Populating 3D Scenes by Learning Human-Scene Interaction

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Abstract

Humans live within a 3D space and constantly interact with it to perform tasks. Such interactions involve physical contact between surfaces that is semantically meaningful. Our goal is to learn how humans interact with scenes and leverage this to enable virtual characters to do the same. To that end, we introduce a novel Human-Scene Interaction (HSI) model that encodes proximal relationships, called POSA for “Pose with prOximitieS and contActs”. The representation of interaction is body-centric, which enables it to generalize to new scenes. Specifically, POSA augments the SMPL-X parametric human body model such that, for every mesh vertex, it encodes (a) the contact probability with the scene surface and (b) the corresponding semantic scene label. We learn POSA with a VAE conditioned on the SMPL-X vertices, and train on the PROX dataset, which contains SMPL-X meshes of people interacting with 3D scenes, and the corresponding scene semantics from the PROX-E dataset. We demonstrate the value of POSA with two applications. First, we automatically place 3D scans of people in scenes. We use a SMPL-X model fit to the scan as a proxy and then find its most likely placement in 3D. POSA provides an effective representation to search for “affordances” in the scene that match the likely contact relationships for that pose. We perform a perceptual study that shows significant improvement over the state of the art on this task. Second, we show that POSA’s learned representation of body-scene interaction supports monocular human pose estimation that is consistent with a 3D scene, improving on the state of the art. Our model and code will be available for research purposes at https://posa.is.tue.mpg.de.

1. Introduction

Humans constantly interact with the world around them. We move by walking on the ground; we sleep lying on a bed; we rest sitting on a chair; we work using touchscreens and keyboards. Our bodies have evolved to exploit the af-
fordances of the natural environment and we design objects to better “afford” our bodies. While obvious, it is worth stating that these physical interactions involve contact. Despite the importance of such interactions, existing representations of the human body do not explicitly represent, support, or capture them.

In computer vision human pose is typically estimated in isolation from the 3D scene, while in computer graphics 3D scenes are often scanned and reconstructed without people. Both the recovery of humans in scenes and the automated synthesis of realistic people in scenes remain challenging problems. Automation of this latter case would reduce animation costs and open up new applications in augmented reality. Here we take a step towards automating the realistic placement of 3D people in 3D scenes with realistic contact and semantic interactions (Fig. 1). We develop a novel body-centric approach that relates 3D body shape and pose to possible world interactions. Learned parametric 3D human models [2, 28, 39, 45] represent the shape and pose of people accurately. We employ the SMPL-X [45] model, which includes the hand and face, as it supports reasoning about contact between the body and the world.

While such body models are powerful, we make three key observations. First, human models like SMPL-X [45] do not explicitly model contact. Second, not all parts of the body surface are equally likely to be in contact with the scene. Third, the poses of our body and scene semantics are highly intertwined. Imagine a person sitting on a chair; body contact likely includes the buttocks, probably also the back, and maybe the arms. Think of someone writing on a whiteboard; their feet are likely in contact with the floor, and the writing hand is in contact with the whiteboard.

Based on these observations, we formulate a novel model, that makes human-scene interaction (HSI) an explicit and integral part of the body model. The key idea is to encode HSI in an ego-centric representation built in SMPL-X. This effectively extends the SMPL-X model to capture contact and the semantics of HSI in a body-centric representation. We call this POSA for “Pose with prOxim-ities and contActs”. Specifically, for every vertex on the body and every pose, POSA defines a probabilistic feature map that encodes the probability that the vertex is in contact with the world and the distribution of semantic labels associated with that contact.

We learn POSA with a conditional Variational Auto-Encoder (cVAE) conditioned on SMPL-X vertex positions. We train on the PROX dataset [22], which contains 20 subjects, fit with SMPL-X meshes, interacting with 12 real 3D scenes. We use the scene semantic annotations provided by the PROX-E dataset [63]. Given a body pose, we can sample likely contacts with the world. We show the value of this representation with two challenging applications.

First, we focus on automatic scene population as illustrated in Fig. 1. That is, given a 3D scene and a body in a particular pose, where in the scene is this pose most likely? As demonstrated in Fig. 1 we first fit SMPL-X to commercial 3D scans of people, and then, conditioned on the body, our cVAE generates a target POSA feature map. We then search over possible human placements while minimizing the discrepancy between the observed and target feature maps. We quantitatively evaluate our approach using the same protocol [62] and find that our method significantly outperforms the recent state of the art.

Second, we use POSA for monocular 3D human pose estimation in a 3D scene. We build on the PROX method [22] that hand-codes contact points, and replace them with our learned feature map, which functions as an HSI prior. This automates a heuristic process, while producing lower pose estimation errors than the original PROX method.

To summarize, POSA is a novel model that intertwines SMPL-X pose and scene semantics with contact. To the best of our knowledge, this is the first learned human body model that incorporates HSI in the model. We think this is important because such a model can be used in all the same ways that models like SMPL-X are used but now with the addition of body-scene interaction. The key novelty is posing such HSI as part of the body representation itself. Like the original learned body models, POSA provides a platform that people can build on. To facilitate this, our model and code will be available for research purposes at https://posa.is.tue.mpg.de.

2. Related Work

Humans & Scenes in Isolation: For scenes [66], most work focuses on their 3D shape in isolation, e.g. on rooms empty of humans [3, 10, 16, 55, 59] or on objects that are not grasped [8, 11, 13, 60]. For humans, there is extensive work on capturing [5, 26, 40, 53] or estimating [41, 50] their 3D shape and pose, but outside the context of scenes.

Human Models: Most work represents 3D humans as body skeletons [26, 53]. However, the missing 3D body surface is important for physical interactions. This is solved by learned parametric 3D body models [2, 28, 39, 45, 61]. For interacting humans we employ SMPL-X [45] that models the body with full face and hand articulation.

HSI Geometric Models: We focus on the spatial relationship between a human body and objects it interacts with. Gleicher [18] uses contact constraints for early work on motion re-targeting. Lee et al. [34] generate novel scenes and motion by deformably stitching “motion patches”, comprised of scene patches and the skeletal motion in them. Lin et al. [37] generate 3D skeletons sitting on 3D chairs, by manually drawing 2D skeletons and fitting 3D skeletons that satisfy collision and balance constraints. Kim et al. [30] automate this, by detecting sparse contacts on a 3D ob-
object mesh and fitting a 3D skeleton to contacts while avoiding penetrations. Kang et al. [29] reason about the physical comfort and environmental support of a 3D humanoid, through force equilibrium. Leimer et al. [35] reason about pressure, frictional forces and body torques, to generate a 3D object mesh that comfortably supports a given posed 3D body. Zheng et al. [64] map high-level ergonomic rules to low-level contact constraints and deform an object to fit a 3D human skeleton for force equilibrium. Bar-Aviv et al. [4] and Liu et al. [38] use an interacting agent to describe object shapes through detected contacts [4], or relative distance and orientation metrics [38]. Gupta et al. [21] estimate human poses “afforded” in a depicted room, by predicting a 3D scene occupancy grid, and computing support and penetration of a 3D skeleton in it. Grabner et al. [20] detect the places on a 3D scene mesh where a 3D human mesh can sit, modeling interaction likelihood with GMMs and proximity and intersection metrics. Zhu et al. [65] use FEM simulations for a 3D humanoid, to learn to estimate forces, and reasons about sitting comfort.

Several methods focus on dynamic interactions [1, 25, 46]. Ho et al. [25] compute an “interaction mesh” per frame, through Delaunay tetrahedralization on human joints and unoccluded object vertices; minimizing their Laplacian deformation maintains spatial relationships. Others follow an object-centric approach [1, 25, 46]. Al-Asqhar et al. [1] sample fixed points on a 3D scene, using proximity and “coverage” metrics, and encode 3D human joints as transformations w.r.t. these. Pirk et al. [46] build functional object descriptors, by placing “sensors” around and on 3D objects, that “sense” 3D flow of particles on an agent.

HSI Data-driven Models: Recent work takes a data-driven approach. Jiang et al. [27] learn to estimate human poses and object affordances from an RGB-D scene, for 3D scene labels estimation. SceneGrok [51] learns action-specific classifiers to detect the likely scene places that “afford” a given action. Fisher et al. [17] use SceneGrok and interaction annotations on CAD objects, to embed noisy 3D room scans to CAD mesh configurations. PiGraphs [52] maps pairs of {verb-object} labels to “interaction snapshots”, i.e. 3D interaction layouts of objects and a human skeleton. Chen et al. [12] map RGB images to “interaction snapshots”, using Markov Chain Monte Carlo with simulated annealing to optimize their layout. iMapper [42] maps RGB videos to dynamic “interaction snapshots”, by learning “scenelets” on PiGraphs data and fitting them to videos. Cao et al. [9] map an RGB scene and 2D pose history to 3D skeletal motion, by training on video-game data. Li et al. [36] follow [58] to collect 3D human skeletons consistent with 2D/3D scenes of [54, 58], and learn to predict them from a color and/or depth image. Corona et al. [14] use a graph attention model to predict motion for objects and a human skeleton, and their evolving spatial relationships.

Another HSI variant is Hand-Object Interaction (HOI); we discuss only recent work [7, 15, 56, 57]. Brahmbhatt et al. [7] capture fixed 3D hand-object grasps, and learn to predict contact; features based on object-to-hand mesh distances outperform skeleton-based variants. For grasp generation, 2-stage networks are popular [43]. Taheri et al. [56] capture moving SMPL-X [45] humans grasping objects, and predict MANO [49] hand grasps for object meshes, whose 3D shape is encoded with BPS [47]. Corona et al. [15] generate MANO grasping given an object-only RGB image; they first predict the object shape and rough hand pose (grasp type), and then they refine the latter with contact constraints [23] and an adversarial prior.

Closer to us, PSI [63] and PLACE [62] populate 3D scenes with SMPL-X [45] humans. Zhang et al. [63] train a cVAE to estimate humans from a depth image and scene semantics. Their model provides an implicit encoding of HSI. Zhang et al. [62], on the other hand, explicitly encode the scene shape and human-scene proximal relations with BPS [47], but do not use semantics. Our key difference to [62, 63] is our human-centric formulation; inherently this is more portable to new scenes. Moreover, instead of the sparse BPS distances of [62], we use dense body-to-scene contact, and also exploit scene semantics like [63].

3. Method

3.1. Human Pose and Scene Representation

Our training data corpus is a set of n pairs of 3D meshes

\[ \mathcal{M} = \{\{M_{b,1}, M_{s,1}\}, \{M_{b,2}, M_{s,2}\}, \ldots, \{M_{b,n}, M_{s,n}\}\} \]

comprising body meshes \(M_{b,i}\) and scene meshes \(M_{s,i}\). We drop the index, i, for simplicity when we discuss meshes in general. These meshes approximate human body surfaces \(S_b\) and scene surfaces \(S_s\). Scene meshes \(M_s = (V_s, F_s, L_s)\) have a varying number of vertices \(N_s = |V_s|\), and triangle connectivity \(F_s\) to model arbitrary scenes as well as a per-vertex semantic label \(L_s\). Human meshes are represented by SMPL-X [45], i.e. a differentiable function

\[ M(\theta, \beta, \psi) : \mathbb{R}^{g|\beta|\psi} \rightarrow \mathbb{R}^{(N_b \times 3)} \]

parameterized by pose \(\theta\), shape \(\beta\) and facial expressions \(\psi\). The pose vector \(\theta = (\theta_b, \theta_f, \theta_{lh}, \theta_{rh})\) is comprised of body, \(\theta_b \in \mathbb{R}^{66}\), and face parameters, \(\theta_f \in \mathbb{R}^{3}\), in axis-angle representation, while \(\theta_{lh}, \theta_{rh} \in \mathbb{R}^{12}\) parameterize the poses of the left and right hands respectively in a low-dimensional pose space. The shape parameters, \(\beta \in \mathbb{R}^{10}\), represent coefficients in a low-dimensional shape space learned from a large corpus of human body scans. The joints, \(J(\beta)\), of the body in the canonical pose are regressed from the body shape. The skeleton has 55 joints, consisting of 22 body joints, 30 hand joints, and 3 head joints (neck and eyes). The mesh is posed using this skeleton and linear blend skinning.
Body meshes $M_b = (V_b, F_b)$ have a fixed topology with $N_b = |V_b| = 10475$ vertices $V_b \in \mathbb{R}^{(N_b \times 3)}$ and triangles $F_b$, i.e., all human meshes are in correspondence. For more details, we refer the reader to [45].

### 3.2. POSA Representation for HSI

We encode the relationship between the human mesh $M_b = (V_b, F_b)$ and the scene mesh $M_s = (V_s, F_s, L_s)$ in an egocentric feature map $f$ that encodes per-vertex features on the SMPL-X mesh $M_b$. We define $f$ as:

$$f : (V_b, M_s) \rightarrow \mathbb{R}^{N_f}$$  \hspace{1cm} (1)

$$f = [f_c, f_s]$$  \hspace{1cm} (2)

where $f_c$ is the contact label and $f_s$ is the semantic label of the contact point. $N_f$ is the feature dimension.

During training, for each vertex $i$ on the body, $V_b^i$, we find its closest scene point $P_s = \arg\min_{P_s \in S_s} \|P_s - V_b^i\|$. Then we compute the distance $f_d$:

$$f_d = \|P_s - V_b^i\| \in \mathbb{R}.$$  \hspace{1cm} (3)

Given $f_d$, we can compute whether a $V_b^i$ is in contact with the scene or not, with $f_c$:

$$f_c = \begin{cases} 1 & f_d \leq \text{Contact Threshold}, \\ 0 & f_d > \text{Contact Threshold}. \end{cases}$$  \hspace{1cm} (4)

The contact threshold is chosen empirically to be 5 cm. The semantic label of the contacted surface $f_s$ is a one-hot encoding of the object class:

$$f_s = \{0, 1\}^{N_o},$$  \hspace{1cm} (5)

where $N_o$ is the number of object classes. A visualization of the proposed representation is in Fig. 2.

### 3.3. Learning

Our goal is to learn a probabilistic function from body pose and shape to the feature space of contact and semantics. That is, given a body, we want to sample labelings of the vertices corresponding to likely scene contacts and their corresponding semantic label. Note that this function, once learned, only takes the body as input and not a scene – it is a body-centric representation.

To train this we use the PROX [22] dataset, which contains bodies in 3D scenes. We also use the scene semantic annotations from the PROX-E dataset [63]. Given pose and shape parameters in a given training frame, we compute a $M_b = M(\theta, \beta, \psi)$. This gives vertices $V_b$ from which we compute the feature map that encodes whether each $V_b^i$ is in contact with the scene or not, and the semantic label of the scene contact point $P_s$.

We train a conditional Variational Autoencoder (cVAE), where we condition the feature map on the vertex positions, $V_b$, which are a function of the body pose and shape parameters. We train the cVAE by optimizing the encoder and decoder parameters to minimize $L_{total}$ using gradient descent:

$$L_{total} = \alpha \cdot L_{KL} + L_{rec}$$  \hspace{1cm} (6)

$$L_{KL} = KL(Q(z|f, V_b)||p(z))$$  \hspace{1cm} (7)

$$L_{rec} (f, \hat{f}) = \lambda_c \cdot \sum_i \text{BCE} (f_c^i, \hat{f}_c^i) + \lambda_s \cdot \sum_i \text{CCE} (f_s^i, \hat{f}_s^i)$$  \hspace{1cm} (8)

where $\hat{f}_c$ and $\hat{f}_s$ are the reconstructed contact and semantic labels, $KL$ denotes the Kullback Leibler divergence, and $L_{rec}$ denotes the reconstruction loss. BCE and CCE are the binary and categorical cross entropies respectively. The $\alpha$ is a hyperparameter inspired by Gaussian $\beta$-VAEs [24], which regularizes the solution; here $\alpha = 0.1$. $L_{rec}$ encourages the reconstructed samples to resemble the input, while $L_{KL}$ encourages $Q(z|x, \theta)$ to match a prior distribution over $z$, which is Gaussian in our case.

Since $f$ is defined on the vertices of the body mesh $M_b$, this enables us to use graph convolution as our building block for our VAE. Specifically, we use the Spiral Convolution formulation introduced in [6, 19]. The spiral convolution operator for node $i$ in the body mesh is defined as:

$$f'_k = \gamma_k \left( \parallel_{j \in S(i,l)} f'_{k-1} \right),$$  \hspace{1cm} (9)

where $\gamma_k$ denotes layer $k$ in a multi-layer perceptron (MLP) network, and $\parallel$ is a concatenation operation of the features of neighboring nodes, $S(i,l)$. The spiral sequence $S(i,l)$ is an ordered set of $l$ vertices around the central vertex $i$. Our architecture is shown in Fig. 3. More implementation
Figure 3: cVAE architecture. For each vertex on the body mesh, we concatenate the vertex positions $x_i, y_i, z_i$, the contact label $f_c$, and the corresponding semantic scene label $f_s$. The latent vector $z$ is concatenated to the vertex positions, and the result passes to the decoder which reconstructs the input features $\hat{f}_c, \hat{f}_s$.

details are included in the Sup. Mat. For details on selecting and ordering vertices, please see [19].

4. Experiments

We perform several experiments to investigate the effectiveness and usefulness of our proposed representation and model under different use cases, namely generating HSI features, scene affordance detection, and improving monocular 3D human pose estimation.

4.1. Random Sampling

We evaluate the generative power of our model by sampling different feature maps conditioned on novel poses using our trained decoder $P(f_{\text{Gen}}|z, V_b)$, where $z \sim \mathcal{N}(0, I)$ and $f_{\text{Gen}}$ is the randomly generated feature map. This is equivalent to answering the question: “In this given pose, which vertices on the body are likely to be in contact with the scene, and what object would they contact?” Randomly generated samples are shown in Fig. 4.

We observe that our model generalizes well to various poses. For example, notice that when a person is standing with one hand pointing forward, our model predicts the feet and the hand to be in contact with the scene. It also predicts the feet are in contact with the floor and hand is in contact with the wall. However this changes for the examples when a person is in a lying pose. In this case, most of the vertices from the back of the body are predicted to be in contact (blue color) with a bed (light purple) or a sofa (dark green).

These features are predicted from the body alone; there is no notion of “action” here. Pose alone is a powerful predictor of interaction. Since the model is probabilistic, we can sample many possible feature maps for a given pose.

4.2. Affordance Detection

The affordance of an object is defined as the quality of that object that allows someone to perform an action on or with it. Detecting affordance in a given scene means evaluating the probability of an action taking place in this scene [20, 30, 32]. Specifically, given a scene, $M_s$, semantic labels of objects present, and a body mesh, $M_b$, our method finds where in $M_s$ this given pose is likely to happen.

We solve this problem in two steps. First, we use the decoder of our cVAE to generate a feature map by sampling $P(f_{\text{Gen}}|z, V_b)$ as in Sec. 4.1. Second, we optimize the objective function:

$$E(\tau, \theta_0, \theta) = \mathcal{L}_{\text{afford}} + \mathcal{L}_{\text{pen}} + \mathcal{L}_{\text{reg}},$$

where $\tau$ is the body translation, $\theta_0$ is the global body orientation and $\theta$ is the body pose. $\mathcal{L}_{\text{afford}}$ is the affordance loss:

$$\mathcal{L}_{\text{afford}} = \lambda_1 * \|f_{\text{Gen}} \cdot f_d\|^2 + \lambda_2 * \sum_i \text{CCE}(f_{\text{Gen}}^i, f_s^i);$$

where $f_d$ and $f_s$ are the observed distance and semantic labels, which are computed using Eq. 3 and Eq. 5 respectively, $f_{\text{Gen}}$ and $f_{\text{Gen}}^s$ are the generated contact and semantic labels, and $\cdot$ denotes dot product. $\mathcal{L}_{\text{pen}}$ is a penetration penalty to discourage the body from penetrating the scene:

$$\mathcal{L}_{\text{pen}} = \lambda_{\text{pen}} * \sum_{f_s < 0} (f_d)^2.$$
$L_{\text{reg}}$ is a regularization term that encourages the estimated pose to remain close to the initial pose $\theta_{\text{init}}$ of $M_b$:

$$L_{\text{reg}} = \lambda_{\text{reg}} \cdot ||\theta - \theta_{\text{init}}||^2_2. \quad (13)$$

Although the body pose is given, we optimize over it, allowing the $\theta$ parameters to change slightly since the given pose $\theta_{\text{init}}$ might not be well supported by the scene. This allows for small pose adjustment that might be necessary to better fit the body into the scene. The weights $\lambda_1, \lambda_2, \lambda_{\text{pen}}$ and $\lambda_{\text{reg}}$ are determined empirically.

The input posed mesh, $M_b$, can come from any source. For example, we can generate random SMPL-X meshes using VPoser [45] which is a VAE trained on a large dataset of human poses. More interestingly, we use SMPL-X meshes fit to realistic Renderpeople scans [44] (see Fig. 1).

We tested our method with both real (scanned) and synthetic (artist generated) scenes. Qualitative examples on a real scene from the PROX [22] test set is shown in Fig. 5 (top); this scene was not used during training. Note that people appear to be interacting naturally with the scene; that is, their pose matches the scene context. Figure 5 (bottom) shows bodies automatically placed in an artist-designed scene (Archviz Interior Rendering Sample, Epic Games).\(^1\) Moreover, the results go beyond previous work [20, 30, 63] to produce realistic human-scene interactions for a wide range of poses like lying down (Fig. 5 top), grasping (Fig. 5 bottom), and reaching out (Fig. 5).

While the poses look natural in the above results, the SMPL-X bodies look out of place in realistic scenes. Consequently, we would like to render realistic people instead, but models like SMPL-X do not yet support realistic clothing and textures. Realistic scans from companies like Renderpeople have high quality but the topology of every scan is different. The consistent topology of a mesh like SMPL-X, however, is critical to learn the feature model.

**Clothed Humans:** We address this issue by using SMPL-X fits to clothed meshes from the AGORA dataset [44]. We then take the SMPL-X fits and minimize an energy function similar to Eq. 10 with one important change. We keep the pose, $\theta$, fixed:

$$E(\tau, \theta_0) = L_{\text{afford}} + L_{\text{pen}}. \quad (14)$$

Since the pose does not change, we just replace the SMPL-X mesh with the original clothed mesh after the optimization converges; we visualize the whole pipeline in Sup. Mat.

Qualitative results for real scenes (Replica dataset [55]) are shown in Fig. 6, and for a synthetic scene in Fig. 1. More results are shown in Sup. Mat. and in our video.

### 4.2.1 Perceptual Study

To quantitatively evaluate our method, we perform two perceptual studies. Both have the form of a two-alternative forced-choice (2AFC) study; users are shown a pair of two options, and choose one according to the statement “Which one of the two examples has more realistic (i.e. natural and physically plausible) human-scene interaction?”

**Comparison to PROX ground truth:** We follow the protocol of Zhang et al. [62] and compare our results to randomly selected examples from PROX ground truth. We take

\(^1\)https://docs.unrealengine.com/en-US/Resources/Showcases/ArchVisInterior/index.html
4 real scenes from the PROX [22] test set, namely MPH16, MPH1Library, NOSSittingBooth and N3OpenArea. We take 100 SMPL-X bodies from the AGORA [44] dataset, corresponding to 100 different 3D scans from Renderpeople. We take each of these bodies and sample one feature map for each, using our cVAE. We then optimize the placement of each sample in all the scenes, one body per scene. For unclothed bodies (Tab. 1, rows 1-3), this optimization changes the pose slightly to fit the scene (Eq. 10). For clothed bodies (Tab. 1, rows 4-5), the pose is kept fixed (Eq. 14). For each variant, this optimization results in 400 unique body-scene pairs. We render each 3D human-scene interaction from 2 views so that raters are able to get a good sense of the 3D relationships from images. Using Amazon Mechanical Turk (AMT), we show these results to 3 different raters. This results in 1200 unique ratings. The results are shown in Tab. 1. POSA (contact only) and the state-of-the-art method PLACE [62] are both almost indistinguishable from the PROX ground truth. However, the proposed POSA (contact + semantics) (row 3) outperforms both POSA (contact only) (row 2) and PLACE [62] (row 1), thus contact and scene semantics are complementary. Lastly, the use of high quality clothed meshes (bottom two rows) influences the perceived realism significantly.

Comparison between POSA and PLACE: We follow the same protocol as above, but this time we directly compare POSA and PLACE. The results are shown in Tab. 2. We see again that POSA, which combines contact and semantic information, performs better than its contact-only variant. The results also show that POSA, clearly outperforms PLACE by a large margin. We think that this is because of three reasons. First, POSA employs denser contact information across the whole SMPL-X body surface, compared to PLACE’s sparse distance information through its BPS representation. Second, POSA uses a human-centric formulation, as opposed to PLACE’s scene-centric one, and this can help generalize across scenes better. Third, POSA uses semantic features that help bodies do the right thing in the scene, while PLACE does not. When human generation is imperfect, inappropriate semantics may make the result seem worse. Please note that PLACE generates a posed body mesh for a given scene, while our method samples one from the AGORA dataset and places it in the scene using a generated POSA feature map. The former is arguably a hard task, while our sampling can both help and harm performance, as samples are scene-agnostic. POSA can be combined with any method that generates body meshes.

Although our method is more realistic than previous work and quantitatively performs well most of the time, the results are not always fully natural; sometimes people sit in strange places or lie where they usually don’t.

| Generation ↑ | PROX GT ↓ |
|-------------|-----------|
| PLACE [62]  | 48.5%     | 51.5%     |
| POSA (contact only) | 46.9% | 53.1% |
| POSA (contact + semantics) | **49.1%** | **50.1%** |
| POSA-clothing (contact) | 55.0% | 45.0% |
| POSA-clothing (semantics) | **60.6%** | **39.4%** |

Table 1: Comparison to PROX [22] ground truth, with a two-alternative forced-choice (2AFC) user study. Users are shown pairs of a generated 3D human-scene interaction and PROX ground truth (GT), and chose the most realistic one. We report the percentage (%) of users over all pairs. Arrows show the values (higher/lower) for realistic generation.

| POsa-variant ↑ | Place ↓ |
|---------------|--------|
| POSA (contact only) | 60.7% | 39.3% |
| POSA (contact + semantics) | **61.0%** | **39.0%** |

Table 2: POSA compared to PLACE for 3D human-scene interaction generation, with a two-alternative forced-choice (2AFC) user study. Users are shown pairs of 3D human-scene interactions generated with POSA and PLACE, and chose the most realistic one. We report the percentage (%) of users over all pairs. Arrows indicate the values (higher/lower) that “favor” POSA over PLACE.

4.2.2 Physical Plausibility and Diversity

Physical Plausibility: We generate 1200 bodies in each of the 4 test scenes of PROX, for a total of 4800 samples, following [62, 63]. Given a generated body mesh, \( M_b \), a scene mesh, \( M_s \), and a scene SDF that stores distances \( d_j \) for each voxel \( j \), we compute the following scores, defined by Zhang et al. [63]: (1) the non-collision score for each \( M_b \), which is the ratio of body mesh vertices with positive SDF values divided by the total number of SMPL-X vertices, and (2) the contact score for each \( M_b \), which is 1 if at least one vertex of \( M_b \) has a non-positive value. We report the mean non-collision score and mean contact score over all 4800 samples in Tab. 3; higher values are better for both metrics. We observe that POSA is on par with the state-of-the-art PLACE [62] method.

Diversity Metric: Using the same 4800 samples as above, we compute the diversity metric, defined by Zhang et al. [63]. We perform K-means (\( k = 20 \)) clustering of the SMPL-X parameters of all generated samples, and report: (1) the entropy of the cluster ID histogram for all samples, and (2) the cluster size, i.e. the average distance between the cluster center and the samples belonging in it. We report the results in Tab. 4; higher values are better. We see again that all methods are on par with each other, but ranking of methods is different from the physical plausibility metric.
the body translation, and \( \beta \), where \( \theta \) (neck, jaw) and the two hands, \( \alpha \) penalizes self-penetrations. For details please see [45].

Extreme bending only for elbows and knees. The term \( E_\alpha \) joints estimated from the RGB image \( I \) projection loss that minimizes the difference between 2D \( \beta \) 2D joints, priors and physical constraints on the body; \( \beta \) function of multiple terms: the re-projection error of \( \alpha \) optimizes SMPL parameters to minimize an objective \( \alpha \) without any scene constraints. Specifically, SMPLify-X \( \beta \) [45], which fits SMPL-X to image features \( \alpha \) to RGB image features and condition the pose on the \( \beta \) scene. Similar to PROX, our work builds on \( \alpha \) PROX with our learned feature map. We fit SMPL-X \( \beta \) to RGB image features and condition the pose on the \( \beta \) scene, but we turn off the PROX contact term. We optimize Eq. 15 first to get a rough pose that matches the image observations and roughly obeys the scene constraints. Then, given this rough body pose, which is not expected to change significantly, we sample features from \( P(f_{Gen}|\alpha, V_\alpha) \) and keep these fixed. Finally, we refine by minimizing the following objective \( E(\beta, \theta, \psi, \tau, m') = \)

\[
E_{SMPLify-X} + ||f_{Gen} \cdot f_d||^2 + \mathcal{L}_{pen}
\]

where \( E_{SMPLify-X} \) represents the SMPLify-X energy term as defined in Eq. 15, \( f_{Gen} \) is the generated contact labels, \( f_d \) is the observed distance, and \( \mathcal{L}_{pen} \) represents the body-scene penetration loss as in Eq. 12. We compare our results to standard PROX in Tab. 5. We also show the results of the RGB baseline introduced in PROX for reference. While our implementation is simple, the learned feature map improves accuracy over the PROX baseline’s heuristically determined contact constraints.

|                | Non-Collision ↑ | Contact ↑ |
|----------------|----------------|-----------|
| PSI [63]       | 0.94           | 0.99      |
| PLACE [62]     | 0.98           | 0.99      |
| POSA (contact only) | 0.97           | 1.0       |
| POSA (contact + semantics) | 0.97           | 0.99      |

Table 3: Evaluation of the physical plausibility metric. Arrows indicate that higher scores are better.

|                | Entropy ↑ | Cluster Size ↑ |
|----------------|-----------|----------------|
| PSI [63]       | 2.97      | 2.53           |
| PLACE [62]     | 2.91      | 2.72           |
| POSA (contact only) | 2.92           | 2.54           |
| POSA (contact + semantics) | 2.91           | 2.52           |

Table 4: Evaluation of the diversity metric. Arrows indicate that higher scores are better.

### 4.3. Monocular Pose Estimation

A useful application of our method is to incorporate scene constraints in monocular human pose estimation. Traditionally, monocular pose estimation methods focus only on the body and ignore the scene. Hence, they tend to generate predictions that are inconsistent with the scene. Here, we compare directly with PROX [22], which adds contact and penetration constraints to the pose estimation formulation. The contact constraint snaps a fixed set of contact points on the body surface to the scene, if they are “close enough”. In PROX, however, these contact points are manually selected and are independent of pose.

Here, we replace the hand-crafted contact points of PROX with our learned feature map. We fit SMPL-X to RGB image features and condition the pose on the 3D scene. Similar to PROX, our work builds on SMPLify-X [45], which fits SMPL-X to image features without any scene constraints. Specifically, SMPLify-X optimizes SMPL-X parameters to minimize an objective function of multiple terms: the re-projection error of 2D joints, priors and physical constraints on the body; \( E_{SMPLify-X}(\beta, \theta, \psi, \tau, m') = \)

\[
E_f + \lambda_\theta E_\theta + \lambda_\alpha E_\alpha + \lambda_\beta E_\beta + \lambda_\tau E_\tau
\]

where \( \theta \) represents the pose parameters of the body, face (neck, jaw) and the two hands, \( \theta = \{\theta_b, \theta_f, \theta_h\}, \tau \) denotes the body translation, and \( \beta \) the body shape. \( E_f \) is a re-projection loss that minimizes the difference between 2D joints estimated from the RGB image \( I \) and the 2D projection of the corresponding posed 3D joints of SMPL-X. \( E_\alpha(\theta_\alpha) = \sum_{i \in \{\text{elbows, knees}\}} \exp(\theta_\alpha) \) is a prior penalizing \( \alpha \) extreme bending only for elbows and knees. The term \( E_\tau \) penalizes self-penetrations. For details please see [45].

We proceed as in PROX to estimate body pose in a 3D scene, but we turn off the PROX contact term. We optimize Eq. 15 first to get a rough pose that matches the image observations and roughly obeys the scene constraints. Then, given this rough body pose, which is not expected to change significantly, we sample features from \( P(f_{Gen}|\alpha, V_\alpha) \) and keep these fixed. Finally, we refine by minimizing the following objective \( E(\beta, \theta, \psi, \tau, m') = \)

\[
E_{SMPLify-X} + ||f_{Gen} \cdot f_d||^2 + \mathcal{L}_{pen}
\]

which \( E_{SMPLify-X} \) represents the SMPLify-X energy term as defined in Eq. 15, \( f_{Gen} \) is the generated contact labels, \( f_d \) is the observed distance, and \( \mathcal{L}_{pen} \) represents the body-scene penetration loss as in Eq. 12. We compare our results to standard PROX in Tab. 5. We also show the results of the RGB baseline introduced in PROX for reference. While our implementation is simple, the learned feature map improves accuracy over the PROX baseline’s heuristically determined contact constraints.

### 5. Conclusions

A traditional statistical 3D body model, like SMPL-X, models the a priori probability of possible body shapes and poses. We argue that human poses in isolation from the scene, make little sense. We introduce POSA, which effectively upgrades a 3D human body model to explicitly represent possible human-scene interactions. Our novel, body-centric, representation encodes the contact and semantic relationship between the body and the scene. We show that this is useful and supports new tasks. For example, we consider placing a 3D human into a 3D scene. Given a scan of a person with a known pose, POSA allows us to search the scene for locations where the pose is likely. This enables us to populate empty 3D scenes with higher realism than the state of the art. We also show that POSA can be used for estimating human pose from an RGB image, and that this removes the need to heuristically define contact manually, as previous work does. In summary, we believe that POSA is a good step towards a richer model of human bodies that goes beyond pose to support the modeling of HSI.
Limitations: Using POSA to put people into scenes or to estimate human pose, requires an accurate scene SDF. Our results degrade if the SDF suffers due to a noisy scene mesh (e.g. holes, non-manifold geometry, flying vertices). To place people in scenes, any optimization-based method is sensitive to initialization and is prone to local minima. A simple user interface would address this, letting naive users roughly place bodies in the scene, and then apply our method to automatically refine for an exact placement.

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Appendices

A. Training Details

The global orientation of the body is typically irrelevant in our body-centric representation, so we rotate the training bodies around the \( y \) and \( z \) axes to put them in a canonical orientation. The rotation around the \( x \) axis, however, is essential to enable the model to differentiate between standing up and lying down. The semantic labels for the PROX scenes are taken from Zhang et al. [63], where scenes were manually labeled following the object categorization of Matterport3D [10], which incorporates 40 object categories.

Our encoder-decoder architecture is similar to the one introduced in Gong et al. [19]. The encoder consists of 3 spiral convolution layers interleaved with pooling layers \( 3 \times \{ \text{Conv}(64) \rightarrow \text{Pool}(4) \} \rightarrow \text{FC}(512) \). Pool stands for a downsampling operation as in COMA [48], which is based on contracting vertices. FC is a fully connected layer and the number in the bracket next to it denotes the number of units in that layer. We add 2 additional fully connected layers to predict the parameters of the latent code, with fully connected layers of \( 256 \) units each. The input to the encoder is a body mesh \( M_b \) where, for each vertex, \( i \), we concatenate \( V_i^b \) vertex positions, and \( f \) vertex features. For computational efficiency, we first downsample the input mesh by a factor of 4. So instead of working on the full mesh resolution of 10475 vertices, our input mesh has a resolution of 655 vertices. The decoder architecture consists of 4 \( \times \{ \text{Conv}(64) \} \rightarrow \text{Conv}(N_f) \). We attach the latent vector \( z \) to the 3D coordinates of each vertex similar to Kolotouros et al. [33].

We build our model using the PyTorch framework. We use the Adam optimizer [31], batch size of 64, and learning rate of \( 1e^{-3} \) without learning rate decay.

B. SDF Computation

For computational efficiency, we employ a precomputed 3D signed distance field (SDF) for the static scene \( S_s \), following Hassan et al. [22]. The SDF has a resolution of \( 512 \times 512 \times 512 \). Each voxel \( c_j \) stores the distance \( d_j \in \mathbb{R} \) of its centroid \( P_J \in \mathbb{R}^3 \) to the nearest surface point \( P_s \in S_s \). The distance \( d_j \) has a positive sign if \( P_j \) lies in the free space outside physical scene objects, while it has a negative sign if it is inside a scene object.

C. Random Samples

We show multiple randomly sampled feature maps for the same pose in Fig. S.1. Note how POSA generate a variety of valid feature maps for the same pose. Notice for example that the feet are always correctly predicted to be in contact with the floor. Sometimes our model predicts the person is sitting on a chair (far left) or on a sofa (far right).

The predicted semantic map \( f_s \) is not always accurate as shown in the far right of Fig. S.1. The model predicts the person to be sitting on a sofa but at the same time predicts the lower parts of the leg to be in contact with a bed which is unlikely.

D. Affordance Detection

The complete pipeline of the affordance detection task is shown in Fig. S.2. Given a clothed 3D mesh that we want to put in a scene, we first need a SMPL-X fit to the mesh; here we take this from the AGORA dataset [44]. Then we generate a feature map using the decoder of our cVAE by sampling \( P(f_{Gen}|z, V_b) \). Next we minimize the energy function in Eq. 17.

\[
E(\tau, \theta_0) = \mathcal{L}_{\text{afford}} + \mathcal{L}_{\text{pen}}
\]

Finally, we replace the SMPL-X mesh with the original clothed.

We show additional qualitative examples of SMPL-X meshes automatically placed in real and synthetic scenes in Fig. S.4. Qualitative examples of clothed bodies placed in real and synthetic scenes are shown in Fig. S.5.

E. Failure Cases

We show representative failure cases in Fig. S.3. A common failure mode is residual penetrations: even with the penetration penalty the body can still penetrate the scene. This can happen due to thin surfaces that are not captured by our SDF and/or because the optimization becomes stuck in a local minimum. In other cases, the feature map might not be right. This can happen when the model does not generalize well to test poses due to the limited training data.
Figure S.1: Random samples from our trained cVAE for the same pose. For each example we show from left to right: $f_c$ and $f_s$. The color code is at the bottom. For $f_c$, blue means contact, while pink means no contact. For $f_s$, each scene category has a different color.

Figure S.2: Putting realistic people in scenes. Pipeline of affordance detection using meshes with clothing. SMPL-X acts as a proxy for the clothed scan. POSA is used to sample features for this pose. These features are then used with the scene mesh to optimize the placement of the body. After convergence, we simply replace SMPL-X with the clothed scan.

Figure S.3: Failure cases.
Figure S.4: Qualitative examples of SMPL-X meshes automatically placed in real and synthetic scenes. The body shapes and poses were not used in training.

Figure S.5: Clothed bodies (from Renderpeople) automatically placed in real and synthetic scenes.