In this paper, we investigate deep image synthesis guided by sketch, color, and texture. Previous image synthesis methods can be controlled by sketch and color strokes but we are the first to examine texture control. We allow a user to place a texture patch on a sketch at arbitrary location and scale to control the desired output texture. Our generative network learns to synthesize objects consistent with these texture suggestions. To achieve this, we develop a local texture loss in addition to adversarial and content loss to train the generative network. The new local texture loss can improve generated texture quality without knowing the patch location and size in advance. We conduct experiments using sketches generated from real images and textures sampled from the Describable Textures Dataset and results show that our proposed algorithm is able to generate plausible images that are faithful to user controls. Ablation studies show that our proposed pipeline can generate more realistic images than adapting existing methods directly.

1 INTRODUCTION

One of the “Grand Challenges” of computer graphics is to allow anyone to author realistic visual content. The traditional 3d rendering pipeline can produce astonishing and realistic imagery, but only in the hands of talented and trained artists. The idea of short-circuiting the traditional 3d modeling and rendering pipeline dates back at least 20 years to image-based rendering techniques [27]. These techniques and later “image-based” graphics approaches focus on re-using image content from a database of training images [20]. For a limited range of image synthesis and editing scenarios, these non-parametric techniques allow non-experts to author photorealistic imagery.

In the last two years, the idea of direct image synthesis without using the traditional rendering pipeline has gotten significant interest because of promising results from deep network architectures such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs). However, there has been little investigation of fine-grained texture control in deep image synthesis (as opposed to coarse texture control through “style transfer” methods).

In this paper we introduce TextureGAN, the first deep image synthesis method which allows users to control object texture. Users “drag” one or more example textures onto sketched objects in a scene and the network realistically applies these textures to the indicated objects.

This “texture fill” operation is difficult for a deep network to learn for several reasons: (1) Existing deep networks aren’t particularly good at synthesizing high-resolution texture details even without user constraints. Typical results from recent deep image synthesis methods are at low resolution (e.g. 64x64) where texture is not prominent or they are higher resolution but relatively flat (e.g. birds with sharp boundaries but few fine-scale details). (2) For TextureGAN, the network must learn to propagate textures to the relevant object boundaries – it is undesirable to leave an object partially textured or to have the texture spill into the background. To accomplish this network must implicitly segment the sketched objects and perform...
texture synthesis, tasks which are individually difficult. (3) The network should additionally learn to foreshorten textures as they wrap around 3d object shapes, to shade textures according to ambient occlusion and lighting direction, and to understand that some object parts (handbag clasps) are not to be textured but should occlude the texture. These texture manipulation steps go beyond traditional texture synthesis in which a texture is assumed to be stationary. To accomplish these steps the network needs a rich implicit model of the visual world that involves some partial 3d understanding.

Fortunately, the difficulty of this task is somewhat balanced by the availability of training data. Like recent unsupervised learning methods based on colorization [21, 40], training pairs can be generated from unannotated images. In our case, input training sketches and texture suggestions are automatically extracted from real photographs which in turn serve as the ground truth for initial training. We introduce local texture loss to further fine-tune our networks to handle diverse textures unseen on ground truth objects.

We make the following contributions:

- We are the first to demonstrate the plausibility of fine-grained texture control in deep image synthesis. In concert with sketched object boundaries, this allows non-experts to author realistic visual content. Our network is feed-forward and thus can run interactively as users modify sketch or texture suggestions.
- We propose a “drag and drop” texture interface where users place particular textures onto sparse, sketched object boundaries. The deep generative network directly operates on these localized texture patches and sketched object boundaries.
- We explore novel losses for training deep image synthesis. In particular we formulate a local texture loss which encourages the generative network to handle diverse textures never seen on existing objects. We also show the benefit of factorizing the image synthesis into grayscale and color components with separate losses applied to each.

2 RELATED WORK

Image Synthesis. Synthesizing natural images has been one of the most intriguing and challenging tasks in graphics, vision and machine learning research. Most of the existing approaches fall into non-parametric and parametric types. On one hand, non-parametric approaches have a long-standing history. They are typically data-driven or example-based, i.e., directly exploit and borrow existing image pixels for the target tasks [1, 2, 6, 13, 27]. Therefore, non-parametric approaches often excel at generating realistic results while having limited generalization ability, i.e., being restricted by the limitation of data and examples, e.g., data bias and long-tail distribution. On the other hand, parametric approaches, especially deep learning based approaches, have achieved promising results in recent years. Different from non-parametric methods, these approaches utilize image datasets as training data to fit deep parametric models, and have shown superior modeling power and generalization ability in image synthesis [11, 19], e.g., hallucinating diverse and relatively realistic images that are different from training data.

Generative Adversarial Networks (GANs) [11] are a type of parametric method that has been widely applied and studied for image synthesis. The main idea is to train paired generator and discriminator networks at the same time, where the goal of the discriminator is to classify between ‘real’ images and generated ‘fake’ images, and the generator aims to fool the discriminator so that the generated images are indistinguishable from real images. Once trained, the generator can be used to synthesize images driven by a compact vector of noise. Compared to the blurry and low-resolution outcome from other methods [4, 19], GAN-based methods [16, 26, 29] generate more realistic results with richer local details and of higher resolution.

Controlable Image Synthesis and Conditional GANs. Practical image synthesis applications require perceptually controllable interfaces, ranging from high-level attributes, such as object classes [28], object poses [4], natural language descriptions [30], to fine-grained details, such as segmentation masks [16], sketches [12, 31], color scribbles [31, 41], and cross-domain images [9, 35]. While the vanilla GAN is able to generate realistic looking images from noise, it is not yet valuable for practical image synthesis applications due to the lack of controllable input. Conditional GANs are a type of models that synthesize images based on input modalities other than simple noise, thus offering more control over the generated results. Compared to vanilla GANs, conditional GANs introduce additional discriminators or losses to guide generators to output images with desired properties, e.g., an object category discriminator [28], a discriminator to judge visual-text association [30], or a simple pixel-wise loss between generated images and target images [16].

It is worth mentioning several recent and concurrent works on sketch or color-constrained deep image synthesis. Scribbler [31] demonstrates an image synthesis framework that takes as input user sketches and short color strokes, and generates realistic looking output that follows the input sketch and has colorization schemes consistent to color strokes. A similar system is employed for automatically painting cartoon images [25]. Recently, an user-guided interactive image colorization system is proposed in [41], offering users the control of color when coloring or recoloring an input image. Distinct from these works, our system simultaneously supports richer user guidance signals including structural sketches, color patches and texture swatches. Moreover, we offer extensive studies on the effect of several variants of improved loss functions and show synthesizing results of various object categories.

Texture Synthesis and Style Transfer. Texture synthesis and style transfer are two closely related important subtopics in image synthesis. Given an input texture image, texture synthesis aims at generating new images with visually similar textures. Style transfer has an extra input of content image, and requires the synthesized images to preserve the major content while exhibit the characteristics of input texture. Non-parametric texture synthesis and style transfer methods typically re-samples given example images to form output [5, 6, 14, 34]. TextureShop [7] is similar to our method in that it aims to texture an object with a user-provided texture, although TextureShop used non-parametric texture synthesis and shape-from-shading to foreshorten the texture so that it appears to follow the object surface.

Recently, a new deep parametric method [8, 9] discovered that the correlations (i.e., Gram matrix) between features extracted from a pre-trained deep neural network capture the characteristics of textures well and showed promising results in synthesizing textures
and transferring styles. In [8, 9], texture synthesis and style transfer are formalized as an optimization problem, where an output image is generated by minimizing a loss function of two terms, one of which measures content similarity between input content image and output, and the other measures style similarity between input style and output using Gram matrix. Shortly after, there have been many work on improving [8, 9] from the aspects for generalization [15, 22, 39], efficiency [17, 33] and controllability [10].

3 TEXTUREGAN

We aim to design an image synthesis pipeline that can generate natural images based on an input sketch and some user-provided texture patches. Users can provide rough sketches that outline the desired objects. Sketches can effectively control the generation of semantic content, e.g. object type and shape, but do not contain enough information to guide the generation of texture details, materials and patterns. To guide the generation of fine-scale details, we want users to somehow control texture properties of objects and scene elements.

Towards this goal, we introduce TextureGAN, a conditional generative network that learns to generate realistic images from two input images. One is a binary image containing the sketch. The other is a color image encoding the appearance, locations and sizes of texture patches. We argue that instead of providing just an unanchored texture sample, users can more precisely control the generated appearance by directly placing small texture patches over the sketch, since locations and sizes of patches provide important information that influence the visual appearance. In this setup, the user can ‘drag’ rectangular texture patches of arbitrary sizes into different sketch regions as additional input to the network. For example, the user can specify a striped texture patch for a shirt and a dotted texture patch for a skirt. The input patches guide the network to propagate the texture information to the relevant regions respecting semantic boundaries (e.g. dots should appear on the skirt but not the legs).

The challenge of allowing arbitrary location and sizes for user-provided texture patches is unknown pixel correspondence between the input texture and the generated appearance. To constrain the network to produce realistic textures, we propose to use local texture loss. The loss is comprised of a learned discriminative loss and a pixel loss between the input texture and samples of generated textures in the whole image. It not only helps the generated texture follow the input faithfully, but also helps the network learn how to propagate the texture patch and synthesize new texture. It will be detailed later in this section.

TextureGAN also allows users to more precisely control the colors in the generated result. One limitation of previous color control with GANs [31] is that the input color constraints in the form of RGB need to fight with the network’s understanding about the semantics, e.g., bags are mostly black and shoes are seldom green. To address this problem, we train the network to generate images in Lab color space. We convert the groundtruth images to Lab, enforce the content, texture and adversarial losses only on the L channel and enforce a separate color loss on the ab channels. We show that combining the controls in this way allows the network to generate realistic photos closely following the user’s color and texture intents without introducing obvious visual artifacts.

Figure 2 shows our training pipeline. We use the network architecture proposed in Scribbler [31]. We also use a 4-channel image as input to the network, but we change the channel specifications to support three different types of controls – one channel for sketch, one channel for texture and two channels for color. Section 4.2 describes the method we used to generate each input channel of the network.

We first train TextureGAN to recover the ground-truth photos given the synthetically generated input control channels. We then generalize TextureGAN to support broader range of textures by fine-tuning the network with a separate database, the Describable Textures Dataset (DTD) [3].

3.1 Ground-truth Pre-training

We aim to replicate the texture information contained in small patches to fill in an entire object. We follow the previous work Scribbler [31] and use feature and adversarial losses to encourage the generation of realistic object structures. But we find that these losses alone cannot reproduce fine-grained texture details. Also, Scribbler uses pixel loss to enforce color constraints, but fails when the input color is rare for that particular object category. Therefore, we redefine the feature and adversarial losses and introduce new losses to improve the replication of texture details and encourage precise propagation of colors. Note that we derive the network’s input channels from ground-truth photos. When computing the losses, we compare the generated images with the ground-truth.
Our objective function consists of multiple terms, each of which encourages the network to focus on different aspects.

**Feature Loss.** It has been shown previously that the features extracted from middle layers of a pre-trained neural network, VGG-19 [32], represent high-level semantic information of an image [12, 31]. Given a rough outline sketch, we would like the generated image to loosely follow the object structures specified by the sketch. Therefore, we decide to use a deeper layer of VGG-19 for feature loss (relu 4_2). To focus the feature loss on generating structures, we convert both the ground-truth image and the generated image from RGB color space to Lab and generate grayscale images by repeating the L channel values. We then feed the grayscale image to VGG-19 to extract features. The feature loss $L_f$ is defined as the L2 difference in the feature space. During back propagation, the gradients passing through the L channel of the output image are averaged from the three channels of the VGG-19 output.

**Adversarial Loss.** Generative adversarial networks (GANs) have been shown to generate realistic images from random noise seeds [11]. In GANs, a generator network and a discriminator network are trained simultaneously in a minimax game. The discriminator tries to distinguish generated images from real photos while the generator tries to generate realistic images tricking the discriminator into thinking they are real. By alternating the optimization of the generator and the discriminator until convergence, the generator would ideally generate images indistinguishable from real photos.

In recent work, the concept of adversarial training has also been adopted in the context of image to image translation. In particular, one can attach a trainable discriminator network at the end of the image translation network and use it to constraining the generated result to lie on the training image manifold. Previous work proposed to minimize the adversarial loss (loss from the discriminator network) together with other standard losses (pixel, feature losses, etc). The exact choice of losses depends on the different applications [12, 16, 31]. Our work follows the same line. We use adversarial loss on top of feature, texture and color losses. The adversarial loss pushes the network towards synthesizing sharp and realistic images, but at the same time constrains the generated images to choose among typical colors in the training images. The network’s understanding about color sometimes conflicts with user’s color constraints, e.g. a user provides a rainbow color constraint for a handbag, but the adversarial network thinks it looks fake and discourages the generator from producing such output. Therefore, we propose applying the adversarial loss $L_{adv}$ only on grayscale image (the L channel in Lab space). The discriminator is trained to disregard the color but focus on generating sharp and realistic details. The gradients of the loss only flow through the L channel of the generator output. This effectively reduces the search space and makes GAN training easier and more stable. We perform the adversarial training using the techniques proposed in DCGAN [29] with the modification proposed in LSGAN [26]. LSGAN proposed replacing the cross entropy loss in the original GAN with linear least square loss for higher quality results and stable training.

**Texture Loss.** In addition to generating the right content following the input sketch, we would also like to propagate the texture details given in the input texture patch. The previous feature and adversarial losses sometimes struggle to capture fine-scale details, since they focus on getting the overall structure correct. Similar to deep learning based texture synthesis and style transfer work [8, 9], we use style loss to specifically encourage the reproduction of texture details, but we apply style loss on the L channel only. We adopt the idea of matching the Gram matrices (feature correlations) of the features extracted from certain layers of the pretrained classification network (VGG-19). The Gram matrix $G^l_{ij} \in \mathbb{R}^{N_l \times N_l}$ is defined as:

$$G^l_{ij} = \sum_k f^l_{ik}f^l_{jk}$$

(1)

where, $N_l$ is the number of feature maps at network layer $l$, $f^l_{ik}$ is the activation of the $i$th filter at position $k$ in layer $l$. We use two layers of the VGG-19 network (relu3_2, relu4_2) to define our style loss, $L_s$.

On top of that, we find that adding certain amount of L2 pixel loss $L_p$ stabilizes the training and leads to the generation of more texture details faithful to the user’s input texture patch. So we define the overall texture loss as: $L_I = w_pL_p + L_s$, where $w_p$ is fixed to be 10. Similar to the feature and adversarial losses, the texture loss is enforced only on the grayscale images.

**Color Loss.** As described above, we intentionally apply feature, adversarial and texture losses on only the L channel of the output to focus them on generating sketch-conforming structures, realistic shadings and sharp high-frequency texture details. To enforce the user’s color constraints, we add a separate color loss $L_c$ that penalizes the L2 difference between the ab channels of the generated result and that of the ground-truth. Our combined objective function is defined as:

$$L = L_f + w_{adv}L_{adv} + w_tL_t + w_cL_c$$

(2)

The exact training details can be found in section 4.4.

3.2 External Texture Fine-tuning

One problem of training with ground-truth images is that the network sees limited texture variations, since most of the ground-truth textures are smooth color gradients without rich details. This is problematic since at test time, the user might want to apply a real texture that lies outside the manifold learnt from the ground-truth. Therefore the network struggles to put high-frequency details in the results especially for difficult textures that are rarely seen during training.

Another problem is that texture patches extracted from the ground-truth photos are always perfectly aligned with the object boundaries. However, we would like to tolerate the inaccuracy of the input patch locations at test time, i.e. even if the user places a patch extending over the object boundary, the network should still be able to propagate the texture properly without introducing bleeding artifacts.

To generalize the network to support broader range of textures, and to make it tolerant to imprecise patch placement, we fine-tune the network with a separate texture database, the Describable Textures Dataset (DTD) [3]. We use all the losses introduced in the previous section, but modify the ways to compute the texture and color losses. In particular, we compare the generated result with the input texture instead of with the ground-truth photo. Naively applying texture loss on the whole image leads to texture bleeding problem, since the network is encouraged to put the same texture
on both the foreground and background regions. Therefore we introduce local texture loss that is applied only within the foreground region.

**Local Texture Loss Using Segmentation Mask.** We utilize segmentation masks (section 4.1) to locate where the foreground object is and enforce the texture loss only within the foreground. We only use segmentation masks for the training objective function and therefore do not require them at test time.

The original texture loss is calculated based on features extracted from pre-trained VGG-19 network. Applying mask to features trained on full images is not straightforward. The receptive field gets larger as the layer goes deeper. Previous work proposed to downsample the input segmentation mask to have the same resolution with the feature map, or identify the neurons of which the receptive fields fall inside the segment boundary [10]. This, however, is still not ideal due to the overlapping receptive fields, especially in the high-level layers.

We propose a **local texture loss** that is only applied to small regions / patches of the image. We use the segmentation mask to ensure we crop patches mostly within the object boundary. On top of the generated result, we randomly choose the patch location among locations that usually cover the object and use a fixed patch size of 50x50. On top of the DTD texture, we use the same patch size but completely randomize the patch location assuming the texture is stationary. We feed the cropped patches into VGG-19 and calculate the feature correlations as style loss $L'_s$. We also calculate the L2 pixel loss $L'_p$. For each input image, we choose two random patches and average their texture losses ($L'_s + w_p L'_p$). We propagate the gradients of texture loss only through the corresponding patch region in the output. We calculate the **local color loss** in a similar way.

With the segmentation mask, we also enforce a whole-image pixel loss only in the background region to reduce the bleeding artifacts.

### 4 TRAINING SETUP

We train TextureGAN on three object-centric datasets, **handbags** [16], **shoes** [36] and **clothes** [23, 24]. They are similar in the way that the photo collections contain large variations of colors, materials and patterns. Precisely controlling the generation of textures is highly desirable for product design applications. For supervised training, we need to generate (input, output) image pairs. For the output of the network, we convert the ground-truth photos to Lab color space. For the input to the network, we process the ground-truth photos to extract 4-channel images. The four channels include one channel for the binary sketch, one channel for the texture patches and two channels for the color controls. In the following sections, we talk about how we obtain the segmentation masks used during training, how we generate each of the input channel for the ground-truth pre-training, and how we utilize the DTD dataset for the network fine-tuning. We also provide the exact training procedure and parameters.

#### 4.1 Segmentation Mask

In order to generate meaningful texture patches and localize texture losses on the correct foreground region, we need segmentation masks. For handbags and shoes, we simply set the white pixels as background pixels. For clothes, the segmentation mask is already given in the dataset. With the segmentation mask, we process the ground-truth photos to white out the background. Note that segmentation masks not used at test time.

#### 4.2 Data Generation for Ground-truth Pre-training

**Sketch.** For handbag and shoes, we generate sketches using the deep edge detection method described in pix2pix [16]. For clothes, we leverage the clothes parsing information provided in the dataset [23, 24]. We apply Canny edge detection on the clothing segmentation mask to extract the segment boundaries as sketch. Different from the sketch generation method proposed by Scribbler [31], we generate much simpler sketches that contain only the general outlines but no object details.

**Texture Patches.** To generate meaningful texture patches, we randomly crop small regions within the foreground objects of the ground-truth images. We randomly choose the patch location and size and evaluate whether the patch overlaps the foreground object more than 70 percent of the time. If not, we randomly choose another location for the patch and reduce the patch size. We repeat this until the overlapping condition is satisfied. We convert each texture patch to the Lab color space and take the L channel only. We discretize the L channel values using integer numbers ranging from 0 to 100.

For handbags and shoes, we generate one texture patch per image. For clothes, we extract two patches from two different semantic regions – top, skirt, pant, dress, bag or scarf. For regions outside the mask, we use an invalid pixel value (i.e. negative value outside of the range).

**Color Patches.** To control the colors in the generated results, the user can specify color patches as input to the network. For training, the color patches are extracted in the same way as texture patches. We crop random regions of the ground-truth image and use the ab channels as the color patches. We discretize the ab values using an integer ranging from -128 to 128. For regions outside the color patches, we set the pixel values to be -200 (invalid value outside the valid ab range).

#### 4.3 Data Generation for DTD Fine-tuning

To achieve efficient synthesis of diverse textures within one single network, we fine tune TextureGAN by applying external texture patches from The Describable Textures Dataset (DTD). DTD consists of 47 texture categories each of which contains around 120 texture images. We withheld 1 image per category for testing.

Figure 3, 4, and 5 show some example inputs to the network. Note that the texture patches are generated from DTD and placed at the same locations for comparison.

#### 4.4 Training Details

For **ground-truth pre-training**, we use a two-phase training strategy. During the first phase, we optimize all losses except for the...
adversarial loss until convergence. The reason for excluding adversarial loss is that the generator is very weak at the beginning and produces noisy results. The gradients from the adversarial loss are not very informative and make training unstable. At 20K iterations, we start the second phase training by adding the adversarial loss. The network focuses on minimizing the adversarial loss to produce sharper and more realistic results while keeping the rest of the losses stable. The adversarial training converges at around 30K-40K iterations depending on the adversarial weight. We stop all training at 50K iterations for fair comparison. We use the Adam optimizer \[18\] with learning rate \(1e^{-2}\) or \(1e^{-3}\). The training is fairly robust with the weights of the feature loss and texture loss, but is sensitive to the weights of color loss and adversarial loss. The network struggles between reproducing the right colors and propagating the detailed textures.

For fine-tuning on the DTD dataset, we optimize all the losses at the same time but use different weight settings. It is important to increase the weight of the localized texture loss \(w_t\) to 0.2 (100 times larger than the weight used for ground-truth training) in order to propagate difficult textures. We also decrease the learning rate to \(1e^{-3}\).

We train most of the models at input resolution of 128x128 except one clothes model at the resolution of 256x256 (Figure 10).

5 RESULTS AND DISCUSSIONS

5.1 Ablation Study

Keeping other settings the same, we perform network trainings using different combinations of losses to analyze how they influence the result quality. In Figure 3, given the input sketch, texture patch and color patch (top row), the network trained with the complete objective function (second row) correctly propagates the color and texture to the entire handbag. If we turn off the texture loss (third row), the texture details within the area of the input patch are preserved, but difficult textures cannot be fully propagated to the rest of the bag. If we turn off the adversarial loss (fourth row), the structure and shading of the handbags are correctly synthesized, but high frequency details are lacking. Note that the model is trained with ground-truth images, but we are testing it with texture patches unseen during the training.

5.2 Training with Varying patch sizes

As described in section 4.2, we randomize the sizes of the texture and color patches when generating the training input for the network. Figure 4 shows that at test time, given the same sketch but texture patches of different sizes (top row), the network trained with varying patch sizes (ranging from 10x10 to 40x40) converges faster and propagates textures better (third row), compared to the network trained with fixed patch size (30x30) (second row). Note that both models are stopped at 28K iterations before convergence for fair comparison. We also observe that at test time, giving larger texture patches as input to the network improves the result quality.

5.3 Color Control

Figure 5 shows the results of applying feature, adversarial and texture losses on RGB (Scribbler) versus applying them on L channel and adding additional color loss on ab channel to enforce color constraints (TextureGAN). Notice that the Lab results follow the input color constraints much more closely. We also find that TextureGAN on Lab produces better texture in general. We hypothesize that limiting the adversarial training on only the L channel significantly reduces the learning difficulty and therefore the adversarial and texture loss are able to focus better on producing high-frequency texture details.
Fig. 5. Comparison between models trained on RGB versus Lab. Enforcing feature, texture and adversarial losses on the L channel and adding a separate color loss on the ab channels significantly improve the color propagation.

Fig. 6. Side-by-side comparison of results before and after DTD fine-tuning. DTD fine-tuning with local texture and color losses is critical for propagating textures with strong regularity, such as striped patterns.

5.4 DTD Fine-tuning Results
We train TextureGAN on three datasets – shoes, handbags, and clothes – with increasing levels of structure complexity. We notice that for object categories like shoes that contain limited structure variations, the network is able to quickly generate realistic shading and structures and focus its remaining capacity for propagating textures. The texture propagation on the shoes dataset works well even without DTD fine-tuning. For more sophisticated datasets like handbags and clothes, DTD fine-tuning is critical for the propagation of difficult textures that contain sharp regular structures, such as stripes.

Figure 6 demonstrates how DTD fine-tuning improves the texture propagation. Texture features with high contrast and strong regularity, e.g. striped, dotted, checkerboard patterns, are rarely seen in the ground-truth, and are therefore not well captured by the models trained only on ground-truth. The pre-trained model encourages placing the input texture patch in the output but cannot learn the texture representation nor propagate it throughout the foreground region. By showing the network difficult texture examples from DTD dataset and enforcing local losses, we nudge the network to incorporate more diverse texture statistics in the learnt manifold. The striped example in the right column and second row shows an interesting phenomenon. The network is able to place the striped texture vertically (bottom part) or horizontally (top part) following the structure of the handbag.

Figure 7 shows the effect of applying segmentation mask on both input patch extraction and loss patch extraction. If we do not use the segmentation mask at all, then the locations of both input texture patches and loss patches are completely randomized which means they might extend outside the object boundary or might
lie completely outside the object boundary. It gives the network a confusing signal that the texture needs to be transferred to the background and therefore makes the training harder causing bleeding artifacts (Figure 7c). If we only use the segmentation mask to constrain the location of the input patch and still use a global texture loss, the bleeding artifacts are reduced but still exist (Figure 7b).

Using segmentation mask for both input patch extraction and loss patch extraction produces the best results (Figure 7a).

Figure 8 shows the results of applying different texture patches to a set of different sketches of handbags and shoes. They represent the typical results we seen at testing.
5.5 Limitations and Future Work

We show promising results on controlling the generation of image details using texture patches, but we would like to point out several limitations for future work.

For faster and more stable training, we first pre-train TextureGAN on ground-truth photos and then fine-tune it with DTD texture database. Through adversarial training, the network gains some understandings about how handbags, shoes and clothes should look and prefers the generated results to fall on the respective learnt manifolds. During DTD fine-tuning, if the provided input texture goes against the understanding of the network, the network will have a hard time propagating details, e.g., in the second column of Figure 8, the network is able to propagate the green paper texture to the handbags, but struggles with putting it on shoes since it thinks shoes with paper textures look fake.

With DTD fine-tuning, TextureGAN is able to support a broad range of stationary textures. However, it struggles with textures containing global structures that cannot be captured by small patches, e.g., second, third and sixth columns from the left in Figure 8, or textures with strong regularity, e.g., striped textures in Figure 6.

We experiment with three categories - shoes, handbags and clothes. We believe that our training pipeline can also generalize well to other categories given similar amount of training time and similar setting. In the future, we hope to explore deep synthesis on more complex scene categories.

A final limitation is that the network does not generalize to badly sketched objects. We believe this could be partially addressed by augmenting the training “sketches” (derived from edge detection, not real human sketches) to be more diverse.

We experiment with the dilated network structure [37]. We use dilated residual network with 34 layers without the additional de-gridding layers [38]. For fair comparison, we train a 22-layer dilated network that contains similar number of parameters to our 34-layer TextureGAN. We find that dilated network training converges much faster. The first phase of training without adversarial loss converges at around 8K iterations, compared to 15K for TextureGAN. After adding back the adversarial loss, the second phase training takes another 2K iterations until final convergence. The two architectures produce results of similar quality. We hypothesize that using a deeper dilated network will further improve the result quality but leave the exploration as future work.

6 CONCLUSION

We have presented a novel approach for controlling deep image synthesis with input sketch and texture patches. With this system, the user can draw the object structure though sketching and precisely control the generated details with texture patches. TextureGAN is feed-forward which allows users to see the effect of their edits in real time. By training TextureGAN with local texture constraints, we demonstrate its effectiveness on sketch and texture-based image synthesis. TextureGAN also operates in Lab color space, which enables separate controls on color and content. Furthermore, our results on fashion datasets show that our pipeline is able to handle a wide variety of texture inputs and generates texture compositions that follow the sketched contours. In the future, we hope to apply our network on more complex scenes.
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