Garment3DGen: 3D Garment Stylization and Texture Generation

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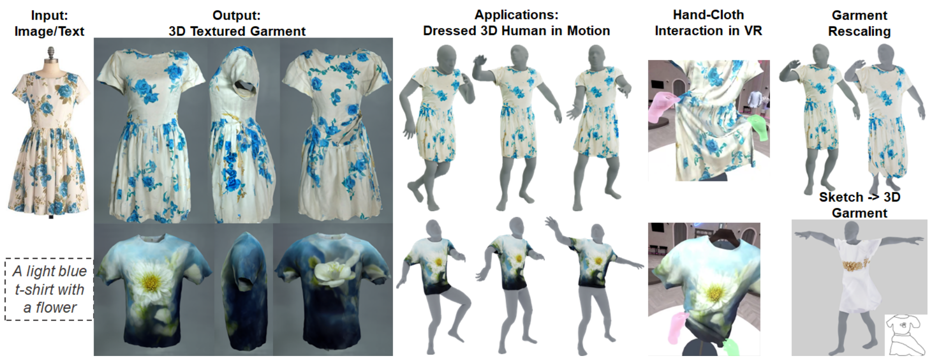

Fig. 1: We present Garment3DGen, a fully-automated method to transform a base garment mesh to simulation-ready asset directly from images or text prompts. Our method enables rapid asset generation in a frictionless manner, commoditizing content creation which would otherwise require specialized software and expertise. We demonstrate applications such as physics-based simulation and hand-cloth interaction in VR.

Abstract. We introduce Garment3DGen a new method to synthesize 3D garment assets from a base mesh given a single input image as guidance. Our proposed approach allows users to generate 3D textured clothes based on both real and synthetic images, such as those generated by text prompts. The generated assets can be directly draped and simulated on human bodies. First, we leverage the recent progress of image-to-3D diffusion methods to generate 3D garment geometries. However, since these geometries cannot be utilized directly for downstream tasks, we propose to use them as pseudo ground-truth and set up a mesh deformation optimization procedure that deforms a base template mesh to match the generated 3D target. Second, we introduce carefully designed losses that allow the input base mesh to freely deform towards the desired target, yet preserve mesh quality and topology such that they can be simulated. Finally, a texture estimation module generates high-fidelity texture maps that are globally and locally consistent and faithfully capture the input guidance, allowing us to render the generated 3D assets. With Garment3DGen users can generate the textured 3D garment of their choice without the need of artist intervention. One can provide a textual prompt describing the garment they desire to generate a simulation-ready 3D asset. We present a plethora of quantitative and qualitative comparisons on various assets both real and generated and provide use-cases of how one can generate simulation-ready 3D garments.

1 Introduction

3D asset creation is the process of designing and generating geometries and materials for 3D experiences. It has direct applications across several industries such as gaming, movies, fashion as well as VR applications. Traditionally, simulation-ready garments are hard to obtain and are created through a laborious time-consuming process requiring specialized software [7,11,64] relying on experienced artists. Currently, creating virtual clothing for simulation is a challenging task. Garments need to be manually designed and draped onto an underlying body. Additionally, the topology of the garment needs to take simulation into consideration in order to enable pleasing results. Low-friction asset creation will be the key enabler in the future to unlock virtual applications at scale. Generative AI will be a cornerstone technology that will allow anyone, ranging from novice users to experts, to create customized avatars and to contribute to building personalized virtual experiences. In addition, it will assist in the design process to facilitate faster exploration and creation of new designs.

To tackle this task, we set out to develop a method termed *Garment3DGen* that creates 3D garments directly from image inputs. Given a base geometry mesh and a single image, Garment3DGen performs topology-preserving mesh-based deformations to match the image guidance and synthesizes new 3D assets on the fly. Our generated garments comprise of posed geometries that stylistically match the input image, and high-resolution texture maps. The provided image guidance can be either from the real world or synthetically generated [12, 56] which enables us to create both real and fantastical 3D garments.

While there are several methods in the literature that have focused on this problem, they all suffer from some key limitations. One way to tackle this problem would be to utilize recent image-to-3D techniques [37]. Given a single image as input, such methods synthesize a specific number of views captured from pre-set viewpoints and then employ multi-view reconstruction techniques to obtain the 3D asset. However, the output geometries tend to be coarse and lack fine-level details due to the use of Marching Cubes to extract the output 3D geometry. Another drawback is that the output garments are watertight, have arbitrary scale making it challenging to drape them om human bodies and simulate them directly as this would require manual intervention to post-process the geometry (*e.g.*, manually create arm/neck/waist holes for a t-shirt geometry as well as re-meshing that would alter the mesh topology). Alternatively, one could follow a NeRF-based approach where a handful of views of the base mesh are utilized to train a NeRF which can be stylized in an iterative manner [24]. Such an approach however does not guarantee multi-view consistency of the newly stylized garment as the NeRF training and stylization are happening in an iterative manner. In addition, it is a time-consuming process and the final geometry is not simulation-ready. Recent works have focused on 3D Gaussian Splatting [29] to generate 3D assets from image inputs. While such methods are fast and of fairly high reconstruction quality, their output splats are hard to be used for any downstream task besides rendering. Another direction of research predicts 2D garment patterns [5, 30, 33, 44] which can be optimized using differentiable simulation. Such approaches generate simulation-ready garments but cannot generalize to fantastical AI-generated garments and cannot benefit from the recent progress of text and image-based diffusion models.

To this end, we carefully designed Garment3DGen to tackle each of the aforementioned challenges: i) reconstruction-based approaches output geometries that are watertight, coarse and the garments cannot be draped on human bodies ii) deformation-based approaches are under-constrained when given a single image/text prompt and their outputs do not faithfully match the provided guidance and iii) simulation-based approaches fail to generalize to new garment types. Garment3DGen is capable of producing high-quality simulation-ready stylized garment assets complete with associated textures. We approach this task from a mesh deformation-based perspective as we believe that it provides better properties and more fine-grained control for the output geometries compared to alternative NeRF-based or reconstruction-based approaches. Mesh-based deformations can preserve the mesh topology which in turn can allow for UV texture transfer, they can preserve the arm/body/head holes of the garment geometry instead of outputting watertight meshes, and can provide output meshes the triangles of which are not distorted and can be draped on human bodies and simulated. Our method takes as inputs a single image and a base template mesh and outputs a deformed mesh that faithfully follows the image guidance while preserving the structure and topology of the base mesh. Our first contribution stems from supervising the mesh deformation process directly in the 3D space which directly allows physics-inspired losses that ensure simulation-readiness instead of solely relying on image-based or embedding-based supervisions [46, 48, 74]. In the absence of 3D ground-truth, we build upon the progress of diffusion-based multi-view consistent image generation to obtain a coarse 3D geometry that can serve as pseudo ground-truth. However, strictly enforcing 3D supervisions using a coarse mesh would result in deformed meshes that lack fine-level details and are not simulation-ready. Thus, we utilize a pre-trained MetaCLIP model [74] since it provides a balanced subset over the metadata distribution and finetune it to garment data while introducing additional supervisions in the image space using differentiable rendering and in the embedding space. Finally, we propose a carefully designed texture estimation module to predict the texture maps required to create the final 3D garment.

We conducted a plethora of experiments that demonstrate that our method can generate 3D garment assets i) directly from images allowing a frictionless experience where users indicate a requested garment by providing a reference image and quickly obtain a corresponding high-quality 3D asset without manual intervention and ii) from textual inputs describing both real and fantastical garments, and iii) even simple garment sketches that one can quickly draw. Moreover, we have developed a body-garment co-optimization framework that enables us to scale and fit the garment to a parametric body model. This allows us to animate the body model and perform physics-based cloth simulation, resulting in a more accurate representation of the garment's behavior in various novel scenarios. In summary, our contributions are as follows:

– We propose a new approach for 3D geometry and texture generation for garments given a base mesh and a single image guidance as inputs. We believe that this is the first work aiming to generate textured garment assets that can be useful for downstream simulation tasks.
– We introduce geometry supervisions directly on the 3D space by generating coarse-guidance meshes from the image inputs and use them as soft constraints during the optimization. In addition, we provide valuable insights on the impact of different losses that ensure that the output geometries are suitable for downstream tasks such as cloth-simulation or hand-garment interaction.
– We introduce a texture enhancement module that generates high-fidelity UV textures from a single image allowing us to render the output geometries.
– We propose a body-cloth optimization framework that fits the generated 3D garment on a parametric body which unlocks applications such as dressing avatars and the accurate simulation of clothes without artist intervention.

2 Related work

Garment Modeling: An important line of work is focused on designing [6, 14], capturing [77], registering, reconstructing [54, 78], and representing [39, 66] clothes and their texture [8] from image or video inputs. Cloth registration is an important task as it allows us to fit parametric garment templates to in-the-wild scans or in controlled environments [23] and then use the registered clothes for downstream tasks. [21] learns a shape diffusion-based prior from captured 4D data in order to enable registration of texture-less cloth, whereas [34] aligns the garment geometry to real world captures using a coarse-to-fine method that leverages intrinsic manifold properties with neural deformation fields. Aiming to accurately model clothes and discover new compact ways to represent them, CaPhy [65] recovers a dynamic neural model of clothing in a similar fashion to SNUG [58] by leveraging 3D supervised training in combination with physics-based losses. [73] introduced a physically-inspired appearance representation by learning view-dependent and dynamic shadowing effects. Finally, recent methods have explored modeling clothes using graph neural networks [19, 22, 50]. An alternative way to represent clothes is via sewing patterns as this ensures an efficient representation of developable [57, 62] and manufacturable garment items which can be easily modified. A plethora of works [2, 4, 30, 52] have followed this approach for garment reconstruction [36, 49, 68, 69], generation [59] and draping [32].
Garment Deformation and Stylization: The recent progress in large language and image-to-3D models has unlocked new ways of representing and reconstructing dressed avatars [27,70] from a single text or image prompt. These methods typically generate a handful of multi-view consistent views [37, 38, 40, 53, 72] given a single image or text input or directly optimize a 3D scene [51] using a 3D scene parameterization, similar to Neural Radiance Fields [47]. However such methods generate coarse, watertight meshes that in the context of garments do not have the required topology and structure to be draped on humans and simulated [63]. Editing and stylizing 3D surfaces has been explored in the

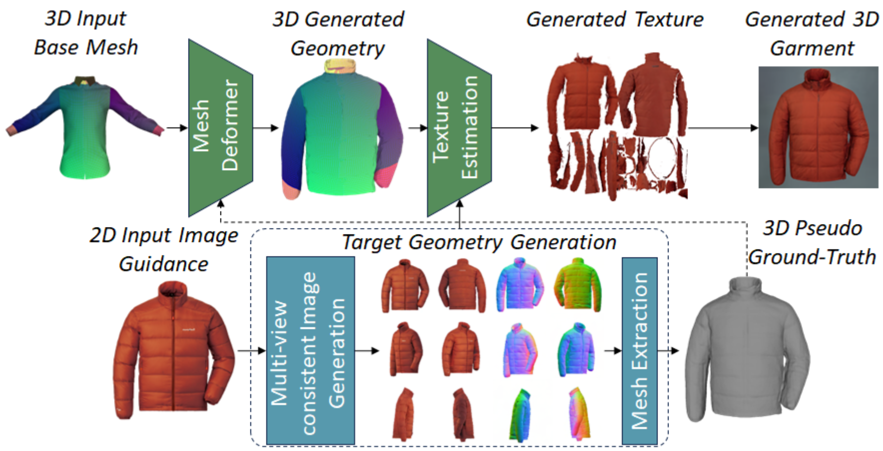

Fig. 2: Overview: Given an input 3D base mesh and a target garment image we first generate 3D pseudo ground-truth using a diffusion-based method and utilize the output geometry as a soft supervision signal during the deformation process. Our 3D generated geometry preserves the topology and structure of the base mesh as depicted by the colors of the sleeves/collar while accurately capturing the geometry of the input image. The texture-estimation module then outputs the corresponding UV texture that along with the geometry comprise our final generated 3D garment.

context of optimizing directly on the 3D space [28, 35, 61] and more recently using triplanes [16] and text-to-mesh formulations [10, 48]. For example, [46] performs mesh stylization by predicting color and local geometric details that follow a text prompt. Deformation-based approaches [3, 17, 20, 26, 67, 71, 76, 80] can leverage these foundation models to enforce supervision signals for text and image-based stylization [13] and manipulation [18] of 3D meshes. Recently, a line of work [9, 55, 75, 79] applied text-to-image generation models to create textures based on the mesh and given text/image. Extending such techniques to clothes is a complex task as the supervision signals of a single image or text-prompt are insufficient to ensure that the deformed clothes will be simulation-ready.

3 Method

Our approach takes as input a single image I and a base garment template mesh M_{in} and performs a topology-preserving deformation of the input geometry given the image guidance to obtain the target deformed mesh $M_{\text{def}} = D(I, M_{\text{in}})$ where D is a function represented by a neural network that optimizes over the input mesh. An overview of our method is depicted in Fig. 2.

3.1 Target Geometry Generation

We propose to leverage the recent progress of single-image-to-3D methods to obtain a coarse geometry of I denoted by $M_{\text{guide}}(I)$ and use it as much stronger supervision both directly in the 3D space as well as in projected 2D space through differentiable rendering. A cross-domain diffusion model [40] is employed which synthesizes RGB and normal images from six views given the input image I captured from the same predefined viewpoint. A multi-view 3D reconstruction algorithm [83] is then utilized that, given the generated views, it outputs a watertight, relatively coarse geometry $M_{\text{guide}}(I)$ along with vertex colors of the garment in the input image. While this mesh cannot serve as the final simulation-ready result due to its poor mesh quality which is due to Marching Cubes [42] or potential inaccuracies of the multi-view generation. Additionally, the fact that it is watertight prevents us from draping the garment on a body (*e.g.* due to missing armholes). Nonetheless, it provides useful information to serve as a pseudo ground-truth that serves as a reference to deform M_{in} towards. Hence, we update the optimization function as follows $M_{\text{def}} = D(I, M_{\text{in}}, M_{\text{guide}}(I))$. The alternative approach would be to rely on the input image I as the sole supervision for mesh deformation which would result in a severely under-constrained optimization with low-quality output meshes that are uncanny, over-deformed, and they fail to capture the subtle details of the image guidance. For example, starting from a template T-shirt geometry with guidance of the image of an armor as input, one could extract CLIP embeddings for both I and the renders of M_{def} following a similar approach to TextDeformer [18]. By enforcing supervisions on the embeddings, the goal is obtain an output mesh that would resemble the requested armor. In practice, the supervision from the embedding of a single exemplar image is not strong enough to produce high quality output.

3.2 Mesh Deformer: Topology-Preserving Deformations

Aiming to preserve the structure and topology of the input base mesh while still allowing for image-base stylizations, we propose an approach which deforms M_{in} instead of generating a new geometry that would be hard to directly use in downstream tasks like reconstruction-based methods would do. Hence, inspired by Neural Jacobian Fields [1], we parameterize M_{in} using a set of per-triangle Jacobians which define a deformation. Following the same formulation, for simplicity we represent per-triangle Jacobians as matrices $J_i \in R^{3x3}$ and solve a Poisson optimization problem to obtain the deformation map Φ^* as the mapping with Jacobian matrices for each triangle that are closest to J_i. More formally this is represented as:

$$\Phi^* = \min_{\Phi} \sum |t_i| \|\Phi \nabla_i^T - J_i\|^2, \tag{1}$$

where $\nabla(\Phi)$ denotes the Jacobian of Φ at triangle t_i, with $|t_i|$ being the area of the triangle. We optimize the deformation mapping Φ indirectly by optimizing the matrices J_i which define Φ^*. These Jacobians are initialized to identity matrices. With the Jacobian representation at hand, we optimize over the triangles of M_{in} by introducing a several losses each one of which addressing a specific issue.

3D Supervisions: We employ the one-directional Chamfer Distance (CD) loss to evaluate the similarity between sets of points $p_{\text{def}} \in S_{\text{def}}$ and $p_{\text{I}} \in S_{\text{I}}$ sampled randomly in each iteration from M_{def} and $M_{\text{guide}}(I)$. This is defined as:

$$L_{\text{CD}} = \frac{1}{|S_{\text{def}}|} \sum_{p_{\text{def}} \in S_{\text{def}}} \min_{p_{\text{I}} \in S_{\text{I}}} \|p_{\text{def}} - p_{\text{I}}\|_2^2. \tag{2}$$

Regularizations: We introduce several regularizations on the deformed 3D mesh to ensure that it maintains key properties. First, we introduce Laplacian smoothing [15] denoted by L_{Lap} to redistribute vertex positions based on the average positions of neighboring vertices. This smoothing process helps to reduce irregularities and improves the overall shape of the mesh. To produce simulation-ready meshes we penalize very small surface area for triangles denoted by L_{triag} as that would result in meshes that are difficult to simulate. We do this by regularizing the edge length and by minimizing the inverse of the squared sum of the triangle areas. Note that there is a trade-off between how much a mesh can freely deform, (*e.g.* a shirt becoming a medieval armor with spikes), and how much regularization it requires such that the new garment can be placed on a parametric body and simulated.

2D Supervisions: We utilize a rasterization-based differentiable renderer [31] denoted by R and pass both the deformed mesh M_{def} in each iteration and target pseudo ground-truth mesh $M_{\mathrm{guide}}(I)$ to obtain K image renders:

$$I_{\mathrm{def}i} = R(M_{\mathrm{def}}, C_i), \quad i = 1 \dots K, \tag{3}$$

from randomly sampled camera views C_i. With $I_{\mathrm{I}i}$ computed in a similar fashion for $M_{\mathrm{guide}}(I)$ we employ the L1 loss between the deformed and target renders:

$$L_{\mathrm{2D}} = \frac{1}{K} \sum_{i=1}^{K} \| I_{\mathrm{def}i} - I_{\mathrm{I}i} |. \tag{4}$$

This supervision in the 2D space captures well the silhouette of the garment from multiple views as well as its fine-level details thereby enforcing the deformed mesh to not deviate far from the target along each step of the optimization.

Embedding Supervisions: We observe that passing garment images through a pre-trained MetaCLIP model [74] results in deformed output garments that are overly distorted, uncanny and fail to capture the fine-level details provided in the input images. This is due to the weak supervision signal contained in these embeddings. Likewise, this holds true for other mesh classes that are not well represented in the data on which MetaCLIP was trained on, such as humans. This is because MetaCLIP fails to capture the subtle differences between different garments, their properties, and materials. To overcome this limitation, we propose to use garment-specific embeddings obtained fine-tuned on fashion data termed as FashionCLIP. The latent space for this model is better tuned for fashion concepts and as a result, the embeddings provide a stronger guidance for the deformations. We represent this loss as:

$$L_{\mathrm{E}} = \frac{1}{K} \sum_{i=1}^{K} \mathrm{CosSim}\left(\mathrm{FashionCLIP}\big(I_{\mathrm{def}i}\big), \mathrm{FashionCLIP}\big(I_{\mathrm{I}i}\big)\right), \tag{5}$$

where *CosSim* is the cosine similarity. This embedding loss acts as a soft supervision signal between the embeddings of the deformed mesh M_{def} and those of the pseudo-ground-truth $M_{\mathrm{guide}}(I)$. This behavior is desired since we aim to benefit from the embedding representations of the MetaCLIP model and sufficiently deform the base mesh towards the target without capturing all of its shortcomings. For example we need to preserve the arm/head holes of the base geometry while the target mesh is watertight, or capture the fine-level details depicted in the input image that $M_{\text{guide}}(I)$ might have failed to represent well. In summary, the total loss L_{T} is defined as follows where w_* is the corresponding weight for each loss:

$$L_{\text{T}} = w_{\text{CD}} L_{\text{CD}} + w_{\text{Lap}} L_{\text{Lap}} + w_{\text{triag}} L_{\text{triag}} + w_{\text{2D}} L_{\text{2D}} + w_{\text{E}} L_{\text{E}}, \tag{6}$$

where the corresponding weights aim to strike a balance between utilizing the 3D pseudo ground-truth with the CD loss while capturing the finer image details through the embedding and 2D losses. We provide additional details in the supplementary material.

3.3 Texture Estimation

Given the untextured deformed 3D geometry M_{def}, we aim to generate high-fidelity textures that match the input image. We leverage a 2D text-to-image generation model to create high-quality, high-resolution textures with vivid details given a text prompt. For garment generation starting from images, a text prompt can automatically be obtained using image caption models or by specifying them manually. Our pipeline consists of the following steps: generating images of the given fashion asset from multiple views and backprojecting these images onto the mesh surface to create UV texture $T \in \mathbb{R}^{H \times W \times C}$. There are two challenges in adapting a 2D generation model to 3D objects: establishing geometry-texture correspondence and ensuring multi-view consistency.

Shape-Aware Generation: To ensure the texture faithfully reflects the underlying shapes, we propose using a depth-aware text-to-image generation model. Given a set of camera poses $\mathcal{C} = \{C_i\}_{i=1}^{n}$, we render the depth D_i of each view from M_{def}, and sample the appearance image I_i of view C_i conditioned on D_i and the text prompt using the text-to-image model.

Multi-view Consistency: Directly conducting view-by-view image synthesis cannot guarantee that the generated views are consistent with each other. To solve this problem, we first synthesize the front and back views simultaneously to implicitly enforce global consistency. In addition, we leverage the fact that the geometry of fashion assets is mostly flat, and conduct depth-aware inpainting for the remaining views to ensure the newly generated textures are locally consistent. To handle occluded areas, we design an automatic view selection algorithm to inpaint the textures in a coarse-to-fine manner: from the remaining unpainted area, we select the view with the most unfilled pixels to generate the textures iteratively from large regions to small pieces.

Texture Enhancement: The above texture generation pipeline can also be applied to texture refinement: given a low-quality, low-resolution initial texture T^{LQ}, we leverage the 2D appearance priors to further enhance the details. We adopt SDEdit [45], which perturbs the above sampling procedure with Gaussian noise and progressively denoises by simulating the reverse stochastic differential equations. As a result, the low-quality I_i^{LQ} is projected onto the manifold of realistic images, yielding I_i^{HQ}. By backprojecting these images, we acquire a high-quality texture T^{HQ}.

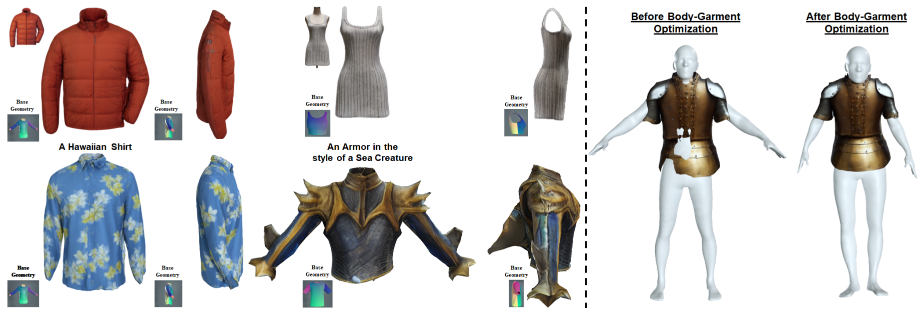

Fig. 3: 3D Garment Generation (left): Given an image or a text prompt as guidance and a base geometry mesh (bottom left inset) that can be far from the target we generate high-quality textured 3D geometries of both real as well as fantastical garments. **Fitting (right)**: We start with the generated textured 3D garment (in this case a medieval armor) and a parametric body in its canonical pose (left) and run the body-garment optimization process to optimize for the body pose and shape parameters such that the generated garment can fit in the body accurately without penetrations.

3.4 Fitting the Generated Garments to Parametric Bodies

While the aforementioned supervisions and regularizations aim to ensure that the quality of the generated garment will be satisfactory enough to be simulated, there are no guarantees that the garment shape, scale, pose and orientation will be those required to drape it on a parametric body [41] and simulate it. To accomplish this task, we run an optimization procedure during which the generated garment remains fixed in the generated pose and the pose and shape of the parametric body are transformed such that the garment can accurately fit the body. This optimization process shown in Fig. 3, starts with a rigid transformation and scaling of the body and continues with an optimization of the body pose and shape using the Chamfer distance loss. Finally, once the optimization has converged, we run an additional optimization step penalizing body-cloth collisions, ensuring that the fit is as accurate and realistic as possible.

4 Experiments

Data: We rely on a handful of artist-created garment templates covering basic cloth categories (*e.g.* T-shirt, shirt, tank-top, dress, etc). These untextured 3D meshes are in a canonical pose and will be publicly released in order to facilitate future 3D garment research. When it comes to images that serve as a guidance, we collect a variety of real images with garments in different poses, different textures, garments that do not exist in our mesh library and even AI generated garments both real and fantastical generated from a textual prompt.

Metrics: Quantitatively evaluating our results is a challenging task in the absence of 2D or 3D ground-truth 2D for what are we trying to accomplish. However we can evaluate how consistent the geometries are to the input image and hence we render the untextured outputs of all methods from 36 views and compute

Table 1: Quantitative Comparisons: Our approach outperforms deformation-based (rows 1,2) and reconstruction-based (rows 3-6) methods across both metrics while generating textured geometries that can be used for downstream tasks which is not the case for any of the prior methods.

Method	CLIP-Sim↑	LPIPS ↓	Faithful to Image	Colored Output	Head/Arm Holes
TextDeformer [18]	0.51	0.42			✓
ImageDeformer [18]	0.54	0.41			✓
Wonder3D [40]	0.56	0.41	✓	✓	
Zero123++ [60]	0.52	0.42	✓	✓	
ZeroShape [25]	0.48	0.46	✓		
T-3DGS [84]	0.57	0.41	✓	✓	
Garment3DGen	**0.59**	**0.39**	✓	✓	✓

their perceptual scores using the LPIPS metric [82] as well as their image-based CLIP similarity score using the cosine distance between their embeddings.
Baselines: We evaluate our approach against: i) TextDeformer [18] which deforms input meshes based on text prompts, ii) ImageDeformer - a variant of TextDeformer we set up - where the input text is replaced with an image, iii) Wonder3D [40] and iv) Zero123++ [60] both of which generate 3D geometries given a single image using 2D diffusion models, v) the newly introduced ZeroShape [25] which performs zero-shot reconstruction and vi) a recent triplane-based 3D Gaussian Splatting approach [84]. The first two works also take as input a base mesh whereas the latter four reconstruct the final result given a single image as input.

4.1 Image-to-3D Garments

Given an image prompt and a base mesh, Garment3DGen generates textured 3D garments matching the input image guidance. We present a plethora of image-to-3D results in Fig. 1, Fig. 3 and Fig. 6 and showcase that the generated 3D assets can be of various topologies, respect the pose, shape and texture of the input image, garments can be both real and fantastical, contain high-quality texture maps, contain fine-level details such as cloth wrinkles and folds and preserve the topology and structure of the input (*e.g.*, head, bottom and armholes are respected such that the garments can be draped on a body). In addition we quantitatively evaluate Garment3DGen against several baseline methods and report our results in Table 1. Our approach outperforms all methods in terms of both embedding as well as perceptual similarity with the input image guidance while it is the only approach that generates textured geometries that can be used for downstream tasks. Deformation-based approaches (rows 1-2) preserve the topology and the holes of the garment but lack strong supervision signals to generate outputs that match the input image. Reconstruction-based approaches (rows 3-6) are good at preserving and reconstructing what is visible in the input image but generate unusable geometries (or splats) and their color estimates for the non-visible regions are usually blurry or single colored (as shown in Fig. 6).

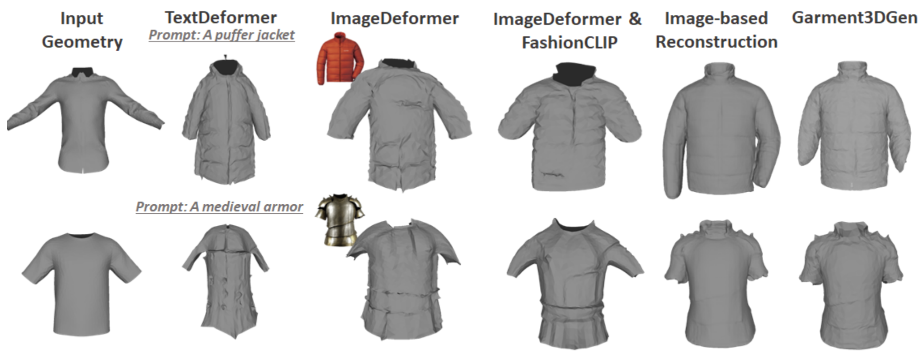

Fig. 4: Ablation Study: Starting from a base input mesh we showcase that our key contributions result in deformed geometries that capture the input image guidance, comprise fine-level garment details and are suitable for our downstream tasks.

4.2 Text-to-3D Garments

Our work can be extended to generating textured 3D garments given textual prompt inputs. Unlike TextDeformer that utilizes a text-prompt we opt for a text-to-image diffusion model as an initial step because image-based supervisions can provide a stronger guidance for our mesh deformation process. Such an approach allows the user to iterate with several text-prompts to generate the image of their desired real or fantastical garment in contrast to providing a text-prompt and waiting for the 3D asset creation process to finish to see if the result matches their intent. In Fig. 3 (row 2) and Fig. 6 (rows 3-6) we present a variety of generated garments using only the provided textual prompt as guidance.

4.3 Ablation Studies

We conduct an ablation study to assess the impact of the key components of our proposed approach. We start from a basic baseline approach and add components one at a time and showcase our findings in Fig. 4. We start with the off-the-shelf TextDeformer [18] where given a text prompt and a base-mesh we deform the input geometry to match the target text using their framework and losses. Text prompts are not ideal to capture the fine-level details of a garment as there can be many "medieval armors" and in addition a pretrained MetaCLIP [74] model is not capable of capturing the subtle differences between a "jacket" and a "puffer jacket". To overcome this limitation we adapt TextDeformer to take image inputs as guidance (ImageDeformer) and observe that the deformed geometries are one step closer to what we are after but still they fail to capture the details of the image. By swapping out the original MetaCLIP model and introducing a model fine-tuned on fashion data we observe that subtle details are better preserved across garments. An image-based reconstruction approach faithfully represents the geometry but generates coarse and watertight meshes that are unusable for downstream tasks. We use these meshes as pseudo ground-truth for our approach. Our Garment3DGen results in garments that faithfully follow the image guidance while containing the wrinkles and fine details. However the

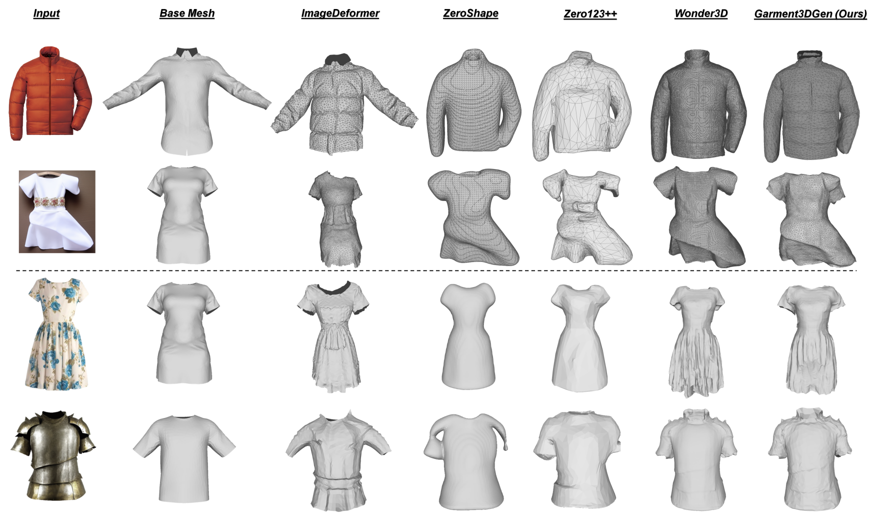

Fig. 5: Mesh Quality (Top) and Geometry Comparisons (Bottom): We showcase the wireframes of all approaches. Our method stands out as the only one that produces geometries that adhere to the input image while maintaining good mesh quality and incorporating necessary holes for physics-based simulation tasks. At the bottom we showcase the output geometry of various techniques to highlight that our approach captures fine geometric details without geometric artifacts (Wonder3D).

quality of the output geometry is not always ideal for physics-based downstream tasks (*e.g.*, cloth simulation) which is why we introduced additional 3D supervisions that preserve a better mesh quality, see Fig. 5. All prior works either do not follow the input image guidance or generate low-quality geometries that cannot be used for downstream tasks.

4.4 Applications & Discussion

Physics-based Cloth Simulation Automatically generated garments by Garment3DGen are simulation-ready and can be used directly in downstream applications, see Fig. 1, Fig. 7 and the supplemental material. We consider the generated 3D shape as rest shape for our simulations and incorporate a zero rest-angle dihedral energy to model the out-of-plane banding of the fabric. Fantastical garments such as armors are not well modeled using a zero rest-angle as they would lose their distinct shape during simulation and wrinkle unnaturally. To obtain visually pleasing results, we take the rest angle to be the 3D generated mesh one which allows it to maintain its shape throughout the simulation.
Hand-Cloth Interaction in VR Our garments are suitable for real-time simulations with hand-interaction using modern VR headsets. The rightmost part of Fig. 1 as well as the last row of Fig. 7 show a user interacting with the garments through real-time simulation with integrated hand-tracked interactions.
Garment Resizing Generated garments can further be manipulated to achieve distinct looks through garment resizing. Fig.1 shows both the generated dress on the left as well as a larger version of it on the right, draped on the same body.

Fig. 6: Qualitative Comparisons: We demonstrate several mesh generation methods starting from an input image shown on the left. We show front and back views of each reconstruction. The 3D Gaussian Splatting [84] method generates distorted frontal colors and dark or blurry back colors while its geometry is not suitable for downstream tasks such as simulation. The second reconstruction approach [40,83] generates watertight meshes with very coarse geometric details and blurred out colors. Our proposed approach outputs 3D geometries that are geometrically correct with fine-level texture details that prior works fail to generate.

Sketch to Garment Fig. 7 shows an application to generate 3D simulation-ready garments starting from a rough sketch shown in the top left. Given a sketch, we generate a realistic image using ControlNet [81] which then serves as the input to our method to generate the corresponding 3D asset. We show simulation results of this automatically generated dress.

Runtime: Our approach takes ~24 mins on a single TITAN RTX to generate the final 3D garment where 60% of this time is dedicated to the MeshDeformer (Sec.3.1), 20% to the target geometry generation (Sec.3.2), 18% to the cloth-body fitting (Sec.3.4) and 2% to the texture estimation (Sec.3.3). Optimizing for speed

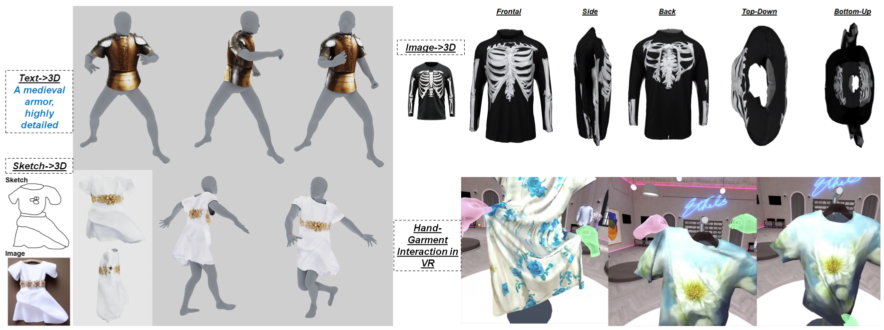

Fig. 7: Applications: Garment3DGen can generate textured 3D garments from images, from text prompts, from simple sketches, that can be fitted to human bodies and drive them with physics-based cloth simulation or even enable interaction between hands and garments in a VR environment.

was not among our objectives but several low-hanging fruits (*e.g.*, early stopping of the deformation) exist and could be tackled to improve performance.

Limitations: Garment3DGen handles a variety of garment types both real and fantastical. Due to the requirement of a template mesh, there is a limitation to what garments can be generated whilst still providing good distortion-free meshes. This can be mitigated by providing a more diverse template library. Our estimated textures, while faithful to the image, sometimes do not fully preserve fine-level details. We plan to address this by tuning the texture enhancement module to be conditioned on the reference image across all views while maintaining its multi-view color consistency properties.

5 Conclusion

We proposed Garment3DGen a new approach to generate high-quality, physically plausible garment assets that can be directly used for downstream applications. We introduced a deformation-based approach that takes a base mesh as input along with an image guidance and outputs a textured geometry that faithfully matches the input image while preserving the structure and topology of the input mesh. Our key contributions stem from utilizing novel diffusion-based generative models to synthesize 3D pseudo ground-truth that can be used as a soft supervision signal along with additional regularizations, a texture enhancement module that generates high-fidelity texture maps and a body-cloth optimization framework that fits the generated 3D garments to parameteric bodies. Our approach clearly outperforms prior work across all metrics while producing physically plausible and high-quality garment assets. Finally, we showcased several applications where the output geometries of Garment3DGen are used for physics-based cloth simulation, hand-garment interaction in a VR environment as well as going directly from a simple sketch image to a drivable 3D garment.

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Supplementary Material

We refer the interested reader to the supplemental video where we provide a wide variety of results ranging from image/text to 3D textured garments as well as applications of our method in downstream tasks such as physics-based cloth simulation, hand-garment interaction in VR using a headset and sketch to 3D garment reconstruction. Below we provide some additional details regarding the implementation of our key components as well as some additional ablation studies to showcase the impact of our design decisions.

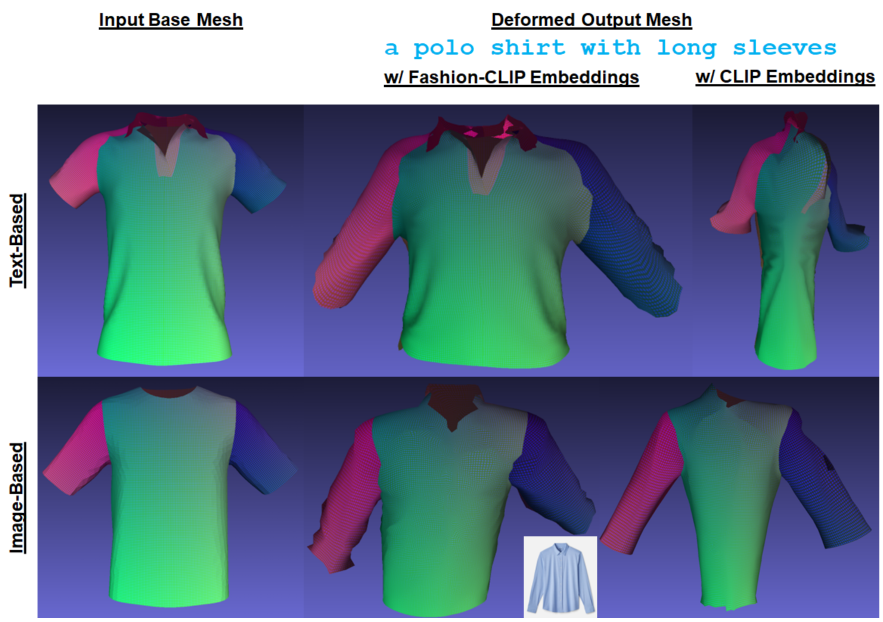

Fig. 8: Impact of the pre-trained CLIP on garment data: We disable all other supervisions and explore the impact of a pre-trained CLIP model on fashion data versus using the regular model to enforce embedding supervisions. We observe that regular CLIP embeddings result in distorted and unusable geometries regardless of whether the input is a text prompt or an image.

Garment3DGen Details

Insights and Key Contributions: We believe that our approach provides three key insights that will be valuable to the community:

1. Mesh-based deformations provide the right properties to generate (or stylize) new garments that we can utilize for downstream tasks other than rendering.
2. A text-prompt or a single image alone cannot provide enough guidance to generate the desired garment exactly the way a user might want it

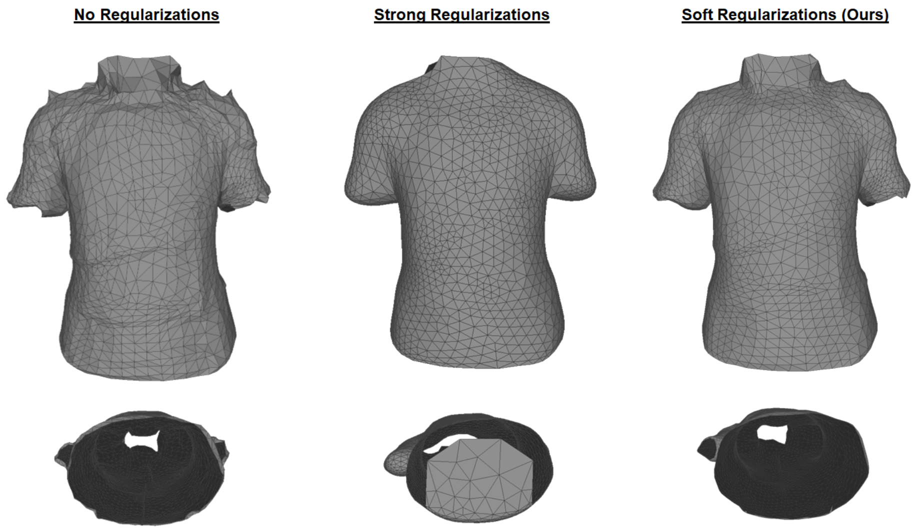

Fig. 9: Impact of regularizations on the final armor geometry: Enforcing no regularizations (Laplacian smoothing, penalization of small triangles etc.) on the output mesh results in a crisp output armor mesh with arm/body holes but its quality is not at the level required to perform physics-based simulation. On the other hand, enforcing strong regularizations results in overly smoothed meshes with closed holes. Our output strikes a good balance between capturing those fine-level details that make an armor geometry look like one yet making it suitable for downstream tasks.

3. 3D supervisions, if done right, can provide strong enough supervision signal in order to generate the desired garments with the proper topology and structure.

Our approach builds upon these insights and introduces a novel yet simple solution to generate high-quality, physically plausible garments. As input to the method, we require only a single garment image (or alternatively, a text prompt that can generate this image using a text to image model) and a base garment template mesh. This template mesh is not required to be similar to the image guidance. For example, we demonstrate results where our method can go from a shirt to a puffer jacket, from a tank-top to a dress or even a T-shirt to a fantastical sea armor. Note that the closer the base mesh is to the target geometry, the easier the task is. For example, starting from a dress mesh to go to a shirt is a difficult task while starting from something closer to the target simplifies this problem.

Differences with Past Works: We highlight the unique and novel aspects of our method and its differences with prior works. Our deformation-based formulation is inspired by the Neural Jacobian Fields [1] work and its application to text-based deformations in TextDeformer [18]. TextDeformer however suffers from some key limitations: a) it can only work for general-purpose objects and text-promts (*e.g.* turning a cow to a giraffe) and fails to capture the intricate details of garments, b) it is a severely under-constrained problem since a single

Fig. 10: Impact of Texture Module: given the left image as a condition, the texture enhancement module enriches the details and enhances the overall image quality by effectively utilizing the powerful 2D priors.

text-prompt is used to guide the deformation and as such the authors enforced additional supervisions (*i.e.*, multi-view consistency, Jacobian regularization) that add marginal value to the solution. Instead our proposed formulation utilizes 3D pseudo ground-truth to supervise the deformation process and as such it does not require any additional consistency losses or Jacobian regularizations. Furthermore several past works [18,46,48] rely on traditional CLIP embeddings to guide their text-to-mesh tasks which provide limited signal for specific domains or categories (*e.g.* garments or humans). Until we have a 3D foundation model that can capture such intricacies well, we believe that fine-tuned domain-specific models can provide valuable guidance for text/image to 3D tasks and we provide an ablation study to showcase this in Fig. 8. Another line of work approaches this task from an image to 3D reconstruction viewpoint. Methods such as Wonder3D, Zero123++ or ZeroShape generate watertight geometries that lack fine-level details (due to the use of Marching Cubes) that require additional post-processing and manual editing (to open holes in the neck, waist and arm regions) in order to be able to be fitted to human bodies. We believe that our approach strikes the right balance between reconstruction-based and deformation-based approaches. It benefits from the ability of reconstruction-based approaches to generate 3D pseudo ground-truth from a single image input that can act as a stronger supervision signal and at the same time remain in the mesh deformation space which better ensures topology preservation and output meshes that can fairly easily be fit to parametric human bodies and simulated.

Automatic View Selection: The goal of this algorithm is to automatically select the least-painted view and paint it. In this way, we can solve the 3D texture generation problem in a coarse-to-fine manner, and ensure the overall consistency. Alg. 1 provides a detailed description of the automatic view selection

Fig. 11: Fantastical Garments generated from text prompts or image inputs: Given a variety of text (or image) inputs along with a base mesh (tank-top, t-shirt and poncho meshes) we deform the base geometry to match the target, generate the corresponding high-fidelity texture and put everything together to render the final results from three different views.

algorithm: given the input UV texture T with painted front and back views, there could be N candidate views. We maintain a binary mask T^B that marks the painted pixel as 1, and unpainted pixel as 0. We can select the view with the most unfilled pixels as the next view to generate the appearance, and update the binary mask T^B. This process is repeated iteratively until most of the pixels are painted, or reaching a certain iteration number.

This approach prioritized filling in the large areas first before moving on to smaller and more occluded regions.

Cloth Simulation and Material Parameter Selection: Our method produces simulation-ready meshes that can be simulated using any cloth simulator. In our examples, we use a GPU implementation of the XPBD [43] algorithm to obtain real-time results. Since different garments are made out of different

Algorithm 1: Automatic View Selection

Input: an input mesh M_{def} with UV texture T with front and back views painted, a binary mask T^B marking the painted pixels of T, and N uniformly distributed candidate views $\{C_i\}_{i=1}^N$;
for *number of iterations* **do**
  Calculate the binary mask T_i^B for each view i from T^B: $\{T_i^B\}_{i=1}^N$;
  Select the least painted view C_j: $j \leftarrow \arg\min_{i=1}^N \sum T_i^B$;
  Generate the appearance image I_i and update T^B;
end

fabrics, we manually pick material parameters to model the difference, e.g. the armor will be modeled using a higher bending and stretching stiffness compared to the other garments. Producing material parameters in conjunction with simulation-ready meshes is out of scope for this work but parameters could be automatically recovered using recent advances in differentiable simulation such as DiffAvatar [33].

Additional Ablation Studies

Supervisions: When it comes to supervisions we observed that: a) utilizing regular CLIP embeddings provides minimal supervision guidance when it comes to garments and results in poorly deformed meshes which is why we opted for a garment fine-tuned model as shown in Fig. 8, b) explicitly enforcing multi-view consistency losses is not necessary as 3D supervisions can provide better guidance, and iii) there is a trade-off between allowing for heavy garment stylizations/deformations and maintaining a good mesh quality that can be used later on as shown in Fig. 9. Thus we propose to use a combination of 3D supervisions to guide the deformation process to obtain an accurate 3D shape along with 2D and embedding supervisions to obtain the fine-level details of the garment that the 3D pseudo ground-truth might fail to capture. We train for ~1000 iterations with the weights of each loss described in Eq. (6) as follows: $w_{CD} = 20, w_{Lap} = 1, w_{triag} = 1, w_{2D} = 2, w_E = 4$ with the weight of W_{CD} gradually decreasing after the first 500 iterations once we have obtained a fairly accurate pose and shape of the garment to allow for the remaining of the supervisions to distill the fine-level garment details. Note that if we were to enforce strong 3D supervisions we would end up with deformed garments that would have no holes for the body, arms and head.
Texture Module: The impact of the texture enhancement module is shown in Fig. 10. The textures directly synthesized by 3D generation models tend to be low-resolution, smooth and over-simplified, which is due to the scarcity of high quality 3D training data. Thus, the texture enhancement module aims to effectively utilize the 2D priors learned from the large high-quality image dataset. After our image-conditioned image enhancement, we bring back vivid details to the texture, improving the perceptual quality.

Additional Results

In Fig. 11 we provide multi-view renders of our 3D textured garments that we generate from text prompts (first two lines) and an image guidance. From these results we gain the following insights: a) Garment3DGen works just as well with fantastical garments (armors or dresses) that are outside the regular garment distribution, b) our texture estimation module results into high-quality textures that closely match the input text prompt and c) our output geometry does not have to be similar to the input base mesh.