

AniGAN: Style-Guided Generative Adversarial Networks for Unsupervised Anime Face Generation

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Abstract

In this paper, we propose a novel framework to translate a portrait photo-face into an anime appearance. Our aim is to synthesize anime-faces which are style-consistent with a given reference anime-face. However, unlike typical translation tasks, such anime-face translation is challenging due to complex variations of appearances among anime-faces. Existing methods often fail to transfer the styles of reference anime-faces, or introduce noticeable artifacts/distortions in the local shapes of their generated faces. We propose AniGAN, a novel GAN-based translator that synthesizes high-quality anime-faces. Specifically, a new generator architecture is proposed to simultaneously transfer color/texture styles and transform local facial shapes into anime-like counterparts based on the style of a reference anime-face, while preserving the global structure of the source photo-face. We propose a double-branch discriminator to learn both domain-specific distributions and domain-shared distributions, helping generate visually pleasing anime-faces and effectively mitigate artifacts. Extensive experiments on selfie2anime and a new face2anime dataset qualitatively and quantitatively demonstrate the superiority of our method over state-of-the-art methods. The new dataset is available at <https://github.com/bing-li-ai/AniGAN>

1. Introduction

Animations play an important role in our daily life and have been widely used in entertainment, social, and educational applications. Recently, *anime*, aka Japan-animation, has been popular in social media platforms. Many people would like to transfer their profile photos into anime images, whose styles are similar to that of the roles in their favorite animations such as *Cardcaptor Sakura* and *Sailor*

*equal contribution

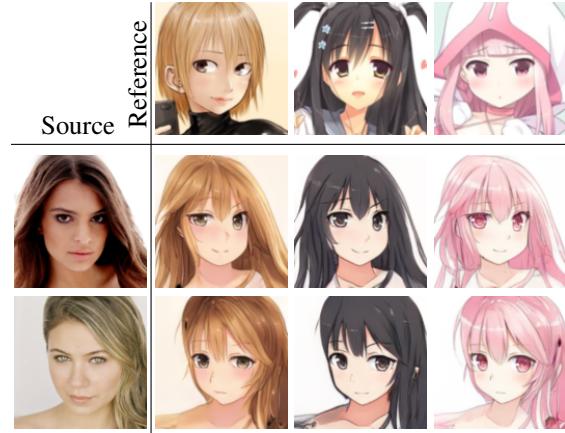


Figure 1: Illustration of some synthesized results with the proposed AniGAN for style-guided face-to-anime translation. The first row and the first column show reference anime-faces and source photo-faces, respectively. The remaining columns show the high-quality anime-faces with diverse styles generated by AniGAN, given source photo-faces with large pose variations and multiple reference anime-faces with different styles.

Moon. However, commercial image editing software fails to do this transfer, while manually producing an anime image in specific styles needs professional skills.

In this paper, we aim to automatically translate a photo-face into an anime-face based on the styles of a reference anime-face. We refer to such a task as *Style-Guided Face-to-Anime Translation* (StyleFAT). Inspired by the advances of generative adversarial networks (GANs) [13], many GAN-based methods (e.g., [19, 24, 45, 51]) have been proposed to automatically translate images between two domains. However, these methods [30, 51] focused on learning one-to-one mapping between the source and target images, which does not transfer the information of the reference image into a generated image. Consequently, the styles of their generated anime-faces [30, 51] are usually dissimilar from that of the reference ones. Recently, a few reference-guided

methods [25,35] were proposed for multi-modal translation which generates diverse results by additionally taking reference images from the target domain as input. These methods, however, usually fail to fulfill the StyleFAT task and generate low-quality anime images.

Different from the image translation tasks of reference-guided methods, StyleFAT poses new challenges in two aspects. First, an anime-face usually has large eyes, a tiny nose, and a small mouth which are dissimilar from natural ones. The significant variations of shapes/appearances between anime-faces and photo-faces require translation methods to largely overdraw the local structures (e.g., eyes and mouth) of a photo-face, different from caricature translation [5] and makeup-face transfer [6, 20, 26] which preserve the identity of a photo-face. Since most reference-guided methods are designed to preserve the local structures/identity of a source image, these methods not only poorly transform the local shapes of facial parts into anime-like ones, but also fail to make the these local shapes style-consistent with the reference anime-face. On the other hand, simultaneously transforming local shapes and transferring anime styles is challenging and has not yet been well explored. Second, anime-faces involve various appearances and styles (e.g. various hair textures and drawing styles). Such large intra-domain variations poses challenges in devising a generator to translate a photo-face into a specific-style anime-face, as well as in training a discriminator to capture the distributions of anime-faces.

To address the above problems, we propose a novel GAN-based model called *AniGAN* for StyleFAT. First, since it is difficult to collect pairs of photo-faces and anime-faces, we train AniGAN with unpaired data in an unsupervised manner. Second, we propose a new generator architecture that preserves the global information (e.g., pose) of a source photo-face, while transforming local facial shapes into anime-like ones and transferring colors/textures based on the style of a reference anime-face. The proposed generator does not rely on face landmark detection or face parsing. Our insight is that the local shapes (e.g., large and round eyes) can be treated as a kind of styles like color/textures. In this way, transforming a face’s local shapes can be achieved via style transfer. To transform local facial shapes via style transfer, we explore *where* to inject the style information into the generator. In particular, the multi-layer feature maps extracted by the decoder represent multi-level semantics (i.e., from high-level structural information to low-level textural information). Our generator therefore injects the style information into the multi-level feature maps of the decoder. Guided the injected style information and different levels of feature maps, our generator adaptively learns to transfer color/textures styles and transform local facial shapes. Furthermore, two normalization functions are proposed for the generator to further improve

local shape transformation and color/textures style transfer.

In addition to the generator, we propose a double-branch discriminator, that explicitly considers large appearance variations between photo-faces and anime-faces as well as variations among anime images. The double-branch discriminator not only learns domain-specific distributions by two branches of convolutional layers, but also learns the distributions of a common space across domains by shared shallow layers, so as to mitigate artifacts in generated faces. Meanwhile, a domain-aware feature matching loss is proposed to reduce artifacts of generated images by exploiting domain information in the branches.

Our major contributions are summarized as follows:

1. To the best of our knowledge, this is the first study on the style-guided face-to-anime translation task.
2. We propose a new generator to simultaneously transfer color/textures styles and transform the local facial shapes of a source photo-face into their anime-like counterparts based on the style of a reference anime-face, while preserving the global structure of the source photo-face.
3. We devise a novel discriminator to help synthesize high-quality anime-faces via learning domain-specific distributions, while effectively avoiding noticeable distortions in generated faces via learning cross-domain shared distributions between anime-faces and photo-faces.
4. Our new normalization functions improve the visual qualities of generated anime-faces in terms of transforming local shapes and transferring anime styles.

2. Related Work

Generative Adversarial Networks. Generative Adversarial Networks (GANs) [13] have achieved impressive performance for various image generation and translation tasks [4, 7, 22, 23, 27, 33, 37, 42, 46, 50]. The key to the success of GANs is the adversarial training between the generator and discriminator. In the training stage, networks are trained with an adversarial loss, which constrains the distribution of the generated images to be similar to that of the real images in the training data. To better control the generation process, variants of GANs, such as conditional GANs (cGANs) [37] and multi-stage GANs [22, 23], have been proposed. In our work, we also utilize an adversarial loss to constrain the image generation. Our model uses GANs to learn the transformation from a source domain to a significantly different target domain, given unpaired training data.

Image-to-Image Translation. With the popularization of GANs, GAN-based image-to-image translation techniques have been widely explored in recent years [9, 18,

[19, 24, 30, 31, 45, 47, 51]. For example, trained with paired data, Pix2Pix [19] uses a cGAN framework with an $L1$ loss to learn a mapping function from input to output images. Wang et al. proposed an improved version of Pix2Pix [45] with a feature matching loss for high-resolution image-to-image translation.

For unpaired data, recent efforts [18, 24, 30, 31, 51] have greatly improved the quality of generated images. CycleGAN [51] proposes a cycle-consistency loss to get rid of the dependency on paired data. UNIT [30] maps source-domain and target-domain images into a shared-latent space to learn the joint distribution between the source and target domains in an unsupervised manner. MUNIT [18] extends UNIT to multi-modal contexts by incorporating AdaIN [17] into a content and style decomposition structure. To focus on the most discriminative semantic parts of an image during translation, several works [24, 28] involve attention mechanisms. ContrastGAN [28] uses the object mask annotations from each dataset as extra input data. UGATIT [24] applies a new attention module and proposes an adaptive layer-instance normalization (AdaLIN) to flexibly control the amount of change in shapes and textures. However, the style controllability of the above methods is limited due to the fact that the instance-level style features are not explicitly encoded. To overcome this, FUNIT [31] utilizes a few-shot image translation architecture for controlling the categories of output images, but its stability is still limited.

Neural Style Transfer. StyleFAT can also be regarded as a kind of the neural style transfer (NST) [11, 12, 21]. In the field of NST, many approaches have been developed to generate paintings with different styles. For example, CartoonGAN [8] devises several losses suitable for general photo cartoonization. ChipGAN [15] enforces voids, brush strokes, and ink wash tone constraints to a GAN loss for Chinese ink wash painting style transfer. APDrawingGAN [49] utilizes a hierarchical GAN to produce high-quality artistic portrait drawings. CariGANs [5] and WarpGAN [41] design special modules for geometric transformation to generate caricatures. Yaniv et al. [48] proposed a method for geometry-aware style transfer for portraits utilizing facial landmarks. However, the above methods either are designed for a specific art field which is completely different from animation, or rely on additional annotations (such as facial landmarks).

3. Proposed Approach

Problem formulation. Let X and Y denote the source and target domains, respectively. Given a source image $x \in X$ and a reference image $y \in Y$, our proposed AniGAN learns multimodal mapping functions $G : (x, y) \mapsto \tilde{x}$ that transfer x into domain Y .

To generate high-quality anime-faces for the StyleFAT task, the goal is to generate an anime-face \tilde{x} that well pre-

serves the global information (e.g., face pose) from x as well as reflects the styles (e.g., colors and textures) of reference anime-face y , while transforming the shapes of facial parts such as eyes and hair into anime-like ones.

To achieve the above goals, a question is posed, *how to simultaneously transform local shape while transferring color/texture information?* Existing methods focus on transferring styles while preserving both local and global structures/shapes from the source image, which, however, cannot well address the above problem. Differently, we here explore *where* to inject style information into the generator, and a novel generator architecture is thereby proposed, as shown in Fig. 2. Different from existing methods which inject style information in the bottleneck of the generator, we introduce two new modules in the decoder of the generator for learning to interpret and translate style information. Furthermore, we also propose two normalization functions to control the style of generated images while transforming local shapes, inspired by recent work [17, 24].

In addition, anime-faces contain significant intra-variations, which poses large challenge for generating high-quality images without artifacts. To further improve the stability of the generated results, a novel double-branch discriminator is devised to better utilize the distribution information of different domains.

Figs. 2 and 3 illustrate the architectures of our proposed generator and discriminator, respectively. The generator takes a source image and a reference image as inputs and then learns to synthesize an output image. The double-branch discriminator consists of two branches, where one branch discriminates real/fake images for domain X , and the other for Y .

3.1. Generator

The generator of AniGAN consists of a content encoder E_c , a style encoder E_s and a decoder F , as shown in Fig. 2.

Encoder. The encoder includes a content encoder E_c and a style encoder E_s . Given a source photo-face x and a reference anime-face y , the content encoder E_c is used to encode the content of the source image x , and the style encoder is employed to extract the style information from the reference y . The functions can be formulated as follows:

$$\alpha = E_c(x), \quad (1)$$

$$(\gamma_s, \beta_s) = E_s(y) \quad (2)$$

where α is the content code encoded by the content encoder E_c , γ_s and β_s are the style parameters extracted from the reference anime-face y .

Decoder. The decoder F constructs an image from a content code and style codes. However, different from typical image translations that transfer styles while preserving both local and global structures of source image, our decoder aims to transform the local shapes of facial parts and

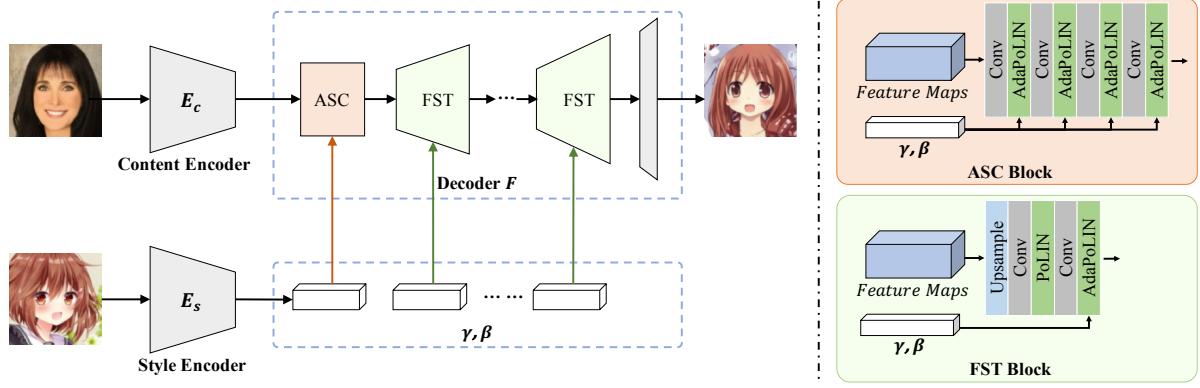


Figure 2: Architecture of the proposed generator. It consists of a content encoder and a style encoder to translate the source image into the output image reflecting the style of the reference image. The grey trapezoids indicate typical convolution blocks. More detailed notations are described in the contexts of Sec. 3.

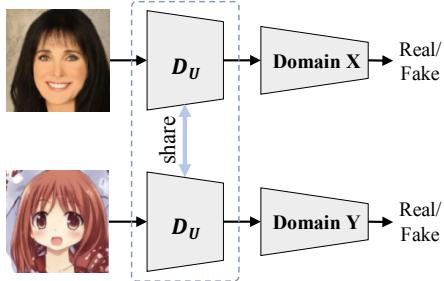


Figure 3: Architecture of the proposed double-branch discriminator, where D_U denotes the shared layers between the two branches for domain X and Y . The discriminator distinguishes real images from fake ones in the two individual branches.

preserve the global structure of the source photo-face during style transfer.

Recent image translation methods [17, 18, 24, 31, 35] transfer the style of the target domain by equipping residual blocks (resblocks) in the bottleneck of the generator with style codes. However, we observe that such decoder architectures cannot well handle the StyleFAT task. Specifically, they are either insufficient to elaborately transfer an anime style, or introduce visually annoying artifacts in generated faces. To decode high-quality anime-faces for StyleFAT, we propose an adaptive stack convolutional block (denoted as ASC block), Fine-grained Style Transfer (FST) block and two normalization functions for the decoder (see Fig. 2)

ASC block Existing methods such as MUNIT [18], FUNIUT [31], and EGSC-IT [35] transfer styles to generate images via injecting the style information of the target domain into the resblocks in the bottleneck of their decoder. However, we observe that resblocks may ignore some anime-style information, which degrades the translation performance of decoder on StyleFAT task. More specifically, although multiple reference images with different anime

styles are given, the decoder with resblocks synthesizes similar styles for specific regions, especially on eyes. For example, the decoder with resblocks improperly renders right eyes with the same color in the generated images (see Fig. 7). We argue that the decoder would "skip" some injected style information due to the residual operation. To address this issue, we propose an ASC block for the decoder. ASC stacks convolutional layers, activation, and our proposed normalization layers, instead of using resblocks, as shown in Fig. 2.

FST block One aim of our decoder is to transform local facial features into anime-like ones, different from existing methods which preserve local structures from a source photo-face. We here explore how to transform local shapes in the decoder when transferring styles. One possible solution is to first employ face parsing or facial landmark detection to detect facial features and then transform local facial features via warping like [41]. However, since the local structure of anime-faces and photo-faces are significantly dissimilar to each other, warping often leads to artifacts in the generated anime-faces. For example, it is difficult to well warp the mouth of a photo-face into a tiny one of a reference anime-face. Instead of employing face parsing or facial landmark detection, our insight is that local structures can be treated as a kind of styles like color/textures and can be altered through style transfer.

Therefore, we propose a FST module to simultaneously transform local shapes of the source image and transfer color/textures information from the reference image. In particular, as revealed in the literature, deep- and shallow-layer feature maps with low and high resolutions in the decoder indicate different levels of semantic information from high-level structures to low-level colors/textures. Motivated by the fact, we argue that the FST block can adaptively learn to transform local shapes and decode color/textures information by injecting the style information into feature maps

with different resolutions. In other words, since the feature map contains high-level structural information, FST can learn to transform local shapes into anime-like ones with the specified style information. Thus, as shown in Fig. 2, FST consists of a stack of upsampling, convolutional, and normalization layers. Furthermore, style codes are injected after the upsampling layer in our FST block, different from the prior works [18, 24, 31] that only injects style codes into the bottleneck of the generator. Consequently, FST block enables the decoder to adaptively synthesize color/textured and transform local shapes, according to both the style codes and different levels of feature maps.

Normalization Recent image translation methods [17, 18, 35] normalize the feature statistics of an image via Adaptive Instance Normalization (AdaIN) to adjust the color/textured styles of the image. However, we aim to devise normalization functions which not only transfer color/textured styles from the reference, but also transform local shapes of the source image based on the reference. Recently, it was shown in [24] that layer normalization (LN) [3] can transform the structure/shape of an image. Besides, AdaLIN was proposed in [24] to control the degree of changes in textures and shapes by adaptively combining AdaIN and LN. However, AdaLIN is insufficient to simultaneously transfer the color/textured information of a local region and its shape information from a reference image to a generated image. That is, since AdaLIN combines IN and LN in a per-channel manner, AdaLIN ignores the correlations among channels. For example, the shape styles of eyes and their color/textured styles may respectively dominate in different channels. In such case, the features learned by AdaLIN often ignore shape styles or color/textured styles. In other words, the combination space of AdaLIN tends to be smaller than that of all-channel combinations of IN and LN.

To address the above issue, we propose two novel normalization functions called point-wise layer instance normalization (PoLIN) and adaptive point-wise layer instance normalization (AdaPoLIN) for the generator. Our PoLIN and AdaPoLIN learn to combine all channels of IN and LN, different from AdaLIN [24].

To achieve all-channel combination of instance normalization (IN) [44] and LN, PoLIN learns to combine IN and LN via a 1×1 convolutional layer as defined below:

$$\text{PoLIN}(z) = \text{Conv} \left(\left[\frac{\mathbf{z} - \mu_I(\mathbf{z})}{\sigma_I(\mathbf{z})}, \frac{\mathbf{z} - \mu_L(\mathbf{z})}{\sigma_L(\mathbf{z})} \right] \right), \quad (3)$$

where $\text{Conv}(\cdot)$ denotes the 1×1 convolution operation, $[\cdot, \cdot]$ denotes the channel-wise concatenation, \mathbf{z} is the feature map of a network layer, μ_I , μ_L and σ_I , σ_L denote the channel-wise and layer-wise means and standard deviations, respectively.

AdaPoLIN adaptively combines IN and LN, while em-

ploying the style codes from the reference anime-faces to retain style information:

$$\begin{aligned} & \text{AdaPoLIN}(z, \gamma_s, \beta_s) \\ &= \gamma_s \cdot \text{Conv} \left(\left[\frac{\mathbf{z} - \mu_I(\mathbf{z})}{\sigma_I(\mathbf{z})}, \frac{\mathbf{z} - \mu_L(\mathbf{z})}{\sigma_L(\mathbf{z})} \right] \right) + \beta_s, \end{aligned} \quad (4)$$

where γ_s and β_s are style codes, and the bias in $\text{Conv}(\cdot)$ is fixed to 0.

Thanks to their all-channel combination of IN and LN, the proposed PoLIN and AdaPoLIN lead to a larger combination space than AdaLIN, thereby making them beneficial to handle color/textured style transfer and local shape transformation for StyleFAT.

3.2. Discriminator

It is challenging to design a discriminator which effectively distinguishes real anime-faces from fake ones for StyleFAT. In particular, both the appearances and shapes vary largely among anime-faces, leading to significant intra-variations in the distribution of anime-faces. Thus, it is difficult for a typical discriminator (e.g. [51]) to well learn the distribution of anime-faces. As a result, the generated anime-faces may contain severely distorted facial parts and noticeable artifacts.

To address the above issues, we propose a double-branch discriminator. In particular, we assume that anime-faces and photo-faces partially share common distributions and such cross-domain shared distributions constitute meaningful face information, since these two domains are both about human faces. In other words, by learning and utilizing the cross-domain shared distributions, the discriminator can help reduce distortions and artifacts in translated anime-faces. Therefore, as shown in Fig. 3, the proposed double-branch discriminator consists of shared shallow layers followed by two domain-specific output branches: one branch for distinguishing real/fake anime-faces and the other for distinguishing real/fake photo-faces. With the Siamese-like shallow layers shared by the photo-face and anime-face branches, the additional photo-face branch aims to assist the anime-face branch to learn domain-shared distributions. As a result, the anime-face branch learns to effectively discriminate those generated anime-faces with distorted facial parts or noticeable face artifacts. On the other hand, each branch contains additional domain-specific deep layers with an extended receptive field to individually learn the distributions of anime-faces and photo-faces¹.

We formulate the two-branch discriminator in terms of domain X and domain Y for generality. Let D_X and D_Y

¹Two separate discriminators without shared shallow layers can also individually learn the distributions of anime-faces and photo-faces. However, we observe that such a design not only consumes more computational cost but also performs worse than our double-branch discriminator.

denote the discriminator branches corresponding to domain X and Y , respectively, and D_U denote the shallow layers shared by D_X and D_Y . An input image h is discriminated either by D_X or by D_Y according to the domain that h belongs to. The discriminator function is formulated as follows:

$$D(h) = \begin{cases} D_X(D_U(h)) & \text{if } h \in X, \\ D_Y(D_U(h)) & \text{if } h \in Y. \end{cases} \quad (5)$$

Our discriminator helps significantly improve the quality of generated images and the training stability of the generator, since it not only individually learns domain-specific distributions using separable branches, but also learns domain-shared distributions across domains using shared shallow layers. In addition, our discriminator is scalable and can be easily expended to multiple branches for tasks across multiple domains.

3.3. Loss Functions

StyleFAT is different from typical image translation tasks which preserve the identity or the whole structure of the input photo-face. If we directly employ loss functions in existing methods [5, 35] that preserves both local and global structures or an identity in the source image, the quality of a generated anime-face would be negatively affected. Instead, besides adversarial loss like in [26, 35], the objective of our model also additionally involves reconstruction loss, feature matching loss, and domain-aware feature matching loss.

Adversarial loss. Given a photo-face $x \in X$ and a reference anime-face $y \in Y$, the generator aims to synthesize from x an output image $G(x, y)$ with a style transferred from y . To this end, we adopt an adversarial loss similar to [31, 37] as follows:

$$\begin{aligned} L_{\text{adv}} = & \mathbb{E}_x[\log D_X(x)] + \mathbb{E}_{x,y}[\log(1 - D_X(G(y, x)))] \\ & + \mathbb{E}_y[\log D_Y(y)] + \mathbb{E}_{y,x}[\log(1 - D_Y(G(x, y)))]. \end{aligned} \quad (6)$$

Feature matching loss. To encourage the model to produce natural statistics at various scales, the feature matching loss [39, 45] is utilized as a supervision for training the generator. Formally, let $D_U^k(h)$ denote the feature map extracted from the k -th down-sampled version of the shared layers D_U of D_X or D_Y for input h , and $\bar{D}_U^k(h)$ denote the global average pooling result of $D_U^k(h)$, the feature matching loss L_{fm} is formulated below:

$$L_{\text{fm}} = \mathbb{E}_h[\sum_{k \in K_1} \|\bar{D}_U^k(h) - \bar{D}_U^k(G(h, h))\|_1], \quad (7)$$

where K_1 denotes the set of selected layers in D_U used for feature extraction. In our work we set $K_1 = \{1, 2\}$ according to the architecture of our discriminator.

Domain-aware feature matching loss. We further utilize the domain-specific information to optimize the generator. In particular, we extract features by the domain-specific discriminator D_X or D_Y , respectively. Similar to $D_U^k(\cdot)$, let $D_X^k(\cdot)$ denote the k -th down-sampling feature map extracted from the branch D_X in domain X , and $\bar{D}_X^k(\cdot)$ denote the average pooling result of $D_X^k(\cdot)$ (similar notations are used for domain Y). Then we define a domain-aware feature matching loss L_{dfm} as follows:

$$L_{\text{dfm}} = \begin{cases} \mathbb{E}_h[\sum_{k \in K_2} \|\bar{D}_X^k(D_U(h)) - \bar{D}_X^k(D_U(G(h, h)))\|_1], & \text{if } h \in X \\ \mathbb{E}_h[\sum_{k \in K_2} \|\bar{D}_Y^k(D_U(h)) - \bar{D}_Y^k(D_U(G(h, h)))\|_1], & \text{if } h \in Y \end{cases} \quad (8)$$

where K_2 represents the set of selected layers in D_X and D_Y used for feature extraction. In our work we set $K_2 = \{3\}$ according to the architecture of our discriminator. With L_{dfm} , the artifacts of generated images can be largely mitigated thanks to the additional domain-specific features.

Reconstruction loss. We aim to preserve the global semantic structure of source photo-face x . Without a well-designed loss on the discrepancy between the generated anime-face and source photo-face, the global structure information of the source photo-face may be ignored or distorted. However, as discussed previously, we cannot directly employ an identity loss to preserve the identity like [26] or a perceptual loss to preserve the structure of the image like [35]. Different from existing methods [26, 35], we impose a reconstruction loss to preserve the global information of photo-face. Specifically, given source photo-face x , we also use x as the reference to generate a face $G(x, x)$. If the generated face $G(x, x)$ well reconstructs the source photo-face, we argue that the generator preserves the global structure information from the photo-face. Thus, we define the reconstruction loss as the dissimilarity between x and $G(x, x)$ by

$$L_{\text{rec}} = \|G(x, x) - x\|_1. \quad (9)$$

This loss encourages the generator to effectively learn global structure information from photo-face, such that the crucial information of x is preserved in the generated image.

Full Objective. Consequently, we combine all the above loss functions as our full objective as follows:

$$L_G = L_{\text{adv}} + \lambda_{\text{rec}} \cdot L_{\text{rec}} + \lambda_{\text{fm}} \cdot (L_{\text{fm}} + L_{\text{dfm}}). \quad (10)$$

$$L_D = -L_{\text{adv}}, \quad (11)$$

where $\lambda_{\text{rec}}, \lambda_{\text{fm}}$ are hyper-parameters to balance the losses.



Figure 4: Example photo-faces and anime-faces of our face2anime dataset. From top to bottom: photo-faces and anime-faces.

4. Experimental Results

We first conduct qualitative and quantitative experiments to evaluate the performance of our approach. We then conduct user studies to evaluate the subjective visual qualities of generated images. Finally, we evaluate the effectiveness of proposed modules by ablation studies.

Baselines We compare our method with CycleGAN [51], UGATIT² [24], and MUNIT [18], the state-of-the-arts in reference-free image translation. In addition, we compare our method with reference-guided image translation schemes including FUNIT [31], EGSC-IT [35], and DRIT++ [25] which are most relevant to our method. Note that MUNIT also allows to additionally take a reference image as the input at the testing stage. We refer to this baseline as RG-MUNIT. However, instead of using a reference image as part of a training image pair, RG-MUNIT takes a random latent code from the target domain as style information for the training (see more details in its github code³). Due to such inadequate reference information during training, while performing StyleFAT with reference faces, RG-MUNIT tends to fail for face images with significant inter-variations between domains or data with large intra-variations within a domain. That is, RG-MUNIT performs much poorer than the original MUNIT that takes a random latent code from the target domain at the test stage. We hence only show the visual results with the original MUNIT in the qualitative comparisons, while evaluating quantitative results for both the original MUNIT and RG-MUNIT. We train all the baselines based on the open-source implementations provided by the original papers⁴.

4.1. Datasets

Selfie2anime. We follow the setup in UGATIT [24] and use the selfie2anime dataset to evaluate our method. For the dataset, only female character images are selected and monochrome anime images are removed manually. Both selfie and anime images are separated into a training set

²We used the full version implementation of UGATIT

³<https://github.com/NVlabs/MUNIT>

⁴As discussed in Section 2, since neural-style transfer methods focus on specific art-style translation, we do not compare these methods for fair comparison.

with 3,400 images and a test set with 100 images.

Face2anime. We build an additional dataset called face2anime, which is larger and contains more diverse anime styles (e.g., face poses, drawing styles, colors, hairstyles, eye shapes, strokes, facial contours) than selfie2anime, as illustrated in Fig. 4. The face2anime dataset contains 17,796 images in total, where the number of both anime-faces and natural photo-faces is 8,898. The anime-faces are collected from the Danbooru2019 [2] dataset, which contains many anime characters with various anime styles. We employ a pretrained cartoon face detector [1] to select images containing anime-faces⁵. For natural-faces, we randomly select 8,898 female faces from the CelebA-HQ [22,34] dataset. All images are aligned with facial landmarks and are cropped to size 128×128 . We separate images from each domain into a training set with 8,000 images and a test set with 898 images.

4.2. Implementation Details

We train and evaluate our approach using the face2anime and selfie2anime datasets. We use the network architecture mentioned in Section 3 as our backbone. We set $\lambda_{fm} = 1$ for all experiments, $\lambda_{rec} = 1.2$ for the face2anime dataset, and $\lambda_{rec} = 2$ for the selfie2anime dataset.

For fast training, the batch size is set to 4 and the model is trained for 100K iterations. The training time is less than 14h on a single Tesla V100 GPU with our implementation in PyTorch [40]. We use RMSProp optimizer with a learning rate of 0.0001. To stabilize the training, we use the hinge version of GAN [4, 29, 38, 50] as our GAN loss and also adopt real gradient penalty regularization [14, 36]. The final generator is a historical average version [22] of the intermediate generators, where the update weight is 0.001.

4.3. Qualitative comparison

Given a source photo-face and a reference anime-face, a good translation result for StyleFAT task should share similar/consistent anime-styles (e.g., color and texture) with the reference without introducing noticeable artifacts, while facial features are anime-like and the global information (e.g.,

⁵Images containing male characters are discarded, since Danbooru2019 only contains a small number of male characters.



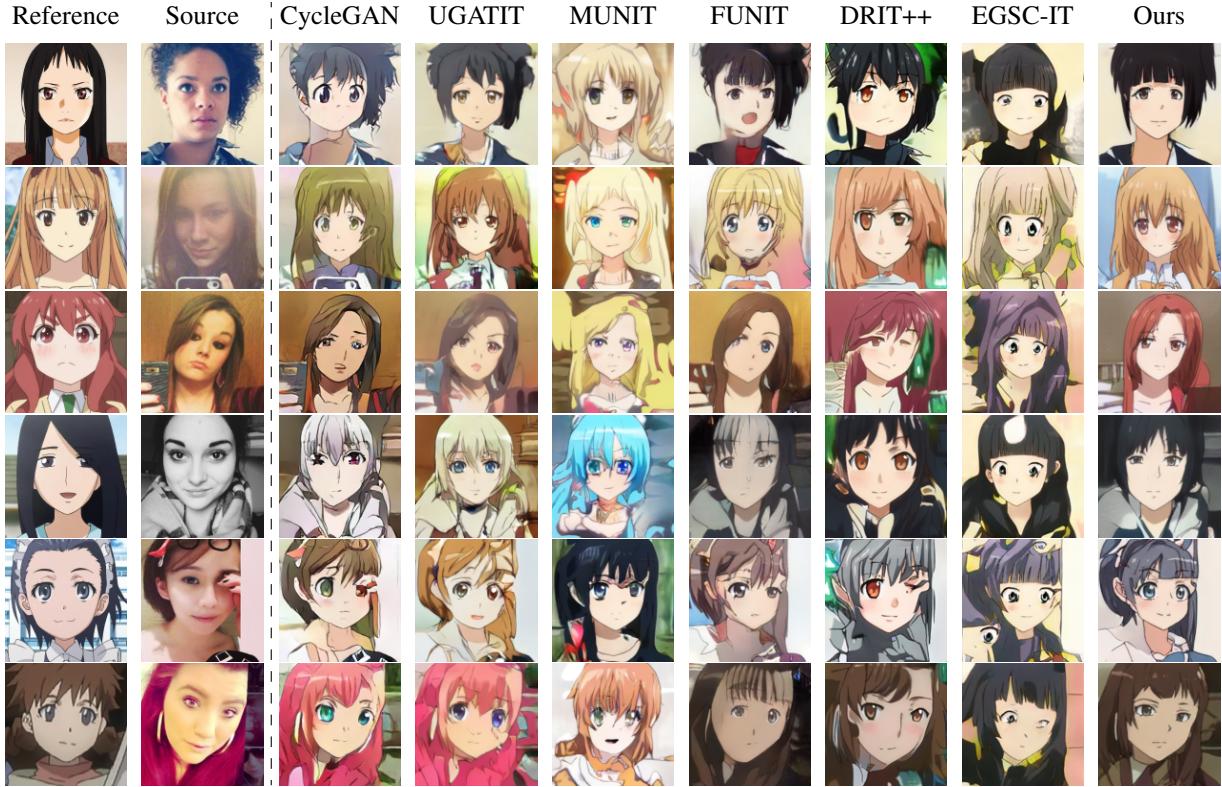


Figure 6: Comparison with image-to-image translation methods on the selfie2anime dataset. From left to right: source photo-face, reference anime-face, the results by CycleGAN [51], MUNIT [18], UGATIT [24], FUNIT [31], DRIT++ [25], EGSC-IT [35] and our AniGAN.

and mouth in an anime-face are dissimilar to the counterparts of the corresponding photo-face. Consequently, EGSC-IT often leads to severe artifacts in the local structures of generated anime-faces (see eyes and hair in the first to third rows). DRIT++ also introduces artifacts into generated faces, when transferring the styles of the reference anime-faces. For example, DRIT++ generates two mouths in the generated face in the third row and distort eyes in the fifth row.

Outperforming the above state-of-art methods, our method generates the highest-quality anime-faces. First, compared with reference-guided methods FUNIT, EGSC-IT, and DRIT++, the styles of generated anime-faces with our method are the most consistent with that of reference faces, thanks to our well-designed generator. Moreover, our method well preserves the poses of photo-faces, although our method does not use perceptual loss like EGSC-IT. Our method also well converts local structures like eyes and mouth into anime-like ones without introducing clearly visible artifacts.

Fig. 6 compares the results of various methods on the selfie2anime dataset. The results show that FUNIT introduces artifacts into some generated faces, as shown in the fourth and sixth rows in Fig. 6. Besides, EGSC-IT tends to

generate anime-faces with similar styles, although the reference anime-faces are of different styles (see the reference and generated images in the fourth to sixth rows in Fig. 6). Similarly, DRIT++ tends to synthesize eyes with similar styles in the generated faces. For example, the synthesized eyes by DRIT++ are orange ellipse in the first, second, fourth and fifth rows in Fig. 6. In contrast, our method generates anime-faces reflecting the various styles of the reference images. In other words, our method achieves the most consistent styles with those of reference anime-faces over the other methods. In addition, our method generates high-quality faces which preserve the poses of source photo-faces, despite a photo-face is partially occluded by other objects (e.g., the hand in the fifth rows of Fig. 6).

4.4. Quantitative Comparisons

In addition to qualitative evaluation, we quantitatively evaluate the performance of our method in two aspects. One is the visual quality of generated images, and the other is the translation diversity.

Visual quality. We evaluate the quality of our results with Frechet Inception Distance (FID) metric [16] which has been popularly used to evaluate the quality of synthetic images in image translation works e.g., [10, 31, 49].

Table 1: Comparison of FID scores on the face2anime and selfie2anime datasets: lower is better

Method	Face2anime	Selfie2anime
CycleGAN	50.09	99.69
UGATIT	42.84	95.63
MUNIT	43.75	98.58
EG-MUNIT	185.23	305.33
FUNIT	56.81	117.28
DRIT	70.59	104.49
EGSC-IT	67.57	104.70
AniGAN (Ours)	38.45	86.04

Table 2: Comparison of average LPIPS scores on the face2anime and selfie2anime dataset: higher is better

	Face2anime	Selfie2anime
DRIT++	0.184	0.201
EGSC-IT	0.302	0.225
AniGAN (Ours)	0.414	0.372

The FID score evaluates the distribution discrepancy between the real faces and synthetic anime-faces. A lower FID score indicates that the distribution of generated images is more similar to that of real anime-faces. That is, those generated images with lower FID scores are more plausible as real anime-faces. Following the steps in [16], we compute a feature vector by a pretrained network [43] for each real/generated anime-face, and then calculate FID scores for individual compared methods, as shown in Table 1. The FID scores in Table 1 demonstrate that our AniGAN achieves the best scores on both the face2anime and selfie2anime datasets, meaning that the anime-faces generated by our approach have the closest distribution with real anime-faces, thereby making they look similar visually.

Translation diversity. For the same photo-face, we evaluate whether our method can generate anime-faces with diverse styles, given multiple reference anime-faces with different styles. We adopt the learned perceptual image patch similarity (LPIPS) metric, a widely adopted metric for assessing translation methods on multimodal mapping [10, 25] in the perceptual domain, for evaluating the translation diversity. Following [10], given each testing photo-face, we randomly sample 10 anime-faces as its reference images and then generate 10 outputs. For these 10 outputs, we evaluate the LPIPS scores between every two outputs⁶. Table 2 shows the average of pairwise LPIPS over all testing photo-faces. A higher LPIPS score indicates that the translation method generates images with larger diversity.

Since CycleGAN, UGATIT focus on one-to-one mapping and cannot generate multiple outputs given a source

⁶Following [10], we uniformly scale all generated images to the size of 256 × 256.

Table 3: Preference percentages of 20 subjects for four methods in user study. Higher is better.

Method	Face2anime	Selfie2anime
FUNIT	17.50%	40.17%
DRIT++	68.17%	47.83%
EGSC-IT	27.33%	30.67%
Ours	87.00%	81.33%

image, we do not include them for comparison of translation diversity. We also do not compare with MUNIT and FUNIT, since MUNIT does not take a references as the input and FUNIT focuses on few-shot learning instead of translation diversity. Instead, we compare with DRIT++ and EGSC-IT, which are state-of-the-arts in reference-guided methods. DRIT++ uses a regularization loss which explicitly encourages the generator to generate diverse results. Although our method does not impose such loss, LPIPS scores in Table 2 shows that our method outperforms DRIT++ and EGSC-IT on translation diversity, thanks to the generator and discriminator of our method.

We compare our method with three reference-guided methods FUNIT, EGSC-IT and DRIT++. Since translation methods (e.g., CycleGAN and UGATIT) do not transfer the information of a reference image, we do not compare with these methods for fair comparison. The subjective user study is conducted for face2anime and selfie2anime dataset, respectively, where 10 pairs of photo-faces and anime-faces in each dataset are fed into these four translation methods to generate anime-faces.

We receive 1,200 answers from 20 subjects in total for each dataset, where each method is compared 600 times. As shown in Table 3, most subjects are in favor of our method for the results on both face2anime and selfie2anime datasets, demonstrating that the anime-faces translated by our method are usually the most visually appealing to the subjects.

4.5. User Study

We conduct a subjective user study to further evaluate our method. 20 subjects are invited to participate in our experiments, whose ages range from 22 to 35.

Following [18, 45], we adopt pairwise A/B test. For each subject, we show a source photo-face, a reference anime-face, and two anime-faces generated by two different translation methods. The generated anime-faces are presented in a random order, such that subjects are unable to infer which anime-faces are generated by which translation methods. We then ask each subject the following question:

”Q: Which generated anime-faces has better visual quality by considering the source photo-face and the anime styles of the reference anime-face? ”

We compare our method with three reference-guided

Table 4: Quantitative comparison for ablation study using FID score. Lower is better

Method	ASC	FST	DB	PoLIN	AdaPoLIN	IN	LIN	AdaIN	AdaLIN	Face2anime	Selfie2anime
w/o ASC		✓	✓	✓						40.52	96.20
w/o FST	✓		✓				✓			44.13	99.91
w/o DB	✓	✓		✓			✓			40.56	92.78
w/o PoLIN w IN	✓	✓	✓		✓		✓			40.73	89.62
w/o PoLIN w LIN	✓	✓	✓		✓			✓		39.30	90.66
w/o AdaPoLIN w AdaIN	✓	✓	✓	✓					✓	40.16	90.31
w/o AdaPoLIN w AdaLIN	✓	✓	✓	✓					✓	39.52	91.93
AniGAN (Ours)	✓	✓	✓	✓		✓				38.45	86.98

Table 5: Quantitative comparison for ablation study using LPIPS score. Higher is better

Method	ASC	FST	DB	PoLIN	AdaPoLIN	IN	LIN	AdaIN	AdaLIN	Face2anime	Selfie2anime
w/o ASC		✓	✓	✓						0.375	0.321
w/o FST	✓		✓				✓			0.391	0.340
w/o DB	✓	✓		✓			✓			0.395	0.342
w/o PoLIN w IN	✓	✓	✓		✓		✓			0.409	0.362
w/o PoLIN w LIN	✓	✓	✓		✓			✓		0.402	0.367
w/o AdaPoLIN w AdaIN	✓	✓	✓	✓					✓	0.400	0.356
w/o AdaPoLIN w AdaLIN	✓	✓	✓	✓					✓	0.397	0.336
AniGAN (Ours)	✓	✓	✓	✓		✓				0.414	0.372

methods FUNIT, EGSC-IT and DRIT++. Since translation methods (e.g., CycleGAN and UGATIT) do not transfer the information of a reference image, we do not compare with these methods for fair comparison. The subjective user study is conducted for face2anime and selfie2anime dataset, respectively, where 10 pairs of photo-faces and anime-faces in each dataset are fed into these four translation methods to generate anime-faces.

We receive 1,200 answers from 20 subjects in total for each dataset, where each method is compared 600 times. As shown in Table 3, most subjects are in favor of our results on both face2anime and selfie2anime datasets, demonstrating that anime-faces translated by our method are usually the most visually appealing to the subjects.

4.6. Ablation Study

We conduct ablation experiments to validate the effectiveness of individual components in our method: (1) ASC block, (2) FST block, (3) PLIN and AdaPLIN, (4) double-branch discriminator.

ASC block. We seek to validate whether the ASC block effectively retains the style information of the reference image and helps the generator transfer the style characteristics. Note that the key differentiating factor in our ASC block is the removal of residual blocks from the bottleneck of our generator, different from start-of-the-art image translation methods (e.g., MUNIT, UGATIT, and FUNIT). We hence implement a baseline called “**w/o ASC**” which adds resid-

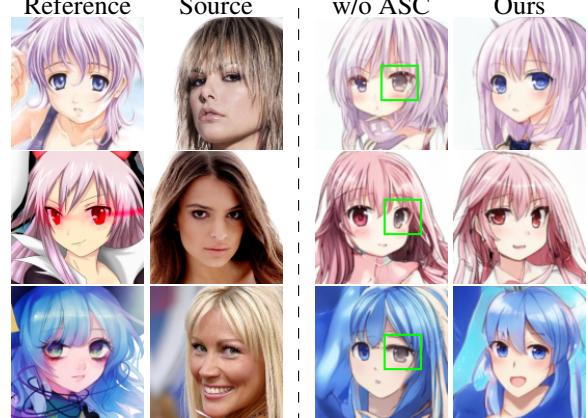


Figure 7: Visual comparison of the contributions of ASC blocks, where “w/o ASC” improperly renders “brown” right eyes in all the generated images.

ual blocks in the bottleneck of our decoder. As shown in Fig. 7, “**w/o ASC**” tends to ignore certain style information due to the additional residual blocks. For example, “**w/o ASC**” ignores the styles of the right eyes in the references and renders “brown” right eyes in all the generated images. In contrast, our method well and consistently renders the style of the left and right eyes, despite no face landmarks or face parsing are used. Clearly, our method outperforms “**w/o ASC**” in transferring the styles of reference anime-faces, thanks to the ASC block.



Figure 8: Visual comparison of the contributions of PoLIN and AdaPoLIN. Row from left to right: (a) reference anime-faces, (b) source photo-faces, generated faces by (c) “w/o PoLIN w/ IN”, (d) “w/o PoLIN w/ LIN”, (e) “w/o AdaPoLIN w/ AdaIN”, (f) “w/o AdaPoLIN w/ AdaLIN” and (g) our method.

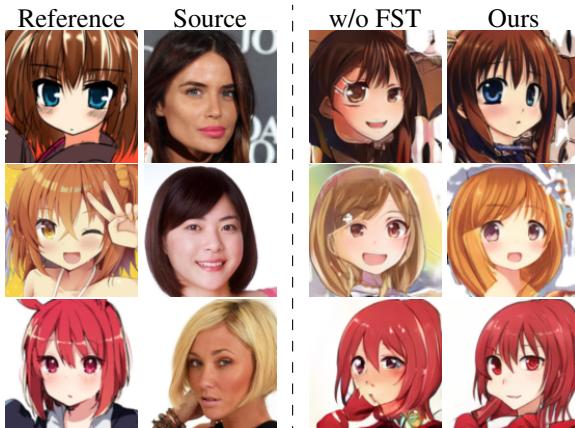


Figure 9: Visual comparison of the contributions of FST blocks

FST block. Different from existing methods (e.g., MUNIT, FUNIT, EGSC-IT) which use typical upsampling blocks in the decoder, FST is additionally equipped with our normalization functions. To validate the effectiveness of FST, we build a baseline (called “**w/o FST**”) which replaces the FST blocks with typical upsampling blocks (like MUNIT, FUNIT, and EGSC-IT) without our normalization functions. As shown in Fig. 9, “**w/o FST**” performs poorly in converting the shape of local facial features and transferring styles. For example, “**w/o FST**” poorly converts the face shapes and eyes and introduces artifacts in the generated faces. In contrast, with FST, our method better converts the local shapes into anime-like ones than “**w/o FST**”. Moreover, our method also better transfers the styles of the reference anime-faces to the generated faces than “**w/o FST**” does. Similarly, the FID of “**w/o FST**” increases in Table 4, indicating that the anime-faces generated by “**w/o FST**” are less plausible than those generated by our method.

In addition, the LPIPS scores of **w/o FST** and our method in Tab. 5 shows that FST is helpful for generating diverse anime-faces.

PoLIN and AdaPoLIN. We build four baselines to evaluate the effectiveness of PoLIN and AdaPoLIN. The first and second baselines are built for evaluating PoLIN, and the third and fourth baseline are for AdaPoLIN. The first baseline, named “**w/o PoLIN w/ IN**”, is constructed by replacing PoLIN with IN in [44]. We build “**w/o PoLIN w/ IN**”, since EGSC-IT, DRIT and FUNIT employ IN in the up-sampling convolutional layers of their decoder, different from our method with PoLIN. The second baseline, named “**w/o PoLIN w/ LIN**”, is constructed by replacing PoLIN with layer-Instance Normalization (LIN). The third baseline, called “**w/o AdaPoLIN w/ AdaIN**”, replaces AdaPoLIN with AdaIN in [17], which was employed by many translation methods e.g., [18, 31, 32, 35]. The fourth baseline, called “**w/o AdaPoLIN w/ AdaLIN**”, replaces AdaPoLIN with AdaLIN which is used in UGATIT.

The FID scores in Table 4 show that our method outperforms the four baselines. Without PoLIN, the performance of transforming local shapes into anime-like ones is degraded, as shown in the results generated by “**w/o PoLIN w/ IN**” and “**w/o PoLIN w/ LIN**” in Fig. 8. For example, “**w/o PoLIN w/ IN**” introduces artifacts in the hair at the right boundary of generated faces in the first row of Figs. 8(c) and (d). Similarly, without AdaPoLIN, both “**w/o AdaPoLIN w/ AdaIN**” and “**w/o AdaPoLIN w/ AdaLIN**” perform worse than our method. Table 4 shows that “**w/o AdaPoLIN w/ AdaIN**” and “**w/o AdaPoLIN w/ AdaLIN**” degrade the performance in terms of translation diversity.

It is worth noting that all the above baselines, that replace our normalization functions with other normalization functions employed by DRIT, EGSC-IT, UGATIT, etc., still achieve better FID and LPIPS scores than state-of-the-art

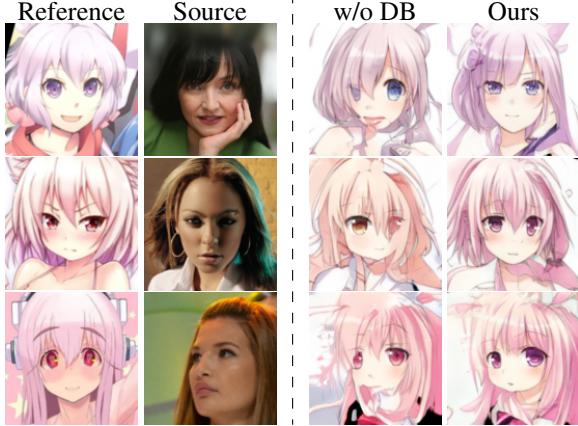


Figure 10: Visual comparison of the contributions of the double-branch discriminator

methods, as shown in Table 1, 2, 4, and 5. This indicates that the architectures of our generator and discriminator are more advantageous for StyleFAT task.

Double-branch discriminator. We implement a baseline “**w/o DB**” that removes the photo-face branch (i.e., the branch that discriminates real/fake photo-faces) from our discriminator. Table 4 shows that it yields poorer FID than our method. Table 5 also shows LPIPS scores of “**w/o DB**” is worse than that of our method. More specifically, as shown in Fig. 10, “**w/o DB**” distorts local facial shapes, leading to low-quality generated faces, especially for challenging source photo-faces. This is because “**w/o DB**” would mainly focus on generating plausible anime images, rather than on generating plausible anime human faces. In contrast, our method generates high-quality anime-faces, thanks to the additional photo-face branch in the discriminator. With the photo-face branch in our discriminator, the photo-face and anime-face branches share the first few shallow layers, which helps the anime-face branch better learn real facial features from photo-faces so as to well discriminate low-quality anime-faces with distorted facial features.

5. Conclusion

In this paper, we propose a novel GAN-based method, called AniGAN, for style-guided face-to-anime translation. A new generator architecture and two normalization functions are proposed, which effectively transfer styles from the reference anime-face, preserve global information from the source photo-face and convert local facial shapes into anime-like ones. We also propose a double-branch discriminator to assist the generator to produce high-quality anime-faces. Extensive experiments demonstrate that our method achieves superior performance compared with state-of-the-art methods.

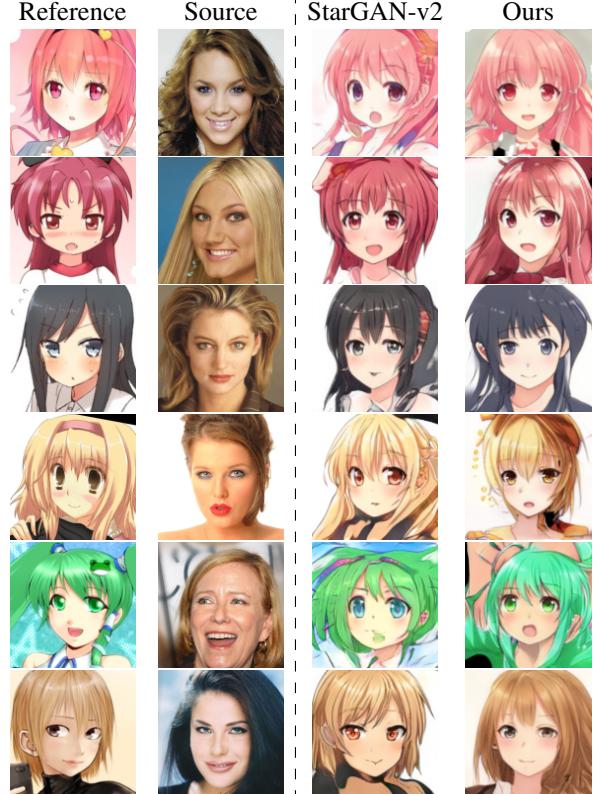


Figure 11: Comparison results on the face2anime dataset. From left to right: source photo-face, reference anime-face, the results by StarGAN-v2 [10] and our AniGAN.

A. Appendix

A.1. Comparisons with StarGAN-v2

StarGAN-v2 [10] achieves impressive translation results on the CelebA-HQ and AFHQ datasets. We hence additionally compare our method with StarGAN-v2. As shown in Fig. 11, StarGAN-v2 generates plausible anime-faces. However, the poses and hair styles of anime-faces generated by StarGAN-v2 are often inconsistent with that of source photo-faces. For example, given the source photo-face with long hair in the second row of Fig. 11, StarGAN-v2 generates a anime-face with short hair which is similar to that of the reference. In other words, StarGAN-v2 ignores the global information of source photo-faces, which dose not meet the requirements of the StyleFAT task. In contrast, our method well preserves the global information of source photo-face and generates high-quality anime-faces.

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