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# Controllable Garment Image Synthesis Integrated with Frequency Domain Features –Supplemental Material–

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# 1. Comparison with Existing Approaches

Figures 1 and 2 show results of our framework compared with FashionGAN [CLGS18], TextureGAN [XSA\*18], MU-NIT [HLBK18], ReferenceGAN [LKL\*20], SSSIM [LZSE21] and DiSS [CCC\*23].

## 2. Ablation Studies

# 2.1. Effectiveness of FFT-based Generator

We show more comparison results between a FFT-based generator (FcF generator [JZYS23]) and a generator without FFT (co-modulated StyleGAN2  $[ZCS^*21]$ ) in Figure 3.

## 2.2. Frequency Perceptual Loss

We show more comparison results between models with and without the frequency perceptual loss in Figure 4.

## 2.3. High Receptive Field Perceptual Loss

We validate the effectiveness of high receptive field perceptual loss  $L_{hp}$ . As shown in Figure 5, it improves the structural details of the synthetic garment images (*e.g.*, details and realism of collar). The quantitative results are shown in Table 1.

### 2.4. Feature Fusion Module

We also study the effectiveness of different feature fusion modules. Our framework uses attention-based SCFT [LKL\*20] to fuse the sketch feature vector and the texture feature vector from the dualbranch encoder. We also evaluation the performance of directly concatenating the two feature vectors in the channel dimension. Table 1 shows the quantitative comparisons.

### 3. Diversity of Texture Patterns

Figure 6 shows the diversity results with various textures.

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Table 1: Ablation study.

	FID↓	LPIPS↓	c-FID $\downarrow$	c-LPIPS↓
w/o $L_{hp}$ Direct concatenation	31.143 17.389	0.264 0.127	44.128 33.197	0.529 0.373
Ours	17.146	0.126	31.796	0.371

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Figure 1: Qualitative comparison with baseline methods. The texture patch of different sizes and the garment sketch in the first and the second columns are used as the inputs.

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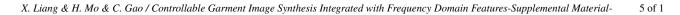
Input Texture	Input Sketch	Ours	FashionGAN	TextureGAN	MUNIT	ReferenceGAN	SSSIS	DiSS
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Figure 2: Qualitative comparison with baseline methods. The texture patch of different sizes and the garment sketch in the first and the second columns are used as the inputs.

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Figure 3: Comparisons between methods with and without FFT-based generator.



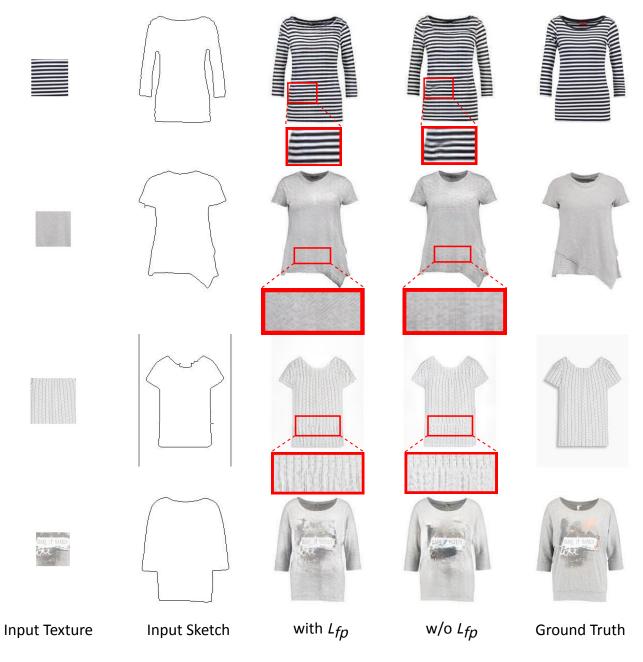


Figure 4: Comparisons between methods with and without our proposed frequency perceptual loss  $(L_{fp})$ .

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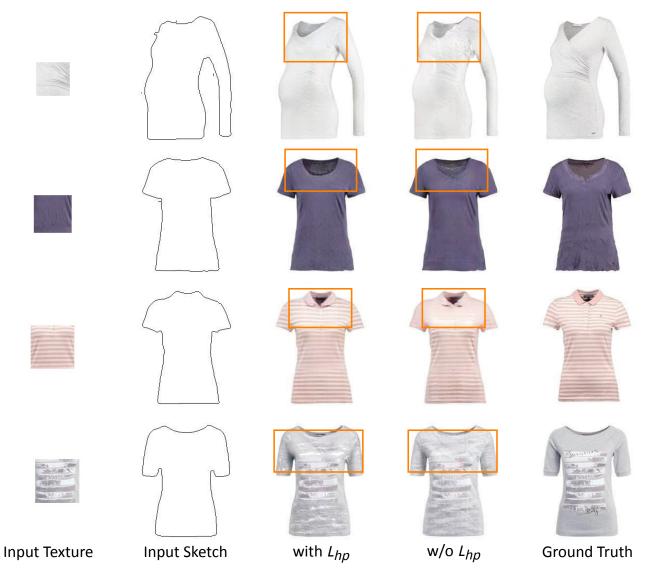


Figure 5: Comparisons between methods with and without high receptive field perceptual loss perceptual loss  $(L_{hp})$ .



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Figure 6: Diversity results with various textures per garment sketch.