Learning Diverse Tone Styles for Image Retouching

Haolin Wang, Jiawei Zhang, Ming Liu, Xiaohe Wu, and Wangmeng Zuo, Senior Member, IEEE

Abstract—Image retouching, aiming to regenerate the visually pleasing renditions of given images, is a subjective task where the users are with different aesthetic sensations. Most existing methods adopt a deterministic model to learn the retouching style from a specific expert, making it less flexible to meet diverse subjective preferences. Besides, the intrinsic diversity of an expert due to the targeted processing of different images is also deficiently described. To circumvent such issues, we propose to learn diverse image retouching with normalizing flow-based architectures. Unlike current flow-based methods which directly generate the output image, we argue that learning in a one-dimensional style space could 1) disentangle the retouching styles from the image content, 2) lead to a stable style presentation form, and 3) avoid the spatial disharmony effects. For obtaining meaningful image tone style representations, a joint-training pipeline is delicately designed, which is composed of a style encoder, a conditional RetouchNet, and the image tone style normalizing flow (TSFlow) module. In particular, the style encoder predicts the target style representation of an input image, which serves as the conditional information in the RetouchNet for retouching, while the TSFlow maps the style representation vector into a Gaussian distribution in the forward pass. After training, the TSFlow can generate diverse image tone style vectors by sampling from the Gaussian distribution. Extensive experiments on MIT-Adobe FiveK and PPR10K datasets show that our proposed method performs favorably against state-of-the-art methods and is effective in generating diverse results to satisfy different human aesthetic preferences. Source code deterministic and pre-trained models are publicly available at https://github.com/SSRHeart/TSFlow.

Index Terms—Image enhancement, image retouching, normalizing flow.

I. INTRODUCTION

With the rapid development of photographic equipment like mobile phone cameras, taking photos has become a very common activity in recent years. Therefore, the demand for image retouching to regenerate visually more pleasing renditions of the photos is also significantly increased. A series of commercial software such as Adobe Photoshop and Lightroom are ready to use for professional photographers, where stunning images can be created with useful functions and appropriate parameters. However, the operations require specialized skills and experience, and it is tedious and time-consuming to deal with a large collection of photos. As a remedy, numerous image retouching methods [1], [2], [3], [4], [5], [6], [7], [8], [9] have been proposed to perform image enhancement automatically by learning from expert-retouched image pairs or exploring non-paired training data in an unsupervised manner. But most of these methods learn the retouching style with a deterministic model and generate only a single retouching style, which greatly limits the practical applications.

In order to support additional retouching styles, researchers have developed some fast adaptation strategies. For example, CSRNet [5] fine-tunes only the lightweight conditional network with additional low-quality and expert-retouched pairs. Sun et al. [9] leverage the low-quality input and an unpaired expert-retouched reference image for flexible inference. Song et al. [7] directly extract latent code from several images with a specific style via a style encoder. Bianco et al. [11] extract the user preference profiles by fitting user-selected/retouched samples. Since additional images with a specific style are required to generate that style, these methods are still far from convenient for ordinary users. There are also some trials on providing extra unseen styles. CSRNet [5] shows the results of interpolating images generated with different styles and provides an interpolation parameter for manual control. Thus, new styles can be created by fusing existing ones. Kosugi and Yamasaki [6] uses reinforcement learning to select the interpretable parameters in image retouching software (e.g., Adobe Photoshop), which builds a basis for further manual adjustment. The former provides limited style space and does not get rid of the need for additional samples with extra styles, while the latter degenerates into complex and professional manual operations.

As one can see, even with the aforementioned efforts, current methods are less flexible to meet different subjective preferences, and there is still much room for generating diverse tone styles in image retouching tasks. Besides, all previous methods regard the images retouched by an expert as a single style, which ignores the intrinsic diversity of the expert due to the targeted processing of different images. In this way, the model is actually learning an average style of the expert. On the contrary, we consider modeling the style space via a normalizing flow framework. Theoretically, normalizing flow learns an invertible mapping between the tone style distribution and a simple Gaussian distribution. In this way, the style of an expert is described by a distribution rather than a fixed point, and new tone styles can be obtained via randomly sampling in the Gaussian distribution.

In fact, normalizing flow has been successfully deployed for many tasks like image generation [12], image super-resolution [13], image denoising [14], etc., which makes the
models able to generate diverse results. The randomness in these tasks is more like a local perturbation. It only influences detailed textures, which will not affect the principal content of the generated images. However, for tasks that modulate the global feature of the images like image colorization [15] and low-light image enhancement [10], directly applying normalizing flow (in the image domain) will cause severe spatial disharmony effects (see Fig. 1). Calculating the mean of different results can mitigate this effect but demolish the diversity [10] conversely. To solve this problem, instead of directly mapping between images and the Gaussian distribution, we propose to learn the normalizing flow in a one-dimensional style space, where the image tone style is represented via a latent vector.

In order to obtain meaningful image tone style representations, we have constructed a joint-training pipeline, which is composed of a style encoder, a conditional RetouchNet, and a tone style normalizing flow (TSFlow) module. In particular, the style encoder predicts the target style vector $s$ for an input image. Then the RetouchNet takes $s$ as conditional information for processing the input. By constraining the output to approximate the expert-retouched reference, the style vector $s$ should contain meaningful image tone style features, and now we can learn the distribution of the styles via the TSFlow module. Interestingly, the style encoder and the conditional RetouchNet can form a traditional image retouching model (the yellow part in Fig. 2), where the image tone style vector of test images is still predicted by the deterministic style encoder. On the contrary, during inference, we can obtain diverse image tone style vectors by sampling random noise vectors from the Gaussian distribution and mapping them to the style space by TSFlow. Therefore, the style encoder in our framework can be safely discarded after training.

It is worth noting that a key factor that influences the training process is the quality of the style representations extracted by the style encoder. With our new framework, the style encoder is only used for training, thus we choose to take the expert-retouched reference image as another input of the style encoder. In this way, the task of the style encoder becomes extracting the style representation from the input-reference pair instead of predicting solely from an input image, which greatly improves the style representation quality. Note that such modification is also consistent with our proposal to describe the style of an expert with a distribution, and guarantees that the style the expert particularly designed for an image is fed into the TSFlow. Besides, it enables the style encoder to support diverse styles. A progressive style correction paradigm is also proposed to further refine the image tone style representation.

Extensive quantitative and qualitative experiments are conducted on two commonly used standard benchmarks (i.e., MIT-Adobe FiveK [16] and PPR10K [17]), which show that our proposed method performs favorably against state-of-the-art methods, and can not only better describe the style distribution of a single/multiple expert(s), but achieve better flexibility on generating diverse unseen tone styles for image retouching.

To sum up, the contributions of this paper involve,

- We propose a normalizing flow-based method to learn diverse tone styles for image retouching. By learning in the style space, the proposed method eliminates the spatial disharmony effects of existing normalizing flow-based methods.
- The image-specific style extraction and progressive style correction strategies are utilized for enhancing the tone style representation quality and modeling the intrinsic style diversity of an expert.
- Extensive experiments show that the proposed model can generate diverse retouching results to satisfy different subjective preferences and outperforms state-of-the-art methods quantitatively and qualitatively.

II. RELATED WORK

In this section, we first review the current image retouching methods, which can be divided into two categories according to the number of styles supported, i.e., single-style and multi-style. Then, the conditional normalizing flow-based methods relevant to this paper are also briefly introduced.

A. Single-Style Image Retouching

Given a low-quality input, single-style image retouching methods produce a single deterministic result. Early explorations include global transformation, histogram equalization, and Retinex-based methods. Gamma correction and log function are widely used for global transformation. Histogram equalization-based methods [18], [19], [20], [21] can modify the color histogram and expand the dynamic range of given images. Retinex-based methods [19], [22], [23], [24], [25] chose to modify the illumination and preserve the reflectance of images.

Since the MIT-Adobe FiveK dataset was collected by Bychkovsky et al. [16], many learning-based methods have been proposed to leverage the power of neural networks [3], [8], [17], [26], [27], [28], [29]. Some methods [4], [27] reformulated image retouching as a curve estimation task. DeepLPF [3] learns parameters of three types of local filters, which achieves local image retouching. Considering the inference time and memory consumption in practical application, [17], [28] chose to learn image-adaptive three-dimensional lookup tables (3D LUTs) for efficient and satisfactory image
B. Multi-Style Image Retouching

As a remedy, some methods tried to generate multiple retouching results to cover diverse human aesthetic preferences [6], [7], [27], [34]. For example, He et al. [5] proposed CSRNet to generate multiple expert styles by fine-tuning the conditional network for different ground truth references. Sun et al. [9] proposed a lightweight conditional generative adversarial network to achieve one-to-many image enhancement with the guidance of various reference images.

To support unseen style preferences of new users, some methods [7], [34] proposed to estimate the different preference representations by providing a few images and then feeding different preference representations into a retouching network to generate results with additional unseen styles. For example, Song et al. [7] proposed StarEnhancer, where a tonal style classifier generates the center embedding of the specific style given some reference images. Kim et al. [34] introduced metric learning to extract the preference vector from a few positive and negative images. References [6] and [27] provided a manner for generating extra results, which predicts explainable retouching parameters (e.g., color mapping curves, Adobe Photoshop parameters, etc.) that can be further adjusted by users. However, all these methods require reference images to obtain unseen styles or need professional skills to modulate the results, which is still very inconvenient for ordinary users, so we propose to sample new styles with the normalizing flow-based framework.

C. Conditional Normalizing Flow

Normalizing flow [12], [35], [36] is a powerful generative model with invertible structures, which maps a complex distribution into a simple one (e.g., Gaussian distribution) in the forward pass, and achieves diverse generations by sampling from the simple distribution in the reverse process. With such characteristics, conditional normalizing flow-based models can be used to model the solution space of many ill-posed problems. For example, SRFlow [13] takes the LR observation as the conditional information for generating diverse SR results. Kim and Son [37] further designed a noise conditional layer to improve the visual quality and diversity. Liang et al. [38] proposed a normalizing flow-based kernel prior for kernel modeling, which can improve the performance of blind SR. Abdelhamed et al. [14] proposed a powerful noise modeling method that can produce realistic noise conditioned on the raw image and a series of camera parameters. Abdal et al. [39] replaced the mapping network of StyleGAN2 [40] with a conditional normalizing flow for image attribute editing. Besides, normalizing flow is also utilized in more global tasks like image colorization [15] and low-light enhancement [10], however, spatial disharmony effect (see Fig. 1) can be observed, leading to visually unpleasant results.

III. Proposed Method

To generate spatially harmonious image retouching results with diverse tone styles, we propose a joint-training framework to model the image tone style distribution. In Sec. III-A, we first explain the motivation in detail. Then, we introduce the learning paradigm and the network structure in Sec. III-B and III-C, respectively. Finally, the learning objectives are formally defined in Sec. III-D.
A. Motivation

Denote by $\mathbf{X}$ and $\mathbf{Y}$ the input low-quality image and the expert-retouched reference image, existing image retouching methods aim to produce an output image $\hat{\mathbf{Y}}$ to approximate the tone style of the reference image $\mathbf{Y}$, i.e.,

$$\hat{\mathbf{Y}} = G(\mathbf{X}; \theta_G),$$

where $G$ denotes the retouching model with parameters $\theta_G$. In these methods, $\theta_G$ will be fixed once the training procedure is finished, which leads to a deterministic result. However, the image retouching task is subjective, and the users have different aesthetic sensations, thus it is appealing to learn a model to generate various image retouching results.

For this purpose, normalizing flow [12], [35], [36] is a reasonable choice, which achieves diverse generation with randomness by design. But directly applying it for image retouching will cause severe spatial disharmony effects (Fig. 1). The reason is that the principal feature is provided by the conditional information (e.g., the low-resolution image in image super-resolution tasks), and the latent representation only encodes the local variations. In the image retouching task, the target style information is unavailable in the input image, so the tone style is dominated by the random noise sampled from the Gaussian distribution, i.e., $\mathbf{Z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. The left column of Fig. 2 shows a vanilla normalizing flow architecture applied for image retouching, where

$$\hat{\mathbf{Y}} = \mathcal{F}^{-1}(\mathbf{Z}; \mathbf{X}, \theta_F),$$

where $\mathcal{F}$ is the invertible structure of the normalizing flow. It can be seen that $\mathbf{Z} \in \mathbb{R}^{H \times W \times 3}$. Although all elements follow identical distributions, the inevitable spatial discrepancies make it difficult for the tone style to be consistent in different regions, and the varying latent representation shape further exacerbates the problem. LLFlow [10] (the middle column of Fig. 2) provides more information by taking the predicted color map $\mathbf{C}$ as the mean of the Gaussian distribution, i.e., $\mathbf{Z} \sim \mathcal{N}(\mathbf{C}, \mathbf{I})$, yet the spatial disharmony problem still remains unsolved.

B. Image Tone Style Representation Learning

With the above analysis, we expect the normalizing flow to model only the global tone style of an image, and propose to separate the image tone style from the content. Specifically, the proposed model is composed of two steps for inference, i.e., first obtaining a style vector $\mathbf{s}$ with the tone style normalizing flow (TSFlow) module, then processing the input image via the RetouchNet $G$ with the guidance of $\mathbf{s}$. The pipeline can be formulated as,

$$\hat{\mathbf{Y}} = G(\mathbf{X}; \mathbf{s}; \theta_G),$$

$$\mathbf{s} = \mathcal{F}^{-1}(\mathbf{Z}; \mathbf{X}, \theta_F),$$

where $\mathbf{Z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$.

Such modification can benefit from several aspects. To begin with, a separate style space can help the model to focus more on the image tone style rather than the content and to better capture the image tone style distribution. Moreover, for the traditional two-dimensional normalizing flow framework, the spatial dimension of the latent representation will change with the input image size, and decomposing the style with the content will result in a more stable one-dimensional style representation form (e.g., a vector). With the stable and disentangled style representation, the randomness is no longer able to cause local perturbations, and the spatial disharmony effects can be naturally eliminated.

For training such a framework, the key problem is to guarantee that $\mathbf{s}$ encodes meaningful image tone style created by the expert. Some existing image retouching methods [5], [7] follow similar configurations to represent the tone styles with a style vector, and achieve decent image retouching results. Nevertheless, as illustrated in the yellow part of Fig. 2, to keep the consistency of the training and inference phase, these methods can only take the low-quality image as input of the style encoder, which is updated with the gradient of the loss calculated on the final output. In other words, for a specific training pair $(\mathbf{X}, \mathbf{Y})$ from the training set $(\mathcal{X}^{tr}, \mathcal{Y}^{tr})$, the style vector $\mathbf{s}$ is predicted based on the overall style of the expert learned by the encoder $E$, rather than the specific style of the reference image $\mathbf{Y}$. In this mode, the performance of learning the tone style distribution with normalizing flow drops, which is proved in Sec. IV-E.

Image-specific Style Extraction

Fortunately, as shown in Eqn. (4), in our proposed framework, the tone style vector is sampled by the TSFlow during inference, so that the style encoder $E$ can be safely discarded after training. Thus, we propose to take $\mathbf{Y}$ as another input of the style encoder, i.e.,

$$\mathbf{s} = E(\mathbf{X}, \mathbf{Y}; \theta_E).$$

On the one hand, the expert will perform targeted processing for each image based on the understanding and experience, so that the reference image $\mathbf{Y}$ provides abundant information about the tone style, and the intrinsic diversity of an expert can be well described. In such a way, the quality of the style representation is greatly enhanced. On the other hand, since the style encoder is relieved from the burden of learning the style of a specific expert, we can utilize the reference retouching results from multiple experts to further enrich the tone style diversity.

Progressive Style Correction

To further improve the image tone style representation quality, we introduce a $n$-step progressive style correction paradigm to refine the image tone style vector. As shown in Fig. 3, the pipeline for each step is similar to the previous single-step one, except that the input at each step $(t)$ is the retouching results of the previous step $(t-1)$, i.e.,

$$\mathbf{s}^{(i)} = \mathbf{s}^{(i-1)} + E(\hat{\mathbf{Y}}^{(i-1)}, \mathbf{Y}; \theta_E^{(i)}),$$

where $\mathcal{F}^{(i)} = \mathcal{F}^{(i-1)}$, $G^{(i)} = G^{(i-1)}$.
both the condition information and a half of the style code

X

the conditional coupling block, we adopt a pre-trained ResNet-

1
×
lightweight model which contains three 1
×
3 convolution layers. As shown in Fig. 4, we design the RetouchNet as a

 intermediate feature

f

i

i

the \( \beta \)th element of the scale / shift parameters \( \alpha \) where

\( \hat{Y} \) aims to reconstruct the expert-retouched result

Y

after training, and there is no need to consider the over-fitting

problem of \( E \) in our experiments. In summary, the learning objective is,

\[
L = L_{\text{Retouch}} + \lambda L_{\text{NLL}},
\]

where \( \lambda \) is the hyperparameter for balancing the loss terms, and we empirically set \( \lambda = 1 \) in our experiments.

IV. EXPERIMENTS

A. Implementation Details

Datasets Our experiments are performed on the MIT-Adobe

FiveK dataset [16] and the PPR10K dataset [17]. The MIT-

Adobe FiveK dataset [16] contains 5,000 RAW images, and for each RAW image, we use five expert-retouched reference images (A/B/C/D/E) and two auto-retouching results (X/Y). We follow the pre-processing pipeline and split setting in [7], where the first 4,500 samples are for training, and the rest 500 samples are for testing. The PPR10K dataset [17] contains 11,161 portrait photos with 1,681 groups, and each RAW photo is processed by three experts (a/b/c) with professional experience. Following [17], the training set in our

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experiments contains 8,875 photos with 1,356 identities, while the remaining 2,286 photos with 325 identities form the test set. We employ the 360p setting in [17], where the shorter edges of the portrait photos are resized to 360 pixels.

**Training Settings and Evaluation Metrics** During training, we feed 16 images into the model in each iteration, which are randomly cropped into 256×256 patches. The proposed framework is optimized by Adam algorithm [43] with a learning rate of 4×10^{-5} and (β1, β2) = (0.9, 0.999). After training, we follow the previous works [7], [17], which calculate the PSNR [44], SSIM [45], MS-SSIM [46], LPIPS [47], and NIMA [48] metrics for the MIT-Adobe FiveK dataset [16], and compare the PSNR [44] and CIELAB color difference 2 (ΔE_ab) for the PPR10K dataset [17]. All experiments are conducted using the PyTorch framework [49] with an Nvidia GeForce RTX 2080Ti GPU.

**B. Comparison With State-of-the-Art Methods**

Since our goal is to learn diverse tone styles for image retouching, the proposed model is designed to produce multiple retouching results for a specific input image via sampling diverse latent code z’s. However, traditional image retouching methods generate only one result for each input or style. In order to compare with state-of-the-art image retouching methods in a fair scheme, we propose a method to obtain a single latent code z̃, which represents the overall image retouching style of an expert. Specifically, once the training is finished, we can use all \{X_i, Y_i\} pairs in the training set to generate tone style embeddings \{s_i\} via Style Encoder E. Then z_i can be obtained via TSFlow F, and we average all \{z_i\} to obtain the \tilde{z}.

\[
s_i = E(X_i, Y_i; \theta_E). \tag{13}
\]

\[
z_i = 1/N \sum_{i=1}^{N} z_i, \tag{14}
\]

\[
\tilde{z} = \frac{1}{N} \sum_{i=1}^{N} z_i, \tag{15}
\]

where \(N\) is the number of training samples. \(\tilde{z}\) is denoted as initial latent code for describing retouching style of a specific expert. Finally, \(\tilde{z}\) roughly represents the retouching style of a specific expert, which is utilized to initialize the following optimization to get the final style representation \(\tilde{z}^*\),

\[
\tilde{z}^* = \arg \min_z \sum_{i=1}^{N} \|G(X_i, F^{-1}(z; X_i, \theta_F); \theta_G) - Y_i\|_1, \tag{16}
\]

which can be used to generate the retouched results via,

\[
\hat{Y}_i = G(X_i, F^{-1}(\tilde{z}^*; X_i, \theta_F); \theta_G). \tag{17}
\]

In this way, \(\hat{Y}_i\) can be used to calculate the evaluation measures for comparing against existing methods in a fair scheme. When exploring the intrinsic diversity of an expert (i.e., Tab. III), we use kmeans to obtain 2 or 3 clustering centers from \{z_i\}, where each cluster center represents a retouching style.

2https://en.wikipedia.org/wiki/Color_difference

Table I shows the quantitative comparison against the state-of-the-art methods on the expert-C subset of MIT-Adobe FiveK dataset [16], including E2POIR [31], unfairHDR [32], EIGAN [9], SpliNet [11], HDRNet [1], DeepUPE [2], Deeplpf [3], CSRNet [5], CURL [42], 3D LUT [28], and the qualitative and quantitative results are given in Fig. 6. Besides, we also compare with state-of-the-art methods on PPR10K dataset [17], including HDRNet [1], CSRNet [5], and 3D LUT [28], and the qualitative and quantitative results are given in Fig. 7 and Tab. II.

Note that all competing models are trained and evaluated under the same dataset configuration. According to the results, one can see that our method can achieve comparable or superior performance against the state-of-the-art methods in...
Fig. 6: Qualitative comparison on MIT-Adobe FiveK dataset. Results generated by our model are more similar with reference on image tone style.

Fig. 7: Qualitative comparison on PPR10K dataset. Results generated by our model are more similar with reference on image tone style.

C. Exploring the Intrinsic Diversity of an Expert

In Sec. IV-B, the power of our method is greatly limited since only one retouching style can be generated for comparison. However, our model is trained to describe an image retouching style distribution, which captures the intrinsic diversity of an expert, rather than a specific style. Therefore, the performance of our model can be further enhanced by generating multiple candidate retouching results for each input image. In particular, instead of averaging all latent codes like Eqn. (15), we can obtain multiple (e.g., $K$) representative latent codes ($\hat{z}_j, 1 \leq j \leq K$) by clustering with the k-means algorithm [50], which are supposed to better describe the image retouching style distribution of the expert. When generating final results, we select the best one among the $K$ results, i.e.,

$$\hat{Y}_i = \arg \max_{Y_{ij}} \text{PSNR}(\hat{Y}_{i,j}, Y_i)$$  \hspace{1cm} (18)$$

with

$$\hat{Y}_{i,j} = G(X_i, F^{-1}(\hat{z}_j; X_i, \theta_F); \theta_G).$$  \hspace{1cm} (19)$$

In Tab. III, we show the results when there are 2 or 3 clustering centers. Accordingly, we also select three best-performed competing methods (i.e., CSRNet [5], 3D LUT [28], and StarEnhancer [7]) for comparison. Specifically, when there are $K$ clustering centers for our method, we take $K$ methods from them, and process each test sample with the $K$ methods. Analogous to Eqn. (18), the retouching result with the highest PSNR among the $K$ results is utilized. Note that all conditions of selecting two from three methods are listed in Tab. III. According to Tab. III, our method can outperform all the competing methods, showing the superior ability to describe

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the retouching style distribution. Our method can generate diverse results easily without consuming memory to contain additional models.

D. Unseen Retouching Style Generation

The experiments in Secs. IV-B and IV-C are still focused on approximating the retouching style of the training set. As shown in Fig. 8, our method can produce diverse image retouching results by sampling multiple $z$’s from the Gaussian distribution, where consistency is observed among different samples processed with the same $z$. In other words, our method provides stable and robust unseen retouching styles rather than random ones. For further verification, we exploit more subsets of the MIT-Adobe FiveK dataset [16], i.e., five subsets processed by expert-A/B/C/D/E and two subsets automatically generated by Adobe Lightroom (denoted by X and Y). In particular, for generating the style of a particular subset, we reuse the formulation of Eqns. (15) and (17), and the only difference is the source of $z_i$. As shown in Tab. IV, we provide the results of our models on generating retouching styles of the seven styles. Note that Ours means the model trained with only
expert-C subset, while *Ours*† means the model trained with five expert-retouched subsets (A/B/C/D/E). We also provide the results of StarEnhancer [7] for comparison. One can see that even trained with only expert-C subset, *Ours* can achieve decent performance on other styles. When trained with more subsets, *Ours*† achieves the best performance.

### E. Ablation Study

1) Latent Space Exploration: With the TSFlow module, the retouching style distribution is mapped into a latent space (i.e., a simple Gaussian distribution). To explore the property of the latent space, we conduct two experiments. (i) Latent code interpolation: we select four latent codes which generate different retouching styles, and obtain more latent codes via interpolation/extrapolation. As shown in Fig. 9, the interpolated/extrapolated latent codes can generate retouching styles with regular patterns. (ii) Latent code modification: thanks to the disentanglement ability of the normalizing flow framework, we further explore the influence of particular dimensions of the latent code $z$. As shown in Fig. 10, by modifying different dimensions of $z$, we can observe diverse retouching results with varying exposure and color temperature. In other words, our method can provide an interactive adjustment for image retouching by operations in the latent space, which further satisfies the users’ aesthetic preferences more conveniently.

2) Dimension of Tone Style Representation: To further investigate the disharmony issue on diverse retouched results, we conduct the variant of learning 2D tone style representation. In order to disentangle style from content, the style encoder takes blurred $X$ and $Y$ as inputs (so that most of the content is filtered out by the low-pass filter). As for the architecture of style encoder, we adopt $1 \times 1$ convolution layers to replace original $3 \times 3$ convolution layers (so that the receptive filed is strictly limited). These changes ensure that the style representation dominates the 2D embedding. Then we adopt 2D normalization flow to learn the 2D style distribution. As shown in Fig. 12, the retouched results still exist disharmony effects. It proves that the disharmony is caused due to the spatial dimension rather than the entanglement of style and content information.

### TABLE IV

**Quantitative Comparison on Diverse Style Retouching.** Note that StarEnhancer [7] is trained with all subsets (A-Y), *Ours* is trained with only expert-C subset, and *Ours*† is trained with five subsets (A-E). Unseen styles during training are highlighted in gray.

| Method                | A   | B   | C   | D   | E   | X   | Y   | Average |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|---------|
| StarEnhancer [7]      | 19.63 | 25.18 | 25.29 | 22.79 | 24.07 | 28.82 | 23.85 | 24.23   |
| Ours                  | 20.31 | 25.29 | 25.57 | 22.34 | 23.29 | 26.90 | 22.96 | 23.81   |
| Ours†                 | **20.74** | **26.17** | 25.36 | **22.89** | 23.66 | 28.15 | **24.24** | **24.46** |

Fig. 9. Latent space interpolation/extrapolation. The images in blue boxes denote four different retouching results, while others are generated by interpolation/extrapolation in the latent space.
3) Image Tone Style Representation Quality: One of the key differences between our method and previous ones is that we regard the retouching style of an expert as a distribution, and describe the image tone style of each retouched image separately. For improving the image tone style representation quality, image-specific style extraction and progressive style correction are utilized in our training scheme. To verify the effectiveness of these components, we conduct experiments with three variants. We first explore the effects of proposed ISE, including ISE w/o X and ISE w/o Y. As shown in Tab. V, without taking X and Y as inputs simultaneously, the PSNR declines significantly. Thus taking both X and Y as inputs, ISE can focus on learning the different part and further extract precise tone style representation. We also conduct experiment by detaching the progressive style correction mechanism (denoted by “w/o PSC”). Performance degradation is also observed without PSC. The PSC also bring benefits to improve the quality of tone style representations. Please refer to Fig. 11 for visual comparison.

4) The Structure of TSFlow: We further conduct experiments to evaluate the design of the TSFlow structure. As shown in Tab. V, TSFlow (uncond.) means the unconditional variant of our TSFlow, where the input image X is no longer deployed as the condition information for the TSFlow module. Such modification leads to severe image quality degradation, showing that the retouching style of an expert is altered according to the image content, and our TSFlow can well capture such knowledge. We also show the influence of the number of flow steps. The experiments on the 4, 8, and 12 flow steps show that 8 flow steps can achieve a trade-off between the computation complexity and performance, which is taken as the final design of our TSFlow module. The visual comparison is also given in Fig. 11.

F. User Study
We conduct two tracks of user studies with 20 participants to prove that our proposed method exceeds other methods on subjective evaluation. To be specific, the participants are asked to rank the retouched results subjectively according to the visual quality. In the first track, the participants are asked to rank four retouched results generated by our method and another three best-performed competing methods (i.e., Starenhancer, 3DLUT, and CSRNet). In the second one, apart from the three best-performed competing methods mentioned above, we provide three retouched results generated by our method (with 3 clustering centers from latent style space).

In each track, 20 images are randomly selected from the testing set, and all retouched results are displayed randomly.

| Method      | PSNR ↑ | SSIM ↑ | LPIPS ↓ |
|-------------|--------|--------|---------|
| TSFlow (no cond.) | 22.62  | 0.888  | 0.115   |
| TSFlow (step=4)   | 25.12  | 0.939  | 0.083   |
| TSFlow (step=12)  | 25.59  | 0.958  | 0.083   |
| ISE w/o X        | 24.27  | 0.908  | 0.097   |
| ISE w/o Y        | 24.62  | 0.888  | 0.115   |
| Ours w/o PSC     | 25.23  | 0.942  | 0.082   |
| Ours             | 25.57  | 0.944  | 0.079   |

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Fig. 11. Qualitative results of our model and its variants on predicting retouching style.

Fig. 12. Diverse results generated by models learning 2D and 1D tone style representation (Ours). Spatial disharmony effects can be observed in the results while learning 2D style embedding, while our results are visually pleasing. Zoom in for better observation.

TABLE VI
THE USER STUDY RESULTS FOR EVALUATING SUBJECTIVE VISUAL QUALITY OF SINGLE RETOUCHEO RESULTS

| Method      | CSRNet | 3DLUT | Starenhancer | Ours |
|-------------|--------|-------|--------------|------|
| Score       | 2.49   | 2.24  | 2.56         | 2.71 |

TABLE VII
THE USER STUDY RESULTS FOR EVALUATING SUBJECTIVE VISUAL QUALITY OF DIVERSE RETOUCHEO RESULTS

| Method      | CSRNet | 3DLUT | Starenhancer | Ours-1 | Ours-2 | Ours-3 |
|-------------|--------|-------|--------------|--------|--------|--------|
| Score       | 2.56   | 3.28  | 3.70         | 3.19   | 4.15   | 4.14   |

to each users. During the subjective evaluation, each method can obtain a score from M to 1 according to the ranking order, where M is the number of methods involved in subjective evaluation. We report the average scores of different methods for subjective evaluation.

As shown in Tab. VI, our method performs favorably against three best-performed methods in terms of subjective visual quality on generating a single retouched result for each input image. As for generating multiple results, among the three styles, Ours-2 and Ours-3 exceed all the other methods (see Tab. VII), while Ours-1 still performs better than CSRNet, showing that our proposed method has the ability of generating diverse retouching styles with high subjective visual quality.

V. CONCLUSION

Existing image retouching methods perform deterministic retouching results, which are inflexible to meet the subjective preferences of users. In this paper, we propose a novel normalizing flow-based framework for generating diverse retouching images. To solve the spatial disharmony effect caused by existing normalizing flow-based methods, we propose an image tone style normalizing flow (TSFlow) module to learn the conditional distribution of the image tone styles, and disentangle the style representation with the image content. An image-specific style encoder and a progressive style correction mechanism are proposed to extract high-quality image tone style representations from the expert-retouched images. Extensive experiments show that our proposed method outperforms the state-of-the-art methods, and can achieve diverse image retouching styles to satisfy different user preferences.

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