Pose aware Outfit Transfer between Unpaired in-the-wild images

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Introduction

- Fashion is one of highest revenue industries in the world.
- Online fashion shopping has some obstacles: Hard to judge a product's look on oneself

Motivation

- However, outfit transfer method has various existing problems:
  - Usually trained on studio photography (No backgrounds)
  - Need for paired data
- We want to handle noisy backgrounds such as in street photography

Studio photography

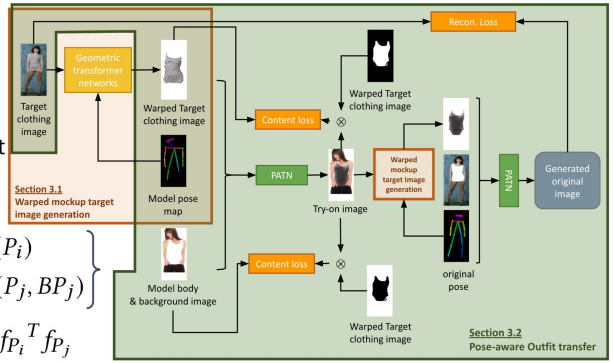
Paired data

Street photography (Noisy background)

Proposed method

Our method has 2 main modules

1. Warp mockup target clothing image generation
   - It is used for generate target clothing image close to target model body shape.



Feature extractor: $\begin{cases} f_{P_i} = F_{e_A}(P_i) \\ f_{P_j} = F_{e_B}(P_j, BP_j) \end{cases}$

Correlation: $c(i,j) = {f_{P_i}}^T f_{P_j}$

Transformation parameter: $\theta(i,j) = Regression(c(i,j))$, Transform image: $W_{P_i}^j = \mathcal{T}_\theta(P_i)$

2. Pose-aware Outfit transfer
   - It is used to generate image of target person wear specific clothing, and the reconstruction part is introduced to train this module as we have real pair data.

Outfit Transfer Image: $O_j^f = PATN\left(B_j, W_{P_i}^j, BP_j\right)$, Reconstructed original Image: $O_i^f = PATN\left(B_i, W_{P_j}^i, BP_i\right)$

Training

- For warp mockup target clothing image generation
  - use L1-Loss to train

$$\mathcal{L}(\theta, \theta_{GT}) = \frac{1}{N}\sum_{i=1}^{N}\left\|G_i' - G_i''\right\|$$

- For pose-aware outfit transfer
  - use GAN-Loss, combination L1-loss and reconstruction loss to train

$$\mathcal{L} = \mathcal{L}_{GAN} + \mathcal{L}_{combL1} + \mathcal{L}_{recon}$$

$$\mathcal{L}_{GAN} = \mathbb{E}_{BP_j \in \mathcal{P}_P, (O_i, O_j) \in X}\left\{\log\left[D_A\left(O_i, O_j\right) \cdot D_S\left(BP_j, O_j\right)\right]\right\} + \mathbb{E}_{BP_j \in \mathcal{P}_P,\ O_j \in X, O_j^f \in \tilde{X}}\left\{\log\left[\left(1 - D_A\left(O_j, O_j^f\right)\right) \cdot \left(1 - D_S\left(BP_j, O_j^f\right)\right)\right]\right\}$$

$$\mathcal{L}_{recon} = \left\|\Psi_k(O_i) - \Psi_k(O_i^f)\right\|_1$$

$$\mathcal{L}_1 = \left\|W_{P_i}^j - (O_j^f \otimes PM_j)\right\|_1 + \left\|B_j - (O_j^f \otimes BM_j)\right\|_1$$

$$\mathcal{L}_{perL1} = \left\|\Psi_k(W_{P_i}^j) - \Psi_k(O_j^f \otimes PM_j)\right\|_1 + \left\|\Psi_k(B_j) - \Psi_k(O_j^f \otimes BM_j)\right\|_1$$

$$\mathcal{L}_{combL1} = \lambda_1\mathcal{L}_1 + \lambda_2\mathcal{L}_{perL1}$$

Evaluation

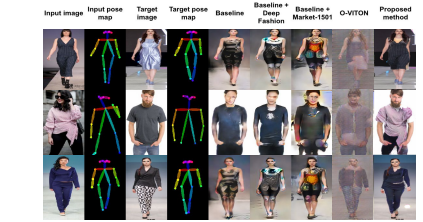
Quantitative results

- Using Structural similarity (SSIM) and Inception score (IS)
- Promising results:
  For SSIM and mask-SSIM,
  around 54% and 45% improvement,
  while for IS around 25% improvement

Model	SSIM	IS	Mask-SSIM	Mask-IS
Baseline	0.302	4.073	0.591	4.444
Baseline + DeepFashion	0.282	4.073	0.580	**4.562**
Baseline + Market-1501	0.256	3.912	0.565	4.064
O-VTON	0.253	2.648	0.320	3.292
Proposed method	**0.467**	**5.096**	**0.860**	3.994

Qualitative results

- Confirms a perception much closer to the expectation
- We can accurately preserve background information while still being able to correctly transfer the outfit



Real scenerio

- Test on myself
  - Outfit images from fashion shopping website
  - My image from webcam or real street photograph