3D Shape-adapted Garment Generation with Sketches

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Abstract. Garment generation or reconstruction is becoming extremely demanding for many digital applications, and the traditional process is time-consuming. In recent years, garment reconstruction from sketch leveraging deep learning and principal component analysis (PCA) has made great progress. In this paper, we present a data-driven approach wherein 3D garments are directly generated from sketches combining given body shape parameters. Our framework is an encoder-decoder architecture. In our network, sketch features extracted by DenseNet and body shape parameters were encoded to latent code respectively. Then, the new latent code obtained by adding two latent codes of the sketch and human body shape is decoded by a fully convolutional mesh decoder. Our network enables the body shape adapted detailed 3D garment generation by leveraging garment sketch and body shape parameters. With the fully convolutional mesh decoder, the network can show the effect of body shape and sketch on the generated garment. Experimental results show that the fully convolutional mesh decoder we used to reconstruct the garment performs higher accuracy and maintains lots of detail compared with the PCA-based method.

Keywords: 3D Garment Reconstruction · Sketch-based Modeling · Body Shape Adapted · Mesh Decoder.

1 Introduction

Designing garments that adapting to the shape of the body is an age-old problem in the fashion industry. In the traditional flowcharts, designing real or virtual garments is a complex and time-consuming process with iterative steps. Firstly, experienced designers carry out design ideas based on the shape of a person, and then draw the sketch of the garment. Then, the pattern maker makes the garment patterns and sews them into a whole garment. This process can be summarized into two steps: the 2D sketches for the initial design, and the 3D garment construction according to the body shape. Mapping the 2D garment

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sketch design to a 3D body requires a good understanding of the 3D space of the human body to adapt to the shape, and it is not an intuitive process. For a garment designer, changes often take place for a new style garment to adapt various body shapes. If the corresponding 3D garment is generated through complicated steps for each modification, the design cycle of the garment will become longer and labor-intensive, especially for designers who do not have much design experience.

To reduce the design cost and shorten the design cycle, a straightforward way is that a garment can be generated automatically by some images or sketches. In this paper, we propose a sketch-based shape adapted garments generation method. Given a human body shape as a reference, users can draw a garment sketch in the white plane. Then using the sketch and the human body shape as input, our method can generate the shape adapted 3D garment. We use a sketch encoder and a body shape encoder to extract the features respectively. Then the sketch feature and the body shape parameters are added together to form the latent code. With this latent code as input, the mesh decoder is applied to reconstruct the 3D garment in the mesh.

Our method is an end-to-end network. To train such a network requires gaining sufficient garment data. However, there is no publicly available garment dataset that both provides the 3D garments and corresponding human body shapes. Thus, we construct a large dataset with garments adapted to various human body shapes.

In summary, the main contributions of our paper are as follows:

- A large 3D garment dataset is constructed. This dataset consists of 3070 sets of 2D garment sketches, 3D garment meshes, and the corresponding human body shape parameters, which can be used to train an end-to-end network for garment generation applications.
- Using the 2D garment sketch as input, combined with human body shape parameters, an end-to-end neural network is proposed to generate a 3D garment mesh that fits a specific human body shape.
- A fully convolutional mesh decoder is integrated into the proposed network to improve the computational performance, precision, and accuracy compared to the PCA-based methods.

2 Related Work

Garment Modeling Taking a single image as input, Zhou *et al.* [31] estimate the pose and body shape of the mannequin, and interpret the garment outline to generate an initial 3D garment model. Similar to Zhou *et al.*, Jeong *et al.* [13] extracted silhouette edges from the input image and lifted them to 3D garments. Danundefinedřek *et al.* [7] take an image as input and obtain the target garment by learning the deformation of the reference garment. Taking RGBD data as input, the system proposed by Chen *et al.* [5] detects and classifies garments components, and then stitchs the templates to model garments. Wang *et al.* [28]

model the garment by learning a shared shape space. Tiwari *et al.* [26] estimate and visualize the dressing effect of a garment in various sizes.

Garment Capture Pritchard *et al.* [22] use a stereo image pair to reconstruct a garment. Color-coded patterns are used by Scholz *et al.* [25] and White *et al.* [29] to reconstruct a garment from a multi-view setup. Bradley *et al.* [4] present a multi-view capture system for garments but eliminating the need for a color-coded pattern. Popa *et al.* [21] add details to the coarse meshes captured from the multi-view video, and Wang *et al.* [27] solve a similar problem using a data-driven approach. Pons-Moll *et al.* [20] capture the body and garment shape from the 3D sequence. Kamel *et al.*[3] propose a comparison algorithm between two skeletons motions based on the quantified metrics, which is helpful for garment capture.

Garment Re-targeting Guan *et al.* [9] propose a parameterized model of the human body shape and pose parameters. Neophytou *et al.* [18] retarget a garment by replacing deformation with residual transformations between a naked mesh and the dressed mesh. Pons-Moll *et al.* [20] estimate the displacement of clothing after computing the minimally clothed shape and a multi-cloth alignment. Wang *et al.* [28] retarget a garment through learning a shared shape space. Gundogdu *et al.* [10] utilize deep networks to fuse garment features at varying levels of details with body features. Santesteban *et al.* [24] used a recurrent neural network to separates global garment from local garment wrinkles. Patel *et al.* [19] decompose the deformation into a high frequency and a low frequency to retarget a garment. Xu *et al.* [30] predict dressing fit for ready-made garments on different individuals. Tiwari *et al.* [26] completed the retargeting through deep learning.

Sketch-based Modeling Robson *et al.* [23] analyze the factors that influenced the silhouettes depicted in the sketches and predict the garment. Jung *et al.* [14] proposed a sketch-based modeling method for developable surfaces. To model freeform shapes with complex curvature patterns, Li *et al.* [16] use a sketch-based modeling method utilizing the bending strokes. The method presented by Wang *et al.* [28] take as input a sketch to predict the garment fitting the specific body.

Due to the irregular sampling and connections in the mesh data, it is hard to use a deep learning method such as convolutional neural networks (CNN) to process mesh directly. Thus many methods [7, 18, 28, 19] introduced Principal Component Analysis (PCA) to obtain a low-frequency vector to represent a garment mesh. However, the information loss due to performing PCA leads to accuracy loss of the mesh. Recently, Zhou *et al.* [32] proposed a fully convolutional mesh autoencoder that can process arbitrary registered mesh data directly, which inspires our work.

3 The Proposed Method

3.1 Overview of the Network Architecture

As illustrated in Fig. 1, our garment generation network is an end-to-end architecture.The proposed network mainly consists of three modules: the sketch encoder the human body shape encoder and the mesh decoder based on a fully convolutional mesh decoder. Firstly, the input sketch image is fed into the DenseNet for features extraction and generates a sketch descriptor **S**. Then the sketch descriptor is encoded by the sketch encoder. Meanwhile, the human body shape parameter **P**, which is a 10-dimensional vector provided by *SMPL*[17] to describe the body shape variation, is encoded by the body shape encoder. Then, two latent code are added up to obtain the latent code **C**. Finally, the fully convolutional mesh decoder takes the latent code **C** as the input and reconstructs the 3D garment which is detailed and adapted to specific human body shape. In our network, the 3D garment is reprensted by the triangular mesh data structure. We will give more details as follows.

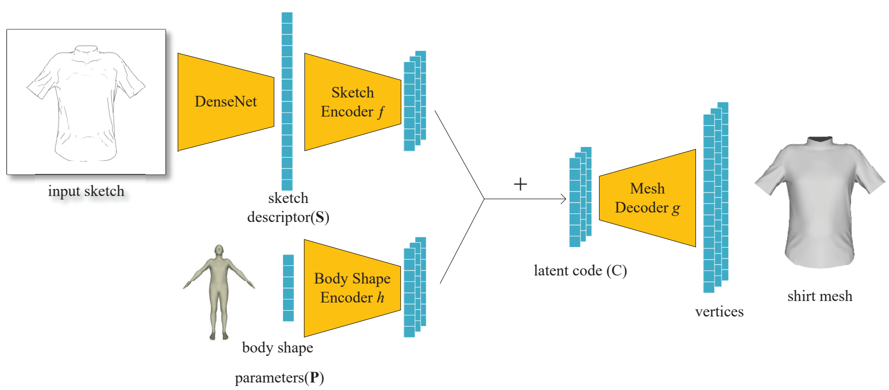

Fig. 1. Overview of the proposed garment generation network based on fully convolutional mesh decoder. It mainly consists of three modules: the sketch encoder module, the body shape encoder module, and the convolutional mesh decoder module.

3.2 Sketch Encoder & Body Shape Encoder

Sketch Encoder The garment sketch is essentially a grey image which is drawed by users or generated by other tools, and it will be transformed into RGB image as the input of the the sketch encoder network. To extract features from the input sketch image, we utilize the DenseNet [11] (the DenseNet-161 architecture provided in the TorchVision library [2]) to generate a 2208-dimensional sketch descriptor **S**. Then the sketch encoder takes the sketch descriptor **S** as input and generate the latent code. The detail parameters of this the sketch encoder is described in Fig. 2. Fully connected blocks are fully connected layers followed by Rectifying Linear Unit (RELU) activations and batch normalization. The 2208-dimensional descriptor **S** is converted to a 100-dimensional vector through series of fully connected blocks. The last max-pooling layer yields a latent code with size 22 and 9 channels.

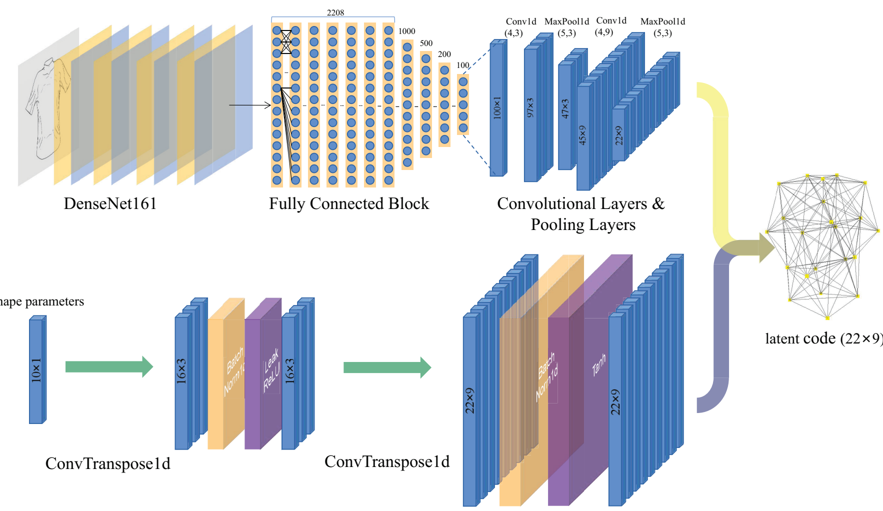

Fig. 2. The Sketch Encoder consists of DenseNet, 10 fully connected layers, 2 convolutional layers, and 2 pooling layers. Each fully connected layer is followed by RELU activation and batch normalization. The Body Shape Encoder is consists of 2 one-dimensional transposed convolution and corresponding batch normalization and activations. The 2 activations are Leak ReLU and Tanh respectively.

Body Shape Encoder The body shape parameter **P** is a 10-dimensional vector provided by *SMPL* to describe the human body shape. To obtain the latent code with the size of 22 and the channel of 9, we compose the body shape encoder with 2 transposed 1D convolution layers which followed by batch normalization and different activations respectively. The detailed architecture of the body shape encoder is illustrated in Fig. 2.

3.3 Fully Convolutional Mesh Decoder

Although the PCA-based methods are able to produce descriptive latent spaces and useful for capturing details of garment meshes, the reduction of dimensionality will result in a loss of accuracy. Inspired by the work in [32], we introduce a fully convolution mesh decoder to conduct the operations in this step.

The variant convolution and TransConv Suppose the output graph $\mathcal{Y}$ which has vertices y_i is sampled from the input graph $\mathcal{X}$ which has vertices x_i. In graph $\mathcal{X}$, let $\mathcal{N}(i)$ is a local region of y_i, and it has E_i vertices $x_{i,j}$, $j = 1, .., E_i$. Given the Weight Basis $B = \{\mathbf{B}_k\}_{k=1}^{M}$ ($\mathbf{B}_k \in \mathbb{R}^{I \times O}$) and locally variant coefficients(vc) $A_{i,j} = \{\alpha_{i,j,k}\}_{k=1}^{M}$,$\alpha \in \mathbb{R}$, then the weights of $x_{i,j}$ is computed as:

$$\mathbf{W}_{i,j} = \sum_{k=1}^{M} \alpha_{i,j,k} \mathbf{B}_k \tag{1}$$

, and convolution can be represented as:

$$\mathbf{y}_i = \sum_{x_{i,j} \in \mathcal{N}(i)} \mathbf{W}_{i,j}^T \mathbf{x}_{i,j} + \mathbf{b} \tag{2}$$

here $\mathbf{b}$ is the learned bias, $A_{i,j}$ are different for each vertex $x_{i,j}$, and B is shared and learned globally.

The vdPool ,vdUnpool,vdUpRes and vdDownRes Within the pooling kernel radius, because the vertices in arbitrary graph are distributed unevenly, the max or average pooling will induce poor performance. To overcome this problem, Zhou *et al.* [32] introduce the variant density(vd) coefficients which are learnable parameters into the network.

The aggregation functions in vdPool and vdUpPooling layers are:

$$M\mathbf{y}_i = \sum_{j \in \mathcal{N}(i)} \rho' x_{i,j}, \qquad \rho' = \frac{|\rho_{i,j}|}{\sum_{j=1}^{E_i} |\rho_{i,j}|} \tag{3}$$

,where M is the average size of a neighborhood $\mathcal{N}(i)$ of $x_{i,j}$, $\rho_{i,j} \in \mathbb{R}$ is the training parameter and $\rho'_{i,j}$ is the density value. Then, the residual layer is defined as:

$$\mathbf{y}_i = \sum_{x_{i,j} \in \mathcal{N}(i)} \rho' \mathbf{C} \mathbf{x}_{i,j} \tag{4}$$

here C is an identity matrix when the input and output feature dimensions are the same, or is a learned matrix when the input and output feature dimensions are different.

Details of the Decoder Network We downsampled the mesh firstly. After multiple downsampling of the mesh, multiple connectivities with different topologies and numbers of vertices are obtained. As shown in Fig. 3, the latent code is decoded to vertices data of the 3D garment mesh by 8 transposed convolutional(TransConv) blocks and 4 up-residual(UpRes) blocks. In each TransConv block, following each TransConv layer is an exponential linear unit(ELU) [6] activations.

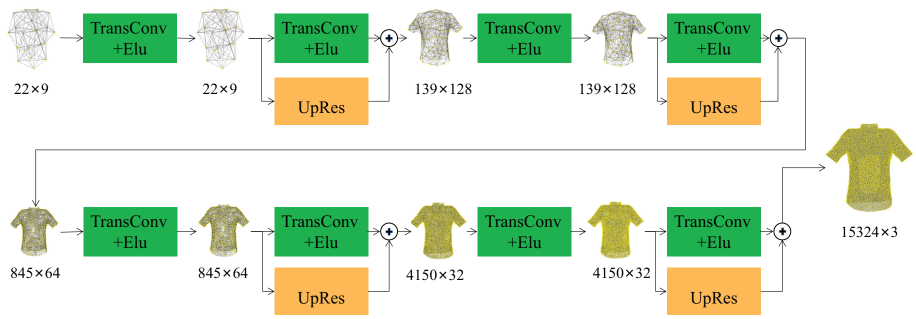

Fig. 3. The structure of the convolutional mesh decoder. It mainly consists of 8 TransConv blocks and 4 UpRes blocks.

3.4 Loss Function

Our loss function for training consists of two items. One is the $L1$ laplacian loss(L_{lap}), and the other is $L1$ geometric loss(L_{geo}):

$$L = \lambda_1 L_{lap} + \lambda_2 L_{geo} \tag{5}$$

The $L1$ laplacian loss is used to smooth the vertices:

$$\begin{gathered} L_{lap} = \frac{1}{m}\sum_{i=1}^{m} |lap_i' - lap_i|, \\ lap_i = \frac{1}{E_i}\sum_{j=1}^{E_i}(y_i - y_j), \qquad lap_i' = \frac{1}{E_i}\sum_{j=1}^{E_i}(y_i' - y_j') \end{gathered} \tag{6}$$

where E_i is the number of vertices in neighborhood $\mathcal{N}(i)$ of y_i or y_i'.
The $L1$ geometric loss is defined as:

$$L_{geo} = \frac{1}{m}\sum_{i=1}^{m} |y_i' - y_i| \tag{7}$$

In our implementation, we set $\lambda_1 = \lambda_2 = 1$ in Eq.(5).

4 Experiments

4.1 Dataset Construction

We construction a dataset with 3730 sets of data. Fig. 4 shows an example in our dataset. Each set of data contains a 3D garment mesh, a corresponding flattened mesh, a sketch image, a 3D male body mesh, and its body shape parameter. To construct the dataset, we firstly sample 746 male bodies with the same A-pose from the FashionPose [15] dataset. We simulated garments over body samples using the cloth simulator in CLO3D [1], and then obtained the draped garments and the flattened meshes of each garment. To ensure the consistency of the mesh topology, we use one of the simulated garments as the standard template. Each flattened mesh corresponding to each garment is aligned with the template flattened mesh via the $ARAP$ [12] deformation. Then we locate the vertices of template flattened mesh in the associated triangle of each flattened garment mesh via the barycentric coordinates. Finally, the vertices of the template 3D garment mesh are mapped to each 3D garment mesh. Then, the 3730 3D garment meshes with the same topology and different shapes are generated using these mentioned steps. With these 3D garment meshes, we generate their corresponding sketches using the Suggestive Contours method [8].

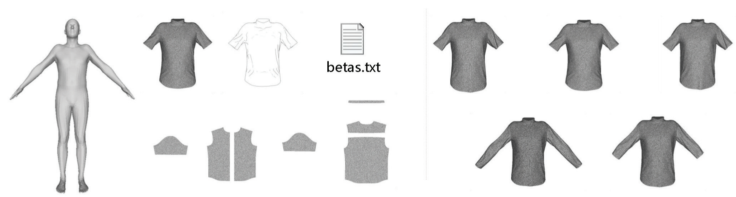

Fig. 4. The dataset includes 5 types of 3D shirt garments. Each set has a male human model with the body shape parameter named "betas.txt", a topology unified mesh, a flattened mesh, and the corresponding 2D sketch.

4.2 Results

We split the dataset into training(80%), evaluating(10%), and testing sets(10%). The network is trained with batch size=32,learning rate=0.0001,learning rate decay=0.9 every epoch, using Geforce RTX 3090,Cuda 11.1 and PyTorch 1.8.0. As listed in Table 1, with 500 epochs of training, the mean test errors of training, evaluating, and testing data are $3.581, 3.717, 3.714$ mm respectively. Table 1 also show the parameter count of both methods. Our method takes an average of 0.033 seconds to generate a 3D garment from the input 2D sketch. We also replaced the decoder with a fully connected neural network and represented the mesh with PCA, and the mean test errors of training, evaluating, and testing data are $13.020, 13.595, 13.294$ mm respectively. It can be seen that our method is significantly better than the PCA-based method.

The result of 3D garments generated from the testing dataset is visualized in Fig. 5. The red color indicates a large error while the blue color indicates a minor error. Obviously, the errors mainly appear in the hem and sleeve part of the garment. Although there are some errors, the generated garments are closed to ground truth garments from the perspective of the shape and the detail. Fig. 5

Table 1. The average per vertex error (mm) on our dataset and the parameter count of both methods. The results of our method are better than the results of PCA-based method.

Dataset	Geometric Error of Ours(mm)	Geometric Error of PCA(mm)
Train	3.581	13.020
Evaluate	3.717	13.595
Test	3.714	13.294
Param	39,417,570	32,360,658

also shows the comparison of the results of using PCA and our method, and our method is better than PCA.

We also compared other clothing modeling methods. As shown in Table 2, we have adopted the same measurement standards as the original paper, and ours results are better.

Table 2. Comparison with other methods. Average per vertex error (mm) and the normalized L^2 distance percentage (%).

	Sizer[26]	Tailornet[19]	Garnet[10]	Wang's[28]	Ours
Error(mm)	15.54	10.2	-	-	**3.714**
Error(%)	-	-	1.15	3.01	**1.12**

We also test the proposed method using the same input sketch with various body shapes. Fig. 6 shows four examples of the results. In this figure, it can be seen that the same garment can be well adapted to different body shapes, and keeps the same style.

In this work, we implement a user interface based on the network(Fig. 7), which allows the user to edit the sketch or body and the 3D draped garment is updated at interactive rates. The 2D sketch can be imported from an image file and edit on the painting board. Different body shapes can be specified by editing the parameters. With different body shapes and sketches, the 3D garments fitting the body is updated in real-time at interactive rates.

5 Conclusion

In this paper, we propose a sketch-based 3D garment generation method. Taking the 2D garment sketch and the parameters of the human body shape as input, our method can generate a 3D garment mesh based on a fully convolutional mesh decoder network. We construct a garment dataset with 3730 sets for the training network. The results of testing show that the proposed method performs well when reconstructing 3D garments. Moreover, the user interface we implemented allows users to edit the sketch or body and 3D draped garment is updated at interactive rates, and the generated 3D garment can be adapted to different human body shapes.

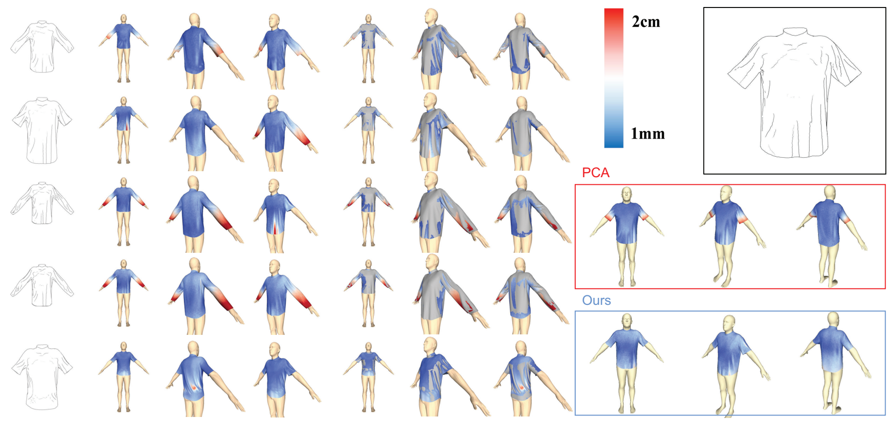

Fig. 5. Error visualization of 5 examples of the generated results. The errors mainly appear in the hem and sleeve part. The ground truth garments are represented by a gray mesh. Compared with the results of using PCA, ours has a better effect.

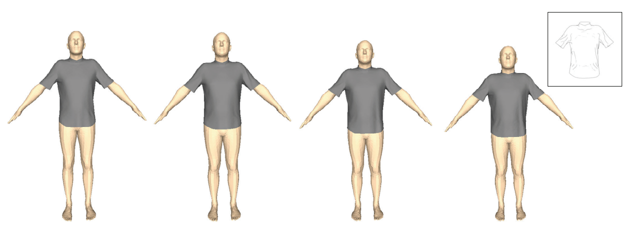

Fig. 6. Four examples of the same 2D garment with different human body shapes. The results show that the same garment can be well adapted to different human body shapes.

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Fig. 7. The user interface allows the user to edit the sketch or body and the 3D draped garment is updated in real-time at interactive rates.

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