Antique Photo Restoration and Colorization via Generative Model

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***Abstract*—In the past, many photographs of famous historical figures and moments were captured in back and white photos. Those captures are often distorted by the limitation of the old-style camera and the negative influence of the poor storing environment. It is obvious that the restoration and colorization of those images can make history lively. Since manually retouching images is time-consuming and hard to be done by people without aesthetic senses, many researchers have proposed models that automatically remove the artifacts in the old photos. However, these methods only solve either image restoration or colorization tasks which cannot fully address the task of image retouching. Consequently, in this work, we propose an effective end-to-end framework, named AIRC, for image retouching. Besides, previous works often use synthesized old photos for training but these pseudo datasets can not replicate exactly the real antique photo and prevent the trained model from being used in reality. To this end, we also introduce a new antique synthetic dataset, namely OldifiedScenes, that resembles real old photos by blending with paper and artifact textures. Quantitative and qualitative results are provided to demonstrate the effectiveness of our proposed method.**

***Index Terms*—Image restoration, image colorization, image inpainting**

I. Introduction

Image retouching is the process of removing flaws such as the sepia effect, film grain, scratches, blotches, etc. from an old black-and-white photograph, and returning a new version of the image without damage and has plausible color. This task has widespread application in numerous fields, including photography technology, film industry, and social advertisement. It also has historical significance, each antique photo has a certain historical value, as many of them capture milestone moments of a country or a person. However, due to the effect of the environment and the limitation of early cameras, old photos represent a faded, monochromatic world which differs from what people experienced at the time. Thus, there exists a demand of reversing such old photos to their qualified and colorful versions. However, this task requires an aesthetic sense to perform image restoration manually. Hence, there is a high demand for creating an automatic tool that can instantly retouch old photos.

In fact, the image retouching problem has gained the attention of the research community. Still, the previous works are often designed to address either image restoration or image colorization. Besides, many of restoration models cannot apply directly to the old photo restoration task as a consequence of the utilized synthetic dataset. Due to the difficulty of collecting paired datasets of old photos and their restored and colorized versions, previous works [1]–[3] often use artificial antique photos. At first, a set of images is collected and then some degradation algorithms are applied to simulate the defects of old photos. The degradation process of old photos is so complex that these synthesis techniques cannot replicate the appearance of actual photo defects. Therefore, the model learned from those synthetic data generalizes poorly on real photos since there is a large semantic gap between synthetic and real data domain.

Due to the lack of end-to-end frameworks for image retouching, in this work, we propose an effective framework, namely AIRC - **A**ntique **I**mage **R**estoration and **C**olorization for antique photo restoration and colorization. Furthermore, we also introduce OldifiedScenes, a synthetic antique dataset that utilizes designed texture images and blends them with clean images. By this proposal, the gap between synthetic and authentic antique photographs is minimized.

To summarize, our contributions are as follows:

- First, we propose AIRC, an end-to-end framework that leverages generative models to automatically restore and colorize antique images.
- Second, we introduce OldifiedScenes, a synthetic antique dataset similar to the real old photos.

The rest of this paper is organized as follows. Section II reviews related work of previous publications supporting our work, Section III presents our proposed method on antique image restoration and colorization. In Section IV, we establish extensive experiments to prove the effectiveness of our proposal. Finally, Section V concludes our work.

II. Related work

A. Image restoration

Single image degradation. Many prior works concentrate on addressing different single image degradation types. The existing defects can be categorized into two groups: unstructured degradations and structured degradations. On the one

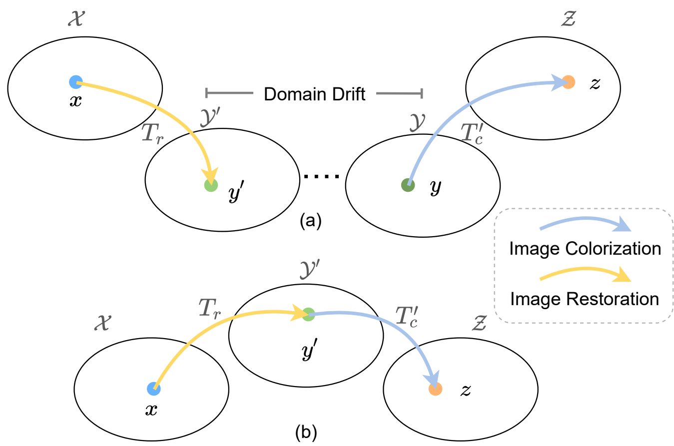

Fig. 1. Illustration of the domain translation between the prior method (a) and ours (b). The prior experiences domain drift problem since the colorization module is trained to learn the mapping $T_c : \mathcal{Y} \mapsto \mathcal{Z}$, but in inference time, it is used to mapping images from domain $\mathcal{Y}'$ to domain $\mathcal{Z}$. Our method tackles this issue by training the colorization module to learn the mapping $T_{c'} : \mathcal{Y}' \mapsto \mathcal{Z}$.

hand, the unstructured degradation models for image denoising, deblurring, and image super-resolution often learn the mappings between the low-quality and the high-quality pairs of images. Such works achieving state-of-the-art results are as follows: [2]–[5]. On the other hand, the latter degradation such as scratches, holes, etc. is more challenging than the unstructured degradation and is often considered as image inpainting task [6].

Mixed image degradation. In the real world, antique photos not only suffer from a single damage factor but also complicated distortions mixed with scratches, loss of resolution, color fading, or film noises. Research aimed at resolving mixed degradation has gained attention from the community. The prior work of RL-Restore [7], the work of Suganuma et al. [1] consist of several convolutional networks. Each individual network is used for solving a specific degradation and designs a mechanism to select the proper operations. However, these supervised learning methods only rely on synthetic data, and thus, cannot generalize to real old photos. Furthermore, these works only concentrated on unstructured defects and disregarded structured defects. To overcome the issues, Wan et al. [6] employ a semi-supervised learning approach and formulate the old photo restoration as a triplet domain translation problem to leverage both real old photos, and synthetic images for the training process. This work also proposes a partial non-local block to specifically address the structured defects.

B. Image colorization.

Image colorization is an exciting topic in computer vision and several techniques have been proposed to address the task. The approach of image colorization can be categorized into user-guided-based, exemplar-based, and learning-based methods.

User-guided-based. This approach requires users to provide local hints, for instance, color scribbles, then propagates to the whole image. The prior works [8], [9] often formulate colorization as an optimization problem that is constrained to the values given by the scribbles. These methods require large amounts of user inputs in particular when dealing with complex textures. To alleviate this, [10] introduces a neural network which is able to colorize the images from provided sparse color points. Although the user-guided approach has convincing results, it requires manual work and the results depend on different users.

Exemplar-based. Many works try to colorize gray-scale image by transferring colors from a similar referenced image to reduce intensive user involvement. The early works [11], [12] transfer colors by matching global statics. Since they ignore the spatial pixel information, these techniques produce unsatisfactory results in many cases. The later works consider more on different levels for more accurate results: superpixel level [13], and pixel-level [14]. Recent works [15], [16] employ deep neural networks to improve the spatial correspondence and colorization results. However, finding references is non-trivial and the automatic solution often involves a complicated image retrieval system.

Learning-based. This approach has received increasing attention in recent years to eradicate the involvements of users. Many methods [17], [18] have achieved automatic colorization by training an end-to-end network to predict colors every pixel of the target image on a large-scale dataset. [19], [20] introduce a two-branch dual-task that jointly learns and fuses local image features and global information (i.e. class label). Zang et al. [21] propose a class rebalance scheme to improve the diversity of color, while [22], [23] predict per-pixel colors distribution instead of a single color. Still, the results of these methods typically suffer from visual artifacts such as color bleeding and color washout. Also, the quality may significantly deteriorate when colorizing objects that are out of the scope of the training data.

III. Proposed Method

A. Our proposed framework

In contrast to the image restoration and image colorization task, antique photo retouching is more challenging. Old photos contain a complex mixture of various degradations. It is also difficult to learn a direct mapping from monochromatic corrupted images domain to target clean images domain. Thus, despite the rapid progress in individual task, the research solving restoration and colorization in a unique framework is less explored. In this work, we focus on solving the combined task of restoration and colorization.

We formulate the antique photo retouching as an image translation problem. However, opposed to general image translation of bridging two domains which trouble with far mapping, we learn mapping across three domains: the old photo domain $\mathcal{X}$, the gray-scale photo domain $\mathcal{Y}$ and the corresponding target domain $\mathcal{Z}$. We denote the images from three domains with $x \in \mathcal{X}$, $y \in \mathcal{Y}$ and $z \in \mathcal{Z}$, where x, y and z [are paired together], y is inferred from z by converting them to gray-scale and x is degraded from y.

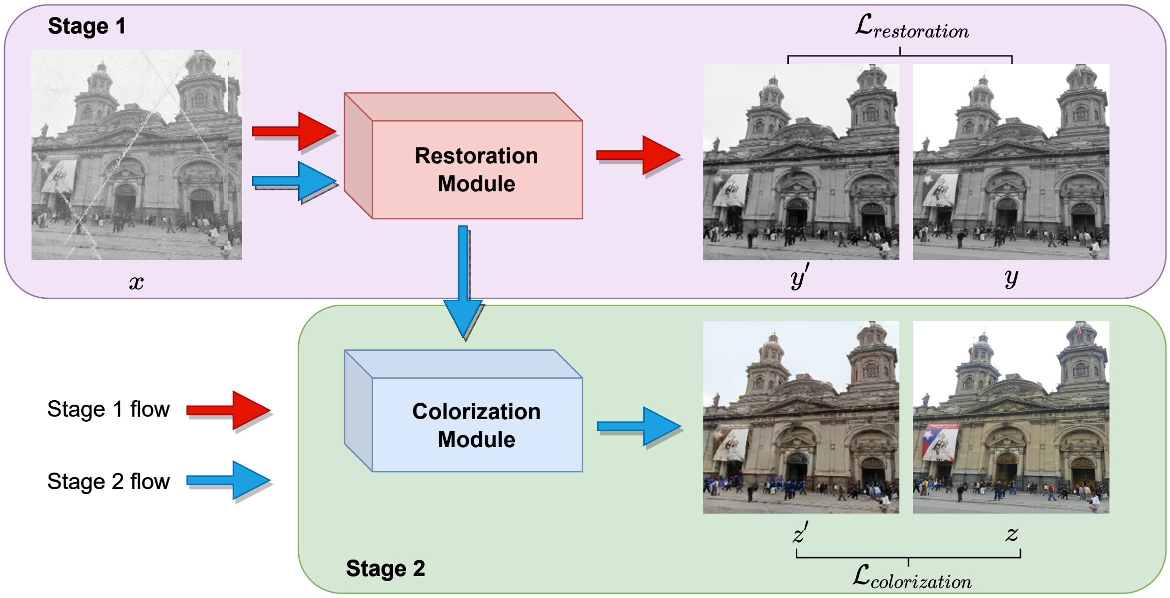

Fig. 2. Our proposed two-stage AIRC framework that leverages generative models to restore and colorize antique images. In the first stage, we train the restoration module to remove the degradation in old photos. Then, in the second stage, we employ it to restore images used for training the colorization module.

As mentioned in [24], Due to the shortage of baseline methods for image retouching, such previous work sequentially applies state-of-the-art methods for each of image restoration and image colorization, respectively. For a more rigorous description, instead of learning a direct mapping from old images $\{x\}_{i=1}^{N}$ to clean color images $\{z\}_{i=1}^{N}$, they propose to decompose into two stages: Restoration $T_r : \mathcal{X} \mapsto \mathcal{Y}$ and Colorization $T_c : \mathcal{Y} \mapsto \mathcal{Z}$ as visualized in Figure 1-a. They simultaneously learn mapping T_r and T_c by utilizing the data pair $\{x, y\}_{i=1}^{N}$ and $\{y, z\}_{i=1}^{N}$, respectively. At inference time, the first map images from domain $\mathcal{X}$ to domain $\mathcal{Y}'$, where $\mathcal{Y}'$ is predicted restored images domain. Then translate $y' \in \mathcal{Y}'$ to the target image z. However, this method experiences *domain drift* problem, although both domain $\mathcal{Y}$ and $\mathcal{Y}'$ share a similar appearance, The restored images y' may contain some degradations. Besides, neural networks are very sensitive to image quality and deep learning model could suffer from a severe performance drop on corrupted images [25], [26]. Therefore, the existing degradations in y can affect the feature extractor in the colorization module and the quality may significantly deteriorate.

To tackle the domain drift problem, instead of acquiring T_r and T_c concurrently, we first learn the mapping T_r, then learn the mapping $T_{c'} : \mathcal{Y}' \mapsto \mathcal{Z}$ The domain mapping of our method is illustrated in Figure 1-b. We have a similar inference phase to the previous phase, the old photos can be restored by sequentially performing the mappings:

$$T_{\mathcal{X} \to \mathcal{Z}} = T_r \circ T_{c'} \tag{1}$$

Our framework is illustrated in Figure 2, it consists of two main modules: image restoration and image colorization.

Restoration module takes the responsibility to remove defects in old photos like sepia effect, film grain, and filling in the damaged areas of scratches and blotches. We leverage the approach of Wan et al. [6], which is a state-of-the-art method for image restoration task. It is specifically designed to address both structured and unstructured degradations.

Colorization module accounts for transforming a grayscale image into its color version. Although there are many approaches for colorizing images as mentioned in Section II-B, we only choose learning-based models to guarantee the automaticity of our framework. We evaluate several colorization techniques to select the appropriate method for our framework. Section IV-B explains in detail the selection process.

Our two-stage training scheme is illustrated in Figure 2. In the first stage, we train the restoration module to learn the mapping T_r using paired data $\{x, y\}_{i=1}^{N}$. In the next stage, we leverage the trained mapping T_r to translate all training the old photos x to the restored photos y'. Then, we utilize the paired data $\{y', z\}_{i=1}^{N}$ to train the colorization module.

B. Realistic degradation model

Training data is the most difficult obstacle preventing the direct application of restoration models to real old photos. Due to the fact that the majority of restoration models rely on synthetic datasets, they fail when applied to the real world situation if the generated dataset cannot simulate the actual antique photos. The previous methods often utilize Gaussian white noise to synthesize film grain; employ Gaussian blur, Box blur, and JPEG compression to reduce the image quality; and randomly remove some regions to simulate the photo damage. However, the pseudo data produced by these techniques is discrepant from the real old photos. Therefore, we introduce a synthesized old photos dataset that resembles real old photos. Code for generating pseudo data is available at https://github.com/manhkhanhad/AntiquePhotoRestoration

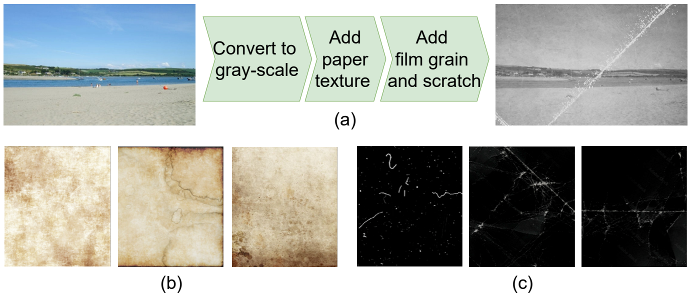

Fig. 3. Sub-figure 3-a illustrates the realistic degradation model: images are first converted to gray-scale then blended with paper and scratch texture. The sub-figure 3-b, 3-c exhibit disordered paper texture and rain and scratch textures, respectively.

The realistic degradation model consists of three main steps as illustrated in Figure 3:

1) Gray-scale conversion: To mimic the monochrome of antique photos, we first convert the RGB color image into gray-scale image using the equation:
$$G = 0.299R + 0.587G + 0.114B$$
2) Paper and old photo texture addition: From the observation that the real antique photos often have the appearance of blotches and splatter that are challenging to simulate by simple image processing techniques. We collect a set of 50 damaged texture images and then random crops, blend them with the gray-scale image. Some samples of disordered paper textures are shown in Figure 3-b.
3) Noise and scratch artifact addition: In the prior model, the film grain as pepper noise and the distribution are based on Gaussian, but in reality, film grain has various shapes and distribute randomly. Besides, the earlier works do not take scratch into account. We model this distortion by adopting the hand-designed film grain and scratch textures as displayed in Figure 3-c. Then we mix them with the result image from the previous stage.

IV. Experiments

A. Training dataset and settings

We employ a subset of $8,266$ training and 200 testing images from the Google Landmark v2 dataset [27], which mainly contains landscape and building images. Then we apply the degradation model introduced in Section III-B. Besides, since the restoration model of Wan et al. [6] requires the involvement of real old photos, we collect 600 images from the Library of Congress [28]. We establish all the experiments on a single GTX 2080 Ti GPU. The models are trained for 200 epochs with learning rates as recommended by the authors [6], [29], [30].

B. The choice of Restoration and Colorization module

We evaluate the mixed degradation model Pix2Pix [29] and the model of Wan et al. [6] for restoration tasks on the pseudo antique photos and select the best one to apply in our proposed image retouching framework. We use Peak-Signal-to-Noise Ratio (PSNR) to estimate the pixel-wise difference between the restored image and the ground truth; the Structural Similarity Index (SSIM) [31] and Learned Perceptual Image Patch Similarity (LPIPS) [32] for evaluating the difference in the image structure. The quantitative results are presented in Table I. The PSNR score of Pix2Pix is 23.75, higher than [6] whose score is 22.37 and turns out to be superior at restoring details. On the other hand, [6] outperforms Pix2Pix in terms of structure evaluated by SSIM and LPIPS being 0.83 and 0.13, respectively.

TABLE I
THE QUANTITATIVE RESULTS OF PIX2PIX [29], WAN ET AL. [6] FOR RESTORATION TASK AND PIX2PIX [29], DEOLDIFY [6] FOR COLORIZATION TASK.

Task	Model	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
Restoration	Pix2Pix [29]	**23.75**	0.80	0.145	-
	Wan et al. [6]	22.37	**0.83**	**0.13**	-
Colorization	Pix2Pix [29]	22.48	0.88	-	82.81
	DeOldify [30]	**25.17**	**0.92**	-	**67.46**

Similar to the choice of restoration module, we evaluate DeOldify [30] and Pix2Pix [29] on gray-scale and color paired dataset $\{y, z\}$ for finding out the best model for the colorization module. Since Pix2Pix is a general framework for image-to-image translation, it can handle a variety of problems, including both image restoration and image colorization. Pix2Pix framework for image colorization uses Lab colorspace instead of RGB, it predicts the ab channel from the L channel and achieves satisfactory results. we adopt PSNR and SSIM for estimating low-level discrepancy between the result and target images, and Frechet Inception Distance (FID) [33] that calculates the distance between the feature distributions of the final outputs and the real images. Qualitatively, DeOldify outperforms Pix2Pix in terms of PSNR, SSIM, and FID (i.e. 25.17 vs. 22.48, 0.92 vs. 0.88, and 67.46 vs. 82.81, respectively).

C. Our Full Framework - AIRC

From the results demonstrated in Section IV-B, we apply the method of Wan et al. [6] as our restoration module because it performs better than Pix2Pix in general restoration. DeOldify [30] is selected to be the colorization module since it is the superior at colorization task. We train two modules based on our framework as described in Section III-A. Then, we evaluate our framework on both synthesized and authentic old photos, the results are displayed in Figure 4. The result shows that our framework can remove both unstructured artifacts such as film grain, dust spots and structured artifacts like scratch, blotches. Since our training approach narrows the gap between the training set and the test set of the colorization module, the colors of the result images are more plausible.

D. Ablation Study

This section investigates the influence of the *domain drift* problem in details. We first restore the antique photos by model of Wan et al. [6], then pass the restored images through a

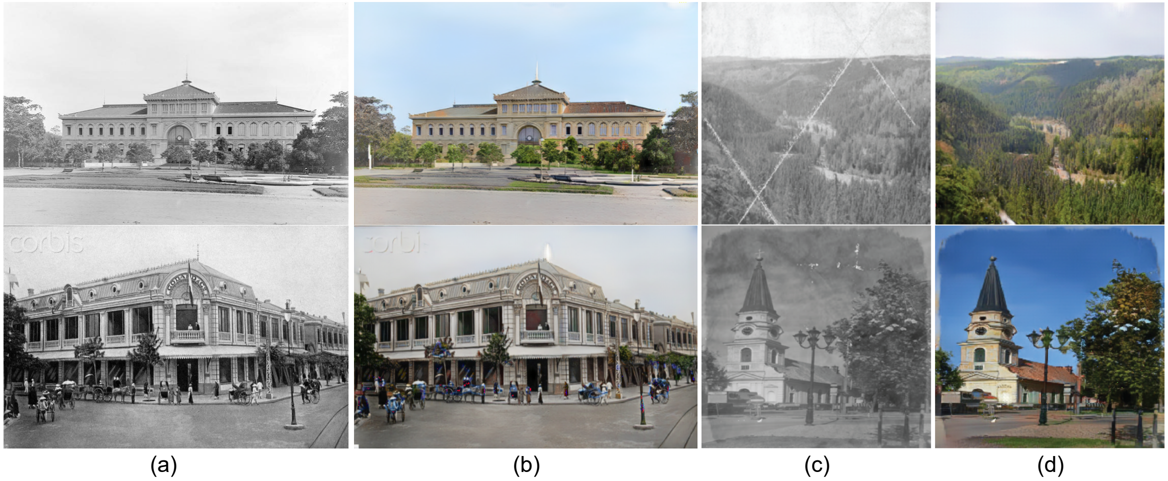

Fig. 4. Exemplary results of our proposed Antique photo restoration and colorization framework. Columns (a) and (c) are real antique photos and pseudo synthetic old photos, respectively; Columns (b) and (d) are their corresponding restored and colorized versions.

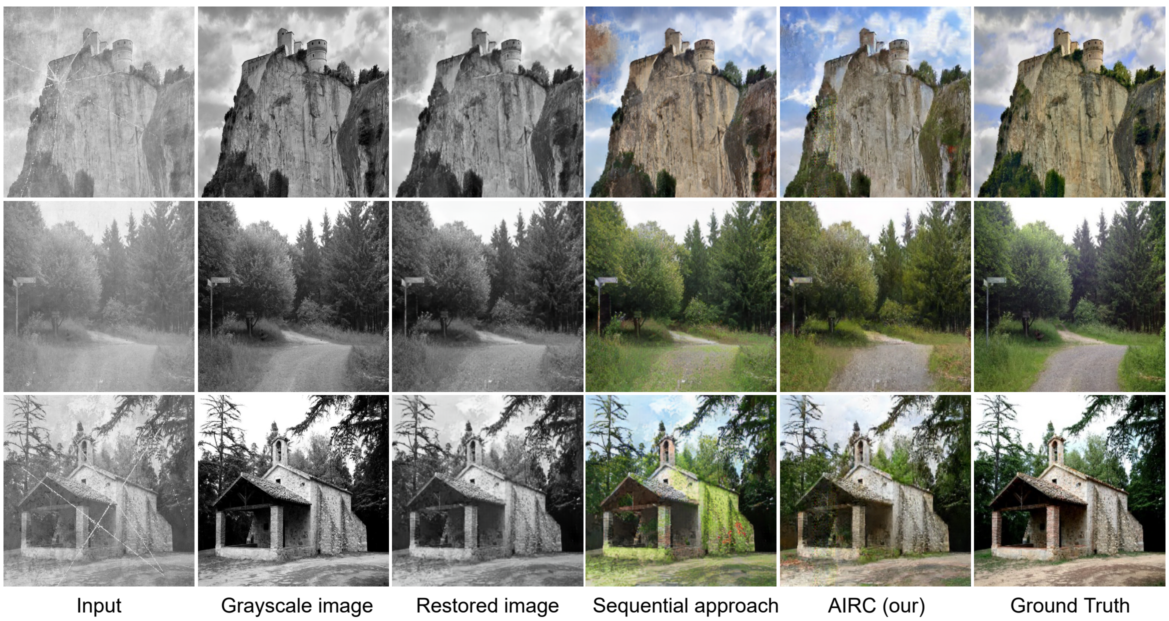

Fig. 5. Visualization of the results in the Ablation study. The Sequential approach trains restoration module and colorization module in an individual manner. Our proposed AIRC first trains the restoration module, then uses the restored image for training the colorization module. Best view with color.

colorization module (i.e. Deoldify [30]) which was trained in different manners such as the Sequential approach and our proposed method - AIRC. In the former approach, the colorization module was trained on a pair of a gray-scale image and a color image $\{y, x\}$. While in the latter approach, the pair of a restored image y' and a clean image z are employed to train the colorization model to avoid the domain drift problem.

TABLE II

THE QUANTITATIVE AND USER STUDY RESULTS OF SEQUENTIAL APPROACH AND OUR PROPOSED AIRC

Method	PSNR ↑	SSIM ↑	User study ↑
Sequential approach	20.11	0.77	28.5 %
AIRC	20.31 (+0.2)	0.73 (-0.04)	71.5 %

The qualitative results of our ablation study is shown in Figure 5. In Figure 5, it is obvious that the result images of our proposed AIRC outperform the counter Sequential approach. In the first row, since the restoration model can not remove the distortion completely, the remaining artifacts in the sky confuse the colorization model which was trained by the Sequential approach due to the domain drift problem. Therefore, the result is the inappropriate images. Meanwhile the colorization model trained with our proposed approach can learn how to resolve these remaining degradations and yield better results. We also report the quantitative results in Table II. The results show that our AIRC framework is better than the Sequential approach in degradation removal. The SSIM of our AIRC and the Sequential approach are 0.73 and 0.77, respectively. However, our AIRC has higher PSNR than the Sequential approach.

As mention before, since image colorization is an ill-posed problem, it is difficult for the quantitative evaluation. Thus, we carry out a user study to compare our proposed approach with the previous Sequential approach to better illustrate the subject quality. We randomly chose 15 images from the test set and performed restoration and colorization by the two approaches. We then ask 40 participants including students and teachers in the field of computer science to choose the better result for each testing sample. Then, we collect the opinions and estimate the proportion of each approach. The results are shown in Table II, our AIRC received more preference from users with 71.5% voting over 28.5% of the Sequential approach.

V. Conclusion

In this work, we propose a novel end-to-end framework - AIRC, for Antique Image Restoration and Colorization utilizing generative models. Compared to the previous works on antique image retouching which only restore or colorize images, our novel framework can address these tasks simultaneously. Before proposing an effective approach, we point out that the Sequential scheme for combining restoration and colorization models suffers from the issue of domain drift. In addition, we introduce OldifiedScenes, a new pseudo-old photos dataset similar to the real photos which can narrow down the gap between the training data and the real-world old images. In the future, we plan to develop a single stage framework for more convenient and productive image restoration and colorization.

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