MontageGAN: Generation and Assembly of Multiple Components by GANs

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Abstract—A multi-layer image is more valuable than a single-layer image from a graphic designer’s perspective. However, most of the proposed image generation methods so far focus on single-layer images. In this paper, we propose MontageGAN, which is a Generative Adversarial Networks (GAN) framework for generating multi-layer images. Our method utilized a two-step approach consisting of local GANs and global GAN. Each local GAN learns to generate a specific image layer, and the global GAN learns the placement of each generated image layer. Through our experiments, we show the ability of our method to generate multi-layer images and estimate the placement of the generated image layers.

I. INTRODUCTION

Layering is one of the most critical concepts in graphic design that has become a must-have feature in popular raster graphic editors such as Adobe Photoshop [1], GIMP [2], and Krita [3]. In graphic design, layering is the stacking of different images, graphics, text, etc., on top of one another. A multi-layer image such as PSD file (Photoshop Document) and XCF file (eXperimental Computing Facility, used by GIMP) is more valuable than a simple single-layer image such as JPEG file and PNG file, in graphic designers’ perspective. Layering makes it easier for designers to design and edit images because they can apply changes to only one particular layer without affecting the other layers. Besides that, layering allows designers to show or hide specific layers to create a slightly altered design version.

Designing an image can be time-consuming and takes a lot of effort. Therefore, there is a need for tools that can automatically and quickly generate images with novel designs. Recently, unsupervised learning with Generative Adversarial Networks (GAN) [4] to learn the deep representation of the training data has gained popularity, especially in image generation. State-of-the-art methods, for instance, StyleGAN [5] (and its improved models, StyleGAN2 [6] and StyleGAN2-ada [7]) and Projected GANs [8], yield significant success in generating not only photo-realistic images such as human faces, buildings, and animals, but also illustration images such as paintings and digital artworks.

We focus on multi-layer image generation using GAN and explore its potential in this work. Despite GAN’s notable success in image generation, most of the proposed methods focus on single-layer image generation, limiting usability and flexibility in graphic design. Unlike traditional image generation, which outputs single-layer images, we generate multiple image layers with alpha channels to handle transparency. These image layers are then alpha-blended finally to form the target overlaid image.

As the target images, we consider the front face of animation (also known as Anime) characters. Specifically, our objective is to generate every face part like eyes, nose, mouth, and hair in separate image layers. As mentioned earlier, generating Anime characters in multi-layer images has several advantages. For example, multi-layer images make it relatively easier to animate the characters afterward than traditional single-layer images. It is also possible to manipulate the character design by swapping between layers generated using different latent variables, achieving layer-wise manipulation.

We propose a GANs framework, called MontageGAN, that generates multi-layer Anime face images. Fig.1 shows our concept of multi-layer image generation. MontageGAN utilizes a two-step approach consisting of local GANs and a global GAN. Each local GAN based on StyleGAN2-ada learns to generate a specific face part; for example, the local GAN of eyes generates only the image layers of the eyes. On the other hand, the global GAN learns to assemble all image layers generated by local GANs into a reasonably-looking face. Note that we aim not only to place the generated parts into the correct position but also to generate layers that match the styles of each other (global styles). In addition to the benefits of generating multi-layer images, we believe that splitting image generation at the layer level will make learning simple, as each local GAN focuses only on its layer.
The main contributions of this paper are summarized as follows:

- As far as the authors know, this is the first image generation model specializing in multi-layer image generation. With both local GANs and global GAN, our method mimics the process of designing multi-layer images.
- We proposed a GANs framework and applied it to Anime face image generation by training the model with a multi-layer image dataset.

II. RELATED WORK

A. Generative Adversarial Networks

As its name suggests, GAN utilizes two adversarial neural networks, usually called the generator and the discriminator [4]. The discriminator learns to determine if the input data was generated or sampled from the training data distribution. On the other hand, the generator learns to generate a fake that fools the discriminator into believing it is a real one.

Much effort has been made to stabilize GAN training and improve the quality of the generated images [10], [11], [12], [13]. A recent state-of-the-art method, StyleGAN [5] (and the improved model, StyleGAN2 [6]), proposed a redesign of generator architecture motivated by style transfer literature, which has notably improved the resulting quality and better disentanglement. The StyleGAN generator’s architecture differs from the traditional GANs; it consists of 2 modules: mapping and synthesis networks. The mapping network is a Multilayer Perceptrons (MLP) that learns a mapping $f : Z \rightarrow W$ from latent variables $z \in Z$ to intermediate latent variables $w \in W$. Conventionally, the latent space $Z$ had to follow the probability density of the training data, leading to some unavoidable entanglement. StyleGAN suggested that the intermediate latent space $W$ has no such limitation, thus improving the disentanglement. The synthesis network is a Convolutional Neural Network (CNN) that generates images from a learned constant input. The intermediate latent variables control the generator through Adaptive Instance Normalization (AdaIN) [14] at each convolution layer of the synthesis network. Also, Gaussian noise is added after each convolution layer to generate stochastic details.

Yet, training a high-quality GAN requires a sufficiently large dataset, usually around $10^5$ to $10^6$ images. Often the problem of GAN with a small dataset is that the discriminator overfits the training samples. The discriminator’s feedback to the generator becomes meaningless, causing the training begins to diverge. StyleGAN2-ada [7] proposed a wide range of non-leaking augmentations to prevent the discriminator from overfitting. The StyleGAN2-ada discriminator is evaluated using only augmented images and does this also when training the generator. StyleGAN2-ada shows comparable results on several datasets, despite using a few thousand training images only. In this work, we create the local GANs based on StyleGAN2-ada.

B. Spatial Transformer Networks

Spatial Transformer Networks (STN) [15] is a learnable module that allows the spatial manipulation of data within the network. STN can be injected into standard neural network architectures, allowing them to spatially transform the feature maps conditional to the feature maps itself, without extra supervision or modification to the current optimization process. STN was initially used to increase the robustness of the image classification model [16], [17], [18], [19]; the image classification model using STN learns invariance to translation, scale, rotation, and more generic warping.

STN consists of 3 parts: localization network, grid generator, and sampler. The localization network is typically a CNN that predicts the transformation parameters $\theta$ based on the input image (or feature map). After that, the grid generator creates a sampling grid $T_\theta(G_{grid})$ (a set of points where the input image needs to be sampled to produce the transformed output image) based on the predicted transformation parameters. Finally, the input image and the sampling grid are inputted to the sampler, creating the output image sampled from the input at the grid points. Equation (1) show the coordinate mapping relationship of a 2D affine transformation $A_\theta$, where $(x_s, y_s)$ and $(x_t, y_t)$ are the source coordinates and target coordinates, respectively. In this work, we extend the STN’s architecture to support multi-layer images and apply it to estimate the placement of parts in layer images.

$$\begin{pmatrix} x_s \\ y_s \end{pmatrix} = T_\theta(G_{grid}) = A_\theta \begin{pmatrix} x_t \\ y_t \\ 1 \end{pmatrix} = \begin{bmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \end{bmatrix} \begin{pmatrix} x_t \\ y_t \\ 1 \end{pmatrix}$$

(1)

C. Differentiable Rendering

Differentiable rendering (DR) is a set of techniques that allows the gradients of 3D objects to be calculated and propagated through images [20]. By differentiating the rendering, neural networks can optimize 3D entities (materials, lights, cameras, geometry, etc.) while operating on 2D projections (RGB image, depth image, silhouette image, etc.). Neural rendering is one DR technique that learns from data instead of handcrafting the rendering differentiation [21]. There are various applications of neural rendering such as semantic photo manipulation, novel view synthesis, facial and body reenactment, etc. In this work, we consider multi-layer images as a type of 3D data, as the image layers stack along the z-axis to form a voxel. Based on the neural rendering method, we first render the multi-layer image into a single-layer image before being input to the global discriminator. It allows MontageGAN to generate multi-layer images, but as with typical GANs, the global discriminator can still make predictions based on the rendered single-layer images.

D. Anime Character Generations

There are several attempts to use generative models in Anime character generation, albeit for not being a multi-layer image generation task that MontageGAN is tackling. For
example, a website called “This Waifu Does Not Exist” [22] provides a demo that utilizes StyleGAN2 in Anime character generation. Besides that, websites that offer interactive Anime character generation that users can finetune the parameters are also available, for instance, Artbreeder [23] and WaifuLabs [24]. A style-guided generative model can generate an image that matches the desired style. For example, AntiGANs [25] is a style-guided GAN that translates a human face into an Anime character based on the styles of a reference Anime character. In addition, an article titled “Talking Head Anime from a Single Image” [26] proposes a generative model that takes an Anime character’s face and the desired pose as input and generates another image of the same character in the given pose.

III. MONTAGEGAN

In this work, we generate multi-layer Anime character images with a two-step approach. First, the local GANs generate the image layers that correspond to face features. Then, the global GAN assembles the generated image layers into a finished image. Fig. 2 shows the overall architecture of MontageGAN. $z \sim N(0, 1)$ denotes a random latent variable fed into the mapping network [7] to output an intermediate latent variable. $G_i$ and $D_i$ denote the generator and discriminator, respectively, while the subscript $i$ indicates the image layer to which they belong. Likewise, $D_{\text{global}}$ denotes the global discriminator. $p$ denotes the parameter of StyleGAN2-ada’s augmentation pipeline [7] to control the augmentation probability.

A. Local GANs

We create the local GANs based on StyleGAN2-ada, with several modifications on top of the official source code\(^1\).

1) Training with RGBA channel images is possible. (As of writing, the official StyleGAN2-ada only supports grayscale and RGB images.)

2) Training with rectangular-shaped images is possible as long as the dimension of both edges has a common divisor that can be represented as $2^n$, where $n \geq 2$ and $n \in \mathbb{N}$. (As of writing, the official StyleGAN2-ada only supports square images.)

We use a shared mapping network between the synthesis networks of the local generators. The mapping network is a 8-layer MLP that outputs intermediate latent variables containing certain styles’ parameters. As local generators should generate images correlated with other layers, we believe there is no reason to use a separated mapping network. We deploy a dedicated augmentation pipeline for each local GAN. The augmentation pipelines [7] in local GANs augment the images before passing them to the local discriminators. The applied augmentation prevents the local discriminators from overfitting, controlled by an augmentation probability. Each local GAN can have a different target resolution to save computational resources; for instance, the local GANs that generate smaller face parts (mouth, nose, etc.) can target smaller resolutions.

B. Renderer

We create the differentiable renderer based on the neural rendering method. Specifically, the renderer utilizes a 5-layer Fully Convolutional Network (FCN) as the neural rendering network. In this work, the renderer learns to blend the multi-layer images $I_{B,L \times C,H,W}$ into single-layer images $I_{B,C,H,W}$ by approximating the alpha blending operation. Where $B, L, C, H, W$ denote the batch size, number of image layers, target resolution, channels, and input dimensions, respectively. The FCN renders each of the generated layers into an image, and they are then combined with the alpha blending operation.

\(^1\)Accessible at https://github.com/NVlabs/stylegan2-ada-pytorch
number of image channels, image height, and image width, respectively. Fig. 3 shows the training method of the renderer. As the source layers, we use the real layers with random translation transformation applied during the pretraining. The source layers are then blended with both alpha blending operation and the renderer, producing the target images and rendered images. Finally, the pixelwise MSE loss between the target and rendered images is calculated and back-propagated to the renderer for optimization.

In theory, the global discriminator still can make predictions directly based on multi-layer images without a renderer, but it tends to overfit quickly. We believe that the global discriminator can easily distinguish between real and fake layers because there is too much information in the multi-layer images. For example, a sample with a poorly generated layer that does not necessarily affect the overall appearance that much could be enough for the overfitted global discriminator to predict it as fake. Hence, the render plays the role of limiting such information by only feeding the rendered images to the global discriminator.

C. Global GAN

The local generators and the part position estimator together play the role of global generator in global GAN. The local generators are given sufficient pretraining in step 1. The generated image layers \( \{I_{B,C,H_i,W_i}, \ldots, I_{B,C,H_i,W_i}\} \) are zero-padded to the largest target resolution \((H,W) = (\max_{i \in 1,\ldots,L} H_i, \max_{i \in 1,\ldots,L} W_i) \) and stacked along the channel axis as fake layers \( I_{B,L \times C,H,W} \). We create the part position estimator by extending the STN’s architecture. Specifically, the part position estimator utilizes a 5-layer CNN connected to a 2-layer MLP as the localization network. The part position estimator takes a batch of fake layers \( I_{B,L \times C,H,W} \) as input and estimates the position of part in each layer \( \theta_{B,L \times 2} \). Although it is possible to learn an arbitrary affine transformation, we only consider each layer’s translation transformation in this work. From the part position output estimator, we can define the affine transformation for each image layer as follows, where \( i \) represents an image layer.

\[
A_i^j = \begin{bmatrix} 1 & 0 & \theta_{i,j}^1 \\ 0 & 1 & \theta_{i,j}^2 \end{bmatrix}, A_0 = \{A_0^1, \ldots, A_0^L\} \tag{2}
\]

Like the local GANs, we utilize the same architecture as StyleGAN2-ada [7] for the augmentation pipeline and global discriminator. The global discriminator learns to predict based on the pretrained renderer’s outputs. Simultaneously, the renderer is also retrained with real and fake layers during global GAN training. Same with StyleGAN2-ada, we use non-saturating GAN loss [4] with \( R1 \) regularization [13] for our global GAN as well. To prevent the part position estimator from placing the part outside the layer’s boundary, we also add a \( L2 \) norm penalty if the position \( \theta \) exceeds the range of \([-1, 1]\).

IV. Experiments

A. Dataset

Although several Anime face datasets are available, such as Danbooru2020 [27], Tagged Anime Illustrations [28], and Safebooru [29], getting a multi-layer image dataset is not trivial. Most graphic designers would not publish the PSD files so that others cannot easily copy or modify their designs, making it extremely difficult to collect a multi-layer image dataset. We overcome the mentioned problem by utilizing the collection of Live2D models [30] on GitHub. Live2D is a software technology that generates 2D animations without frame-by-frame animation or 3D models, only by morphing the part in the image layers. The Live2D models mentioned above are mostly taken from various game resources that utilizing Live2D. These models became the starting point for our dataset collection, as the model itself contains many image layers.

We made a tool\(^2\) that renders a Live2D model and outputs the image layers as multiple PNG files, which allows us to train our GANs. Since we only want to generate Anime characters' faces, we first detect and crop the face area from the image layers using \( lbpcascade\_animeface \) [31]. Then, we discard all the image layers that are not related to the detected face area. We resized the image layers to the resolution of \( 256 \times 256 \) pixels, upscaling with \( \text{waifu2x} \) [32] when necessary. In most cases, the number of layers exceeds the number considered in this paper. Therefore, we merge the obtained images into nine layers manually according to these groups: #1\_hair\_back, #2\_body, #2\_ear, #3\_face, #4\_eye, #4\_mouth, #4\_nose, #5\_hair\_front, and #6\_brow. Through these processes, we managed to collect 1,022 samples of multi-layer images. However, the dataset is currently lacking in variety, as training samples are primarily originated from a game called BanG Dream! Girls Band Party!. Fig 4 shows a sample from our dataset.

B. Experiment details

We used a learning rate of 0.0025, a batch size of 32 (through gradient accumulation of 8 rounds, each round with batch size of 4), and \( Adam \) optimizers [33] for local GANs and

\(^2\)Available at https://github.com/jeffshee/live2d
TABLE I: Convolution configurations for each synthesis network in local generators.

| Layer         | Initial resolution (pixels) | Target resolution (pixels) | Number of 2x up-sampling |
|---------------|----------------------------|---------------------------|--------------------------|
| #1_hair_back  | 8 x 8                      | 256 x 256                 | 5 times                  |
| #2_body       | 8 x 8                      | 256 x 256                 | 5 times                  |
| #2_eye        | 16 x 16                    | 256 x 256                 | 4 times                  |
| #3_face       | 8 x 8                      | 256 x 256                 | 5 times                  |
| #4_ear        | 16 x 16                    | 192 x 192                 | 4 times                  |
| #4_mouth      | 6 x 6                      | 64 x 64                   | 4 times                  |
| #4_nose       | 8 x 4                      | 64 x 64                   | 3 times                  |
| #4_hair_front | 8 x 8                      | 256 x 256                 | 5 times                  |
| #6_brow       | 4 x 10                     | 64 x 100                  | 4 times                  |

global GAN. The parameter of R1 regularization, $\gamma$ was set to 10. During the step 1, the local GANs were pretrained for 2500 kimg (thousand of real images seen by discriminator). As we utilize nine sets of local GAN in our model, the required GPU memory is massive. To overcome this issue, we cut down the memory usage by using different convolution configurations for each local GANs. Specifically, we used a smaller convolution for small image layers, for example, the image layer of eyes, nose, and mouth. Table I shows the convolution configurations for each synthesis network in local generators. We used two convolution layers for each 2x up-sampling. The convolution configurations for each local discriminator are the likewise as its counterpart, except it performs 2x down-sampling instead. That is, the initial and target resolutions listed in Table I are reversed for the discriminators.

C. Qualitative analysis

Fig. 5 shows the generated samples of MontageGAN. The samples shown in Fig. 5a are all multi-layer images. As a prove, Fig. 5b shows the layer-by-layer views of the pickup samples. Despite the small dataset, MontageGAN can already produce some reasonably-looking faces. The generated image layers are generally coherent with each other, indicating the global GAN had learned the global styles successfully. For example, from Fig. 5b, we can find that the color and style of #1_hair_back and #5_hair_front seem to match each other, which did not happen during the pretraining of local GANs. We also find that the position of part in each layer is generally well-estimated, except for the layer such as #2_ear and #4_nose. The part in layer #2_ear is relatively hidden compared to other layers, as it often exists underneath the layers such as #5_hair_front. Also, the part in layer #4_nose is relatively small compared to other layers. We hypothesize that layers with small or hidden parts might be relatively challenging to learn due to less noticeable appearance changes.

D. Quantitative analysis

For quantitative analysis, we compare the Fréchet Inception Distance (FID) [34] and Inception Score (IS) [35] of MontageGAN and StyleGAN2-ada. Since both metrics use a pretrained Inception-v3 [36] model, they only support the evaluation of single-layer RGB images. To calculate both metrics in our experiments, we first alpha-blended both real and fake layers into single-layer images, then added a white background to all images, making them RGB images. Since there is no other comparison method for generating multi-layer images, we extended the implementation of StyleGAN2-ada (modified StyleGAN2-ada), allowing it to generate multi-layer images. Specifically, the generator of modified StyleGAN2-ada generates a tensor $I_{B,L \times C,H,W}$ as layers. Correspondingly, the discriminator of modified StyleGAN2-ada also predicts based on the input tensor $I_{B,L \times C,H,W}$. Based on the single-layer image performance, Table II shows FID and IS’s comparison results against our dataset.

For IS, it shows that both MontageGAN and StyleGAN2-ada give comparable results. On the other hand, FID shows that MontageGAN’s single-layer image performance is suboptimal compared to StyleGAN2-ada. We hypothesize that MontageGAN, which generates multi-layer images, has an inevitable rise in complexity that causes the drop of single-layer image performance.

On the plus side, MontageGAN achieved the best performance among the multi-layer image generation methods. Through our experiment, the modified StyleGAN2-ada could not even learn stably; it had a severe mode collapse issue and the training also started to collapse at around 2100 kimg due to the discriminator overfit. This suggests the importance and effectiveness of our renderer in limiting the excess information of multi-layer images fed to the discriminator.

V. CONCLUSION

In this work, we proposed MontageGAN, a GANs framework specializing in multi-layer image generation. We applied MontageGAN to Anime face image generation and showed its potential of generating multi-layer images. We also showed our method to collect a multi-layer Anime face dataset that makes the training of MontageGAN possible.

Our future work would be fine-tuning our model to improve the image quality. One idea is to incorporate gated convolution into the synthesis networks of local generators. As the image layers will be alpha-blended to form the finished image, there are many transparent pixels in each layer image. When generating such a layer image, we believe it is more efficient to consider the image’s alpha channel as a soft-gate instead of a color value like RGB, which adds another dimension of complexity to the training process.

\(^4\)StyleGAN2-ada’s result is from 2620 kimg, which is the same extent to MontageGAN’s total training duration.

\(^5\)Modified StyleGAN2-ada’s result is from 2000 kimg, which is about 100 kimg before the training collapsed.
Fig. 5: The generated samples of MontageGAN. The result is from 2600 kimg. (At step 1, local GANs were pretrained for 2500 kimg. At step 2, the global GAN was trained for 100 kimg.) The position of the part in each layer is generally well-estimated. Also, the generated image layers are generally coherent with each other.
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