Deformable GANs for Pose-based Human Image Generation

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Abstract

In this paper we address the problem of generating person images conditioned on a given pose. Specifically, given an image of a person and a target pose, we synthesize a new image of that person in the novel pose. In order to deal with pixel-to-pixel misalignments caused by the pose differences, we introduce deformable skip connections in the generator of our Generative Adversarial Network. Moreover, a nearest-neighbour loss is proposed instead of the common $L_1$ and $L_2$ losses in order to match the details of the generated image with the target image. We test our approach using photos of persons in different poses and we compare our method with previous work in this area showing state-of-the-art results in two benchmarks. Our method can be applied to the wider field of deformable object generation, provided that the pose of the articulated object can be extracted using a keypoint detector. Our code and our trained models are publicly available.$^1$

1. Introduction

In this paper we deal with the problem of generating images where the foreground object has a deformable shape, such as the articulated human body. Specifically, inspired by Ma et al. [12], our goal is to generate a human image conditioned on two different variables: (1) the appearance of a specific person in a given image and (2) the pose of the same person in another image. The task our networks need to solve is to preserve the appearance details (e.g., the texture) contained in the first variable while performing a deformation on the structure of the foreground object according to the second variable. We focus on the human body which is an articulated “object”, important for many applications (e.g., computer-graphics based manipulations or re-identification dataset synthesis). However, our approach can be used with other deformable objects such as human faces or animal bodies, provided that a significant number of keypoints can be automatically extracted from the object of interest in order to represent its pose.

 Pose-based human-being image generation is motivated by the interest in synthesizing videos [18] with non-trivial human movements or in generating rare poses for human pose estimation [1] or re-identification [22] training datasets. However, most of the recently proposed, deep-network based generative approaches, such as Generative Adversarial Networks (GANs) [4] or Variational Autoencoders (VAEs) [7] do not explicitly deal with the problem of articulated-object generation. Common conditional methods (e.g., conditional GANs or conditional VAEs) can synthesize an image whose appearance depends on some conditioning variable (e.g., a label or another image). For instance, Isola et al. [5] recently proposed an “image-to-image translation” framework, in which an input image $x$ is transformed into a second image $y$ represented in another “channel” (see Fig. 1a). However, most of these methods have problems when dealing with large spatial deformations between the conditioning and the target image. For instance, the U-Net architecture used by Isola et al. [5] is based on skip connections which help preserving local information between $x$ and $y$. Specifically, skip connections are used to copy and then concatenate the feature maps of the generator “encoder” (where information is downsampled using

\[L_1(x, y) + \lambda L_2(x, y)\]

Figure 1: (a) In an image-to-image “translation” task, the input and output images share a common underlying geometric structure. (b) In pose-based person image generation, the input and output are not spatially aligned.

\[\text{https://github.com/AliaksandrSiarohin/pose-gan}\]
conventional layers) to the generator “decoder” (containing the upconvolutional layers). However, the assumption used in [5] is that $x$ and $y$ are roughly aligned with each other and they represent the same underlying structure. This assumption is violated when the foreground object in $y$ undergoes to large spatial deformations with respect to $x$ (see Fig. 1b). As shown in [12], skip connections cannot reliably cope with misalignments between the two poses.

Ma et al. [12] propose to alleviate this problem using a two-stage generation approach. In the first stage a U-Net generator is trained using a masked $L_1$ loss in order to produce an intermediate image conditioned on the target pose. In the second stage, a second U-Net based generator is trained using also an adversarial loss in order to generate an appearance difference map which brings the intermediate image closer to the appearance of the conditioning image.

In contrast, the GAN-based method we propose in this paper is end-to-end trained by explicitly taking into account pose-related spatial deformations. More specifically, we propose deformable skip connections which “move” local information according to the structural deformations represented in the conditioning variables. These layers are used in our U-Net based generator. In order to efficiently move information according to a specific spatial deformation, we decompose the overall deformation by means of a set of local affine transformations involving subsets of joints, then we deform the convolutional feature maps of the generator according to these transformations and we use common skip connections to transfer the transformed tensors to the decoder’s fusion layers. Moreover, we also propose to use a nearest-neighbour loss as a replacement of common pixel-to-pixel losses (such as, e.g., $L_1$ or $L_2$ losses) commonly used in conditional generative approaches. This loss proved to be helpful in generating local information (e.g., texture) similar to the target image which is not penalized because of small spatial misalignments.

We test our approach using the benchmarks and the evaluation protocols proposed in [12] obtaining higher qualitative and quantitative results in all the datasets. Although tested on the specific human-body problem, our approach makes few human-related assumptions and can be easily extended to other domains involving the generation of highly deformable objects.

2. Related work

With the emergence of deep learning techniques, image generation has become an active research topic in recent years. Most common deep-network-based approaches for visual content generation can be categorized as either Variational Autoencoder (VAE) [7] or Generative Adversarial Network (GAN) [4] methods. VAEs are based on probabilistic graphical models and are trained by maximizing a lower bound of the corresponding data likelihood. GAN models are based on two networks: a generator and a discriminator. These two networks are trained simultaneously such that the generator tries to “fool” the discriminator and the discriminator learns how to distinguish between real and fake images.

Isola et al. [5] propose a conditional GAN framework for image-to-image translation problems. In analogy to automatic language translation, image-to-image translation is defined as the problem of “translating” a given scene representation into another. The main assumption behind this framework is that there exits a spacial correspondence between the low-level information of the conditioning and the output image. VAEs and GANs have been combined in [20] to generate realistic-looking multi-view cloth images from a single-view input image. The target view is filled to the model via a viewpoint label as front or left side and a two-stage approach is adopted: pose integration and image refinement. Adopting a similar pipeline, Lassner et al. [8] generate images of people with different clothes in a given pose. This approach is able to generate visually satisfying results at the cost of expensive annotations (fined-grained segmentation with 18 clothing labels), and a complex conditioning 3D pose representation.

Ma et al. [12] propose a more general approach which allows to synthesize person images in any arbitrary pose. Similarly to our proposal, the input of their model is a conditioning image of the person and a target new pose defined by 18 joint locations. The target pose is described by means of binary heat-maps where small circles represent the joint locations. Similarly to [8, 20], the generation process is split in two different stages: pose generation and texture refinement. In contrast, in this paper we show that a single-stage approach, trained end-to-end, can be used for the same task obtaining higher quantitative and qualitative results.

Jaderberg et al. [6] propose a spatial transformer layer, which learns how to transform a feature map in a “canonical” view, conditioned on the feature map itself. However only a global, parametric transformation can be learned (e.g., an affine transformation), while in this paper we deal with non-parametric deformations of articulated objects which cannot be described by means of a unique global affine transformation. In [2], deformable convolution networks are proposed, which are based on the idea of deforming the spatial sampling locations in convolutional layers with specific offsets and learning these offsets from the target task. While the goal in [2] is to make the convolutional sampling mechanism more general, in this paper we deal with the problem of “moving” relatively large and connected portions of the feature map, corresponding to body parts, conditioned on the target pose.

Generally speaking, U-Net based architectures are frequently adopted for pose-based person-image generation tasks [8, 12, 18, 20]. However, common U-Net skip con-
connections are not well-designed for large spatial deformations because local information in the input and in the output images is not aligned (Fig. 1). In contrast, we propose deformable skip connections to deal with this misalignment problem and “shuttle” local information from the encoder to the decoder driven by the specific pose difference. In this way, differently from previous work, we are able to simultaneously generate the overall pose and the texture-level refinement.

Finally, our nearest-neighbour loss is similar to the style-transfer spatial-analogy approach recently proposed in [9]. However, the patch-based similarity adopted in [9] to compute a dense feature correspondence is very computationally expensive and, differently from what we propose in this paper, this dense field is not used as a loss.

3. The network architectures

In this section we describe the architectures of our generator ($G$) and discriminator ($D$) and the proposed deformable skip connections. We start introducing some notation. At testing time our task, similarly to [12], consists in generating an image $\hat{x}$ showing a person whose appearance (e.g., clothes, etc.) is similar to an input, conditioning image $x_a$ but with a body pose similar to $P(x_b)$, where $x_b$ is a different image of the same person and $P(x) = (p_1, ..., p_k)$ is a sequence of $k$ 2D points describing the locations of the human-body joints in $x$. In order to allow a fair comparison with [12], we use the same number of joints ($k = 18$) and we extract $P(i)$ using the same Human Pose Estimator (HPE) [1] used in [12]. Note that this HPE is used both at testing and at training time, meaning that we do not use manually-annotated poses and the so extracted joint locations may have some localization errors or missing detections/false positives.

At training time we use a dataset $\mathcal{X} = \{(x_a^{(i)}, x_b^{(i)})\}_{i=1,...,N}$ containing pairs of conditioning-target images of the same person in different poses. For each pair $(x_a, x_b)$, a conditioning and a target pose $P(x_a)$ and $P(x_b)$ is extracted from the corresponding image and represented using two tensors $H_a = H(P(x_a))$ and $H_b = H(P(x_b))$, each composed of $k$ heat maps, where $H_j$ ($1 \leq j \leq k$) is a 2D matrix of the same dimension as the original image. If $p_j$ is the j-th joint location, then:

$$H_j(p) = \exp\left(-\frac{\|p - p_j(x)\|}{\sigma^2}\right),$$ (1)

whith $\sigma = 6$ pixels. The generator $G$ is fed with: (1) a noise vector $z$, drawn from a noise distribution $Z$ and implicitly provided using dropout [5] and (2) the triplet $(x_a, H_a, H_b)$. Note that, at testing time, the target pose is known, thus $H(P(x_b))$ can be computed. Note also that the joint locations in $x_a$ and $H_a$ are spatially aligned (by construction), while in $H_b$ they are different. Hence, differently from [12, 5] $H_b$ is not concatenated with the other input tensors. Indeed the convolutional layers in the encoder part of $G$ have a small receptive field which cannot capture large spatial displacements. For instance, a large movement of a body limb in $x_b$ with respect to $x_a$, is represented in different locations in $x_a$ and $H_b$ which may be too far apart each other to be captured by the receptive field of the convolutional layers, especially in the first layers of the encoder, which represent low-level information. Hence, the convolutional filters cannot simultaneously process texture-level information (from $x_a$) and the corresponding pose information (from $H_b$).

For this reason we independently process $x_a$ and $H_a$ from $H_b$ in the encoder. Specifically, $x_a$ and $H_a$ are concatenated and processed using a convolutional stream of the encoder while $H_b$ is processed by means of a second convolutional stream, with no-shared weights (see Fig. 2). The feature maps of the first stream are then fused with the layer-specific convolutional feature maps of the second stream in the decoder part of $G$ after a pose-driven spatial deformation performed by our deformable skip connections (see Sec. 3.1).

Our discriminator network is based on the conditional, fully-convolutional discriminator proposed by Isola et al. [5]. In our case, $D$ takes as input 4 tensors: $(x_a, H_a, y, H_b)$, where either $y = x_b$ or $y = \hat{x} = G(z, x_a, H_a, H_b)$ (see Fig. 2). These four tensors are concatenated at the input layer. The discriminator’s output is a scalar value indicating its confidence on the fact that $y$ is a real image.

3.1. Deformable skip connections

As mentioned above, similarly to [5], the goal of the deformable skip connections is to “shuttle” local information from the encoder to the decoder part of $G$. The local information to be transferred is, generally speaking, contained in a tensor $F$, which describes the feature map activations of a given convolutional layer of the encoder. However, differently from [5], we need to “pick” the information to shuttle taking into account the object-shape deformation which is described by the difference between $P(x_a)$ and $P(x_b)$. To do so, we decompose the global deformation in a set of local affine transformations, defined using subsets of joints in $P(x_a)$ and $P(x_b)$. Using these affine transformations and local masks constructed using the specific joints, we deform the content of $F$ and then we use common skip layers to copy the transformed tensor and concatenate it with the corresponding tensor in the destination layer (see Fig. 2). Below we describe in more detail the whole pipeline.

Decomposing an articulated body in a set of rigid sub-parts. The human body is an articulated “object” which can be roughly decomposed into a set of rigid sub-parts. We chose 10 sub-parts: the head, the torso, the left/right upper/lower arm and the left/right upper/lower leg. Each of
them corresponds to a subset of the 18 joints defined by the HPE [1] we use for extracting \( P() \). Using these joint locations we can define rectangular regions which enclose the specific body part. In case of both the head and the torso, the region is simply chosen to be the axis-aligned enclosing rectangle of all the corresponding joints. Concerning the body limbs, each limb corresponds to only 2 joints. In this case we define a region to be a rotated rectangle whose major axis \( (r_1) \) corresponds to the line between these two joints, while the minor axis \( (r_2) \) is orthogonal to \( r_1 \) and with a length equal to one third of the mean of the torso’s diagonals (this value is used for all the limbs). In Fig. 3 we show an example. Let \( R_{h}^{a} = \{ p_1, ..., p_4 \} \) be the set of the 4 rectangle corners in \( x_a \) defining the \( h \)-th body region \((1 \leq h \leq 10)\). Note that these 4 corner points are not joint locations. Using \( R_{h}^{a} \) we can compute a binary mask \( M_h(p) \) which is zero everywhere except those points \( p \) lying inside \( R_{h}^{a} \). Moreover, let \( R_{h}^{b} = \{ q_1, ..., q_4 \} \) be the corresponding rectangular region in \( x_b \). Matching the points in \( R_{h}^{a} \) with the corresponding points in \( R_{h}^{b} \) we can compute the parameters of a body-specific affine transformation (see below).

Note that either in \( x_a \) or in \( x_b \) some of the body regions can be occluded, truncated by the image borders or simply miss-detected by the HPE. In this case we leave the corresponding region \( R_{h}^{b} \) empty and the \( h \)-th affine transform is not computed (see below). Note also that our body-region definition is the only human-specific part of the proposed approach. However, similar regions can be easily defined using the joints of other articulated objects such as those representing an animal body or a human face.

**Computing a set of affine transformations.** During the forward pass (i.e., both at training and at testing time) we decompose the global deformation of the conditioning pose with respect to the target pose by means of a set of local affine transformations, one per body region. Specifically, given \( R_{h}^{a} \) in \( x_a \) and \( R_{h}^{b} \) in \( x_b \) (see above), we compute the 6 parameters \( k_h \) of an affine transformation \( f_h() \) using Least Squares Error:

\[
\sum_{p_j \in R_h^a} \| q_j - f_h(p_j; k_h) \|^2
\]

The parameter vector \( k_h \) is computed using the original image resolution of \( x_a \) and \( x_b \) and then adapted to the specific resolution of each involved convolutional feature map \( F \). Similarly, we compute scaled versions of each \( M_h \). In case either \( R_h^a \) or \( R_h^b \) is empty (i.e., when any of the specific body-region joints has not been detected using the HPE, see above), then we simply set \( M_h \) to be a matrix with all elements equal to 0 (\( f_h \) is not computed).

Note that computing \( (f_h(), M_h) \) and their lower-resolution variants needs to be done only once per each pair of real images \( (x_a, x_b) \in X \) and, in case of the training phase, this is can be done before starting training the networks (but in our current implementation it is done on the fly).

**Combining affine transformations to approximate the object deformation.** Once \( (f_h(), M_h) \), \( h = 1, ..., 10 \) are computed for the specific spatial resolution of a given tensor \( F \), the latter can be transformed in order to approximate the global pose-dependent deformation. Specifically, we first compute for each \( h \):

\[
F'_h = f_h(F \odot M_h),
\]

where \( \odot \) is a point-wise multiplication and \( f_h(F(p)) \) is used to “move” all the channel values of \( F \) corresponding to point \( p \). Finally, we merge the resulting tensors using:

\[
d(F(p, c)) = \max_{h=0, ..., 10} F'_h(p, c),
\]
that, when two body regions partially overlap each other, the final deformed tensor $d(F)$ is obtained by picking the values of the maximum-activation points. Preliminary experiments performed using average pooling obtained slightly worse results.

4. Training

$D$ and $G$ are trained using a combination of a standard conditional adversarial loss $\mathcal{L}_{cGAN}$ with our proposed nearest-neighbour loss $\mathcal{L}_{NN}$. Specifically, in our case $\mathcal{L}_{cGAN}$ is given by:

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{(x_a, x_b) \in \mathcal{X}} \left[ \log D(x_a, H_a, x_b, H_b) + \log (1 - D(x_a, H_a, \hat{x}, H_b)) \right],$$

(5)

where $\hat{x} = G(z, x_a, H_a, H_b)$.

Previous works on conditional GANs proposed to combine the adversarial loss with either an $L_2$ [13] or an $L_1$-based loss [5,12] which is used only for $G$. For instance, the $L_1$ distance computes a pixel-to-pixel difference between the generated and the real image, which, in our case, is:

$$L_1(\hat{x}, x_b) = ||\hat{x} - x_b||_1.$$  

(6)

However, a well-known problem behind the use of $L_1$ and $L_2$ is the production of blurred images. We hypothesize that this is also due to the inability of these losses to tolerate small spatial misalignments between $\hat{x}$ and $x_b$. For instance, suppose that $\hat{x}$, produced by $G$, is visually plausible and semantically similar to $x_b$, but the texture details on the clothes of the person in the two compared images are not pixel-to-pixel aligned. Both the $L_1$ and the $L_2$ loss will penalize this inexact pixel-level alignment, although not semantically important from the human point of view. Note that these misalignments do not depend on the global deformation between $x_a$ and $x_b$, because $\hat{x}$ is supposed to have the same pose as $x_b$. In order to alleviate this problem, we propose to use a nearest-neighbour loss $\mathcal{L}_{NN}$ based on the following definition of image difference:

$$L_{NN}(\hat{x}, x_b) = \sum_{p \in \hat{x}} \min_{q \in \mathcal{N}(p)} ||g(\hat{x}(p)) - g(x_b(q))||_1,$$

(7)

where $\mathcal{N}(p)$ is a $n \times n$ local neighbourhood of point $p$. We use $5 \times 5$ and $3 \times 3$ neighbourhoods for the DeepFashion and the Market datasets, respectively (see Sec. 6). $g(\hat{x}(p))$ is a vectorial representation of a patch around point $p$ obtained using convolutional filters (see below for more details). Note that $L_{NN}()$ is not a metric because it is not symmetric. In order to efficiently compute Eq. 7, we compare patches in $\hat{x}$ and $x_b$ using their representation $g(\cdot)$ in a convolutional map of an externally trained network. In more detail, we use VGG-19 [16], trained on ImageNet (and not fine-tuned) and, specifically, its second convolutional layer (called conv1_2). The first two convolutional maps in VGG-19 (conv1_1 and conv1_2) are both obtained using a convolutional stride equal to 1. For this reason, the feature map $(C_x)$ of an image $x$ in conv1_2 has the same resolution of the original image $x$. Exploiting this fact, we compute the nearest-neighbour field directly on conv1_2, without losing spatial precision. Hence, we define: $g(x(p)) = C_x(p)$, which corresponds to the vector of all the channel values of $C_x$ with respect to the spatial position $p$. Note that $C_x(p)$ has a receptive field of $5 \times 5$ in $x$, thus effectively representing a patch of dimension $5 \times 5$ using a cascade of two convolutional filters. Using $C_x$, Eq. 7 becomes:

$$L_{NN}(\hat{x}, x_b) = \sum_{p \in \hat{x}} \min_{q \in \mathcal{N}(p)} ||C_x(p) - C_{x_b}(q)||_1,$$

(8)

In Sec. A.1 we show how Eq. 8 can be implemented using GPU-based parallel computing.

The final $L_{NN}$-based loss is:

$$L_{NN}(G) = \mathbb{E}_{(x_a, x_b) \in \mathcal{X}, z \in Z} L_{NN}(\hat{x}, x_b).$$

(9)

Combining Eq. 5 and Eq. 9 we obtain our objective:

$$G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda L_{NN}(G),$$

(10)

where we set $\lambda = 0.01$ in all our experiments. The value of $\lambda$ is small because it acts as a normalization factor in Eq. 8 with respect to the number of channels in $C_x$ and the number of pixels in $\hat{x}$ (see Sec. A.1 for more details).

5. Implementation details

We train $G$ and $D$ for 90k iterations, with the Adam optimizer (learning rate: $2 \times 10^{-4}$, $\beta_1 = 0.5$, $\beta_2 = 0.999$).
Following [5] we use instance normalization. Let $CN_s^m$ denote a convolution-instance normalization-ReLU layer with $m$ filters and stride $s$. Moreover, let $CD_s^m$ be like $CN_s^m$ with the addition of dropout at rate 50%. Then the encoder part of the generator is given by two streams (Fig. 2), each of which is composed of the following sequence of layers:

$$CN_{64}^1 - CN_{128}^2 - CN_{256}^2 - CN_{512}^2 - CN_{512}^1 - CN_{512}^2.$$

The decoder part of the generator is given by:

$$CD_{512}^1 - CD_{512}^1 - CD_{512}^2 - CD_{256}^2 - CD_{256}^2 - CD_{128}^2 - CN_{1}^2.$$

Instance normalization is not applied and ReLU replaced with $tanh$ in last convolutional layer.

The discriminator architecture is:

$$CN_{64}^2 - CN_{128}^2 - CN_{256}^2 - CN_{512}^2 - CN_{512}^2.$$

In this case, instance normalization is not applied and ReLU replaced with $sigmoid$ in last convolution layer.

The generator for the DeepFashion dataset has one additional convolution block ($CN_{256}^3$) both in the encoder and in the decoder, because images in this dataset have a higher resolution.

6. Experiments

Datasets The person re-identification Market-1501 dataset [21] contains 32,668 images of 1,501 persons captured from 6 different surveillance cameras. This dataset is challenging because of the low-resolution images and the high diversity in pose, illumination, background and viewpoint. The image resolution is $128 \times 64$. To train the proposed model, we need pairs of images of the same person in two different poses. As the Market-1501 dataset is relatively noisy, we first automatically remove those images in which no human body is detected using the HPE, leading to 263,631 training pairs. For testing, following the protocol proposed in [12], we randomly select 12,000 pairs.

We also perform experiments on the DeepFashion dataset (In-shop Clothes Retrieval Benchmark) [11] that consists of 52,712 clothes images and 200,000 pairs of identical clothes with two different poses and/or scales of the persons wearing these clothes. The images are released at a resolution of $256 \times 256$ pixels. Following [12], we create pairs of images, each pair depicting the same person with identical clothes but in different poses. Since the authors in [12] do not specify how these “seed” clothes are selected, we randomly select 1,000 clothes for testing and we used the remaining 12,029 for training. After removing those images in which the HPE does not detect any human body, we finally collected 101,268 pairs for training and 8,670 pairs for testing.

Metrics Evaluation in the context of generation tasks is a problem in itself, but two measures have emerged in the literature: Structural Similarity (SSIM) [19] and Inception Score (IS) [15]. However, since no background information of the target image is input to $G$, the network cannot guess what the target background looks like. For this reason, Ma et al. [12] propose to use also a person-specific mask to make these two metrics independent of the generated background. Accordingly, we test our models also using person-specific masks which are applied to both the target and the generated image before computing SSIM and IS. These variants are respectively called mask-SSIM and mask-IS [12]. Note that the evaluation masks we use to compute both the mask-IS and the mask-SSIM values do not correspond to the masks ($\{M_h\}$) we use for training. The evaluation masks have been built following the procedure proposed in [12] and adopted in that work both for training and evaluation. Consequently, the mask-based metrics may be biased in favor of their method.

Another evaluation issue is that in our task there is only one object class in each image (the person class). However, the IS metrics [15] is based on the entropy computed over the classification neurons of an external classifier [17], thus domains with only one class are not very suitable for this metric. We indeed frequently observed a weak correlation of the IS values with the quality of the generated images. For this reason we propose to use an additional metrics that we call Detection Score (DS). Similarly to the classification metrics proposed in [14], DS is based on the detection outcome of the state-of-the-art object detector SSD [10], trained on Pascal VOC 07 [3] (and not fine-tuned on our datasets). At testing time, we use the person-class detection scores of SSD computed on each generated image $\hat{x}$. $DS(\hat{x})$ corresponds to the maximum-score box of SSD on $\hat{x}$ and the final DS value is computed by averaging the scores of all the generated images. In other words, DS measures the confidence of a person detector in the presence of a person in the image. Given the high accuracy of SSD in the challenging Pascal VOC 07 dataset [10], we believe that it can be used as a good measure of how realistic (person-like) is a generated image.

Finally, in our tables we also include the value of each metrics computed using the real images of the test set. Since these values are computed on real data, they can be considered as a sort of an upper-bound to the results a generator can obtain. Notice that these values are not actual upper bounds in the strict sense: for instance the DS metrics on the real datasets is not 1 because of SSD failures.

6.1. Comparison with previous work

In Tab. 1 we compare our proposal with [12]. Note that there are no other works to compare with on this task yet. On the Market-1501 dataset our method reports the highest performance with all but the IS metrics. Conversely, on the DeepFashion dataset, our approach significantly improves the IS value but returns a slightly lower SSIM value. The
Table 1: Comparison with the state of the art.

| Model      | Market-1501 | DeepFashion |
|------------|-------------|-------------|
|            | SSIM | IS | mask-SSIM | mask-IS | DS | SSIM | IS | DS |
| Ma et al. [12] | 0.253 | 3.460 | 0.792 | 3.435 | – | 0.762 | 3.090 | – |
| Ours       | 0.290 | 3.185 | 0.805 | 3.502 | 0.72 | 0.761 | 3.351 | 0.966 |
| Real-Data  | 1.00 | 3.86 | 1.00 | 3.36 | 0.74 | 1.000 | 3.898 | 0.980 |

mask-based metrics are not reported in [12] for the DeepFashion dataset.

Figure 4: Some qualitative results on the Market-1501 dataset. Columns 1, 2 and 3 represent the input of our model. Column 4 corresponds to the ground truth. The last three columns show the output of our approach with respect to different baseline.

6.2. Ablation study and qualitative analysis

In this section we present an ablation study to clarify the impact of each part of our proposal on the final performance. We first describe the compared models, obtained by “amputating” important parts of the full-pipeline presented in Sec. 3-4. Note that the discriminator architecture is the same for all the models.

- **Baseline**: We use the standard U-Net architecture similarly to [5] without deformable skip connections. The inputs of $G$ and $D$ and the way pose information is represented (see the definition of tensor $H$ in Sec. 3) is the same as in the full-pipeline. However, in $G$, $x_a$, $H_a$, and $H_b$ are concatenated at the input layer. Hence, the encoder of $G$ is composed of only one stream, whose architecture is the same as the two streams described in section 5.
Table 2: Quantitative ablation study on the Market-1501 and the DeepFashion dataset.

| Model                       | SSIM  | IS   | Market-1501 | DeepFashion |
|-----------------------------|-------|------|-------------|-------------|
|                             | mask-SSIM | mask-IS | DS          | SSIM | IS   |
| Baseline                    | 0.256 | 3.188| 0.784       | 3.580 | 0.595 | 0.760 | 3.299 |
| DSC                         | 0.272 | 3.442| 0.476       | 3.666 | 0.629 | 0.671 | 3.393 |
| Full                        | 0.290 | 3.185| 0.805       | 3.502 | 0.720 | 0.761 | 3.351 |
| Baseline with dropout       | 0.231 | 3.374| 0.775       | 3.466 | 0.520 | 0.755 | 3.262 |
| DSC with dropout            | 0.253 | **3.690**| 0.798 | 3.577 | 0.555 | 0.758 | 3.378 |
| Full with dropout           | 0.272 | 3.418| 0.801       | 3.614 | 0.666 | 0.759 | 3.340 |
| Real-Data                   | 1.00  | 3.86 | 1.00        | 3.36  | 0.74  | 1.000 | 3.898 |

- **DSC**: $G$ is implemented as described in Sec. 3, introducing our Deformable Skip Connections (DSC). Both in DSC and in Baseline, training is performed using an $L_1$ loss together with the adversarial loss.

- **Full**: This is the full-pipeline whose results are reported in Tab. 1, and in which we use the proposed $\mathcal{L}_{NN}$ loss (see Sec. 4).

In Tab. 2 we report a quantitative evaluation on the Market-1501 and on the DeepFashion dataset with respect to the three different versions of our approach. In this analysis we omit to report $DS$ values on the DeepFashion dataset because they are all close to the value $\sim 0.96$ (due to the high image resolution and the uniform background, the generated images on the DeepFashion dataset are easy to be recognized as humans by SSD).

The results reported in the table are split into two different testing modalities: with and without dropout. In [5] dropout is used both at training and at testing time. However, we generally observed better results when the output of $G$ is deterministically dependent on the conditioning inputs. Both with and without dropout, Tab. 2 shows a progressive increase with respect to most of the metrics in both datasets, from Baseline to Full.

We believe that the $DS$ scores are particularly significant, being a high $DS$ value a strong evidence that the generated images are realistic. Looking to the column corresponding to the $DS$ scores, the performance increase of DSC in the Market-1501 dataset with respect to Baseline and Full with respect to DSC is evident.

In Fig. 4 and Fig. 5 we show some qualitative results. These figures show the progressive improvement through the three baselines which is quantitatively presented above. In fact, while pose information is usually well generated by all the methods, the texture generated by Baseline often does not correspond to the texture in $x_a$ or is blurred. In some cases, this improvement is quite drastic, such as the drawing on the shirt of the girl in the second row of Fig. 5 or the stripes on the clothes of the persons in the third and in the fourth row of Fig. 4.

Generally speaking, we believe that the results of our full-pipeline are sufficiently realistic and correspond to the double task of conditioning the generation process on both the texture and the pose of two different images. Compared to the results shown in [12], most of the times our end-to-end approach generates images which are more realistic, sharper and with local details more similar to the details of the conditioning image (see Sec. A).

7. Conclusions

In this paper we presented a GAN-based approach for image generation of persons conditioned on the appearance and on the pose. We introduced two novelties: deformable skip connections and nearest-neighbour loss. The first is used to solve common problems in U-Net based generators when dealing with deformable objects. Local-structure misalignments between the conditioning image and the target pose is directly addressed by providing to the decoder with texture-level information “picked” in the corresponding positions. The second novelty is used to alleviate a different type of misalignment between the generated image and the ground-truth image.

Our experiments show that the proposed method is able to outperform previous work on this task in two datasets and with almost all the common automatic evaluation metrics. The qualitative results show that both the pose and the texture generated by our networks correspond to the input variables and are usually sufficiently realistic.

Despite the proposed method was tested on the specific task of human-generation, only few assumptions are used which refer to the human body and we believe that our proposal can be easily extended to address other deformable-object generation tasks.

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A. Appendix

In this Appendix we report some additional implementation details and we show other qualitative results. Specifically, in Sec. A.1 we explain how Eq. 8 can be efficiently implemented using GPU-based parallel computing, while in Sec. A.2 we show how the human-body symmetry can be exploited in case of missed limb detections. In Sec. A.3 we show a direct (qualitative) comparison of our method with the approach presented in [12] and in Sec. A.4 we show other images generated by our method, including some failure cases. Note that some of the images in the DeepFashion dataset have been manually cropped (after the automatic generation) to improve the overall visualization quality.

A.1. Nearest-neighbour loss implementation

Our proposed nearest-neighbour loss is based on the definition of $L_{NN}(\hat{x}, x_b)$ given in Eq. 8. In that equation, for each point $p$ in $\hat{x}$, the “most similar” (in the $C_x$-based feature space) point $q$ in $x_b$ needs to be searched for in a $n \times n$ neighborhood of $p$. This operation may be quite time consuming if implemented using sequential computing (i.e., using a “for-loop”). We show here how this computation can be sped-up by exploiting GPU-based parallel computing in which different tensors are processed simultaneously.

Given $C_{x_b}$, we compute $n^2$ shifted versions of $C_{x_b}$: \( \{C_{x_b}^{i,j}\} \), where \((i, j)\) is a translation offset ranging in a relative $n \times n$ neighborhood (i.e., \(i, j \in \{-\frac{n-1}{2}, ..., +\frac{n-1}{2}\}\)) and $C_{x_b}^{i,j}$ is filled with the value $+\infty$ in the borders. Using this translated versions of $C_{x_b}$, we compute $n^2$ corresponding difference tensors \( D^{i,j} \), where:

\[
D^{i,j} = |C_{\hat{x}} - C_{x_b}^{i,j}|
\]

(11)

and the difference is computed element-wise. Note that $D^{i,j}(p)$ contains the channel-by-channel absolute difference between $C_{\hat{x}}(p)$ and $C_{x_b}(p + (i, j))$. Then, for each $D^{i,j}$, we sum all the channel-based differences obtaining:

\[
S^{i,j} = \sum_c D^{i,j}(c),
\]

(12)

where $c$ ranges over all the channels and the sum is performed pointwise. $S^{i,j}$ is a matrix of scalar values, each value representing the $L_1$ norm of the difference between a point $p$ in $C_{\hat{x}}$ and a corresponding point $p + (i, j)$ in $C_{x_b}$:

\[
S^{i,j}(p) = ||C_{\hat{x}}(p) - C_{x_b}(p + (i, j))||_1.
\]

(13)

For each point $p$, we can now compute its best match in a local neighbourhood of $C_{x_b}$, simply using:

\[
M(p) = min_{(i,j)} S^{i,j}(p),
\]

(14)

Finally, Eq. 8 becomes:

\[
L_{NN}(\hat{x}, x_b) = \sum_p M(p).
\]

(15)

Since we do not normalize Eq. 12 by the number of channels nor Eq. 15 by the number of pixels, the final value $L_{NN}(\hat{x}, x_b)$ is usually very high. For this reason we use a small value $\lambda = 0.01$ in Eq. 10 when weighting $L_{NN}$ with respect to $L_{GAN}$.

A.2. Exploiting the human-body symmetry

As mentioned in Sec. 3.1, we decompose the human body in 10 rigid sub-parts: the head, the torso and 8 limbs (left/right upper/lower arm, etc.). When one of the joints corresponding to one of these body-parts has not been detected by the HPE, the corresponding region and affine transformation are not computed and the region-mask is filled with 0. This can happen because of either that region is not visible in the input image or because of false-detections of the HPE.

However, when the missing region involves a limb (e.g., the right-upper arm) whose symmetric body part has been detected (e.g., the left-upper arm), we can “copy” information from the “twin” part. In more detail, suppose for instance that the region corresponding to the right-upper arm in the conditioning image is $R_{ \text{runa} }$ and this region is empty because of one of the above reasons. Moreover, suppose that $R_{ \text{runa} }$ is the corresponding (non-empty) region in $x_b$ and that $R_{ \text{luna} }$ is the (non-empty) the left-upper arm region in $x_a$. We simply set $R_{ \text{runa} } := R_{ \text{luna} }$ and we compute $f_{ \text{runa} }$ as usual, using the (now, no more empty) region $R_{ \text{runa} }$ together with $R_{ \text{luna} }$.

A.3. Comparison with previous work

In this section we directly compare our method with the results generated by Ma et al. [12]. The comparison is based on the pairs conditioning image-target pose used in [12], for which we show both the results obtained by Ma et al. [12] and ours.

Figs. 6-7 show the results on the Market-1501 dataset. Comparing the images generated by our full-pipeline with the corresponding images generated by the full-pipeline presented in [12], most of the times our results are more realistic, sharper and with local details (e.g., the cloth texture or the face characteristics) more similar to the details of the conditioning image. For instance, in the first and the last row of Fig. 6 and in the last row of Fig. 7, our results show human-like images, while the method proposed in [12] produced images which can hardly be recognized as humans.

Figs. 8-9 show the results on the DeepFashion dataset. Also in this case, comparing our results with [12], most of the times ours look more realistic or closer to the details of the conditioning image. For instance, the second row of Fig. 8 shows a male face, while the approach proposed
in [12] produced a female face (note that the DeepFashion dataset is strongly biased toward female subjects [12]). Most of the times, the cloth texture in our case is closer to that depicted in the conditioning image (e.g., see rows 1, 3, 4, 5 and 6 in Fig. 8 and rows 1 and 6 in Fig. 9). In row 5 of Fig. 9 the method proposed in [12] produced an image with a pose closer to the target; however it wrongly generated pants while our approach correctly generated the appearance of the legs according to the appearance contained in the conditioning image.

We believe that this qualitative comparison using the pairs selected in [12], shows that the combination of the proposed deformable skip-connections and the nearest-neighbour loss produced the desired effect to “capture” and transfer the correct local details from the conditioning image to the generated image. Transferring local information while simultaneously taking into account the global pose deformation is a difficult task which can more hardly be implemented using “standard” U-Net based generators as those adopted in [12].

A.4. Other qualitative results

In this section we present other qualitative results. Fig. 10 and Fig. 11 show some images generated using the Market-1501 dataset and the DeepFashion dataset, respectively. Note that, for the sake of clarity, we used a skeleton-based visualization of $P(x)$ but, as explained in Sec. 3, only the point-wise joint locations are used in our method to represent pose information (i.e., no joint-connectivity information is used).

Similarly to the results shown in Sec. 6.2, also these images show that, despite the pose-related general structure is sufficiently well generated by all the different versions of our method, most of the times there is a gradual quality improvement in the detail synthesis from Baseline to DSC to Full.

Finally, Fig. 12 and Fig. 13 show some failure cases (badly generated images) of our method on the Market-1501 dataset and the DeepFashion dataset, respectively. Some common failure causes are:

- Errors of the HPE [1]. For instance, see rows 2, 3 and 4 of Fig. 12 or the wrong right-arm localization in row 2 of Fig. 13.

- Ambiguity of the pose representation. For instance, in row 3 of Fig. 13, the left elbow has been detected in $x_b$, although it is actually hidden behind the body. Since $P(x_b)$ contains only 2D information (no depth or occlusion-related information), there is no way for the system to understand whether the elbow is behind or in front of the body. In this case our model chose to generate an arm considering that the arm is in front of the body (which corresponds to the most frequent situation in the training dataset).

- Rare poses. For instance, row 1 of Fig. 13 shows a girl in an unusual rear view with a sharp 90 degree profile face ($x_b$). The generator by mistake synthesized a neck where it should have “drawn” a shoulder. Note that rare poses are a difficult issue also for the method proposed in [12].

- Rare object appearance. For instance, the backpack in row 1 of Fig. 12 is light green, while most of the backpacks contained in the training images of the Market-1501 dataset are dark. Comparing this image with the one generated in the last row of Fig. 10 (where the backpack is black), we see that in Fig. 10 the colour of the shirt of the generated image is not blended with the backpack colour, while in Fig. 12 it is. We presume that the generator “understands” that a dark backpack is an object whose texture should not be transferred to the clothes of the generated image, while it is not able to generalize this knowledge to other backpacks.

- Warping problems. This is an issue related to our specific approach (the deformable skip connections). The texture on the shirt of the conditioning image in row 2 of Fig. 13 is warped in the generated image. We presume this is due to the fact that in this case the affine transformations need to largely warp the texture details of the narrow surface of the profile shirt (conditioning image) in order to fit the much wider area of the target frontal pose.
Figure 6: A qualitative comparison on the Market-1501 dataset between our approach and the results obtained by Ma et al. [12]. Columns 1 and 2 show the conditioning image and the target image, respectively, which are used as reference by both models. Columns 3 and 4 respectively show the images generated by our full-pipeline and by the full-pipeline presented in [12].
Figure 7: More qualitative comparison on the Market-1501 dataset between our approach and the results obtained by Ma et al. [12].
Figure 8: A qualitative comparison on the DeepFashion dataset between our approach and the results obtained by Ma et al. [12].
Figure 9: More qualitative comparison on the DeepFashion dataset between our approach and the results obtained by Ma et al. [12].
Figure 10: Other qualitative results on the Market-1501 dataset.
Figure 11: Other qualitative results on the DeepFashion dataset.
| $x_a$ | $P(x_a)$ | $P(x_b)$ | $x_b$ | Baseline (ours) | DSC (ours) | Full (ours) |
|-------|----------|----------|-------|-----------------|------------|------------|

Figure 12: Some failure cases on the Market-1501 dataset. See the text for more details.
Figure 13: Some failure cases on the DeepFashion dataset.