DeepPortraitDrawing: Generating Human Body Images from Freehand Sketches

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Abstract—Researchers have explored various ways to generate realistic images from freehand sketches, e.g., for objects and human faces. However, how to generate realistic human body images from sketches is still a challenging problem. It is, first because of the sensitivity to human shapes, second because of the complexity of human images caused by body shape and pose changes, and third because of the domain gap between realistic images and freehand sketches. In this work, we present DeepPortraitDrawing, a deep generative framework for converting roughly drawn sketches to realistic human body images. To encode complicated body shapes under various poses, we take a local-to-global approach. Locally, we employ semantic part auto-encoders to construct part-level shape spaces, which are useful for refining the geometry of an input pre-segmented hand-drawn sketch. Globally, we employ a cascaded spatial transformer network to refine the structure of body parts by adjusting their spatial locations and relative proportions. Finally, we use a global synthesis network for the sketch-to-image translation task, and a face refinement network to enhance facial details. Extensive experiments have shown that given roughly sketched human portraits, our method produces more realistic images than the state-of-the-art sketch-to-image synthesis techniques.

I. INTRODUCTION

Creating realistic human images benefits various applications, such as fashion design, movie special effects, and educational training. Generating human images from freehand sketches can be more effective since even non-professional users are familiar with such a pen-and-paper paradigm. Sketches can not only represent the global structure of a human body but also depict the local appearance details of the body as well as garments.

Deep generative models, such as generative adversarial networks (GANs) [1] and variational auto-encoders (VAEs) [2], have recently made a breakthrough for image generation tasks. Based on these generative models, many methods [3–6] have been proposed to generate desired images from input sketches by solving a general image-to-image translation problem. Some other methods have focused on generating specific types of images, including human faces [7, 8] and foreground objects [9]. Such methods can better handle freehand sketches by incorporating the relevant domain knowledge.

Compared to many other types of images, human body images have more complicated intrinsic structures and larger shape and pose variations, making the sketch-based synthesis task difficult for the following reasons. First, existing human portrait image datasets [10] only cover a small subset of all possible human images. Such methods can better handle freehand sketches by incorporating the relevant domain knowledge.

In this work, we present DeepPortraitDrawing, a novel deep generative approach for generating realistic human images from coarse, rough freehand sketches (Figure 2). Instead of trying to increase the generalization ability of sketch-to-image algorithms, our key idea is to project an input test sketch to part-level shape spaces constructed based on image-based training data. This can assist to bridge the gap between the training and test data, and also the gap between freehand sketches and realistic images. This idea makes sense for our task since roughly drawn sketches do not provide hard constraints for geometric interpretation. By properly recombining part-level information in different training images we are able to cover a significant portion of all possible human images.

To this end, we take a local-to-global approach to encode complicated body shapes under various poses. For each semantic body part, we employ an auto-encoder to define a part-level latent shape space by training on part-level edge maps extracted from images. Our system takes as input a semantically segmented sketch, whose individual body parts are projected onto the constructed part-level shape spaces. This results in a geometrically refined sketch map and a corresponding parsing map (i.e., labeled regions). Next, we employ a cascaded spatial transformer network to structurally
refine the sketch and parsing maps by adjusting the locations and relative proportions of individual body parts. Finally, we use a global synthesis network to produce a realistic human image from the transformed maps, and use a face refinement network to improve the local details of facial landmarks.

Extensive experiments demonstrate the effectiveness and practicability of our method. We are able to satisfy novice users’ need for creating visually pleasing human images from hand-drawn sketches. In our self-collected dataset of freehand sketches, our method produces visually more pleasing results with more realistic local details, compared to the previous sketch-based image generation techniques (Figure 7). The main contributions of our paper can be summarized as follows:

- We are the first to consider the problem of synthesizing realistic human images from roughly drawn sketches;
- We present a local-to-global deep generative solution to geometrically and structurally refine an input sketched human before image synthesis.
- We collect a hand-drawn sketch dataset of human images (containing 308 segmented sketches), which can facilitate future research.

II. RELATED WORK

A. Sketch-to-image generation

Generating desired images from hand-drawn sketches is a difficult task, since sketches often exhibit different levels of abstraction. To address this domain gap, traditional methods take a retrieval-composition approach, essentially considering sketches as soft constraints. For example, a pioneering work by Chen et al. [11] first retrieves images from the Internet using input sketches with text descriptions, and fuses the retrieved foreground and background images into desired pictures. A similar idea is used in PhotoSketcher [12]. PoseShop [13] constructs image scenes with human figures but requires users to provide 2D poses for retrieval. Since such retrieval-based approaches directly reuse portions of existing images for reconstruction, their performance is highly dependent on the scale of image datasets, as well as the composition quality.

By using deep learning models, (e.g., conditional GANs [14]), recent sketch-based image synthesis works adopt a reconstruction-based approach. Some works [3], [15], [16] aim at general-purpose image-to-image translation and can handle sketches as one of the possible input types. Other works focus on using sketches as the condition for GANs. For example, Scribbler [4] can control textures in generated images by grayscale sketches and colorful strokes. Contextual-GAN [5] updates latent vectors for input sketches through back propagation and produces images by a pre-trained model. SketchyGAN [6] and iSketchNFill [9] are able to generate multi-class images for diverse sketches by introducing gated conditions. Gao et al. [17] propose an approach to produce scene images from sketches, by generating each foreground object instance and the background individually. Recently, Ho et al. [18] propose a coarse-to-fine generation framework and incorporate human poses to synthesize human body images.

While impressive results were presented in the above works, these techniques do not generalize well to rough or low-quality sketches, which have very different characteristics compared to image edge-maps used for training the generative models. Additionally, since sketches are largely used as hard constraints in these techniques, the synthesized images would inherit geometric distortions if they exist in the input sketches (Figure 7).

Our approach has been inspired by the recent work DeepFaceDrawing [8], which takes a projection-reconstruction approach for synthesizing realistic human face images from sketches. The key idea of DeepFaceDrawing is to refine the input sketches before synthesizing the final image. This refinement is achieved by projecting the input sketches to component-level spaces spanned by edge maps of realistic faces. DeepFaceDrawing achieves impressive results even for rough or incomplete sketches but is limited to the synthesis of frontal faces. We extend their approach to synthesizing human body images under various poses and viewpoints. Our extension explicitly uses the semantic information in the whole pipeline, and contributes a spatial transformation module, essentially leading to a projection-transformation-reconstruction pipeline.

B. Label-to-image generation

There are many semantic synthesis approaches generating images from segmentation label maps. For example, Pix2pix [3] is a general image-to-image translation framework based on a U-Net [19] generator and a conditional discriminator. Chen and Koltun [20] present a cascaded refinement network and use multi-layer perceptual losses to achieve photographic images from segmentation maps. Pix2pixHD [16] employs multi-scale generators and discriminators, and incorporates a feature matching loss to build a high-resolution image-to-image translation framework. GauGAN [21] introduces the SPADE layer to control image styles directly by semantic segmentation. Zhu et al. [22] present a semantically multi-modal synthesis model to generate images with diverse styles for each semantic label. LGGAN [23] combines local class-specific sub-generators and a global image-level generator for semantic scene generation. DAGAN [24] present two novel attention modules to capture spatial-wise and channel-wise attention individually. Different from the above reconstruction-based approaches, Qi et al. [25] introduce a retrieval-reconstruction image synthesis method. They retrieve image segments from a dataset using segmentation maps as query and employ a global refinement network to produce globally consistent results. Although segmentation labels can be used to generate plausible images, they are less expressive than sketches in describing local details and geometric textures of user-desired images. (e.g., collars and sleeves in Figure 7).

C. Human body image generation

Human-body image synthesis is challenging, because of human sensitivity to human shapes. There is a need to make the global body structure reasonable and to produce realistic local
textures. Most researchers have focused on the human pose transfer task [26, 27], which synthesizes the same person from a source image in target poses. To achieve this, some methods utilize component masks [28, 29], human parsing [30, 31], or correspondence flows [32–34] to transform local source features into target areas, thus preserving the appearance of the same person in target poses. Other methods [35, 36] employ dense pose [37] or statistical human models like SMPL [38] to provide the human body structure as a prior. Several methods [36, 39, 40] construct a surface texture map from a source human body image, and then render the texture map on a target human image. Recently, HumanGAN [41] proposes novel part-based encoding and warping modules for generating diverse human images with high quality. These pose transfer techniques focus on preserving texture details from source images, while our method focuses on generating body textures and garments according to hand-drawn sketches.

Besides pose, other approaches synthesize human images by modifying other properties. For example, FashionGAN [42] encodes the shape, appearance, and text, allowing to edit garment textures of human images through text descriptions. Many researchers have attempted to address the virtual try-on problem [43, 44], i.e., dressing a source person with given clothes through proper geometric transformations. Ak et al. [45] and Men et al. [46] use attribute vectors to represent appearance information and then control the clothes and textures of human images via such attribute vectors. Dong et al. [47] leverage a parsing map as guidance and introduce an attention normalization layer to edit human images by sketches and colors. These methods are able to change certain properties for a source human image, but they cannot generate a brand-new human image from scratch.

III. METHOD

We propose a projection-transformation-reconstruction approach for generating realistic human body images from freehand sketches. As illustrated in Figure 2, it is achieved through three modules operated in sequence: a geometry refinement module, a structure refinement module, and an image generation module. The geometry refinement module takes a semantically segmented sketch as input and refines the geometry of its individual body parts by retrieving and interpolating the exemplar body parts in the latent spaces of the learned part-level auto-encoders. This module results in a refined sketch map and a corresponding parsing map. The structure refinement module spatially transforms the sketch and parsing maps to better connect and shape individual parts, and refine the relative proportions of body parts. Finally, the image generation module translates the transformed maps into a realistic human body image.

A. Geometry refinement module

This module aims to refine an input freehand sketch by using human portrait images to train several part-level networks. This has two advantages. First, locally pushing the input sketch towards the training edge maps, and second reducing the geometric errors in the input sketch. This assists the image generation module in generating more realistic images.

Due to the complexity of human images, it is very unlikely to find in our training dataset an image that is globally similar to an input sketch (Figure 7). On the other hand, it is much easier to retrieve similar body parts and learn a component-level shape space for each body part. We thus follow the idea in DeepFaceDrawing [8] to perform manifold projection at the component level.

DeepFaceDrawing has focused on the synthesis of frontal faces and relies on a shadow interface to guide users to sketch face components that are well aligned with the training examples. This alignment is critical for synthesizing realistic faces with DeepFaceDrawing. In contrast, we aim to handle portrait images under various poses and viewpoints. Hence, we cannot use a single layout template for body components. Instead, we propose to use the semantic segmentation information through the entire pipeline, since semantic labels provide a natural way to establish corresponding body parts in different images.

Let $S$ denote a test sketch or a training edge map. We assume that $S$ has been semantically segmented into $C = 8$ parts, including hair, face, top-clothes, bottom-clothes, left and right arms, left and right legs. We denote the part sketches as $\{S^c\}_{c=1,...,C}$. Each body part $S^c$ is cropped by a corresponding bounding box (Seg$^c$ will be a white image if part-$c$ is absent from $S$). We use an auto-encoder architecture to extract a feature vector for each body part to facilitate the subsequent manifold projection task, as illustrated in Figure 2.

In the testing stage, given a semantically segmented sketch denoted as $\{S^c\}_{c=1,...,C}$, we project its body parts to the underlying part-level manifolds for geometric refinement. We adopt the Locally Linear Embedding (LLE) algorithm [48] to perform manifold projection without explicitly constructing each part-level manifold. Specifically, each part sketch $S^c$ is first encoded into a latent vector $v^c$ by a corresponding encoder $E^c$. Based on the local linear assumption, we use a retrieve-and-interpolate approach. In more detail, we first retrieve $K$ nearest neighbors $\{v^c_k\}_{k=1,...,K}$ for $v^c$ in the latent space $\{v^c\}$ for part $c$ using the Euclidean distance. $\{v^c\}$ collected from a set of training images can be considered as the samples that build the underlying part-level manifold for part $c$. We then interpolate the retrieved neighbors to approximate $v^c$ by minimizing the mean squared error as follows:

$$\min \left\| v^c - \sum_{k=1}^{K} w^c_k \cdot v^c_k \right\|_2^2, \quad \text{s.t. } \sum_{k=1}^{K} w^c_k = 1, \quad (1)$$

where $K = 10$ in our experiments and $w^c_k$ is the unknown weight of the $k$-th vector candidate. For each body part, $\{w^c_k\}$ can be found independently by solving a constrained least-squares problem. After the weights $\{w^c_k\}$ are found, we can calculate the projected vector $\hat{v}^c$ by linear interpolation:

$$\hat{v}^c = \sum_{k=1}^{K} w^c_k \cdot v^c_k. \quad (2)$$
Next, the sketch decoder $D_S$ and the mask decoder $D_M$ for part $c$ process the projected vector $\hat{v}^c$, resulting in a refined part sketch $\hat{S}^c$ and a part mask $\hat{M}^c$, respectively. Finally, all projected part sketches $\{\hat{S}^c\}$ and masks $\{\hat{M}^c\}$ are combined together to recover the global body shape, resulting in a geometry-refined sketch map $\hat{S}$ and a human parsing map $\hat{M}$.

In the training stage, we first train the encoder $E^c$ and the sketch decoder $D_S$ to avoid the distraction from the mask branch. Since $E^c$ and $D_S$ need to reconstruct the input $S^c$ with consistent shapes and fine details, we employ the $L_2$ distance as the reconstruction loss to train them. Then, we fix the weights of the parameters in $E^c$ and train the mask decoder $D_M$. We use the cross-entropy loss for this training since it is a binary segmentation task.

**B. Structure refinement module**

The geometry refinement module focuses only on the refinement of the geometry of individual body parts in a sketch. However, relative positions and proportions between body parts in a hand-drawn sketch might not be accurate. We thus employ the structure refinement module to refine the relative positions and proportions of body parts to get a globally more consistent body image.

To refine the body structure, we use the pose keypoints (see Figure 3), which provide a simple and effective way to represent a human body structure. According to the physiological characteristics of human beings, the positions of pose keypoints should obey two rules. First, a joint of a body part should connect to the same joint of its neighboring body part. Second, the relative length of different body parts should be globally consistent. Therefore, we aim to transform the keypoints of different body parts and make them conform to these rules.

As illustrated in Figure 3, we first utilize a pose estimation network $P$ to predict heatmaps $H^c$ for the position of each keypoint from each refined part sketch map $\hat{S}^c$. Note that we need to predict the same joint repeatedly for neighboring body parts. Then, we leverage all the part heatmaps $\{H^c\}$ as guidance to recover the global structure of the sketched human body. The different body parts should preserve proper relative lengths, and connect with each other based on the inherent relationships among them. To achieve this, we apply affine transformations to the body parts predicted by a spatial transformer network $T$, so that the part heatmaps $\{H^c\}$ are transformed to reasonable locations $\{\tilde{H}^c\}$ learned from real human poses. We apply the same predicted affine transformations to the refined part sketch maps $\{\hat{S}^c\}$ and the part mask maps $\{\hat{M}^c\}$, resulting in $\{\tilde{S}^c\}$ and $\{\tilde{M}^c\}$, respectively.

Since neighboring body parts may influence each other, it is very difficult to recover the entire human structure...
in one step transformation. Therefore, we use a cascaded refinement strategy, employing a multi-step spatial transformer network to update the results iteratively. To leverage the global information, we combine all the part sketch maps as $\hat{S}$ and all the part heatmaps as $H$, and then feed $\hat{S}$ and $H$ to the spatial transformer network. The transformed sketch map $\hat{S}$ and heatmaps $\hat{H}$ in the $j$-th step are the input to the transformer network in the $(j+1)$-th step. In our experiments, we used a three-step refinement, as illustrated in Figure 3.

To train the pose estimation network $P$ and the cascaded spatial transformer network $T$, we need to simulate the inconsistencies of the global structure we may find at the test time. We apply random affine transformations to all part edge maps $\{S^c\}$ and part heatmaps $\{H^c\}$ in the training set, except for a selected reference part. We select the top-clothes part (i.e., the upper body) as the reference part and keep it unchanged in our experiments. The pose network $P$ needs to predict all part heatmaps $\{\hat{H}^c\}$ from each randomly transformed edge map $\hat{S}$. We adopt the stacked hourglass architecture [50] for $P$ and use the mean squared error to train it.

The goal of the cascaded spatial transformer network $T$ is to refine the size and location of each body part. Therefore, the predicted pose heatmaps $\{\hat{H}^c\}$ should be transformed so that they are as close to the ground-truth $\{H^c\}$ as possible. Similarly, we require the randomly transformed part edge maps $\{\hat{S}^c\}$ to be close to the ground-truth part edge maps $\{S^c\}$. We have found that extremely large transformations may lead to training instability. We thus append a regularization term to penalize transformation matrices that are too large. The spatial transformer network $T_{j+1}$ in the $(j+1)$-th step is fed with the transformed edge map $\hat{S}_j$ and the combined heatmaps $\hat{H}_j$ in the $j$-th step. Its initial input is $\hat{S}_0$ and $\hat{H}_0$. The loss function of $T$ can be formulated as:

$$
L(T) = \sum_{j=0}^{2} \sum_{c=1}^{C} \lambda_H \| F(T_j^{c+1}(\hat{S}_j, \hat{H}_j), \hat{H}_j^c) - H^c\|_2^2 + \lambda_S \| F(T_j^{c}(\hat{S}_j, \hat{H}_j), \hat{S}_j^c) - S^c\|_2^2 + \lambda_L \| T_j^{c+1}(\hat{S}_j, \hat{H}_j) - \hat{F}_j\|_2^2
$$

(3)

where $F$ represents an affine transformation operation and $\hat{F}$ denotes the identity matrix. $T_j^{c+1}(\hat{S}_j, \hat{H}_j)$ denotes the predicted transformation matrix for the $c$-th body part in the $(j+1)$-th step. We set $\lambda_H = 100$ and $\lambda_S = \lambda_L = 1$ in our experiment to balance the three terms.

**C. Image generation module**

Finally, we need to generate a desired human image $I$ from the transformed sketch map $\hat{S}$ and the transformed parsing map $\hat{M}$ after the structure refinement module, as illustrated in Figure 5. We adopt GauGAN [21] as our basic architecture for the global synthesis network $G$, since it has achieved impressive results for the label-to-image translation task. The SPADE layer in GauGAN [21] takes the parsing map $\hat{M}$ as input by default. To prevent losing the information in the sketch map $\hat{S}$, we concatenate it to the parsing map $\hat{M}$ and feed them together into the SPADE layer. This way, the parsing map $\hat{M}$ controls the image style in each semantic region, while the sketch map $\hat{S}$ provides the geometric features for local details.

The global synthesis network $G$ is able to generate an acceptable result $\hat{I}$ globally. However, the human visual system is more sensitive to the quality of synthesized faces. Since hand-drawn human body sketches might not describe facial landmarks clearly, $G$ may fail to produce rich details for the face area. Inspired by Chan et al. [51], we utilize a face refinement network $F$ to enhance the facial details in the human image $\hat{I}$. We crop a square patch from $\hat{I}$ according to the face label in $\hat{M}$. The square patch and the face mask are then fed into the face refinement network $F$ to produce a residual image for the face area. The final result $\hat{I}$ is the sum of $\hat{I}$ and the residual image. To train $F$ to achieve a realistic human face, we adopt both an adversarial loss and a perceptual loss, similar to Chan et al. [51].

To train the global synthesis network $G$, we could simply take the edge maps $\{S_i\}$ and the parsing maps $\{M_i\}$ in the training set as input. However, we have found that the synthesis network $G$ trained this way cannot address freehand sketches well. Although the geometry refinement module can refine the geometric shape of an input sketch $S$, the resulting sketch $\hat{S}$ still differs from edge maps found in the training set. The main reason is that edge maps extracted from natural human images contain many texture details, and these can violate the local linear assumption [48] used in the step of manifold projection. Instead, to simulate the input at the test time, we take the projected version of each edge map in the training set as the input to train $G$. We retrieve $K$ nearest neighbors in the underlying manifold for each edge map $S_j$. Then, the edge maps $\{S_i\}$ and the parsing maps $\{M_i\}$ decoded by the projected vectors are fed into $G$. Similar to GauGAN [21], we adopt the adversarial loss, the perceptual loss, and the feature matching loss [16] together to train $G$.

**IV. Experiments**

To get the paired data for training, we construct a large-scale sketch dataset of human images from DeepFashion [10], as described in Sec IV-A. Sec IV-B introduces the architecture of our proposed networks and the implementation details of model training. We conduct comparison experiments with several sketch-to-image techniques in Sec IV-C to show the superiority of our method for generating human images from hand-drawn sketches. The ablative study in Sec IV-D evaluates the contribution of individual components in our method. Sec IV-E shows that our method is able to produce multi-style human images from the same input sketches.

**A. Data preparation**

Training the global synthesis network $G$ needs a dataset of paired images and sketches. Similar to previous methods [3], [4], [8], we extract edge maps from human images of $256 \times 256$ resolution in DeepFashion [10] to build our synthetic sketch dataset. At first, we filter the DeepFashion dataset to remove images of the lower body. Then we apply the edge detection
Fig. 4: In our experiments, a geometrically refined sketch map $\hat{S}$ is transformed iteratively for three steps to get a structurally refined sketch map.

Fig. 5: Illustration of the image generation module. The transformed sketch and parsing maps are fed into the SPADE layer of the global synthesis network to produce a human image result. Then the face refinement network enhances the facial details for the final result.

Fig. 6: The process of building our training and validation sets of sketches. (a): Input human image. (b): Edge extraction of (a) by Im2Pencil [52]. (c): Sketch simplification of (b) by the method of Simo-Serra et al. [53]. (d): Part segmentation of (c) by PGN [54].

method proposed by Im2Pencil [52] to get an edge map for each human image (Figure 5 from (a) to (b)). By employing the sketch simplification method proposed by Simo-Serra et al. [53], we clean noise curves in the extracted edge maps (Figure 6 (c)) so they resemble hand-drawn sketches more. This results in a new large-scale sketch dataset of human images with paired data. This dataset contains 37,844 pairs in total. We randomly select 2,000 pairs as the validation set and the remaining 35,844 pairs as the training set.

Our models also require human parsing maps and pose heatmaps for training. We utilize PGN [54] to predict a parsing map for each human image in our dataset. To simplify the problem, we merge several labels in the parsing maps, resulting in $C = 8$ types of body parts altogether. The merged parsing maps are regarded as the ground-truth. These maps also allow us to segment the paired edge maps to obtain semantically segmented edge maps (Figure 5 (d)). To prepare the data for training the transformer network, we first employ OpenPose [55] to predict the 2D pose keypoints from the human images, and then generate pose heatmaps from the keypoints based on the Gaussian distribution to better capture spatial features.

To evaluate the usefulness of our method in practice, we have collected freehand sketches from 12 users (6 males, 6 females). Four of them have good drawing skills, while the others are less proficient. The users were asked to imitate a given human image or just draw an imagined human. They were instructed to draw a segmented sketch part by part, taking around one minute to complete one sketch on average. We have collected 308 hand-drawn sketches of human images in total to construct our test set. We plan to release our dataset of paired human images and synthetic edge maps as well as hand-drawn sketches publicly for future research.

B. Implementation details

In the geometry refinement module. We share the left and right arms/legs with the same auto-encoders by leveraging the human body symmetry, so there are in total 6 part auto-encoders. Each part encoder $E^c$ contains five downsampling convolutional layers, with each downsampling layer followed by a residual block. A fully-connected layer is appended in the end to encode the features into the latent vector $v^c$ of 512 dimensions. Similarly, the part decoders $D^c_S$ and $D^c_M$ each contain five upsampling convolutional layers and five residual blocks in total. The final convolutional layers in $D^c_S$ and $D^c_M$ reconstruct the part sketch $S^c$ and the part mask $M^c$, respectively. To train the structure refinement module, we preprocess the training set by applying random affine transformations, which are composed of translation, rotation, resizing, and shearing transformations. The spatial transformer network $T_j$ in each step consists of five downsampling convolutional layers, five residual blocks, and the last two fully-connected layers to predict the affine transformation matrices for all body parts.

We use the Adam [56] solver to train all the networks. We set the learning rate to 0.0002 initially and linearly decay it to 0 after half iterations. For each part auto-encoder, we first train the encoder $E^c$ and the sketch decoder $D^c_S$ for 100
epochs and then train the mask decoder $D^*_M$ for 50 epochs. We train the pose estimation network $P$ and the cascaded spatial transformer network $T$ both for 50 epochs. We set the batch size to 16 for the above networks. We train the global synthesis network $G$ for 100 epochs of batch size 8 and the face refinement network $F$ for 10 epochs of batch size 10. We conduct the experiments by using an Intel(R) Core(TM) i7-4770 CPU @ 3.40GHz with 4 cores and NVidia GTX 1080 Ti GPUs. Please refer to the supplementary materials for more training and architecture details.

C. Comparison with state-of-the-art methods

To demonstrate the effectiveness of our method for synthesizing realistic human images from freehand sketches, we compare our method with four state-of-the-art sketch-based image synthesis methods, including pix2pix [3], pix2pixHD [16], GauGAN [21] and DAGAN [24]. For a fair comparison, we train all the four models on our training set for the same epochs as our method. Please note that we employ the first-stage generator of pix2pixHD [16], since the image resolution of our dataset is limited to $256 \times 256$. We also compare our method with a sketch-based image retrieval approach. To achieve this, we train an auto-encoder for an entire edge map and collect all latent vectors in the training set. Given an input sketch, we encode it into a vector and retrieve the nearest neighbor from the training set. We regard the human image corresponding to the nearest vector as the retrieval result. To eliminate the influence of facial areas, we remove the face enhancement module in our method for comparison.

Figure 7 shows several representative results of our method and the other five approaches on our test sketches. Compared to the four state-of-the-art sketch-to-image synthesis techniques, our method performs much better with visually more pleasing results. Even when the face enhancement module is removed, our method still produces more realistic texture details and more reasonable body structures, owing to the geometry and structure refinement guided by the semantic parsing maps. Compared to the sketch-based image retrieval approach, our method can produce brand-new human images which respect user inputs more faithfully. Please refer to the supplementary materials for more comparison results.

To further evaluate the results, we have applied FID [57] as a quantitative metric, which measures perceptual distances between generated images and real images. Table I shows that our method outperforms the other three sketch-to-image synthesis methods [3], [16], [21], indicating more realistic results by our method. However, as claimed by [8], this perceptual metric might not measure the quality of results correctly, since it does not take the geometry and structure of the human body into consideration. Therefore, we also conducted a user study to compare our method with the three sketch-to-image synthesis techniques [3], [16], [21]. We randomly selected 30 sketches from the test set and showed each sketch along with the four results by the compared methods in a random order to users, who were asked to pick the most realistic results. There were 17 participants in total, resulting in 510 votes. Our method received significantly more votes than the other methods, as shown in Table I. The participants were also asked to give a score of faithfulness for each result by GauGAN [21] (we select it as the representative one of the sketch-to-image synthesis methods), the sketch-based image retrieval method, and our method. The scores ranged from 1 to 10, the higher the better. Table I shows that the results of our method conform with input sketches better than the image retrieval method and are comparable to GauGAN [21]. For a fair comparison, we also removed the face enhancement module in our method to produce the results used in the user study.

D. Ablation study

We have conducted an ablation study to demonstrate the contributions of the different components of our method. Each time, we remove the parsing map guidance, the projection of latent vectors, the spatial transformation, and the face enhancement, respectively, while keeping the other components unchanged. As shown in Figure 8 without the guidance of the human parsing map, our method cannot produce locally consistent results in the same semantic regions (e.g., legs in the second and third rows). Without the projection component, our method cannot refine the geometry of local details, resulting in obvious artifacts. Without the spatial transformation component, our method will produce results with incorrect connection relationships of joints (e.g., shoulders in the second and third rows) or unreasonable body proportions (e.g., the first and fourth rows). Without the face enhancement, our method may not generate realistic facial details.

E. Multi-modal synthesis

Similar to previous image-to-image translation methods [16, 21], our method can be easily extended to generate multi-modal human images from the same input sketches. To achieve this, we append an image encoder ahead of the global synthesis network $G$ and train both of them together with an extra KL-divergence loss [3]. The feature vector encoded by the image encoder can control the texture style of a generated image. Therefore, given the feature vectors encoded by reference human images, our method can produce human images with texture styles similar to the reference images (Figure 9a). Besides, given random feature vectors, our method
V. CONCLUSION AND FUTURE WORK

We have proposed a projection-transformation-reconstruction approach for generating realistic human images from hand-drawn sketches. Our method consists of three modules, including a geometry refinement module, a structure refinement module, and an image generation module. The geometry refinement module plays an important role in converting roughly drawn sketches into semantic sketch maps, which are locally similar to the edge maps of real human images. This successfully bridges the gap between realistic images and freehand sketches. The structure refinement module locally adjusts spatial connections between body parts and their relative proportions to get a globally more consistent structure. The image generation module produces visually pleasing human images with fine facial details. Comparison experiments have shown that our approach outperforms three state-of-the-art sketch-to-image synthesis methods, which cannot address freehand sketches well.

Still, the geometry and structure refinement modules are restricted to the data distribution in the training set. Therefore, our method cannot produce human images which are very different from the images in DeepFashion [10]. For example, as shown in Figure 10 (Left), our method generates an unsat-
Fig. 8: Comparison results in the ablation study. We remove the parsing map guidance, the projection of latent vectors, the spatial transformation, and the face enhancement in our method, respectively.

Fig. 9: For a given input sketch, our method can generate multiple results with texture styles similar to the reference images (a) or random styles (b).

isfying result for a hand-drawn sketch of a child. The structure refinement module is also limited to recover the human body structure of an adult only since there are only adult models in DeepFashion [10]. As we do not divide the latent vectors of different genders for retrieval, our method is sometimes confused with the gender, as shown in Figure 10 (Right). We will collect more types of human images to improve the generalization ability of our method in the future work. It will also be interesting to introduce colorful strokes to control the texture styles more exactly.

REFERENCES
[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, 2014, pp. 2672–2680.
[2] D. P. Kingma and M. Welling, “Auto-encoding variational bayes,” arXiv preprint arXiv:1312.6114, 2013.
[3] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, “Image-to-image translation with conditional adversarial networks,” in IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 1125–1134.
[4] P. Sangkloy, J. Lu, C. Fang, F. Yu, and J. Hays, “Scribbler: Controlling deep image synthesis with sketch and color,” in IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 5400–5409.
[5] Y. Lu, S. Wu, Y.-W. Tai, and C.-K. Tang, “Image generation from sketch constraint using contextual gan,” in European Conference on Computer Vision, 2018, pp. 205–220.
[6] W. Chen and J. Hays, “Sketchygan: Towards diverse and realistic sketch to image synthesis,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 9416–9425.
[7] Y. Li, X. Chen, B. Yang, Z. Chen, Z. Cheng, and Z.-J. Zha, “Deepfacepencil: Creating face images from freehand sketches,” in ACM International Conference on Multimedia, 2020, pp. 991–999.
[8] S.-Y. Chen, W. Su, L. Gao, S. Xia, and H. Fu, “Deepfacedrawing: deep generation of face images from sketches," ACM Transactions on Graphics (TOG), vol. 39, no. 4, pp. 72–1, 2020.
[9] A. Ghosh, R. Zhang, P. K. Dokania, O. Wang, A. A. Efros, P. H. Torr, and E. Shechtman, “Interactive sketch & fill: Multiclass sketch-to-image translation,” in IEEE international conference on computer vision, 2019, pp. 1171–1180.
[10] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, “Deepfashion: Powering robust clothes recognition and retrieval with rich annotations,” in IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1096–1104.
[11] T. Chen, M.-M. Cheng, P. Tan, A. Shamir, and S.-M. Hu, “Sketch2photo: Internet image montage,” ACM transactions on graphics (TOG), vol. 28, no. 5, pp. 1–10, 2009.
[12] M. Eitz, R. Richter, K. Hildebrand, T. Boubekeur, and M. Alexa, “Phototketcher: interactive sketch-based image synthesis,” IEEE Computer Graphics and Applications, vol. 31, no. 6, pp. 56–66, 2011.
[13] T. Chen, P. Tan, L.-Q. Ma, M.-M. Cheng, A. Shamir, and S.-M. Hu, “Poseshop: Human image database construction and personalized content synthesis,” IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 5, pp. 824–837, 2013.
[14] M. Mirza and S. Osindero, “Conditional generative adversarial nets,” arXiv preprint arXiv:1411.1784, 2014.
[15] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 2223–2232.

[16] T.-C. Wang, M.-Y. Liu, J.-Y. Zhu, A. Tao, J. Kautz, and B. Catanzaro, “High-resolution image synthesis and semantic manipulation with conditional gans,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8798–8807.

[17] C. Gao, Q. Liu, Q. Xu, L. Wang, J. Liu, and C. Zou, “Sketchy: coc: image generation from freehand scene sketches,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 5174–5183.

[18] L. Ma, Q. Sun, S. Georgoulis, L. Van Gool, B. Schiele, and M. Fritz, “Guided scene generation,” in ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), vol. 16, no. 3, pp. 1–18, 2020.

[19] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical Image Computing and Computer-Assisted Intervention, 2015, pp. 234–241.

[20] Q. Chen and V. Koltun, “Photographic image synthesis with cascaded refinement networks,” in IEEE International Conference on Computer Vision, vol. 1, 2017.

[21] T. Park, M.-Y. Liu, T.-C. Wang, and J.-Y. Zhu, “Semantic image synthesis with spatially-adaptive normalization,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 2337–2346.

[22] Z. Zhu, Z. Xu, A. You, and X. Bai, “Semantically multi-modal image synthesis,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 5467–5476.

[23] H. Tang, D. Xu, Y. Yan, P. H. Torr, and N. Sebe, “Local class-specific and global image-level generative adversarial networks for semantic-guided scene generation,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 7870–7879.

[24] H. Tang, S. Bai, and N. Sebe, “Dual attention gans for semantic image synthesis,” in ACM International Conference on Multimedia, 2020, pp. 1994–2002.

[25] X. Qi, Q. Chen, J. Jia, and V. Koltun, “Semi-parametric image synthesis,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8808–8816.

[26] L. Ma, X. Jia, Q. Sun, B. Schiele, T. Tuytelaars, and L. Van Gool, “Pose guided person image generation,” in Advances in Neural Information Processing Systems, 2017, pp. 405–415.

[27] L. Ma, Q. Sun, S. Georgoulis, L. Van Gool, B. Schiele, and M. Fritz, “Disentangled person image generation,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 99–108.

[28] G. Balakrishnan, A. Zhao, A. V. Dalca, F. Durand, and J. Guttig, “Synthesizing images of humans in unseen poses,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 8340–8348.

[29] A. Siarohin, E. Sangineto, S. Lathuilière, and N. Sebe, “Deformable gans for pose-based human image generation,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 3408–3416.

[30] H. Dong, X. Liang, K. Gong, H. Lai, J. Zhu, and J. Yin, “Soft-gated warping-gan for pose-guided person image synthesis,” in Advances in Neural Information Processing Systems, 2018, pp. 474–484.

[31] X. Han, X. Hu, W. Huang, and M. R. Scott, “Clothflow: A flow-based model for clothed person generation,” in IEEE International Conference on Computer Vision, 2019, pp. 10471–10480.

[32] Y. Li, C. Huang, and C. C. Loy, “Dense intrinsic appearance flow for human pose transfer,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 3693–3702.

[33] W. Liu, Z. Piao, J. Min, W. Luo, L. Ma, and S. Gao, “Liquid warping gan: A unified framework for human motion imitation, appearance transfer and novel view synthesis,” in IEEE International Conference on Computer Vision, October 2019.

[34] Y. Ren, X. Yu, J. Chen, T. H. Li, and G. Li, “Deep image spatial transformation for person image generation,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 7690–7699.

[35] C. Lasserre, G. Pons-Moll, and P. V. Gehler, “A generative model of people in clothing,” in IEEE International Conference on Computer Vision, 2017, pp. 853–862.

[36] N. Neverova, R. Alp Guler, and I. Kokkinos, “Dense pose transfer,” in European Conference on Computer Vision, 2018, pp. 123–138.

[37] R. Alp Guler, N. Neverova, and I. Kokkinos, “Denspose: Dense human pose estimation in the wild,” in IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 7297–7306.

[38] M. Loper, N. Mahmood, J. Romero, G. Pons-Moll, and M. J. Black, “Smpl: A skinned multi-person linear model,” ACM transactions on graphics (TOG), vol. 34, no. 6, p. 248, 2015.

[39] K. Sarkar, D. Mehta, W. Xu, V. Golyanik, and C. Theobalt, “Neural re-rendering of humans from a single image,” in European Conference on Computer Vision, 2020.

[40] L. Liu, W. Xu, M. Zollhoefer, H. Kim, F. Bernard, M. Habermann, W. Wang, and C. Theobalt, “Neural rendering and reenactment of human actor videos,” ACM Transactions on Graphics (TOG), vol. 38, no. 5, pp. 1–14, 2019.

[41] K. Sarkar, L. Liu, V. Golyanik, and C. Theobalt, “Humangan: A generative model of humans images,” arXiv preprint arXiv:2103.06902, 2021.

[42] S. Zhu, R. Urtasun, S. Fidler, D. Lin, and C. Change Loy, “Be your own prada: Fashion synthesis with structural coherence,” in IEEE International Conference on Computer Vision, Oct 2017.

[43] X. Han, Z. Wu, Z. Wu, R. Yu, and L. S. Davis, “Viton: An image-based virtual try-on network,” in IEEE conference on computer vision and pattern recognition, 2018, pp. 7543–7552.

[44] B. Wang, H. Zheng, X. Liang, Y. Chen, L. Lin, and M. Yang, “Toward characteristic-preserving image-based virtual try-on network,” in European Conference on Computer Vision, 2018, pp. 589–604.

[45] K. E. Ak, J. H. Lim, J. Y. Tham, and A. A. Kassim, “Attribute manipulation generative adversarial networks for fashion images,” in IEEE International Conference on Computer Vision, 2019, pp. 10541–10550.

[46] Y. Men, Y. Mao, Y. Jiang, W.-Y. Ma, and Z. Lian, “Controllable person image synthesis with attribute-decomposed gan,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 5084–5093.

[47] H. Dong, X. Liang, Y. Zhang, X. Zhang, X. Shen, Z. Xie, B. Wu, and J. Yin, “Fashion editing with adversarial parsing learning,” in IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 8120–8128.

[48] S. T. Roweis and L. K. Saul, “Nonlinear dimensionality reduction by locally linear embedding,” Science, vol. 290, no. 5500, pp. 2323–2326, 2000.

[49] M. Jaderberg, K. Simonyan, A. Zisserman et al., “Spatial transformer networks,” in Advances in neural information processing systems, 2015, pp. 2017–2025.

[50] A. Newell, K. Yang, and J. Deng, “Stacked hourglass networks for human pose estimation,” in European Conference on Computer Vision, 2016, pp. 483–499.

[51] C. Chan, S. Ginosar, T. Zhou, and A. A. Efros, “Everybody dance now,” in IEEE International Conference on Computer Vision, 2019.

[52] Y. Li, C. Fang, A. Hertzmann, E. Shechtman, and M.-H. Yang, “Im2pencil: Controllable pencil illustration from photographs,” in IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 1525–1534.

[53] E. Simo-Serra, S. Iizuka, and H. Ishikawa, “Mastering sketching: adversarial augmentation for structured prediction,” ACM Transactions on Graphics (TOG), vol. 37, no. 1, pp. 1–13, 2018.

[54] K. Gong, X. Liang, Y. Li, Y. Chen, M. Yang, and L. Lin, “Instance-level human parsing via part grouping network,” in European Conference on Computer Vision, 2018, pp. 770–785.

[55] Z. Cao, G. Hidalgo Martinez, T. Simon, S. Wei, and Y. A. Sheikh, “Openpose: Realtime multi-person 2d pose estimation using part affinity fields,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017.

[56] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[57] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, and S. Hochreiter, “Gans trained by a two time-scale update rule converge to a local nash equilibrium,” in Advances in neural information processing systems, 2017, pp. 6626–6637.