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A Skeleton-Driven Neural Occupancy Representation for Articulated Hands

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Figure 1. We introduce a novel neural implicit surface representation of human hands (HALO) that is fully driven by keypoint-based skeleton articulation. Taking 3D keypoints as input, a fully differentiable implicit occupancy representation produces high-fidelity reconstruction of the hand surface (top row). We show that HALO facilitates the conditional generation of articulated hands that grasp 3D objects in a realistic and physically plausible manner (bottom row).

Abstract

We present Hand ArticuLated Occupancy (HALO), a novel representation of articulated hands that bridges the advantages of 3D keypoints and neural implicit surfaces and can be used in end-to-end trainable architectures. Unlike existing statistical parametric hand models (e.g. MANO), HALO directly leverages the 3D joint skeleton as input and produces a neural occupancy volume representing the posed hand surface. The key benefits of HALO are (1) it is driven by 3D keypoints, which have benefits in terms of accuracy and are easier to learn for neural networks than the latent hand-model parameters; (2) it provides a differentiable volumetric occupancy representation of the posed hand; (3) it can be trained end-to-end, allowing the formulation of losses on the hand surface that benefit the learning of 3D keypoints. We demonstrate the applicability of HALO to the task of conditional generation of hands that grasp 3D objects. The differentiable nature of HALO is shown to improve the quality of the synthesized hands both in terms of physical plausibility and user preference.

1. Introduction

Humans grasp and manipulate objects with their hands. Modeling 3D poses and surfaces of human hands is important for numerous applications such as animation, games, augmented and virtual reality. Existing hand representations in the literature can be categorized into two paradigms: skeleton representations [19, 28, 40, 41, 71] and mesh-based representations [39, 51]. Even though 3D skeletons are defined in the Euclidean space and are easy to interface with deep neural networks, they lack surface information, therefore not suitable for reasoning about hand-object interaction. In contrast, mesh-based hand models provide surfaces and can thus explicitly reason about physical interactions, such as hand-object manipulation [25, 59]. However, their pose and shape parametrizations are often hard to directly interpret and more difficult to learn in an end-to-end fashion than 3D keypoints.

In this work, we aim to bridge the gap between 3D keypoints and dense surface models. To this end, we propose Hand ArticuLated Occupancy (HALO), a novel hand representation that is driven by keypoint-based skeleton artic-
To demonstrate the utility of the HALO model, we systematically compare HALO with several baseline methods. Recently, several template-based approaches such as MANO [51], regressing MANO parameters [1, 2, 4, 25, 26, 68], or directly predicting the full dense surface of the hand [20, 30, 39, 61]. The methods that directly predict 3D key points usually achieve better performance, however, they do not yield dense surface which is crucial for hand interaction. Iteratively fitting a templated-based model such as MANO to the key points could recover the dense surface but also make the process non-differentiable [44, 46, 62]. Alternatively, the dense surface can also be estimated from 3D or 2D key points [11, 65, 70]. However, such estimation could result in a change of hand pose from the input key points. In contrast, our model produces a hand surface that faithfully respects the input pose and allows surface or volumetric losses to back-propagate directly to the keypoints.

Hand representation. The surface of 3D hands can be represented explicitly or implicitly. The commonly used template-based approaches such as MANO [51] induce a prior of poses and shapes over its learned parameter space for regularization. However, using the learned parameters
also increases the learning complexity as image features do not directly correspond to the learned parameters of a hand model. In [1, 4, 25, 26, 68], the MANO parameters are predicted using weak supervision such as hand masks [1, 68] or 2D annotations [4, 68]. Another way of representing 3D hand is to directly store the dense vertex locations of the MANO template [20, 30, 38]. While being more generalizable by avoiding constraints in the parameter space, these approaches require the corresponding dense 3D annotations, which might be difficult to acquire. Our work differs in the way that we can recover dense hand surfaces from 3D keypoints, eliminating the need for estimating model parameters or predicting 3D vertex locations.

**Implicit representation.** Several works represent object shapes by learning an implicit function using neural networks [10, 14, 21, 22, 35, 37, 47, 55], which allows for the modeling of arbitrary object topologies with dynamic resolution. Many approaches for learning such implicit functions from various input types were also proposed [32, 33, 45, 48, 52, 56]. These works focus on rigid objects and do not permit shape deformation. Recently, the interest is also on learning an articulated implicit function for human body [3, 15, 27, 36, 63]. NASA [15] represents human bodies using a set of implicit functions, but the model is limited to a specific body shape. LEAP [36] proposes to learn inverse linear blend skinning functions for multiple body shapes, however, it relies on ground truth bone transformation matrices instead of 3D joint locations. To the best of our knowledge, there are no implicit hand representations that can generalize well to various shapes. Grasping Field [29] learns an implicit function for hand and objects together to represent contact but treats every posed hand as a rigid object. As a result, the complexity of learning a wide range of poses increases significantly. In this work, we leverage biomechanical constraints of human hand to learn a novel hand model that only takes a skeleton as input and generalizes to different hand shapes and poses.

**Hand-object interaction.** There have been many studies into hand interaction with objects in various settings [5, 7, 9, 12, 17, 18, 23, 24, 29, 31, 42, 59]. Recently, the community has begun exploring the task of generating plausible hand grasps given an object with notable studies including [12, 29], and [59]. GanHand [12] generates grasp poses for each object in a given RGB image by first predicting a grasp type from grasp taxonomy [17] and its initial orientation, and then optimizing for better contact with the object. GrabNet [59] uses Basis Point Set [49] to represent 3D objects as input to generate MANO parameters. The predicted hand is then fed to a refinement model to improve the contact. Grasping Field [29] learns a signed distance field for both hand surface and object surface in one space, allowing the contact to be learned as regions where distances to both surfaces are zeros. However, the output surface cannot be articulated and requires hand model fitting. Our work differs from others in the way that we use the proposed hand representation to model the contact while keeping the synthesis task as simple as generating 3D keypoints.

3. **HALO: Hand ArticuLated Occupancy**

The HALO model is a skeleton-driven neural occupancy function, formally defined as $\mathcal{O}_w(x|J) \rightarrow \{0, 1\}$. Parameterized by neural network weights $w$, it maps a 3D point $x$ to its occupancy value given the hand skeleton represented by a set of 3D keypoint locations $J$. In this section, we first describe how to convert an arbitrary 3D joint skeleton to the reference canonical pose in a differentiable and consistent manner, then we introduce our simple yet effective neural occupancy network for hands.

**Notations.** Given a hand skeleton represented by 3D key points $J : \mathbb{R}^{21 \times 3}$, we denote $\theta_i^F$ and $\theta_i^c$ to be the flexion/extension and abduction/adduction angles of bone $i$ relative to its parent, respectively. For simplicity, we refer to them as flexion and abduction angle. The angle between a palmar bone $i$ and its adjacent palmar bone $i + 1$ is denoted as $\theta_i^p$. Lastly, $\theta_i^p$ is the palmar plane angle between plane $n_i$ and $n_{i+1}$ spanned by the palmar bone $i - 1$, $i$, $i + 1$ respectively. We denote the properties of the reference canonical hand with $^c(\cdot)$. We refer to Supp. Mat. for further details.

3.1. **Canonicalization of 3D Hand Skeleton**

Our goal is to learn a neural representation of the surface of human hands in the canonical space. Furthermore, we want to deform this shape based on the spatial configuration of the underlying skeleton, represented by 3D keypoints. To do so, we require a mechanism that allows us to convert the 3D keypoints into valid skeletons in the canonical pose in terms of joint angles. As the keypoints have no notion of the surface, naively converting them to axis-angles does not work due to the unconstrained twist of bones. While twist
does not affect keypoints, they affect the surface.

We take inspiration from Spurr et al. [57] which defines a consistent local coordinate system for each bone to measure the bone angles for semi-supervised learning. Our objective is to derive a differentiable mapping layer that i) provides means to convert predicted keypoints to the rest pose and back, and ii) ensures that the skeleton is free of implausible twists that would influence the surface.

Building on [57], we represent each finger bone by two rotation angles, flexion and abduction, relative to its parent bone (Fig. 2). Each bone cannot rotate about itself, thus, no twist. However, such formulation ignores the palm configuration, which is needed for defining the canonical pose. In this work, we propose a method to parameterize the pose of a palm in order to define a consistent canonical pose. We decouple the palmar bone configuration into i) finger spreading and 2) palm arching. The spreading of fingers is captured via the angles between two adjacent palmar bones. The arching of the palm is defined by the angle between the two planes spanned by three adjacent palmar bones. The resulting palmar region then serves as a frame of reference for the remaining fingers. Please refer to Supp. Mat. Fig. B.1 for better visualization.

Converting 3D Keypoints to Bone Transformations. Formally, we seek the unique set of transformations \( \{ B^{-1}_i \} \) that maps the skeleton \( J_1 \) to the canonical pose \( ^cJ_1 \). Given a skeleton, we obtain the set \( \{ B^{-1}_i \} \) by sequentially performing the following operations: First, we rotate each finger to match the description of our canonical palm pose, which we define as a flat hand with fixed angles between palmar bones; Second, we compute joint angles and local coordinate systems following [57] (Fig. 2b), which we use to iteratively undo the angles along the kinematic chain (Fig. 2a) to acquire the canonical pose. By combining the transformations from both steps, then adjust for the conversion from keypoints to bone vectors, we could obtain a set of transformation matrices \( \{ B^{-1}_i \} \) that maps the given skeleton \( J \) to our canonical pose \( ^cJ \). Formally,

\[
^cJ_i = B_i^{-1}J_i, \quad \text{where} \quad B^{-1} = TSE'R^cFPK.
\]

Here \( K : \mathbb{R}^{3 \times 21} \rightarrow \mathbb{R}^{3 \times 20} \) is a function that maps the keypoints \( J \in \mathbb{R}^{21 \times 3} \) to bone vectors by translating them to the local origin and scaling to unit norm; \( P \) normalizes the palmar bone and palmar planes angles; \( F \) then maps the bones to their local coordinate frames; \( R^c \) rotates each bone to have the same flexion and abduction angles as the canonical pose. Finally, \( F' \) maps each coordinate frame back to the global coordinate system; \( S \) reverts bones back to their original length and \( T \) translates the bones to the tip of their parent bones.

This set of transformations is unique for each skeleton pose and only allows biomechanically valid transformation. For details, we kindly refer the reader to our Supp.Mat.

3.2. Neural Occupancy Networks for Hands

Here, we describe how to leverage the unique mapping \( \{ B^{-1}_i \} \) between the posed skeleton and the canonical skeleton to learn the neural hand representation that generalizes to different shapes with highly articulated poses. We draw inspirations from NASA [15] and explore similar neural network structure due to its simplicity and efficacy.

NASA [15]. NASA learns an implicit representation of a human body \( O_w(x|\theta) \rightarrow \{0,1\} \), conditioned on the pose descriptor \( \theta \). Specifically, it defines the implicit surface for each body part separately. Let \( B_b^{-1} \) be the transformation to the canonical pose for bone \( b \), NASA can be denoted by:

\[
O_w(x|\theta) = \max_b \{ \hat{O}_w^b(B_b^{-1}x, \Pi^b_w(B^{-1}t_0)) \}.
\]

where the pose descriptor \( \theta \) is defined by a collection of transformation matrices \( \{ B_b^{-1} \}_{b=1}^5 \) and the probability of \( O_w(x|\theta) \) is derived from the maximum occupancy probability across \( B \) child occupancy functions \( \hat{O}_w^b(\cdot,\cdot) \), where each represents the body part of the bone \( b \). For a query point \( x \), each child function \( \hat{O}_w^b(\cdot,\cdot) \) maps \( x \) to its local coordinate system by the transformation matrix \( B_b^{-1} \), so that the local shape of each body part can be learned. The term \( \Pi^b_w(\cdot) \) is used to provide global pose information to each child function. Essentially, by querying the occupancy value and the transformation matrix \( B_b^{-1} \), the NASA model learns a template shape and the correction based on the global pose with \( \Pi^b_w(\cdot) \). Note that, the bone transformation \( \{ B_b^{-1} \}_{b=1}^5 \) is assumed to be given. For more details, we kindly refer the reader to [15].

Neural Occupancy Networks for Hands. A naive adaptation of the NASA model for human hand results in erroneous surface reconstructions as shown in Sec. 5.1 (Fig. 5). In order to represent hands with highly articulated poses and diverse shapes, we propose to learn the child occupancy functions by conditioning on a shape descriptor \( \beta \), effectively learning \( O_w(x|\theta, \beta) \). We assume that the identify-dependent deformations of the hand are highly correlated to the bones, hence, we propose the use of a collection of bone lengths as the shape descriptor. In particular, we propose a simple yet effective bone length encoder \( f^b(D) \) that takes \( D = [d_1, d_2, \ldots, d_B] \in \mathbb{R}^B \) the bone length of individual bones as inputs. We emphasize that under the proposed formulation, we could learn the hand surface using only the key points \( J \), as the pose descriptor \( B_b^{-1} \) is derived from \( J \) by Eq. 1. Our final occupancy function is given by:

\[
O_w(x|\theta, \beta) = \max_b \{ \hat{O}_w^b(B_b^{-1}x, \Pi^b_w(B^{-1}t_0), f^b(D)) \}
\]

where each implicit function \( \hat{O}_w^b \) learns the corresponding part shape based on the hand pose descriptor \( \Pi^b_w(B^{-1}t_0) \) and our bone length descriptor \( f^b(D) \).
3.3. Skeleton-driven Articulated Hand Model

To build a skeleton-driven articulated hand model, we combine the previously described canonicalization layer and the neural hand surface together. Specifically, HALO takes the input 3D keypoints to compute bone transformations \( \{ B^{-1} \} \) for the occupancy networks using the canonicalization layer. As the canonicalization layer is differentiable, the model can be trained end-to-end and allows volume-based losses from the surface to back-propagate to the keypoints. The overview of HALO is shown in Fig. 3. Note that the bone lengths \( D \) can also be computed from the keypoints. During inference, only 3D keypoints are needed as input to reconstruct hand surface.

4. Human Grasps Generation

We show the utility of the HALO model in the challenging task of grasps generation. Given an object, we generate diverse grasps with natural and plausible hand-object interaction. Our grasp generation pipeline consists of two parts: a 3D keypoints generator based on a variational autoencoder (VAE) and the HALO model for obtaining the hand surface.

**HALO-VAE Architecture.** The architecture of the HALO-VAE model is illustrated in Fig. 4. During training, the object point cloud is first passed to the object encoder, which is a modification of PointNet [50] with residual connection [35], to obtain an object latent code. The object latent code is then concatenated to the 3D hand joint location, \( J \in \mathbb{R}^{21 \times 3} \), and passed to the VAE encoder. The decoder reconstructs the 3D hand joint positions conditioned on the hand and object latent representation. From the key points, the surface is obtained using HALO through the skeleton canonicalization layer.

The advantages of using HALO are two-fold. First, we decouple the complexity of learning the pose, represented by the skeleton, from that of learning the surface that corresponds to the pose; Second, the implicit model enables fast intersection tests between hand and object, which can be used to efficiently compute an interpenetration loss. Combined with the differentiable skeleton canonicalization layer, the interpenetration loss can be used to improve the keypoints generator in both end-to-end training and post-optimization refinement.

Our grasp generation pipeline is similar to [59] and [29], but with the following key differences. First, in [29], the output is a rigid implicit surface that cannot be articulated. To obtain an animatable hand for downstream tasks, additional MANO model fitting is required. Second, in [59], the grasps generator is trained to produce the MANO parameters which is not directly related to the Euclidean space where the hand and the object live in. The challenge of interfacing the MANO parameters with deep neural networks
is reflected in the GrabNet (CoarseNet) [59] results which will be discussed in the experiments section.

4.1. Learning and Losses

To train the VAE model, we use the following losses: the KL-divergence loss on the hand latent $Z$, L2 loss on the predicted key points, L1 bone lengths loss, and the bone angle losses. The bone angle losses are used to provide additional supervisions for learning the hand structure which consists of 1) flexion angles $\theta^f_i$, 2) abduction angles $\theta^a_i$, and 3) angles between adjacent palmar bones $\theta^p_i$. The bone angles are the same as used in Sec. 3. The losses are defined as L1 angle difference between the prediction and the ground truth.

Interpenetration loss. In addition to the losses on the keypoints, we also use the interpenetration loss on the hand surface to avoid collision between hand and object. The key idea is to penalize every point inside the object that is also occupied by the hand. Concretely, for a set of points sampled inside the object $P_o$ and the predicted key points $\tilde{J}$, the interpenetration loss is defined as:

$$L_{in}(\tilde{J}) = \sum_{p \in P_o} O_w(p|\Theta(\tilde{J}), f_y(D_{\tilde{J}})), \text{ where } O_w(\cdot) > 0.5$$  \hspace{1cm} (4)

where $D_{\tilde{J}}$ is the bone length vector for $\tilde{J}$ and $\Theta(\tilde{J})$ maps the predicted key points to the HALO pose vector $\theta$ using the differentiable transformation matrices in Eq. 1.

4.2. Optimization-based Refinement

To demonstrate that the efficient intersection tests enabled by HALO can be used for optimization, we refine the sampled hands by changing the global translation $t$ to avoid collision with the object. The refinement is run for 10 steps with the interpenetration loss term in Eq. 4. The optimization objective is:

$$\min_t L_{in}(\tilde{J} + t)$$ \hspace{1cm} (5)

This simple optimization step aims at refining the contact after the initial prediction of HALO-VAE. It is analogous to the RefineNet in [59], but with an explicit objective to avoid collision instead of being a neural network denoiser.

5. Experiments

In this section, we assess our skeleton-driven hand model and the grasp synthesis pipeline. First, in Sec. 5.1, we validate the efficacy of HALO as a neural implicit hand model and compare it to the surface baseline [15] and keypoints-to-surface baselines [11, 70]. Second, we show in Sec. 5.2 that HALO can be used effectively in generative tasks which require surface-based reasoning in form of grasp synthesis. For more experiments, please see supplementary materials.

### Table 1. Evaluation on IOU, Chamfer-distance (L1), and normal consistency score (Norm.) between NASA [15] and HALO.

| Methods                     | IOU ↑ | Cham. (mm) ↓ | Norm. ↑ |
|-----------------------------|-------|--------------|--------|
| NASA [15]                   | 0.896 | 1.057        | 0.955  |
| NASA+surf.                  | 0.883 | 1.177        | 0.944  |
| NASA+surf.+local b.         | 0.913 | 0.884        | 0.950  |
| HALO (ours)                 | 0.932 | 0.719        | 0.959  |
| HALO keypoints (ours)       | 0.930 | 0.740        | 0.959  |

### Table 2. Comparison between the estimated, root-aligned surfaces when only 3D keypoints are given as input.

| Methods            | IOU ↑ | Cham. (mm) ↓ | MPJPE (mm) ↓ |
|--------------------|-------|--------------|--------------|
| Choi et al. [11]   | 0.43  | 4.651        | 14.1         |
| Zhou et al. [70]   | 0.54  | 2.811        | 7.95         |
| HALO keypoints (ours) | 0.93  | 0.740        | 0 |

5.1. Neural Hand Model

We first evaluate the performance of the proposed implicit surface representation and analyze the effect of the keypoint-to-transformation mapping layer.

Training data. To train our neural occupancy hand model, we utilize MANO [51] hand meshes. Following [15], for each mesh we sample points with two strategies: 1) uniformly sampling in the hand bounding box, 2) sampling on the surface with additional isotropic Gaussian noise. Only the uniformly sampled points are used for evaluation. The associated occupancy value of each query point is computed by casting a ray from the sampled point and counting the number of intersections along the ray. The ground truth bone transformation matrices are computed along the kinematic chain to transform the template MANO hand into the target pose. The skinning weights are taken from the skinning weights of MANO. We use the Youtube3D (YT3D) hands dataset [30] in all our experiments. The YT3D training set contains 50,175 hand meshes of hundreds of subjects performing a wide variety of tasks in 102 videos. The test set covers 1,525 meshes from 7 videos.

Evaluation metrics. For 3D surface reconstruction evaluation, we compute the mean Intersection over Union (IoU), Chamfer-L1 distance, and normal consistency score [35].

5.1.1 Comparison to implicit surface baseline

Here we investigate the generalization ability of the proposed HALO model to represent articulated hands with var-
ious poses and shapes. The results are summarized in Tab. 1

Baseline. We use the NASA model [15] as our baseline. The NASA model is designed to represent an implicit function of an articulated body. However, by changing the input dimension and the number of part-models to match the number of hand parts, it can also be used to represent an articulated hand. We train the baseline model using the bone transformation matrices taken from MANO and the sampled query points. For details on implementation and network architecture we refer to the supplementary.

Surface vertex re-sampling. In [15], the surface vertices \( v \) used for enforcing the part models in the skinning loss \( L_s \) are the mesh vertices of SMPL [34]. Similarly, we use MANO surface vertices during training. However, we notice that the human-designed mesh often has many more vertices in the area around the joints which could cause the part models to bias toward the bone endpoints. Thus, we propose to re-sample the surface vertices uniformly on the mesh surface. This result is performance degradation but the bone connections are more natural with less artifact.

Local and global bone encoders. The bone lengths of a human hand greatly influence the hand shape. Therefore, for the local bone encoder, we add the bone length \( d_i \) to the back-projected query point as input to the part model \( B^{-1}_j x; d_i \). As shown in Tab. 1, the local bone encoder improves the reconstruction quality both in terms of IoU and Chamfer-L1 distance. We further extend the local bone encoder by considering all the bone lengths as input. A concatenated vector of bone lengths is first fed into a small feed-forward neural network to get the global bone feature \( f_g(D) \), which is then concatenated with the query point \( x \) and the local bone length \( d_i \) as input to the part model.

Results. By combining the local and global bone encoders, HALO significantly improves the 3D surface reconstruction quality compared to NASA. As shown in Tab. 1, the IoU is increased from 0.896 to 0.932 and the Chamfer-L1 distance is decreased from 1.057mm to 0.719mm.

We provide a qualitative comparison between NASA, and HALO in Fig. 5, confirming the quantitative results. The proposed HALO representation generalizes well for highly articulated poses, whereas the NASA model produces severe artifacts at the connection between parts.

5.1.2 3D keypoints to hand surface

Tab. 1 also shows the result from HALO that only takes 3D keypoints as input. The keypoint model achieves compara-
ble surface reconstruction performance as when the ground truth transformation are given, showing the effectiveness of our method. We show the qualitative results in Fig. 1 and 5.

In addition, to evaluate the keypoint-to-surface pipeline, we then compare HALO to the equivalent component in [70] and [11] which estimates hand surface from 3D keypoints. The evaluation is done on same the Youtube3D test set where the ground truth 3D keypoints are given as input. As [11] requires both 2D and 3D coordinates as inputs, the 2D keypoint is obtain by projecting the 3D keypoints perpendicular to the palm. For evaluation, we also report the 3D joint error between the predicted hand and the input joints. This metric measures if the input keypoints are faithfully respected by the models. By design, the HALO model does not change the keypoint locations from input to output, thus does not have this error. The comparison in Tab. 2 shows that [70] and [11] change the hand pose and shape in the prediction while HALO faithfully reconstructs the hand surface according to the given keypoints.

5.2. Grasp Synthesis

To assess the utility of HALO in downstream tasks we demonstrate our grasp generative model, HALO-VAE.

Dataset. We leverage the recently introduced GRAB dataset [6, 59] and compare our results to GrabNet [59]. We compare both to the initial (coarse) predictions of GrabNet [59] and the refined results which matches with our own two-stage generation process. The test set contains 6 unseen objects. For each object, we fix the object orientation and sample 20 hand proposals from each model.

Physics Metrics. Following [67, 69], we evaluate the physical plausibility (interpenetration volume and contact ratio) and diversity, and provide results from a perceptual study. To evaluate the interpenetration and contact, we measure the ratio of frames in which the hand is in contact with the object and average the interpenetration volume. The volume is calculated by voxelizing hand and object mesh with 1mm cubes and counting the number of intersecting cubes.

User study. We asked 75 participants in a forced-alternative-choice perceptual study to ‘select the grasp that is more realistic’. For each question, the user is shown 4 views per grasp and forced to select one. We compare all possible combinations on the same object. Each question is assigned to at least 2 participants, totaling 4,800 data points per pair of model comparison. To ensure that the grasps from HALO-VAE and GrabNet have the exact same texture, we fit MANO to our generated key points for rendering.

Diversity. Following [69], we compute the diversity of the sampled grasps by performing k-means with 20 clusters on all samples, then evaluate the entropy of the cluster assignment and the average cluster size. More diversity results in higher value for both metrics. We use the flatten key point locations of the hands after aligning the root joint and the plane spanned by middle and index palmar bone as features.

Results. We first validate the efficacy of the interpenetration loss (Eq. 4). We compare the HALO-VAE models with and without the interpenetration loss. The results show that the interpenetration loss helps in: 1) reducing the collision between the objects and the generated hands (Tab. 3, col. 1-2), and 2) largely improves the user preference of the corresponding model (Tab. 4, first row), demonstrating the efficacy of the proposed neural occupancy representation of articulated hand for reasoning about hand-object interaction.

Next, we compare HALO-VAE with GrabNet [59]. Both HALO-VAE and GrabNet-coarse are CVAE based generative models and end-to-end trainable, the key difference is that GrabNet-coarse generates MANO model parameters whereas HALO-VAE generates 3D keypoints. As shown in Tab. 3, HALO-VAE outperforms GrabNet-coarse by a large margin for interpenetration volume and sample diversity. Moreover, the HALO-VAE model without interpenetration also compares favorably to GrabNet-coarse, suggesting that the 3D keypoints-based representation is well suited to interface with deep neural networks.

Finally, we compare our optimization-based refinement with GrabNet-refine. To the best of our knowledge, the RefineNet is not trained end-to-end with GrabNet-coarse and used for three steps during the inference. As shown in Tab. 4, our refined grasps attain a higher user score, suggesting they are more realistic and natural compared to the grasps refined by GrabNet-refine.

6. Discussion and Conclusion

In this work, we introduce HALO, a novel surface representation for articulated hands that can generalize to different hand poses and shapes. We address the issue of the transformation matrix requirement for inferring the 3D occupancy hand by proposing a skeleton canonicalization algorithm that computes valid transformations from 3D keypoints. The experiments show that our proposed hand model outperforms the baseline and can represent a wide range of hand poses and shapes. Finally, we demonstrate the HALO can be used to train an end-to-end grasp generator conditioned on an object and produces hand grasps with natural and realistic interaction. We believe that HALO can be useful in future work attempting to reconstruct the surface of articulated hands directly from images via differentiable rendering and for several downstream tasks that need to perform surface-based computation such as collision detection and response.

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