

Instant Photorealistic Style Transfer: A Lightweight and Adaptive Approach

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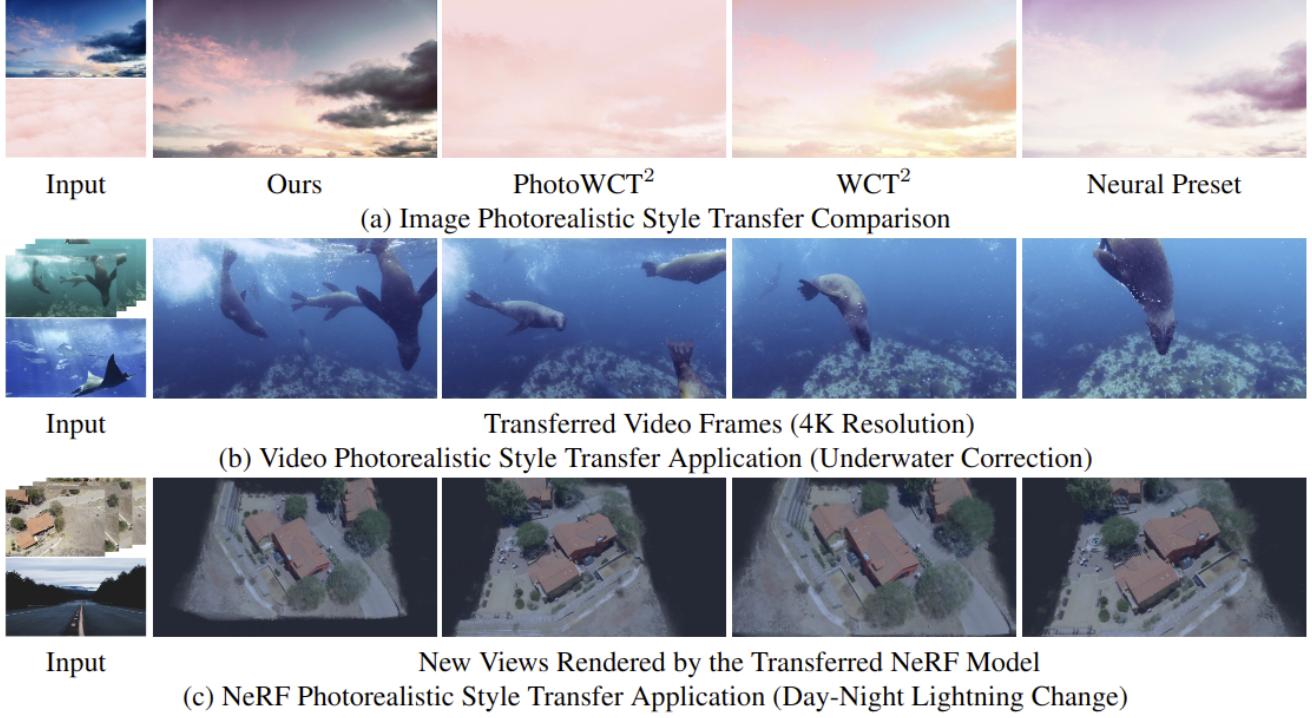


Figure 1. Photorealistic stylization results. Our method outperforms competing approaches in terms of emphasizing photorealism in content (as demonstrated by a comparison between our approach and PhotoWCT² [4]) and applying desired style effects (as shown in comparisons with WCT² [26] and Neural Preset [13]). Furthermore, our approach retains non-color information, such as temporal and multi-view consistency from the input, enabling multi-frame transfer applications (e.g. video and NeRF [19]). It's important to note that our approach achieves these results without pre-training on annotated datasets or imposing extra constraints.

Abstract

In this paper, we propose an Instant Photorealistic Style Transfer (IPST) approach, designed to achieve instant photorealistic style transfer on super-resolution inputs without the need for pre-training on pair-wise datasets or imposing extra constraints. Our method utilizes a lightweight StyleNet to enable style transfer from a style image to a content image while preserving non-color information. To further enhance the style transfer process, we introduce an instance-adaptive optimization to prioritize the photoreal-

ism of outputs and accelerate the convergence of the style network, leading to a rapid training completion within seconds. Moreover, IPST is well-suited for multi-frame style transfer tasks, as it retains temporal and multi-view consistency of the multi-frame inputs such as video and Neural Radiance Field (NeRF) [19]. Experimental results demonstrate that IPST requires less GPU memory usage, offers faster multi-frame transfer speed, and generates photorealistic outputs, making it a promising solution for various photorealistic transfer applications.

1. Introduction

The emergence of movies with extremely high resolution and definition provides an immersive experience to the viewer and a challenge to the film crew due to the cost of shooting under such high standards. However, the costly professional cinematic lighting can be circumvented via video style transfer by simply choosing an existing style image as an input and having the algorithm do all the re-lighting of the original video. Meanwhile, with the rise of Neural Radiance Field (NeRF) [19], rebuilding an accurate 3D scene from an array of calibrated images becomes possible, albeit acquiring such an array is also costly. Performing a style transfer to regenerate the scene in different seasons or daytime would be ideal as it makes the best use of the obtained images with no need for another round of the costly image collection. Those two style transfer problems can all be categorized as multi-frame style transfer. Relative to previous image style transfer methods, multi-frame style transfer of movie-spec video and calibrated images for 3D reconstruction presents new challenges as 1) the size of the inputs may bring an enormous cost of computation time and memory, and 2) the multi-frame inputs inherently require the output to retain the temporal consistency or multi-view consistency which can not be handled at the same time by the previous methods.

Ever after Gatys *et al.* [7] put forward Neural Style Transfer, using deep learning methods for transferring the style of the content image has become popular. Photorealistic style transfer methods [15, 16] are developed besides arbitrary style transfer methods [2, 5, 10, 11, 14] which are not ideal for producing a photorealistic output as they normally fail to keep the content image’s spatial details or take up huge computation cost. Early photorealistic style transfer methods [15, 16, 26] had an unsatisfying performance as their output demonstrated distortion and unwanted artifacts. Meanwhile, the processing speed and memory cost have severely limited their availability. Performing deterministic color mapping can be one possible solution for dealing with artifacts. The filter-based methods [8, 12] lack the ability to generalize to complex color transformation due to the inherent limitation of filters. The LUT-based methods [17, 23] face the problem that LUTs have a large number of parameters that are hard to optimize which leads them to propose their own way to bypass directly predicting the LUTs. Ke *et al.* [13] proposed a 2-stage color mapping procedure that enables fast style change. However, these methods still have suboptimal results and require a pair-wise dataset for training while limiting their application to image and video.

To this end, we propose Instant Photorealistic Style Transfer (IPST) which can perform style transformation on the super-resolution inputs in real-time, without any training dataset needed extra constraints imposed, and produce comparative results, if not better, against state-of-the-art

methods. When dealing with the style transferring task of multi-frame inputs, like video and multi-view stereo tasks, IPST performs the transformation of the whole frames by only training on the first frame. Due to our lightweight style net, we can perform inference on the remaining frames in a matter of milliseconds. Our model also expresses multi-view consistency which enables its application in multi-view style transfer tasks like NeRF.

Our contributions are as follows:

1. We propose a lightweight StyleNet designed to facilitate instant style transfer while preserving non-color information, resulting in consistent and realistic outputs.
2. We introduce an instance-adaptive optimization involving an adaptive coefficient and early-stopping technique. This optimization strategy emphasizes the photorealism of the output and accelerates the training process.
3. We present an Instant Photorealistic Style Transfer (IPST) approach capable of achieving photorealistic style transfer on super-resolution inputs. IPST preserves the non-color information of content inputs, enabling its application in multi-frame tasks such as video and NeRF style transfer. Remarkably, IPST doesn’t require any paired datasets for pre-training and also serves as a universal photorealistic style transfer pipeline.

2. Related work

2.1. Image Style Transfer

Based on Gatys *et al.* [7], using learning methods to perform style transfer on images becomes the trend. Although some artistic style transfer methods [2, 5, 10, 11, 14] focusing on transferring the content’s style from photos shot in the real world into artistic ones achieved breathtaking results, the photorealistic style transferring’s requirement is different as it requires the content input to hold its spatial structure after the transferring of the style without distortion or artifacts. Although Gatys *et al.* [7] has proposed a foundational pipeline to perform style transfer, its results are not satisfying as distortion and unnatural color exist. By considering the style transfer problem as whitening and coloring transform (WCT), both WCT [15] and PhotoWCT[16] can perform style transfer in a photorealistic way that alleviates but still fails to prevent the distortion and unwanted artifacts in the output. Yoo *et al.* [26] exploited wavelet pooling/unpooling to further reduce distortion as this process can preserve the high-frequency details. Chiu *et al.* [4] proposed a block-wised coarse-to-fine training pipeline with high-frequency skip connections to preserve image quality. Another direction is to form the style transformation as deterministic color mapping. While the filter-based methods [8, 12] are capable of holding the spatial structure of the content input, they normally can’t generalize well. Applying filters for style transformation is limited to basic

changes like brightness or tune and can only perform well on limited image pairs. Xia *et al.* [23] and Lin *et al.* [17] utilized color LUTs (look up table) for deterministic color mapping. However, due to the large number of LUTs' parameters, it's not feasible to directly optimize those parameters. So they performed their own modified LUT prediction process by either leveraging a bilateral grid to simplify the LUT [23] or learning a network that predicts the parameters of the LUT [17]. Ke *et al.* [13] presented the style transferring process in 2 stages by first mapping the color of the content image into a normalized image space and then mapping the normalized image space to the target style from the style image with both mapping processes carried out in two learned deterministic color mapping modules. However, those methods normally suffer from three limitations. First, they require a pair-wised dataset to train on. This can be problematic as pair-wised datasets are hard to collect. Secondly, the distortion and artifacts are not robustly prevented. Lastly, some of them require huge computation resources.

2.2. Multi-frame Style Transfer

While huge progress in transferring the style of an image has been made, directly performing the same style-transferring technique on an image sequence with consistency requirements can not guarantee a successful style transfer. Previous video style transfer techniques need to incorporate constraints to ensure that the stylistic transformation doesn't introduce flickering artifacts or incontinuity, impairing temporal consistency across frames.[3, 6, 9, 21, 24]. This is achieved by imposing constraints through mechanisms such as enforcing temporal coherency loss between consecutive frames [3, 21, 24] or by coupling the style features with the corresponding content features throughout the video sequence [6]. In contrast, our method avoids the flickering phenomenon and holds the temporal consistency in our output even without such constraints being imposed. Besides temporal consistency, our method also keeps multi-view consistency when we apply it to NeRF [19] object style transformation. A work closely related to this part of our work is from Zhang *et al.* [27]. However, their method focuses on arbitrary style transfer while our method carries out photorealistic style transfer.

3. Instant Photorealistic Style Transfer

Instant Photorealistic Style Transfer (IPST), presented in Figure 3, is the integration of lightweight StyleNet and an instance-adaptive optimization method.

Because of instance-adaptive optimization, IPST is a universal photorealistic style transfer pipeline without the need for prior training on paired datasets and laboriously manual hyperparameter fine-tuning. Furthermore, IPST excels in preserving the non-color information of input con-

tent, enabling it to perform multi-frame transfer applications (*e.g.* video and NeRF) without adding extra constraints. This is achieved by training on the first frame and subsequently applying the learned style to the remaining frames.

In the following sections, we will provide a comprehensive illustration of IPST. Section 3.1 offers an exploration of the lightweight StyleNet, while Section 3.2 delves into the details of the instance-adaptive optimization method.

3.1. Lightweight StyleNet

The architecture of StyleNet is depicted in Figure 2. StyleNet performs transformations within a normalized space using mean and standard deviation values derived from the ImageNet. Therefore, we begin by defining a normalization and denormalization function. The normalization function maps RGB color space to the normalized space $N : [0, 1]^{3 \times h \times w} \rightarrow \mathbb{R}^{3 \times h \times w}$. Given an RGB image \mathbf{I} , the mean \mathbf{M} and standard deviation Σ of the ImageNet, the normalization function is defined as follows:

$$N(\mathbf{I}) = (\mathbf{I} - \mathbf{M}) \oslash \Sigma, \quad (1)$$

where \oslash denotes the element-wise division. Conversely, to convert the normalized output \mathbf{I}' back to the RGB space for the final result, a denormalization function is utilized $D : \mathbb{R}^{3 \times h \times w} \rightarrow [0, 1]^{3 \times h \times w}$, which is given by:

$$D(\mathbf{I}') = \mathbf{I}' \odot \Sigma + \mathbf{M}, \quad (2)$$

where \odot represents the element-wise multiplication.

Next, we illustrate the procedure of StyleNet. Given an input content image $\mathbf{C} \in \mathbb{R}^{3 \times h \times w}$, StyleNet first normalizes it by

$$\mathbf{C}' = N(\mathbf{C}). \quad (3)$$

Then, it diverges into two branches: a style transfer branch and a content shortcut branch.

In the style transfer branch, the normalized image \mathbf{C}' is initially downsampled to Standard Definition (SD) resolution (480p) to facilitate resolution-agnostic and efficient transformation computations:

$$\overline{\mathbf{C}'} = \downarrow \mathbf{C}', \quad \overline{\mathbf{C}'} \in \mathbb{R}^{3 \times 480 \times \frac{480h}{w}}, \quad (4)$$

where \downarrow is the downsampling operation.

Subsequently, we formulate the color transformation in the style transfer branch as a segmentation task where the targeted output is the whole color space $[0, 1]^3$ instead of being restricted to specific classification labels. Hence, the transformation is defined as $f : \mathbb{R}^{3 \times 480 \times \frac{480h}{w}} \rightarrow \mathbb{R}^{3 \times 480 \times \frac{480h}{w}}$. Here, f is a convolutional neural network inspired by [20]. It follows a symmetrical structure, with the first half comprising Convolutional layers and the second half consisting of UpConvolutional layers. The initial part

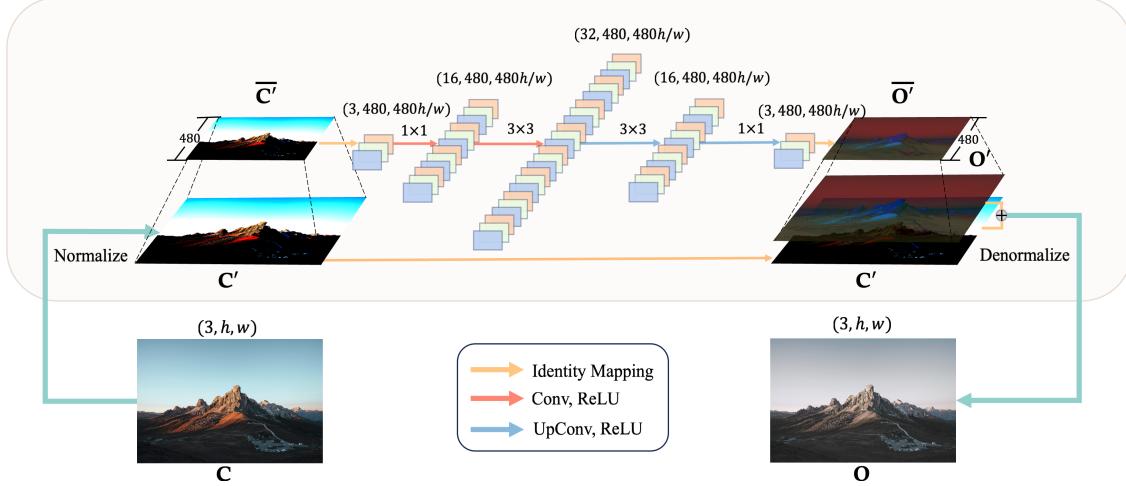


Figure 2. Architecture of Lightweight StyleNet. The StyleNet operates through a sequential process. 1) It begins by normalizing the given input using the mean and standard deviation values derived from the ImageNet dataset. The StyleNet then diverges into two branches: a style transfer branch and a content shortcut branch. 2) Within the style transfer branch, the input is downsampled to the SD (480p) resolution, ensuring the resolution-agnosticism and effective computation of the network. The style branch comprises a lightweight and compact neural network designed for applying color transformation. Notably, the transformations exclusively manipulate input channels while preserving the spatial information untouched. The outcome of this diminutive neural network is a color transformation mask, which is subsequently upsampled to match the original resolution, serving as the ultimate output from the style transfer branch. Concurrently, the content shortcut branch executes an identity mapping process, thereby aiding the preservation of non-color information within the StyleNet. 3) Upon completing their respective tasks, the outputs from the two branches are added and then denormalized to generate the final output.

encodes the input into feature maps within a latent space, progressively expanding the number of channels. The subsequent part decodes these feature maps into a segmentation mask, serving as a color transformation mask that is applied to the input content.

Kernel	Padding	Input Channel	Output Channel
1×1	0	3	16
3×3	1	16	32
3×3	1	32	16
1×1	0	16	3

Table 1. Hyperparameter of the transformation f

Notably, we adopt a proper hyperparameter setting, as detailed in Table 1, to ensure the preservation of spatial information during the transformation performed by f . This table also facilitates the calculation of trainable parameters in the transformation f , totaling 9,312. This lightweight design enables the potential for instant photorealistic style transfer applications. With the definition of the transformation f and the downsampled image \bar{C}' , we generate color transformation mask output \bar{O}' by

$$\bar{O}' = f(\bar{C}'). \quad (5)$$

Following the relatively intensive transformation computation, we upsample the mask back to the original resolution

\bar{O}' by

$$\bar{O}' = \uparrow \bar{O}', \quad \bar{O}' \in \mathbb{R}^{3 \times h \times w}, \quad (6)$$

where \uparrow denotes the upsampling operation.

Simultaneously with the color transformation mapping, an identity mapping establishes a shortcut in StyleNet, aiding in preserving non-color information in the final output.

By combining these two branches, we generate the ultimate output \mathbf{O} of StyleNet:

$$\mathbf{O} = D(\mathbf{C}' + \bar{O}'). \quad (7)$$

3.2. Instance-adaptive Optimization

In order to enable photorealistic priority and rapid convergence of StyleNet, we develop an instance-adaptive optimization method, drawing inspiration from [7], to train StyleNet.

Given an image denoted as \mathbf{I} , the feature map extracted by VGG in the first layer of the CNN block b is represented as $\mathbf{I}_f^b \in \mathbb{R}^{n_b \times h_b w_b}$, where n_b stands for the channel number of the feature map, and h_b and w_b are the height and width of the feature map.

With this feature map definition, given the content image \mathbf{C} and output result \mathbf{O} , we can compute the feature maps of the fourth block, namely \mathbf{C}_f^4 and \mathbf{O}_f^4 . The content loss can then be defined as follows:

$$\mathcal{L}_{content}(\mathbf{C}, \mathbf{O}) = \frac{1}{n_4 h_4 w_4} \sum (\mathbf{C}_f^4 - \mathbf{O}_f^4)^2. \quad (8)$$

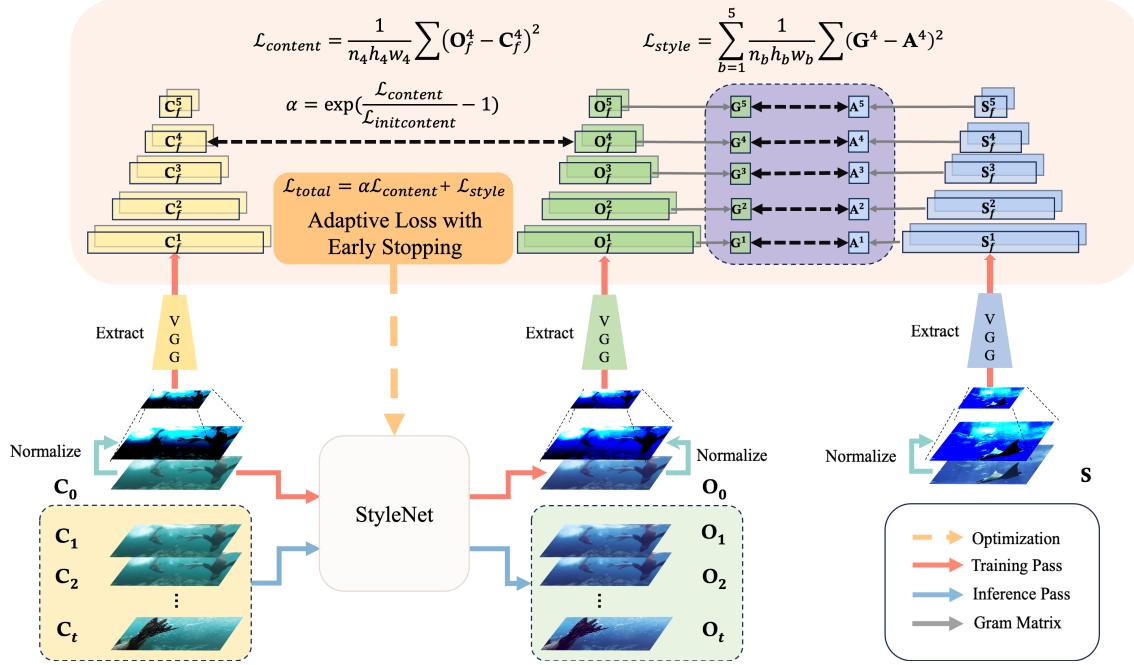


Figure 3. Overview of Instant Photorealistic Style Transfer (IPST) pipeline and instance-adaptive optimization. IPST consists of a key component and is divided into two stages: the StyleNet, and the stages of training and inference. The StyleNet takes a single image as input and generates the transferred output. In the initial training stage, the output of StyleNet cannot accurately capture the desired transformation due to its limited training. However, as the training progresses, StyleNet becomes capable of generating outputs that closely mirror the style reference image. Throughout the training process, we employ an instance-adaptive optimization method including an instance-adaptive coefficient α and an early stopping technique, which collectively accelerate the training process. For the task of image transfer, only the training stage is required. In cases where a set of images with contextual consistency serves as input, the first image goes through the training stage, while the subsequent images undergo the inference stage. During the inference stage, the StyleNet, now equipped with learned style transformation, is directly applied to the following images.

Moreover, the style loss is assessed using Gram matrices between two feature maps. Given a feature map I_f^b , the Gram matrix is computed as follows:

$$\mathbf{G}^b = I_f^b I_f^{b\top}, \quad \mathbf{G}^b \in \mathbb{R}^{n_b \times n_b}. \quad (9)$$

Assuming that \mathbf{G}^b and \mathbf{A}^b are the style Gram matrices for the output result \mathbf{O} and style image \mathbf{S} in block b , the style loss is defined as:

$$\mathcal{L}_{style}(\mathbf{O}, \mathbf{S}) = \sum_{b=1}^5 \frac{1}{n_b h_b w_b} \sum (\mathbf{G}^b - \mathbf{A}^b)^2. \quad (10)$$

With the definition of content and style loss, the total loss is expressed as:

$$\mathcal{L}_{total}(\mathbf{C}, \mathbf{O}, \mathbf{S}) = \alpha \mathcal{L}_{content}(\mathbf{C}, \mathbf{O}) + \mathcal{L}_{style}(\mathbf{O}, \mathbf{S}), \quad (11)$$

where α serves as a hyperparameter that controls the weight ratio between content and style. The original hyperparameter α typically demands meticulous manual tuning and remains a fixed value throughout the training process, which

can be problematic for photorealistic results. Initially, when content loss is low and style loss is high, the optimizer emphasizes style over content. As training progresses, this causes conflicts and instability as the optimizer tries to balance content preservation and style transfer.

To address this issue, we propose an instance-adaptive optimization method, presented in Algorithm 1. This method involves redefining the hyperparameter α and incorporating an early stopping technique. We first introduce a redefinition of the hyperparameter α as an instance-adaptive coefficient that exponentially increases with rising content variations. During the first epoch, when the content loss equals the initial content loss, α is equal to one, assigning equal importance to content and style. As the output gradually stylizes towards the reference style image, α starts to exponentially increase in response to the growing content loss. This approach places a higher emphasis on achieving photorealism in the output and effectively mitigates conflicts between content and style optimization, ultimately stabilizing and accelerating the convergence during training. Additionally, we integrate an early stopping technique to further expedite the training process. At the beginning of

Algorithm 1 Instance-adaptive optimization

Input: $C, S, \text{StyleNet}$
Output: StyleNet

```
optimizer ← Adam(lr=0.001)
best_loss ← ∞
patience ← 10
while patience ≠ 0 do
     $O \leftarrow \text{StyleNet}(C)$ 
    content_loss, style_loss ← get_loss( $C, O, S$ )
    if best_loss = ∞ then                                ▷ First epoch
        initial_content_loss ← content_loss
        initial_total_loss ← content_loss
    end if
     $\alpha \leftarrow \exp\left(\frac{\text{content\_loss}}{\text{initial\_content\_loss}} - 1\right)$ 
    total_loss ←  $\alpha \times \text{content\_loss} + \text{style\_loss}$ 
    if  $\frac{\text{total\_loss}}{\text{initial\_total\_loss}} - \text{best\_loss} < 0.01$  then
        best_loss ←  $\frac{\text{total\_loss}}{\text{initial\_total\_loss}}$ 
        patience ← 10
    else
        patience ← patience - 1
    end if
    StyleNet ← optimizer(total_loss)
end while
return StyleNet
```

the optimization, we record the initial total loss to serve as a reference for subsequent total loss measurements. We calculate the loss change rate by normalizing subsequent total loss measurements relative to the initial total loss. If the total loss fails to decrease by at least 1% relative to the initial total loss over ten epochs, we terminate the training early.

4. Experimental results

In this section, we first provide an overview of our experimental setup, involving details about the evaluation dataset and the quantitative metrics employed. Subsequently, we delve into ablation studies on the StyleNet architecture and the Instance-adaptive optimization approach. Furthermore, we extensively compare IPST with other competing methods based on transfer effects and efficiencies.

Evaluation Dataset. To conduct both quantitative and qualitative comparisons, we utilized the DPST dataset [18], comprising sixty content-style pairs. This dataset encompasses a mix of pairs, some align roughly correct segmentation while others pose challenges. Notably, the 23rd pair requires a segmentation map, so we substitute it with a 4K mountain landscape pair shown in Figure 6.

Quantitative Metrics. Prior studies [1, 23, 26] have employed content structural similarity and Gram matrix style loss for quantitative evaluation of photorealistic style transfer results. For enhancing the precision of structural simi-

larity measurement, Neural Preset [13] upgraded the edge detection model from HED [25] to LDC [22] for finer edge detail representation. Additionally, a discriminator model was trained on annotated data to assess color style similarity. Nevertheless, after conducting several tests, concerns arose regarding the universality and reliability of the discriminator model. In response, we adopted LDC to output the content similarity score and utilized the normalized Gram matrix style loss to compute the style similarity score. The style similarity score is defined as $\text{style_sim} = \max(0, 3000 - \mathcal{L}_{\text{style}})/3000$, where 3000 is a relatively large style loss for normalization purposes. We also computed the F-1 score of the content and style similarity to provide a comprehensive evaluation.

4.1. Ablation Studies

The comprehensive evaluation of ablation is depicted in Figure 4, with (a) representing the content-style input pair and (b) denoting the optimal configuration introduced in Section 3. The quantitative comparison table is provided as Table 2 for reference.

Effectiveness of Instance adaptive optimization. Instance adaptive optimization serves to prioritize the photorealism of the result and accelerate the convergence of StyleNet. For comparison analysis, we configured epoch to 150 with early stopping disabled and α to 1 to produce the results without the adaptive optimization. Figure 4 (c) showcases that the absence of adaptive optimization leads to overfitting the style image and generating unrealistic artifacts. Moreover, Table 2 reveals that the results obtained without adaptive optimization exhibit a high style similarity due to their overfitting to the style image, which negatively impacts content similarity. This leads to a lower F-1 score compared to results obtained with adaptive optimization. Additionally, it's worth noting that StyleNet converges 1.76 times faster when adaptive optimization is employed.

Model Size. StyleNet employs a lightweight structure to ensure the transfer speed. We explored the effects of enlarging or reducing the size of StyleNet. In general, larger models can learn more complex transformations, but they might overfit with limited data, while smaller ones may underfit the data and cannot perform the transfer task well. We tested this by making the model four times bigger and then a quarter of its original size. The larger model in Figure 4 (c) had a higher style score but a lower content score, indicating overfitting to the style image. In contrast, the smaller model in Figure 4 (d) was too small and underfit the style image. Despite having more parameters, the larger model processed faster due to early stopping with adaptive optimization. The smaller model, with fewer parameters, has its training extended by adaptive optimization to complete its convergence.

Content preservation. StyleNet adopts a content short-

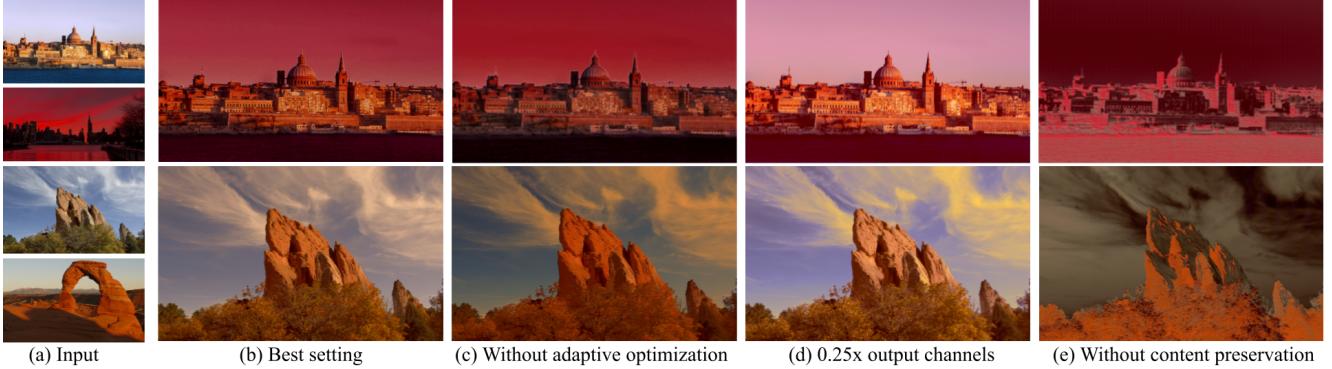


Figure 4. **Qualitative result of ablation studies** conducted on the instance-adaptive optimization and StyleNet architecture

	Best setting	w/o adaptive optimization	4x channels	0.25x channels	w/o spatial preservation
Content	0.7484	0.6460	0.6834	0.7872	0.7001
Style	0.8568	0.9075	0.8637	0.7656	0.7398
F-1	0.7989	0.7548	0.7630	0.7762	0.7194
Speed (fps)	0.4464	0.2532	0.4444	0.3367	0.3921

Table 2. **Quantitative result of ablation studies** conducted on the instance-adaptive optimization and StyleNet architecture

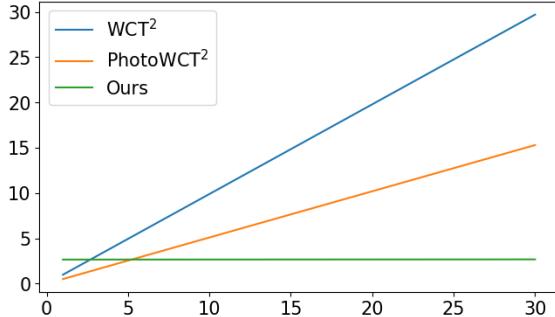


Figure 5. **Processing speed comparison** of multi-frame inputs

cut and proper padding setting to safeguard the content information during the transfer process. Figure 4 (e) displays the results without these content preservation techniques. Notably, the absence of a content shortcut leads to severe overfitting to the style image, while the lack of proper padding results in the emergence of grid pattern artifacts.

4.2. Comparisons

We qualitatively and quantitatively compare IPST with WCT² [26], PhotoWCT² [4], and Neural Preset [13], for which the authors have released access to codes or demos.

Qualitative comparison In Figure 6, we present a comprehensive comparison highlighting the superior quality of our approach. Our approach emphasizes the photorealism of the results, resulting in the preservation of high-quality non-color information, including intricate textures and con-

sistent brightness and contrast properties inherited from the content image. Additionally, our approach is instance-adaptive, allowing for precise application of the style effects extracted from the reference style image to the final output. In contrast, WCT² struggles to preserve the original resolution of content input, resulting in unavoidable blurriness. On the other hand, PhotoWCT² often overfits the style image, yielding results closely resembling the style image itself. While it produces strong style-effect results, it tends to introduce style-like artifacts. Neural Preset performs well by maintaining content structure from the content image. However, due to its pre-trained nature, it may not always accurately extract color information from the style image, occasionally resulting in color tone deviations of outputs.

Quantitative comparison. The findings in Table 4 align consistently with those presented in Figure 6, affirming that our approach yields an overall superior performance. In contrast, WCT² fails to generate clear, high-quality results, resulting in lower overall scores. PhotoWCT² exhibits a superior Style score at the expense of overfitting issues. The Neural Preset, on the other hand, excels in producing results with high content similarity scores but encounters challenges in achieving a universal color transformation.

Transfer Efficiency. As presented in Table 3, PhotoWCT² [4] and WCT² [26] demand significant memory resources for the transfer process and are unable to handle super-resolution transfer tasks. In contrast, our method only requires a small memory and excels at handling super-resolution transfer tasks. Because of the universal transfer purpose, our method requires training during the transfer

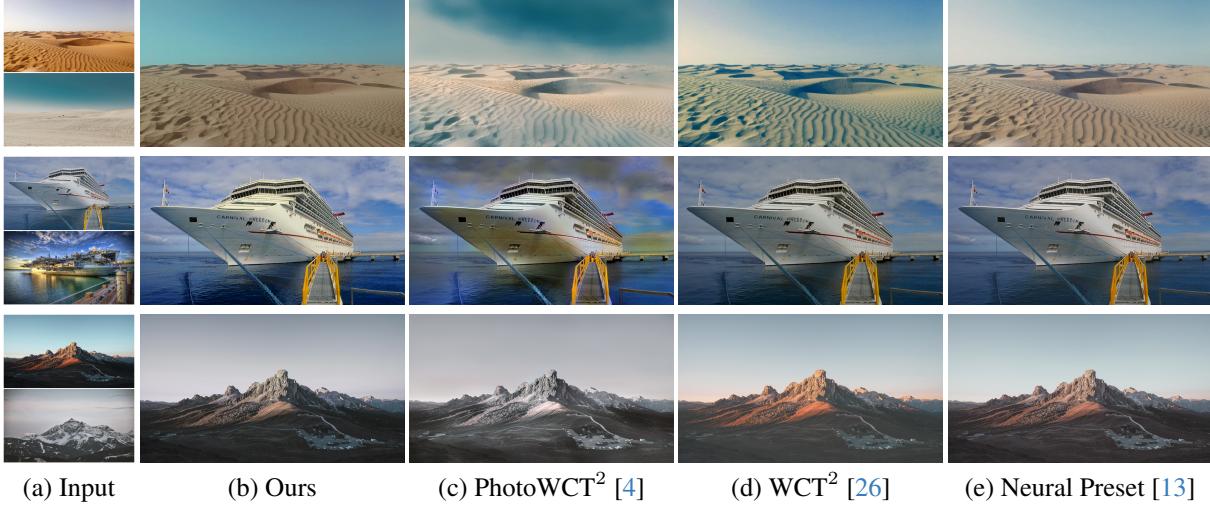


Figure 6. **Qualitative comparison.** Given (a) an input pair consisting of content (top) and style (bottom), the results produced by (b) Ours, (c) PhotoWCT² [4], (d) WCT² [26], and (e) Neural Preset [13] are presented. Our approach outperforms others in prioritizing content photorealism and transferring desired style effects. Note that IPSI achieves these results without pre-training on annotated datasets.

Method	GPU consuming Time / Memory				Model Size Number of Parameters
	FHD (1920 × 1080)	2K (2560 × 1440)	4K (3840 × 2160)	8K (7680 × 4320)	
PhotoWCT ² [4]	0.51 s / 13.47 GB	0.91 s / 17.47 GB	1.89 s / 23.36 GB	OOM	7.05 M
WCT ² [26]	0.99 s / 21.03 GB	OOM	OOM	OOM	10.12 M
Ours (Train)	2.66 s / 3.22 GB	2.75 s / 3.32 GB	3.15 s / 3.62 GB	6.34 s / 4.91 GB	9312
Ours (Inference)	0.74 ms / 0.67 GB	0.91 ms / 0.75 GB	1.38 ms / 0.95 GB	3.63 ms / 2.06 GB	9312

Table 3. **Transfer efficiency comparison.** We conducted the evaluation on an NVIDIA GeForce RTX 4090 GPU with 24GB memory. The units “s”, “ms”, “GB”, and “M” mean seconds, milliseconds, gigabytes, and millions, respectively. “OOM” means out-of-memory issue.

	Content	Style	F-1
Neural Preset [13]	0.7115	0.7786	0.7435
WCT ² [26]	0.6172	0.8098	0.7005
PhotoWCT ² [4]	0.7007	0.8234	0.7571
Ours	0.7484	0.8568	0.7989

Table 4. Photorealistic stylization comparison

stage, which can result in slower transfer speeds compared to others if the input is a single image. However, our method outperforms them when a set of images is provided as input. In our approach, after using the first frame to train the StyleNet, the subsequent frames will be inferred by trained StyleNet, leading to approximately 1000 times transfer efficiency. This efficiency gain is illustrated in Figure 5, where if the total number of input frames exceeds five, our method becomes more time-efficient. This discrepancy becomes even more pronounced as the total number of frames increases. Note that Neural Preset [13] is not included in this transfer efficiency comparison, as its code has not been publicly available.

5. Conclusion

We have developed a lightweight and adaptable instant photorealistic style transfer (IPST) pipeline, facilitating instant style transfers for super resolutions and various input formats without pre-training on annotated datasets. Our experimental findings demonstrate that our approach outperforms others in terms of photorealism and the speed of sequence style transfers.

Nonetheless, IPST does come with its own limitations. One challenge is finding meaningful content-style pairs for transformation, as improper input combinations can lead to unrealistic results. Additionally, IPST lacks the ability to specify specific regions for transformation. One promising direction for future development involves the integration of semantic maps into IPST, which would empower IPST with the ability to transfer specific regions of interest. Furthermore, replacing VGG with other lightweight CNN models has the potential to expedite the optimization process.

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