

# *Supplementary Materials*

## Dense Hand-Object(HO) GraspNet with Full Grasping Taxonomy and Dynamics

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### 1 Additional Evaluation

Here, we present additional experimental results with HOGraspNet that are not included in the main paper. We provide detailed descriptions of the evaluation setups and the quantitative results across each split type we defined. Additionally, we show qualitative comparisons between HOGraspNet and the publicly available datasets [19, 17, 4].

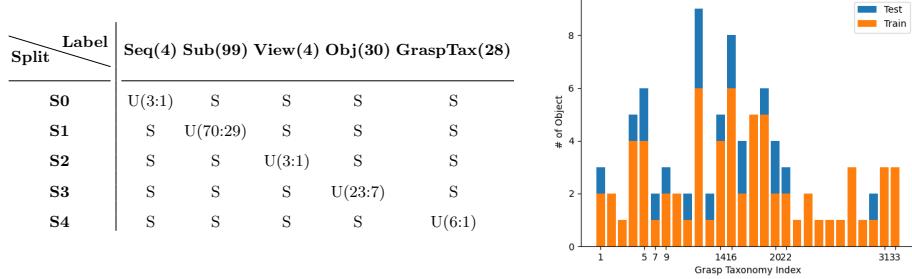
#### 1.1 Evaluation Setup

**Split Protocol.** The S0 split follows the traditional sequence split, where the first trial of each subject and grasp scenario is assigned to the test set. For the S1 split, the 99 subjects are randomly divided into train and test sets at a ratio of roughly 7:3. For the S2 split, the data from the four camera views are divided at a ratio of 3:1. Each view corresponds to a different side of the subjects (back, left, front, and right), and the right-side camera is selected as the test set. In the S3 split, 30 objects are divided into train and test sets at a ratio of 23:7, ensuring that all grasp classes are represented in the train set. The cumulative grasp classes for the objects in both sets are shown in Fig. 1. Lastly, the S4 split separates the total of 28 grasp classes at a ratio of 6:1, with four classes identified as *Intermediate* (please refer to Fig. 11) assigned to the test set.

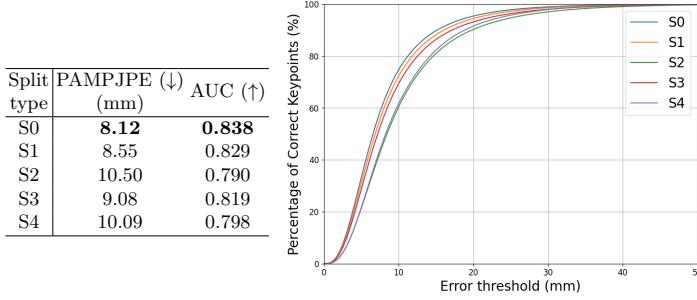
**Baseline Network.** We report the hand reconstruction results using HFLnet [12] trained on each split. We train each network for 5 epochs using the Adam optimizer with a learning rate of 1e-4 and a decaying gamma of 0.9 per 2 epochs, while other parameters are set to the default values.

#### 1.2 Evaluation Results

**Hand Pose Estimation.** We summarize the hand estimation results in Fig. 2. The S0 split exhibits the highest performance, while the S2 split demonstrates the lowest, with S4 showing the second lowest performance. As the S0 partitions the dataset only by sequences, it generally shares common pose spaces between



**Fig. 1. (left)** Detailed experimental protocols (train:test splits). **U** denotes unseen factor, **S** denotes seen factors. We consider sequence, subject, view, object, and grasp taxonomy as split factors. **(right)** Distribution of grasp taxonomy in **S3**. All grasp classes are present in S3 (unseen object) train set.



**Fig. 2. (left)** 3D hand pose estimation results, **(right)** PCK curve for each split type.

the train and test sets, which results in the lowest pose error. Conversely, the S2 split with viewpoint exhibits the lowest performance. As our dataset contains 4 sparse viewpoints (back, left, front, and right) following the existing literature [10], the RGB frames among different viewpoints may exhibit high disparity, potentially making the network generalization difficult. Thus, we have anticipated that S2 would be the most challenging split due to the unseen camera view in the test set. The second lowest performance is shown by the S3 split categorized by grasp taxonomy. As mentioned earlier, there are distinct variations in hand poses among grasp taxonomies, which results in inconsistencies in the performance of the trained model on the test set. On the other hand, in the S1 split with unseen subjects, shape variations exist between the train and test sets. However, since the same grasp guidelines were provided to all subjects, differences in hand poses among subjects are relatively small, resulting in relatively good joint pose estimation performance. The S3 split for unseen objects, which includes all grasps but not all objects, shows relatively lower performance due to

**Table 1. 6D object pose estimation results in ADD-0.1D( $\uparrow$ ) per object.** We used HFL-Net [12] trained on each split.

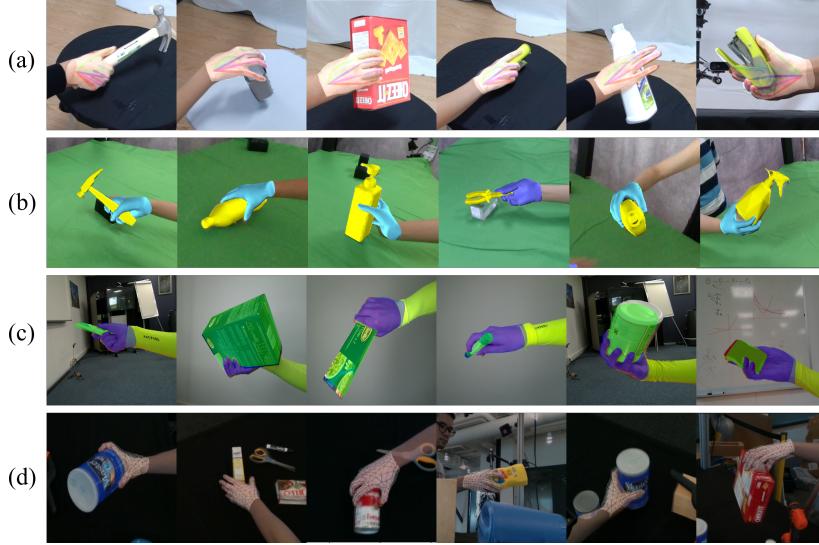
	S0	S1	S2	S3	S4	avg		S0	S1	S2	S3	S4	avg	
1: cracker_box	51.46	39.55	22.80	-	-	37.94	16: golf.ball	1.29	1.47	0.06	-	-	0.94	
2: potted_meat.can	19.19	12.95	8.18	0.07	-	10.10	17: credit.card	2.15	3.31	1.17	-	1.97	2.15	
3: banana	14.43	20.12	0.55	-	-	11.70	18: dice	0.0	0.02	0.04	-	0.04	0.03	
4: apple	11.36	14.57	1.40	0.24	-	6.89	19: disk.lid	30.61	32.12	1.98	-	-	21.64	
5: wine.glass	22.96	15.64	1.76	-	-	13.46	20: smartphone	12.81	16.40	2.75	0.06	9.69	7.93	
6: bowl	26.78	19.43	6.34	0.03	22.82	14.07	21: mouse	12.13	12.16	2.42	-	-	8.90	
7: mug	25.23	21.36	3.60	-	-	16.73	22: tape	9.61	1.75	7.78	-	5.04	6.05	
8: plate	23.76	29.73	1.52	-	25.81	20.21	23: master.chef.can	29.51	28.15	16.87	-	-	24.85	
9: spoon	15.64	19.07	12.87	-	16.70	16.08	24: scrub.cleanser.bottle	52.61	40.23	42.35	-	-	45.07	
10: knife	12.92	10.97	3.95	5.31	-	8.29	25: large.marker	7.65	5.05	3.19	-	-	5.30	
11: small.marker	6.17	6.91	3.53	1.39	-	4.50	26: stapler	26.57	26.97	6.80	-	-	20.12	
12: spatula	2.15	20.64	0.94	0.04	-	12.10	27: note	43.62	61.99	0.69	-	41.92	37.06	
13: flat.screwdriver	13.99	12.08	0.46	-	-	8.85	28: scissors	20.87	14.66	1.26	-	7.40	11.05	
14: hammer	28.24	30.79	1.98	-	-	20.34	29: foldable.phone	8.68	8.00	0.78	-	6.28	5.94	
15: baseball	7.24	5.77	2.75	-	-	5.56	30: cardboard.box	6.44	5.14	1.55	-	-	4.38	
<b>Avg</b>	S0 : 18.86		S1: 18.10		S2: 5.15		S3: 1.02		S4: 13.76					

the characteristics of the HFL baseline model, which estimates hand pose given the object information.

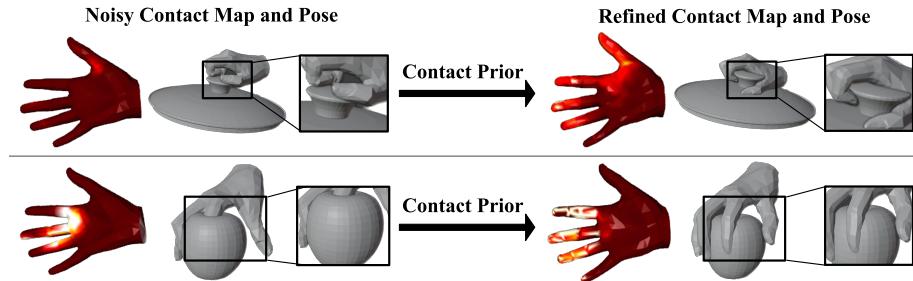
**Object Pose Estimation.** We show the object pose estimation results in Tab. 1. Recall that S3 is an unseen object split and S4 is an unseen grasp taxonomy split. However, S4 does not consist of all objects in the training set due to the fixed grasps per object, leading to several invalid object poses in both splits (denoted as -). Overall, the baseline achieves the best object pose estimation performance on the S0 split, which has a minimal disparity between the train and test sets. Notably, small objects like dice, golf balls, and credit cards, which are mostly absent in existing datasets, show the lowest performance due to significant occlusion caused by the interaction with the hand. Furthermore, objects with intricate textures, such as cracker boxes and scrub cleanser bottles, generally yield high accuracy due to providing reliable cues for the network model. Unlike the object pose estimation experiment in the main paper (Sec. 4.3), this experiment does not account for the object’s symmetry during the metric calculation, resulting in lower accuracy for symmetric objects like markers, cardboard boxes, and tape.

**Qualitative Comparison Between Datasets.** Fig. 3 shows the qualitative results of randomly sampled data from each recent dataset. Minor discrepancies between real and rendered meshes are found across examined datasets, with overall annotation quality being supposed to be consistent. Additionally, mesh discrepancies in the wrist area are observed in several samples, likely resulting from inherent limitations in the representation of the MANO [16] hand model.

**Refinement results on noisy hand-object contact maps and poses** Regarding in-the-wild experiments, recent works train a generative prior on 3D shapes and use it to regularize the plausibility of poses estimated from in-the-wild images, achieving new state-of-the-art accuracy [20,11]. The diversity in the training 3D shape set is the key to building a strong prior. We thus believe that HOGraspNet can play an important role in this direction. Although this



**Fig. 3. Qualitative comparison of random samples of different datasets. (a) HOGraspNet (ours). (b) OakInk [19]. (c) SHOWMe [17]. (d) DexYCB [4].**



**Fig. 4. Refinement results of our prior model trained on HOGraspNet on noisy hand-object contact maps and poses.**

was not the original scope of our dataset collection work, we report the preliminary results following the experimental setup in [9], where we trained a prior model of hand-object shapes represented as contact maps and used it to refine the noisy hand-object poses (e.g., estimated from images). Fig. 4 shows that the prior model trained on HOGraspNet can successfully refine the noisy contacts and enforces more plausible pose estimation. We observed that incorporating our per-sample grasp type (which is not provided by most of the existing datasets) further improves the performance of the prior model, increases the hand and object contact F1 scores by 6% and 5%, respectively. We will further investigate this direction as future work.

## 2 Additional Survey on Interaction Datasets

In this section, we provide more details on the existing hand-object interaction datasets discussed in Sec. 2 in the main paper. We then report the missing grasp types in the existing datasets [10,4,3] to show that ours capture more comprehensive grasps.

**More Details on Hand-Object Datasets.** **FPHA** [8] captures first-person dynamic hand actions interacting with 3D objects. It consists of over 100K RGB-D frames of 1.1K action samples across 45 categories by manipulating 26 objects. The hand joint is annotated using six magnetic sensors and inverse kinematics. However, the FPHA does not fully provide the 6D object pose, and the presence of magnetic sensors on the hand corrupts the RGB-D images. **YCB-Affordance** [5] consists of 133K annotated frames featuring over 28M synthetic grasps to depict diverse human grasp affordances. It has manual annotations of 367 different hand-object poses, according to the 33-grasp taxonomy [7]. These hand poses are rendered upon the YCB-Video [18] dataset. However, YCB-Affordance captures less diverse grasp configurations since the hand poses are replicated through the rotation symmetry of the object. Also, the synthetic images may lead to less effective network training due to the discrepancy between the synthetic and real image domains. **ContactDB** [1] captures detailed hand-object contact of grasping using a thermal camera. It consists of 3.7K 3D meshes of 50 household objects textured with contact maps and 375K frames of synchronized RGB-D+thermal images. **ContactPose** [2] expands ContactDB by including 3D joint locations and multi-view RGB-D grasp images. It has 2.3K unique grasps of 25 household objects by 50 participants and more than 2.9M RGB-D grasp images. However, ContactPose does not support dynamic grasp, where the thermal camera can only capture one contact map for each interaction sequence. **EPIC-KITCHEN** [6] is a large-scale egocentric hand-object dataset. It captures the kitchen activities of 32 identities of 10 different nationalities. However, it does not provide mesh annotations; thus, it cannot be used to train hand-object dense shape reconstruction networks. **HOI4D** [13] captures 4D egocentric category-level human-object interaction. HOI4D consists of 2.4M RGB-D egocentric video frames over 4K sequences collected by 4 participants interacting with 800 object instances from 16 categories over 610 indoor rooms. HOI4D provides annotations for frame-wise panoptic segmentation, motion segmentation, 3D hand pose, rigid and articulated object pose, and action segmentation. Although diverse objects were obtained, it is limited to the 16 types of object categories, which do not cover full taxonomies (e.g., grasps that can only be acquired through flat or small objects).

**Missing Grasp Classes in Existing Datasets.** In Fig. 5, we present a list of grasp classes that are absent in the existing datasets (MOW [3], HO3D [10], and DexYCB [4]), which we manually identified. This further demonstrates that our dataset more comprehensively captures hand grasps, covering more grasp types.

	Missing grasps of each dataset for 33 grasp taxonomy									
Ours	 6: Prismatic 4 Finger  8: Prismatic 2 Finger  15: Fixed Hook  21: Tripod Variation  32: Ventral									
MOW (ICCV21)	 11: Power Sphere  21: Tripod Variation  23: Adduction Grip  25: Lateral Tripod  26: Sphere 4 Finger  31: Ring									
HO3D (CVPR20)	 5: Light Tool  6: Prismatic 4 Finger  7: Prismatic 3 Finger  11: Power Sphere  15: Fixed Hook  19: Distal Tripod  20: Writing Tripod  21: Tripod Variation  23: Adduction Grip   24: Tip Pinch  25: Lateral Tripod  26: Sphere 4 Finger  27: Quadpod  29: Stick  30: Palmar  31: Ring  32: Ventral  33: Inferior Pincer									
DexYCB (CVPR21)	 5: Light Tool  6: Prismatic 4 Finger  8: Prismatic 2 Finger  9: Palmar Pinch  10: Power Disk  11: Power Sphere  15: Fixed Hook  17: Index Finger Extension  21: Tripod Variation  23: Adduction Grip   24: Tip Pinch  25: Lateral Tripod  26: Sphere 4 Finger  27: Quadpod  28: Sphere 3 Finger  29: Stick  31: Ring  32: Ventral  33: Inferior Pincer									

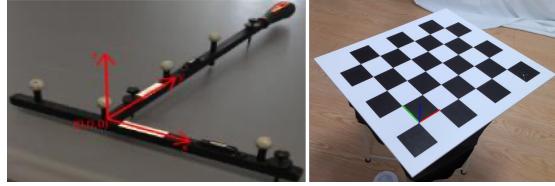
**Fig. 5.** Missing grasp types in the existing datasets (MOW [3], HO3D [10], and DexYCB [4]).

### 3 Details of Annotation Procedure

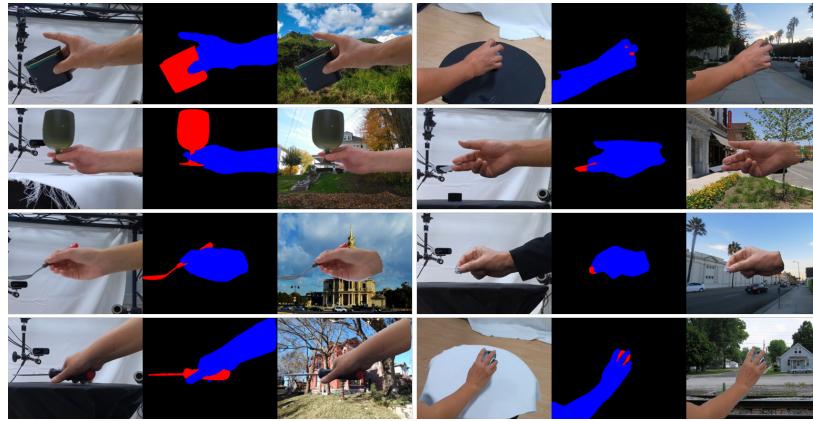
In this section, we provide more details on our camera calibration (Sec. 3.1), segmentation (Sec. 3.2), and hand-object model fitting procedures (Sec. 3.3).

#### 3.1 Camera Calibration

We use 4 RGB-D cameras to record the frames and 8 IR cameras to acquire object 6D poses. The RGB-D cameras and the IR cameras are temporally synchronized with electric signals, and we manually align the starting frames between them with a blinking LED. The transformations among the RGB-D cameras are calibrated with a checkerboard and a T-shaped wand with optical markers for IR cameras. To align coordinates between the RGB-D and IR cameras, three optical markers are placed on the checkerboard, which is positioned on the table. Although the capture system remains fixed, this calibration process is performed for each sequence.



**Fig. 6. (left)** T-shaped wand. IR cameras capture the visible optical markers of a traversing wand. **(right)** Checkerboard. Optical markers are placed at the end of red and green lines.



**Fig. 7. Examples of our pseudo GT segmentation masks and background augmentation.**

### 3.2 Segmentation

The quality of the pseudo-ground truth in our annotation pipeline is crucially tied to the final annotation quality. The hand and object masks were improved using a fine-tuned segmentation model, with examples in Fig. 7. These results demonstrate plausible masks for each object, achieved through tuning the model with our manually annotated segmentation masks.

### 3.3 MANO and Object Model Fitting

In this subsection, we provide more details on our MANO [16] and object model fitting process discussed in Sec. 3.5 in the main paper. Recall that our goal is to align MANO hand and object mesh models with RGB-D data captured from multiple cameras based on the initial poses of the hand and the object. Here, the MANO model is parameterized by pose parameter  $\theta \in \mathbb{R}^{48}$  and shape parameter  $\beta \in \mathbb{R}^{10}$ . The object model is represented using the standard 6D pose representation  $\phi \in \mathbb{R}^6$ , consisting of a 3D rotation matrix and a 3D translation vector.

**Multi-view Multi-frame Gradual Hand-Object Model Fitting.** To annotate hand and object parameters, we formulate an optimization problem with the objective discussed in the main paper (Eq. 1). To avoid local minima, we gradually fit the partial hand pose parameters across several stages. Through preliminary experiments, we found that optimizing the hand pose parameters starting from the wrist outward yielded promising results. With this insight, we perform the optimization progressively in the subsequent order: (1) global hand orientation, (2) partial hand poses extended from the wrist, and (3) the full hand and object parameters.

**Details on Loss Terms.** We now provide the details on each loss term in Eq. 1 in the main paper.  $\mathcal{L}_h^{2D}$  is 2D hand joint loss, which is defined as the L2 distance between pseudo GT 2D joint  $j_i$  and 2D projection  $\Pi^c$  of the models 3D joint  $\tilde{j}_i^{3D}$  over camera view  $c$  with the visibility  $v_i$ :

$$\mathcal{L}_h^{2D} = \lambda_h^{2D} \sum_c \sum_{i=1}^{21} \left\| j_i^c - \Pi^c(\tilde{j}_i^{3D}) \right\|_2 \cdot v_i. \quad (1)$$

$\mathcal{L}_o^{3D}$  is 3D object marker loss, which is also defined as the L2 distance between the 3D marker position  $m_n^{3D}$  and the corresponding vertex position of object model  $v_n$ :

$$\mathcal{L}_o^{3D} = \lambda_o^{3D} \cdot \sum_c \sum_{n=1}^{3 \sim 5} \left\| v_n^c - \Pi^c(m_n^{3D}) \right\|_2. \quad (2)$$

$\mathcal{L}_{seg}$  is segmentation loss computed for hand and object via the L1 distance between predicted mask  $M$  and the rendered mask from mesh model  $\tilde{M}$  over the camera view  $c$ :

$$\mathcal{L}_{seg} = \lambda_{seg} \cdot \sum_c \left\| M^c - \tilde{M}^c \right\|_1. \quad (3)$$

$\mathcal{L}_{depth}$  is depth loss, which is also computed as the L1 distance between captured depth image  $D$  and the rendered depth map  $\tilde{D}$  but for both hand and object:

$$\mathcal{L}_{depth} = \lambda_{depth} \cdot \sum_c \left\| D^c - \tilde{D}^c \right\|_1. \quad (4)$$

Following [21], we also incorporate the pose and shape regularize  $\mathcal{L}_{reg}$  to the MANO model to regularize the hand model and additional L2 norm between current hand model parameter  $\theta_t, \beta_t$  and previous parameter  $\theta_{t-1}, \beta_{t-1}$  for temporal consistency:

$$\mathcal{L}_{reg} = \lambda_{pose} \cdot \left\| \tilde{\theta} \right\|_2 + \lambda_{shape} \cdot \left\| \tilde{\beta} \right\|_2 + \lambda_{temporal} \cdot (\| \theta_t - \theta_{t-1} \|_2 + \| \beta_t - \beta_{t-1} \|_2). \quad (5)$$

To additionally regularize the fitted hand and object meshes to be physically plausible, we incorporate a regularization term  $\mathcal{L}_{phy}$ , which is designed

as a weighted sum of penetration loss and contact loss:  $\mathcal{L}_{phy} = \lambda_{pen}\mathcal{L}_{pen} + \lambda_{contact}\mathcal{L}_{contact}$ . For penetration loss  $\lambda_{pen}$ , we use a vertex normal projection-based technique used in [10]. Let  $\mathbf{V}_h \in \mathbb{R}^{N_h \times 3}$  and  $\mathbf{V}_o \in \mathbb{R}^{N_o \times 3}$  be the vertex matrices of hand and object, respectively. Then, the penetration loss  $\mathcal{L}_{pen}$  is defined as:

$$\mathcal{L}_{pen} = \sum_{i,j \in \mathcal{S}(\mathbf{V}_h, \mathbf{V}_o)} \max(-(\mathbf{n}_o^j)^T \mathbf{V}_h^i - \mathbf{V}_o^j, 0), \quad (6)$$

where  $\mathcal{S}(\cdot, \cdot)$  is a function that returns the hand vertex index  $i \in \mathbb{N}$  and its nearest object index  $j \in \mathbb{N}$  in the Euclidean space, and  $\mathbf{n}_o^j$  denotes a normal vector at  $j$ -th object vertex. Equation 6 projects a vector joining the nearest vertices of the hand and object onto the normal vector at the object to approximate the amount of penetration in a differentiable manner.

$\mathcal{L}_{pen}$  enforces the penetrated hand and object surfaces to repel each other, however, it is also important to regularize the closely located hand and object surface regions to be in actual contact to model physically plausible grasps. We use contact loss  $\mathcal{L}_{contact}$  that aims to minimize the distances between hand and object vertices below a distance threshold  $\tau$ :

$$\mathcal{L}_{contact} = \sum_{i,j \in \mathcal{S}(\mathbf{V}_h^i, \mathbf{V}_o^j)} \|\mathbf{V}_h^i - \mathbf{V}_o^j\|_2, \quad \text{where } d(\mathbf{V}_h^i, \mathbf{V}_o^j) < \tau. \quad (7)$$

In the above equation,  $d(\cdot, \cdot)$  denotes a distance function<sup>1</sup>. Note that we set  $\tau$  as 8mm in our experiments.

Finally, we implement the overall fitting process using PyTorch[14] to minimize:

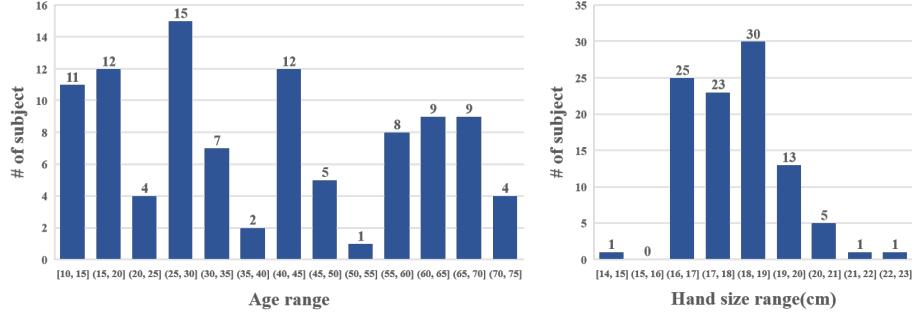
$$\hat{\theta}, \hat{\beta}, \hat{\phi} = \underset{\tilde{\theta}, \tilde{\beta}, \tilde{\phi}}{\operatorname{argmin}}(\mathcal{L}(\tilde{\theta}, \tilde{\beta}, \tilde{\phi})). \quad (8)$$

## 4 Taxonomies and Statistics for HOGraspNet

In this section, we report additional statistics of the HOGraspNet and the details of the taxonomies. We organized the subject’s gender with a ratio of 50:49 for males to females. The age distribution is also evenly dispersed, with proportions of 23%, 26%, 25%, and 25% across 20-year intervals from age 0 to 80. Hand sizes, measured from the wrist to the tip of the middle finger, are distributed as shown in Fig. 8. Fig. 9 shows each 3 grasp types for each of the 30 types of objects, resulting in a total of 90 interaction scenarios. We also show the data samples from HOGraspNet for each combination in Fig. 10. Lastly, the hand grasping and object taxonomies in Fig. 4 in the paper are provided on a larger scale in Fig. 11 and Fig. 12.

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<sup>1</sup> We use `point_to_mesh_distance` function in Pytorch3D [15].

**Fig. 8. Additional statistics of HOGraspNet**

## References

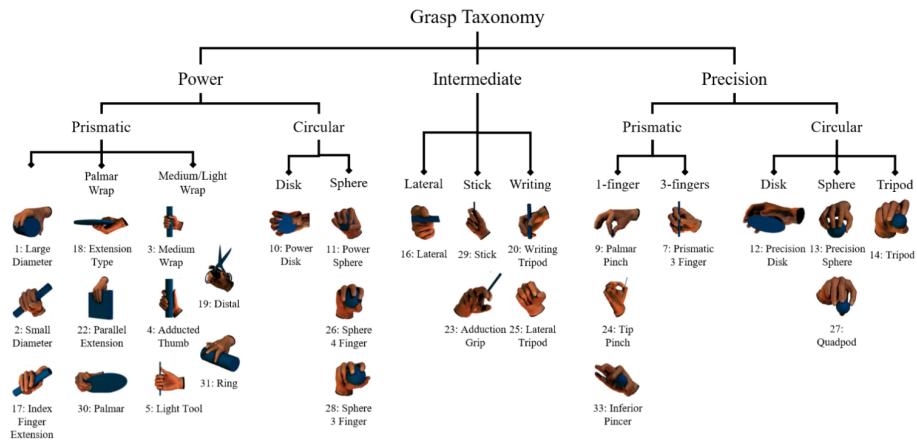
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Object Name / Image	Taxonomies per Object			Object Name / Image	Taxonomies per Object		
1: cracker_box				16: golfball			
2: potted_meat_can				17: credit card			
3: banana				18: dice			
4: apple				19: disk lid			
5: wine_glass				20: smartphone			
6: bowl				21: mouse			
7: mug				22: tape			
8: plate				23: master_chef_can			
9: spoon				24: scrub_cleanser_bottle			
10: knife				25: large_marker			
11: small_marker				26: stapler			
12: spatula				27: note			
13: flat_screwdriver				28: scissors			
14: hammer				29: foldable_phone			
15: baseball				30: cardboard_box			

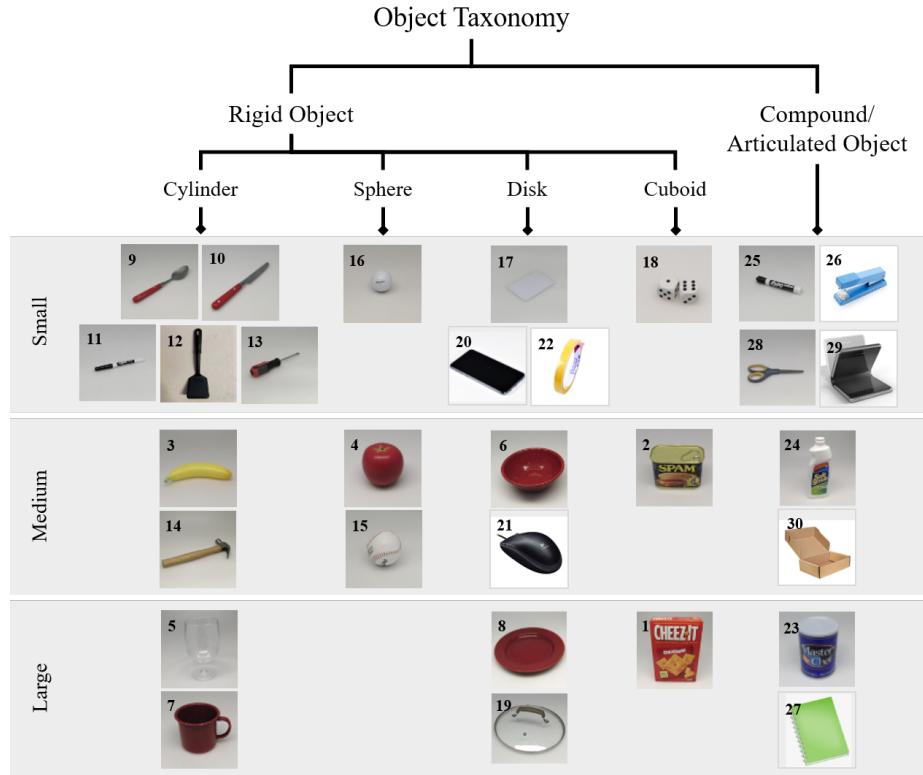
Fig. 9. Grasp classes for each object.



**Fig. 10. Samples of grasps per objects.** A total of 90 interaction instances comprising 3 classes of grasps across 30 objects.



**Fig. 11. Hand grasping taxonomy.**



**Fig. 12. Object taxonomy.**

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