease adoption, we collect visual data that is commonly required for grasping algorithms and generate 3D models for use in simulation. We use the scanning rig used to collect the BigBIRD dataset [1]. The rig, shown in Figure 9, has 5 RGBD sensors and 5 high-resolution RGB cameras arranged in a quarter-circular arc. Each object is placed on a computer-controlled turntable, which is rotated by 3 degrees at a time, yielding 120 turntable orientations. Together, this yields 600 RGBD images and 600 high-resolution RGB images. The process is completely automated, and the total collection time for each object is under 5 minutes.

We then use Poisson surface reconstruction to generate watertight meshes. Currently, the bottoms of the objects are not scanned, and therefore the bottoms of the meshes are not textured. Afterwards, we project the meshes onto each image to generate segmentation masks. Note that Poisson reconstruction

Fig. 8: BigBIRD Object Scanning Rig: the box contains a computer-controlled turntable.

Fig. 9: Point cloud and textural data overlays on two YCB objects: mustard bottle and power drill.

fails on certain objects with missing depth data; specifically, transparent or reflective regions of objects usually do not register depth data. We will later provide better models for these objects using algorithms that take advantage of the high-resolution RGB images for building models.

In total, for each object, we provide:

- 600 RGBD images
- 600 high-resolution RGB images
- Segmentation masks for each image
- Calibration information for each image
- Texture-mapped 3D mesh models

The object scans can be found at [27].

C. Models

Based on the scans of the objects, there are several ways in which object models can be easily integrated into a variety of robot simulation packages. For example, in the MoveIt [5] simulation package, the mesh can be used as a collision object directly. Furthermore, a Unified Robot Description Format (URDF) file can be automatically constructed to integrate with ROS [28]. This provides a way of specifying mass properties, and can link to alternate representations of the mesh for visualization and collision. Integration with the OpenRAVE [29] simulation package is similarly straight-forward where we link to the display and collision meshes from a KinBody XML file. Using the scans, we have created URDF and KinBody files for all of the objects in the dataset, provided alongside the scans at [27].

Once in a simulation environment, a variety of motion planners and optimizers can use these models either as collision or manipulation objects. Some algorithms, such as CHOMP [30], require signed-distance fields to avoid collisions which can be computed from the included watertight meshes. In other cases such as CBiRRT [31] compute collisions directly using an optimized mesh collision checker.

In many cases, collision checking is a computational bottleneck for motion planning. Execution time can be reduced using a simplified mesh produced either by hand or with automatic decimation methods [32]. We have not yet provided simplified meshes in this dataset, but view this as an opportunity in future work to further explore mesh approximation algorithms and their impact on motion planning problems using the standardized benchmarks.

IV. Functional Demonstration

Figure 10 demonstrates the entire pipeline. Here, we see the HERB [33] robot preparing to grasp the virtual drill object. This demonstration uses an integration of ROS and OpenRAVE. ROS is used to provide communication between the various hardware and software components of the robot, while OpenRave handles planning and collision checking.

Inside OpenRAVE, the HERB robot uses CBiRRT, the OMPL [34] library and CHOMP to plan and optimize motion trajectories. Using these tools, chains of several actions can be executed in sequence. The simulation environment also provides a mechanism for incorporating feedback from perception systems, which similarly benefit from this dataset. The provided images, meshes and physical objects can all be used as training data for various object detection and pose estimation algorithms, which can then be incorporated into the manipulation pipeline.

Access to both the physical object and a corresponding model for simulation is important for developing and testing new planning and manipulation algorithms. This dataset vastly reduced the time required to set up this example by providing access to objects and meshes that have already been prepared for this purpose. This removed the burden of scanning or modeling new objects and provides benchmark environments that streamline experimental design.

V. Conclusion and Future Work

This paper proposes a set of objects and related tasks, as well as high-resolution scans and models of those objects, intended to serve as a widely-distributed and widely-utilized set of standard performance benchmarks for robotic grasping and manipulation research. The objects were chosen based on an in-depth literature review of other objects and tasks previously proposed and utilized in robotics research, with additional consideration to efforts in prosthetics and

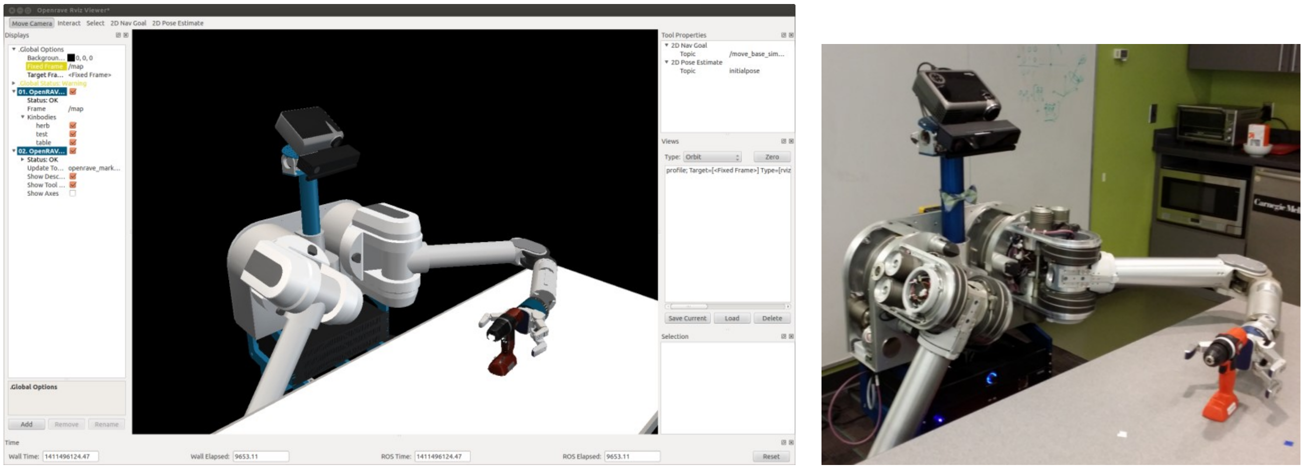

Fig. 10: (left) Screen-capture from Openrave simulation and planning environment showing the HERB robot planning a grasp of the power drill object in the set. (right) actual grasp being executed by the robot on the physical object.

rehabilitation. Furthermore, a number of practical constraints were considered, including a reasonable total size and mass of the set for portability, low cost, durability of the objects, and the likelihood that the objects would remain mostly unchanged in years to come. High-resolution RGBD scans of the objects were done and models of the objects have been constructed to allow easy portability into simulation and planning environments. All of these data are freely available in the associated repository [27]. The objects sets will be freely distributed to a large number of research groups through workshops/tutorials associated with this effort, and will be made available to purchase otherwise.

While a common set of widely-available objects is a much-needed contribution to the manipulation research community, the objects themselves are just the beginning. One major missing piece that we are now beginning to address is the generation of more detailed tasks and protocols involving the objects. While some of these are fairly straight-forward to specify (e.g. the box-and-blocks test, which simply examines the number of blocks that can be moved from one side to the other in a fixed amount of time), many will involve much more detail, possibly including specification of not only the task to be completed (e.g. simulated meal preparation), but also the nature of the system configuration(s) to be utilized (e.g. whether the a priori object models should be used during task performance). We plan to involve the research community in this effort via a web portal and arXiv-style working documents for proposed protocols, and will work towards having the majority of those protocols come from the user community rather than the authors. Additionally, we plan to have on this portal a "records" keeping functionality to keep track of the current "world records" for the different tasks and protocols, along with video and detailed descriptions of the approaches utilized, generating excitement, buzz, motivation, and inspiration for the manipulation community to compare approaches and push forward the state of the art.

Other efforts that we plan to undertake include more detail about the objects proposed, including information about the inertia of the objects, as well as frictional properties between the objects and common surfaced. Additionally, we will expand our treatment of the modelling of the objects, including addressing the tradeoffs between number of "triangles" and the reliable representation of the object geometry. Furthermore, before final publication and distribution of the object set, we will seek additional input from the research community on the specific objects in the set.

It is our hope that this work will help to address the long-standing need for common performance comparisons and benchmarks in the research community and will provide a starting point for further focused discussion and iterations on the topic.

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