

ArtFlow: Unbiased Image Style Transfer via Reversible Neural Flows

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Abstract

Universal style transfer retains styles from reference images in content images. While existing methods have achieved state-of-the-art style transfer performance, they are not aware of the content leak phenomenon that the image content may corrupt after several rounds of stylization process. In this paper, we propose ArtFlow to prevent content leak during universal style transfer. ArtFlow consists of reversible neural flows and an unbiased feature transfer module. It supports both forward and backward inferences and operates in a projection-transfer-reversion scheme. The forward inference projects input images into deep features, while the backward inference remaps deep features back to input images in a lossless and unbiased way. Extensive experiments demonstrate that ArtFlow achieves comparable performance to state-of-the-art style transfer methods while avoiding content leak.

1. Introduction

Neural style transfer aims at transferring the artistic style from a reference image to a content image. Starting from [11, 13], numerous works based on iterative optimization [12, 44, 30, 34] and feed-forward networks [23, 53, 3, 63] improve style transfer from either visual quality or computational efficiency. Despite tremendous efforts, these methods do not generalize well for multiple types of style transfer. Universal style transfer (UST) is proposed to improve this generalization ability. The representative UST methods include AdaIN [20], WCT [32], and Avatar-Net [45]. These methods are continuously extended by [15, 22, 60, 1, 45, 33, 40, 31, 2, 56]. While achieving favorable results as well as generalizations, these methods are limited to disentangling and reconstructing image content during the stylization process. Fig. 1 shows some examples. Existing methods [32, 20, 45] effectively stylize

*J. An and S. Huang contribute equally. This work is done when J. An is an intern in Tencent AI Lab. The code is available at <https://github.com/pkuanjie/ArtFlow>.

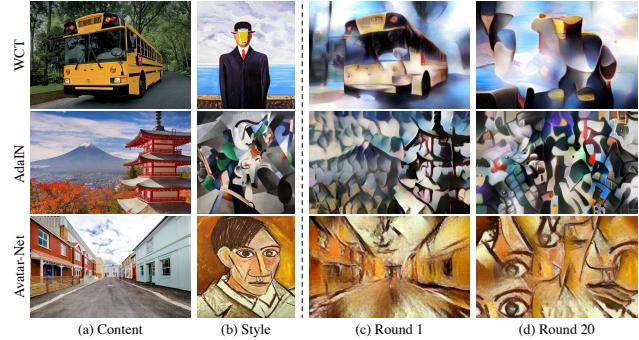


Figure 1. Content leak visualization. Existing style transfer methods are not effective to preserve image content after several rounds of stylization process as shown in (d), although their performance is state-of-the-art in the first round as shown in (c).

content images in (c). However, image contents are corrupted after several rounds of stylization process where we send the reference image and the output result into these methods. We define this phenomenon as content leak and provide an analysis in the following:

Content leak appears due to the design of UST methods that usually consist of three parts: the first part is a fixed encoder for image embedding, the second part is a learnable decoder to remap deep features back to images, and the third part is a style transfer module based on deep features. We observe that the first part is fixed. The appearance of content leak indicates the accumulated image reconstruction errors brought by the decoder, or the biased training process of either the decoder or the style transfer module. Specifically, the content leaks of WCT [32] and its variants [31, 40, 56] is mainly caused by the image reconstruction error of the decoder. The content leak of AdaIN series [20, 22, 60] and Avatar-Net [45] are additionally caused by the biased decoder training and a biased style transfer module, respectively. Sec. 3 shows more analyses.

In this work, we propose an unbiased style transfer framework called ArtFlow to robustify existing UST methods upon overcoming content leak. Different from the prevalent encoder-transfer-decoder structure, ArtFlow in-

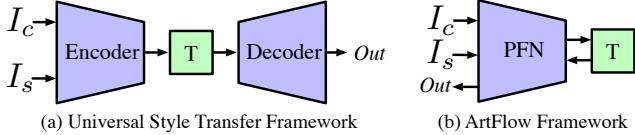


Figure 2. A comparison between the auto-encoder based style transfer framework and the proposed ArtFlow framework.

troduces both forward and backward inferences to formulate a projection-transfer-reversion pipeline. This pipeline is based on neural flows [5] and only contains a Projection Flow Network (PFN) in conjunction with an unbiased feature transfer module. The neural flow refers to a number of deep generative models [5, 18] which estimate density through a series of reversible transformations. Our PFN follows the neural flow model GLOW [28] which consists of a chain of reversible operators including activation normalization layers, invertible 1×1 convolutions, and affine coupling layers [6]. Fig. 2 shows the structure of ArtFlow. It first projects both the content and style images into latent representations via forward inference. Then, it makes unbiased style transfer upon deep features and reconstructs the stylized images via reversed feature inference.

The proposed PFN avoids the image reconstruction error and image recovery bias which usually appear in the encoder-decoder framework. PFN allows unbiased and lossless feature extraction and image recovery. To this end, PFN facilitates the comparison of style transfer modules in a fair manner. Based on PFN, we perform theoretical and empirical analyses of the inherent biases of style transfer modules adopted by WCT, AdaIN, and Avatar-Net. We show that the transfer modules of AdaIN and WCT are unbiased, while the transfer module of Avatar-Net is biased towards style. Consequently, we adopt the transfer modules of AdaIN and WCT as the transfer modules for ArtFlow to achieve an unbiased style transfer.

The contributions of this work are three-fold:

- We reveal the Content Leak issue of the state-of-the-art style transfer algorithms and identify the three main causes of the Content Leak in AdaIN [20], WCT [32], and Avatar-Net [45].
- We propose an unbiased, lossless, and reversible network named PFN based on neural flows, which allows both theoretical and empirical analyses of the inherent biases of the popular style transfer modules.
- Based on PFN in conjunction with an unbiased style transfer module, we propose a novel style transfer framework, *i.e.*, ArtFlow, which achieves comparable style transfer results to state-of-the-art methods while avoiding the Content Leak issue.

2. Related Work

Image Style Transfer. Image style transfer is a long-

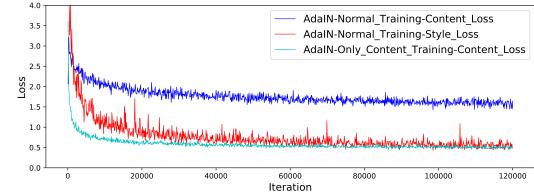


Figure 3. Loss curves of AdaIN [20] training: Using both content and style losses *vs.* only using the content loss.

standing research topic. Before deep neural networks [49, 37, 59, 57] are applied to the style transfer, several algorithms based on stroke rendering [16], image analogy [17, 46, 10, 48, 35, 51, 50], and image filtering [61] are proposed to make artistic style transfer. These methods usually have to trade-off between style transfer quality, generalization, and efficiency. Gatys *et al.* [11, 13] introduce a Gram loss upon deep features to represent image styles, which opens up the neural style transfer era. Inspired by Gatys *et al.*, numerous neural style transfer methods have been proposed. We categorize these methods into one style per model [29, 54, 23, 53, 55, 58, 44, 30], multi-style per model [7, 3, 19, 14], and universal style transfer methods [4, 32, 20, 45, 15, 2, 56, 38, 60, 1] with respect to their generalization abilities. In this paper, our ArtFlow belongs to universal style transfer and it consists of reversible neural flows. The forward and backward inferences are utilized for lossless and unbiased image recovery.

Neural flows. Neural flows refer to a subclass of deep generative models, which learns the exact likelihood of high dimensional observations (*e.g.*, natural images, texts, and audios) through a chain of reversible transformations. As a pioneering work of neural flows, NICE [5] is proposed to transform low dimensional densities to high dimensional observations with a stack of affine coupling layers. Following NICE, a series of neural flows, including RealNVP [6], GLOW [28], and Flow++ [18], are proposed to improve NICE with more powerful and flexible reversible transformations. The recently proposed neural flows [28, 18, 39] are capable of synthesizing high-resolution natural/face images, realistic speech data [43, 26], and performing make-up transfer [8]. In this work, the proposed ArtFlow consists of a reversible network PFN and an unbiased feature transfer module. The content leak can be addressed via lossless forward and backward inferences and unbiased feature transfer. In comparison, BeautyGlow [8] shares the similar spirits but is not applicable for unbiased style transfer.

3. Pre-analysis

Before introducing the proposed ArtFlow, we first make a pre-analysis to uncover the Content Leak phenomenon of the state-of-the-art style transfer algorithms and analyze the



Figure 4. Multiple rounds of image encoding and decoding using the auto-encoder of AdaIN [20].

causes of Content Leak. We make the aforementioned pre-analysis by answering two questions: What Content Leak is and why Content Leak happens.

3.1. What is Content Leak?

For a style transfer algorithm, Content Leak occurs because the stylization results lose some content information. Although the existing state-of-the-art style transfer algorithms, *e.g.*, AdaIN [20], WCT [32], and Avatar-Net [45], can produce good style transfer results, they still suffer from the Content Leak issue. Since it is hard to directly extract the content information from the stylized image and compare it with the input content image, we adopt an alternative way to show empirical evidence of the Content Leak phenomenon. More specifically, we first perform the style transfer with an input content-style pair based on a style transfer algorithm. We then take the stylized image as the new content and repeatedly perform the style transfer process for 20 times. Fig. 1 shows the results of our experiments for AdaIN (row 1), WCT (row 2), and Avatar-Net (row 3). According to Fig. 1, when we perform style transfer for 20 rounds, we can hardly recognize any detail of the content image. Such an empirical evidence indicates that the Content Leak phenomenon occurs in all AdaIN, WCT, and Avatar-Net. In the following, we discuss the causes of the Content Leak, which imply that the Content Leak issue also exists in other state-of-the-art style transfer algorithms.

3.2. Why Does Content Leak Happen?

Taking AdaIN [15], WCT [32], and Avatar-Net [45] as three representatives of style transfer algorithms, we study the causes of the Content Leak phenomenon.

Reconstruction error. A straightforward explanation to Content Leak is that the decoder of existing style transfer algorithms cannot achieve lossless image reconstruction of the input content image. For example, all AdaIN, WCT, and Avatar-Net adopt VGG19 [47] as the encoder and train a structurally symmetrical decoder to invert the features of VGG19 back to the image space. Although an image reconstruction loss [32] or a content loss [20] is used to train the decoder, Li *et al.* [32] acknowledge that the decoder is far from perfect due to the loss of spatial information brought by the pooling operations in the encoder. Consequently, the

accumulated image reconstruction error may gradually disturb the content details and lead to the Content Leak.

Biased decoder training. The above-mentioned reconstruction error can only partially explain the Content Leak phenomenon. In addition, biased decoder training is another cause. We take the training scheme of AdaIN as an example to explain how its loss function settings lead to Content Leak. AdaIN trains the decoder with a weighted combination of a content loss L_c and a style loss L_s , where

$$L_c = \|F(G(t)) - t\|_2, \quad (1)$$

$$\begin{aligned} L_s &= \sum_{i=1 \dots L} \|\mu(\phi_i(G(t))) - \mu(\phi_i(s))\|_2 \\ &\quad + \sum_{i=1 \dots L} \|\sigma(\phi_i(G(t))) - \sigma(\phi_i(s))\|_2. \end{aligned} \quad (2)$$

Here t denotes the output of the adaptive instance normalization, F and G represent the encoder and the decoder, respectively, ϕ_i denotes a layer in VGG19 used to compute the style loss, and μ, σ represent the mean and standard deviation of feature maps, respectively. Due to L_s , the decoder is trained to trade off between L_c and L_s , rather than trying to reconstruct images perfectly. Fig. 3 shows the training loss curves of AdaIN with and without L_s . When we train the decoder of AdaIN with only L_c , the converged value of L_c (cyan curve) is significantly smaller than training with the weighted combination of L_c and L_s (blue curve). Consequently, the auto-encoder of AdaIN is biased towards rendering more artistic effects, which causes Content Leak. Fig. 4 shows the image reconstruction results by propagating through the auto-encoder of AdaIN for 50 rounds. We take the output of the auto-encoder in the previous round as the input of the next round and perform image reconstruction repeatedly. With the increase of the inference rounds, weird artistic patterns gradually appear in the produced results, which indicates that the auto-encoder of AdaIN may memorize image styles in training and bias towards the training styles in inference.

Biased style transfer module. Biased style transfer module is another cause of the Content Leak. We take the Style Decorator in Avatar-Net as an example. For the normalized content feature f_c and style feature f_s , the key mechanism of the Style Decorator is motivated by the deep image analogy [35], which is composed of two steps. In the first step, the algorithm finds a corresponding patch in f_s for every patch in f_c according to the content similarity between two patches. In the next step, f_{cs} is formed by replacing patches in f_c with the corresponding patches in f_s . Since such a patch replacement is irreversible, f_c cannot be recovered from f_{cs} , which makes f_{cs} be biased towards style and consequently causes the Content Leak phenomenon.

We summarize and illustrate three main causes of Content Leak in Fig. 5. While the reconstruction error may disturb the content information in the output image, the biased

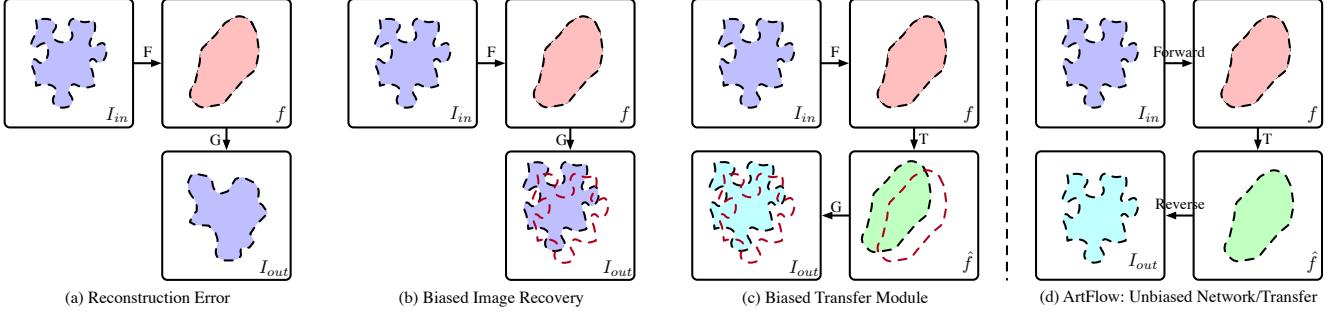


Figure 5. Causes of the Content Leak phenomenon. (a) Reconstruction error, *i.e.*, the content of output image is disturbed. (b) Biased image recovery, *i.e.*, the output image shifts to a biased style via the decoder. (c) Biased style transfer module, *i.e.*, the stylized feature shifts to a biased style via feature stylization. The red dash lines in (b) and (c) denote unbiased positions of the manifolds. (d) The proposed ArtFlow scheme, where both the network and the transfer module are not biased, while the backbone network does not introduce any reconstruction error. Notations – F and G : encoder and decoder used by existing style transfer algorithms, respectively. T : style transfer module, *e.g.*, AdaIN or WCT. I_{in} and I_{out} : input and output images. f and \hat{f} : vanilla and stylized deep features of I_{in} .

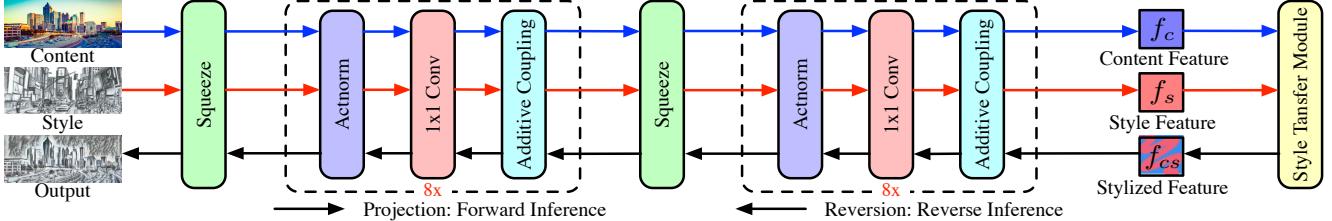


Figure 6. The framework of the proposed ArtFlow. For style transfer, Artflow works in a *projection-transfer-reversion* scheme. *Projection*: Extracting deep features of content and style images via the forward inference. *Transfer*: Transferring the content and style features to the stylized feature via the style transfer module. *Reversion*: Transforming the stylized feature to the stylized image via the reverse inference.

image recovery and the biased transfer module may lead to a style shift in the output image.

4. Method

4.1. Overview of the ArtFlow Framework

In this work, we present a novel unbiased style transfer framework named ArtFlow to address the Content Leak issue of the state-of-the-art style transfer approaches. Different from the *encoder-transfer-decoder* scheme commonly used in existing neural style transfer algorithms, ArtFlow performs image style transfer through a *projection-transfer-reversion* scheme. As shown in Fig. 6, ArtFlow relies on a reversible neural flow model, named Projection Flow Network (PFN). In the *projection* step, the content images and style images are fed into PFN for lossless deep feature extraction via the forward propagation of PFN. In the *transfer* step, the content and style features are transferred to the stylized feature with an unbiased style transfer module. In the *reversion* step, the stylized feature is reconstructed to a stylized image via the reverse propagation of PFN. Since the information flow in PFN and the unbiased style transfer module are both lossless and unbiased, ArtFlow achieves unbiased image style transfer to avoid the Content Leak.

In the following, we first discuss the details of PFN in

Section 4.2. Then, we discuss the choice of the unbiased style transfer module by performing both theoretical and quantitative analyses of the inherent biases of existing transfer modules in Section 4.3.

4.2. Projection Flow Network

Projection Flow Network (PFN) serves as both the deep feature extractor and image synthesizer of our ArtFlow framework. In this work, we construct PFN by following the effective Glow model [28]. As shown in Fig. 6, PFN consists of a chain of three learnable reversible transformations, *i.e.*, additive coupling, invertible 1×1 convolution, and Actnorm. All the components of PFN are reversible, making PFN fully reversible that the information is lossless during the forward and reverse propagation. In the following, we describe the three reversible transformations.

Additive coupling. Dinh *et al.* [5, 6] proposed an expressive reversible transformation named affine coupling layer. In this work, we adopt a special case of affine coupling, *i.e.*, additive coupling, for PFN. The forward computation of additive coupling is

$$\begin{aligned} x_a, x_b &= \text{split}(x) \\ y_b &= \text{NN}(x_a) + x_b \\ y &= \text{concat}(x_a, y_b). \end{aligned}$$

The `split()` function splits a tensor into two halves along the channel dimension. `NN()` is (any) neural network where the input and the output have the same shape. The `concat()` function concatenates two tensors along the channel dimension. The reverse computation of additive coupling can be easily derived.

We observe that a flow model with additive coupling layers is sufficient to handle the style transfer task in experiments. Moreover, the additive coupling is more efficient and stable than the affine coupling in model training. Therefore, we employ additive coupling instead of affine coupling as the expressive transformation layer in PFN.

Invertible 1×1 convolution. Since the additive coupling layer only processes a half of the feature maps, it is necessary to permute the channel dimensions of feature maps, so that each dimension can affect all the other dimensions [5, 6]. We follow Glow [28] to use a learnable invertible 1×1 convolution layer for flexible channel permutation, as

$$y_{i,j} = Wx_{i,j}. \quad (3)$$

W is the weight matrix of shape $c \times c$, where c is the channel dimension of tensor x and y . Its reverse function is $x_{i,j} = W^{-1}y_{i,j}$.

Actnorm. We follow Glow [28] to use the activation normalization layer (Actnorm) as an alternative to batch normalization [21]. Actnorm performs per-channel affine transformation on tensor x , as

$$y_{i,j} = w \odot x_{i,j} + b, \quad (4)$$

where i, j denote a spatial position on the tensor. w and b are the scale and bias parameters of affine transformation, and they are learnable in model training. The reverse function is $x_{i,j} = (y_{i,j} - b)/w$.

In addition to the three reversible transformations, the squeeze operation is inserted into certain parts of PFN to reduce the spatial size of 2D feature maps. The squeeze operation splits the features into smaller patches along the spatial dimension and then concatenates the patches along the channel dimension.

4.3. Unbiased Content-Style Separation

Which style transfer module should ArtFlow use to achieve the unbiased style transfer? To answer this question, we first make a theoretical analysis of the biases of two popular style transfer modules, *i.e.*, the adaptive instance normalization in AdaIN, and the whitening and coloring transforms in WCT.

The mechanism of the universal style transfer methods can be regarded as a natural evolution of the bilinear model proposed by Tenenbaum and Freeman in [52], which separates an image into a content factor C and a style factor S and then makes style transfer by replacing

the style factor S in the content image with that in the target image. Similarly, the universal style transfer methods assume that the content information and the style information in the deep feature space are disentangled explicitly [20, 32, 31, 40, 2, 1, 56, 22, 60] or implicitly [4, 45]. For example, AdaIN [20] separates deep features into normalized feature maps and mean/std vectors, which can be regarded as the content factor C and style factor S , respectively.

Following the theoretical framework of the Bilinear Model [52], we can define the unbiased style transfer as:

Definition 1 Suppose we have a bilinear style transfer module $f_{cs} = C(f_c)S(f_s)$, where C, S denote the content factor and the style factor in the bilinear model, respectively. f_{cs} is an unbiased style transfer module if $C(f_{cs}) = C(f_c)$ and $S(f_{cs}) = S(f_s)$.

Based on Def. 1, we have the following two theorems.

Theorem 1 The adaptive instance normalization in AdaIN is an unbiased style transfer module.

Theorem 2 The whitening and coloring transform in WCT is an unbiased style transfer module.

The proofs for Theorems 3 and 4 can be found in the supplementary material. The Style Decorator in Avatar-Net [45] does not fit the bilinear model, while the empirical analysis in Sec. 3.2 shows that *Style Decorator is a biased style transfer module*.

In addition to the theoretical analyses, we also quantitatively verify the unbiased property of the transfer modules in AdaIN and WCT. Quantitatively studying the property of popular style transfer modules is an unsolved question because the auto-encoder used by existing universal style transfer methods has significant image reconstruction errors and may be biased towards styles as discussed in Sec. 3.2. Consequently, the produced style transfer results using auto-encoders cannot precisely reflect the effects of the style transfer modules upon deep features. The proposed PFN addresses this issue. Specifically, if we take the forward inference and the reverse inference of the proposed PFN as the encoder and decoder, respectively, we can obtain a lossless and unbiased “auto-encoder” for style transfer, which can avoid the influence of the image reconstruction error and the biased image recovery brought by the decoder.

By using the proposed PFN as the lossless feature projector/inverter, we make a quantitative analysis about the content and style reconstruction errors of the transfer modules in AdaIN and WCT. Fig. 7 demonstrates two findings: 1) Considering (a) vs. (b) and (c) vs. (d), the proposed PFN can indeed make lossless and unbiased content and style reconstruction while the auto-encoder based on VGG19 cannot.

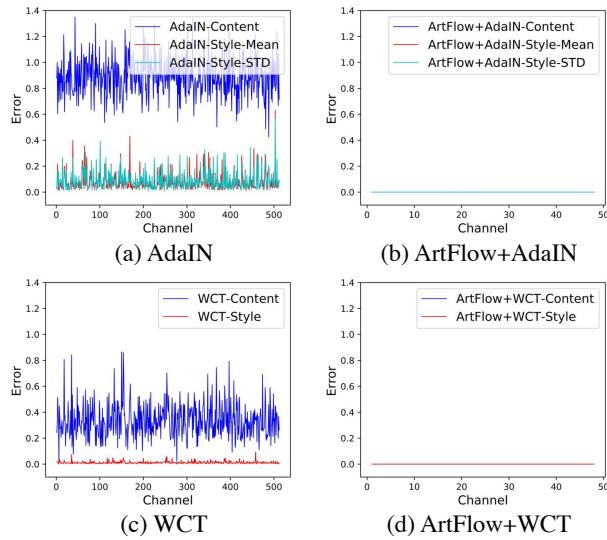


Figure 7. Content error between $F(G(f_{cs}))$ and f_c and the style error between $F(G(f_{cs}))$ and f_s . ArtFlow with the transfer modules of AdaIN/WCT achieves lossless content/style reconstruction.

2) (b) and (d) quantitatively verify that the transfer module of AdaIN and WCT are unbiased.

Based on theoretical and quantitative analyses to transfer modules in AdaIN and WCT, we let the adaptive instance normalization and the whitening and coloring transforms be two options for ArtFlow to achieve unbiased style transfer.

5. Experiments

To demonstrate that ArtFlow can achieve unbiased style transfer, we conduct extensive experiments. We make a comparison between the proposed ArtFlow and state-of-the-art style transfer algorithms in terms of stylization effect, computing time, content leak, and content factor visualization. Moreover, we present a new interesting application named reverse style transfer, which can only be performed by ArtFlow. More qualitative results, portrait style transfer images, and user study results are available in supplementary materials.

5.1. Experimental Settings

Dataset. Following the existing style transfer methods [20, 32], we use the MS-COCO dataset [36] as the content images and the WikiArt dataset [41] as the style images. In training, we resize the input images to 512×512 and randomly crop each image to 256×256 .

Network architecture. As shown in Fig. 6, the proposed PFN consists of two flow blocks, where each block contains eight neural flows. Each flow is a stack of an Actnorm layer, an invertible 1×1 convolution, and an additive coupling layer. More studies on the number of blocks and flows can be found in the supplementary material.

Training. We implement our ArtFlow on the PyTorch framework [42]. We train ArtFlow for 60,000 iterations using an Adam optimizer [27] with a batch size of 2, an initial learning rate of $1e-4$, and a learning rate decay of $5e-5$. The training of ArtFlow takes about 12 hours on a single RTX 2080Ti GPU. We adopt the content loss L_c in Eq. 1 and style loss L_s in Eq. 2 as the training objective of ArtFlow. The loss weights of L_c and L_s are set to 0.1 and 1, respectively.

5.2. Style Transfer Results

To demonstrate the style transfer ability of the proposed ArtFlow, we compare the style transfer results of ArtFlow in conjunction with the transfer module of AdaIN/WCT with the state-of-the-art universal style transfer algorithms, *i.e.*, StyleSwap [4], AdaIN [20], WCT [32], LinearWCT [31], OptimalWCT [40], and Avatar-Net [45].

Visual comparison. Fig. 8 shows the style transfer results by all the compared algorithms. While all the compared methods can produce good style transfer results, different methods create distinct artistic effects, *e.g.*, WCT and OptimalWCT can create more colorful artistic effects, LinearWCT, AdaIN, ArtFlow can preserve more content details, and Avatar-Net can render more fine textures. The proposed ArtFlow in conjunction with AdaIN/WCT can produce visually comparable style transfer results to the state-of-the-art style transfer algorithms. It is worth noting that the style transfer results by ArtFlow preserve more details of the content image (please zoom in to compare the details of the billboards in the top row results), which confirms that ArtFlow corrects the biased style transfer issue of the compared methods and avoids the Content Leak. Moreover, we also perform portrait style transfer with the proposed ArtFlow. To train the portrait style transfer model, we use FFHQ [25] as the content and Metfaces [24] as the style. As Fig. 9 shows, ArtFlow can also achieve good artistic style transfer results on portrait images.

Quantitative comparison. In addition to the visual comparison, we also make a quantitative comparison. Inspired by [62], we adopt the Structural Similarity Index (SSIM) and the content loss between the original contents and stylized images as the metric to measure the performance of the content information preservation in style transfer. To measure the ability to create artistic effects of a style transfer algorithm, inspired by [32], we use the mean square error of Gram matrices between the style and the style-transferred images. As Tab. 1 shows, ArtFlow achieves the highest SSIM score, which indicates that the proposed methods have a stronger ability to preserve more content information. While StyleSwap achieves the best content loss and a good SSIM score, its style transfer results do not look as good as the results produced by ArtFlow. Regarding the Gram loss, since ArtFlow mainly addresses the

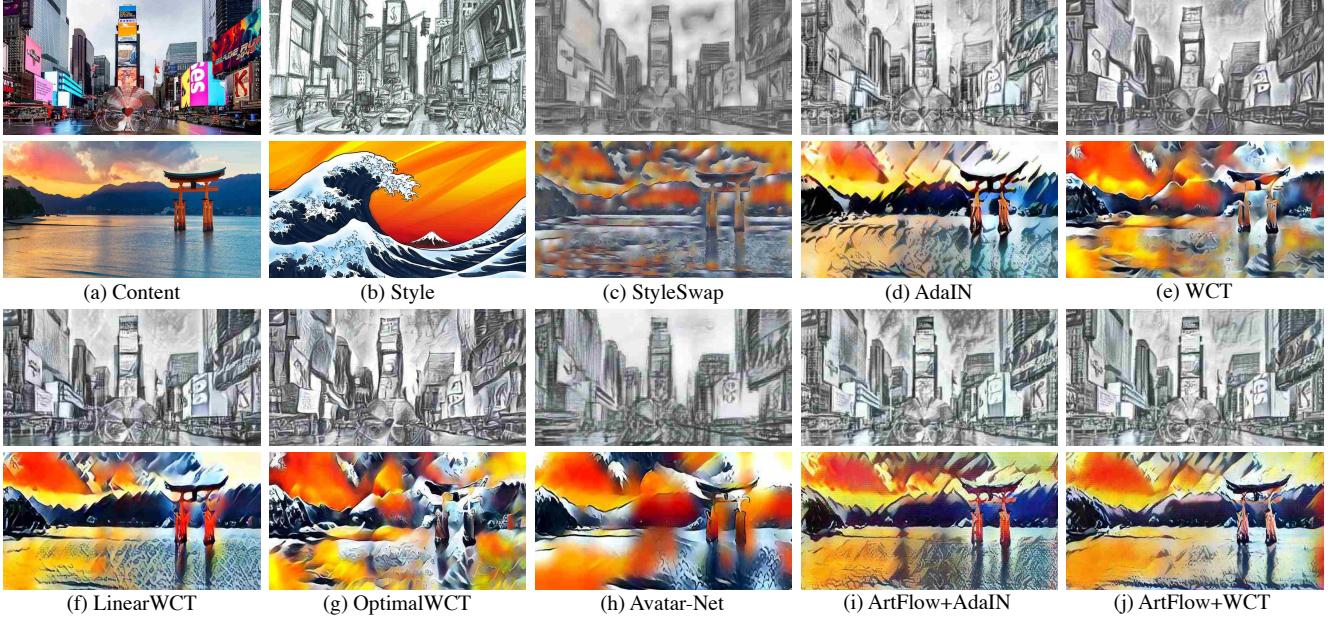


Figure 8. Style transfer results of the state-of-the-art universal style transfer algorithms.

Table 1. Quantitative evaluation results of universal stylization methods. The computing time is evaluated on 512×512 images.

Method	StyleSwap	AdaIN	WCT	LinearWCT	OptimalWCT	Avatar-Net	Self-Contained	ArtFlow+AdaIN	ArtFlow+WCT
SSIM \uparrow	0.44	0.29	0.27	0.35	0.21	0.31	0.23	0.45	0.47
Content Loss \downarrow	2.22	3.10	3.35	2.57	4.33	3.35	3.00	2.58	2.80
Gram Loss \downarrow	0.00482	0.00127	0.00074	0.00093	0.00035	0.00099	0.00473	0.00098	0.00078
Time (seconds) \downarrow	0.272	0.064	0.997	0.092	1.808	9.129	0.156	0.408	0.428

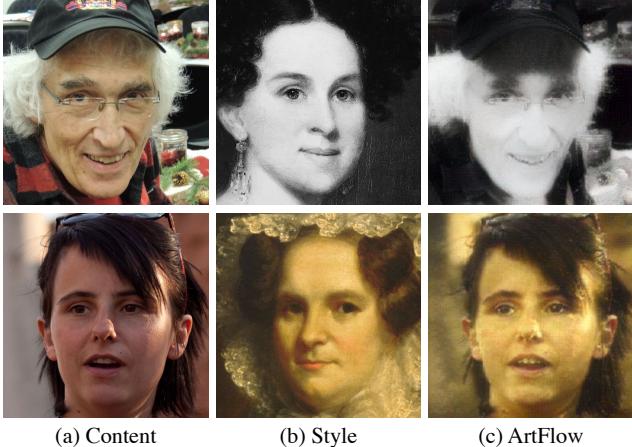


Figure 9. Portrait style transfer results using the proposed ArtFlow.

Content Leak issue and corrects the biases towards style images, it is reasonable that ArtFlow does not achieve the lowest Gram loss. It is worth noting that ArtFlow in conjunction with AdaIN achieves a lower Gram loss than vanilla AdaIN while ArtFlow in conjunction with WCT has a similar Gram loss compared with WCT itself, indicating that ArtFlow can solve the Content Leak issue without hurting the stylization ability of AdaIN/WCT. In the third row of Tab. 1, we also show the computing time for all the compared methods. ArtFlow+AdaIN is slower than vanilla

AdaIN since PFN does not adopt any pooling operations. Therefore, it requires more computations in the higher layers than AdaIN. Comparing with WCT, since ArtFlow does not need the multi-level stylization strategy used by WCT, ArtFlow+WCT is faster than vanilla WCT.

5.3. Content Leak

As discussed in Sec. 3, if the Content Leak happens, the content information would gradually disintegrate when we perform style transfer repeatedly. To demonstrate that the proposed ArtFlow can avoid the Content Leak phenomenon, we use the above way to visualize and compare the Content Leak phenomenon in AdaIN, WCT, Avatar-Net, and their counterparts in conjunction with the proposed ArtFlow. We also show the result by [9] because it also addresses the content leak issue. As Fig. 10 shows, the Content Leak appears in vanilla AdaIN, WCT, Avatar-Net, and Self-Content [9] when we perform the style transfer for 20 rounds. In contrast, when we replace the VGG19 based auto-encoder with the proposed PFN in AdaIN/WCT, the Content Leak disappears completely, which indicates that ArtFlow in conjunction with AdaIN/WCT can effectively solve the Content Leak problem and therefore achieve unbiased style transfer. Regarding Avatar-Net, as discussed in Sec. 3.2, since the Style Decorator in Avatar-Net is inherently biased towards style, ArtFlow combining the Style

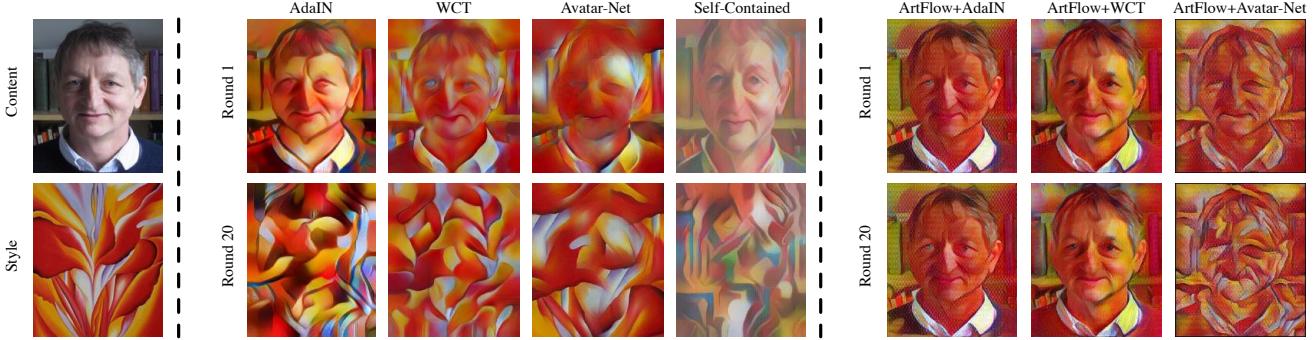


Figure 10. A comparison of the Content Leak phenomenon. We show the style transfer results of the first round and the 20-th round.

Table 2. User study results of universal stylization methods.

Method	StyleSwap	AdaIN	WCT	LinearWCT	OptimalWCT	Avatar-Net	ArtFlow
Votes \uparrow	7	19	64	257	60	78	314

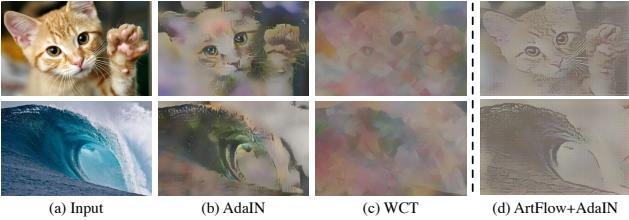


Figure 11. Visualization of content features of AdaIN, WCT, and the proposed ArtFlow.

Decorator as the transfer module cannot achieve unbiased style transfer. However, by replacing the auto-encoder with PFN, the Content Leak phenomenon is still significantly alleviated by Avatar-Net.

5.4. Content-Style Separation

As discussed in Sec. 4.3, AdaIN and WCT can be regarded as an evolution of the Bilinear Model in [52]. Taking the view of the bilinear model, the mechanism of AdaIN and WCT can be regarded as: 1) disentangling the content and style factors in the deep feature space, and 2) replacing the style factor of the content image with the style factor of the style image. Since such a disentangled representation of the content and style exists in the feature space, we can visualize the pure content by inverting the content factor back to an image. Fig. 11 shows the inverted content factor in AdaIN, WCT, and ArtFlow in conjunction with AdaIN. Compared with the inverted content factor of AdaIN and WCT, the results by ArtFlow contain significantly less style effects (*e.g.*, colors) along with sharper image structures. Fig. 11 shows that ArtFlow can achieve unbiased content-style separation while AdaIN and WCT cannot.

6. User Study

To quantitatively demonstrate that the proposed ArtFlow has the comparable style transfer performance with the state-of-the-art algorithms, we perform a user study. Our

user study is based on the validation dataset that consists of 43 content images and 27 style images. We obtain the style transfer results of StyleSwap, AdaIN, WCT, LinearWCT, OptimalWCT, Avatar-Net, and the proposed ArtFlow on every content-style pair, respectively. We finally obtain 1161 style transfer results for each method. In user study, we list all style transfer results of a content-style pair and let the user to choose ONE most preferable style transfer result. We eventually collect 799 effective votes. Tab. 2 shows the style transfer results. The proposed ArtFlow obtains more votes compared with other style transfer methods, which demonstrates that our method has comparable style transfer performance with the state-of-the-art methods.

7. Conclusion

In this paper, we reveal a common issue in the state-of-the-art style transfer algorithms, *i.e.*, the Content Leak phenomenon. Upon analyzing the main causes of the Content Leak, we present a new style transfer framework named ArtFlow. Unlike the existing style transfer algorithms, which adopt the VGG19 based auto-encoder to extract deep features, ArtFlow introduces a reversible neural flow-based network named PFN, thus enabling both the forward and reverse inferences to project images into the feature space and invert features back to the image space, respectively. ArtFlow in conjunction with an unbiased style transfer module, *e.g.*, either AdaIN or WCT, achieves comparable style transfer results while avoiding the Content Leak phenomenon. Furthermore, because PFN can achieve lossless and unbiased image projection and reversion, the proposed ArtFlow can facilitate a better content-style separation and thus enable the reversion of the style transfer in a lossless manner.

8. Acknowledgement

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A. Pseudocode of ArtFlow

Algorithm 1 Unbiased style transfer process of ArtFlow

Require: an input content image I_c , an input style image I_s , an unbiased style transfer module T , the proposed new network PFN;

- feed I_c and I_s to PFN;
- perform the forward propagation of PFN and obtain the content feature f_c and the style feature f_s , respectively;
- obtain the style-transferred feature f_{cs} based on T in the manner of $f_{cs} = T(f_c, f_s)$;
- obtain the style-transferred image I_{cs} by running the reverse propagation of PFN.

return I_{cs}

B. Proof of the Theorem 1

Theorem 3 *The adaptive instance normalization in AdaIN is an unbiased style transfer module.*

Proof B.1 *Without loss of generality, we assume both f_c and f_s is centered. Therefore, we have,*

$$f_{cs} = \frac{f_c}{\sigma(f_c)} \sigma(f_s), \quad (5)$$

where,

$$C(f) = \frac{f}{\sigma(f)}, \quad S(f) = \sigma(f). \quad (6)$$

Since,

$$\sigma(f_{cs}) = \sigma\left(\frac{f_c}{\sigma(f_c)}\right)\sigma(f_s) = 1 \cdot \sigma(f_s) = \sigma(f_s), \quad (7)$$

we have,

$$C(f_{cs}) = \frac{f_{cs}}{\sigma(f_{cs})} = \frac{f_c}{\sigma(f_c)} = C(f_c), \quad (8)$$

$$S(f_{cs}) = \sigma(f_{cs}) = \sigma(f_s). \quad (9)$$

Therefore, the adaptive instance normalization in AdaIN is unbiased. ■

C. Proof of the Theorem 2

Theorem 4 *The whitening and coloring transforms in WCT is an unbiased style transfer module.*

Proof C.1 *Without loss of generality, we assume both f_c and f_s is centered. Therefore, we have,*

$$\text{Whitening : } \hat{f}_c = E_c D_c^{-1/2} E_c^T f_c, \quad (10)$$

$$\text{Coloring : } f_{cs} = E_s D_s^{1/2} E_s^T \hat{f}_c. \quad (11)$$

where f_c, f_{cs} represent the content and style-transferred features, $f_c f_c^T = E_c D_c E_c^T$ and $f_s f_s^T = E_s D_s E_s^T$. Therefore, the style-transferred features f_{cs} can be expressed as,

$$f_{cs} = E_s D_s^{1/2} E_s^T E_c D_c^{-1/2} E_c^T f_c. \quad (12)$$

Here

$$C(f) = ED^{-1/2} E^T f, \quad S(f) = ED^{1/2} E^T \quad (13)$$

Since,

$$f_{cs} f_{cs}^T = f_s f_s^T = E_s D_s E_s^T, \quad (14)$$

we have,

$$C(f_{cs}) = E_s D_s^{-1/2} E_s^T f_{cs} \quad (15)$$

$$= E_c D_c^{-1/2} E_c^T f_c \quad (16)$$

$$= C(f_c), \quad (17)$$

$$S(f_{cs}) = E_s D_s^{1/2} E_s^T = S(f_s). \quad (18)$$

Therefore, the whitening and coloring transforms in WCT is unbiased. ■

D. Training Loss Trends

In Fig. 12, we show the training losses of the proposed ArtFlow in comparison with AdaIN. Due to the reversible property of the proposed PFN, our content loss shown in (a) starts from a low value, and the remaining iterations trade-off between the content and style losses. It is worth noting that the converged style loss and the reconstruction error of ArtFlow is significantly lower than AdaIN, which demonstrates that the proposed PFN has a stronger representation ability in making style transfer than existing auto-encoder based framework. Moreover, ArtFlow maintains the image reconstruction error to be zero across the training loop, which reinforces that the proposed PFN can achieve lossless image projection/recovery.

E. Network Structure Analysis of PFN

In addition to the proposed PFN, we also conduct experiments on three alternative network architectures based on neural flows: ArtFlow-Flow8-Block1, ArtFlow-Flow16-Block1, and ArtFlow-Flow4-Block4, where the number after “Flow” represents the number of cascades flow modules within a flow block, while the number after “Block” denotes the number of flow blocks. In the experimented network, each flow is a stack of an Actnorm layer, an invertible 1×1 convolution, and an additive coupling layer. According to this naming scheme, the proposed PFN is ArtFlow-Flow8-Block2. Fig. 13 shows the style transfer results by the proposed PFN and all the compared architectures. As Fig. 13 (e) and (f) show, the style transfer results by

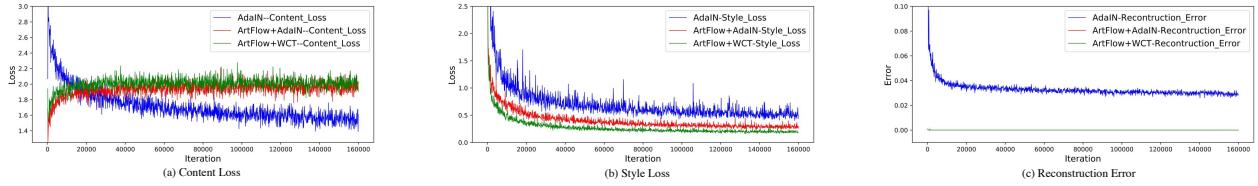


Figure 12. A comparison of the training losses of AdaIN and the proposed ArtFlow.

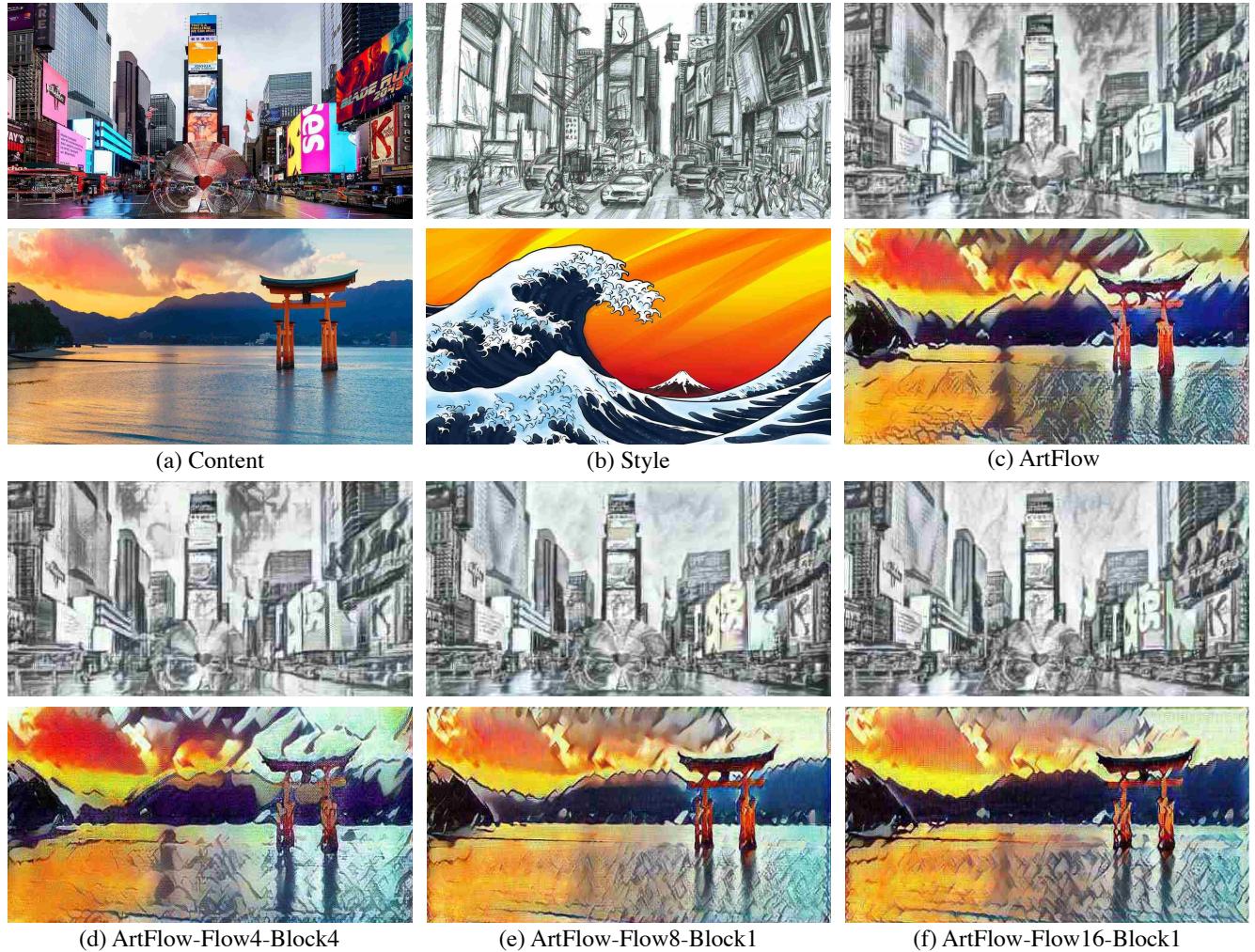


Figure 13. A comparison of the style transfer result by different neural flow architectures.

Table 3. Quantitative evaluation results different flow architectures.

Method	ArtFlow (PFN)	ArtFlow-Flow4-Block4	ArtFlow-Flow8-Block1	ArtFlow-Flow16-Block1
SSIM \uparrow	0.45	0.401	0.482	0.480
Gram Loss \downarrow	0.00098	0.00130	0.00139	0.00137

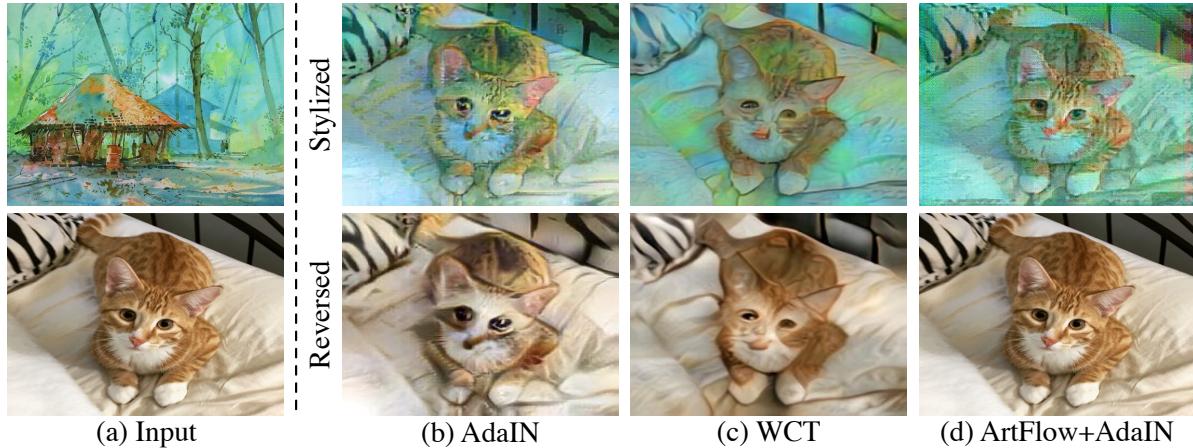


Figure 14. A comparison of reverse style transfer results.

ArtFlow-Flow16-Block1 and ArtFlow-Flow16-Block1 are not as colorful as other compared architectures, which indicates that these two architectures have compromised stylization abilities. Regarding ArtFlow-Flow4-Block4, it can produce comparable style transfer results to the proposed PFN. However, in terms of the details, the proposed PFN is better than ArtFlow-Flow4-Block4. Please zoom in to see the details of the Itsukushima Shrine, where the proposed PFN creates more colorful results. We also conduct a quantitative comparison between the proposed ArtFlow and three alternative architectures. As Tab. 3 shows, the proposed PFN achieves a better trade-off between the SSIM index and the Gram loss.

E.1. Reverse Style Transfer

Because the proposed PFN can achieve lossless and unbiased image projection and reversion, ArtFlow enables a very interesting application, where if we perform style transfer on a style-transferred image with the original content image as the new style image, we can recover the original content image in a lossless manner. We name this application the *Reverse Style Transfer*. Fig. 14 shows the reverse style transfer results by AdaIN, WCT, and the proposed ArtFlow. It is remarkable that only the proposed ArtFlow can reverse the style transfer process and recover all the details of the original content image.

F. More Style Transfer Results

We show more comparisons of style transfer results between the proposed ArtFlow and state-of-the-art algorithms in Fig. 15, Fig. 16, Fig. 17, Fig. 18, and Fig. 19.

G. Portrait Style Transfer Results

We use the proposed ArtFlow to make style transfer on portrait images. To train the portrait style transfer model, we use images of the FFHQ [25] dataset as the content and images of the Metfaces [24] dataset as the style. Fig. 20 and Fig. 21 show the portrait style transfer results by the proposed ArtFlow.

H. More Content Leak Results

We show more comparisons of the *Content Leak* phenomenon in Fig. 22 and Fig. 23.

I. More Content Factor Reconstruction Results

We show more comparisons of the content factor reconstruction results in Fig. 24.



(a) Content



(b) Style



(c) StyleSwap



(d) AdaIN



(e) WCT



(f) LinearWCT



(g) OptimalWCT



(h) Avatar-Net



(i) ArtFlow+AdaIN



(j) ArtFlow+WCT

Figure 15. A comparison of the style transfer results between the proposed ArtFlow and state-of-the-art algorithms.



(a) Content



(b) Style



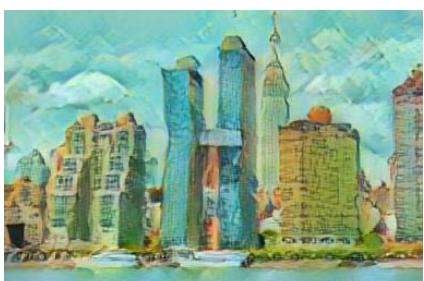
(c) StyleSwap



(d) AdaIN



(e) WCT



(f) LinearWCT



(g) OptimalWCT



(h) Avatar-Net



(i) ArtFlow+AdaIN



(j) ArtFlow+WCT

Figure 16. A comparison of the style transfer results between the proposed ArtFlow and state-of-the-art algorithms.



(a) Content



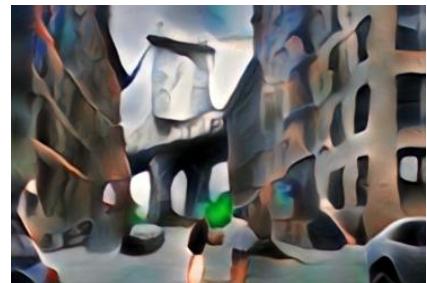
(b) Style



(c) StyleSwap



(d) AdaIN



(e) WCT



(f) LinearWCT



(g) OptimalWCT



(h) Avatar-Net



(i) ArtFlow+AdaIN



(j) ArtFlow+WCT

Figure 17. A comparison of the style transfer results between the proposed ArtFlow and state-of-the-art algorithms.



(a) Content

(b) Style

(c) StyleSwap

(d) AdaIN

(e) WCT

(f) LinearWCT

(g) OptimalWCT

(h) Avatar-Net

(i) ArtFlow+AdaIN

(j) ArtFlow+WCT

Figure 18. A comparison of the style transfer results between the proposed ArtFlow and state-of-the-art algorithms.

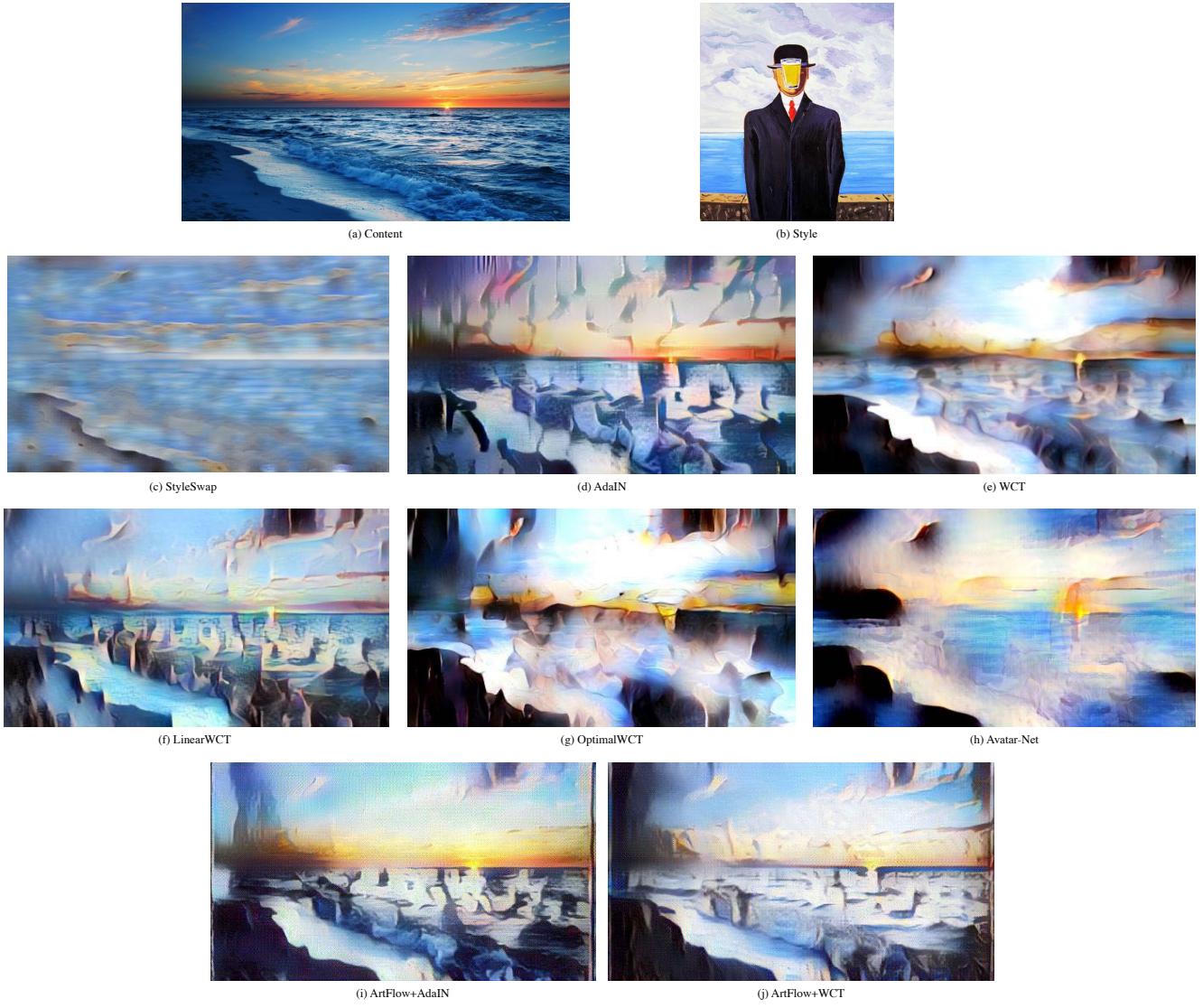


Figure 19. A comparison of the style transfer results between the proposed ArtFlow and state-of-the-art algorithms.

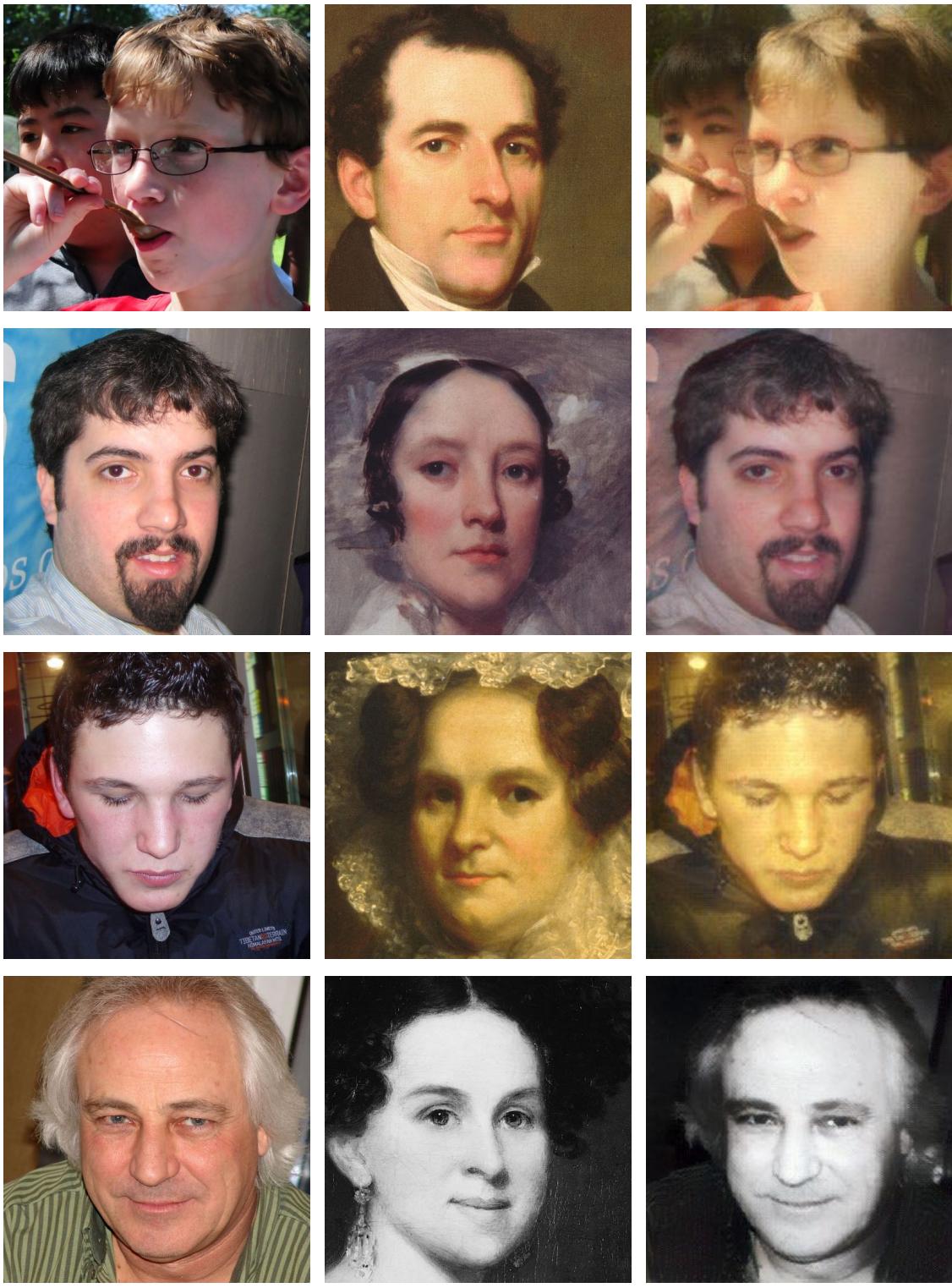


Figure 20. Portrait style transfer results by the proposed ArtFlow.

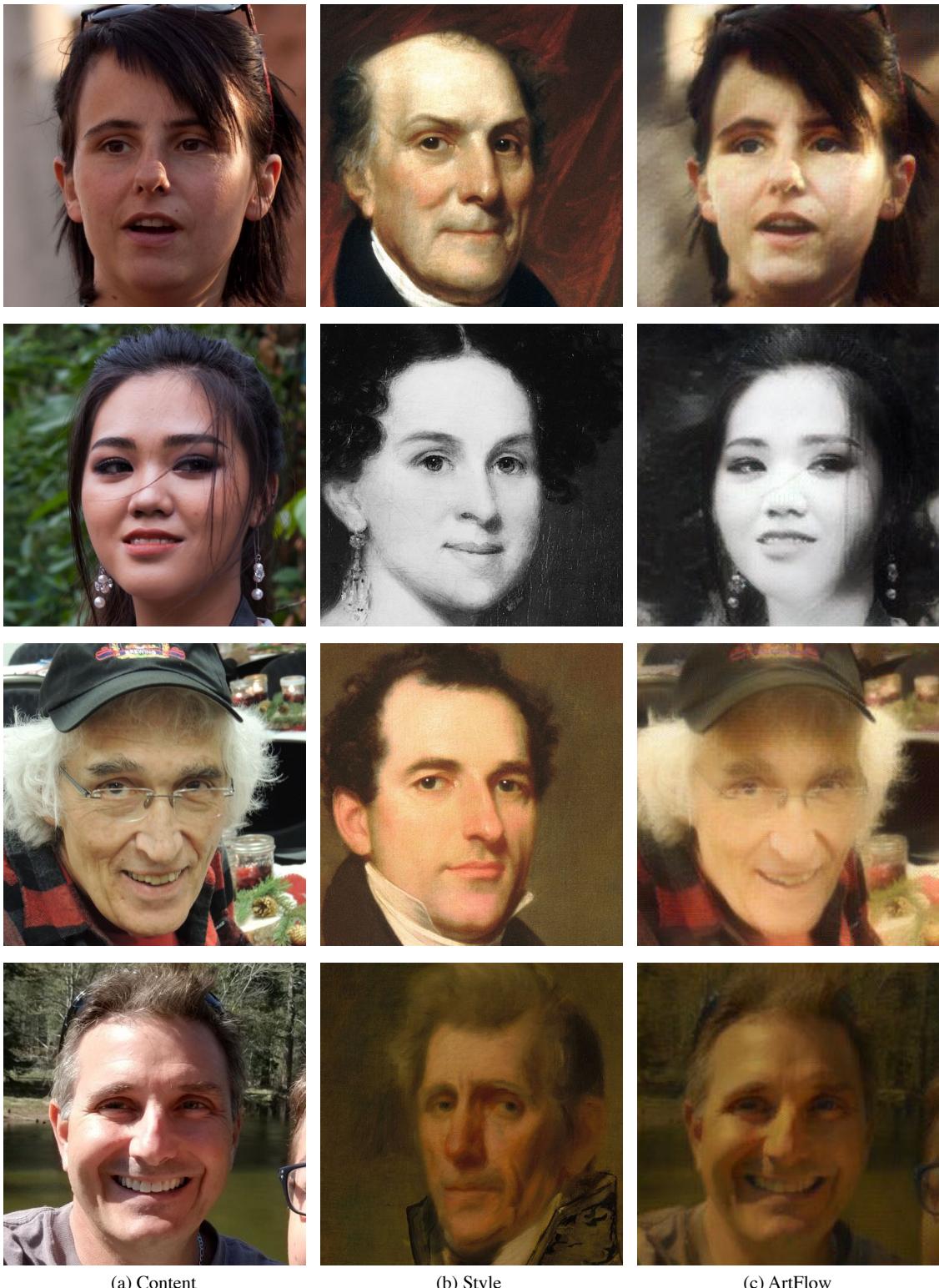


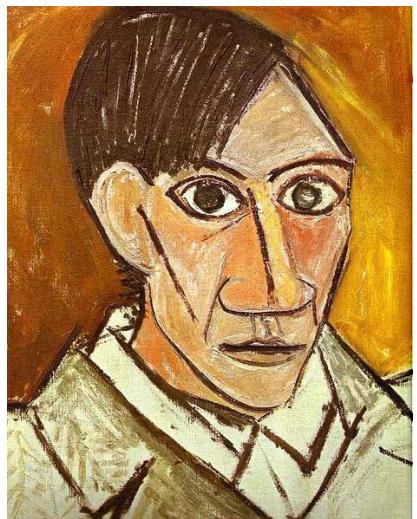
Figure 21. Portrait style transfer results by the proposed ArtFlow.



Figure 22. A comparison of the *Content Leak* phenomenon.



Content



Style



Figure 23. A comparison of the *Content Leak* phenomenon.



Content



AdaIN



WCT



ArtFlow

Figure 24. A comparison of the reconstructed content factor.