Measuring Generalisation to Unseen Viewpoints, Articulations, Shapes and Objects for 3D Hand Pose Estimation under Hand-Object Interaction

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Abstract

In this work, we study how well different type of approaches generalise in the task of 3D hand pose estimation under hand-object interaction and single hand scenarios. We show that the accuracy of state-of-the-art methods can drop, and that they fail mostly on poses absent from the training set. Unfortunately, since the space of hand poses is highly dimensional, it is inherently not feasible to cover the whole space densely, despite recent efforts in collecting large-scale training datasets. This sampling problem is even more severe when hands are interacting with objects and/or inputs are RGB rather than depth images, as RGB images also vary with lighting conditions and colors. To address these issues, we designed a public challenge to evaluate the abilities of current 3D hand pose estimators (HPEs) to interpolate and extrapolate the poses of a training set. More exactly, our challenge is designed (a) to evaluate the influence of both depth and color modalities on 3D hand pose estimation, under the presence or absence of objects; (b) to assess the generalisation abilities w.r.t. four main axes: shapes, articulations, viewpoints, and objects; (c) to explore the use of a synthetic hand model to fill the gaps of current datasets. Through the challenge, the overall accuracy has dramatically improved over the baseline, especially on extrapolation tasks, from 27mm to 13mm mean joint error. Our analyses highlight the impacts of: Data pre-processing, ensemble approaches, the use of MANO model, and different HPE methods/backbones.

1. Introduction

3D hand pose estimation is crucial to many applications including natural user-interaction in AR/VR, robotics, tele-operation, and healthcare. The recent successes primarily come from large-scale training sets [48], deep convolutional neural networks [11, 25], and fast optimisation for model fitting [17, 26]. State-of-the-art methods now deliver satisfactory performance for viewpoints seen at training time and single hand scenarios. However, as we will show, these methods substantially drop accuracy when applied to egocentric viewpoints for example, and in the presence of significant foreground occlusions. If we look into the existing benchmarks [6, 23, 24], these cases are not well represented on the training sets. The challenges become even more severe when we consider RGB images and hand-object interaction scenarios. These issues are well aligned with the observations from the former public challenge HANDS 2017 [46]. The state-of-the-art methods dropped accuracy from frontal to egocentric views, and from open to closure hand postures. The average accuracy was also significantly lower under hand-object interaction [6].

Given the difficulty to interpolate and extrapolate poses from the training set, one may opt for creating even larger training sets. Unfortunately, an inherent challenge in 3D hand pose estimation is the very high dimensionality of the problem, as hand poses and shapes and camera viewpoints have a large number of degrees-of-freedom that can vary independently. This complexity increases even more when
we consider the case of a hand manipulating an object. Despite the recent availability of large-scale datasets [48], and the development of complex calibrated multi-view camera systems to help the annotation or synthetic data [15, 32, 52], capturing a training set that covers completely the domain of the problem remains extremely challenging.

In this work, we therefore study in depth the ability of current methods to interpolate and extrapolate the training set, and how this ability can be improved. To evaluate this ability, we consider the three tasks depicted in Figure 1, which vary the input (depth and RGB images) or the camera viewpoints, and introduce the possible manipulation of an object by the hand. We carefully designed training and testing splits in order to evaluate the generalisation performance to unseen viewpoints, articulations, and shapes of the submitted methods.

The challenge fostered dramatic accuracy improvement compared to a baseline we provided, which is a ResNet-50 [11] based 3D joint regressor trained on the provided training set, from 27mm to 13mm. We provide in this paper an in-depth analysis of the different factors that made this improvement possible.

2. HANDS 2019 Challenge Overview

The challenge consists of three different tasks, in which the goal is to predict the 3D locations of the hand joints given an image. For training, images, hand pose annotations, and a 3D parametric hand model [30] for synthesizing data are provided. For inference, only the images and the hand’s bounding boxes are given to participants. These tasks are defined as follows:

Task 1: Depth-Based 3D Hand Pose Estimation: This task builds on BigHand2.2M [48] dataset, as for the HANDS 2017 challenge [46]. No objects appear in this task. Hands appear in both third person and egocentric viewpoints.

Task 2: Depth-Based 3D Hand Pose Estimation while Interacting with Objects: This task builds on the F-PHAB dataset [6]. The subject manipulates objects with her/his hand, as captured from an egocentric viewpoint. Some object models are provided by [6].

Task 3: RGB-Based 3D Hand Pose Estimation while Interacting with Objects: This task builds on the HO-3D [9] dataset. The subject manipulates objects with her/his hand, as captured from a third person viewpoint. The objects are from the YCB dataset [41].

The BigHand2.2M [48] and F-PHAB [6] datasets have been used by 116 and 123 unique institutions to date. Hands’19 received 80 requests to access the datasets,
and 17, 10 and 9 participants have entered their methods on Task 1, Task 2 and Task 3, respectively.

3. Evaluation Criteria

The challenge uses the mean joint error (MJE) \[26\] as a main evaluation metric. Results of the participants are ranked according to \textbf{Total/Extrapolation} criterion which measures the total extrapolation power of the approaches with MJE as introduced below. Success rates based on a maximum allowed distance for each frame and each joint is also used in this study for further analysis.

To be able to measure generalization power of HPEs, we define the training and the test splits using the ground-truth joint annotations and by labeling each frame based on each axis viewpoint, articulation, shape and object type that is present in the image. Carefully designed splits help to define the following measures with MJE scores:

\textbf{Extrapolation}:

\begin{itemize}
  \item \textbf{Total/Extrapolation}: viewpoints, articulations, hand shapes, and objects not present in the training set. We refer it as Extrapolation in the rest of the paper.
  \item \textbf{Articulation}: hand articulations not present in the training set.
  \item \textbf{Viewpoint}: viewpoints not present in the training set. Viewpoints are defined as elevation and azimuth angles of the hand \textit{w.r.t.} the camera.
  \item \textbf{Shape}: shapes not present in the training set.
  \item \textbf{Object}: objects not seen in the training set.
\end{itemize}

\textbf{Interpolation}:

viewpoints, articulations, shapes and objects present in the training set.

Figure 2 summarises the six evaluation strategies on the four main axes, and Figure 3 shows the accuracies obtained by the best approaches that entered the challenged, measured by the three common evaluation criteria among the tasks. Overall, the extrapolation errors are about three times larger than the interpolation errors in all three tasks. The shape is a bottleneck among other attributes. Lower errors on Task 3 compared to Task 2 are likely due to the fact that the ground truth wrist position was provided for Task 3. We discuss the results in much more details in the rest of the paper.

4. Datasets

In this section, we present the details of the datasets used in each task.

\textbf{Data Statistics.} Given a task, the training set is the same for the 6 evaluation criteria and the test samples used to evaluate each criteria can be different or overlapped. The number of training frames are 175k, 45k and 10k for Task 1, 2 and 3 respectively. The sizes of the test sets for each evaluation criterion are shown in Table 1.

Figure 4 shows the distributions of training and testing data for each task. For the viewpoint axis, the azimuth and elevation angles are considered separately for the splits. The articulation distribution of the dataset is obtained by clustering on the joint angles in a fashion similar to \[20\], by using binary representations (on/off) of each finger, which ends up with $2^5 = 32$ clusters. We split to training and test data using the cluster indices. Note that the use of low-dimension embedding such as PCA or t-SNE is not adequate here to

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline
\textbf{Dataset} & \textbf{Task id} & \textbf{Total} & \textbf{Ext.} & \textbf{Int.} & \textbf{Art.} & \textbf{View.} & \textbf{Sha.} & \textbf{Obj.} & \textbf{#Subjects} & \textbf{#Objects} & \textbf{#Actions} & \textbf{#Seq.} \\
\hline
\textbf{Test} & 1 & 125K & 20% & 16% & 16% & 32% & 16% & \textbf{14} & 14 & 27% & 5 & 5 & 1 & 5 \\
& 2 & 25K & 14% & 32% & \textbf{37} & \textbf{37} & 17% & 4 & 37 & 71 & 292 & & & & \\
& 3 & 6.6K & 24% & 35% & \textbf{14} & 14 & 27% & 5 & 5 & 1 & 5 & & & & \\
\hline
\textbf{Training} & 1 & 175K & & & & & & & & & & & & \\
& 2 & 45K & & & & & & & & & & & & \\
& 3 & 10K & & & & & & & & & & & & \\
\hline
\end{tabular}
\caption{Detailed analytics on the number of frames provided on the training and test sets for the different tasks.}
\end{table}
Figure 4: Distributions of the training and test datasets for Task 1 (top), Task 2 (bottom left) and Task 3 (bottom right). The splits are used to measure the extrapolation power of the approaches and decided based on the viewpoint, articulation cluster of the hand pose, shape of the hand and type of the object present.

compare the two data distributions, because the dimensionality of the distributions is very high and a low-dimension embedding would not be very representative. Figure 4 also shows the re-partition in terms of subjects/shapes, where five seen subjects and five unseen subjects are present. Similarly, the data partition was done on objects and actions. This way we gained a control on data differences to define five extrapolation, and one interpolation scenarios. The results in Section 6 are correlated to these data distributions.

Use of 3D Hand Models for HPEs. A series of methods [1, 3, 8, 10, 49] have been proposed in the literature to make use of 3D hand models for supervision of 3D HPEs. Ge et al. [8] proposed to use Graph CNNs for mapping RGB images to infer the vertices of 3D meshes. Hasson et al. [10] jointly infers both hands and object meshes and investigated the effect of the 3D contact loss penalizing the penetration of object and hand surfaces. Others [1, 3, 49] attempted to make use of MANO [30], a parametric 3D hand model by learning to estimate low-dimensional PCA parameters of the model and using it together with differentiable model renderers for 3D supervision. All the previous works on the use of 3D models in learning frameworks have shown to help improving the given tasks performance. Recently, [18] showed fitting a 3D body model during the estimation process can be accelerated by using better initialization of the model parameters however, our goal is slightly different since we aim to
explore the use of 3D models for better generalisation from the methods. Since the hand pose space is huge, we make use of a 3D hand model to fill the gaps in the training data distribution to help approaches to improve their extrapolation capabilities. In this study, we make use of MANO hand model by providing the model’s parameters for each training image. We fit the 3D model for each image in an optimization-based framework which is described in more details next.

Gradient-based Optimization for Model Fitting. We fit the MANO model’s shape $s = \{s_j\}_{j=1}^{10}$, camera $c = \{c_j\}_{j=1}^{8}$ and articulation $a = \{a_j\}_{j=1}^{45}$ parameters to the $i$-th raw skeletons of selected articulations $z = \{z_i\}_{i=1}^{K}$, by solving the following equation:

$$\begin{align*}
(s^*_t, c^*_t, a^*_t) &= \arg\min_{(s, c, a)} O(s, c, a, z^i), \forall i \in [1, K],
\end{align*}$$

where our proposed objective function $O(s, c, a, z^i)$ for the sample $i$ is defined as follows:

$$O(s, c, a, z^i) = ||f_{reg}(V(s, c, a)) - z^i||_2^2 + \sum_{j=1}^{10} ||s_j||_2^2 + R_{Lap}(V(s, c, a)), \quad (2)$$

$V(s, c, a)$ denotes the parametric 3D mesh with three parameters $s, c, a$. Eq. 2 is composed of the following terms: i) the Euclidean distance between 3D skeleton ground-truths $z^i$ and the current MANO mesh model’s 3D skeleton values $f_{reg}(V(s, c, a))$; ii) A shape regularizer enforcing the shape parameters $s$ to be close to their MANO model’s mean values, normalized to zero as in [30], to maximize the shape likelihood; and iii) A Laplacian regularizer $R_{Lap}(V(s, c, a))$ to obtain the smooth mesh surfaces similar to [16]. Eq. 1 is solved iteratively by using the gradients from Eq. 2 as follows:

$$\begin{align*}
(s_{t+1}, c_{t+1}, a_{t+1}) &= (s_t, c_t, a_t) - \gamma \cdot \nabla O(s_t, c_t, a_t, z^i), \quad \forall t \in [1, T],
\end{align*}$$

where $\gamma = 10^{-3}$ and $T = 3,000$ are empirically set. This process is similar to the refinement step from [38], which refines estimated meshes by using the gradients from the loss. In Figure 5 both the target and the fitted depth images during the process described by Eq. 3 are depicted. The obtained meshes are slightly different from their original inputs, however, this is not a problem for our purpose given that we will generate input and output pairs of the fitted model by exploiting fitted meshes’ self-data generation capability while ignoring original depth and skeletons. Here the aim of fitting the hand model is to obtain a plausible and complete articulation space.

5. Evaluated Methods

In this section, we present the gist of carefully selected 14 methods among 36 participants (Task 1 - 17, Task 2 - 10, Task 3 - 9) to further analyze their results in Section 6. Methods are categorized based on their main components coordinates. This regressor is provided with the MANO model and its weights are fixed during the process.

Figure 5: Depth renderings of the hand model for different iterations in gradient-based optimization fitting. Target image (joints) (a), optimization iterations 0, 100, 300, 400, 600, 700 (b), final fitted hand pose at iteration 3000 (c).
### Table 2: Task 1 - Methods’ Overview

| Username | Description | Input | Pre-processing | Post-processing | Synthetic Data | Backbone | Loss | Optimizer |
|----------|-------------|-------|----------------|----------------|----------------|----------|------|-----------|
| Rokid    | 2D CNN joint regression | Depth 224 x 224 | Initial pose est. to crop | × | 570K Synthetic + Mixed Synthetic | EfficientNet-b0 | × | Adamax |
| A2J [42] | 2D CNN, offset + depth regression with anchor points and weighting | Depth 256 x 256 | Bbox crop | Scale-rotation, 10 backbone models ensemble | ResNet-152 | Smooth L1 | Adam |
| AWR [13] | 2D CNN, dense direction & offset rep. Leamable adaptive weighting | Depth 256 x 256, 128 x 128 pose est. | Bbox crop | ESPNet-v5 for binary segm. refinement of CoM | ResNet-50 & 101 | SRN | HRNet | Adam |
| NTIS     | 3D CNN | Voxels 88 x 88 x 88 | Multi-scale CoM refinement hand cropping | Models from 6 training epochs N confident sub-voxel pred. | ResNet-50 | L2 | RMSProp |
| Strawberryfy [39] | Integral Pose Regression | Depth image 256 x 256 | Coarse-to-fine hand cropping by thresholding | × | × | ResNet-50 | L1 | RMSProp |
| BT [19] | 3D supervision with cloud recon. Permutation invariant | Point cloud 512 3D vectors | View correction | × | × | ResPel | L2 | Chamfer and EMD KL constraint | Adam |

### Table 3: Task 2 - Methods’ Overview

| Username | Description | Input | Pre-processing | Post-processing | Synthetic Data | Backbone | Loss | Optimizer |
|----------|-------------|-------|----------------|----------------|----------------|----------|------|-----------|
| NTIS     | 3D CNN | Voxels 88 x 88 x 88 | Multi-scale com-ref-net for hand cropping | Models from 6 training epochs N sub-voxel pred., Truncated SVD and temporal smoothing refinement | ResNet-50 | L2 | RMSProp |
| A2J [42] | 2D CNN offset and depth regression with anchor points and weighting | Depth 256 x 256 | Bbox crop | Ensemble predictions from 3 training epochs | SEResNet-101 | Smooth L1 | Adam |
| CrazyHand | Tree-like branch structure regression with hand morphology | Depth 128 x 128 | Iterative CoM | × | × | ResNet-50 | L2 | - |
| Differentiable | Mano layer | Point cloud 512 3D points | View correction | × | 32K synthetic + random objects from HO-3D | ResPel | L2 pose | Adam |

### Table 4: Task 3 - Methods’ Overview

| Username | Description | Input | Pre-processing | Post-processing | Synthetic Data | Backbone | Loss | Optimizer |
|----------|-------------|-------|----------------|----------------|----------------|----------|------|-----------|
| ETH/NVIDIA | 2D CNN, 2D location + relative depth | RGB 128 x 128 | Bbox crop | × | × | ResNet-50 | L1 | SGD |
| NLE [27] | 2D hand proposals + classification of multiple anchor poses + regression of 2D-3D keypoint offsets w.r.t. the anchors | RGB 640 x 480 | Ensemble multiple pose proposals and ensemble over rotated images | × | ResNet-101 | Smooth L1 for reg. Log loss for classif. RPN [25] for localization loss | SGD |
| BT [19] | Multi-modal input with latent space alignment | RGB 256 x 256, Point cloud -356 | Bbox cropping | 100K synthetic + random objects from HO-3D | EncDecMano: ResNet-18 | DecoderMano: 6 fully-connected | L2 pose, L2 Mano vert. Chamfer, Normal and Edge length for mesh KL constraint | Adam |
and properties. We refer the readers to Table 2, Table 3 and Table 4 for a glance of the methods in Hands’19.

2D and 3D supervision for HPEs. Approaches that embed and process 3D data obtain high accuracies but less efficient in terms of their complexity compared to 2D-based approaches [46].

3D-based methods use 3D convolutional layers for point-clouds input similar to NTIS and BT. NTIS uses an efficient voxel-based representation as V2V-PoseNet [22] with a deeper architecture and weighted sub-voxel predictions on quarter of each voxel representations for robustness. AWR [13] adopts a learnable and adaptive weighting operation that is used to aggregate spatial information of different regions in dense representations with 2D convolutional CNNs. The weighting operation adds direct supervision on joint coordinates and draw consensus between training and inference as well as it enhances the models accuracy and generalisation ability by adaptively aggregating spatial information from related regions. Strawberryfg [39] employs a render-and-compare stage to enforce voxel-wise supervision for model training and adopts a 3D skeleton volume renderer to re-parameterize an initial pose estimate obtained similar to [39]. BT uses a permutation invariant feature extraction layer [19] to extract point-cloud features and uses a two branch framework for point-to-pose voting and point-to-latent voting. In BT way of adding 3D supervision varies from task to task. Latent vector is used to reconstruct a point-cloud in Task 1 whereas 3D hand model parameters are predicted and used in a differentiable model renderer for 3D supervision for the other tasks.

2D CNN approaches has been a standard way for learning regression models as used by Rokid [50] where they adopt a two stage regression-based approach. The first regression model is used to predict an initial pose and second model built on top of the first model. A2J [42] uses a 2D supervised method based on 2D offset predictions and depth predictions with anchor points. Anchor points are densely set on the input image behave as local regressors for the joints and able to capture global-local spatial context information. CrazyHand uses a hierarchically structured regression network by following the joints distribution on hand-morphology. ETH_NVIDIA [14] adopts latent 2.5D heatmap regression and an additional MLP is used for denoising the absolute root depth and absolute 3D pose in a scale-normalized space is obtained with the pinhole camera equations. NLE [29] first performs a classification of the observed hand into a set of canonical hand poses (obtained by clustering on the poses in the training set), followed by a fine class-specific regression of the hand joints in 2D and 3D. NLE adopts the only approach proposing multiple hand poses in a single stage with a Region Proposal Network (RPN) [28] integration.

Detection, regression and combined HPEs. Detection methods are based on key-points by producing a probability density maps for each joint. NTIS uses a 3D CNN to estimate per-voxel likelihood [22] of each joint. Regression-based methods estimate the joint locations by learning a direct mapping from the image input to hand joint locations or the joint angles of a hand model [33, 51]. Rokid [50] uses joint regression models within two stages to estimate an initial hand pose for hand cropping and estimates the final pose from the cleaned hand image. A2J adopts regression framework by regressing offsets from anchors to final joint location. BT [19]’s point-wise features are used in a voting scheme which behaves as a regressor to estimate the pose.

Some approaches take advantage of both detection-based and regression-based methods. Similarly, AWR [13], Strawberryfg [39] estimates hand joint probability maps to estimate joint locations with a differentiable soft-argmax operation [55]. CrazyHand’s hierarchical approach regresses the joint locations from joint probability maps, ETH_NVIDIA [14] estimates 2D joint locations from estimated probability maps and regresses relative depth distance of the hand joints w.r.t. a root joint. NLE [29] first localizes the hands and classifies them to anchor poses and the final pose is regressed from the anchors.

Method-wise ensembles. A2J uses densely set anchor points in the voting stage which contributes to predict the positions of joints in an ensemble way for better generalisation by taking into account uncertainties of reference point detection. Strawberryfg adopts latent patch refinement [40] where refinement models have adopted to refine limb orientations as well as using the initial pose estimate. BT uses the permutation equivariant features extracted from the point-cloud in a point-to-pose voting scheme where the point votes are ensembled to estimate the pose. NLE adopts ensembling in their approach by combining multiple regressed poses from different anchor poses to estimate the final pose.

Ensembles in post-processing. Rather than a single pose estimator, an ensemble approach has been adopted in multiple entries. Usually, they randomly replicate their baseline methods, and fuse the multiple predictions in the post-prediction stage, as in A2J, AWR, NTIS, NLE and Strawberryfg.

A2J ensembles predictions from 10 different backbone architectures in Task 1 as similar to AWR (5 backbones) and augments test images to ensemble the predictions with different scales and rotations as similar to rotation augmentation adopted by NLE. NTIS uses predictions gathered from the same model at 6 different training epochs. A similar approach is also adopted by A2J in Task 2 by ensembling predictions from 3 different training epochs. NTIS adopts a different strategy where N most confident sub-voxel predictions are ensembled to further use the predictions in a refinement stage with Truncated SVDs and applies temporal smoothing (only for Task 2). NLE takes advantage of
ensembles from multiple pose proposals [29]. Strawberryfg employs a different strategy and they take advantage of ensembling the predictions from models trained combination of different input representations.

**Multi-modal inputs for HPEs.** BT adopts [43] in Task 3 to align latent spaces from depth and RGB input modalities to embed the inherit depth information in depth images during the learning phase. Strawberryfg makes use of multi-inputs where each has obtained from different representations of the depth image, e.g. point-cloud, 3D point projection [7], multi-layer depth map [31], depth voxel [22].

We compare four methods in Task 1, BT in Task 2 and Task 3 make use of the provided MANO [30] model parameters to synthesize further training samples. Rokid follows a strategy to make use of the synthesized images and mixes real and synthetic images, as in Figure 6 to train their initial pose regression network which effectively boosts accuracies, see Table 8. However, the amount of synthetic data created is limited to 570K for Rokid and 32K in Task 2, 100K in Task 3 for BT. Considering the continuous high-dimensional hand pose space with or without objects, if we sub-sample uniformly and at minimum, for instance, $10^5$(azimuth/elevation angles)$\times2^5$(articulation)$\times10^4$(shape)$\times10^4$(object) = 320K, the number is already big, causing a huge compromise issue for memory and training GPU hours. In principle, they applied random sampling, without any priors on data distribution, or smart sampling techniques [41, 42]. BT considers generating synthetic images with objects and hands together similar to [23] but they randomly place the objects from [9] nearby hand locations without taking into account the penetration of hand and object interaction. The rest of methods use provided real training data only.

**Dominating HPE backbones.** ResNet [11] architectures with residual connections have been a very popular backbone choice among many HPEs as well as it is well employed by the Hands’19 participants, e.g. A2J, AWR, NTIS, Strawberryfg. CrazyHand, ETH-NVIDIA, NLE or implicitly by BT in ResPEL [19] architectures. On the other hand, Rokid adopts EfficientNet-b0 [36] as their backbone which is proposed with a scaling method that uniformly scales the network architecture’s depth, width and resolution.

### 6. Results and Discussion

We share our insights and analysis of the results obtained by the participants’ approaches: 6 in Task 1, 4 in Task 2 and 3 in Task 3. Our analyses highlight the impacts of data pre-processing, ensemble approach, the use of MANO model, different HPE methods and backbones and different post-processing strategies for estimated pose refinement.

**Analysis of Task 1 Methods.** We consider the participated methods’ main properties and the evaluation axes for comparisons. Figure 7 and Table 5 show that the participants can achieve lower errors for low distance $d$ thresholds since there is no object interaction and hand is less occluded compared to other two tasks. 2D-based approaches like Rokid [50], with the advantage of additional data synthesizing, or A2J [42], with cleverly designed local regressors, are considered to be best when MJE score is considered on the Extrapolation axis. A 3D-based approach with adaptive weighting AWR [13] obtains comparable results to such 2D-based approaches obtaining the lowest MJE errors on the Interpolation and Articulation axes. We observe that AWR is more accurate to estimate joints of the frames for distances less than 50mm on overall generalisation as well as better generalisation to unseen Viewpoints and Articulations, while excelling on the Interpolation axis. A similar trend is also observed with another 3D-voxel-based approach NTIS. However, other 3D supervised methods like Strawberryfg [39] and BT [19] show lower generalisation capability compared to other approaches. While Strawberryfg and BT performs comparable on Articulation, Shape generalisation and Interpolation axes, they perform worse on full Extrapolation and Viewpoint axes. Errors obtained by the participants based on the test set structures for different evaluation axes are shown in the supplementary document provided with this submission.

Table 5: Task 1 - MJE (mm) and ranking of the methods on five evaluation axes. Best results on each evaluation axes are highlighted.

| Username   | Extrapolation | Interpolation | Shape       | Articulation | Viewpoint |
|------------|---------------|---------------|-------------|--------------|-----------|
| Rokid      | 13.66 (1)     | 4.10 (2)      | 10.27 (3)   | 4.74 (3)     | 7.44 (1)  |
| A2J        | 13.74 (2)     | 6.33 (6)      | 11.23 (4)   | 6.05 (6)     | 8.78 (6)  |
| AWR        | 13.76 (4)     | 3.93 (1)      | 11.75 (5)   | 3.65 (1)     | 7.50 (2)  |
| NTIS       | 15.57 (7)     | 4.54 (3)      | 12.05 (6)   | 4.21 (2)     | 8.47 (4)  |
| Strawberryfg| 19.63 (12)    | 8.42 (10)     | 14.21 (10)  | 7.50 (9)     | 14.16 (12) |
| BT         | 23.62 (14)    | 18.78 (16)    | 21.84 (16)  | 16.73 (16)   | 19.48 (14) |

**Analysis of Task 2 Methods.** We compare four methods that took part in Task 2 where a hand interacts with an object in ego-centric viewpoint. A summary of the methods and

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**Figure 6: Visualization of synthetic depth images used by Rokid [50]:** (a) input depth image, (b) rendered depth image using 3D hand model, (c) the mixed by using the pixels with the closest depth values from real and synthetic images.
MJEs obtained by each method are shown in Table 5 and Table 6, respectively. Figure 9(a,b,d,e) further analysis the success rates of each method and their performance on different shapes (c) and objects (f). Please note the difficulty of total extrapolation axis where it is hard to correctly estimate any frames where estimation errors of all joints’ estimation errors are less than 15mm. On the other hand, all methods can estimate 20% to 30% of the joints correctly with less than 15mm error by other criteria in this task.

NTIS - a voxel-based learning approach - A2J [42] - anchor points weighted local regressors - perform similarly when MJEs for all joints considered in the test set. However, NTIS obtains better success rates over frame-based evaluation on all evaluation axes for low distance thresholds (d) to the ground-truth annotation, see Figure 9. As voxels embed 3D information, their performance is much higher...
when extrapolation is considered, especially when frames with unseen objects are considered. 3D models better embed the hand structure with the existence of seen/unseen objects. NTIS interpolates well when low $d$ used to measure the success rate. We should note that first three ranked methods, NTIS, A2J and CrazyHand- a structured detection-regression-based HPE - perform very similar for higher distances e.g. $d > 30$mm.

CrazyHand uses a structured detection-regression-based HPE where they employ heatmap regression for the joints from palm to tips in a sequential manner which is highly valuable for ego-centric viewpoints and this helps to obtain comparable results with A2J where the structure is implicitly refined by local anchor regressors.

### Analysis of Task 3 Methods

We select 3 approaches where their key properties are quite different from each other to further analyse in this section. In this task it is much difficult to estimate frames with low errors compared to previous tasks. None of the methods can estimate frames that have all joints estimated with less than 25mm error, where as they can estimate with 47% to 63% accuracy under 25mm, see Figure 11. 25mm distance threshold shows the difficulty of estimating a hand pose accurately from RGB input modality. Please note that participants of this task are provided with the ground-truth wrist joint location to estimate the other joint locations w.r.t. the wrist.

The task is based on hand-object interaction in RGB modality and it is not straightforward to explicitly capture the depth information. Therefore, the problem raises the importance of using multi-modal data as input and learn from different modalities (depth and RGB). BT [44] uses the provided MANO parameters by the organizers to synthesize 100K images and randomly places objects near the hand. This approach supports the claim on importance of multi-modality and filling the real data gaps with synthetic data with their close performance to the other two higher ranked methods. Comparing the generalisability perfor-

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**Figure 8**: Task 1 - Visualization of the ground-truth annotations and estimations of Rokid [50], A2J [42], AWR [13], NTIS, Strawberryfg [39], BT [19].

**Table 6**: Task 2 - MJE (mm) and ranking of the methods on four evaluation axes.

| Username | Extrapolation | Interpolation | Object | Shape |
|----------|---------------|---------------|--------|-------|
| NTIS     | 33.48 (1)     | 17.42 (1)     | 29.07 (2) | 23.62 (2) |
| A2J [42] | 33.66 (2)     | 17.45 (2)     | 27.76 (1) | 23.39 (1) |
| CrazyHand| 38.33 (4)     | 19.71 (4)     | 32.60 (4) | 26.26 (4) |
| BT [19]  | 47.18 (5)     | 24.95 (6)     | 38.76 (5) | 32.36 (5) |
Figure 9: Task 2 - Frame success rate analysis (a,b,d,e) and interpolation (unseen, transparent bars) and extrapolation (seen, solid bars) MJE errors for shape (c) and object (f) axes.

Table 7: Task 3 - MJE (mm) and ranking of the methods on four evaluation axes.

| Username | Extrapolation | Interpolation | Object | Shape |
|----------|---------------|---------------|--------|-------|
| ETH/NVIDIA | 24.74 (1) | 6.70 (3) | 27.36 (2) | 13.21 (1) |
| NLE [29] | 29.19 (2) | 4.06 (1) | 18.39 (1) | 15.79 (3) |
| BT [44] | 31.51 (3) | 19.15 (5) | 30.59 (3) | 23.47 (4) |

Table 8: Impact of synthetic data reported by Rokid [50] with learning from different ratios of synthetic data and the Task 1 training set. 100% = 570K.

| Synthetic Data % | Extrapolation MJE (mm) |
|------------------|------------------------|
| -                | 30.11 16.70 16.11 15.81 15.73 |
| 10%              |                        |
| 30%              |                        |
| 70%              |                        |
| 100%             |                        |
performance from $MJE$ of $30.11\text{mm}$ to $15.73\text{mm}$ which yields to $\sim 50\%$ improvement. Moreover, the use of mixed depth images, see Figure 6 has also proven to lower the total extrapolation error ($26.16\text{mm}$) compared to the use of depth renderings as it is ($30.13\text{mm}$) or the renderings averaged ($31.92\text{mm}$) with the real input images when used in $Rokid$ experiments with a regression model trained for 10 epochs.

For Task 2 and Task 3, the team $BT$ uses synthetic images in a very small amount of $32K$ and $100K$, since reconstruction complexity is high to train in large scale.

6.1. Evaluation Axis Analysis based on the Structured Test Set

Figure 7(f-i) shows the average errors obtained on the different evaluation axis in Task 1 based on if the evaluation criterion has seen in the training set or not. Overall, while unseen shapes and viewpoints are harder to extrapolate in most of the cases, some unseen articulations are easier to extrapolate than some seen articulations which are hard to estimate the hand pose from. These accuracies are also more meaningful when refer to the training and test data distribution in Figure 4. 

**Viewpoint extrapolation.** Approaches tend to have larger errors on extreme angles like $[-180, -150]$ or $[150, 180]$ for azimuth viewpoint or similarly in elevation viewpoint and it is harder to extrapolate to unseen viewpoints in the training. While the approach by $Rokid$ fills those unseen gaps with the generated synthetic data, other approaches mostly rely on their ensemble-based methodologies or their 3D properties. Please see Section 5 for their properties.

Viewpoint analysis are shown in Figure 7(g) for azimuth angles and (h) for elevation angles. Most of the extrapolation intervals (except the edges since both edges used to evaluate extrapolation) show distributions similar to a Gaussian which is expected since the mid-intervals are most far away viewpoints from a seen viewpoint from the training set. While both elevation and azimuth extrapolation errors are always higher than the interpolation error obtained with the corresponding methods, however the azimuth extrapolation tends to be varying more than the elevation extrapolation for some angles.

**Articulation extrapolation.** Figure 7(i) shows the average errors for 32 articulation clusters. 16 of those clusters have already seen in the training set while 16 have never seen and only available in the test set. While the samples that fall into some clusters, (e.g. 16, 18, 19, 20 and 31) tend to be harder to estimate most of the time, however some articulations without depending on seen (e.g. 1, 7, 8, 17) or unseen are hard to estimate as well because of the type of
the articulation. Appendix [19] shows the example frames for the 32 clusters.

**Shape extrapolation.** Figure [7] (f) shows average errors obtained for different shape types seen/unseen. All approaches have higher errors on unseen hand shapes (2, 3, 4, 5, 9) compared to errors obtained on shapes (1, 6, 7, 8, 10) seen in the training set.

Figure [11] shows the MJE analysis based on seen/unseen shapes (c) and objects (f) and a list of objects appearing in the Task 3 test set can be found in Appendix [21]. Although shape ‘S5’ refers to an unseen shape only appears in the test set, all methods can extrapolate to this shape better than some other seen shapes in the training set. This can be explained with ‘S5’ being similar to some other shapes and it has the lowest number of frames (easy examples) compared to number of test frames from other shapes in the test set, see Figure [6] (bottom right) for the distributions of the training and test set. A similar aspect has been observed in [47] where different hand shape analysis has been provided as showed in Figure [20]. However, all methods tend to have higher errors on the frames from another unseen test shape ‘S3’ as expected.

**Object extrapolation.** Poses for hands with unseen objects, ‘O3’ power drill and ‘O6’ mug, are harder to extrapolate by most methods since their shapes are quite different than the other seen objects in the training set. Please note that seen ‘O2’ object has the lowest number of frames in the test set. Some example frames for the listed objects are showed in Figure [21].

### 6.2. Further Ablation Analysis

In this section we further show the analysis by methods for ablation comparisons. We categorize per method’s experiments to point out studies on different backbone architectures and various ensembling strategies.

Note that more experiments are presented in Appendix [A.1] for the analysis of more methods from the challenge based on frame success rates, followed by the analysis on joint accuracies of the presented approaches in Appendix [A.2].

#### 6.2.1 Experiments with Different Backbone Architectures

While Residual Network (ResNet) [11] backbones are well adopted by many approaches and ResNet-50 or ResNet-101 architectures obtain better results compared to other backbone models as reported in experiments of AWR and NLE.
However, most approaches adopt ensembling predictions from models trained with different backbone architectures and this improves the performance as showed in Table 9 and Table 10.

Table 9 shows the experiments for impact of different network backbones and different ways of obtaining the hand center by AWR. Changing the way of attaining hand center from ‘center1’ to ‘center2 + original’ yields an improvement of $5.81 \text{mm}$, ‘center2 + segmented’ further improves by $0.14 \text{mm}$. The best result is obtained with a backbone of ResNet-101, $14.44 \text{mm}$.

At the final stage, multiple models are ensembled (see Table 9 model ensemble) including ResNet-101 (center2+segmented), ResNet-101 (center2+original), ResNet-50 (center2+original), SRN_multi_size_ensemble and HR-Net_Resnet50_shape_ensemble. Since ESPNetv2 [21] sacrifices accuracy for speed to some extent, the segmentation results are not accurate enough and may contain wrists or lack part of the fingers, therefore cropping hand regions from original depth images sometimes yields better performance.

Among the ensembled networks, SRN [27] is a stacked regression network which is robust to self-occlusion and when depth values are missing. It performs the best for Shape extrapolation, but is sensitive to the cube size that are used when cropping hand region. The mean error of a single-stage SRN with cube size 200mm already reaches $16 \text{mm}$. Ensembling SRN with cube size $180 \text{mm}$, $200 \text{mm}$ and $220 \text{mm}$, the results of SRN_multi_size_ensemble is $15.20 \text{mm}$.

SRN performs the best on the shape evaluation axis. For example, single SRN can achieve $12.32 \text{mm}$ and
Figure 13: Visualization of ground-truth hand pose (in black) and estimated poses with varying level of MJE$s$, $<5\text{ mm}$, $<10\text{ mm}$, $<20\text{ mm}$, $<30\text{ mm}$, $<40\text{ mm}$, $<60\text{ mm}$. More specifically, the MJE (mm) of the visualized poses are 1.75, 6.88, 13.94, 25.32, 35.67, 52.15, respectively. Best viewed in color.

Table 9: Extrapolation MJE obtained with different backbone architectures in AWR [13] experiments. ‘center1’ denotes using thresholds to compute hand center, ‘center2 + original’ denotes using semantic segmentation network to compute hand center and extract hand region from original depth images, ‘center2 + segmented’ denotes using semantic segmentation network to compute hand center while extract hand region from network’s output mask.

| Backbone                  | Extrapolation MJE (mm) |
|---------------------------|------------------------|
| Resnet50 (center1)        | 20.70                  |
| Resnet50 (center2 + original) | 14.89                 |
| Resnet50 (center2 + segmented) | 14.75                |
| Resnet101 (center2 + original) | 14.57                |
| Resnet101 (center2 + segmented) | 14.44                |
| HRNet48                   | 17.23                  |
| SRN                       | 16.00                  |
| SRN_multi_size_ensemble   | 15.20                  |
| HRNet_Resnet50_shape_ensemble | 14.68              |
| model_ensemble            | 13.67                  |

SRN_multi_size_ensemble can achieve $11.85\text{ mm}$. HRNet-48 makes a major success in human pose estimation, but we do not get desired results after applying it. The mean error of single HRNet-48 is $17.23\text{ mm}$. Although it converges faster and has relatively lower loss than ResNet-50 and ResNet-101 in the training stage, it performs worse during inference. HRNet-48 predicts well on some of the shapes. Therefore, the depth images are divided into 20 categories according to the proportion of hand pixels over all pixels. The prediction error in training set is used to compute the weight of each category, which is used to weight the test set results. The weighted results depicted with HRNet_Resnet50_shape_ensemble reaches mean error of $14.68\text{ mm}$.

The model_ensemble refers to ensembling predictions of five models including ResNet-101 ($14.44\text{ mm}$), ResNet-101_noseg ($14.57\text{ mm}$), ResNet-50_noseg ($14.89\text{ mm}$), HRNet_Resnet50_shape_ensemble ($14.68\text{ mm}$), SRN_multi_size_ensemble ($15.20\text{ mm}$). Among them, the first four models are based on adaptive weighting regression (AWR) network with different backbones.

Table 10: Impact of different network architectures, in NLE [29] experiments. No color jittering is applied during training in these experiments. MJE (mm) metric is used. Please note that for this experiment while ResNet-50 and ResNet-152 backbones results are obtained with 10 different anchor poses while the rest use 5 different anchor poses in NLE$^*$ settings for Pose Proposal Integration (PPI).

| Backbone                  | Extrapolation MJE (mm) |
|---------------------------|------------------------|
| ResNet-50                 | 34.63                  |
| ResNet-101                | 32.56                  |
| ResNet-152                | 37.56                  |
| ResNext-50                | 33.88                  |
| ResNext-101               | 38.09                  |
| ResNet-101                | 17.79                  |
| ResNet-152                | 18.68                  |
| ResNet-101                | 18.50                  |
| ResNet-152                | 17.79                  |
| ResNext-50                | 18.50                  |
| ResNext-101               | 19.70                  |
| ResNet-101                | 20.93                  |
| ResNet-152                | 20.93                  |

Table 10 shows comparison of different residual based backbones. Deeper backbones can obtain lower errors on interpolation axis however, they tend to obtain higher errors on extrapolation axes and ResNet-101 a medium depth seems to be a reasonable choice in most cases in NLE experiments. While errors on different evaluation axes with ResNext based architectures tend to vary a lot, ResNet based backbones are more solid.

Table 11: Impact of widening the architecture used in V2V-PoseNet [22] in NTIS experiments. The number of kernels in each block in V2V-PoseNet architecture is quadrupled (wider).

| Architecture V2V-PoseNet [22] | Extrapolation MJE (mm) |
|-------------------------------|------------------------|
| Original                      | 38.33                  |
| Wider                         | 36.36                  |

Components of V2V-PoseNet architecture include: Volumetric Basic Block, Volumetric Residual Block, and Volumetric Downsampling and Upsampling Block. NTIS uses the same individual blocks as in V2V-PoseNet [22] but with a wider architecture. NTIS$^*$ experiment, see Table 11 shows that quadrupling the number of kernels in individual blocks provides the best results.
6.2.2 Impact of Ensembling Techniques

In this section, we provide the experiments to show the importance of ensembling techniques. These techniques include ensembling in data pre-processing, methodological ensembles and ensembles as post-processing.

*NLE*’ experiments on methodological and post-processing ensembling techniques. *NLE* adopts an approach based on LCR-Net++[29] where poses in the training set are clustered to obtain anchor poses and during inference, the test samples are first classified to these anchors and the final hand pose estimation is regressed from the anchor poses. Table 12 shows the impact of using different number of anchor poses. Shape extrapolation axis is heavily affected with the number anchor poses. While the number of obtained anchor poses from the training set increases from 1 to 50, the shape extrapolation error decreases from 21.08mm to 16.55mm. On the other hand, the number of anchor poses does not seem to have an observable impact on the other axes, however; this can be because of the size of Task 3 test set and also because of the low hand pose variances in Task 3.

Table 12: Impact of number of anchor poses, in *NLE* [29] experiments, obtained with k-means clustering for Pose Proposal Integration (PPI). No color jittering is applied during training in these experiments. ResNet-101 backbone architecture and MJE (mm) metric is used.

| #Anchor poses | Extrapolation | Interpolation | Object | Shape |
|---------------|---------------|---------------|--------|-------|
| 1             | 37.68         | 3.99          | 28.69  | 21.08 |
| 5             | 32.56         | 4.49          | 18.68  | 18.50 |
| 10            | 37.57         | 4.35          | 19.38  | 18.33 |
| 20            | 34.67         | 4.38          | 21.10  | 16.94 |
| 50            | 35.64         | 4.86          | 17.84  | 16.55 |

*NLE*’s experiments later show the impact of learning and inferring both 2D and 3D pose, and the impact of pose proposal integration [29] (PPI) compared to non-maximum suppression approach to obtain the poses. Learning to estimate 2D pose of a hand significantly impacts the extrapolation capability especially in Object axis. We believe this is because the objects occlude the hands and 2D information can be better obtained and help to guide estimation of the 3D hand poses. Later the pose proposal with 5 anchor poses brings a significant boost for extrapolation capabilities of the method.

*NLE* adopts another ensembling technique in the post-processing stage where test images are rotated by uniformly covering the space and the predictions obtained from each rotated test sample is ensembled. Experiments of *NLE* show that rotation as a post-processing ensemble technique helps significantly on shape extrapolation as well as interpolation axis and has minor impacts on other extrapolation axes. Table 14 shows the impact of different number of rotation ensembles.

Table 14: Importance of rotation data augmentation in *NLE* [29] experiments, conducted with a ResNet-101 backbone architecture and 5 anchor poses. MJE (mm) metric is used.

| #Test Rot. | Extrapolation | Interpolation | Object | Shape |
|------------|---------------|---------------|--------|-------|
| 1          | 29.55         | 4.85          | 18.09  | 17.35 |
| 4          | 28.83         | 4.63          | 18.06  | 16.77 |
| 12         | 29.19         | 4.06          | 18.39  | 15.79 |

Strawberryfg [39] ensembling as data pre-processing and orientation refinement per limb. Strawberryfg makes use of different input types obtained from the depth input image and their combinations to use them in their approach. Different input types include 3D joints projection, multilayer depth and voxel representations and a list of input types and their combinations adopted to train different models are listed in Table 15. The impact of each mentioned experiment is reported in Table 16. The model used with different combination of different input types obtained from the depth images has no significant impact on evaluation axes. We believe that this is because each different input type has different characteristics for the model to learn from and it’s hard for the model to adapt to each type. Maybe a kind of adaptive weighting technique as adopted by some other approaches participated in the challenge can help in this case. However, as ensembling results of different models is proven to be helpful with all the approaches adopted the technique seems to be helpful in this case as well. ‘Combined’ model as depicted in Table 16 obtains the best results for all evaluation axes. Strawberryfg’ experiment report to have 10.6% on articulation, 10% on interpolation, 8.4% on viewpoint, 7.2% on extrapolation, 6.2% on shape axes improvements with ensembling of 4 models.

Table 17 using Strawberryfg shows the impact of patch orientation refinement networks adopted for each limb of a hand to show the impact. Orientation refinement brings a
Table 15: Input data types for four different models used in Strawberryfg [39] experiments.

| Model Id | Input Type                       | Depth Image | 3D Points Projection | Multi-layer Depth | Depth Voxel |
|----------|----------------------------------|-------------|----------------------|-------------------|-------------|
| 1        |                                  | ✓           | ✓                    |                   |             |
| 2        |                                  | ✓           | ✓                    |                   |             |
| 3        |                                  | ✓           | ✓                    |                   |             |
| 4        |                                  | ✓           | ✓                    |                   |             |

Table 16: MJE (mm) obtained in Strawberryfg [39] experiments by using different models trained with different input types, see Table 15. 'Combined' model refers to ensembling predictions from all 4 models.

| Model Id | Extrapolation | Viewpoint | Articulation | Shape | Interpolation |
|----------|---------------|-----------|--------------|-------|--------------|
| 1        | 20.99         | 14.70     | 8.42         | 14.85 | 9.35         |
| 2        | 21.39         | 15.34     | 8.25         | 15.21 | 9.17         |
| 3        | 21.02         | 16.12     | 8.52         | 15.30 | 9.61         |
| 4        | 21.19         | 15.78     | 8.36         | 15.23 | 9.32         |
| Combined | 19.63         | 14.16     | 7.50         | 14.21 | 8.42         |

Table 17: Impact of local patch refinement (ref.) and volume rendering (ren.) supervision adopted by Strawberryfg [39]. Model 4 with 4 different inputs are used in this evaluation, see Table 15.

| Model Id | Extrapolation | Viewpoint | Articulation | Shape | Interpolation |
|----------|---------------|-----------|--------------|-------|--------------|
| 4 - w/o ref. & ren. | 22.36          | 16.77     | 9.30         | 15.83 | 10.15        |
| 4 - w/ ref. & ren.   | 21.19          | 15.78     | 8.36         | 15.23 | 9.32         |

significant impact with 1mm lower error on all evaluation axes.

**A2J** [42] ensembling in post-processing. At inference stage, A2J applies rotation and scale augmentations. More specifically, A2J rotates the test samples with $-90^\circ/45^\circ/90^\circ$, and scales with factor $1/1.25/1.5$. Then these predictions are averaged. Several backbone models are trained, including ResNet-50/101/152, SE-ResNet-50/101, DenseNet-169/201, EfficientNet-B5/B6/B7. Input image sizes are $256 \times 256/288 \times 288/320 \times 320/384 \times 384$. The best single model is ResNet-152 with input size $384 \times 384$, it achieves $14.74$mm on the extrapolation axis. Finally, these predictions are ensembled with weights to obtain a final error of $13.74$mm on the extrapolation axis.

**NTIS ensembling in post-processing with confident joint locations, Truncated SVDs and temporal smoothing.** NTIS adopts a post-processing technique for refinement of hand poses where several inverse transformations of predicted joint positions are applied; in detail, NTIS uses truncated singular value decomposition transformations (Truncated SVDs; 9 for Task 1 and 5 for Task 2) with number of components $n \in [10, 15, 20, 25, 30, 35, 40, 45, 50]$ obtained from the training ground-truth hand pose labels and prepares nine refined pose candidates. These candidates are combined together as final estimation that is collected as weighted linear combination of pose candidates with weights $w \in [0.1, 0.2, 0.0, 0.4, 0.8, 1.0, 1.8/4.7]$. Table 18 shows the impact of ensembling confident joint predictions and refinement stage with Truncated SVDs.

Table 18: Impact of refinement with Truncated SVDs in NTIS experiments on Task 1. Improvement is 1%. $N = 100$ most confident joint locations are ensembled for this experiment. Results reported in MJE (mm) metric.

| SVD refinement | Extrapolation |
|----------------|---------------|
| w/             | 15.81         |
| w/o            | 15.98         |

Since Task 2 is based on sequences and test samples are provided in order, NTIS applies temporal smoothing on the predictions from each frame and provides experimental results in Table 19 with different context sizes for smoothing. While temporal smoothing helps to decrease the extrapolation error, large context sizes do not impact much on the error.

Table 19: Impact of temporal smoothing and the context size (k) for smoothing in NTIS experiments on Task 2 using exact same V2V-PoseNet [22] architecture.

| Smoothing Context Size (k) | Extrapolation MJE (mm) |
|---------------------------|------------------------|
| 0                         | 39.76                  |
| 3                         | 38.32                  |
| 5                         | 38.31                  |
| 7                         | 38.33                  |

**AWR** [13] methodological ensembling with AWR operation. Figure 14 shows the impact of learnable adaptive weighting regression (AWR) approach on the probability maps of the target joints. When the target joint is visible and easy to distinguish, the weight distribution of AWR tends to focus more on pixels around it as standard detection-based methods do, which helps to make full use of local evidence. When depth values around the target joint are missing, the weight distribution spreads out to capture information of adjacent joint. Later, Table 20 shows the impact of the AWR operation on two other datasets, NYU [37] and HANDS’17 [47].

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Figure 14: Impact of AWR \[13\] operation on the target joints’ probability maps.

Table 20: AWR \[13\] experiments for w/o adaptive weighting on NYU [37] and HANDS’17 [47] datasets. Results reported in MJE (mm) metric.

| Dataset     | w/o AWR | w/ AWR |
|-------------|---------|--------|
| NYU [37]    | 7.87    | 7.48   |
| HANDS’17 [47]| 7.98    | 7.48   |

7. Conclusion

We carefully designed structured training and test splits for 3D HPEs and organized a challenge for the hand pose community to show state-of-the-art methods tend to fail to extrapolate when the pose space is large which inherently makes the problem hard. Our analyses highlight the impacts of using ensembles, the use of synthetic images, different type of HPEs e.g. 2D, 3D or local-estimators and post-processing. While ensemble techniques, both methodologically in 2D and 3D HPEs and as post-processing strategies, help many approaches to boost their performance for extrapolation axes, a few methods show the use of synthetic data to fill the gaps for better extrapolation.

HPE’s are proven to be successful while interpolating in all the tasks, but their extrapolation capabilities vary significantly. Scenarios such as hands interacting with objects present the biggest challenges to extrapolate by most of the evaluated methods both in depth and RGB modalities.

Given the extrapolation capabilities of the methods, usage of synthetic data for filling the gaps is an option. 570K synthetic images used by the winner of Task 1 is still a very small number compared to how large, potentially infinite, it could be. We believe that investigating these possibilities, jointly with data subsampling strategies and real-synthetic domain adaptation, is a promising and interesting line of work. What would be the outcome if we sample ‘dense enough’ in the continuous and infinite pose space and how ‘dense enough’ is defined when we are limited by hardware and time.

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A. Appendix

A.1. Frame Success Rates for All Participated Users in the Challenge

Figure 15 shows the analysis of all participated users in the challenge’s tasks. We analysed the selected methods (6 for Task 1, 4 for Task 2 and 3 for Task 3) based on their methodological variances and results. The challenge have received 16 submissions for Task 1, 9 submissions for Task 2 and 7 for Task 3 to be evaluated from different users.

Figure 15: All participated methods’ total extrapolation accuracy analysis for each task. (a,c,e) represents the frame success rates where each frames’ error is estimated by considering the maximum error of all joints in that frame. (b,d,f) shows the joint success rates.
A.2. Joint Success Rates of the Analysed Approaches

Figure 16: Task 1 - Joint success rate analysis on different evaluation axis where each joints’ error in the set is evaluated for measuring the accuracy.
Figure 17: Task 2 - Joint success rate analysis on different evaluation axis where each joints’ error in the set is evaluated for measuring the accuracy.
Figure 18: Task 3 - Joint success rate analysis on different evaluation axis where each joints’ error in the set is evaluated for measuring the accuracy.
A.3. Visualizations for Articulation Clusters, Hand Shapes and Object Types
Figure 19: Examples frames for 32 articulation clusters used in the evaluations. Each row shows cluster ids and their respective binary representations for two example images of three clusters. Each binary representation is constructed from thumb to pinky fingers with 0 representing closed and 1 representing open fingers.

Figure 20: Visualization of different hand shape distributions, appear in [47], by using the first two principal components of the hand shape parameters. Figure is taken from [47].
Table 21: Task 3 - List of objects and their appearance in the training set.

| Object Id | Object Name     | Seen in the Training Set |
|-----------|-----------------|--------------------------|
| O1        | cracker box     | ✓                        |
| O2        | pitcher base    | ✓                        |
| O3        | power drill     | ✗                        |
| O4        | sugar box       | ✓                        |
| O5        | mustard bottle  | ✓                        |
| O6        | mug             | ✗                        |

Figure 21: Example frames for the objects appear in Task 3, HO-3D [9] dataset.