

# A Generative Multi-Resolution Pyramid and Normal-Conditioning 3D Cloth Draping

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## Abstract

RGB cloth generation has been deeply studied in the related literature, however, 3D garment generation remains an open problem. In this paper, we build a conditional variational autoencoder for 3D garment generation and draping. We propose a pyramid network to add garment details progressively in a canonical space, i.e. unposing and unshaping the garments w.r.t. the body. We study conditioning the network on surface normal UV maps, as an intermediate representation, which is an easier problem to optimize than 3D coordinates. Our results on two public datasets, CLOTH3D and CAPE, show that our model is robust, controllable in terms of detail generation by the use of multi-resolution pyramids, and achieves state-of-the-art results that can highly generalize to unseen garments, poses, and shapes even when training with small amounts of data. The code can be found at: <https://github.com/HunorLaczko/pyramid-drape>

## 1. Introduction

Cloth generation and reconstruction is an active topic in computer vision with applications in virtual try-on, fashion, gaming, and movie editing, just to name a few [12].

Unfortunately, garment generation is still an open problem due to challenges such as variable topology, shape, size, style, fabric, and texture, as well as highly dynamic behavior. The problem has been tackled in the literature from different points of view: 2D image generation [13, 16, 17, 23, 42], image-based 3D reconstruction [1, 2, 20, 22, 41, 45–47] and 3D garment draping and manipulation [3, 4, 7, 18, 27, 29, 32, 37, 39, 43]. This paper is focused on the latter category.

Proposed solutions mainly depend on the garment representation. Meshes have been widely used to represent 3D surfaces [3, 4, 7, 8, 28, 32, 37]. However, designing architectures to effectively deal with variable mesh topologies is

	Gen.	GarmUns.	Interp.	Repr.
SCALE [27]	✗	✗	✗	Patch point cloud
Neural-GIF [39]	✗	✗	✗	Implicit function
TailorNet [32]	✗	✗	✓	Mesh
POP [29]	✗	✗	✗	Point cloud
PBNS [5]	✗	✗	✓	Mesh
Santesteban <i>et al.</i> [37]	✗	✗	✗	Mesh
DeepPSD [7]	✗	✓	✗	Mesh
Zakharkin <i>et al.</i> [43]	✗	✓	✗	Point cloud
HOOD [18]	✗	✓	✓	Mesh
CAPE [28]	✓	✓	✗	Mesh
CLOTH3D [3]	✓	✓	✗	Mesh
Ours	✓	✓	✓	UV map

Table 1. We compare our approach to state-of-the-art 3D garment generation and draping w.r.t. to their solution’s properties: 1) is it Generative (*Gen.*)?, 2) is it Garment Unspecific (*GarmUns.*) i.e. does not require training on many different cloth categories?, 3) does it produce Interpretable (*Interp.*) results?, and 4) what is the Representation (*Repr.*)? Most of the available approaches train their specific models per each particular cloth type. Also, there are very few generative models that can output different cloth dynamics for the same input pose. Lastly, some approaches provide explainable predictions either w.r.t. local dynamics (TailorNet and ours) or physically based losses (PBNS and HOOD). Our approach covers all these points while outperforming state-of-the-art and generalizing well to unseen poses.

not a trivial task. Recently, point cloud representation has received special attention thanks to the use of implicit functions [19, 20, 22, 39, 41] or point representations [27, 29, 43]. Although these functions generate high-fidelity details (after converting point clouds to mesh surfaces) with an arbitrary number of output points, their high computational cost and limited quality of the generated surface when applied to unseen cases are major concerns. Lastly, UV maps representations, from texture to 3D body and cloth, have shown successful results in different application scenarios [10, 11, 24, 31, 33, 38, 40, 44], since they can be wrapped to a mesh at no cost while handling arbitrary topologies. We apply UV map representations in our work.

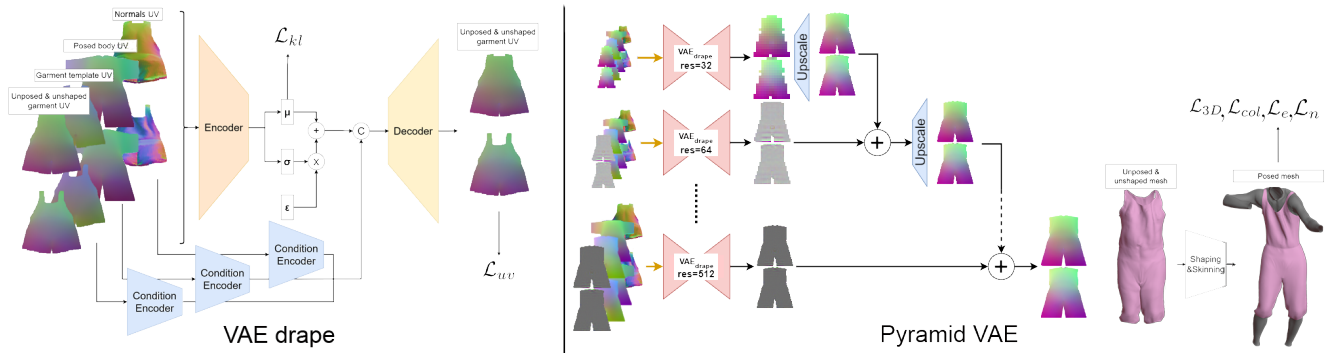


Figure 1. The proposed pyramid pipeline (right) contains basic VAE modules for each draping level ( $VAE_{drape}$ , left).  $VAE_{drape}$  receives conditioning inputs and garment offsets and reconstructs the unposed and unshaped garment offsets as UV image. In the case of the first level instead of offsets, absolute coordinates are used (as shown on the left) as this will serve as a base for subsequent levels. The conditioning variables (normals, posed body, and garment template UV images) are given into three pre-trained and frozen encoders to fuse with the  $VAE_{drape}$  latent code. These conditioning encoders are trained separately in an autoencoder manner (note that normals are trained through  $VAE_{norm}$ ). Finally, the reconstructed UV image is converted to a mesh and passed to the skinning module after reshaping. Then, in the pyramid module, the lowest resolution level predicts low-frequency garments while the other levels are learned as offsets over their previous level. Each level output is upscaled with the proposed upscaling network and summed to the next level. At inference time, we sample from  $VAE_{norm}$  and  $VAE_{drape}$  and pass the template garment and posed body UV images.

Regardless of the chosen representation, available techniques are commonly applied to (i) generate 3D garment templates in a canonical pose or (ii) drape/animate a given 3D template w.r.t. the body pose. Most state-of-the-art approaches, like ours, are based on the latter case [3, 4, 6, 7, 27, 29, 32, 36, 37, 39, 43]. However, there are some common limitations in most of these techniques. Firstly, cloth draping is a one-to-many problem, i.e. for a given pose and template garment there are many valid animated garments, and each garment type has different dynamical behavior. This is while these techniques overfit to the training set to predict just one single solution. Although this may be valid for some applications, it does not provide any control over the prediction. Secondly, either every single garment has its own trained model (can be categorized as supervised or unsupervised neural simulator) [5, 27, 29, 36, 37] or one model is trained per each garment category [8, 32], which limit applicability for real-world scenarios.

In order to cope with the aforementioned limitations, one of the main aims of this work is to train all sorts of garments in a **minimal** number of generative models. Generative cloth architectures have been studied before in [3, 28] using convolutional graph networks. In this paper, we develop a variational autoencoder (VAE) on CNN architecture backbones, thanks to the use of UV maps, which have shown great results in generating plausible RGB images. Additionally, we condition the VAE on normal maps, as intermediate representations, which increases stochasticity and has been shown to be effective in gaining high-fidelity results [41].

Finally, there have been substantial efforts in convolutional data processing to learn features specific to dif-

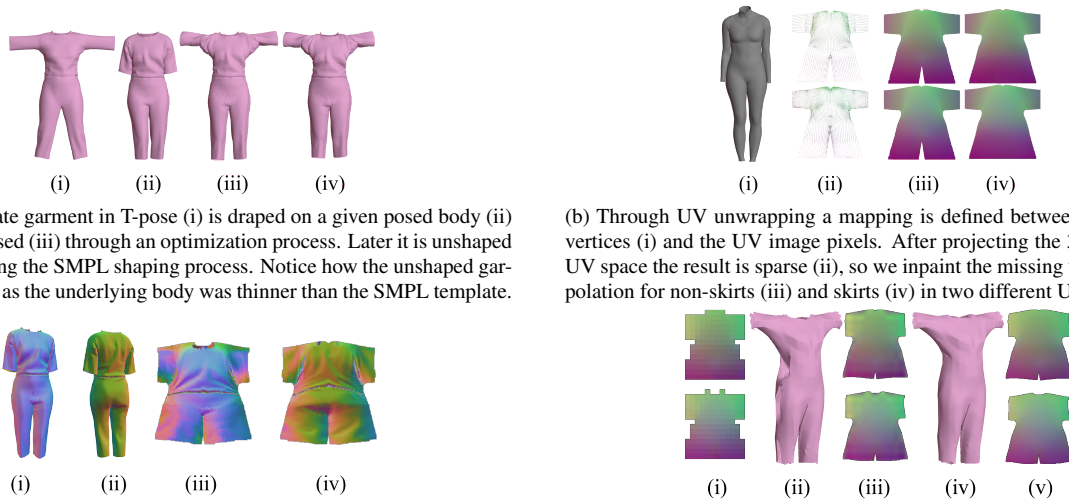
ferent frequency domains [14, 15, 21, 34]. Following this trend, we build a pyramid conditional VAE, with a series of VAEs each trained on a different image resolution. Thus, the lowest resolution VAE is responsible for learning low-frequency cloth dynamics while the other VAEs learn high-frequency details as offsets, progressively added to the previous level.

Our contributions are:

- We develop a pyramid VAE for 3D cloth draping using a ConvNeXt backbone architecture [25] and 3D surface coordinates represented as UV images.
- We condition the network on the surface normals unwrapped in UV maps.
- We show state-of-the-art (SOTA) 3D generative cloth draping results by progressively improving the error and surface quality on two public datasets, CAPE [28] and CLOTH3D [3].

## 2. Related works

We compare our proposed architecture to the state-of-the-art in Tab. 1. Most of the available works are deterministic approaches [5, 7, 18, 27, 29, 32, 37, 39, 43] in which a single solution is predicted for the given inputs. There has been a set of approaches [5, 27, 29, 37, 39], among deterministic works, in which a single garment instance is trained over many given body poses, called neural simulation, depicting cloth simulation in graphic engines. The works of [27, 29, 35] convert the given body surface into



(a) The template garment in T-pose (i) is draped on a given posed body (ii) which is unposed (iii) through an optimization process. Later it is unshaped (iv) by reversing the SMPL shaping process. Notice how the unshaped garment is wider, as the underlying body was thinner than the SMPL template.

(b) Through UV unwrapping a mapping is defined between the 3D mesh vertices (i) and the UV image pixels. After projecting the 3D mesh to the UV space the result is sparse (ii), so we inpaint the missing values by interpolation for non-skirts (iii) and skirts (iv) in two different UV templates.

(c) We calculate normal vectors for each vertex, visible on the front (i) and back (ii) of the mesh which are converted to front (iii) and back (iv) UV maps.

(d) Upscaling from a low-resolution UV image (i) results in artifacts around the boundaries (ii-iii) using regular upscaling. By the proposed upscaling (iv-v) this can be avoided.

Figure 2. Examples of preprocessed data. a) Cloth unposing and unshaping. b) 3D mesh to UV map. c) Surface normals calculation. d) UV image down/upscaling.

a UV map and learn 2D body pose features through CNN architectures, similar to us. In [29] an additional garment geometry feature tensor is learned through auto-decoding. Later 2D sampled features along with positional encodings are given to a shared MLP to predict an offset vector added to the sampled body point. Authors in [39] use a combination of several MLPs as an implicit function to first unpose sampled points and add offset vectors to them. The updated points along with pose encodings are given to a signed distance function to predict the point occupancy. Learning features in a canonical pose has been a common technique in state-of-the-art. Similar to us, [37] preprocess the garments to form a collision-free unposed and unshaped garment. Later a VAE is trained to learn garment-specific deformations. Although they use a VAE for training, their approach is not designed to be generative at inference time. Rather, they predict the encoded features from the body shape parameters and motion information. In a different solution, TailorNet [32] decomposes the garment into high and low-frequency surfaces in a canonical pose. Then the wrinkles are formed by a mixture of high frequencies. All the aforementioned approaches were trained supervisedly. PBNS [4] is the first unsupervised approach that uses physically based losses to train a lightweight neural network. They apply an MLP to extract features from the pose which is multiplied to an optimizable garment geometry matrix. The outputs are offsets added to the template garment in a canonical pose. Later, this type of solution has been extended to include temporal information [6, 36].

Among deterministic approaches, several works develop garment unspecific models in which a single model is

trained to handle all sorts of garments. DeePSD [7] is inspired by the physically-based simulation formulation and can handle variable topologies during training without registration. They train the network by a combination of supervised and unsupervised losses. Zakharkin *et al.* [43] transforms the posed body point cloud into the final garment by conditioning on the garment latent code. HOOD [18] develops a new message-passing mechanism in graph neural networks and trains the network with self-supervised physically based losses.

To the best of our knowledge, there are a few generative methodologies in 3D garment draping [3, 28]. These works apply VAE graph neural networks on registered meshes in a canonical pose. CLOTH3D [3] proposes a new topology for the body to model skirts-like clothes. CAPE [28] trains the network by an additional adversarial loss. Our approach decomposes the surface into different frequencies and learns the details progressively showing accurate reconstruction capabilities.

### 3. Generative 3D cloth draping

The proposed 3D cloth draping pipeline is: 1) generative and stochastic, 2) efficient, 3) general, as it does not require separate models for each garment type, and 4) able to handle both high and low-frequency details. We assume a) SMPL body pose and shape parameters [26] plus a garment template in canonical pose (T-pose for example) are available for the draping, b) the garment size is matched with the body shape<sup>1</sup>, c) the garment has a low elasticity,

<sup>1</sup>Although garment resizing is possible as a preprocessing to match the body shape, we consider it as out-of-the-scope of this paper.

thus the mesh edge lengths should not change drastically after the draping, and d) the garment has a single surface layer (e.g. pockets are not considered). Also, we apply our experiments to daily life clothes. Next, we explain the details and architectural choices to fulfill the aforementioned goals. The architecture pipeline is shown in Fig. 1.

### 3.1. Preprocessing

#### 3.1.1 Cloth unposing and unshaping

We follow the trends in the literature [3,27–29,32] that force the network to make predictions in a canonical pose space to improve the results. We explore this idea in several aspects: 1) eliminating the global rotation, 2) unposing, and 3) unshaping. Let  $\theta \in \mathbb{R}^{24 \times 3 \times 3}$  and  $\beta \in \mathbb{R}^{1 \times 10}$  be the SMPL pose and shape parameters,  $B \in \mathbb{R}^{10 \times (m \times 3)}$  and  $W \in \mathbb{R}^{m \times 24}$  the SMPL blend shape and blend weights,  $D \in \mathbb{R}^{m \times 3}$  the shaped and posed SMPL body vertices,  $G_t \in \mathbb{R}^{n \times 3}$  a template garment with  $n$  vertices registered on SMPL mesh (see next section for details) and  $M \in \{0, 1\}^m$  its registration mask (note  $n = \sum M$ ), and  $G \in \mathbb{R}^{n \times 3}$  the  $G_t$  garment draped on  $D$ . To eliminate the global orientation, we first update the garment and body vertices by  $G \cdot \theta^0$  and  $D \cdot \theta^0$ , and the  $\theta$  root joint rotation ( $\theta^0$ ) by an identity matrix. Then, we transform  $G$  to a canonical pose space by:

$$G_c = \arg \min_{G_c} \|\mathcal{S}(G_c + [\beta \cdot B]^M, \theta; W) - G\|, \quad (1)$$

where  $\mathcal{S}$  is the skinning function and  $[\cdot]^M$  is the indexing based on mask  $M$ . An example can be seen in Fig. 2(a).

#### 3.1.2 Cloth registration

We follow CLOTH3D [3] protocol for registration, that is 1) increasing SMPL resolution and removing head, hands, and feet vertices ( $m = 14475$  after this update), and 2) creating an extra body mesh for skirt-like garments. Additionally, we apply laplacian smoothing to the body and template garment and use a non-rigid ICP to warp the template garment to the body surface this way achieving a less noisy registration. The mask  $M$  is extracted by taking the nearest body vertices. Finally, we compute the registration as follows.

The simplest registration solution is by taking body vertices and finding the nearest vertex on the warped garment. However, it is possible that a garment vertex is assigned to two or more body vertices. This causes null faces on the garment which degrades the garment resolution and leads to noisy loss functions. Instead of the nearest mesh vertex, we find the nearest point on the garment surface through a fast numerical approximation. To do so, we generate a random vector  $\omega^{k \times 3}$  for each garment face in which  $1 = \sum_{j=1}^3 \omega_{ij}$  where  $i \in \{1..k\}$ . We use  $\omega$  as a weighting over the face vertices coordinates to sample points on each garment face.

Finally, we find the nearest points from this randomly sampled set and save the  $\omega$  values for the nearest point and its corresponding face index. This is used to reconstruct the garment in any frame represented by SMPL topology.

#### 3.1.3 3D mesh to UV map

UV map representation has been used by several approaches [10, 11, 24, 33, 38, 40, 44]. Its advantage over meshes is that it is a 2D image, which makes it applicable in history-rich GPU-efficient CNN models. However, a UV map is only partially continuous, unlike a mesh. The reason is that to unwrap a 3D mesh into 2D, the surface is torn into several segments to fit in. To minimize the number of segments and distortions, we follow [30] in which seamlines at the sides of the body are manually defined where they divide the body into two segments: front and back. Based on this idea we create UV images with a  $512 \times 256$  resolution. In the supplementary material, we explain the details of how we create the UV pixel coordinates corresponding to 3D vertices to have a 3D reconstructed surface. An example can be seen in Fig. 2(b). Through this operation we convert  $D$ ,  $G$ ,  $G_t$  and  $G_c$  into  $D^{uv}$ ,  $G^{uv}$ ,  $G_t^{uv}$  and  $G_c^{uv}$ , respectively. Also, the mask  $M$  is updated to  $M^{uv}$  accordingly.

Note that although vertex indices are identical between skirt-like and trousers-like clothes after registration, they do not follow the body in the same way and also have different dynamic behaviors. Therefore, a single template for UV coordinates for both of them is not valid. For this reason, we group garments into skirts and non-skirts, create two UV templates for each, and train them independently. This allows us to cover all garment types minimally with only two models, unlike other methods that require a separate model for each type.

#### 3.1.4 Surface normals

Surface frequency details can be partially reflected in the surface normals as the direction of the normals and their relative change compared to their neighborhood correlate to the details of the surface. An example can be seen in Fig. 2(c). As the figure shows, small wrinkles and even large deformations are easy to identify. This helps guide the model to be able to recreate these details.

#### 3.1.5 UV image down/upscaling

Regular RGB images can be rescaled by simple bilinear or bicubic algorithms. Applying these techniques to UV images will result in invalid values and artifacts near the boundary areas (reflecting in the seamline between the two sides of the mesh) due to zero background pixels. Fortunately, downsampling can be done by a fast nearest neighbor interpolation to fill the background. However, it is not

accurate for upscaling. To overcome this, we develop a fast and differentiable interpolation block by utilizing a CNN with five convolutional layers only to fill the background. For training, we use MS-SSIM loss on the already available data from the previously downscaled images. Later, to train the pyramid VAE, we freeze this upscaling network. We apply image scaling by a factor of 2 and have UV resolutions in the range  $64 \times 32$  and  $512 \times 256$ . The results can be seen in Fig. 2(d).

### 3.2. Conditional pyramid VAE

In the basic definition of cloth draping, a garment is draped on the body given a pose. However, this problem has unlimited valid solutions. Therefore, models with a single solution do not truly formulate the problem. Generative models are able to deal with this issue, though sometimes they suffer from not being stochastic and become one-to-one functions. Cloths are highly dynamic objects and some approaches either converge to smooth and average dynamics [3, 28] or overfit to specific categories and poses [32]. To cope with these issues, we build our generative model based on a VAE (called  $VAE_{drape}$ ) that is conditioned on the garment template  $G_t^{uv}$ , posed body  $D^{uv}$  and normal map  $N^{uv}$ , and reconstructs  $\hat{G}_c^{uv}$ <sup>2</sup>. Then, the 3D garment  $\hat{G}$  can be obtained by:

$$\hat{G} = \mathcal{S}([\hat{G}_c^{uv}]^{J \odot M} + [\beta \cdot B]^M, \theta, W) \quad (2)$$

where  $J$  contains corresponding UV indices to SMPL vertices masked by  $M$  and  $\odot$  is element-wise product.

Although the normal map is not available at inference time, its generation and sampling is a much easier problem than 3D cloth draping. Therefore, we build a second VAE for normals (called  $VAE_{norm}$ ) that is again conditioned on  $G_t^{uv}$  and  $D^{uv}$ , and reconstructs  $\hat{N}^{uv}$ . Due to its simplicity, adaptation, and performance, we adapt ConvNeXt architecture [25] as the VAEs' encoders, thanks to the usage of UV images. Decoders are mirrors of encoders (downsampling convolutional layers are replaced with transpose convolutions). We explain the adapted architecture and training details in the supplementary material.

As a common problem for CNNs in 3D space, low-frequency dynamics are learned first and high-frequency details are ignored. To solve this issue, we propose a pyramid network that starts from a low-resolution image to learn the global shape of the cloth. Then, the surface quality is progressively improved in the next higher resolution levels as offsets to the previous level. Note that we use the idea in Sec. 3.1.5 to upscale images between consecutive levels. See Fig. 1 for architecture details.

### 3.3. Losses

<sup>2</sup>We use the following loss functions to train the network:

<sup>2</sup>: means estimated by the network.

- L2 loss between  $\hat{G}_c^{uv}$  and  $G_c^{uv}$  masked by  $M^{uv}$  ( $\mathcal{L}_{uv}$ ).
- KL loss ( $\mathcal{L}_{kl}$ ).
- L2 loss between  $\hat{G}$  and  $G$  ( $\mathcal{L}_{3D}$ ).
- Garment against body collision loss ( $\mathcal{L}_{col}$ ) [7]:

$$\mathcal{L}_{col} = \sum_{(i,j) \in \mathcal{N}} \min(\mathbf{v}_{j,i} \cdot \mathbf{N}_j - \epsilon, 0)^2, \quad (3)$$

where  $\mathcal{N}$  is the set of nearest neighbor correspondences between the predicted cloth and body,  $\mathbf{v}_{j,i}$  is the connecting vector between the  $j$ -th body vertex to the  $i$ -th cloth vertex,  $\mathbf{N}_j$  is the  $j$ -th body vertex normal, and  $\epsilon = 4\text{mm}$  is a small threshold. This loss works well when the cloth is close to the body and pushes back collided vertices back to the nearest body vertex.

- L1 loss on the mesh edges lengths between  $\hat{G}$  and  $G$  ( $\mathcal{L}_e$ ).
- L1 loss on 3D surface normals between  $\hat{G}$  and  $G$  ( $\mathcal{L}_n$ ).

Then, we define the regularization, reconstruction, and final losses as:

$$\mathcal{L}_{reg} = \mathcal{L}_{col} + \mathcal{L}_e + \mathcal{L}_n + \mathcal{L}_{3D}, \quad (4)$$

$$\mathcal{L}_{rec} = \mathcal{L}_{uv} + \lambda \cdot \mathcal{L}_{reg}, \quad (5)$$

$$\mathcal{L} = \mathcal{L}_{rec} + \delta \cdot \mathcal{L}_{kl}, \quad (6)$$

where  $\lambda$  is a coefficient controlling the regularization losses and  $\delta$  is a balancing term between the reconstruction loss and the KL divergence. Tuning  $\delta$  is important to preserve the stochasticity of the VAE while still reaching a low reconstruction error. Therefore, we use  $\beta$ -VAE technique [9] to train the network. We start the training by setting  $\delta < 10^{-3}$  and once we observe a flat  $\mathcal{L}_{rec}$  we linearly increase  $\delta$ .

## 4. Experiments

**Datasets.** We use two common 3D human bodies and garments datasets CLOTH3D [3] and CAPE [28] to train our model and compare against SOTA. First, we use CLOTH3D, a large-scale synthetic dataset of clothed humans. It contains more than two million frames from several thousand sequences with a large variety of garment types, topologies, shapes, and motions. We use 20 percent of the original training dataset to speed up the training and evaluate our method on the defined test set.

Second, we use CAPE, a smaller dataset created with high-resolution 3D scans of real subjects. As it is smaller, it captures a smaller variety of garment types and subjects but still covers a wide range of motions. The scans are registered on top of the SMPL body and encoded as offsets

Data	Experiment	Pyr. 1	Pyr. 2	Pyr. 3	Pyr. 4
<b>Non-skirt</b> (baseline: 7.11)					
	Incremental training	11.97	7.62	7.20	7.14
	End-to-end w/o reg.	10.07	5.41	4.33	3.79
	End-to-end w/ reg.	<b>9.68</b>	<b>5.30</b>	<b>4.10</b>	<b>3.78</b>
<b>Skirt</b> (baseline: 9.79)					
	Incremental training	15.78	9.49	9.13	8.90
	End-to-end w/o reg.	12.00	6.74	5.38	4.60
	End-to-end w/ reg.	<b>11.94</b>	<b>6.60</b>	<b>5.00</b>	<b>4.28</b>
<b>Combined</b> (baseline: 8.01)					
	Incremental training	13.24	8.24	7.84	7.72
	End-to-end w/o reg.	10.72	5.85	4.68	4.05
	End-to-end w/ reg.	<b>10.43</b>	<b>5.73</b>	<b>4.40</b>	<b>3.95</b>

Table 2. Detailed V2V results of the ablation study on CLOTH3D dataset. We can see the effect of each contribution across each level of the pyramid. It is also compared to the baseline, non-pyramid model. Note that the combined error is not the average of the non-skirt and skirt numbers, but the average of the six garment categories combined.

over the minimally clothed body. Unlike CLOTH3D, the bodies and garments are available as a single entity and the model needs to predict them as a single mesh. The dataset is split into two separate datasets for female and male subjects, both containing four cloth types. Each of these datasets contains around 20-30K frames for training and around 5K for testing.

**Metrics.** Since we have SMPL body-garment registration available for both datasets, we are able to calculate a simple point-to-point Euclidean distance averaged across the garment. Therefore, we follow SOTA protocol to report the *reconstruction error*<sup>3</sup> with two common metrics: the average per vertex Euclidean error (V2V) and the Chamfer distance (CD) in mm. Following SOTA, the reported errors are the averages over the average per garment type. We also calculate additional qualitative metrics: 1) the percentage of collided vertices and 2) the absolute difference of the surface area between the draped and template garments in  $m^2$ . In the second metric, we analyze the amount of stretching or compression imposed by the model on the input template garment. While small differences are expected, large changes indicate that the prediction does not conform to the input template.

#### 4.1. Ablation results

We perform an ablation of our approach on the CLOTH3D dataset.

<sup>3</sup>Note that to do so, we use the full VAE model including encoders and decoders.

	$\mathcal{L}_e$		$\mathcal{L}_n$		Collision (%)	
	Non-sk.	Skirt	Non-sk.	Skirt	Non-sk.	Skirt
Baseline	0.580	1.326	0.150	0.161	5.49	2.64
Increment.	0.578	1.581	0.159	0.184	5.45	3.10
E2e w/o reg.	0.706	1.058	0.126	0.133	2.00	0.63
E2e w/ reg.	<b>0.447</b>	<b>0.906</b>	<b>0.124</b>	<b>0.132</b>	<b>1.98</b>	<b>0.61</b>

Table 3. Regularization loss values for the ablation experiments

#### 4.1.1 Contributions

We specifically create and train four different models to validate our contributions:

- **Baseline:** A single level  $VAE_{drape}$  at full resolution ( $512 \times 256$ ).
- **Incremental:** Pyramid architecture built from several  $VAE_{drape}$  submodels at different resolutions. Trained incrementally, one level at a time. In this approach, we start by training the lowest resolution level, then freeze it, add the next level, and train again. We repeat until we train all levels.
- **End-to-end:** Final pyramid model where all levels were trained at the same time. The condition encoders are still frozen. See details in the supplementary material.
- **End-to-end with regularization:** Final pyramid model where all levels were trained at the same time with the regularization losses ( $\mathcal{L}_{reg}$  in Sec. 3.3) applied during training. A  $\lambda = 0.1$  was used.

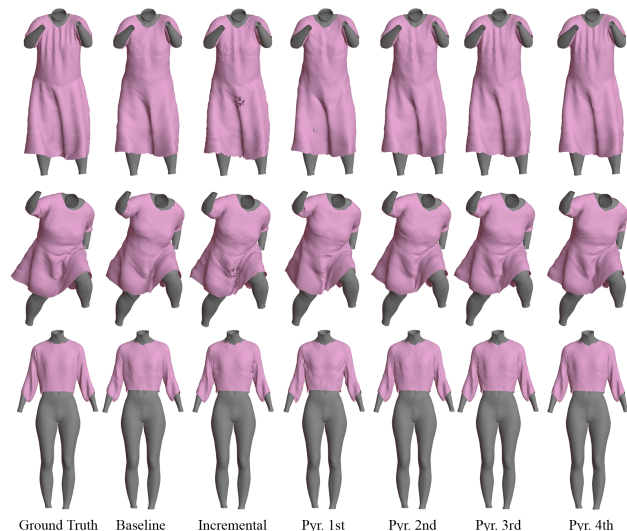


Figure 3. Effectiveness of the pyramid architecture on three examples. Ground truth, with baseline and last output of the incremental method, followed by the output of the final pyramid after each level after skinning and shaping. Notice that each subsequent layer adds details to the previous output.

We compare the contributions quantitatively and qualitatively in Tab. 2 and Fig. 3, respectively. The baseline results are comparable with the pyramid network when trained incrementally. In Fig. 3 it can be seen that the baseline produces good results, but lacks finer details.

Next, we see the output of the incremental method. The aim of this approach is to provide a stable training process and more control over the individual levels. In this case, higher levels do not affect the prediction of lower levels. From Fig. 3, we can see that while this approach achieves a low error, the outputs present some noise along with some artifacts. Since there is no feedback from higher levels if there is an error in one of the lower levels, this needs to be corrected later, which is not always possible.

Furthermore, we present our end-to-end trained model, where each pyramid level was trained simultaneously. By adding supervision at the output of each level, we can still have stable training, where each level outputs a valid prediction. In this approach, there is information flowing both ways between levels. As such, the higher levels can help the lower levels produce more accurate details which in turn lowers the amount of corrections needed to be learned in higher levels. Overall, end-to-end training helps to improve the results by a large margin over the incremental training. Fig. 3 shows that each new level does not only add more details to the garment, but it can also fix small errors or artifacts present in lower levels.

We also explore the use of different regularization losses during training as presented in Sec. 3.3. As we can see in Tab. 2, these losses help to improve the results while they have a higher impact on skirts compared to non-skirts. We further analyze the impact of these losses in Tab. 3. It can be seen that adding the regularization decreases the edge loss and the percentage of the cloth vertices colliding with the body. A lower value on the edge loss means that the model is more robust against compression and stretching of the topology of the mesh.

### 4.1.2 Sampling

First, we sample the normal maps from  $VAE_{norm}$  as these are not available at inference time. Further details about  $VAE_{norm}$  can be found in the supplementary material.

After sampling normal maps, we can also study how they can help  $VAE_{drape}$  in the generation of drapings dealing with the one-to-many assignment problem. By fixing the template garment and body pose, we randomly sample from  $VAE_{norm}$  and  $VAE_{drape}$  and generate garment UV maps. The results in Fig. 4 show diverse dynamics in different garment parts. We can also see that the surface areas of the samples only vary around 8%. These minor variations can be attributed to the stretching or compression of the garment. Therefore, the resulting garments negligibly

differ from their template shape.

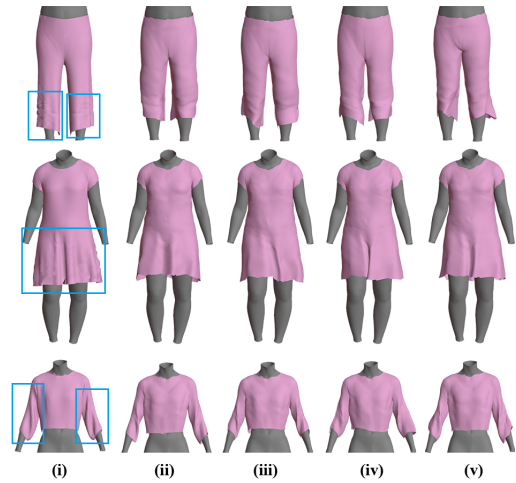


Figure 4. Sampling capabilities of the model. (i) ground truth, (ii-v) results by sampling the VAE latent spaces. Notice the produced changes in the blue rectangles. The shown examples have an average area difference of less than 8% compared to the ground truth.

## 4.2. SOTA comparison

We compare our final contribution to generative (CLOTH3D) and non-generative (DeePSD and DeepCloth) SOTA on the CLOTH3D dataset in Tab. 4. As can be seen, our methodology outperforms the SOTA by a large margin (79.46% relative improvement). We also use the qualitative metrics introduced at the beginning of Sec. 4 to compare our approach with HOOD and DeePSD. We follow the instructions in their GitHub pages and train these methods on the same CLOTH3D subset we used to train our model. As it can be seen in Tab. 6, we achieve a small area difference similar to DeePSD, while HOOD over-stretches the garment to favor the collision. DeepSD has the worst collision among others. HOOD shows the worst CD error. However, given that it is a self-supervised model, comparing it to the ground truth is not fair. We qualitatively compare with SOTA in Fig. 5. Although HOOD shows realistic draping, it drastically changes the template shape. In our experiments with HOOD, changing the elasticity hyperparameter made very small differences. DeePSD shows the least level of detail among others. Additionally, we observe an over-emphasized presence of physical forces, like gravity, in both HOOD and DeePSD. Overall, our method shows better qualitative results than SOTA.

We also compare our method to CAPE, a generative SOTA, on their dataset. As one can see in Tab. 5, our pyramid model progressively improves the results and we achieve a relative improvement of 40.5% on the male split, and 13.9% on the female split of the CAPE dataset at the third level of the pyramid. We also notice some overfitting towards the last level of the pyramid architecture. This can

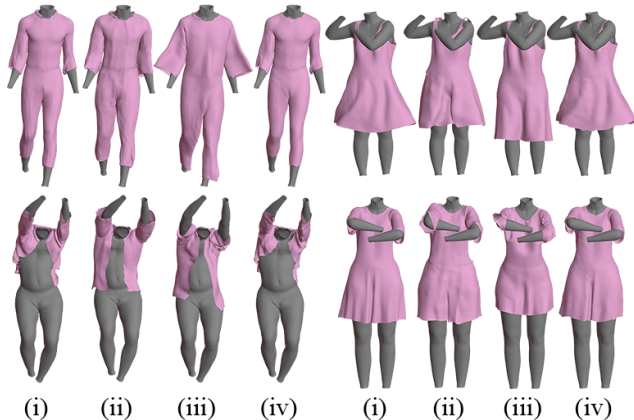


Figure 5. Qualitative comparison of ground truth (i) with predictions from DeePSD (ii), HOOD (iii) and our method (iv). HOOD shows improvement over DeePSD in the level of detail. However, it over-stretches the garment. Our method offers a high level of detail while having the minimum stretching and compression over the template shape.

Method	V2V error	Method	Female	Male
CLOTH3D [3]	29.00	Pyr. 1 lvl	6.63	8.94
DeePSD [7]	23.78	Pyr. 2 lvl	3.92	5.44
DeepCloth [38]	19.23	Pyr. 3 lvl	<b>3.11</b>	<b>3.66</b>
Ours	<b>3.95</b>	Pyr. 4 lvl	3.36	4.00
		CAPE [28]	3.61	6.15

Table 4. SOTA comparison on CLOTH3D dataset. We show large performance improvements over SOTA.

Table 5. SOTA comparison on CAPE dataset (V2V error). CAPE [28] numbers are taken from the authors’ GitHub page.

Method	CD error	Collision (%)	Area diff
DeePSD [7]	36.85	3.29	0.05429
HOOD [18]	42.99	<b>0.44</b>	0.13211
Ours	<b>11.59</b>	1.04	<b>0.05282</b>

Table 6. Qualitative metrics comparing with SOTA on CLOTH3D dataset.

be attributed to the fact that the meshes are lower resolution compared to CLOTH3D, and they contain fewer details. Qualitative results in Fig. 6 show how our approach reconstructs more cloth details while CAPE resembles the body.

### 4.3. Performance

Thanks to the convolutional architecture and having relatively light models, we can achieve fast inference times. The whole pyramid architecture has 40M parameters and without VAE encoders it decreases to 26M. Using an Nvidia 3090 GPU, we can achieve an inference time (for sampling and generation without encoders) of 50ms and 60ms using

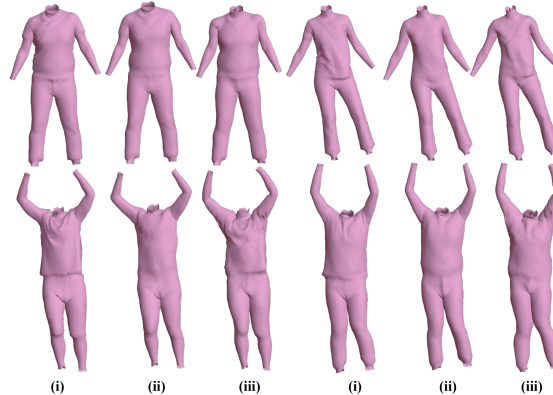


Figure 6. Qualitative examples from CAPE dataset comparing ground truth (i) to CAPE (ii) and ours (iii).

a batch size of 1 and 4, respectively. This allows near real-time inference.

## 5. Conclusions

We presented an effective approach to solve the problem of 3D garment draping and generation. By projecting the 3D meshes to UV images we were able to leverage established convolutional methods to create a pyramid VAE architecture. We observed how different pyramid levels allow the model to add different levels of detail to the generated cloth meshes. We further conditioned the network on normal maps, which provide additional regularization for the network to better focus on the details. Our results show SOTA performance on two public datasets, CAPE and CLOTH3D. We further showed that we can generalize to several garment types with a minimal number of models.

**Limitations and future work.** There are some limitations of our work that remain interesting for future research. Our current approach requires garment registration on top of the SMPL model as a preprocessing. The results also depend on the quality of the registration. Our model does not handle multi-layer garments. Finally, although we obtained SOTA results by using default SMPL blend weights, learning garment, and pose-dependent blend weights may provide extra improvements to surface quality.

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