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GP-VTON: Towards General Purpose Virtual Try-on via Collaborative Local-Flow Global-Parsing Learning

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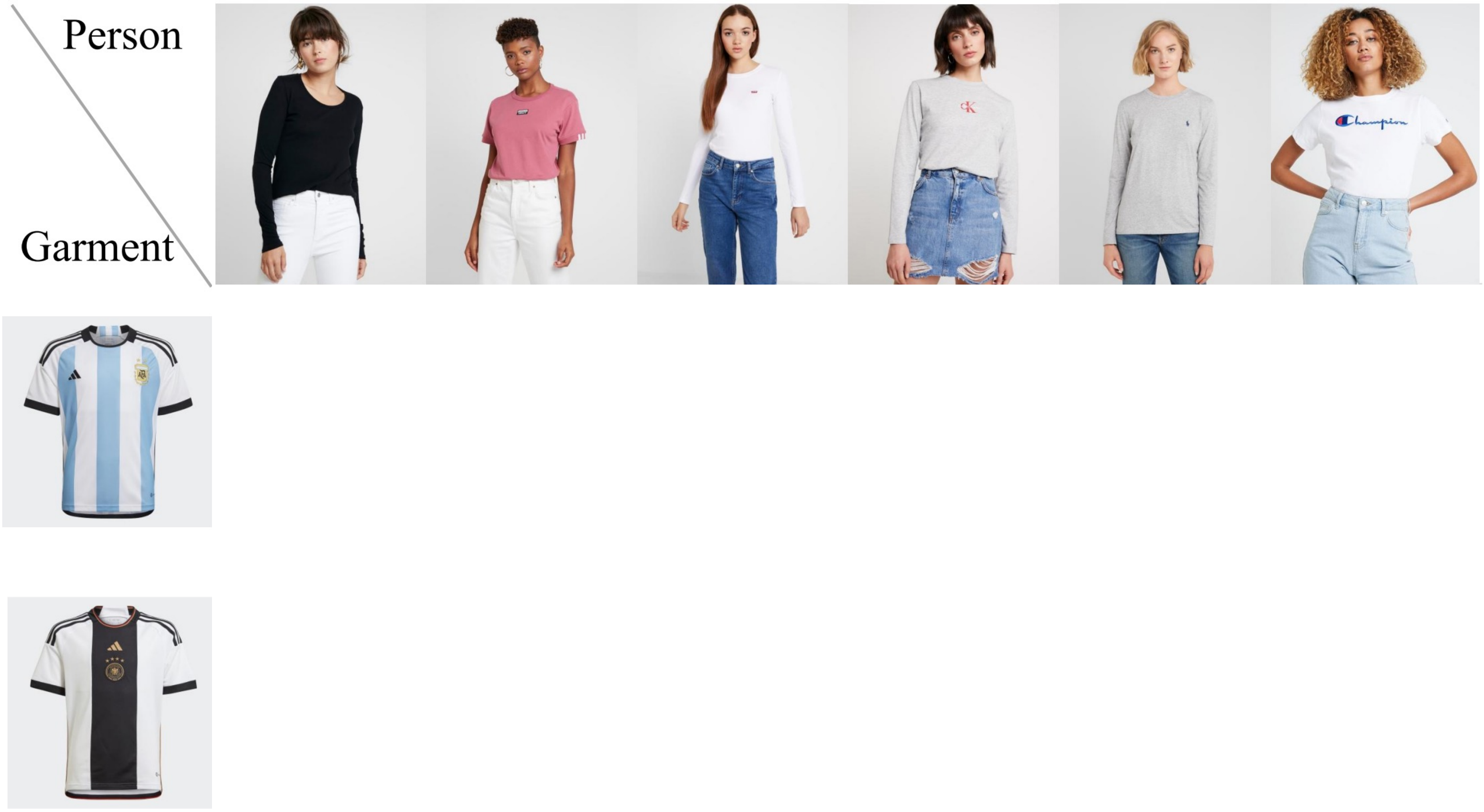
Paper Tag：THU-PM-281

Contributions

- Propose a unified framework, GP-VTON, for ***diverse virtual try-on scenarios***.
- Propose LFGP warping module for ***semantic-correct garment deformation***.
- Introduce DGT training strategy for ***distortion-free garment deformation***.
- Outperform existing SOTAs on two virtual try-on benchmarks.

Task Definition

- Given a **source person** and a **target garment**,



Task Definition

- Given a **source person** and a **target garment**, image-based virtual try-on aims to **transfer the garment onto the specific person**.

Motivation

➢ Problem of Existing Methods

- Fail to handle ***challenging inputs*** (e.g., intricate pose, hard garment)

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  - Suffer from ***texture distortion*** in the warped result

- Motivation
  - Exploit local warping flow for ***semantic-correct*** deformation
  - Exploit global parsing to ***combine different local warped results***
  - Introduce a novel training strategy for ***distortion-free*** deformation

Method Overview

- Garment Warping Module
  - Local-Flow Global-Parsing (LFGP) Warping Module
  - Dynamic Gradient Truncation (DGT) Training Strategy
- Try-on Generator

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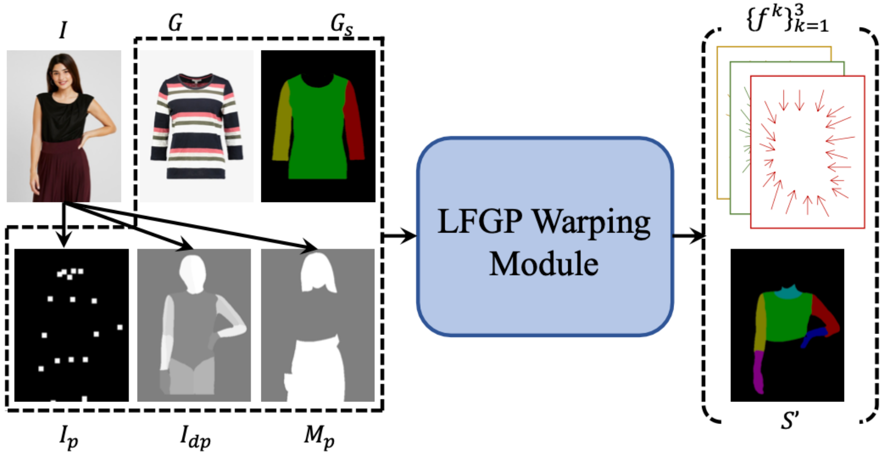

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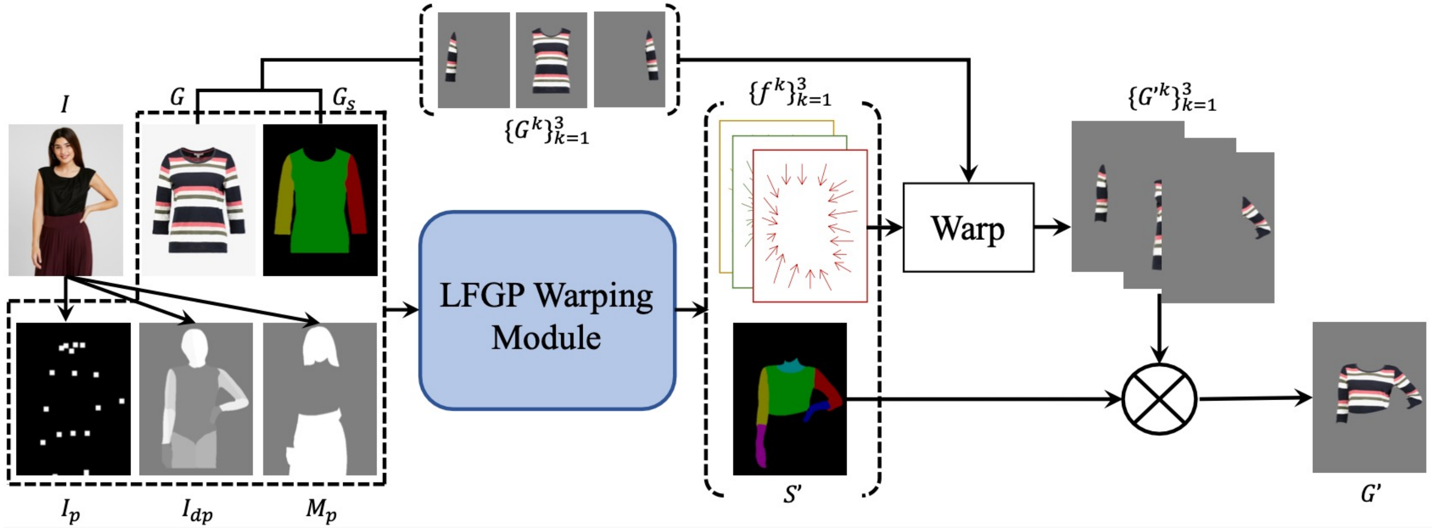

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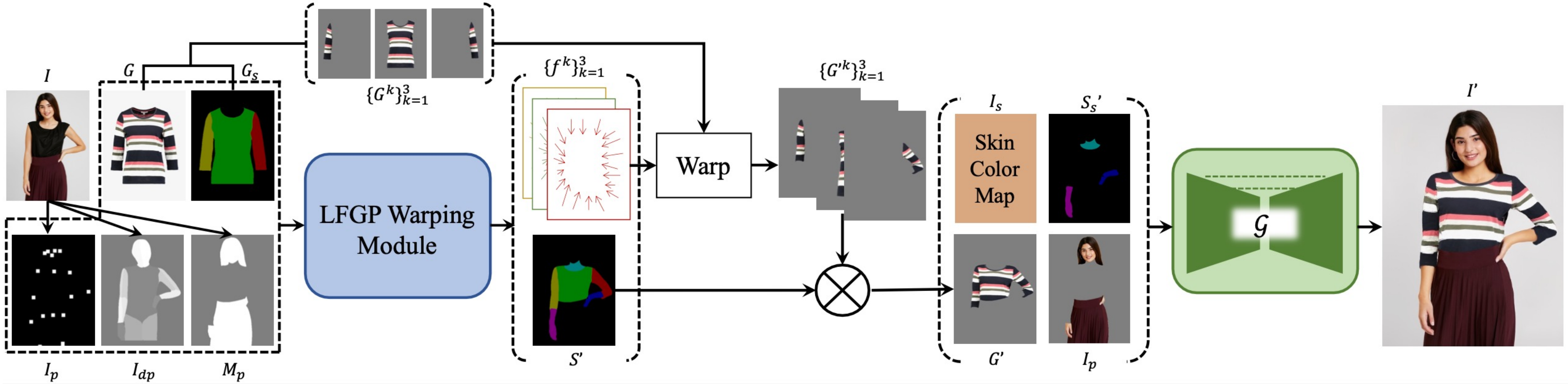
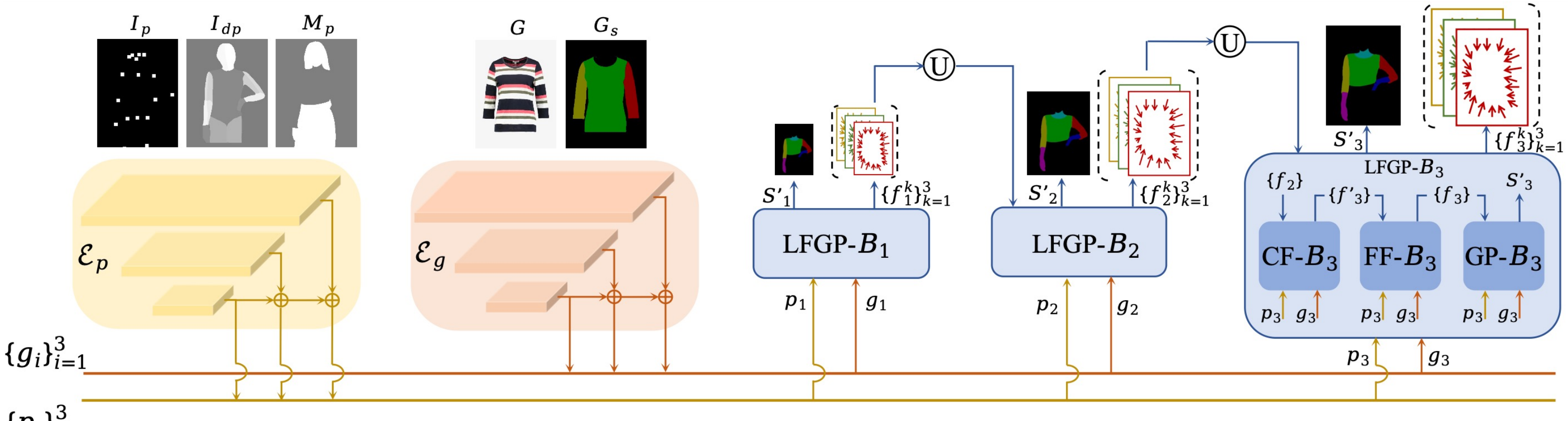


LFGP Warping Module

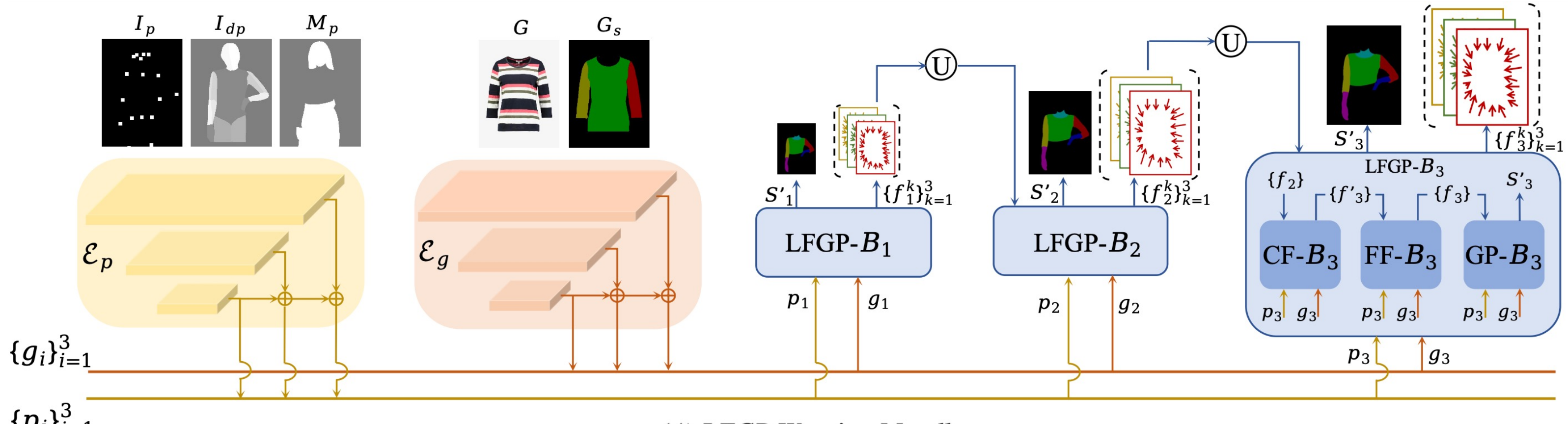
- LFGP Warping Module consists of a person encoder, a garment encoder and cascade local-flow global-parsing estimation blocks.



(A) LFGP Warping Moudle

LFGP Warping Module

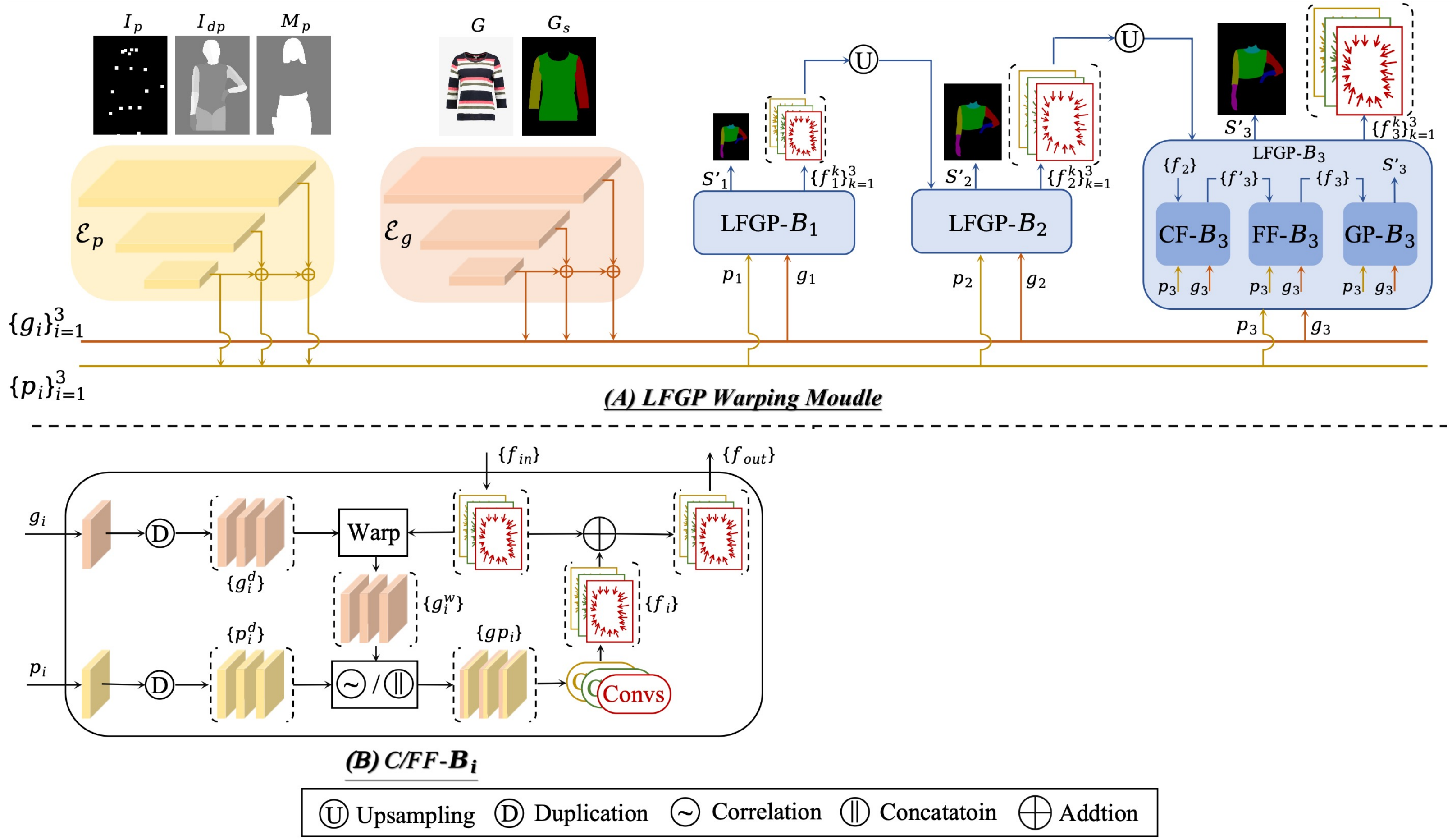
- Each LFGP estimation block consist of the two flow estimation blocks and one parsing estimation block.



(A) LFGP Warping Moudle

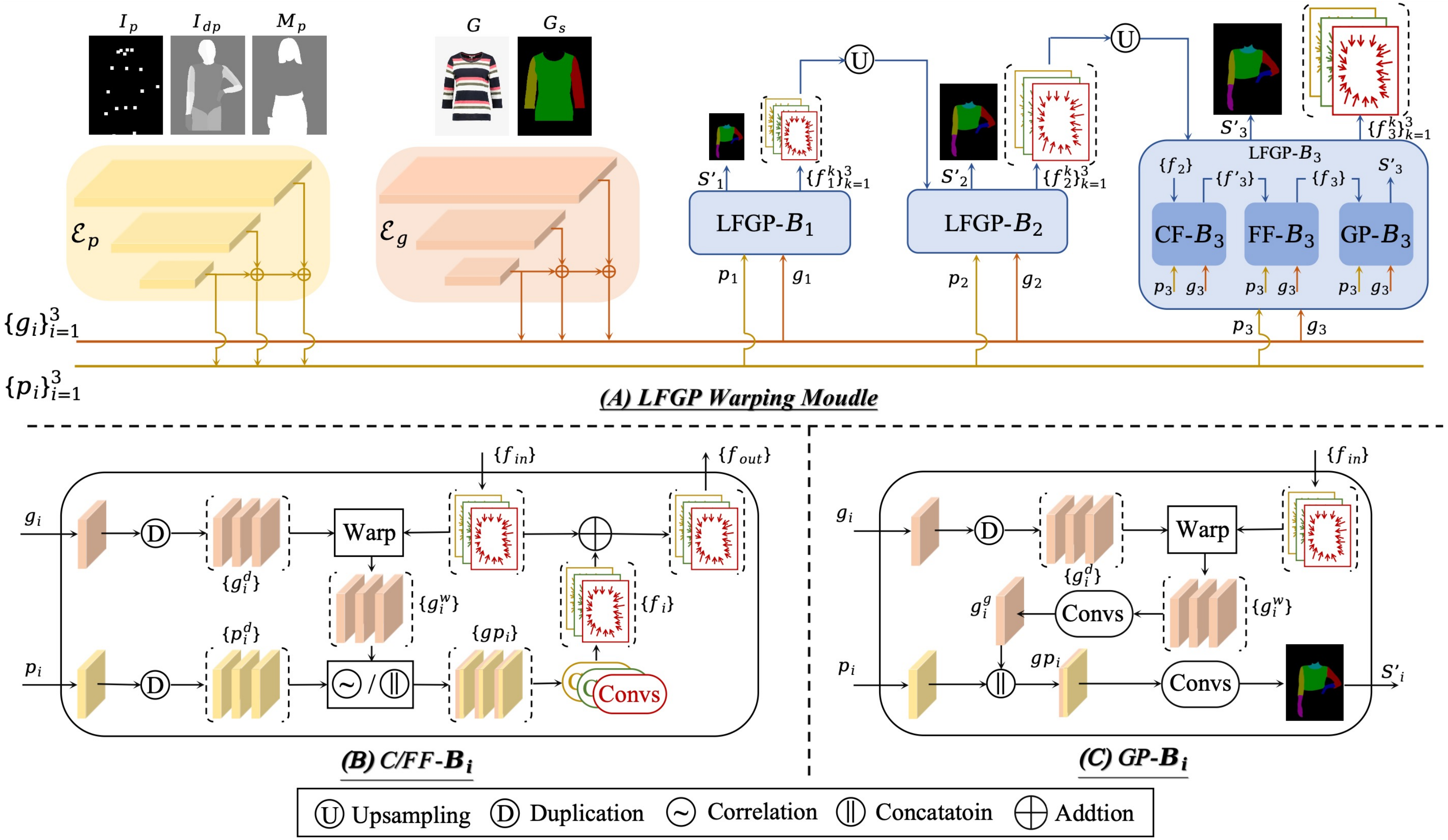
LFGP Warping Module

- The flow estimation block takes as inputs the person feature, garment feature and the previous estimated flow, then outputs the current estimated flow .



LFGP Warping Module

- The parsing estimation block takes as inputs the person feature, garment feature and the previous estimated flow, then outputs the estimated parsing.



DGT Training Strategy

- Out DGT training strategy **dynamically penalized the overlapping region** in warped garment according to the **wearing style** of the person image.

- **Red region:** the warped result will be penalized and the **gradient will be backpropagated**.
- **Green region:** the warped result will be neglected and the **gradient will be truncated**.

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$$R_{style} = \frac{R^{warped}}{R^{flat}} \quad (1)$$

$$R^{*} = \frac{H^{*}}{W^{*}}. \quad (2)$$

Experiment Results

- Qualitative Comparisons on VITON-HD dataset

Experiment Results

- Qualitative Comparisons on DressCode dataset

Experiment Results

- Quantitative Comparisons on VITON-HD and DressCode dataset

Method	SSIM ↑	FID ↓	LPIPS ↓	mIoU ↑	HE ↑
PF-AFN [12]	0.8858	9.475	0.0871	0.8412	14.9%
FS-VTON [19]	0.8829	9.552	0.0906	0.8357	8.80%
HR-VITON [29]	0.8623	16.21	0.1094	0.6949	9.10%
SDAFN [1]	0.8821	9.400	0.0922	0.5927	16.3%
GP-VTON (Ours)	**0.8939**	**9.197**	**0.0799**	**0.8764**	**50.9%**

Table 1. Quantitative comparisons on VITON-HD dataset [6]

Dataset	DressCode-Upper					DressCode-Lower					DressCode-Dresses				
Method	SSIM ↑	FID ↓	LPIPS ↓	mIoU ↑	HE ↑	SSIM ↑	FID ↓	LPIPS ↓	mIoU ↑	HE ↑	SSIM ↑	FID ↓	LPIPS ↓	mIoU ↑	HE ↑
PF-AFN [12]	0.9454	14.32	0.0380	0.8392	14.0%	0.9378	18.32	0.0445	0.9463	12.3%	0.8869	13.59	0.0758	0.8743	15.0%
FS-VTON [19]	0.9457	13.16	0.0376	0.8381	5.33%	0.9381	17.99	0.0438	0.9478	14.7%	**0.8876**	13.87	0.0745	0.8760	8.33%
HR-VITON [29]	0.9252	16.86	0.0635	0.6660	3.00%	0.9119	22.81	0.0811	0.8670	2.67%	0.8642	16.12	0.1132	0.7209	2.33%
SDAFN [1]	0.9379	12.61	0.0484	0.5046	11.3%	0.9317	**16.05**	0.0549	0.4543	13.3%	0.8776	**11.80**	0.0852	0.5945	19.3%
GP-VTON (Ours)	**0.9479**	**11.98**	**0.0359**	**0.8766**	**66.3%**	**0.9405**	16.07	**0.0420**	**0.9601**	**57.0%**	0.8866	12.26	**0.0729**	**0.8951**	**55.0%**

Table 2. Quantitative comparisons on DressCode dataset [32]

Experiment Results

- Ablation Study

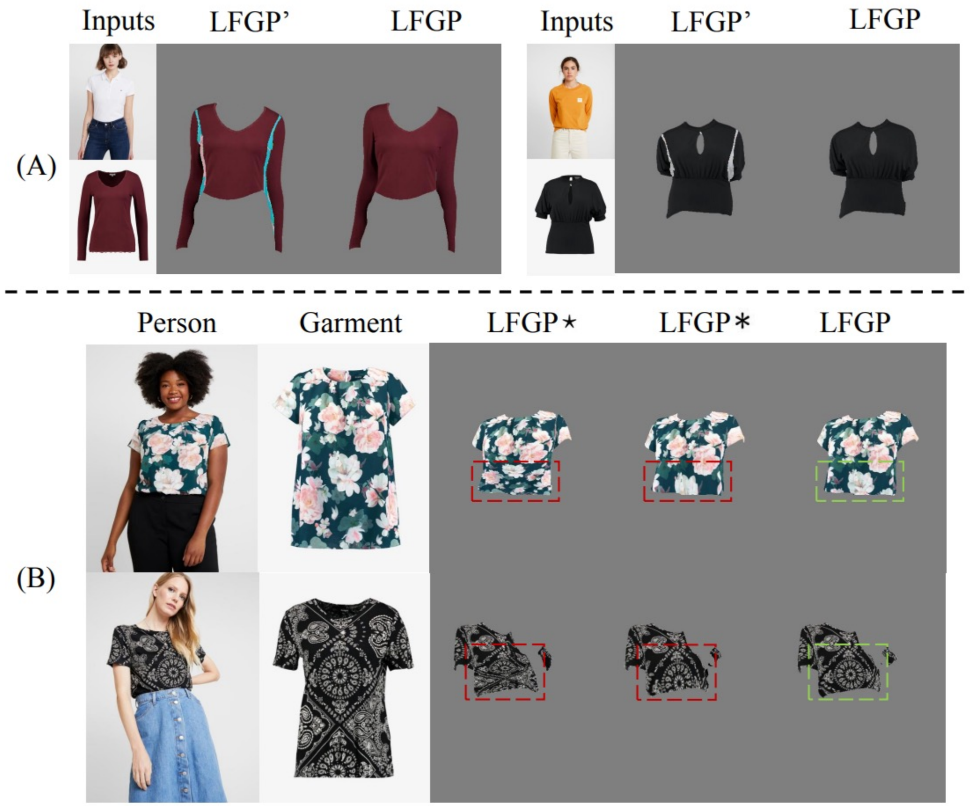

Figure 8. Ablation studies on the effectiveness of (A) the global parsing during the parts assembling process and (B) the dynamic gradient truncation training strategy.

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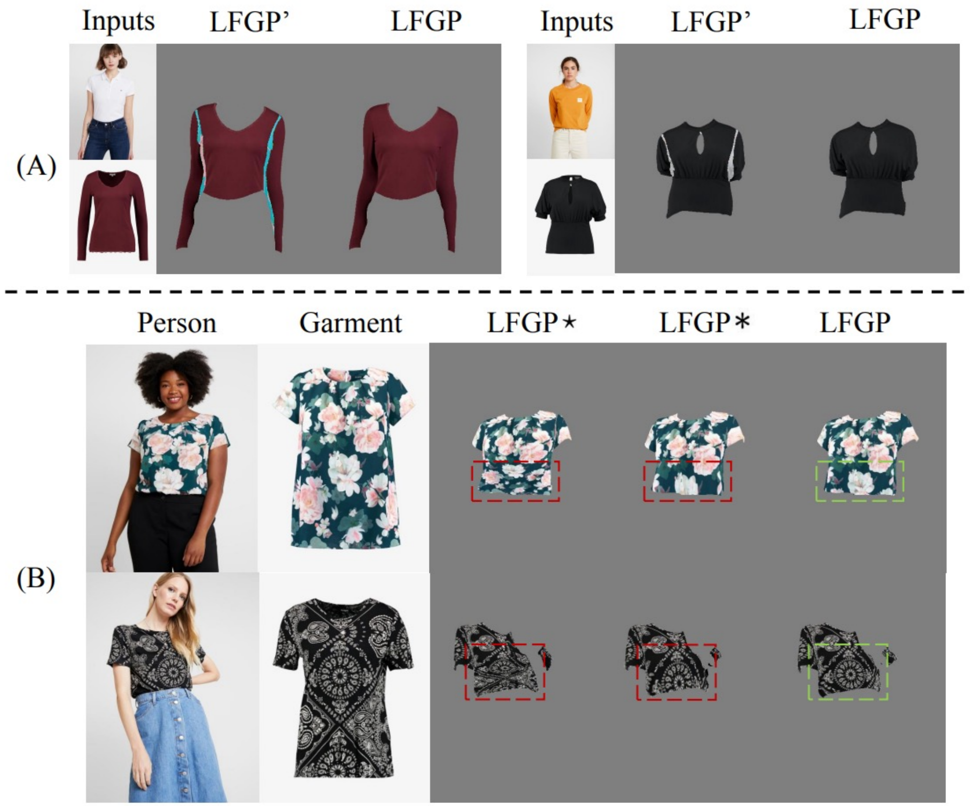

Figure 8. Ablation studies on the effectiveness of (A) the global parsing during the parts assembling process and (B) the dynamic gradient truncation training strategy.

Method	LF	GT	DGT	SSIM ↑	LPIPS ↓	mIoU ↑	R_{diff} ↓
LFGP †	✗	✗	✗	0.9016	0.0950	0.8412	0.3058
LFGP ⋆	✓	✗	✗	0.9039	0.0911	**0.8784**	0.3003
LFGP ∗	✓	✓	✗	**0.9053**	0.0900	0.8774	0.2409
LFGP	✓	✗	✓	0.9050	**0.0884**	0.8764	**0.1655**

Table 3. Ablation study of the Local FLow (LF), Gradient Truncation (GT), and Dynamic Gradient Truncation (DGT) on the VITON-HD dataset [6].

- Hight-width Difference Metric: $R_{diff} = |R^{warped} - R^{flat}|$

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Carnegie Mellon University

鹏城实验室 PCL Peng Cheng Laboratory

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Thanks for Listening

Paper

Code