ECON: Explicit Clothed humans Obtained from Normals

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Abstract

The combination of deep learning, artist-curated scans, and Implicit Functions (IF), is enabling the creation of detailed, clothed, 3D humans from images. However, existing methods are far from perfect. IF-based methods recover free-form geometry, but produce disembodied limbs or degenerate shapes for unseen poses or clothes. To increase robustness for these cases, existing work uses an explicit parametric body model to constrain surface reconstruction, but this limits the recovery of free-form surfaces such as loose clothing that deviates from the body. What we want is a method that combines the best properties of implicit and explicit methods. To this end, we make two key observations: (1) current networks are better at inferring detailed 2D maps than full-3D surfaces, and (2) a parametric model can be seen as a “canvas” for stitching together detailed surface patches. Based on these, our method, ECON, has three main steps: (1) It infers detailed 2D normal maps for the front and back side of a clothed person. (2) From these, it recovers 2.5D front and back surfaces, called d-BiNI, that are equally detailed, yet incomplete, and registers these w.r.t. each other with the help of a SMPL-X body mesh recovered from the image. (3) It “inpaints” the missing geometry between d-BiNI surfaces. If the face and hands are noisy, they can optionally be replaced with the ones of SMPL-X. As a result, ECON infers high-fidelity 3D humans even in loose clothes and challenging poses. This goes beyond previous methods. Quantitative evaluation on the CAPE and Renderpeople datasets shows that ECON is more accurate than the state of the art. Perceptual studies also show that ECON’s perceived realism is better by a large margin. Code and models are available for research purposes at xiuyuliang.cn/econ

1. Introduction

Human avatars will be key for future games and movies, mixed-reality, tele-presence and the “metaverse”. To build realistic and personalized avatars at scale, we need to faithfully reconstruct detailed 3D humans from color photos taken in the wild. This is still an open problem, due to its challenges; people wear all kinds of different clothing and accessories, and they pose their bodies in many, often imaginative, ways. A good reconstruction method must accurately capture these, while also being robust to novel clothing and poses.
Initial, promising, results have been made possible by using artist-curated scans as training data, and deep implicit functions (IF) \[51, 54\] as a 3D representation. Seminal work on PIFu \[60\] and PIFuHD \[61\] uses “pixel-aligned” IF and reconstructs detailed clothed 3D humans with unconstrained topology. However, these methods tend to overfit to the poses seen in the training data, and have no explicit knowledge about the human body’s structure. Consequently, they tend to produce disembodied limbs or degenerate shapes for images with unseen poses; see the second row of Fig. 2. Follow-up work \[25, 67, 69, 75\] accounts for such artifacts by regularizing the IF using a shape prior provided by an explicit body model \[47, 55\], but this can limit generalization to novel clothing while attenuating shape details; see the third and fourth rows of Fig. 2. In other words, there are trade-offs between robustness, generalization and detail.

What we want, however, is the best of both worlds, the robustness of explicit anthropomorphic body models, and the flexibility of IF to capture arbitrary topologies. To that end, we make two key observations: (1) While inferring detailed 2D normal maps from color images is relatively easy \[29, 61, 67\], inferring a 3D geometry with equally fine details is still challenging \[11\]. Thus, we exploit networks to infer detailed “geometry-aware” 2D maps that we then lift to 3D. (2) A body model can be seen as a low-frequency “canvas” that “guides” the stitching of detailed surface parts.

With these in mind, we develop ECON, a novel method for “Explicit Clothed humans Obtained from Normals”. ECON takes as input an RGB image and a SMPL-X body inferred from the image. Then, it outputs a 3D human in free-form clothing with a level of detail and robustness that goes beyond the state of the art (SOTA); see the bottom of Fig. 2. Specifically, ECON takes three steps.

**Step 1: Front & back normal reconstruction.** We predict front- and back-side clothed-human normal maps from the input RGB image, conditioned on the body estimate, with a standard image-to-image translation network.

**Step 2: Front & back surface reconstruction.** We take the previously predicted normal maps, and the corresponding depth maps that are rendered from the SMPL-X mesh, to produce detailed and coherent front-/back-side 3D surfaces, \(\{M_F, M_B\}\). To this end, we extend the recent BiNI method \[9\], and develop a novel optimization scheme that is aimed at satisfying three goals for the resulting surfaces: (1) their high-frequency components agree with clothed-human normals, (2) their low-frequency components and the discontinuities agree with the SMPL-X ones, and (3) the depth values on their silhouettes are coherent with each other and consistent with the SMPL-X-based depth maps. The two output surfaces, \(\{M_F, M_B\}\), are detailed yet incomplete, i.e., there is missing geometry in occluded and “profile” regions.

**Step 3: Full 3D shape completion.** This module takes two inputs: (1) the SMPL-X mesh, and (2) the two d-BiNI surfaces, \(\{M_F, M_B\}\). The goal is to “inpaint” the missing geometry. Existing methods struggle with this problem. On one hand, Poisson reconstruction \[35\] produces “blobby” shapes and naively “infills” holes without exploiting a shape distribution prior. On the other hand, data-driven approaches, such as IF-Nets \[12\], struggle with missing parts caused by (self-)occlusions, and lose details present in given high-quality surfaces, producing degenerate geometries.

We address above limitations in two steps: (1) We extend and re-train IF-Nets to be conditioned on the SMPL-X body, so that SMPL-X regularizes shape “infilling”. We discard the triangles that lie close to \(\{M_F, M_B\}\), and keep the remaining ones as “infilling patches”. (2) We stitch together the front- and back-side surfaces and “infilling patches” via Poisson reconstruction; note that holes between these are small enough for a general purpose method. The result is a full 3D shape of a clothed human; see the bottom of Fig. 2.

We evaluate ECON both on established benchmarks (CAPE \[50\], Renderpeople \[58\]) and in-the-wild images. Quantitative analysis reveals that ECON outperforms SOTA. A perceptual study echos this, showing that ECON is significantly preferred over competitors on challenging poses and loose clothing, and competitive with PIFuHD on fashion images. Qualitative results show that ECON generalizes better than the SOTA to a wide variety of poses and clothing, even with extreme looseness or complex topology; see Fig. 7.

ECON combines the best aspects of explicit and implicit surfaces, to recover 3D clothed humans with a good level of detail and robustness. Code and models are available for research purposes at xiuyuliang.cn/econ

**Figure 2. Summary of SOTA.** PIFuHD recovers clothing details, but struggles with novel poses. ICON and PaMIR regularize shape to a body shape, but over-constrain the skirts, or over-smooth the wrinkles. ECON combines their best aspects.
2. Related Work

Image-based clothed human reconstruction. Regarding geometric representation, we group the mainstream clothed human reconstruction approaches into two categories:

1) Explicit-shape-based approaches use either a mesh-based parametric body model [33, 47, 55, 59, 68], or a non-parametric depth map [21, 62], or point cloud [71] to reconstruct 3D humans. Many methods [14, 18, 34, 36–38, 41, 63, 72, 72] estimate or regress minimally-clothed 3D body meshes from RGB pixels and ignore clothing. To account for clothed human shapes, another line of work [2–5, 39, 56, 65, 78] adds 3D offsets on top of body mesh. This is compatible with current animation pipelines, as they inherit the hierarchical skeleton and skinning weights from the underlying statistical body model. However, this “body-offset” approach is not flexible enough to model loose clothing, which deviates significantly from the body topology, such as dresses and skirts. To increase topological flexibility, some methods [8, 31] reconstruct 3D clothed humans by identifying the type of clothing and using the appropriate model to reconstruct it. Scaling up this “cloth-aware” approach to many clothing styles is nontrivial, limiting generalization to in-the-wild outfit variation.

2) Implicit-function-based approaches are topology-agnostic and, thus, can be used to represent arbitrary 3D clothed human shapes. SMPLicit [15] and ClothWild [52] learn a generative clothing model with neural distance field [13, 51, 54] from a 3D clothing dataset. Given an image, the clothed human is reconstructed by estimating a parametric body and optimizing the latent space of the clothing model. However, the results usually do not align well with the image and lack geometric detail.

PIFu [60] introduces pixel-aligned implicit human shape reconstruction and PIFuHD [61] significantly improves the geometric details with a multi-level architecture and the normal maps predicted from the RGB image. However, these two methods do not exploit knowledge of the human body structure. Therefore, these methods overfit to the body poses in the training data, e.g. fashion pose, failing to generalize to unseen poses, thus producing non-human shapes with broken or disembodied limbs. To address these issues, several methods introduce different geometric priors to regularize the deep implicit representation: GeoPIFu [25] introduces a coarse shape of volumetric humans, Self-Portraits [45], PINA [17], and S3 [69] use depth or LIDAR information to regularize shape and improve robustness to pose variation.

Another direction leverages parametric body models, which represent human body shape well, model the kinematic structure of human body, and can be reliably estimated from the RGB images of clothed people. Such a representation can be viewed as a base shape upon which to model clothed humans. Therefore, several methods combine parametric body models with expressive implicit representations to get the best of both worlds. PaMIR [75] and DeepMultiCap [74] condition the pixel-aligned features on a posed and voxelized SMPL mesh. JIFF introduces a 3DMM face prior to improve the realism of the facial region. ARCH [28] and ARCH++ [26] both use SMPL to uppose the pixel-aligned query points from a posed space to a canonical space. To further generalize to unseen poses on in-the-wild photos, ICON [67] regresses shapes from locally-queried features. However, the above approaches gain robustness to unseen poses at the cost of generalization ability to various, especially loose, clothing topologies. We argue that this is because loose clothing differs greatly from human body and that conditioning on the SMPL body in 3D makes it harder for networks to make full use of 2D image features.

Our work is also inspired by “sandwich-like” monocular reconstruction approaches, represented by Moduling Humans [21], FACSIMILE [62] and Any-Shot GIN [66]. Moduling Humans has two networks: a generator that estimates the visible (front) and invisible (back) depth maps from RGB images, and a discriminator that helps regularize the estimation via an adversarial loss. FACSIMILE further improves the geometric details by leveraging a normal loss, which is directly computed from depth estimates via differentiable layers. Recently, Any-Shot GIN generalizes the sandwich-like scheme to novel classes of objects. Given RGB images, it predicts front and back depth maps as well, and then exploits IF-Nets [12] for shape completion. We follow a similar path and extend it, to successfully reconstruct clothed human shapes with SOTA pose generalization, and better details from normal images.

3. Method

Given an RGB image, ECON first estimates front and back normal maps (Sec. 3.1), then converts them into front and back partial surfaces (Sec. 3.2), and finally “inpaints” the missing geometry with the help of IF-Nets+ (Sec. 3.3). See ECON’s overview in Fig. 3.

3.1. Detailed normal map prediction

Trained on abundant pairs of RGB images and normal images, a “front” normal map, , can be accurately estimated from an RGB image using image-to-image translation networks, which has been demonstrated in PIFuHD [61] or ICON [67]. Both methods also infer a “back” normal map, , from the image. But, the absence of image cues lead to over-smooth . To address this, we finetune ICON’s backside normal generator, , with additional MRF loss [64].

To guide the normal map prediction and make it robust to various body poses, ICON conditions the normal map prediction module on the body normal maps, , rendered from estimated body . Thus, it is important to accurately align the estimated body and clothing silhouette. Apart from the and used in ICON [67], we also apply 2D
We expect these 2.5D surfaces to satisfy three conditions: (1) the coarse prior, depth maps, and silhouette consistency. Method \[9\] to full-body mesh reconstruction by harnessing variational normal integration methods \[9, 57\]. Specifically, we tailor the recent bilateral normal integration (BiNI) method to jointly optimize for the front and back clothed depth maps, \(\tilde{Z}_b^c\) and \(\tilde{Z}_b^b\):

\[
d\text{-BiNI}(\hat{N}_F^c, \hat{N}_B^b, Z_b^b, Z_b^b) \rightarrow \tilde{Z}_F^c, \tilde{Z}_B^b.
\]

Here, \(\hat{N}_F^c\) is the front or back clothed normal map predicted by \(G^N_b\) from \(\{I, N_b^b\}\), and \(Z_b^b\) is the front or back coarse body depth image rendered from the SMPL-X mesh, \(M^b\).

Specifically, our objective function consists of five terms:

\[
\min L_n(\tilde{Z}_F^c; \hat{N}_F^c) + L_f(\tilde{Z}_F^c; \hat{Z}_F^c) + L_d(\tilde{Z}_F^c; \tilde{Z}_F^b) + L_d(\tilde{Z}_B^b; \tilde{Z}_B^b) + L_n(\tilde{Z}_B^b; \hat{N}_B^b) + L_d(\tilde{Z}_B^b; \tilde{Z}_B^b),
\]

where \(L_n\) is front and back BiNI terms introduced by BiNI \[9\], \(L_f\) is front and back depth prior terms, and \(L_d\) is a front-back silhouette consistency term. For a more detailed discussion on these terms, see Sec. A.2 in Appx.

With Eq. (3), we make two technical contributions beyond BiNI \[9\]. First, we use the coarse depth prior rendered from the SMPL-X body mesh, \(Z_b^b\), to regularize BiNI:

\[
L_d(\tilde{Z}_i^c; \tilde{Z}_i^b) = |\tilde{Z}_i^c - \tilde{Z}_i^b|, \quad i \in \{F, B\}.
\]

This addresses the key problem of putting the front and back surfaces together in a coherent way to form a full body. Optimizing BiNI terms \(L_d\) remains an arbitrary global offset between front and back surfaces. The depth prior terms \(L_d\) encourage the surfaces with undecided offsets to be consistent with the SMPL-X body. For further intuitions on \(L_n\) and \(L_d\), see Fig. A.3 and Fig. A.4 in Appx.
Second, we use a silhouette consistency term to encourage the front and back depth values to be the same at the silhouette boundary:

$$L_s(\hat{Z}_F, \hat{Z}_B) = |\hat{Z}_F - \hat{Z}_B|_{\text{silhouette}}.$$  \hspace{0.5cm} (5)

The silhouette term improves the physical consistency of the reconstructed front and back clothed depth maps. Without this term, d-BiNI produces intersections of the front and back surfaces around the silhouette, causing “blobby” artifacts and hurting reconstruction quality; see Fig. A.5 in Appx.

### 3.3. Human shape completion

For simple body poses without self-occlusions, merging front and back d-BiNI surfaces in a straight-forward way, as done in FACSIMILE [62] and Modulating Humans [21], can result in a complete 3D clothed scan. However, often poses result in self-occlusions, which cause large portions of the surfaces to be missing. In such cases, screened Poisson Surface Reconstruction (sPSR) [35] leads to blobby artifacts.

**sPSR completion with SMPL-X (ECONEX).** A naive way to “infill” the missing surface is to make use of the estimated SMPL-X body. We remove the triangles from $\mathcal{M}^b$ that are visible to front or back cameras. The remaining triangle “soup” $\mathcal{M}^\text{all}$ contains both side-view boundaries and occluded regions. We apply sPSR [35] to the union of $\mathcal{M}^\text{all}$ and d-BiNI surfaces $\{\mathcal{M}_F, \mathcal{M}_B\}$ to obtain a watertight reconstruction $\mathcal{R}$. This approach is denoted as ECONEX. Although ECONEX avoids missing limbs or sides, it does not produce a coherent surface for the originally missing clothing and hair surfaces because of the discrepancy between SMPL-X and actual clothing or hair; see ECONEX in Fig. 4.

**Inpainting with IF-Nets+ ($\mathcal{R}_{IF}$).** To improve reconstruction coherence, we use a learned implicit-function (IF) model to “inpaint” the missing geometry given front and back d-BiNI surfaces. Specifically, we tailor a general-purpose shape completion method, IF-Nets [12], to a SMPL-X-guided one, denoted as IF-Nets+. IF-Nets [12] completes the 3D shape from a deficient 3D input, such as an incomplete 3D human shape or a low-resolution voxel grid. Inspired by Li et al. [42], we adapt IF-Nets by conditioning it on a voxelized SMPL-X body to deal with pose variation; for details see Sec. A.3 in Appx. IF-Nets+ is trained on voxelized front and back ground-truth clothed depth maps, $\{\hat{Z}_F, Z^b\}$, and a voxelized (estimated) body mesh, $\mathcal{M}^b$, as input, and is supervised with ground-truth 3D shapes. During training, we randomly mask $\{\hat{Z}_F, Z^b\}$ for robustness to occlusions. During inference, we feed the estimated $\hat{Z}_F, \hat{Z}_B$, and $\mathcal{M}_b$ into IF-Nets+ to obtain an occupancy field, from which we extract the inpainted mesh, $\mathcal{R}_{IF}$, with Marching cubes [48].

**sPSR completion with SMPL-X and $\mathcal{R}_{IF}$ (ECONIF).** To obtain our final mesh, $\mathcal{R}$, we apply sPSR to stitch (1) d-BiNI surfaces, (2) sided and occluded triangle soup $\mathcal{M}^\text{all}$ from $\mathcal{R}_{IF}$, and optionally, (3) face or hands cropped from the estimated SMPL-X body. Although $\mathcal{R}_{IF}$ is already a complete human mesh, we only use its side and occluded parts because its front and back regions lack sharp details compared to d-BiNI surfaces. This is due to the lossy voxelization of inputs and limited resolution of Marching cubes; see the local difference between ECONIF$_{EX}$ and $\mathcal{R}_{IF}$ in Fig. 4. Further, we use the face or hands cropped from $\mathcal{M}^b$ because these parts are often poorly reconstructed in $\mathcal{R}_{IF}$, see difference in Fig. 5. The approach is denoted as ECONIF.
4. Experiments

4.1. Datasets

Training on THuman2.0. THuman2.0 [70] contains 525 high-quality human textured scans in various poses, which are captured by a dense DSLR rig, along with their corresponding SMPL-X fits. We use THuman2.0 to train ICON’s variants, IF-Nets+, IF-Nets, PIFu and PaMIR.

Quantitative evaluation on CAPE & Renderpeople. We primarily evaluate on CAPE [50] and Renderpeople [58]. Specifically, we use the “CAPE-NFP” set (100 scans), which is used by ICON to analyze the robustness on complex human poses. Moreover, we select another 100 scans from Renderpeople, containing loose clothing, such as dresses, skirts, robes, down jackets, costumes, etc. With such clothing variance, Renderpeople helps numerically evaluate the flexibility of reconstruction methods w.r.t. shape topology. Samples of the two datasets are shown in Fig. 6.

![Datasets for numerical evaluation.](image)

Figure 6. Datasets for numerical evaluation. We evaluate ECON on images with unseen poses (left) and unseen outfits (right) on CAPE [50] and Renderpeople [58] datasets, respectively.

4.2. Metrics

Metrics for coarse geometric errors. We report the commonly used Chamfer distance (bi-directional point-to-surface) and P2S distance (1-directional point-to-surface) between ground-truth and reconstructed meshes, in cm.

Metric for fine geometric details. We report the L2 error between normal images rendered from reconstructed and ground-truth surfaces, by rotating a virtual camera around these by \{90°, 180°, 270°\} w.r.t. to a frontal view.

4.3. Evaluation

Quantitative evaluation. We compare ECON with body-agnostic methods, i.e., PIFu [60] and PIFuHD [61], and body-aware methods, i.e., PaMIR [75] and ICON [67]; see in Tab. 1. For fair comparison, we use re-implementations of PIFu and PaMIR from ICON [67], because they have the same network settings and input data. ECON outperforms other methods by a large margin on images containing out-of-distribution poses (CAPE), with a reconstruction error below 1cm. In terms of out-of-distribution outfits (Renderpeople), ECON performs on par with PaMIR, and much better than PIFuHD. When it comes to high-frequency details measured by normals, both variants of ECON (ECON\_f, ECON\_x), achieve SOTA performance in quantitative evaluation.

![Perceptual study.](image)

Table 1. Evaluation against the state of the art. All models use a resolution of 256 for marching cubes. *Method is re-implemented in ICON for a fair comparison in terms of network settings and training data. †Official model is trained on Renderpeople dataset.

| Methods          | OOD poses (CAPE) | OOD outfits (Renderpeople) |
|------------------|-----------------|-----------------------------|
|                  | Chamfer ↓       | P2S ↓ | Normals ↓ | Chamfer ↓ | P2S ↓ | Normals ↓ |
| PIFu *           | 1.722           | 1.548 | 0.0674    | 1.706     | 1.642 | 0.0709    |
| PIFuHD           | 3.767           | 3.591 | 0.0994    | 1.946     | 1.983 | 0.0658    |
| PaMIR *          | 1.004           | 1.004 | 0.0821    | 1.334     | 1.486 | 0.0523    |
| ICON             | 1.272           | 1.139 | 0.0605    | 1.510     | 1.653 | 0.0868    |
| ECON\_f          | 0.837           | 0.829 | 0.0331    | 1.409     | 1.506 | 0.0521    |
| ECON\_x          | 0.844           | 0.841 | 0.0332    | 1.384     | 1.455 | 0.0511    |

Table 2. Perceptual study. Numbers denote the chance that participants prefer the reconstruction of a competing method over ECON for in-the-wild images. A value of 0.5 indicates equal preference. A value of < 0.5 favors ECON, while of > 0.5 favors competitors.

|                  | ICON [67] | PIFuHD [61] |
|------------------|-----------|-------------|
| Challenging poses| 0.423     | 0.182       |
| Loose clothing   | 0.213     | 0.457       |
| Fashion images   | 0.335     | 0.519       |

Perceptual study. We further evaluate ECON on in-the-wild photos. We divide the test images into three categories: “challenging poses”, “loose clothing”, and “fashion images”. Examples of challenging poses and loose clothing can be seen in Fig. 7. Fashion images contain common photos of online clothing shopping, for examples see Fig. 9.

Due to the lack of ground-truth geometry, we perform a perceptual study. Participants are asked to choose the reconstruction they perceive as more realistic, between a baseline method and ECON. We compute the chances that each baseline is preferred over ECON in Tab. 2.

As Tab. 2 shows, the result of perceptual study echos the quantitative evaluation. For images containing challenging poses, ECON is significantly preferred over PIFuHD and outperforms ICON. On images of people wearing loose clothing, ECON is preferred over ICON with a large margin and outperforms PIFuHD. The reasons for slight preference of PIFuHD over ECON on fashion images are discussed in Sec. 6. This proves that, ECON combines d-BiNl with a body prior in a highly effective way; on the one hand, it is robust to unseen poses, while on the other hand, it is capable of reconstructing loose clothing and geometric details, as reconstructed shape is not over-constrained to the topology of a SMPL-X body. Figure 2 visualizes some comparisons. For more examples, see Figs. A.6 to A.8 in Appx.
Figure 7. **Qualitative results on in-the-wild images.** We show 8 examples for reconstructing detailed clothed 3D humans from images with: (a) challenging poses and (b) loose clothing. For each example we show the input image along with two views (front and rotated) of the reconstructed 3D humans. Our approach is robust to pose variations, generalizes well to loose clothing, and contains detailed geometry.

4.4. Ablation study

**d-BiNI vs BiNI.** We compare d-BiNI with BiNI using 600 samples (200 scans x 3 views) from CAPE and Renderpeople where ground-truth normal maps and meshes are available. We report in Tab. 3 the “root mean squared error” (RMSE) and “mean absolute error” (MAE) between estimated and rendered depth maps. d-BiNI significantly improves the reconstruction accuracy by about 50% compared to BiNI. This demonstrates the efficacy of using the coarse body mesh as regularization and taking the consistency of both front and back surface into consideration. Besides, d-BiNI accelerates the optimization by 33% than BiNI.

**IF-Nets+ vs IF-Nets.** Following the metrics of Sec. 4.2, we compare IF-Nets [12] with our IF-Nets+ on \( R_{IF} \). We show the quantitative comparison in Tab. 4. The improvement for out-of-distribution poses (“OOD poses”) shows that IF-Nets+ is more robust to pose variations than IF-Nets, as it is conditioned on the SMPL-X body. Figure 4 compares the geometry “inpainting” of both methods in case of occlusions.

5. Applications

**Multi-person reconstruction.** Thanks to the shape completion module, ECON can deal with occlusions. This makes it possible to reconstruct multiple persons from an image with inter-person occlusions, even though ECON has not been trained for this. Figure 8 shows three examples. The occluded parts, colored in red, are successfully recovered.

**Detailed 3D humans for in-the-wild datasets.** Datasets of real clothed humans with 3D ground truth [1,6,50,58,70,76] are limited in size. In contrast, datasets of images without 3D ground truth are widely available in large sizes [20, 22, 46]. We can “augment” such datasets by reconstructing detailed 3D humans from their images. We apply ECON on SHHQ [20] and recover normal maps and 3D humans. Figure 9 shows some examples. As ECON-like methods mature, they could produce 3D pseudo ground truth from large-scale photos, to help people train pose regressors, or generate clothed avatars with details [7, 10, 23, 27, 32, 53, 73].
Figure 8. **Multiple humans with occlusions.** We detect humans from image, and apply ECON for each human separately. Although ECON is not designed for multiple persons, it is robust to inter-person occlusions. We show three examples, and for each: (top) input image and the predicted front and back normal maps, (bottom) ECON’s reconstruction. Red areas on the estimated mesh indicate occlusions.

Figure 9. **SHHQ 3D reconstruction.** For each image we show a front and side view of ECON’s reconstruction and a SMPL-X fit.

6. Discussion

**Limitations.** ECON takes as input an RGB image and an estimated SMPL-X body. However, recovering SMPL-X bodies (or similar models) from a single image is still an open problem, and not fully solved. Any failure in this could lead to ECON failures, such as in Fig. 10-A and Fig. 10-B. The reconstruction quality of ECON primarily relies on the accuracy of predicted normal maps. Poor normal maps could result in overly close-by or even intersecting front and back surfaces, as shown in Fig. 10-C and Fig. 10-D.

**Future work.** Apart from addressing the above limitations, several other directions are useful for practical applications. Currently, ECON reconstructs only 3D geometry. One could additionally recover an underlying skeleton and skinning weights, e.g., with SSDR [40], to obtain fully-animatable avatars. Moreover, inferring back-view texture would result in fully-textured avatars. Disentangling clothing, hair, or accessories from the recovered geometry would enable the synthesis, editing and transfer of styles for these. Finally, ECON’s reconstructions could be useful as pseudo ground truth for training neural avatars [16, 19, 30].

Figure 10. **Failure examples of ECON.** (A-B) Failures in recovering a SMPL-X body result, e.g., bent legs or wrong limb poses, cause ECON failures by extension. (C-D) Failures in normal-map estimation provide erroneous geometry to ECON to work with.

**Possible negative impact.** As the reconstruction matures, it opens the potential for low-cost realistic avatar creation. Although such a technique for sure benefits entertainment, film production, tele-presence and future metaverse applications, it could also facilitate deep-fake avatars. Regulations must be established to clarify the fair use of such technology.

7. Conclusion

We propose ECON, a method to reconstruct detailed clothed 3D humans from a color image. ECON combines the best of explicit parametric models and deep implicit functions; it estimates detailed 3D surfaces for the human body and clothing without being limited to specific topology, while being robust to challenging unseen poses and clothing. To this end, it employs the latest advances in variational normal integration and shape completion, and effectively extends these to the task of human reconstruction from color images. We believe this work can lead to both real-world applications and useful data augmentation for the 3D vision community, thus, we release our models and code.
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Appendices
In the following, we provide more details and discussion on normal prediction, d-BiNI and IF-Nets+, as well as more qualitative results in the perceptual study, as an extension of Sec. 3, Sec. 4 and Sec. 5 of the main paper. Please check the video on our website for an overview of the method and more results.

A. Implementation details

A.1. Normal map prediction

We set the loss weights $\lambda_{d,\text{diff}}, \lambda_{N,\text{diff}},$ and $\lambda_{S,\text{diff}}$ in Eq. (1) to 5.0, 1.0, and 1.0 respectively. However, if the overlap ratio between clothing and body mask is smaller than 0.5, it means humans are dressed with loose clothing. In this situation we trust the 2D joints more and increase the $\lambda_{d,\text{diff}} = 50.0$. Similarly, when the overlap between body mask inside the clothing mask and full body mask is smaller than 0.98, occlusion happens. In such cases we set $\lambda_{S,\text{diff}} = 0.0$ to avoid limb self-intersection after pose refinement.

During inference, following ICON [67], we iteratively refine SMPL-X and the predicted clothed-body normal maps for 50 interactions, with 1.10 iter/s speed on a Quadro RTX 5000 GPU. We use rembg\footnote{https://github.com/danielgatis/rembg} plus Mask R-CNN (ResNet50-FPN-V2) [24] for multi-person segmentation, Mediapipe [49] to estimate full-body landmarks, pypoisson\footnote{https://github.com/mmolero/pypoisson} for poisson reconstruction, and MonoPort [43, 44] for fast implicit surface query.

A.2. d-BiNI

Optimization details. To better present the optimization details, we first write the d-BiNI objective function in a matrix form. Figure A.1 shows the four inputs to d-BiNI. We vectorize the front and back clothed and prior depth maps $\{\tilde{Z}_F, \tilde{Z}_B, z_F, z_B\}$ within $\Omega$, as $\{\tilde{z}_F, \tilde{z}_B, z_F, z_B\}$; all vectors are of length $|\Omega|$; d-BiNI then jointly solves for the front and back clothed depth $\tilde{z}_F$ and $\tilde{z}_B$ by minimizing the objective function consisting of the five terms:

$$
\mathcal{L}(\tilde{z}_F, \tilde{z}_B) = (A_F \tilde{z}_F - b_F)^\top W_F (A_F \tilde{z}_F - b_F) + (A_B \tilde{z}_B - b_B)^\top W_B (A_B \tilde{z}_B - b_B) + \lambda_d (\tilde{z}_F - z_F)^\top M (\tilde{z}_F - z_F) + \lambda_d (\tilde{z}_B - z_B)^\top M (\tilde{z}_B - z_B) + \lambda_s (\tilde{z}_F - \tilde{z}_B)^\top S (\tilde{z}_F - \tilde{z}_B).
$$

(A.1)

Here, $A_F \in \mathbb{R}^{4|\Omega| \times |\Omega|}$ and $b_F \in \mathbb{R}^{4|\Omega|}$ are constructed from the front normal map following Eq. (21) of BiNI [9]; $A_B$ and $b_B$ are from the back normal map. $W_F$ and $W_B \in \mathbb{R}^{4|\Omega| \times 4|\Omega|}$ are bilateral weight matrices for front and back depth maps, respectively; both are constructed following Eq. (22) of BiNI [9] and depend on the unknown depth. $M$ and $S$ are $|\Omega| \times |\Omega|$ diagonal matrices whose diagonal entries indicate the pixels with depth priors and located at the silhouette, respectively. Specifically, the $i$-th diagonal entry $m_i$ of $M$ is

$$
m_i = \begin{cases} 1, & \text{if } i\text{-th entry of } \tilde{z}_F \text{ in } \Omega, \\ 0, & \text{otherwise} \end{cases},
$$

(A.2)

while the $i$-th diagonal entry $s_i$ of $S$ is

$$
s_i = \begin{cases} 1, & \text{if } i\text{-th entry of } \tilde{z}_B \text{ in } \partial\Omega, \\ 0, & \text{otherwise} \end{cases}.
$$

(A.3)

Stacking $\tilde{z}_F$ and $\tilde{z}_B$ as $\tilde{z} = [\tilde{z}_F \tilde{z}_B]$, Eq. (A.1) then reads

$$
\mathcal{L}(\tilde{z}) = (A \tilde{z} - b)^\top W (A \tilde{z} - b) + \lambda_d (\tilde{z} - z)^\top M (\tilde{z} - z) + \lambda_s \tilde{z}^\top S \tilde{z},
$$

(A.4)

where

$$
A = [A_F \ A_B], \ b = [b_F \ b_B], \ W = [W_F \ W_B], \ z = [z_F \ z_B], \ M = [M \ M], \ S = [S \ -S \ -S \ S].
$$

To minimize Eq. (A.4), we perform an iterative optimization similar to BiNI [9]. At each iteration, we first fix the weights $W$ and jointly solve for the front and back depth $\tilde{z}$, then compute the new weights from the updated depth. When $W$ is fixed and treated as a constant matrix, solving for the depth becomes a convex least-squares problem. The
Voxelize
Voxelize
IF
Input Reconstruction
0/1
Multi-scale voxel encoder Implicit regressor
local
global
SMPL-X
d-BiNI
\( \Omega_n \)
\( \Omega_s \)
\( N^S_F \)
\( N^S_B \)
\( Z^B_F \)
\( Z^B_B \)

Figure A.1. The four inputs to d-BiNI. \( \Omega_n \) is the domain of pixels where normal vectors are estimated and identical for front and back normal maps; \( \Omega_s \) is where depth priors are rendered from the SMPL-X mesh and identical for front and back depth maps. \( \Omega_n \) is, in general, different from \( \Omega_s \). \( \partial \Omega_n \) is the silhouette of normal maps.

necessary condition for the global optimum is obtained by equating the gradient of Eq. (A.4) to 0:

\[
(A^\top W A + \lambda_d \tilde{M} + \lambda_s \tilde{S})\tilde{z} = A^\top W b + \lambda_d \tilde{M} z. \tag{A.5}
\]

Equation (A.5) is a large-scale sparse linear system with a symmetric positive definite coefficient matrix. We solve Eq. (A.5) using a CUDA-accelerated sparse conjugate gradient solver with a Jacobi preconditioner. 3

Hyper-parameters. d-BiNI has three hyper-parameters: \( \lambda_d \), \( \lambda_s \), and \( k \). \( \lambda_d \) and \( \lambda_s \) are used in the objective function Eq. (3), which control the influence of coarse depth prior term Eq. (4) and silhouette consistency term Eq. (5) separately. \( k \) is used in the original BiNI [9] to control the surface stiffness (See Sup.Mat-A in BiNI [9] for more explanation of \( k \)). Empirically, we set \( \lambda_d = 1e^{-4} \), \( \lambda_s = 1e^{-6} \), and \( k = 2 \).

Discussion of hyper-parameters. Figure A.3 shows the d-BiNI integration results under different values of \( k \). It can be seen that a small \( k \) leads to tougher d-BiNI surfaces where discontinuities are not accurately recovered, while a large \( k \) softens the surface, and redundant discontinuities and noisy artifacts are introduced. Figure A.4 shows the effects of \( \lambda_d \), which controls how much d-BiNI surfaces agree on the SMPL-X mesh. Small \( \lambda_d \) causes misalignment between the d-BiNI surface and the SMPL-X mesh, which will produce stitching artifacts. While an excessively large \( \lambda_d \) enforces d-BiNI to rely over heavily on SMPL-X, thus smoothing out the high-frequency details obtained from normals. Figure A.5 justifies the necessity of the silhouette consistency term. Without this term, the front and back d-BiNI surfaces intersect each other around the silhouettes, which will cause “bloppy” artifacts after screened Poisson reconstruction [35].

A.3. IF-Nets+

Network structure. As Fig. A.2 shows, similar to IF-Nets [12], IF-Nets+ applies multi-scale voxel 3D CNN encoding on voxelized d-BiNI and the SMPL-X surface, namely \( F^\text{d-BiNI}_i \) and \( F^\text{SMPL-X}_i \), generating multi-scale deep feature grids to account for both local and global information, \( F_1, F_2, \ldots, F_n, F_k \in \mathbb{R}^{K \times K \times K \times C}, n = 6 \). These deep features are with decreasing resolution \( K = \frac{N}{2^k}, N = 256 \) and variable dimension channels \( C = \{32, 64, 128, 128, 128, 128\} \). Following Li et al. [14], the positional embedding (Nfreqs = 6) of query points is concatenated with multi-scale deep features to account for high-frequency details. All these features are then fed into an implicit function regressor, parameterized by a Multi-Layer Perceptron (MLP), to predict the occupancy value of point \( P \). This MLP regressor is trained with BCE loss.

Training setting. IF-Nets and IF-Nets+ share the same training setting. The voxelization resolution for both SMPL-X and d-BiNI surfaces is 256. We use RMSprop as an optimizer, with a learning rate \( 1e^{-4} \), and weight decay by a factor of 0.1 every 10 epochs. These networks are trained on an NVIDIA A100 for 20 epochs with a batch size of 48. Following ICON [67], we sampled 10000 points with the mixture of cube-uniform sampling and surface-around sampling, with standard deviation of 5cm.

Dataset details. We augment THuman2.0 [70] by (1) rotating the scans every 10 degrees around the yaw axis, to generate \( 525 \times 36 = 18900 \) samples in total, and (2) randomly selecting a rectangle region from the d-BiNI depth maps, and erasing its pixels [77]. In particular, the erasing operation is being performed with \( p = 0.8 \) probability, the range of aspect ratio of erased area is between 0.3 and 3.3, and its range of proportion are \( \{0.01, 0.05, 0.2\} \).

B. Qualitative results

Figures A.6 to A.8 show more comparisons used in our perceptual study, containing the results on in-the-wild images with challenging poses, loose clothing, and standard fashion poses, respectively. For each image, we display the results obtained by ECON, PIFuHD [61], and ICON [67] from the top to the bottom row. In each row, we show normal maps rendered in four views \( \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \). The video on our website shows more reconstructions with a rotating virtual camera.
Figure A.3. **The effects of the hyper-parameter $k$ on d-BiNI results.** $k$ controls the stiffness of the target surface [9]. A smaller $k$ leads to smooth d-BiNI surfaces, while a large $k$ introduces unnecessary discontinuities and noise artifacts.

Figure A.4. **The effects of the hyperparameter $\lambda_d$ on d-BiNI results.** $\lambda_d$ controls how much d-BiNI surfaces agree with the SMPL-X mesh. A small $\lambda_d$ causes a misalignment between the d-BiNI surface and the SMPL-X mesh, thus it produces stitching artifacts. An excessively large $\lambda_d$ enforces d-BiNI to rely too heavily on SMPL-X, thus it smooths out the high-frequency details obtained from normals.

Figure A.5. **Necessity of silhouette consistency.** This term can be regarded as the mediator between front and back d-BiNI surfaces, preventing these surfaces from intersecting. Such intersection causes blobby artifacts after screened Poisson reconstruction [35].
Figure A.6. **Results on in-the-wild images with challenging poses.** For each example (gray box) the format is as follows. **Top → bottom:** ECON, PIFuHD [61] and ICON [67]. **Left → right:** Virtual camera rotated by \{0°, 90°, 180°, 270°\}. **Zoom in** to see 3D details.
Figure A.7. Results on in-the-wild images with loose clothing. For each example (gray box) the format is as follows. Top → bottom: ECON, PIFuHD [61] and ICON [67]. Left → right: Virtual camera rotated by \( \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \). **Zoom in** to see 3D details.
Figure A.8. **Results on in-the-wild fashion images.** For each example (gray box) the format is as follows. **Top → bottom:** ECON, PIFuHD [61] and ICON [67]. **Left → right:** Virtual camera rotated by \{0°, 90°, 180°, 270°\}. **Zoom in** to see 3D details.
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