Deep Translation Prior: Test-time Training for Photorealistic Style Transfer

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Abstract
Recent techniques to solve photorealistic style transfer within deep convolutional neural networks (CNNs) generally require intensive training from large-scale datasets, thus having limited applicability and poor generalization ability to unseen images or styles. To overcome this, we propose a novel framework, dubbed Deep Translation Prior (DTP), to accomplish photorealistic style transfer through test-time training on given input image pair with untrained networks, which learns an image pair-specific translation prior and thus yields better performance and generalization. Tailored for such test-time training for style transfer, we present novel network architectures, with two sub-modules of correspondence and generation modules, and loss functions consisting of contrastive content, style, and cycle consistency losses. Our framework does not require offline training phase for style transfer, which has been one of the main challenges in existing methods, but the networks are to be solely learned during test-time. Experimental results prove that our framework has a better generalization ability to unseen image pairs and even outperforms the state-of-the-art methods.

Introduction
Photorealistic style transfer is one of appealing image manipulation and editing tasks, which aims to, given a pair of images, i.e., the content and style image, synthesize an image by transferring the style to the content. Recent approaches for this task leverage statistics of content and style features extracted by deep convolutional neural network (CNNs) (Gatys, Ecker, and Bethge 2016; Li et al. 2017; Ulyanov, Vedaldi, and Lempitsky 2017), which can be divided into optimization-based and learning-based methods. Optimization-based methods (Gatys, Ecker, and Bethge 2016; Li and Wand 2016; Luan et al. 2017) directly obtain a stylized image by optimizing an image itself with well-defined content and style loss functions. As the seminal work, Gatys et al. (Gatys, Ecker, and Bethge 2016) present the style loss function based on Gram matrix and optimize the stylized image with the loss function, of which many variants were also proposed (Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017). Since the loss function for style transfer is often non-convex, most methods leverage an iterative solver to optimize the output image itself (Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017), and thus they can benefit from error feedback for stylization. Moreover, they are limited to encode an image translation prior on synthesized images, and thus often generate artifacts and show limited photorealism.

In contrast, recent learning-based methods (Li et al. 2017, 2018; Gu et al. 2018; Yoo et al. 2019; Huang and Belongie 2017; Park and Lee 2019) attempt to address these limitations by learning such image translation prior within networks from large-scale datasets (Deng et al. 2009; Lin et al. 2014), often followed by pre- or post-processing (Li et al. 2018; Yoo et al. 2019; Huang and Belongie 2017). Since it is notoriously challenging to collect training pairs for photorealistic style transfer due to its subjectivity, most methods alternatively leverage an auto-encoder to learn a decoder that captures the translation prior (Huang and Belongie 2017; Chen and Schmidt 2016; Li et al. 2017). However, during the training, these methods (Li et al. 2018, 2019) do not leverage explicit content and style loss functions, and thus may have poor generalization ability on unseen images or styles. In addition, adopting fixed network parameters at test-time may not account for the fact that a pair of images may require their own prior, namely an image pair-specific translation prior.

In this paper, we explore an alternative, dubbed Deep Translation Prior (DTP), to overcome aforementioned limitations of both optimization- and learning-based methods. Our work accomplishes this without need of intensive training process using large-scale dataset or paired data, but through a test-time training on given input image pair. We argue that the translation prior does not necessarily need to be learned from intensive learning. Instead, an image pair-specific translation prior can be captured by solely minimizing explicit content and style loss functions on the image pair with untrained network for stylization. Tailored to this framework, we formulate novel network architectures consisting of two sub-modules, namely correspondence and generation modules, which are learned with well-designed content, style, and cycle consistency loss functions at test-time.

Our experiments on standard benchmark for photorealistic style transfer (Luan et al. 2017; An et al. 2020; CelebA-HQ (Liu et al. 2015), and Flickr Faces HQ (FFHQ) (Karras, Laine, and Aila 2019) demonstrate that our framework con-
Related Work

Style Transfer. Traditional optimization-based methods for style transfer (Gatys, Ecker, and Bethge 2016; Li and Wand 2016; Luan et al. 2017) using pre-trained feature extractors, such as VGG networks (Simonyan and Zisserman 2015), can be divided into parametric and non-parametric methods. Categorized as parametric methods, some methods (Gatys, Ecker, and Bethge 2016; Berger and Memisevic 2016) designed Gram matrix to capture global statistics of features. However, the loss function based on Gram matrix leads to poor results as it captures the per-pixel feature correlations and does not constrain the spatial layout. To address this issue, non-parametric approaches (Li and Wand 2016; Luan et al. 2017; Aberman et al. 2018) match a style on patch-level. Categorized as non-parametric methods, some works have realized style transfer inspired by an image analogy (Hertzmann et al. 2001), which is based on dense correspondence (Shih et al. 2014; Liao et al. 2017). STROTSS (Kolkin, Salavon, and Shakhnarovich 2019) uses optimal transport algorithm. The aforementioned optimization-based methods are limited to encode an image translation prior, thus often generating artifacts and showing limited photorealism.

On the other hand, recent learning-based methods (Chen and Schmidt 2016; Li et al. 2017; Huang and Belongie 2017; Gu et al. 2018; Sanakoyeu et al. 2018; Li et al. 2018; Yoo et al. 2019; Park and Lee 2019; Lü et al. 2021) tried to solve style transfer by data-driven ways. They mostly focused on designing loss functions, and often included pre- or post-processing (Li et al. 2018) to produce spatially smooth output. For instance, contextual loss is proposed (Mechrez, Talmi, and Zelmin-Manor 2018), which trains CNNs solely using the content images without need of large-scale paired dataset. Several works (Huang and Belongie 2017; Gu et al. 2018; Yoo et al. 2019; Qu, Shao, and Qi 2019; Park and Lee 2019) trained a decoder network with MS-COCO dataset (Lin et al. 2014) or ImageNet dataset (Deng et al. 2009), or needed training the whole network per style (Sanakoyeu et al. 2018) before optimization process. However, they may be biased to the training images or styles and may not generalize well to unseen data.

Image Prior. Deep Image Prior (DIP) (Ulyanov, Vedaldi, and Lempitsky 2018) proves the structure of generator network itself can serve as a prior for image restoration, against the assumption that learning from large-scale data is necessary to capture realistic image prior (Zhang et al. 2017), of which many variants were proposed, tailored to solve an inverse problem (Burger et al. 2005; Dabov et al. 2007; Burger, Schuler, and Harmeling 2012). SinGAN (Shaham, Dekel, and Michaeli 2019) and SimIR (Yoo and Chen 2021) fine-tune GAN or AE on a single input and can be applied to image manipulation and restoration. GAN inversion (Jahanian, Chai, and Isola 2020; Menon et al. 2020; Gu, Shen, and Zhou 2020) aims at generating an image by solely optimizing a latent code of pre-trained GAN given a target image. Different from the aforementioned methods that attempts to learn an image prior, our framework is the first attempt to learn the image translation prior.

Methodology

Motivation
Photorealistic style transfer aims at transferring the style of image $I_C$ to the content of image $I_s$ to synthesize a stylized image $I_{C\rightarrow S}$. To achieve this, traditional methods (Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017) focused on an image optimization technique, from which deep convolutional features were extracted from content and style images, denoted by $F_C = \Phi(I_C)$ and $F_S = \Phi(I_S)$ with feature extractor $\Phi(\cdot)$, and used to define an objective function, consisting of content loss $L_{cont}$ and style loss $L_{style}$ functions, as in Fig. 1(a):

$$I_{C\rightarrow S} = \arg\min_I (L_{cont}(\Phi(I), F_C) + L_{style}(\Phi(I), F_S)).$$

(1)

Since it is often a non-convex optimization, most methods leverage an iterative solver, e.g., gradient descent (Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017), and thus they benefit from an error feedback to find better stylized images. However, they are limited to encode an image translation prior on synthesized images, and thus often...
generate artifacts and limited photorealism.

To overcome these limitations, recent learning-based methods [Li et al. 2017; Huang and Belongie 2017; Li et al. 2018; Gu et al. 2018; Yoo et al. 2019] attempt to learn such translation prior within the networks during training. Starting with feature extraction module, they designed feature fusion module, e.g., AdaIN [Huang and Belongie 2017] or WCT [Li et al. 2017], and trained decoder module on large-scale image data, e.g., ImageNet [Deng et al. 2009] or MS-COCO [Lin et al. 2014], as in Fig. 1(b), which can be formulated as:

\[
\omega^* = \arg\min_{\omega} \sum_{n} \mathcal{L}_{\text{cont}}(\Phi(F_{C,n}, F_{S,n}; \omega), I_{C\rightarrow S,n}),
\]

where \(F_{C,n}\) and \(F_{S,n}\) are features from \(n\)-th image pair and \(I_{C\rightarrow S,n}\) is \(n\)-th stylized image sample from massive training data. \(\Phi(\cdot; \omega)\) is a feed-forward process with decoder parameters \(\omega\). \(\mathcal{L}_{\text{cont}}\) is an image reconstruction loss function [Gatys, Ecker, and Bethge 2016; Liu, Breuel, and Kautz 2017; Huang and Belongie 2017; Li et al. 2018; Gu et al. 2018; Yoo et al. 2019]. In practice, since it is notoriously challenging to collect training pairs for style transfer, \(\{(F_{C,n}, F_{S,n}, I_{C\rightarrow S,n})\}_{n \in \{1, \ldots, N\}}\), due to its subjectivity, most methods [Li et al. 2017; Huang and Belongie 2017; Li et al. 2018; Gu et al. 2018; Yoo et al. 2019] alternatively leverage an auto-encoding setting to learn the decoder with parameters \(\omega\) to reconstruct an input image itself learned by \(\mathcal{L}_{\text{cont}}(\Phi(I; \omega), I)\). At test-time, given \(F_{C}\) and \(F_{S}\), a stylization process can be formulated as follows:

\[
I_{C\rightarrow S} = \mathcal{F}(F_{C}, F_{S}; \omega^*).
\]

These methods are based on the assumption that the image translation prior can be learned within the model itself from massive training data. However, during the training phase, these methods do not leverage explicit content and style loss functions, as done in optimization methods [Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017], thus providing limited stylization performance when their assumptions are violated, e.g., under unseen images or styles. In addition, adopting fixed network parameters at test-time may not capture an image pair-specific translation prior.

**Overview**

To overcome aforementioned limitations and take the best of both approaches, we present Deep Translation Prior (DTP) framework. We argue that the translation prior does not necessarily need to be learned from intensive learning or datasets. Instead, an image pair-specific translation prior can be captured by solely minimizing explicit content and style loss functions on the image pair, like what is done by conventional optimization-based methods [Li and Wand 2016; Gatys, Ecker, and Bethge 2016; Luan et al. 2017], with an untrained network for stylization, which takes benefits of large capacity and robustness of networks as in recent learning-based methods [Li et al. 2017; Huang and Belongie 2017; Li et al. 2018; Gu et al. 2018; Yoo et al. 2019], as in Fig. 1(c), formulated as:

\[
\omega^* = \arg\min_{\omega} \left\{ \mathcal{L}_{\text{cont}}(\Phi(F_{C}, F_{S}; \omega)), F_{C} \right\} + \mathcal{L}_{\text{style}}(\Phi(F(F_{C}, F_{S}; \omega)), F_{S}) \right\},
\]

where \(\omega^*\) is overfitted to the input image pair, which encodes the image pair-specific translation prior. Unlike conventional optimization-based methods [Gatys, Ecker, and Bethge 2016; Li and Wand 2016], our framework generates better stylization results while eliminating the artifacts thanks to the structure of networks that can encode the image pair-specific prior during test-time training. In addition, unlike recent learning-based methods [Li et al. 2017; Huang and Belongie 2017; Li et al. 2018; Gu et al. 2018; Yoo et al. 2019], our framework does not require an intensive training for decoder, but only requires an off-the-shelf feature extractor and untrained generator, thus having better generalization ability to unseen images or styles.
Tailored for such test-time training for style transfer, we design our stylization networks in a two-stage fashion, as illustrated in Fig. 2. On one hand, the model predicts a translation hypothesis by first computing the similarity between each content point and all style points by means of the feature vectors $F_C$ and $F_S$, called correspondence module, and on the other, the model refines the hypothesis through the decoder for more plausible stylization, called generation module. Since the generated output is expected to preserve the structure of the content image $I_C$ while faithfully stylizing from semantically similar parts in the style image $I_S$, we present contrastive content loss function and style loss function to boost the convergence of our test-time training framework.

It should be noted that there exist similar literature for image restoration tasks, e.g., Deep Image Prior (DIP) (Ulyanov, Vedaldi, and Lempitsky, 2018), that have shown that the structure of a generator network can capture a low-level image prior by optimizing a randomly-initialized network with a task-dependent fidelity term on a single image. To the best of our knowledge, our framework is the first attempt to learn the translation prior at test-time for photorealistic style transfer.

**Network Architecture**

**Correspondence Module.** We first present a correspondence module to measure the similarities between each point in content feature $f_C$ and all other points in style feature $f_S$, enabling generating a translation hypothesis. It is inspired by the classical matching pipeline (Rocco, Arandjelovic, and Sivic, 2017) in that we first extract the feature vectors and then compute the similarity between them.

Following the previous approaches for style transfer, we first extract the deep convolution features, e.g., VGGNet (Simonyan and Zisserman, 2015) pretrained on ImageNet (Deng et al., 2009), as follows:

$$
\begin{align*}
    f_C &= \Phi(I_C; \omega_f) \in \mathbb{R}^{HW \times C}, \\
    f_S &= \Phi(I_S; \omega_f) \in \mathbb{R}^{HW \times C},
\end{align*}
$$

where $H$ and $W$ are spatial size, with $C$ channels of $f$, $\omega_f$ are feature extraction parameters. Unlike most existing methods that use fixed feature extraction parameters, we adaptively fine-tune the parameters to the input image pair. We then compute a correlation matrix $M \in \mathbb{R}^{HW \times HW}$, of which each term is a pairwise feature correlation such that

$$
M(u, v) = \frac{\hat{f}_C(u)^T \hat{f}_S(v)}{\|\hat{f}_C(u)\| \|\hat{f}_S(v)\|},
$$

where $u$ and $v$ represent all the points in the content and style images, respectively. $\hat{f}_C(u)$ and $\hat{f}_S(v)$ are channel-wise centralized features of $f_C(u)$ and $f_S(v)$ as

$$
\hat{f}_C(u) = f_C(u) - \bar{f}_C, \quad \hat{f}_S(v) = f_S(v) - \bar{f}_S,
$$

where $\bar{f}_C$ is an average of $f_C(u)$ across all the points in the content, $\bar{f}_S$ is similarly defined. Since $M(u, v)$ represents a similarity between $u$ and $v$, the higher, the more similar.

By using the correlation matrix $M$, we synthesize a warped style feature $r_{C \leftarrow S}$, i.e., the style feature spatially-aligned to the content image. The warping function can be formulated in many possible ways, but we borrow the technique in (Zhang et al., 2020) that uses a reconstruction:

$$
r_{C \leftarrow S}(u) = \sum_v \Omega(M(u, v) / \tau) f_S(v),
$$

where $\Omega$ means the softmax operator across $v$, and $\tau$ is a temperature parameter. Matched points in our framework is visualized in Fig. 3.

**Generation Module.** Our generation module aims at reconstructing an image from warped feature $r_{C \leftarrow S}$. We present the decoder that has a symmetric structure of feature extractor architecture, similar to (Li et al., 2017; Huang and Belongie, 2017). This decoding process can be formulated as follows:

$$
I_{C \leftarrow S} = F(r_{C \leftarrow S}; \omega_g),
$$

where $\omega_g$ is decoding parameters. As described above, the parameters are first randomly-initialized and then learned with explicit loss functions for style transfer at test time.

However, due to non-convexity of the loss functions for style transfer, generating the image $I_{C \leftarrow S}$ through the decoder directly is extremely hard to converge. To elevate the stability and boost the convergence, we exploit not only warped style feature $r_{C \leftarrow S}$, but also warped style image $R_{C \leftarrow S}$ extracted such that $R_{C \leftarrow S}(u) = \sum_v \Omega(M(u, v) / \tau) I_S(v)$, as a guidance for style transfer, where the networks only learn the residual for the final result as follows:

$$
I_{C \leftarrow S} = \lambda_w F(r_{C \leftarrow S}; \omega_g) + (1 - \lambda_w) R_{C \leftarrow S},
$$

where $\lambda_w$ is a weight parameter. By leveraging such a residual prediction, convergence of our test-time training could be greatly improved. Moreover, it enables directly flowing the loss gradients to both feature extractor with $\omega_f$ and image generator with $\omega_g$, which helps to boost the performance.

**Iterative Formulation.** Since the loss function for style transfer, which will be discussed later, is non-convex, we formulate our test-time training as an iterative framework, as exemplified in Fig. 4. As evolving the iteration, the image $I_t^{C \leftarrow S}$ at $t$-th iteration converges to better stylization results, since it is generated from the updated feature extractor parameters $\omega_f$ and decoder parameters $\omega_g$. Since the image $I_t^{C \leftarrow S}$ is getting close to the optimal, if the content image $I_C$ can be substituted by $I_t^{C \leftarrow S}$ in a recurrent fashion, the iterative solver can converge faster and boost performance. However, at early stages during optimization, $I_t^{C \leftarrow S}$ contains blurry regions and noises, which prohibit using such an explicit recurrent formulation. To overcome this limitation, we adopt a moving averaging technique similar to (Kim et al., 2019; Schmidt et al., 2020) in a manner that we smoothly substitute the content...
We define the exponential of inner product function of two vectors to express the equation more comfortably. To improve the stability during Cycle Consistency Loss.

Our style loss is defined as below: more suitable for photo realistic style transfer. Similar to the parametric methods (Gatys, Ecker, and Bethge 2016; Li et al. 2017; Chen and Koltun 2017; Li et al. 2018; Yoo et al. 2019) that enforce the style loss globally, we adopt the like parametric methods (Gatys, Ecker, and Bethge 2016; Li et al. 2017; WCT2 (Yoo et al. 2019), STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), SinIR (Yoo and Chen 2021). We also compared with image-to-image translation tasks, such as CoCosNet (Zhang et al. 2020), and Swapping Autoencoder (Park et al. 2020).

We used three kinds of datasets to evaluate our method, including standard datasets for photorealistic style transfer (Luan et al. 2017; An et al. 2020), CelebA-HQ (Liu et al. 2015), and Flickr Faces HQ (FFHQ) (Karras, Laine, and Aila 2019). We compared our method with recent state-of-the-art style transfer methods, such as Gatys et al. (Gatys, Ecker, and Bethge 2016), WCT (Li et al. 2017), WCT2 (Yoo et al. 2019), STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), SinIR (Yoo and Chen 2021). We also compared with image-to-image translation tasks, such as CoCosNet (Zhang et al. 2020), and Swapping Autoencoder (Park et al. 2020).

It should be emphasized that learning-based style transfer methods (Li et al. 2017; Yoo et al. 2019) and image-to-image translation methods (Zhang et al. 2020; Park et al. 2020) are trained on tremendous training data, while our method just trains the networks at test-time with a pair of images.

**Experimental Results**

**Qualitative Evaluation.** In this section, we evaluated photorealistic style transfer results of our method compared with state-of-the-art methods, with respect to two aspects, including synthesized image quality and semantic consistency. Qualitative results are shown in Fig. 5 and Fig. 6. Our generated results are realistic and contain both global-local
Figure 5: Comparison of DTP with other methods on standard benchmark (Luan et al. 2017; An et al. 2020): Given content and style images, stylized results are achieved by (a) Gatys et al. (Gatys, Ecker, and Bethge 2016), (b) WCT (Li et al. 2017), (c) WCT2 (Yoo et al. 2019), (d) STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), (e) SinIR (Yoo and Chen 2021), and (f) Ours. Compared to others, our model generates realistic results while successfully transferring both global and local style information and preserving structure. Our model does not require any mask, pre- or post-processing.

Figure 6: Comparison of DTP with other methods on CelebA-HQ dataset (Liu et al. 2015) and FFHQ dataset (Karras, Laine, and Aila 2019): Given content and style images, translation results are achieved by (a) Gatys et al. (Gatys, Ecker, and Bethge 2016), (b) STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), (c) Swapping Autoencoder (Park et al. 2020b), (d) CoCosNet (Zhang et al. 2020), (e) SinIR (Yoo and Chen 2021), and (f) Ours. The results show that our networks can translate local features as well as global features from both structure and style. Note that CoCosNet (Zhang et al. 2020) was trained on CelebA-HQ, including segmentation masks, and Swapping Autoencoder (Park et al. 2020b) was trained on FFHQ.

Table 1: Quantitative evaluation on standard benchmark for photorealistic style transfer (Luan et al. 2017; An et al. 2020), CelebA-HQ (Liu et al. 2015), and FFHQ (Karras, Laine, and Aila 2019).

| Methods     | Photo-R | CelebA-HQ | FFHQ | Avg. |
|-------------|---------|-----------|------|------|
|             | PE      | SSIM      | PE   | SSIM |
| Gatys et al.| 3.09    | 0.44      | 4.37 | 0.66 |
| WCT         | 2.48    | 0.22      | -    | -    |
| WCT2        | 1.99    | 0.70      | -    | -    |
| STROTSS     | 3.23    | 0.37      | 1.81 | 0.60 |
| Swap. AE    | 2.92    | 0.22      | 0.89 | 0.60 |
| CoCosNet    | -       | 1.56      | 0.43 | -    |
| SinIR       | 1.00    | 0.84      | 1.56 | 0.84 |
| DTP (λ = 4/5)| 1.46   | 0.75      | 0.79 | 0.86 |
| DTP (λ = 1/5)| 1.09   | 0.82      | 0.47 | 0.96 |

Quantitative Evaluation. We further evaluate our method with the quantitative results as in Table 1 on photorealistic style transfer examples, CelebA-HQ dataset, and Flicker-Faces dataset (FFHQ) with metrics of Pieapp (Prashnani et al. 2018) (PE) and Structural Similarity (SSIM) (Wang et al. 2004). Pieapp is a reference-based quality assessment used for semantic consistency. SSIM index is an error measure.
Ablation Study

In order to validate the effectiveness of each component in our method, we conduct a comprehensive ablation study. In particular, we analyze the effectiveness of warped feature and image, cycle consistency loss $\mathcal{L}_{\text{cyc}}$, feature moving average, and generation module in Fig. 7. To validate the effect of the warped feature and image in our model, we conduct ablation experiments by replacing the warped feature with random Gaussian noise and eliminating the residual connection with warped image. Without the warped feature, it fails to preserve edges while the result without the warped image fails to capture any style information. We also validate the influence of cycle consistency loss, which makes the optimization process more stable. Feature moving average makes the synthesized image more vivid because the previous synthesized feature can give guidance for content and style feature correlation. Without the generation module, the output cannot converge to the optimal result. With all these components, our work is more effective in resulting style relevant outputs while preserving content clearly.

User Study

We also conducted a user study on 80 participants to evaluate the quality of synthesized images in the experiments with the following questions: "Which do you think has better image quality / similar content to content image / style relevance to style image?". On photorealistic style transfer examples, CelebA-HQ (Liu et al. 2015) and FFHQ dataset (Karras, Laine, and Aila 2019), our method ranks the first in every cases, which can be found in Fig. 8.

Conclusion

In this paper, we proposed, for the first time, a novel framework to learn the style transfer network on a given input image pair at test-time, without need of any large-scale dataset, hand-labeling, and task-specific training process, called Deep Translation Prior (DTP). Tailored for such test-time training for style transfer, we formulate overall networks as two sub-modules, including correspondence module and generation module. By training the untrained networks with explicit loss functions for style transfer at test-time, our approach achieves better generalization ability to unseen image pairs or style, which has been one of the major bottlenecks of previous methods. Experimental results on a variety of benchmarks and in comparison to state-of-the-art methods proved that our framework outperforms the existing optimization- and learning-based solutions.
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In this section, we describe detailed network architecture and provide pseudo-code, additional qualitative results and quantitative results.

**Network architecture of DTP**

We first summarize the detailed network architecture of our DTP in Table 2. Specifically, every convolution layer is followed by ReLU activation. The parameters, \((in, out, k, s, p)\), are the number of input channels, number of output channels, size of the kernel, stride and padding, respectively, in the convolution operation. ‘Upsample’ indicates bilinearly upsampling the features from the previous layer.

| Layer     | Parameters \((in, out, k, s, p)\) | Output shape \((C \times H \times W)\) |
|-----------|-----------------------------------|---------------------------------------|
| Conv-1-1  | \((3, 64, 3, 1, 1)\)              | \((64, 256, 256)\)                   |
| Conv-1-2  | \((64, 64, 3, 1, 1)\)             | \((64, 256, 256)\)                   |
| MaxPool-1 | -                                 | \((64, 128, 128)\)                   |
| Conv-2-1  | \((64, 128, 3, 1, 1)\)            | \((128, 128, 128)\)                  |
| Conv-2-2  | \((128, 128, 3, 1, 1)\)           | \((128, 128, 128)\)                  |
| MaxPool-2 | -                                 | \((128, 64, 64)\)                    |
| Conv-3-1  | \((128, 256, 3, 1, 1)\)           | \((256, 64, 64)\)                    |
| Conv-3-2  | \((256, 256, 3, 1, 1)\)           | \((256, 64, 64)\)                    |
| Conv-3-3  | \((256, 256, 3, 1, 1)\)           | \((256, 64, 64)\)                    |
| Conv-3-4  | \((256, 256, 3, 1, 1)\)           | \((256, 64, 64)\)                    |
| MaxPool-3 | -                                 | \((256, 32, 32)\)                    |
| Conv-4-1  | \((256, 512, 3, 1, 1)\)           | \((512, 32, 32)\)                    |
| Conv-4-2  | \((512, 512, 3, 1, 1)\)           | \((512, 32, 32)\)                    |
| Conv-4-3  | \((512, 512, 3, 1, 1)\)           | \((512, 32, 32)\)                    |
| Conv-4-4  | \((512, 512, 3, 1, 1)\)           | \((512, 32, 32)\)                    |
| MaxPool-4 | -                                 | \((512, 16, 16)\)                    |
| Conv-5-1  | \((512, 512, 3, 1, 1)\)           | \((512, 16, 16)\)                    |
| Conv-5-2  | \((512, 512, 3, 1, 1)\)           | \((512, 16, 16)\)                    |
| Up (Conv-4-3) | \((256, 256, 3, 1, 1)\) | \((256, 64, 64)\) |
| Up (Conv-4-2) | \((256, 256, 3, 1, 1)\) | \((256, 64, 64)\) |
| Up (Conv-4-1) | \((256, 256, 3, 1, 1)\) | \((256, 64, 64)\) |
| Upsample  | -                                 | \((128, 128, 128)\)                  |
| Up (Conv-3-4) | \((128, 128, 3, 1, 1)\) | \((128, 128, 128)\) |
| Up (Conv-3-3) | \((128, 128, 3, 1, 1)\) | \((128, 128, 128)\) |
| Up (Conv-3-2) | \((128, 128, 3, 1, 1)\) | \((128, 128, 128)\) |
| Up (Conv-3-1) | \((128, 64, 3, 1, 1)\) | \((64, 128, 128)\) |
| Upsample  | -                                 | \((64, 256, 256)\)                   |
| Up (Conv-2-3) | \((64, 64, 3, 1, 1)\) | \((64, 256, 256)\) |
| Up (Conv-2-2) | \((64, 64, 3, 1, 1)\) | \((64, 256, 256)\) |
| Up (Conv-2-1) | \((64, 32, 3, 1, 1)\) | \((32, 256, 256)\) |
| Up (Conv-1-3) | \((32, 32, 3, 1, 1)\) | \((32, 256, 256)\) |
| Up (Conv-1-2) | \((32, 32, 3, 1, 1)\) | \((3, 256, 256)\) |
| Up (Conv-1-1) | \((32, 3, 3, 1, 1)\) | \((3, 256, 256)\) |
| Correlation| -                                 | \((1, 4096, 4096)\)                  |
| Warping   | -                                 | \((3, 256, 256)\)                    |

Table 2: **Network architecture of our DTP.**
Pseudo-code.
Here we provide the (PyTorch-like) pseudo-code for DTP in Fig. 9.

```python
# Input: content(1x3x256x256), style (1x3x256x256).
# Input: optimal_step is the number of steps for optimization.
# Input: temp is the temperature used in calculating the correlation map.
# Input: lam is the leveraging parameter between residual and prediction.
# Input: m is the leveraging parameter of moving average technique.
# Output: synthesized image.

def optimization(content, style, temp, lam, m):
    step = 0 # number of optimization iterations.
    while(step < optimal_step):
        content_feat_dict = Encoder(content)
        style_feat_dict = Encoder(style)

        # "r34" follows the notation of torchvision models vgg19.
        c_feat = content_feat_dict['r34'].view(1,c,h*w)
        s_feat = style_feat_dict['r34'].view(1,c,h*w)

        # If the step is bigger than 0, use moving average technique.
        if step > 0:
            c_feat = (m)*c_feat + (1-m)*out_features_dict['r34']

        norm_c_feat, norm_s_feat = norm(c_feat), norm(s_feat)
        corr_map = torch.bmm(norm_c_feat.permute(0,2,1),norm_s_feat)
        soft_corr_map = F.softmax(corr_map/temp, dim=-1)
        warped_feat = torch.bmm(soft_corr_map, s_feat)

        style_down = F.adaptive_avg_pool2d(style, 64).view(h*w,3)
        warped_img = torch.bmm(corr_map, style_down)
        up_warped_img = F.interpolate(warped_img,size=(256,256))
        out = (lam)*Decoder(warped_feat) + (1-lam)*up_warped_img

        # content and style loss calculation as described in paper.
        out_features_dict = Encoder(out)
        content_loss = c_loss_cal(c_features_dict, out_features_dict)
        style_loss = s_loss_cal(s_features_dict, out_features_dict)
        loss = content_loss + style_loss
        loss.backward()
        optimizer.step() # both correspondence and generation module
        step += 1
    return out
```

Figure 9: PyTorch-like pseudo-code.
User study on Ablation Study.
We conducted user study on ablation study, as shown in Table 3. Total 40 sets of images were asked to 52 subjects, in which subjects had to choose one among six synthesized images.

|                | WF | WI | FMA | L | G. Module | Ours |
|----------------|----|----|-----|---|-----------|------|
| Content relevance | 0.0% | 15.2% | 4.0% | 21.1% | 0.7% | 59.8% |
| Best stylization | 17.4% | 1.3% | 2.9% | 0.5% | 1.0% | 76.9% |
| Most preferred   | 1.8% | 3.2% | 1.5% | 3.6% | 0.1% | 89.8% |

Table 3: User study results on ablation study.

Additional Visual Results.
In the main paper, we have shown our results of photorealistic style transfer and image-to-image translation. Here, we show additional results in Fig. 10, Fig. 11 and Fig. 12 to demonstrate the robustness of ours.

Additional Examples on Ablation Study.
In the main paper, we have examined the impacts of i) warped feature (WF), ii) warped image (WI), iii) feature moving average (FMA), iv) cycle consistency regularization, and v) generation module (G. Module) in our framework. We conduct the experiments with more examples from standard photorealistic style transfer (Luan et al. 2017; An et al. 2020). The results are shown in Fig. 13. We can observe the best stylization results of the final column. However, in the last two row, the better high frequency details are preserved in the w/o FMA than our final outputs.

Effects of Different Content-Style Weight.
In this section, we show the effect of changing weight of content and style loss. We set style weight as $\lambda_c$ and content weight as $1-\lambda_c$. We vary the style weight as 1/5, 2/5, 3/5, 4/5 with default settings. Our results are shown in Fig. 14. Larger style weight tends to preserve more style details from style image, while larger content weight tends to produce results with more similar structure to content image.

Effects of random seed.
In this section, we show our results with respect to the random seed after running experiments multiple times. Our results are shown in Fig. 15 with various kinds of random seed, which demonstrate that our model is robust to any random seed.
Figure 10: Results on standard photorealistic style transfer benchmarks \cite{an2020}. Given an input pair, we compare the results with WCT2 \cite{yoo2019}, STROTSS \cite{kolkin2019}, SinIR \cite{yoo2021} and ours (DTP).
Figure 11: Results on standard photorealistic style transfer benchmarks (Luan et al. 2017). Given an input pair, we compare the results with WCT2 (Yoo et al. 2019), STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), SinIR (Yoo and Chen 2021) and ours (DTP).
Figure 12: Results on CelebA-HQ (Liu et al. 2015) and FFHQ (Karras, Laine, and Aila 2019) benchmarks. Given an input pair, we compare the results with Swap AE (Park et al. 2020b), STROTSS (Kolkin, Salavon, and Shakhnarovich 2019), SinIR (Yoo and Chen 2021) and ours (DTP).
Figure 13: Additional examples on ablation study on priors, cycle consistency loss, generation module and feature moving average: warped features (WF) and images (WI) help better converge. $L_{cyc}$ helps to optimization process to be stable and feature moving average (FMA) makes the results more stylized.
Figure 14: Examples of leveraging losses between content and style loss. The larger $\lambda_c$ gives more weight to the style term.
Figure 15: Our results with various random seed.