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

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## 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:

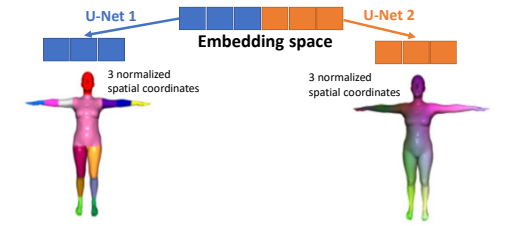
- Fitting the parametric human shape model SMPL [LMR\*15]** to monocular depth images.
  - Aligning the joint positions estimated on the image to the ones of the parametric model [JCZ19].
  - Limitations:** objective function criterion is based on very sparse information (dozen of joint center positions).
- 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

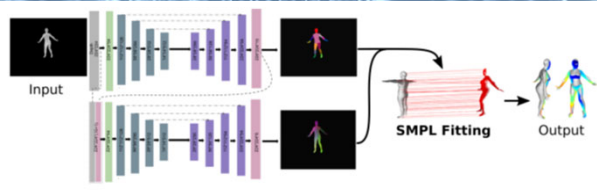
**Input:** 1 depth image containing a close-fitting clothed person  
**Output:** a mesh M (6 890 vertices) representing the corresponding 3D human posed shape in the input camera coordinate frame.  
**Human representation:** SMPL [LMR\*15], parametric deformable mesh  $M(\beta, \theta, \gamma)$   
 $\beta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

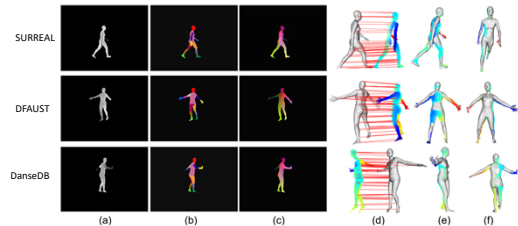
- Batchsize of 12 using the RMSprop optimizer
- Learning rate of  $6.14e^{-4}$ .
- We run the optimization for 20 iterations.

## RESULTS

### Datasets

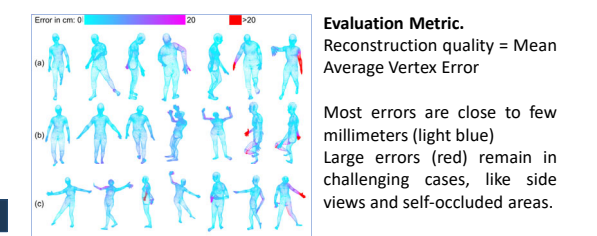
- Standard datasets of **3D close-fitting clothed human shape in motion:** SURREAL [VRM\*17] (synthetic data), DFAUST [BRPMB17] (real data) and DanseDB (dancedb.eu) (synthetic human models fitted to real motion capture data).
- Datasets rendered to **simulate depth images of same resolutions but with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

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