SUPPLEMENTARY MATERIAL (NEURAL RESTORATION OF GREENING DEFECTS IN HISTORICAL AUTOCHROME PHOTOGRAPHS BASED ON PURELY SYNTHETIC DATA)

Anonymous submission

Submission ID : 1638

1. RESTORATION OF GREENING DEFECTS WITH PHOTOSHOP

1.1. Generative Fill

To remove the greening defects using the ”Generative Fill” feature, we first annotated the defects using the lasso tool. We left the prompt empty to ensure that the restoration relied solely on the underlying image structure and context. Following a brief generation process, we evaluated the three variations of the filled area, selecting the most appropriate one. Our assessment revealed that while plausible results were achieved over stationary textured regions, specific structures were altered, and larger defects could not be entirely removed.

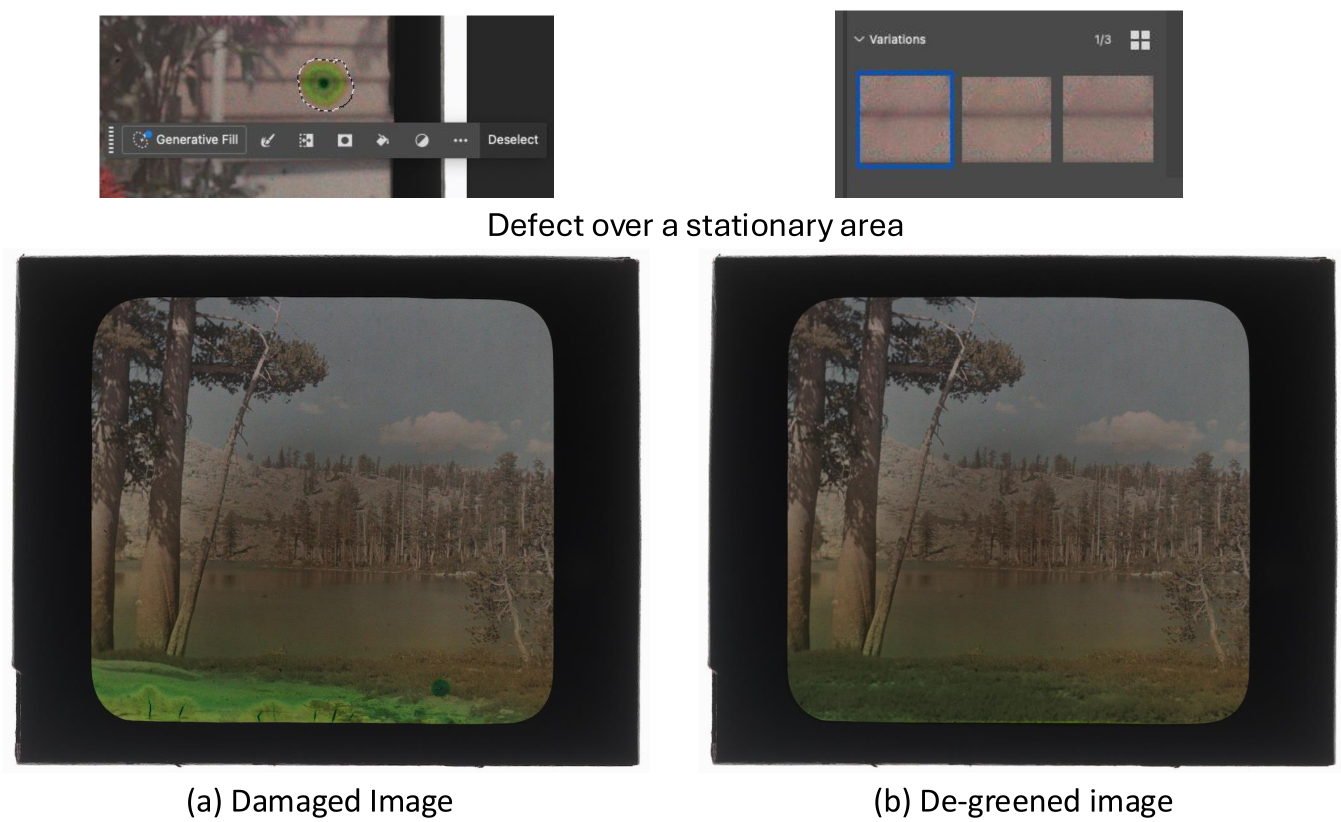

Fig. 1. Restored regions of greened defects using the Generative Fill method of Photoshop

1.2. Manual method

To optimize greening defects, we used the ”Channel Mixer” under ”Adjustments.” The default values are set to 100 percent for the respective color value of the output channels. We lowered the green output value to 70 percent and slightly increased the blue and red values. We adjusted for orange outer rings of defects individually and applied feathering on the layer mask for smooth transitions. A manually corrected version of the image is shown in Figure 2.

(a) Damaged Image　　(b) De-greened image

Fig. 2. Greening defect corrected using Photoshop (Manual method)

2. DATASET

Some example non-defected autochromes of the Harold Taylor collection are presented in Figure 3.

Fig. 3. Example autochromes of the Harold Taylor collection without defects

2.1. Color histograms

The color channels of an image are highly correlated signals, often represented as color histograms, where intensity values are plotted on the x-axis and the corresponding pixel counts on the y-axis. Histograms help identify color imbalances and characterize an image's colors. Color balancing can be achieved by applying different scale factors to each channel. Histogram equalization seeks to map intensity values to a desired color distribution. It is crucial to ensure that scaling does not amplify image noise during this process. An example histogram for an image in the Harold Taylor collection is shown in Fig. 3

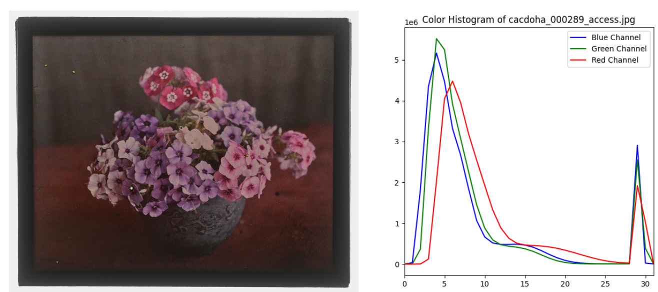

Fig. 4. Color histogram of an example image in the Harold Taylor collection

2.2. Fast Fourier Transform

The Fast Fourier Transform (FFT) converts images from the spatial to the frequency domain, revealing structures and patterns that may not be visible in the spatial domain. Figure 5 illustrates the FFT for an example image in the dataset.

3. SYNTHETIC DATA GENERATION

The dictionary used for generating synthetic defects v2 is presented in Algorithm 1. Area and spot-shaped defects are created by generating ellipses, which are distorted by random adjustments to their boundary radii. Point defects originate within the autochrome and are always point-shaped, while some larger defect areas are represented by larger ellipses with origins outside the image. This simulates liquid leakage outside the autochrome that damages it upon entry.

Fig. 5. Fast Fourier transform (FFT) of an example image in the Harold Taylor collection

Algorithm 1 Dictionary for Color Channel Adjustments

Ring ID	**Modification Values**	**Description**
9	[0.6, 0.85, 1.05]	Outer orange ring
1	[0.5, 1.2, 0.8]	Light green ring
2	[0.4, 0.8, 0.6]	Middle ring
3	[0.4, 0.8, 0.6]	Middle ring
4	[0.2, 0.6, 0.1]	Dark green second
99	[0.2, 0.2, 0.1]	Dark middle area
20	[0.4, 0.95, 0.6]	Large defect area

A comparison of the different types of synthetic defect (v1 and v2) and corresponding real defects are presented in Figure 6.

Synthetic greening defect (v1): In the initially generated dataset (v1), defects were simulated by applying photography color filters, specifically using green filters on the foreground layer to create defects, represented by the equation:

$$D(x, y) = F_g(x, y) \cdot \alpha + B_a(x, y) \cdot (1 - \alpha) \tag{1}$$

where $D(x, y)$ is the resulting defect image, $F_g(x, y)$ is the foreground layer with the green filter applied, $B_a(x, y)$ is the autochrome background layer, and α is the blending factor ($0 \leq \alpha \leq 1$). The green filter is resized to match the autochrome dimensions, with slight random brightness adjustments. Opacity values of the defects are interpolated to reflect the natural flow of liquid, decreasing in intensity from one corner to the opposite, with a base alpha value randomly selected between 0.3 and 0.6. These values, along with the opacity gradient and defect mask, are combined through multiplication. Finally, the prepared green filter is merged with the autochrome using the composition formula using equation 1, and the centers of the spot-shaped defects are darkened to emphasize the characteristic dark core.

4. RESULTS

An overview of the algorithms used for evaluation is presented in Table 1. The user interface of the De-greening application is presented in Fig. 11.

4.1. Qualitative results

Figure 8 displays the degreening results using v1 of the dataset. The results indicate that the degreening process does not target the correct regions. Consequently, we updated our dataset and opted for a channel-based algorithm for color correction. Figure 9 presents selected autochrome results obtained using chair_v2_transfer for qualitative analysis.

4.2. Post-processing using Photoshop

The post-processed results of Photoshop using our output are shown in Fig. 10. The results confirm that it is possible to restore the greening defects effectively using de-greened results of the chair_v2_transfer model.

4.3. Effectiveness of deep learning in restoration of greening defects

Deep learning methods, particularly the trained ChaIR models, effectively detect areas with greening defects in autochrome images, removes the greening in those regions while preserving the underlying structures.

4.4. Comparison with manual approaches

After training, the deep learning model becomes easier and more versatile to use, enabling quicker trial runs on images, although user influence on the results remains limited. Manual fine-tuning can be done afterward with tools like Photoshop. Adobe Photoshop's "Generative Fill" tool excels in handling small, unstructured defects but struggles with complex areas because it fully regenerates image information. Additionally, the color correction process in Photoshop requires considerable manual effort and skill to effectively address ring structures associated with defects.

4.5. Limitations

The models' performance heavily relies on the quality of the training dataset, as the effectiveness of synthetic datasets directly impacts their performance on real image data. A significant challenge is the limited availability of unaffected autochromes for generating synthetic datasets.

4.6. Outlook

The restoration methods for greening defects discussed in this paper are applicable to other autochrome defects as well. Defects that provide insight into the original appearance, such as oranging and emulsion cracking (illustrated in Figure 7), can be similarly restored using AI-based techniques. However, more severe damages, like large missing areas, present greater challenges. AI can facilitate the restoration of autochromes,

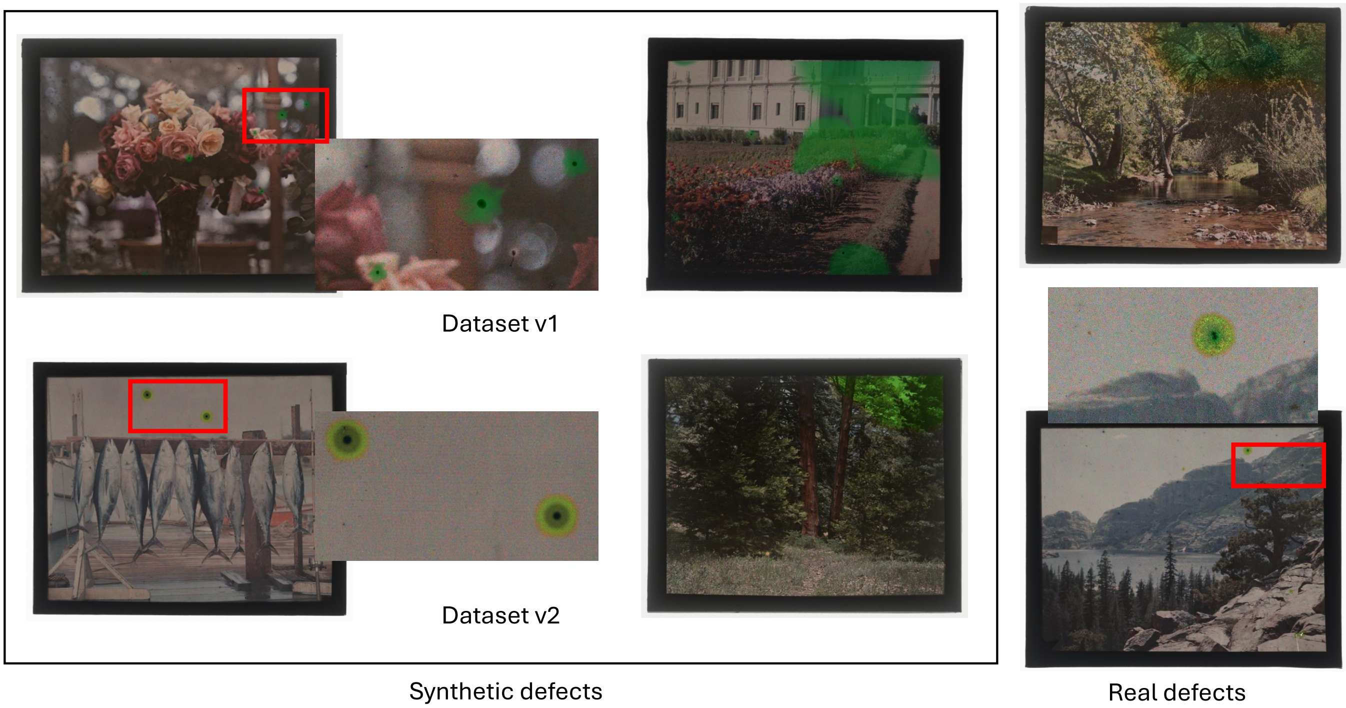

Fig. 6. Examples of synthetic defects (v1 and v2) and real defects

Table 1. Overview of conducted experiments

Method	**Dataset**	**Training Parameters**	**Experiment Name**
Photoshop	real greening samples	"Generative Fill" method	ps_genfill
Photoshop	real greening samples	manual color correction method	ps_mancc
Pix2Pix [1]	v1	changed discriminator architecture	p2p_v1_netdpixel
CycleGAN [2]	v1	default parameters of the used repository	cg_v1_default
ChaIR[3]	RESIDE-indoor [4]	provided pretrained model on indoor dataset	chair_its_pretrain
ChaIR[3]	RESIDE-outdoor [4]	provided pretrained model on outdoor dataset	chair_ots_pretrain
ChaIR[3]	v1	default parameters of the used repository	chair_v1_default
ChaIR[3]	v2	default parameters of the used repository	chair_v2_default
ChaIR[3]	RESIDE-outdoor + v2	transfer learning using the pretrained outdoor model	chair_v2_transfer
ChaIR[3]	v2	customized loss function, which weights defect areas twice	chair_v2_loss2
ChaIR[3]	v2	customized loss function, which weights defect areas by a factor of ten	chair_v2_loss10

which can then be fine-tuned using tools like Adobe Photoshop. The restored images enhance the viewer's understanding of the photographer's intentions and provide insight into the historical context of autochromes. It's important to recognize that greening defects represent a significant historical aspect of the autochrome era, stemming from the technology of the time. Therefore, artworks with defects should always be displayed alongside their restored counterparts.

5. REFERENCES

[1] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in *CVPR*, 2017, pp. 5967–5976.

[2] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *ICCV*, 2017, pp. 2242–2251.

[3] Y. Cui and A. Knoll, "Exploring the potential of channel interactions for image restoration," *Knowledge-Based Systems*, vol. 282, 2023.

[4] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, and Z. Wang, "Benchmarking single-image dehazing and beyond," *IEEE Trans. Image Process.*, vol. 28, no. 1, pp. 492–505, 2019.

(a) Oranging (a) Emulsion cracking

Fig. 7. Other types of defects in autochromes

(a) Original Image (b) result (c) cg_v1_default (c) cg_v1_default

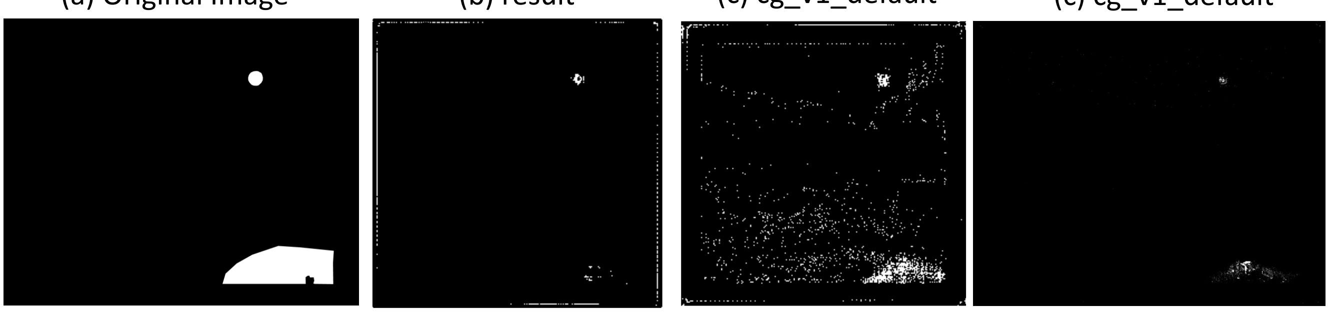

Fig. 8. De-greened results of models trained on version 1 dataset

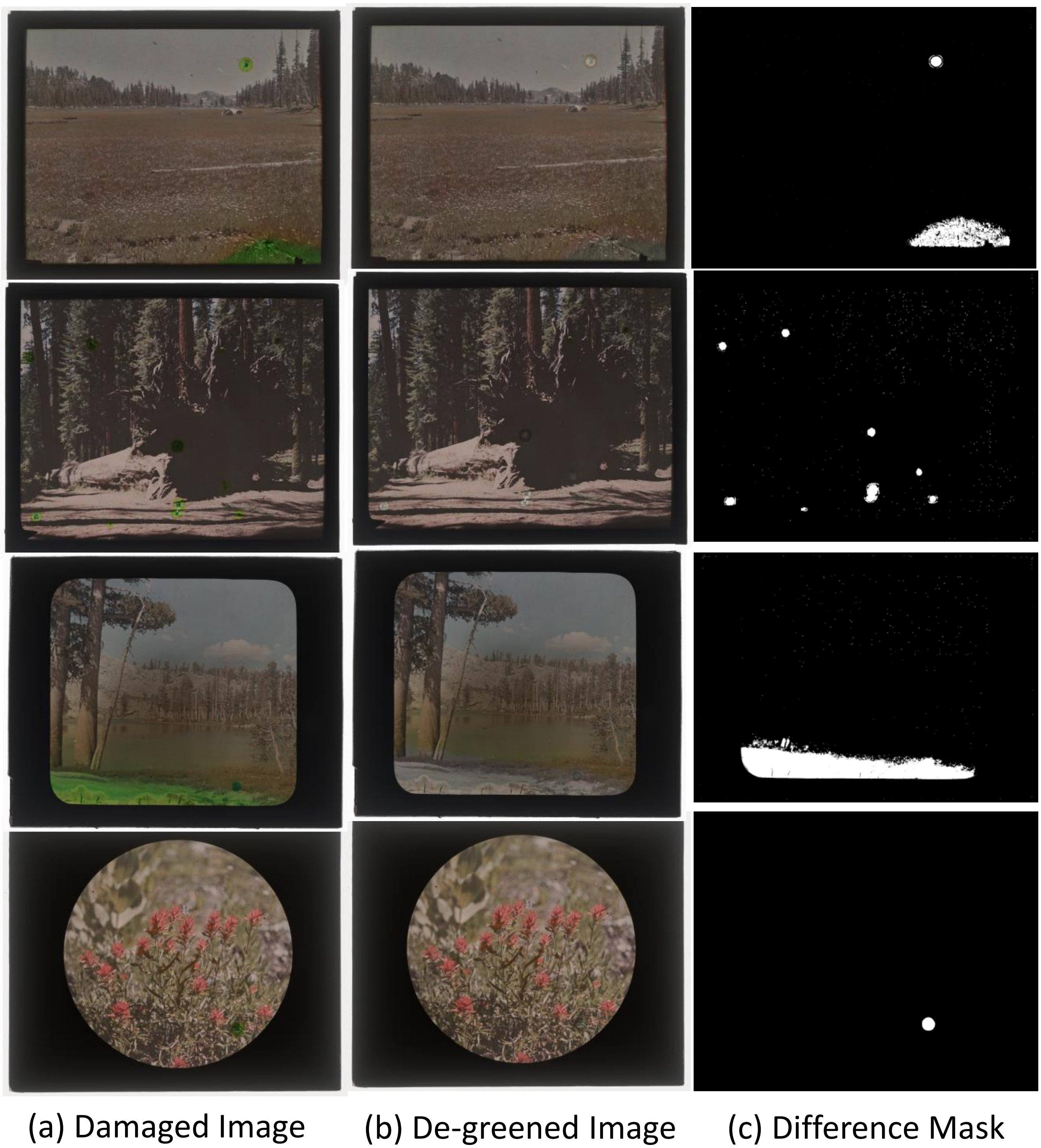

Fig. 9. De-greened results using the chair_v2_transfer model

Fig. 10. Images corrected by Photoshop utilizing the De-greened result

Fig. 11. User interface of the De-greening application