



**HAL**  
open science

# 3D Human Shape and Pose from a Single Depth Image with Deep Dense Correspondence Enabled Model Fitting

X Wang, Adnane Boukhayma, Stéphanie Prevost, Eric Desjardin, C Loscos,  
Franck Multon

► **To cite this version:**

X Wang, Adnane Boukhayma, Stéphanie Prevost, Eric Desjardin, C Loscos, et al.. 3D Human Shape and Pose from a Single Depth Image with Deep Dense Correspondence Enabled Model Fitting. Eurographics 2022 - 43rd Annual Conference of the European Association for Computer Graphics, Apr 2022, Reims, France. pp.1-2, 10.2312/egp.20221008 . hal-03664189

**HAL Id: hal-03664189**

**<https://hal.science/hal-03664189>**

Submitted on 10 May 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



# 3D Human Shape and Pose from a Single Depth Image with Deep Dense Correspondence Enabled Model Fitting

X. Wang<sup>1</sup>, A. Boukhayma<sup>3</sup>, S. Prevost<sup>1</sup>, E. Desjardin<sup>2</sup>, C. Loscos<sup>1</sup> and F. Multon<sup>3</sup>

1. LICIIS, University of Reims Champagne-Ardenne, France  
 2. CRESTIC, University of Reims Champagne-Ardenne, France  
 3. Inria, Univ. Rennes, CNRS, IRISA, M2S, France

## OVERVIEW

**Goal:** 3D human shape and pose estimation

**Interest:** Several applications, notably for creating avatars in virtual and augmented reality applications.

**Key challenges:** **Reconstructing** both **shape** and **pose** of an actor using a **single RGB or RGB-D view**.

**Our proposition:** a **hybrid method** benefiting from the advantages of Deep Learning (DL) and optimization approaches.

- DL network: estimation of the **dense correspondence** between pixels in a **depth image** and **each vertex of a human template**.
- optimization framework: optimal template configuration (shape and pose) to **align the resulting labeled point cloud** with the surface of the template.

## RELATED WORK

**Focus:** **monocular depth image input** containing a **single person with close-fitting clothing**.

Two groups of DL based methods stand out:

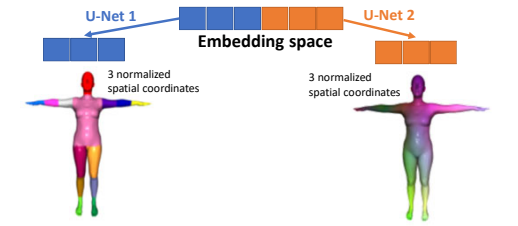
- Fitting the parametric human shape model SMPL [LMR\*15]** to monocular depth images.
  - Aligning the joint positions estimated on the image to the ones of the parametric model [JCZ19].
  - Limitations:** objective function criterion is based on very sparse information (dozen of joint center positions).
- Computing the dense correspondence between a template body shape SMPL and a point cloud** (computed using the depth image).
  - Learned by:
    - amassing training datasets with ground truth correspondence [ZKB20],
    - feature descriptors attached to RGB, depth or point cloud [HYVH20].
  - Limitations:** can fail when the inputs are far from of the training data distribution.

## METHODOLOGY

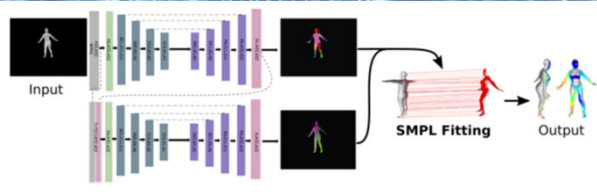
**Input:** 1 depth image containing a close-fitting clothed person  
**Output:** a mesh M (6 890 vertices) representing the corresponding 3D human posed shape in the input camera coordinate frame.  
**Human representation:** SMPL [LMR\*15], parametric deformable mesh  $M(\beta, \theta, \gamma)$   
 $\beta \in \mathbb{R}^{10}$ : human shape parameter  
 $\theta \in \mathbb{R}^{72}$ : pose parameter  
 $\gamma \in \mathbb{R}^3$ : translation

### Step 1 - Dense correspondence

**Inputs:** 1 depth image + 1 template geometry mesh (fig 2)  
**Goal:** map pixels of the depth image to the template geometry embedding space (6D embedding). **2 U-Net [RFB15] networks**



- U-Net 1:** depth input image → **body part segmentation** (15 template classes). 1 class = 1 color. Training with the combination of cross-entropy loss.
  - U-Net 2: (regression branch):** body part segmentation + depth image → 3-channel image. Training with an L2 loss on the output of the normalized color.
- **Estimate a Pixel-to-Vertex Correspondence:** vertex j matching pixel i (nearest template vertex in the embedding space)



**Figure 1:** overview of the two-steps process  
 Step 1) Mapping between pixels of a depth input image and a template geometry with a double U-Net network to predict body part segmentation and to regress normalized canonical vertex coordinates.  
 Step 2) SMPL model fitting to the labelled point cloud.

### Step 2 - Model fitting

Using the template Geometry Embedding, fits the SMPL model to the 3D point cloud → compute **human shape (β) and pose (θ) parameters**

$$E(\theta, \beta, \gamma) = \lambda_D E_D(\theta, \beta, \gamma) + \lambda_\theta E_\theta(\theta) + \lambda_\beta E_\beta(\beta)$$

- $E_D$ : data term = L2 penalty between pixel i's 3D point  $p_i$ , obtained using the intrinsic matrix and the pixel's depth value, and the corresponding vertex  $v_c(i)$ , summed over all pixels that belong to the body region in the segmentation map.
- $E_\theta$ : body pose prior penalizes joints that bend unnaturally.  $E_\theta(\theta) = \sum \exp(\theta_j)$
- $E_\beta$ : shape prior = L2 regularization on the shape parameters  $E_\beta(\beta) = \|\beta\|^2$ .
- $\lambda_D, \lambda_\theta, \lambda_\beta$ : trade-off weights between the objective function terms.

### Training

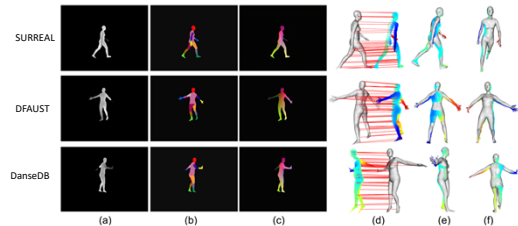
- Batchsize of 12 using the RMSprop optimizer
- Learning rate of  $6.14e^{-4}$ .
- We run the optimization for 20 iterations.

## RESULTS

### Datasets

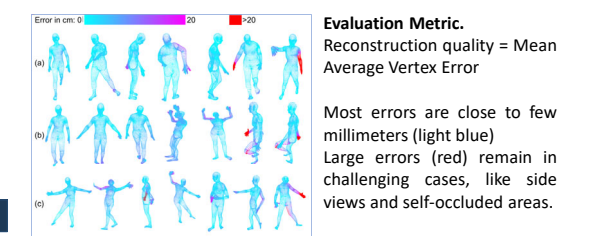
- Standard datasets of **3D close-fitting clothed human shape in motion:** SURREAL [VRM\*17] (synthetic data), DFAUST [BRPMB17] (real data) and DanseDB (dancedb.eu) (synthetic human models fitted to real motion capture data).
- Datasets rendered to **simulate depth images of same resolutions but with different viewpoints.** **50,000 training frames** and **10,000 testing frames** uniformly sampled.

### Qualitative results



**Figure 2:** Results. (a) Input depth image; (b) Output human part segmentation; (c) Regressed template vertex color; (d) Correspondences between the depth point cloud and the fitted mesh; (e) & (f) Output fitted mesh visualized from 2 different viewpoints. The point cloud is colored according to the depth values.

### Error Visualization



**Figure 3:** Spatial distribution of reconstruction errors on (a) SURREAL, (b) DFAUST and (c) DanseDB.

**Evaluation Metric.** Reconstruction quality = Mean Average Vertex Error

**Computation time:**

- NN inference stage: about 35ms
- Optimization stage: 6.43s on a NVIDIA 1080Ti GPU.

These results show the robustness of our method to changes in body poses, shapes, self-occlusions and viewpoints.  
**The accurate and dense mapping** between depth pixels and fitted 3D model topology provides more detailed information compared to optimization methods that use only the joint centers.

## REFERENCES

[BRPMB17] BOGO F., ROMERO J., PONS-MOLL G., BLACK M. J.: Dynamic faust: Registering human bodies in motion. In Proceedings of the IEEE conference on computer vision and pattern recognition (2017), pp. 6233–6242.

[HYVH20] HUANG X., YANG H., VOUGA E., HUANG Q.: Dense correspondences between human bodies via learning transformation synchronization on graphs. Advances in Neural Information Processing Systems 33 (2020).

[JCZ19] JIANG H., CAI J., ZHENG J.: Skeleton-aware 3d human shape reconstruction from point clouds. In Proceedings of the IEEE/CVF International Conference on Computer Vision (2019), pp. 5431–5441.

[KPD19] KLOTOUROUS N., PAVLAKOS G., DANILIDIS K.: Convolutional mesh regression for single-image human shape reconstruction. In CVPR (2019).

[LMR\*15] LOPER M., MAHMOOD N., ROMERO J., PONS-MOLL G., BLACK M. J.: SMPL: A skinned multi-person linear model. ACM Trans. Graphics (Proc. SIGGRAPH Asia) 34, 6 (Oct. 2015), 248:1–248:16.

[RFB15] RONNEBERGER O., FISCHER P., BROX T.: U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (2015). Springer, pp. 234–241.

[VRM\*17] VAROL G., ROMERO J., MARTIN X., MAHMOOD N., BLACK M. J., LAPTEV I., SCHMID C.: Learning from synthetic humans. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2017), pp. 109–117.

[WHC\*16] WEI L., HUANG Q., CEYLAN D., VOUGA E., LI H.: Dense human body correspondences using convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2016), pp. 1544–1553.

[WXZ\*20] WANG K., XIE J., ZHANG G., LIU L., YANG J.: Sequential 3d human pose and shape estimation from point clouds. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (2020), pp. 7275–7284.

[ZKB20] ZHU T. L., KARLSSON P., BREGLER C.: Simpose: Effectively learning densepose and surface normals of people from simulated data. In ECCV (2020).

## ACKNOWLEDGEMENT

