WG-VITON: Wearing-Guide Virtual Try-On for Top and Bottom Clothes

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Abstract

Studies of virtual try-on (VITON) have been shown their effectiveness in utilizing the generative neural network for virtually exploring fashion products, and some of recent researches of VITON attempted to synthesize human image wearing given multiple types of garments (e.g., top and bottom clothes). However, when replacing the top and bottom clothes of the target human, numerous wearing styles are possible with a certain combination of the clothes. In this paper, we address the problem of variation in wearing style when simultaneously replacing the top and bottom clothes of the model. We introduce Wearing-Guide VITON (i.e., WG-VITON) which utilizes an additional input binary mask to control the wearing styles of the generated image. Our experiments show that WG-VITON effectively generates an image of the model wearing given top and bottom clothes, and create complicated wearing styles such as partly tucking in the top to the bottom.

1. Introduction

Virtual try-on (i.e., VITON) is a task to synthesize an image of a fitting model wearing target garments while maintaining other characteristics of the model such as his/her identity and pose. Various studies have been proposed to improve the quality of the synthesized images wearing given top clothes [1, 4–6, 9, 12, 17, 20] based on available dataset such as [6]. Then, VITON technology was extended for applying multiple types of garment [2,10,13]. However, when a person wearing multiple types of the products (e.g., top and bottom clothes), there are diverse wearing styles depending on his/her individual taste. For example, the person can tuck in the top to the bottom, tuck a part of the top to the bottom, or let the top loosely over the bottom. Such wearing styles is one of the most important aspects to decide which and how to wear clothes.

In this paper, we propose a method called WG-VITON which generates virtual try-on images using the top and bottom clothes simultaneously with various wearing styles. Wearing-Guide Parsing Generation Module (i.e., Sec.2.2) estimates a segmentation map of model with various wearing styles by considering the given combination of the clothes and Wearing-guide Mask. Then following Structure-aware Clothes Warping Module (i.e., in Sec.2.3) warps images of the given clothes depending on the estimated segmentation map. Lastly, Try-On Module (i.e., in Sec.2.4) uses the estimated segmentation map and the warped clothes to synthesize a realistic image of the model. The result of the experiment shows WG-VITON effectively synthesizes model’s images considering the given top and bottom clothes simultaneously. In addition, the proposed
2. Wearing-Guide Virtual Try-On

We firstly explain a composition of the dataset because a composition of the dataset in the paper is differ from available VITON dataset such as [3, 6]. Sec.2.1 formulates data and introduces a data pre-processing method for constructing wearing-agnostic input. Then, Sec.2.2–Sec.2.4 introduce the overall architecture of WG-VITON and how to train the network.

2.1. Data and Pre-processing

We construct a dataset of VITON for the top and bottom clothes by constructing sub-dataset of [14]. We name the dataset as FashionTB. FashionTB provides images of models, tops, and bottoms and they are defined by $I_h \in \mathbb{R}^{3 \times H \times W}$, $I_{top} \in \mathbb{R}^{3 \times H \times W}$, and $I_M \in \mathbb{R}^{3 \times H \times W}$, respectively. Differ from other public dataset for VITON [3, 6], each model and product have manual annotations. For the model data, we have human pose map $P_h \in \mathbb{R}^{17 \times H \times W}$ and segmentation $S_h \in \mathbb{R}^{17 \times H \times W}$. The top and bottom products have their own segmentation labels for their sleeves and torso (legs and hips for the bottom) $S_{top} \in \mathbb{R}^{3 \times H \times W}$ and $S_{bt} \in \mathbb{R}^{3 \times H \times W}$, respectively. Fig.2 is a visualization of FashionTB and our research is performed under the dataset.

We construct two test set. One is $T_{pair}$ which has its own ground-truth image and labels, and the other is $T_{unpair}$ whose wearing information is randomly mixed to test arbitrary combination of the model and the products. We alleviate a dependency of input and training target by extending the pre-processing method in [1]. Specifically, we eliminate the area of clothes in input model’s image while remaining the area of model’s hair, face, hands, and feet. Fig.3 illustrates the altered input $I_h'$ and $S_h'$, and the images do not have clues for what the model originally wears.

2.2. Wearing-Guide Parsing Generation Module

Prior VITON methods only for the top item generally maintained the bottom area and it provides clues for how to wear a given top product [1, 5, 9, 20]. When a model of $I_h$ tuck in the top to the bottom, the final result of the existing studies follows the way of wearing. However, the wearing agnostic input of WG-VITON inevitably eliminates information to infer how to wear the top and bottom clothes, as Fig.3 describes. In this circumstance, the machine becomes confused because multiple answers exist for the identical input (i.e., combination of model and products). Thus, we propose Wearing-Guide Parsing Generation Module (WGPGM) to alleviate the aforementioned problem by designing Wearing-guide Mask and Wearing-guide Loss.

Wearing-guide Mask $M_{wg}$ is a binary mask indicating the region where the bottom should not violate in the result of the parsing map. In the training phase, each pixel $(x, y)$ of $M_{wg}$ is assigned as

$$M_{wg}(x, y) = \begin{cases} 1, & y \leq \text{maxy}(S_{h_{(top,torso)})} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

where $\text{maxy}$ is a function to estimate the maximum y-coordinates of valid pixels and $S_{h_{(top,torso)}}$ is the segmenta-
tion map for torso of the top.

Now, a function \(WGPGM\) can be formulated by

\[
\hat{S}_h = f_{WGPGM}(S_h', P_h, I_{top}, I_{bt}, M_{wg})
\]

(2)

where \(P_h\) is a set of human keypoints.

Fig.4 (a) illustrates an overview architecture of WGPGM. We employ conditional GAN with U-Net [16] and two PatchGAN discriminators [8]. While the first discriminator evaluates the entire generating parsing map, the second discriminator judges only the result of the lower half of the body (i.e., regions for a bottom item, legs, and feet.). The discriminator for the lower body part leverages the generation performance of the lower body part where FashionTB dataset has a larger variation. For example, the low body part in the dataset could be trousers, short pants, long/short skirt, or even empty when the model wears a long dress.

The training loss of the generator of WGPGM consists of cross-entropy loss, adversarial losses using LS-GAN [11], feature matching losses [18] and Wearing-guide Loss (Eq. 6), and it can be formulated as

\[
\begin{align*}
L_{WGPGM} &= \lambda_C L_C + \lambda_{adv} L_{adv} + \lambda_{FM} L_{FM} + \lambda_{wg} L_{wg} \\
L_{adv} &= L_{adv, D} + L_{adv, D_{low}} \\
L_{FM} &= L_{FM, D} + L_{FM, D_{low}} \\
L_{wg} &= |0 - M_{wg} \odot \hat{S}_{hbt}|
\end{align*}
\]

(3)

(4)

(5)

(6)

where all \(\lambda\)s are weights for the training and \(\hat{S}_{hbt}\) indicates regions for the bottom product.

2.3. Structure-aware Clothes Warping Module

Structure-aware Clothes Warping Module (SCWM) utilizes Thin-Plate Spline (TPS) transformation [1, 6, 15] and we extend it to simultaneously warp the top and bottom products. SCWM is a function \(f_{SCWM}\) to estimate warping parameters for the given garments from the estimated segmentation in WGPGM, human pose, and an image of the top and bottom such as Eq.7.

\[
\theta_{top}, \theta_{bt} = f_{SCWM}(\hat{S}_{htop}, \hat{S}_{hbt}, P_h, I_{top}, I_{bt})
\]

(7)

where \(\theta_{top}\) and \(\theta_{bt}\) are parameters for the TPS transform for the top and bottom products, respectively.

The model’s information (i.e., \(P_h, \hat{S}_{htop}, \text{and } \hat{S}_{hbt}\)) and product images (i.e., \(I_{top}\) and \(I_{bt}\)) are analyzed by each set of convolution layers, and the top and bottom clothes sequentially go through the identical convolution layers rather than concatenating them. We perform correlation matching twice with the estimated features, and then apply the TPS transform using the estimated parameters \(\theta_{top}\) and \(\theta_{bt}\). In contrast to existing studies which train the warping using L1 loss only for color, we add L1 losses for semantic segmentation (3-channel masks) of the clothes. The approach has two main advantages: (i) SCWM is properly trained by considering not only the color, but also structure of the clothes distinguishing the area of torso and sleeves or hip and legs and (ii) SCWM is still able to warp the items when the colors of target clothes and background are similar (e.g., white clothes with a white background).

2.4. Try-On Module

Try-On Module (TOM) finally synthesizes a model image using the estimation results from the previous modules. Specifically, \(\hat{S}_h\) from WGPGM, \(I_{top}\) and \(I_{bt}\) from SCWM, and \(I'_h\) and \(P_h\) from data are the inputs of TOM. Then, the function TOM can be formulated by

\[
\hat{I}_h = f_{TOM}(I'_h, P_h, \hat{S}_h, I_{top}, I_{bt})
\]

(8)

We use U-Net based generator and the mask composition [6, 16, 17]. Specifically, U-Net estimates two binary masks for the composition (i.e., \(M_{top}\) and \(M_{bt}\)), and a base of the synthesized image (i.e., \(I_{base}\)). We synthesize the final result by compositing \(I'_h, I_{top}, I_{bt}\), and \(\hat{I}_h\) using the masks \(M_{top}\), \(M_{top}\), and \(M_{bt}\). Specifically, three mask compositions are sequentially performed to make the result of the synthesis \(\hat{I}\).

3. Experiments

We perform quantitative and qualitative evaluations for WG-VITON. All experiments in this work utilize FashionTB dataset mentioned in Sec.2.1 because no public dataset contain mapping between the tops, bottoms, and models.

3.1. Evaluation

Qualitative Evaluation Fig.5 illustrates the final result of the proposed method and its intermediate estimations. Images in the 1st–3rd columns are inputs for WG-VITON and we omit \(S_h\) and \(P_h\) of each sample. The 4th column depicts a result of WGPGM. WGPGM effectively estimates segmentation regions considering the given model and clothes. Following SCWM applies TPS transform to \(I_{top}\) and \(I_{bt}\) by referring \(\hat{S}_h\) from WGPGM, and warps images of the clothes \(\hat{I}_{top}\) and \(\hat{I}_{bt}\) (overlapped image in the 5th column). With the estimation results and wearing-agnostic human image \(I'_h\) (the 6th column), TOM synthesizes the model image wearing given clothes while maintaining other characteristics of model such as identity and pose (the last column).

Quantitative Evaluation We use Structural Similarity (SSIM) [19], Fréchet Inception Distance (FID) [7], and Learned Perceptual Image Patch Similarity (LPIPS) [21] to
Figure 5. The result of WG-VITON in $T_{unpair}$ with intermediate estimation results of each modules. For $\hat{I}_{top}$ and $\hat{I}_{bt}$, we overlap two transparent images. Images in the last column indicate the final result of WG-VITON.

| Resol. | SSIM↑ ($T_{pair}$) | LPIPS↓ ($T_{pair}$) | FID↓ ($T_{pair}$) | FID↓ ($T_{unpair}$) |
|--------|---------------------|---------------------|-------------------|---------------------|
| 256×192 | 0.901               | 0.065               | 10.184            | 12.663              |
| 512×384 | 0.911               | 0.069               | 12.991            | 16.359              |

Table 1. Qualitative evaluation of WG-VITON. Up arrow in the table indicates that the higher value is the better for the evaluation metric. We mention a related test dataset below the name of each metric.

evaluate the baseline network. SSIM and LPIPS are applied to $T_{pair}$ which has the ground-truth image for wearing pairs, and FID is used for both $T_{pair}$ and $T_{unpair}$. Table 1 shows results under the four evaluation cases.

3.2. Style Generation using WGPGM

Verifying the effectiveness of the wearing-guide scheme introduced in Sec.2.2, we synthesize $T_{pair}$ samples with different $M_{wg}$ as Fig.1 shows. The 1st column of the figure shows the ground-truth image of $T_{pair}$. Without the wearing-guide scheme, parsing map generator will estimate a map that minimizes the training loss among various wearing styles in the training set. On the other hand, as the 2nd–4th columns illustrate, WG-VITON can simulate various wearing styles by controlling $M_{wg}$. Specifically, the results in the 3rd column use the ground-truth $M_{wg}$ so their styles are similar to those of the ground-truth. The 2nd and 4th columns show the results when we decrease and increase $M_{wg}$ by 20 pixels, respectively. As a result, images with smaller $M_{wg}$ tend to enlarge an area of the bottom item while images with higher $M_{wg}$ expand the top to cover the hips of the model. In addition, when we use a relatively complicated mask like Fig.6(a), WG-VITON can synthesize an image where a model wears the top tucked in only a part into the bottom, which is one of the trendy wearing styles as Fig.6(b) illustrates.

4. Conclusion

In this paper, we propose WG-VITON which synthesizes the model’s image wearing the target top and bottom clothes with various wearing styles. Using the given clothes and model, WG-VITON can generate parsing map with various wearing styles, warp the images of the garments according to the target model, and make the model’s image using the results of the previous modules. In specific, in Wearing-Guide Parsing Generation Module (i.e., WGPGM), we can control a length of the top clothes in output image controlling Wearing-guide Mask. Moreover, when the Mask having complicated shape, we can simulate wearing styles such as tucking in a part of the top to the bottom clothes. We believe that WG-VITON provides interesting insights of simulating wearing styles in fashion and lead the following researches to make VITON technology more applicable.
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