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Preserving Artistic Legacy: A Frame-Guided Approach for Color Recovery in Aged Tangka Paintings

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Abstract: Over time, the colors in old Tangka paintings can fade due to various factors, including exposure to light, air pollution, humidity, and dust deposition. Interestingly, the frame acts as a physical barrier between the artwork and its surroundings, offering some protection against the harmful factors that contribute to color fading. In this paper, we propose a novel approach to recover the faded colors of Tangka paintings by leveraging the visual cues provided by the frame-covered area. Our method involves the development of an interactive annotation pipeline and the utilization of histogram matching for color restoration. We applied this approach to faded, aged Tangka paintings in Palace Museum's collection and achieved visually plausible color recovery, even for intricate patterns that are challenging to restore manually.

Keywords: tangka conservation; color recovery; color space analysis

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1. Introduction

Over time, the colors in old paintings can fade due to various factors such as exposure to light, air pollution, humidity, and dust deposition. The pigments used in the paints may be sensitive to these environmental factors, causing them to deteriorate or change in appearance. Light, particularly ultraviolet (UV) light, is one of the primary causes of color fading in paintings. Exposure to sunlight or strong artificial light sources over an extended period can accelerate the fading process. Pigments made from organic materials or certain inorganic pigments are especially prone to fading. Art conservators and restorers often employ various techniques to help restore faded colors in old paintings. These methods such as Marczak et al. (2008); Pei et al. (2004) may include careful cleaning, inpainting, or retouching to reintroduce lost or faded colors while preserving the original aesthetic and historical integrity of the artwork. Specifically for Tangka, commonly adopted approaches for protection and restoration involve processes such as dust removal, reinforcement, stitching, and reshaping. Museums and institutions working on this field adhere to principles such as *maintaining the original state* and *minimal intervention*. Additionally, the restoration process must be *reversible*. Therefore, the restoration of missing elements and the fading colors in Tangka relies on virtual simulation or manually crafted replicas.

In many scenarios, frames can provide some level of protection to paintings by shielding them from direct light, dust, and other environmental elements (as shown in Figure 1). The frame creates a physical barrier between the artwork and its surroundings, helping to reduce exposure to harmful factors that can cause color fading. Frames can be constructed in a way that covers the edges of the painting, known as a "frame rabbet." This design choice ensures that the edges of the painting are not exposed to light or air, offering some degree of protection against fading or deterioration. By covering the edges, the frame helps to create a controlled environment for the artwork within. In this work, we make two assumptions. Firstly, we assume that the area protected by the frame is well preserved and consider its color as the original color of the artwork. Secondly, we assume that the areas not covered by the frame have faded uniformly due to evenly distributed harmful environmental factors and elements.

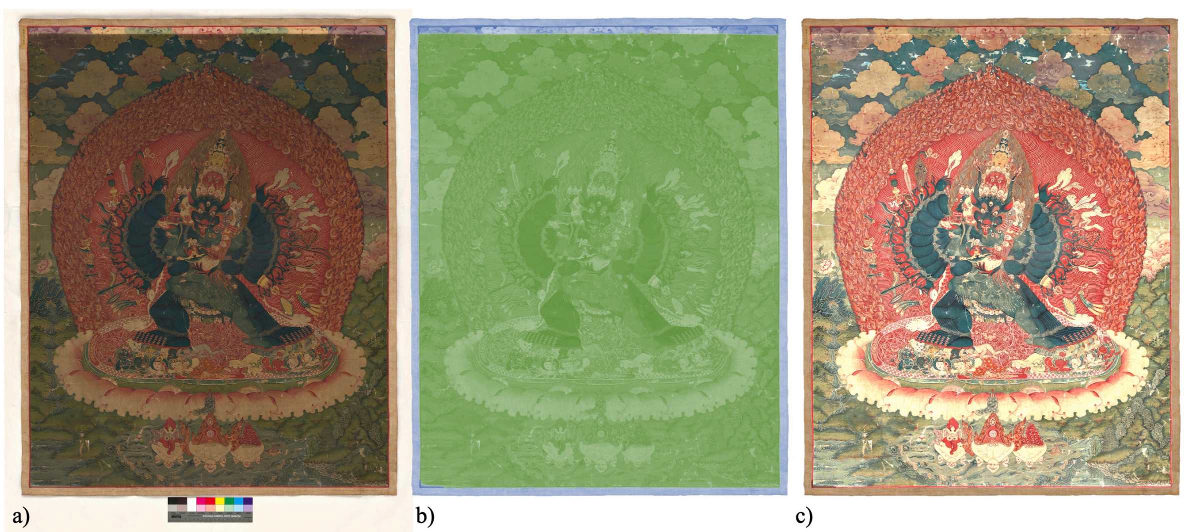

Figure 1: Starting from a scanned Tangka image (**a**), the frame-protected area (blue) and color faded area (green) is manually annotated in (**b**). Our method recovers the color faded area guided by the frame-protected area as shown in (**c**).

To recover the color of the faded areas, we leverage the visual cues preserved by the frame's coverage. Specifically, we learn the histogram distribution of the color in the frame-protected area and apply linear mapping to align the histogram of the non-protected area (Hertzmann 2001). However, as the content may vary significantly across different areas of the painting, a universal color transfer approach may introduce bias from the content of the frame-protected edge region. To address this challenge, we developed an interactive annotation workflow that allows users to mark corresponding regions of interest (ROI) between the frame-protected area and the rest of the painting. Each correspondence will produce a specific color mapping. Different mappings will be blended linearly for each pixel based on the similarity score from the target pixel to the annotated correspondences.

We validate our method with Tangka paintings from the collections of the Palace Museum where the edge preserved by the frame is a very common scenario. The Tangka paintings are mostly from the Hall of Mental Cultivation. The Hall of Mental Cultivation served as Emperor Qianlong's private Buddhist shrine, signifying its importance as it was established within the Emperor's sleeping palace. The hall was renovated and Tangka paintings were first hung in the twelfth year of Qianlong's reign (1747), and it has a history of over 270 years to this day. The fabrics used to mount these Tangka paintings are exceptionally exquisite, but some of the woven borders have detached, separating from the central painted portions. This allows for the observation of the original colors of the concealed parts of the artwork (Fang 2021). We show that our approach produces visually plausible and theoretically tractable results on their collection. Furthermore, a user study indicates our solution may significantly improve the efficiency comparing to manual color adjustment.

2. Related Work

Tangka conservation Tangka, a religious scroll painting on colored silk with pigments or other materials, is a distinctive form of art with strong local characteristics (Jia et al. 2021). The structure of Tangka demands precision in depicting religious portraits, requiring strict adherence to facial features, head, chest, waist, and other elements. As a result, Tangka painters often undergo years of practice to master this intricate art form, making the preservation of Tangka paintings a challenging endeavor. Unfortunately, the well-maintained Tangka paintings are dwindling in number due to the detrimental effects of humidity, water stains, mildew, and dirt. The Palace Museum houses over 2,000 Tangka paintings in its collection. Currently, some of these Tangka paintings are stored in the museum's storage facilities, while others remain on display in their original settings within the palace, maintaining their presentation as it has been since the Qing Dynasty. These Tangka paintings themselves have experienced aging, including fabric deterioration, pigment loss, and fading, compounded by various preservation-related issues, making the task of protection and restoration extremely challenging. To resolve this issue, researchers have explored both digital and physical methodologies in recent years to better preserve these valuable artworks, such as Fan (2015). Additionally, advancements in machine learning technologies have opened up avenues for content analysis, enabling a deeper understanding of Tangka paintings (Chen et al. 2021). By combining traditional conservation techniques with modern innovations, efforts are being made to ensure the safeguarding of Tangka paintings for future generations.

Image style transfer Image stylization techniques have been extensively explored in the fields of computer vision and graphics over the years. In the early stages, the focus was primarily on example-based approaches, such as Image Analogies (Hertzmann et al. 2001), leveraging patch-level texture synthesis algorithms (Efros and Leung 1999). Image Analogies introduced a stylization method based on a reference painting, allowing for color preservation and separate stylization control for different regions. The technique utilized a coarse-to-fine texture synthesis process to improve speed. Since then, there have been advancements in optimization methods, and novel applications (Ramanarayanan and Bala 2006) have been proposed. Patch-based methods have also integrated CNN features (Champandard 2016), leading to enhanced texture representations and better stylization outcomes. More recently, Neural Style Transfer (Gatys et al. 2016) has showcased remarkable results in example-based image stylization. This approach relies on a parametric texture model defined by summary statistics on CNN responses and offers several advantages over patch-based synthesis. Notably, it demonstrates greater flexibility during the stylization process, enabling the creation of new image structures that might not exist in the source images.

3. Methodology

In this section, we describe our algorithm for color recovery of an aged fading Tangka painting guided by the frame-protected area. Given a scanned Tangka painting, $\mathcal{T}$, as shown in Figure 1a, we denote frame covered area as $\mathcal{T}_A$ and the rest as $\mathcal{T}_B$. We manually segmented the scanned painting into $\mathcal{T}_A$ and $\mathcal{T}_B$ (Figure 1b) via the selection algorithm from image editing tools, e.g., Quick Selection Tools of Photoshop (Adobe Software 2021). Assume the value of a pixel in location $\omega \in \mathcal{T}_B$ is p_ω, our goal is to find a mapping $\mathbf{f} : \mathbb{R}^3 \mapsto \mathbb{R}^3$ so that $\mathbf{f}(p_\omega)$ recovers the fading artifacts in area $\mathcal{T}_B$ (Figure 1c). Without loss of generality, we choose RGB (Joblove and Greenberg 1978) color space for appearance modeling. Since the color fading of the painting is a comprehensive process which cannot be physically correctly modeled by any existing color space models, e.g., HSV (Huang and Liu 2007) or CMY (Baqai et al. 2005), we observe that RGB color space is proved to be more suitable for our task (Section 4) comparing to other alternative options.

3.1. Linear Histogram Mapping

We formulate the color transfer problem as a linear mapping of the color space. The color value of one pixel in the scanned image can be understood as a 3D vector. Therefore, the pixels in $\mathcal{T}_A$ are represented a set of 3D points colored by green and the pixels in $\mathcal{T}_B$ are another set of 3D points colored by blue. As shown in Figure 2, due to the color fading, the 3D point cloud in blue is naturally not overlapped with the point cloud in green. Intuitively, our goal is to find a mapping that aligns the blue points with distribution of green one, resulting in the red points.

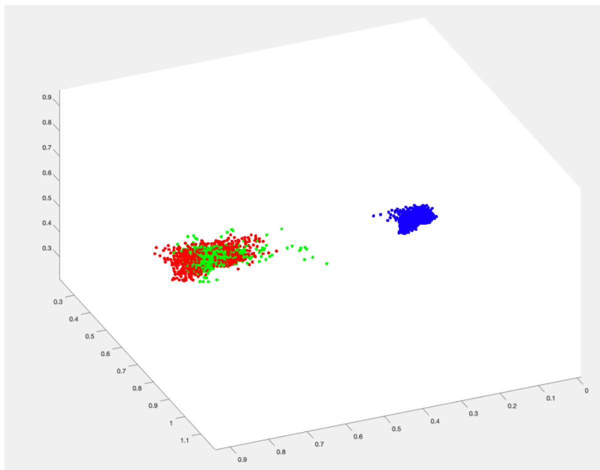

Figure 2: Linear histogram mapping. Starting from two distributions blue and green, linear histogram mapping learns a global transformation that transform the blue points into red points so that their distribution is indistinguishable to the green points.

Specifically, given the $p_\omega \in \mathbb{R}^3$ where $\omega \in \mathcal{T}_B$, we want to find a transformation to a new color space $q_\omega = \mathbf{f}(p_\omega)$ so that the new color space have a desired mean and covariance (Hertzmann 2001):

$$mean(\mathbf{f}(p_\omega)|\omega \in \mathcal{T}_B) = mean(p_\gamma|\gamma \in \mathcal{T}_A)$$

and

$$COV(\mathbf{f}(p_\omega)|\omega \in \mathcal{T}_B) = COV(p_\gamma|\gamma \in \mathcal{T}_A)$$

where γ is a location in $\mathcal{T}_A$.

We further assume $\mathbf{f}$ is a linear mapping so that $\mathbf{f}(p_\omega) = \beta p_\omega + \alpha$, we have

$$\frac{1}{n}\sum_\gamma p_\gamma = \frac{1}{m}\sum_\omega \mathbf{f}(p_\omega) = \beta\frac{1}{m}\sum_\omega p_\omega + \alpha$$

and

$$\frac{1}{n}\sum_\gamma(p_\gamma - \frac{1}{n}\sum_\gamma p_\gamma)(p_\gamma - \frac{1}{n}\sum_\gamma p_\gamma)^T = \frac{1}{m}\sum_\omega(\mathbf{f}(p_\omega) - \frac{1}{m}\sum_\omega \mathbf{f}(p_\omega))(\mathbf{f}(p_\omega) - \frac{1}{m}\sum_\omega \mathbf{f}(p_\omega))^T \quad (1)$$

$$= \beta\frac{1}{m}\sum_\omega(p_\omega - \frac{1}{m}\sum_\omega p_\omega)(p_\omega - \frac{1}{m}\sum_\omega p_\omega)^T\beta^T \quad (2)$$

where n, m is the number of pixels in $\mathcal{T}_A$ and $\mathcal{T}_B$, respectively. As a result, we have

$$\beta = (\frac{1}{n}\sum_\gamma(p_\gamma - \frac{1}{n}\sum_\gamma p_\gamma)(p_\gamma - \frac{1}{n}\sum_\gamma p_\gamma)^T)^{1/2}(\frac{1}{m}\sum_\omega(p_\omega - \frac{1}{m}\sum_\omega p_\omega)(p_\omega - \frac{1}{m}\sum_\omega p_\omega)^T)^{-1/2}$$

and the mapping $\mathbf{f}$ can be rewritten as

$$\mathbf{f}(p_\omega) = \beta(p_\omega - \frac{1}{m}\sum_\omega p_\omega) + \frac{1}{n}\sum_\gamma p_\gamma$$

3.2. Similarity-Driven Mapping Blending

Given the fact that the frame covered area is a narrow edge due to the nature of frame structure, the frame-protected content usually does not cover the diversity of the main painting. This introduces a strong bias in the distribution of the pixels in $\mathcal{T}_A$. Applying a global linear transformation **f** as described in Section 3.1 may lead to color shift for content not covered by the guidance, $\mathcal{T}_A$, as shown in Figure 3a).

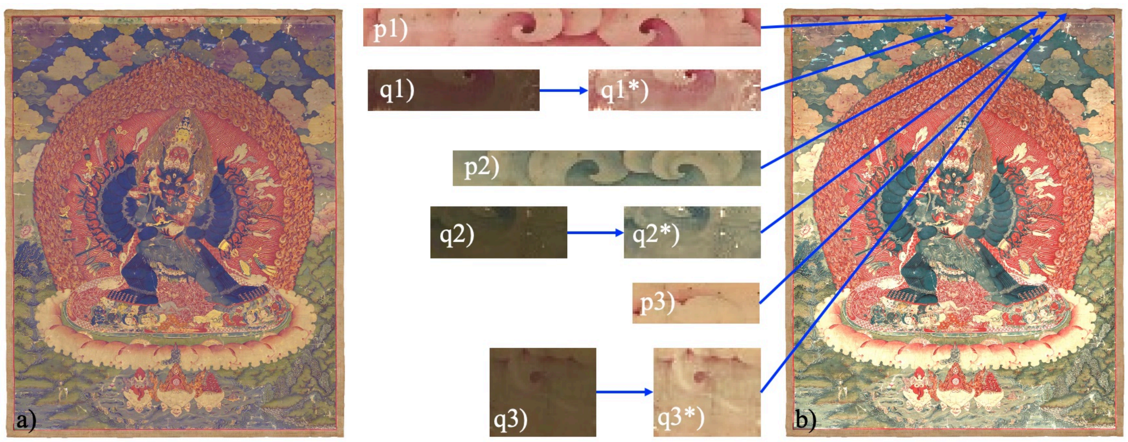

Figure 3: Learning a color transformation globally can be strongly biased by the content variation as shown in (**a**). We adopt patch based solution (**b**), so that the content not directly observed from the reference guidance can still be reasonably modeled.

To mitigate such a bias caused by the limited area covered by the frame, we implemented a patch annotation system which allows the user to select some corresponded patches (p_i, q_i) along the boundary between $\mathcal{T}_A$ and $\mathcal{T}_B$. We learn $\mathbf{f}_i$ for each correspondence so that $q_i^* = \mathbf{f}_i(q_i)$ aligns well with p_i. When processing the pixels in $\mathcal{T}_B$, we blend the mappings $\mathbf{f}_i$ where $i = 1, 2, 3, \cdots$ linearly based on the similarity between the current pixel p_ω and patch q_i. For the sake of simplicity, we calculate the similarity score as the l_2 distance between p_ω and average pixel value in q_i. Our similarity-driven mapping blending technique allows the local mapping better content-aware, therefore, leads to a more plausible outcome.

4. Application

We tested our approach on the scanned Tangka collections from the Palace Museum. We show examples in Figures 1 and 4 to validate our method. Our results are qualitatively plausible as the color of the faded region of the painting is restored vividly. Quantitatively, we also crop a few corresponding patches in Figure 4 along the boundary of frame-protected area for validation purpose and calculate the difference of mean and covariance after the color transfer. We conclude that the error of the validation patch is 0.35% for mean and 0.27% for covariance, which is barely noticeable for human's eye observation.

We further tested our approach with HSV color model, as shown in Figure 5. We adopt a similar setup by using the same patch correspondence as used in the RGB color model. However, we will only align the saturation and value dimension for each pixel while keeping the hue not change. As shown on the Figure 5, HSV model is not capable of capturing such fading phenomena in a plausible manner.

Figure 4: Test case from the collection of Tangka paintings in Palace Museum. A test case from the collection of Tangka paintings in Palace Museum. (**a**) the raw scanning of the Tangka painting; (**b**) the result of our color recovery method.

Figure 5: Applying color correction in HSV color space leads to strong artifacts due to the fading of color is not correctly formulated by HSV color model.

5. Conclusions

In this paper, we described a workflow of color recovery for aged Tangka painting guided by the frame-protected area. We adopt a linear mapping algorithm to adjust the color histogram for frame covered area and uncovered area. Instead of a global linear solution, we enable local linearity to better mitigate the bias caused by content variation across the whole image. Experimental results indicate our approach can generate highly plausible color recovery for faded Tangka paintings. The experimental methods and results presented in this paper provide direct and fundamental references for the current stage of artifact restoration, preservation, replication, and research. They also offer a simulated restoration approach and calculation standards for the future authentic restoration of Tangka paintings.

Limitation and Future work In this work, we treat the color in the frame-protected area as the target for color restoration. However, it's important to note that while frames can offer some protection, fading can still occur over time due to other factors such as ambient light in the room or environmental conditions. To faithfully restore the authentic appearance of Tangka paintings, it is necessary to combine research results from various aspects, including pigment composition analysis, aging experiments, and Tangka aesthetic analysis. Further studies on the fading process for the frame-covered area can be an promising future work direction.

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