Diversified Patch-based Style Transfer with Shifted Style Normalization

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Abstract

Gram-based and patch-based approaches are two important research lines of image style transfer. Recent diversified Gram-based methods have been able to produce multiple and diverse reasonable solutions for the same content and style inputs. However, as another popular research interest, the diversity of patch-based methods remains challenging due to the stereotyped style swapping process based on nearest patch matching. To resolve this dilemma, in this paper, we dive into the core style swapping process of patch-based style transfer and explore possible ways to diversify it. What stands out is an operation called shifted style normalization (SSN), the most effective and efficient way to empower existing patch-based methods to generate diverse results for arbitrary styles. The key insight is to use an important intuition that neural patches with higher activation values could contribute more to diversity. Theoretical analyses and extensive experiments are conducted to demonstrate the effectiveness of our method, and compared with other possible options and state-of-the-art algorithms, it shows remarkable superiority in both diversity and efficiency.

1. Introduction

Committed to automatically transforming the style of one image to another, style transfer has become a vibrant community that attracts widespread attention from both industry and academia. The seminal work of (Gatys et al., 2015b) first utilized the Convolutional Neural Networks (CNNs) to extract hierarchical features and transfer the style by iteratively matching the Gram matrices (i.e., feature correlations) of one image to another image. Since then, significant efforts have been made to improve the efficiency (Johnson et al., 2016), quality (Lu et al., 2019) and generality (Huang & Belongie, 2017), etc. Recently, the diversity of style transfer has also revealed its importance, and begun to attract the attention of some researchers. (Li et al., 2017a) and (Ulyanov et al., 2017) introduced the diversity loss to allow the feed-forward networks to generate diverse outputs in a learning-based mechanism. Alternatively, in a learning-free manner, (Wang et al., 2020a) proposed to use deep feature perturbation based on WCT (whitening and coloring transform) to perturb the deep image feature maps while keeping their Gram matrices unchanged.

Intrinsically, style transfer is an underdetermined problem, where a large number of solutions can satisfy the same content and style constraint (Wang et al., 2020a). While existing Gram-based methods have been able to produce a large number of results with significant diversity, unfortunately, these diversified technologies cannot be simply migrated to patch-based methods, since these methods are neither learning-based nor WCT-based. As another important research interest of style transfer, patch-based method is first formulated by (Li & Wand, 2016a;b). They combined Markov Random Fields (MRFs) and CNNs to extract and match the local neural patches of the content and style images. Later, (Chen & Schmidt, 2016) swapped the content patches with the best-matched style patches in a bottleneck layer of CNNs, and built an “inverse network” to directly yield the stylized results. Since then, many successors were further designed for higher quality (Sheng et al., 2018) and extended applications (Champandard, 2016).

Let’s start with the most essential problem, what limits the diversity of patch-based style transfer? Whether using iterative optimization (Li & Wand, 2016a) or feed-forward networks (Chen & Schmidt, 2016), the core of patch-based methods is to substitute the patches of the content image with the best-matched patches of the style image (which we call “style swapping” (Chen & Schmidt, 2016) in this paper), where a Normalized Cross-Correlation (NCC) approach is mostly adopted to measure the similarities of two patches. However, as we all know, the NCC heavily depends on the consistency of local variations (Sheng et al., 2018), and this stereotyped patch matching process restricts each content patch to be bound to its nearest style patch, thus limiting the diversity of final results. Though it has been proved to be effective on locally semantic-level style transfer (e.g., face-to-face), for more general artistic styles, there is little semantic-level correspondence between them and
the contents, and even for human beings, it is still hard to say which patches match best. Therefore, we believe that for artistic style transfer, it should be more reasonable to relax the restricted style swapping process and allow some meaningful variations but maintain those inherent characteristics (e.g., the approximate semantic matching). As with the superiority of the aforementioned diversified methods (Li et al., 2017a; Ulyanov et al., 2017; Wang et al., 2020a), this could give users more choices to select the most satisfactory results according to their own preferences.

However, making such meaningful variations is a challenging task. First, neural patches are with high dimensions and hard to control. Maybe a small change would result in a significant quality degradation, or a big change might not lead to a marked visual difference. Therefore, the difficulty is to find the neural patches that are critical to visual variations, and control them gracefully. Second, the visual effects and quality of the final results are also determined by the inherent correspondence between the content and style patches. That is to say, how to manipulate this complicated correspondence to obtain diverse visual effects while maintaining the original quality is another problem to be solved.

Based on the above analyses, in this work, we dive into the core style swapping process of patch-based style transfer and explore possible ways to diversify it. As shown in Fig. 1, an important intuition we will use is that, the visual effects of output images are determined by the local neural patches of the intermediate activation feature maps, and the patches with higher activation values often contribute more to perceptually discriminative information such as semantics, salient colors and edges, thereby they could also contribute more to diversity. Top: Some style exemplars. Bottom: Heat maps of the activation feature maps (upsampled to the full image resolution) extracted from Relu_{4,1} of a pre-trained VGG19 (Simonyan & Zisserman, 2014).

are also investigated here. Compared with them and other state-of-the-art algorithms, our method achieves remarkable superiority in both diversity and efficiency. Furthermore, we also discuss the compatibility and mutual promotion between our method and existing diversified approaches.

Overall, the main contributions of our work are fourfold:
- We explore the challenging problem of diversified patch-based style transfer, and dive into its core style swapping process to achieve diversity. Several possible diversified options are investigated and compared with the proposed method.
- We propose the shifted style normalization (SSN), a simple yet effective method, to achieve more significant diversity in patch-based methods and provide graceful control between diversity and quality.
- Our SSN is highly efficient and learning-free and can be easily integrated into existing patch-based approaches with almost no extra computation and time cost.
- We analyze and demonstrate the effectiveness and superiority of our method, as well as the compatibility and mutual promotion with other possible diversified options and prior arts.

2. Related Work

The seminal work of (Gatys et al., 2015b) has ushered in a new era of style transfer, namely, Neural Style Transfer (NST) (Jing et al., 2017), where the CNNs are used to decouple and recombine the styles and contents of arbitrary images. After the rapid development in recent years, various kinds of methods have been proposed, among which the Gram-based and patch-based are the most representative.

Gram-based methods. The methods proposed by (Gatys et al., 2015b;a; 2016) are Gram-based, using so-called Gram matrices of the feature maps extracted from CNNs to represent the styles of images, and could achieve visually stunning results. However, it relies on an iterative optimization procedure which is prohibitively slow. To tackle this
issue, (Johnson et al., 2016) and (Ulyanov et al., 2016) approximated the iterative back-propagating procedure to feed-forward generative networks. But these methods have to train an independent network for every style, which is inflexible. For further improvement, some methods (Chen et al., 2017; Dumoulin et al., 2017; Li et al., 2017a; Zhang & Dana, 2018; Shen et al., 2018) are proposed to incorporate multiple styles into one single model, but they are still limited to a fixed number of pre-trained styles. Recently, several methods (Huang & Belongie, 2017; Li et al., 2017b; 2018; 2019; Lu et al., 2019; Yoo et al., 2019) appeared to allow arbitrary style transfer in a single feed-forward network.

Patch-based methods. Patch-based style transfer is another important research interest. (Li & Wand, 2016a;b) firstly combined MRFs and CNNs for arbitrary style transfer. It extracts local neural patches to represent the styles of images, and searches the most similar patches from the style image to satisfy the local structure prior of the content image. Later, (Champandard, 2016) incorporated the segmentation masks for semantic style transfer, (Liao et al., 2017) proposed Deep Image Analogy for accurate semantic-level patch matching, and (Gu et al., 2018) used Deep Feature Reshuffle to add a global constraint. Furthermore, (Chen & Schmidt, 2016) proposed to swap the content activation patch with the best-matched style activation patch using a “style swapping” operation, and then use a de-VGG network to reconstruct the stylized results for fast patch-based style transfer. Based on these, many successors (Sheng et al., 2018; Mechrez et al., 2018; Wang et al., 2020b; Yao et al., 2019; Zhang et al., 2019) are further designed for better performance and extended applications.

Diversified methods. Recently, the diversity of style transfer has also revealed its importance, and received the special attention of some researchers. (Ulyanov et al., 2017) and (Li et al., 2017a) introduced the diversity loss to train the feed-forward networks to generate diverse outputs by mutually comparing and maximizing the variations between the generated results in mini-batches. However, these methods are learning-based, and have restricted generalization, limited diversity and poor scalability (Wang et al., 2020a). To overcome these limitations, (Wang et al., 2020a) proposed a learning-free method called Deep Feature Perturbation, to empower the WCT (whitening and coloring transform)-based methods (Li et al., 2017b; Sheng et al., 2018; Li et al., 2018) to generate diverse results. This method is universal for arbitrary styles, but unfortunately, it relies on WCT and is not applicable to patch-based methods.

For broader fields of image generation, (Zhu et al., 2017; Huang et al., 2018; Lee et al., 2018) resolved the multimodal image-to-image translation problem by separating the latent image space into a domain-specific style space and a domain-invariant content space. (Mao et al., 2019) and (Yang et al., 2019) proposed a regularization that maximizes the pairwise distance between the images and their corresponding latent codes to encourage diversity in cGANs (Mirza & Osindero, 2014), which can be embedded into many image synthesis methods. (Zhao et al., 2020) proposed UCTGAN that learns unsupervised cross-space translation to achieve diverse image inpainting results. (Chen et al., 2020) proposed style transfer with GANs to generate creative and diverse artworks. While these methods can generate multimodal outputs, the diversity is mainly learned and sampled from the distribution of a target domain/dataset, which is essentially different from our work, since our goal is to generate diverse results given only a single style image.

Discussions. While there have been some efforts (Li et al., 2017a; Ulyanov et al., 2017; Wang et al., 2020a) to improve the diversity of style transfer, they are all Gram-based, which are not applicable to patch-based methods. As another important research interest, the diversity of patch-based style transfer remains challenging, and our work, so far as we are aware, takes the first step forward in this direction. By incorporating with our proposed approach, existing patch-based methods (Li & Wand, 2016a; Chen & Schmidt, 2016; Sheng et al., 2018) can be empowered to generate diverse results. Compared with state-of-the-art diversified algorithms, our approach can achieve much higher diversity as well as higher efficiency. Moreover, it is learning-free and universal for arbitrary styles and can be simply implemented in even a single line of code, which makes it quite easy to embed into existing patch-based methods.

3. Proposed Approach

In this section, we first depict the basic workflow of core style swapping process of patch-based style transfer. Then, we introduce the proposed shifted style normalization (SSN) and theoretically analyze its feasibility in generating diverse solutions and helping vary more significant neural patches with higher activation values. Finally, we investigate other possible diversified options to achieve diversity.

3.1. Basic Workflow of Style Swapping

The basic workflow of style swapping process is depicted in Fig. 2 (step 1-5). Suppose $F_s$ and $F_c$ are style and content activation feature maps extracted from a certain layer (usually $\text{Relu}_A$) of a pre-trained CNN (usually VGG (Simonyan & Zisserman, 2014), pre-trained for ImageNet classification (Russakovsky et al., 2015)). The detailed style swapping procedure is as follows:

1. Extract the style patches for style feature map $F_s$, denoted as $\{\phi_j(F_s)\}_{j=1,...,n_s}$, where $n_s$ is the number of patches extracted.

2. Normalize each style patch by dividing its $L2$ norm
To obtain different solutions, an intuitive way is to match the stereotyped style swapping process aims to search the distances between the content and style patches. Alternatively, this process can be implemented by directly adjusting the distances between the content and style patches. However, as analyzed in Section 1, the key to obtain more meaningful diversity is to control and vary those significant patches with higher activation values. Therefore, we propose the shifted style normalization (SSN) to explicitly alter the distances between the content and style patches while implicitly restricting the swapping process to vary more significant style patches with higher activation values.

Concretely, our SSN simply adds a random positive deviation $\sigma$ to shift the L2 norm of each style patch to normalize the style patches, as illustrated in Fig. 3 (b).

$$\{\hat{\phi}_j(F_c) = \frac{\phi_j(F_c)}{\|\phi_j(F_c)\|}\}_{j \in \{1, \ldots, n_s\}}.$$  

(3) Calculate the similarities between all pairs of the style and content patches by the Normalized Cross-Correlation (NCC), $S_{i,j} = \langle \phi_i(F_c), \hat{\phi}_j(F_c) \rangle$ (the normalization of content patch $\phi_i(F_c)$ is unnecessary as it is constant with respect to the argmax operation in the next step (4)). This process can be efficiently implemented by using a convolutional layer with the normalized style patches $\{\phi_j(F_c)\}$ as filters and content feature map $F_c$ as input. The computed result $T$ has $n_s$ feature channels and each spatial location is a vector of NCC between a content patch and all style patches.

(4) Determine the nearest style patch for each content patch, $\phi_i(F_{cs}) = \arg\max_{j \in \{1, \ldots, n_s\}} S_{i,j}$. It can be implemented by first finding the channel-wise argmax for each spatial location of $T$, and then replacing it with a channel-wise one-hot encoding. The result is denoted as $T$.

(5) Reconstruct the swapped feature $F_{cs}$ by a deconvolutional layer with the original style patches $\{\phi_j(F_c)\}$ as filters and $T$ as input.

3.2. Shifted Style Normalization

The stereotyped style swapping process aims to search the nearest style patch for each content patch, which only produces one deterministic solution, as illustrated in Fig. 3 (a).

To obtain different solutions, an intuitive way is to match other plausible style patches instead of the nearest ones. Alternatively, this process can be implemented by directly adjusting the distances between the content and style patches.

However, as analyzed in Section 1, the key to obtain more meaningful diversity is to control and vary those significant patches with higher activation values. Therefore, we propose the shifted style normalization (SSN) to explicitly alter the distances between the content and style patches while implicitly restricting the swapping process to vary more significant style patches with higher activation values.

Concretely, our SSN simply adds a random positive deviation $\sigma$ to shift the L2 norm of each style patch to normalize the style patches, as illustrated in Fig. 3 (b).

$$\{\hat{\phi}_j(F_c) = \frac{\phi_j(F_c)}{\|\phi_j(F_c)\| + \sigma}\}_{j \in \{1, \ldots, n_s\}}.$$  

(1)

This operation can be easily integrated into step (2) of the basic style swapping workflow, as shown in Fig. 2 (a).

Now, we theoretically analyze the feasibility of our SSN in generating diverse solutions and helping vary more significant style patches with higher activation values. For simplicity, we only take one content and two style activation patches to illustrate, which are denoted as $P^c$, $P^s_1$ and $P^s_2$, respectively. Note that the values in these vectors are non-negative because they are extracted from the ReLU activation layers (e.g., Relu, $A_J$) of VGG model (Simonyan & Zisserman, 2014). Specifically, we first suppose that they satisfy the following matching relationship:

$$\frac{\langle P^c, P^s_1 \rangle}{\|P^c\| \|P^s_1\|} = \cos \theta_1 > \frac{\langle P^c, P^s_2 \rangle}{\|P^c\| \|P^s_2\|} = \cos \theta_2 > 0,$$  

(2)

which means $P^s_1$ matches $P^c$ better than $P^s_2$, where $\theta_1$ is the angle between vector $P^c$ and $P^s_1$, $\theta_2$ is the angle between vector $P^c$ and $P^s_2$. If we want to change their matching relationship by randomly shifting the L2 norms of the style
Another possible way to adjust the distances between the content and style patches is to perturb the content patches instead of the style patches. The schematic diagram is illustrated in Fig. 3 (c), where a noise tensor $T$ can be directly used to perturb the content feature map.

\[ F_c = F_c + T, \]

where $T$ has the same size with $F_c$. The intensity of diversity is directly controlled by the sampling range of $T$. This option can be attached to step (3) of the basic workflow to achieve diversity, as shown in Fig. 2 (b).

**Option II: Top-k Nearest Selection**

Apart from adjusting the distances between the content and style patches, we can also directly select the other style patches that come close to the content patches. That is, first search the Top-k nearest style patches for each content patch, and then randomly select one as the best matching style patch, the schematic diagram is illustrated in Fig. 3 (d).

\[ \phi_i(F_c) = \odot_1(Top_k)_{j \in \{1, \ldots, n_2\}} S_{i,j}, \]

where $\odot$ is a random selection operation to select a random one from the Top-k nearest style patches. As shown in Fig. 2 (c), it can be attached to step (4) of the basic workflow, where the diversity is affected by the value of $k$.

**Option III: Feature Reshuffle**

One more possible practice is to reassemble the original best-matched style patches with the reshuffled content feature locations, the schematic diagram is illustrated in Fig. 3 (e).

\[ \hat{T}_{\text{reshuffle}} = \otimes_r \otimes_c (\hat{T}), \]

where $\otimes_r$ and $\otimes_c$ are row and column reshuffle operations, respectively. This reshuffled feature is then blended with the original feature to inject diversity.

\[ \hat{T} = \lambda \hat{T}_{\text{reshuffle}} + (1 - \lambda) \hat{T}, \]

where $\lambda$ is a hyperparameter to control the intensity of...
4. Experimental Results

4.1. Implementation Details

**Baselines.** We integrate our SSN into two types of patch-based stylization methods based on (1) iteration optimization (CNNMRF (Li & Wand, 2016a)) and (2) feedforward networks (Style-Swap (Chen & Schmidt, 2016), WCT+ (Li et al., 2017b), and Avatar-Net (Sheng et al., 2018)). We keep the default settings of the original baselines and finetune the sampling range of \(\sigma\) (sampled from a uniform distribution) to make our quality similar to previous works, i.e., \((0, 10^3]\) for CNNMRF, \((0, 10^5]\) for Style-Swap, \((0, 5 \times 10^4]\) for WCT+, and \((0, 5 \times 10^3]\) for Avatar-Net. We will discuss these settings in later sections.

**Evaluation.** To evaluate the diversity, we collect 36 content-style pairs released by (Wang et al., 2020a). For each pair, we randomly produce 20 outputs, so there are totally \(20 \times 36 = 6840\) pairs (each pair has the same content and style) of outputs generated by each method, which is exactly the same as (Wang et al., 2020a). We adopt the average pixel distance \(D_{\text{pixel}}\) (Wang et al., 2020a) and LPIPS (Learned Perceptual Image Patch Similarity) distance \(D_{\text{LPIPS}}\) (Zhang et al., 2018) to measure the diversity in pixel space and deep feature space, respectively.

4.2. Comparisons with Other Diversified Options

In this section, we demonstrate and analyze the superiority of our SSN over the other possible diversified options (I-III) based on Style-Swap, WCT+, and Avatar-Net. For SSN,

1. We replace the deepest whitening + coloring transform in WCT (Li et al., 2017b) with a whitening + style swapping + coloring transform, so as to better compare with (Wang et al., 2020a).

we use the default settings as described in Section 4.1. For other three options, we manually determine the best settings to achieve as much diversity as possible while maintaining the original quality (see supplementary material).

**Qualitative Comparison.** The qualitative results are shown in Fig. 4. We can observe that compared with random matching (4\(^{th}\) column), our SSN and option I-III could all generate varied results while maintaining the original quality and some inherent characteristics. However, our SSN achieves much more obvious variations than other options, e.g., the patterns in the red rectangle areas. It is worth noting that these significant patterns often correspond to the regions with higher activation values of the heat maps displayed in the 2\(^{nd}\) column (e.g., the red eyes in the top, the land patterns in the middle, and the rainbow in the bottom), which verifies that our SSN could help vary more significant style patches with higher activation values. Note that different
baselines may reach different diversity bottlenecks due to their inherent characteristics. Take Style-Swap (top row) as an example, its results are less stylized, thus resulting in relatively lower diversity compared with WCT$^+$ and Avatar-Net, which can also be validated by the scores in Table 1.

**Quantitative Comparison.** The quantitative results are shown in Table 1. As marked in bold, our SSN achieves the highest $D_{\text{pixel}}$ and $D_{\text{LPIPS}}$ scores compared to the other options on all baselines, which verifies its superiority in generating higher diversity. In terms of efficiency, our SSN also obtains the minimum extra time increase on the original baselines, which means it achieves the highest efficiency. Note that affected by the implementation frameworks and algorithmic details, the extra time increased by the same option may be different for different stylization approaches.

**Analysis.** Our SSN significantly outperforms the other three possible options (I-III) in terms of diversity, which can be attributed to the following factors: (i) The variations are produced on a global scale by shifting the normalization of all style patches, which ensures the scope of diversity. (ii) It implicitly helps vary more significant style patches with higher activation values, thus achieving more meaningful diversity. By contrast, option I can also make variations on a global scale by perturbing all content patches, but it cannot help vary more significant patches with higher activation values. Furthermore, due to the change of content information, it is more prone to damage quality, which in turn also limits the diversity. Note that our SSN would not directly change the content or style information, because the shifted normalized style patches are only used for diversifying the correspondence between the content and style patches, the final swapped feature $F_{\text{sw}}$ is reconstructed by the original style patches.

For option II and III, since only local style patches (Top-k nearest ones or best-matched ones) are manipulated, they only achieve local variations and limited diversity. For efficiency, as our SSN only involves a few extra floating-point addition operations, it is highly efficient and much faster than other options.

**Mutual Promotion of Our SSN and Other Options.** Since our SSN and option I-III are mutually independent, they can be used simultaneously. We found that these methods can promote each other when used together properly, see our supplementary material for the results.

### 4.3. Comparisons with Prior Arts

As there is no other technique that explicitly aims at the diversification of patch-based methods, we compare our SSN with three state-of-the-art diversified Gram-based methods, i.e., Multi-Texture-Synthesis (MTS) (Li et al., 2017a), Improved-Texture-Nets (ITN) (Ulyanov et al., 2017), and Improved-Texture-Nets (ITN) (Chen & Schmidt, 2016). For option II and III, since only local style patches (Top-k nearest ones or best-matched ones) are manipulated, they only achieve local variations and limited diversity. For efficiency, as our SSN only involves a few extra floating-point addition operations, it is highly efficient and much faster than other options.

**Table 2. Quantitative comparisons with prior arts.**

| Baseline | Method | $D_{\text{pixel}}$ | $D_{\text{LPIPS}}$ | Efficiency |
|----------|--------|------------------|------------------|------------|
| MTS      | Original | 0.080 | 0.175 | - |
| ITN      | Original | 0.077 | 0.163 | - |
| WCT$^+$  | Original | 0.000 | 0.000 | 3.565s |
|          | + DFP   | 0.143 | 0.398 | 4.156s |
|          | + Our SSN | 0.204 | 0.508* | 4.158s |
|          | + DFP + SSN | 0.211* | 0.508* | 4.158s |
| Avatar-Net | Original | 0.000 | 0.000 | 3.920s |
|          | + DFP   | 0.102 | 0.264 | 4.268s |
|          | + Our SSN | 0.128 | 0.320 | 3.932s |
|          | + DFP + SSN | 0.143* | 0.401* | 4.303s |
| Style-Swap | Original | 0.000 | 0.000 | 10.571s |
|          | + DFP   | N/A | N/A | N/A |
|          | + Our SSN | 0.065 | 0.234 | 10.582s |
| CNNMRF   | Original | 0.084 | 0.257 | 118.44s |
|          | + DFP   | N/A | N/A | N/A |
|          | + Our SSN | 0.142 | 0.378 | 140.91s |

*1 Due to the memory limitation, we only test the images of size 448 x 448px for CNNMRF.

**Figure 5.** Qualitative comparisons with prior arts. From left to right, the top row shows the content image, the style image (with the heat map of its activation feature map in the lower right corner), and the original style transfer outputs of the baseline methods, respectively. In each column of the bottom two rows, we show two exemplar diverse results (randomly selected) generated by one diversified method (best viewed in color and zoomed-in on screen), and more can be found in supplementary material.
Deep-Feature-Perturbation (DFP) (Wang et al., 2020a). Their results are obtained by running the author-released codes or pre-trained models with default configurations.

**Qualitative Comparison.** As shown in Fig. 5, MTS and ITN only achieve subtle diversity which is hard to perceive. DFP can diversify WCT+ and Avatar-Net to generate diverse results, but the diversity is still limited, almost unnoticeable (especially for Avatar-Net). Compared on the same baselines (i.e., WCT+ and Avatar-Net), our SSN achieves much more significant diversity, e.g., the red and blue colors changed on the sky and building. Moreover, it can also diversify Style-Swap and CNNMRF, which is beyond the capacity of existing diversified approaches.

**Quantitative Comparison.** The quantitative results are shown in Table 2. Consistent with the qualitative results, MTS and ITN obtain low diversity scores in both Pixel and LPIPS distance. Compared on the same baselines (i.e., WCT+ and Avatar-Net), our SSN is clearly superior to DFP in both diversity scores and computational efficiency (DFP involves some CPU-based SVD operations to obtain orthogonal noise matrix, so it takes much more time than ours). In addition, our SSN can also diversify Style-Swap and help improve the diversity of CNNMRF, while DFP is not applicable for these methods. Note that due to the use of noise initialization and iterative optimization process, CNNMRF has been able to produce some varied results and the extra time increased by our SSN is more than other baselines.

**Mutual Promotion of Different Diversified Methods.** Since both WCT+ and Avatar-Net use a whitening + style swapping + coloring process, we can integrate DFP and our SSN into them simultaneously. We keep their default settings when used alone, and the results shown in Fig. 5 and Table 2 (marked with “+ DFP + SSN”) demonstrate the compatibility and mutual promotion between them.

**User Study.** To demonstrate how users may prefer the outputs from the diversified methods over the deterministic ones, we conducted a user study to evaluate our method based on WCT+ and Avatar-Net, and compare it with DFP. 20 users unconnected with the project are recruited. For each diversified method, we give each user 30 groups of images (each group contains one output of the original method and one random output of the diversified method), and ask him/her to select the preferred one. The statistics show that both our method and DFP can help users obtain more satisfactory results (ours: 63.2% over WCT+ and 67.1% over Avatar-Net, DFP: 57.6% over WCT+ and 52.3% over Avatar-Net), and our method outperforms DFP by a considerable margin (9.7% on WCT+ and 28.3% on Avatar-Net).

4.4. Ablation Study

**Trade-off between Diversity and Quality.** We visualize the trade-off between diversity and quality by sampling the deviations σ from different ranges. As shown in the 2nd to 5th columns of Fig. 6, with the increase of sampling range, the generated results gain more diversity, but may degrade the quality. When proper range (e.g., (0, 10^3)) is applied, we can obtain the sweet spot of the two: the results exhibit considerable diversity, and also maintain the original quality and some inherent characteristics. For different baseline stylization methods, the proper range of σ can be easily determined via only a few trials and errors, and our experiments verify that these constant range values can work stably on different content and style inputs.

**Effects of Different Sampling Distributions.** We also try other sampling distributions instead of the default uniform one. As shown in the last column of Fig. 6, sampling σ from a normal distribution could achieve similar performance (e.g., the top image), but the results may be erratic and sometimes produce unwanted effects (e.g., the hazy blocks in the bottom image). This problem may be caused by the concentration property of the normal distribution. However, it does not occur when using a uniform distribution.

**Effects of Different Patch Sizes.** For the effects of different patch sizes on our SSN, see supplementary material.

5. Concluding Remarks

In this work, we explore the challenging problem of diversified patch-based style transfer, and introduce a simple yet both effective and efficient method (i.e., the shifted style normalization, SSN) to resolve it. Compared with other investigated possible diversified options and prior arts, our method could achieve much more significant diversity as well as higher efficiency. By easily incorporating with this universal and learning-free method, existing patch-based style transfer approaches can be empowered to generate diverse results for arbitrary styles. Experimental results demonstrate the effectiveness and superiority of our method as well as its compatibility and mutual promotion with other diversified approaches. We hope our analyses and investigated methods can help readers better understand the crux of patch-based methods and inspire future works in neural style transfer and many other similar fields, such as synthesis (Ren et al., 2018), inpainting (Ruzic & Pizurica, 2015), and denoising (Chatterjee & Milanfar, 2012), etc.
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