Supplemental Material for Neural Garment Dynamic Super-Resolution

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Fig. 1. We visualize the distribution of motion sequences used for generating training data (House and swing) and the testing data (rumba, salsa, samba, samba variant, boxing warm-up, normal walking, happy walking) via t-SNE [Van der Maaten and Hinton 2008].

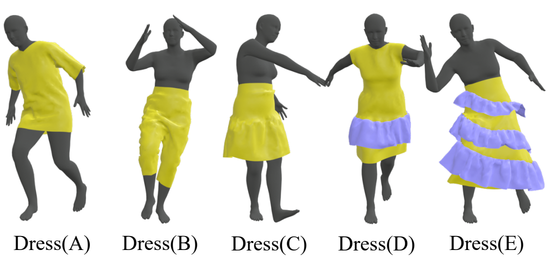

Fig. 2. We design 5 garment outfits to train the network of our method.

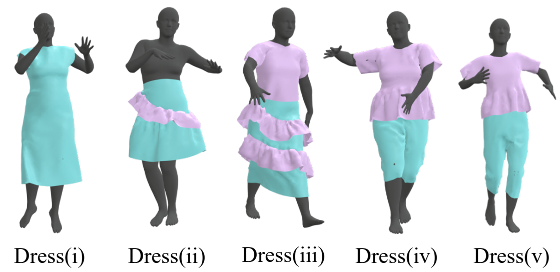

Fig. 3. We design 5 garment outfits to test the generalization ability of our method across different garment types.

1 DATA GENERATION

We employ SMPL [Loper et al. 2015] to extract body shapes, and subsequently utilize rigging and animation techniques through Mixamo[1] to generate 9 sequences of motion.

We train our network using dance sequences of *swing dancing* (714 frames) and *house dancing* (794 frames) on a fixed body shape, while we conduct testing on rumba dancing (365 frames),salsa dancing (580 frames), samba dancing (609 frames), samba variant (513 frames), boxing warm-up (203 frames), normal walking (1510 frames) and happy walking (1510 frames). We visualize the distribution of the motion sequences via t-SNE [Van der Maaten and Hinton 2008] in Figure 1.

To generate garments, we employ physics-based simulation through Marvelous Designer[2] with a material of silk chamuse and generate low- and high-simulation with particle distance set at 30mm and 10mm, respectively. We model 5 garment outfits (colored in yellow or purple) to generate training data with the pre-defined training motion sequences: (A) a long sleeve t-shirt, (B) a pair of long pants, (C) a pleated short skirt, (D) a double-layered dress, (E) a triple-lace long skirt. We illustrate the garment types of training data in Figure 2.

To test the generalization capability of our method across out-of-training garment types, we generate 5 new garment outfits (colored in teal or pink): (i) a single-layered long dress, (ii) a laced pleated short skirt, (iii) a full-body combination of short sleeve t-shirt and double-lace long skirt, and a full-body combination of lace t-shirt and pants in large size (iv) and small size (v). We illustrate the garment types of training data in Figure 3. With the low-resolution simulation as input, we train our network in a fully supervised manner with the high-resolution simulation as the ground truth. We test our network directly with the low resolution simulation as input. We list the number of garment vertices of both our training and testing data in Table 1.

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[1]https://www.mixamo.com/
[2]https://marvelousdesigner.com/

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Table 1. We list the number of garment vertices for both our training and testing data. Our method generates high resolution garment geometry with approximately 10 times the number of vertices of the low resolution simulation input.

training garment			testing garment		
Dress	LR	HR	Dress	LR	HR
(A)	2063	18445	(i)	2485	22044
(B)	1783	16083	(ii)	2272	19618
(C)	1161	14528	(iii)	4771	41554
(D)	3176	27855	(iv)	3607	32025
(E)	5010	43257	(v)	2519	22538

2 ROBUSTNESS OF LONG ROLL-OUT PREDICTION

We use average stretching and shearing energies[Baraff and Witkin 1998] of garment mesh triangles to evaluate the stability of high-resolution garment deformation with our method under long roll-out predictions. We compute the deformation mapping matrix $w(G_t)$ from the 2D cloth plane coordinate (u, v) to the garment G_t in the world space. We define the stretching energy as $E_u = \|\|w_u(G_t)\| - 1\|^2$ and $E_v = \|\|w_v(G_t)\| - 1\|^2$, along the u and v directions respectively. Thus, the garment mesh triangle is un-stretched whenever $E_u = 0$ and $E_v = 0$. We define the shearing energy as $E_{uv} = (w_u(G_t) \cdot w_v(G_t))^2$. When $E_{uv} = 0$, the triangle is un-sheared. Table 2 shows that under long roll-out predictions of up to 1500 frames, our method produces reasonable high-resolution garment geometry. The stretching and shearing energies remain stable within a small range, preventing excessive deformations.

Table 2. We apply the average stretching energy (E_u, E_v) and shearing energy (E_{uv}) of the garment mesh triangles to evaluate the stability of garment mesh deformation with our method under long roll-out predictions. Our method produces reasonable high-resolution garment geometry with the stretching and shearing energies remaining stable within a small range, preventing excessive deformations.

seen garment: Dress(E)					
	1-step	roll-50	roll-100	roll-1000	roll-1500
E_u	0.020	0.038	0.029	0.028	0.029
E_v	0.012	0.022	0.017	0.013	0.016
E_{uv}	0.034	0.050	0.048	0.041	0.046
unseen garment: Dress(iii)					
	1-step	roll-50	roll-100	roll-1000	roll-1500
E_u	0.028	0.031	0.032	0.041	0.036
E_v	0.012	0.016	0.019	0.024	0.019
E_{uv}	0.042	0.056	0.056	0.065	0.059

3 COMPARISONS

To evaluate the similarity of the detailed wrinkle patterns to the high-resolution simulation, we conducted a quantitative assessment using the Structural Similarity Index Measure (SSIM) [Wang et al. 2004] on sequences of normal maps rendered from the garment geometries. As shown in Table 3, our method outperforms the baseline approaches [Halimi et al. 2023; Zhang et al. 2021], producing high-resolution garment geometries with wrinkle patterns that more closely align with the high-resolution simulation references in terms of wrinkle detail structure.

Table 3. With low-resolution simulation as input, we employ the Structural Similarity Index Measure (SSIM) [Wang et al. 2004] to compare the performance of our GDSR, DDE[Zhang et al. 2021], PhysGraph [Halimi et al. 2023] and its variant (PhysGraph(-)) on a t-shirt (A), a pleated short skirt (C), and a triple-lace long skirt (E). We report the average SSIM over 300 frames of normal maps from an unseen motion sequence.

Dress	PhysGraph	PhysGraph(-)	DDE	GDSR
(A)	0.831	0.848	0.855	**0.879**
(C)	0.746	0.779	0.783	**0.816**
(E)	0.685	0.723	0.735	**0.788**

4 COMPUTATION TIME

Table 4 presents the computation time required to simulate a single frame of high-resolution garment geometry for Dress (C), (D), and (E), with 14,528, 27,855, and 43,257 vertices respectively. Compared to the high-resolution physics-based simulation in Marvelous Designer (MD), our method achieves significantly better efficiency, particularly for complex garment types. For instance, while the high-resolution simulation with MD takes 0.559 seconds, our GDSR method requires only 0.115 seconds to enhance wrinkle details on the low-resolution simulation, including 0.083 second running in MD for coarse garment generation.

We also compared the computation time of our method with DDE and PhysGraph. Our method synthesizes high-resolution wrinkle details on the coarse garment shape for Dress (C) in just 0.014 seconds, significantly outperforming DDE, which takes 0.202 seconds due to its time-consuming normal-guided garment geometry deformation process, and PhysGraph, which takes 0.057 seconds as it operates on the high-resolution garment meshes up-sampled from the coarse input. All running times for MD and the detail enhancement methods were tested in the same computational environment: a 12th generation Intel Core i7 and a GeForce RTX 3090.

Table 4. We report the computation time required to simulate a single frame of high-resolution garment geometry for Dress (C), (D), and (E), with 14,528, 27,855, and 43,257 vertices respectively. We compare the running efficiency of our GDSR method with high-resolution physics-based simulation in Marvelous Designer (MD), as well as with DDE [Zhang et al. 2021] and PhysGraph [Halimi et al. 2023]. The reported times are in seconds. For GDSR, PhysGraph and DDE, we report the algorithm running time plus ('+') the time cost of low-resolution simulation in MD.

Dress	PBS	GDSR	PhysGraph	DDE
(C)	0.194	**0.014**+0.045	0.057+0.045	0.202+0.045
(D)	0.374	**0.024**+0.058	-	-
(E)	0.559	**0.032**+0.083	-	-

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