Visual Design from Cultural Heritage through Inpainting-based Restoration

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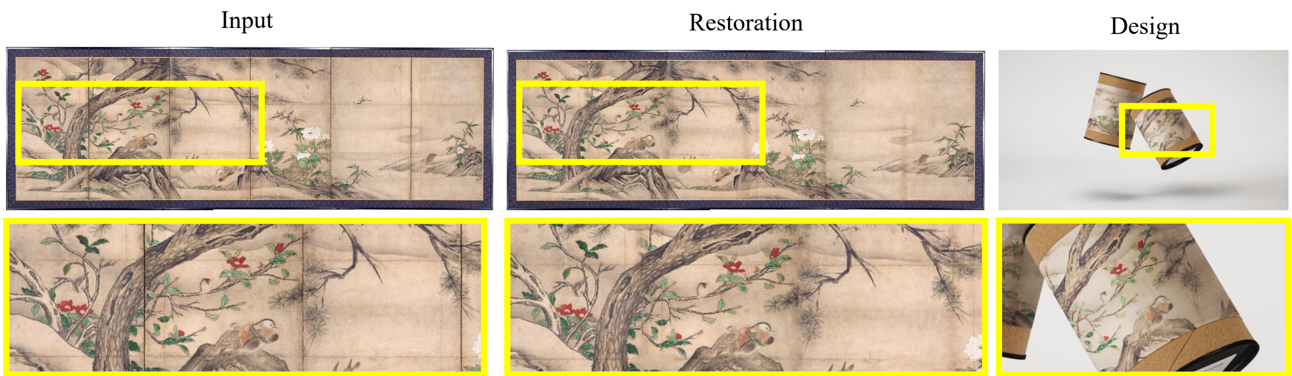

Figure 1. **Cultural product design by our framework.** We restore damaged paintings using inpainting before generating commercial package design.

Abstract

We explore an inpainting-based restoration framework for generating commercial designs from cultural heritage. Cultural heritage artworks often exhibit accumulated damage including surface contamination, color alteration, and physical deterioration, which compromises the quality of generative design outputs when processed directly. Our approach addresses this challenge by preprocessing damaged cultural heritage images through specialized inpainting techniques before applying generative design algorithms. We employ damage-specific restoration strategies that include cleaning to remove surface contamination, coloring to restore the paint layer, and pattern extraction to isolate decorative elements. Through comparative analysis of designs generated from damaged originals versus restored images, we demonstrate that inpainting preprocessing significantly enhances visual quality while preserving cultural authenticity. The restored designs show improved commercial viability and meet contemporary design market standards. This approach bridges historical preservation with modern design innovation, offering market-ready designs that maintain rich cultural resonance in diverse applications.

1. Introduction

Generative models fundamentally transform the digital design and creative industries [5, 7, 9]. Visual design platforms such as Adobe Firefly [1], Canva PatternedAI [3], and MYTH AI [15] revolutionize traditional design workflows, providing up to 70% cost reduction compared to conventional processes [4]. Design platforms have become essential for securing competitive advantages in the textiles, fashion, packaging, and home décor industries [2, 16].

Despite advances in generative design, applying existing systems to cultural heritage presents significant challenges. Historical paintings and cultural artifacts often exhibit accumulated damage over time, including surface contamination, color alteration, physical deterioration, restoration traces, and digital artifacts from scanning or photography. When generative design algorithms process damaged images directly, the generated designs inherit imperfections, compromising both cultural authenticity and aesthetic quality. Inherited flaws distort the original artistic intent and fail to meet contemporary design market standards, ultimately limiting commercial viability.

To address this challenge, we propose preprocessing cultural heritage images with inpainting before applying generative design algorithms. The approach, as shown in Fig. 1, first restores damaged regions using inpainting methods, then utilizes the restored images as input for design generation. The study examines various visual designs generated through our approach and compares two distinct approaches: direct generation from damaged originals versus generation from inpainting-restored images. Results demonstrate that inpainting preprocessing significantly improves design quality while preserving cultural authenticity.

2. Related Works

2.1. Generative Design

Recent advances in generative models have revolutionized visual design capabilities in commercial applications. StyleGAN [12] established controllable image generation through style manipulation, while Diffusion models [18] have further enhanced the quality and diversity of generated visual content. These foundational architectures have spawned numerous commercial design platforms [1, 3, 14, 22] that democratize creative workflows and enable rapid prototyping of visual concepts. This democratization of design expertise accelerates innovation cycles and allows exploration of novel aesthetic approaches that emerge from AI-human collaborative processes.

However, applying these generative design systems to cultural heritage presents distinct challenges that current commercial tools inadequately address. Historical paintings and cultural artifacts exhibit various forms of deterioration accumulated over time. When contemporary generative design algorithms process damaged heritage images directly, the generated outputs inherit and amplify imperfections. The generative models trained to recognize and reproduce visual patterns cannot distinguish between authentic artistic elements and damage-induced artifacts. This inheritance of imperfections creates a dual problem: the resulting designs fail to accurately represent cultural heritage while falling short of contemporary design market standards. Consequently, direct application of existing generative design tools to damaged heritage materials produces commercially unviable outputs that neither honor the source culture nor meet modern consumer expectations.

2.2. Inpainting

Cultural heritage images present unique challenges due to accumulated deterioration from environmental factors, aging, and historical damage. Traditional digitization efforts often capture artifacts with visible deterioration, creating datasets that inadequately support downstream applications. These damaged source materials limit the effectiveness of creative applications that depend on high-quality visual input.

Inpainting has become an essential tool for the preservation of cultural heritage, enabling the restoration of damaged artifacts. Early restoration methods relied on manual techniques that required specialized expertise and a large investment of time [6, 8, 20]. Recent advances in deep learning have revolutionized this field, with AI frameworks combining Diffusion [18] and LoRA [10] demonstrating superior performance in reconstructing damaged areas compared to traditional approaches [24].

Contemporary applications span diverse cultural contexts, from European medieval frescoes [13] to Asian traditional paintings [17], with specialized models such as SGR-GAN [11] achieving significant improvements in restoration quality. However, current inpainting research primarily targets restoration as an end goal rather than preprocessing for creative applications. The potential for combining heritage restoration with generative design workflows remains largely unexplored, creating a significant gap in bridging cultural preservation with contemporary commercial design needs.

3. Method

Our method apply inpainting to restore damaged cultural heritage images, then use restored images for commercial visual design generation. We employ damage-specific restoration models to address surface contamination and paint deterioration, followed by generating market-ready designs. This approach demonstrates how heritage restoration improves the quality and commercial viability of culturally-inspired designs.

3.1. Restoration

We utilize IOPaint [19], an open-source image inpainting tool powered by state-of-the-art models. IOPaint employs various inpainting and segmentation models to perform cleaning, coloring, and pattern extraction tasks on cultural heritage images. We select the tool for high flexibility and support for diverse inpainting models. IOPaint provides a web-based interface that allows conservators and designers to intuitively upload images and perform various restoration tasks without requiring technical expertise. The platform offers preview functionality for step-by-step verification and adjustment of the restoration process and enables sequential application of multiple models to effectively handle complex damage patterns.

3.1.1. Damage Type-Specific Strategies

Cleaning Cultural heritage artworks often contain various forms of surface contamination that obscure original artistic details. To address these cleaning tasks, we employ the Large Mask Inpainting (LaMa) [21] model. Users employ the brush tool to manually mask contaminated regions, then apply LaMa to reconstruct the underlying content. LaMa utilizes fast Fourier convolution to generate consistent tex-

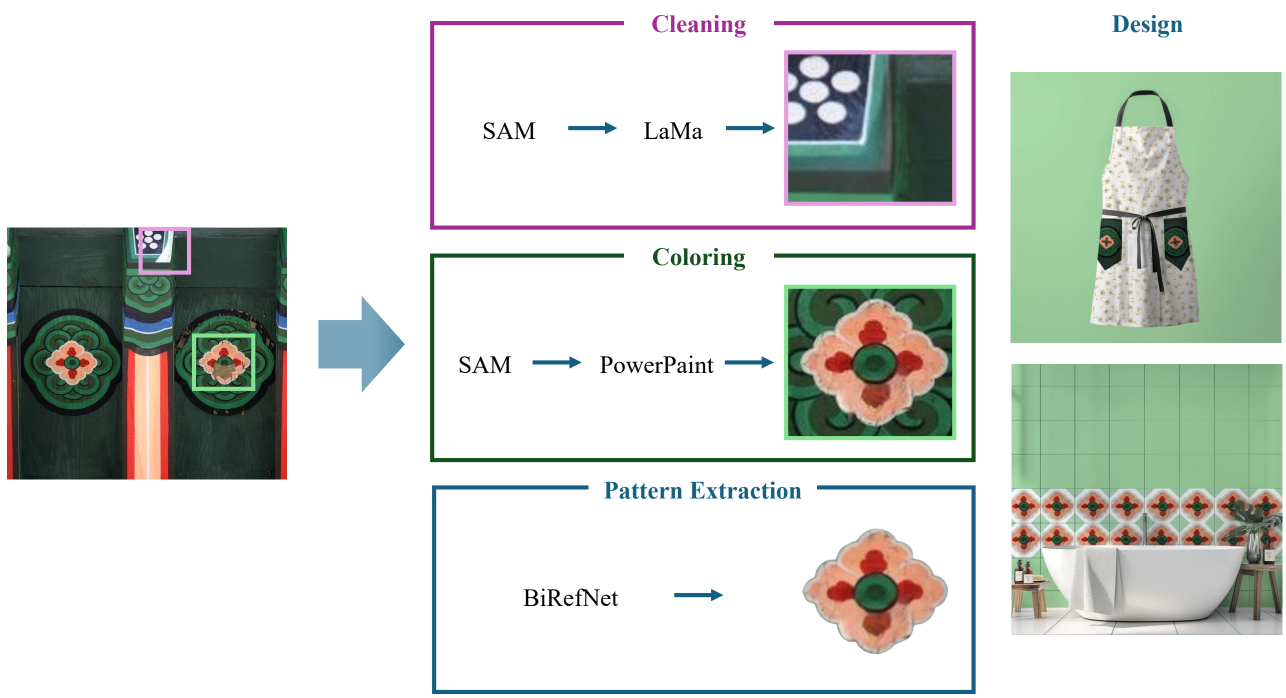

Figure 2. **Overview of our method.**

ture and structure even across large masked areas. This approach effectively removes irregular damage such as surface dirt, cracks, and stains while maintaining natural visual continuity with surrounding undamaged regions.

Coloring Cultural heritage artworks frequently suffer from paint layer deterioration, including flaking, fading, and color loss that compromises their visual integrity. For restoring these damaged areas, we employ PowerPaint [26], a ControlNet [23]-based conditional generative model. Users mask the affected regions, and PowerPaint generates contextually appropriate content that maintains semantic coherence rather than relying on simple texture replication. This approach ensures visual harmony with the original artwork's style and composition. For areas experiencing color loss or fading, PowerPaint's colorization functionality reconstructs missing colors by analyzing surrounding color information and considering the original work's palette.

Pattern Extraction Cultural heritage artworks often contain intricate traditional patterns and decorative elements that serve as valuable sources for contemporary design applications. For extracting specific objects and motifs, we employ BiRefNet [25], a specialized model for precise object segmentation. BiRefNet excels at background removal by accurately separating complex patterns and objects from surrounding contexts. In cases where patterns show damage or deterioration, we first apply cleaning and coloring restoration processes before proceeding with extraction to ensure optimal pattern quality. Users can leverage BiRefNet to isolate traditional patterns, decorative motifs, and other culturally significant elements required for textile design and commercial applications.

3.2. Visual Design Generation

Restored cultural heritage images serve as high-quality, pristine source material for commercial design generation. This clean visual content provides designers with versatile resources that can be effectively utilized across multiple design contexts. Commercial design platforms process these restored images to generate initial concepts and develop production-ready prototypes across diverse applications, including textile patterns, packaging designs, and promotional materials.

4. Findings

We investigate the effectiveness of inpainting-based restoration with generative design to create commercial visual designs from cultural heritage images. We demonstrate diverse design applications and compare designs generated from damaged original images versus restored images.

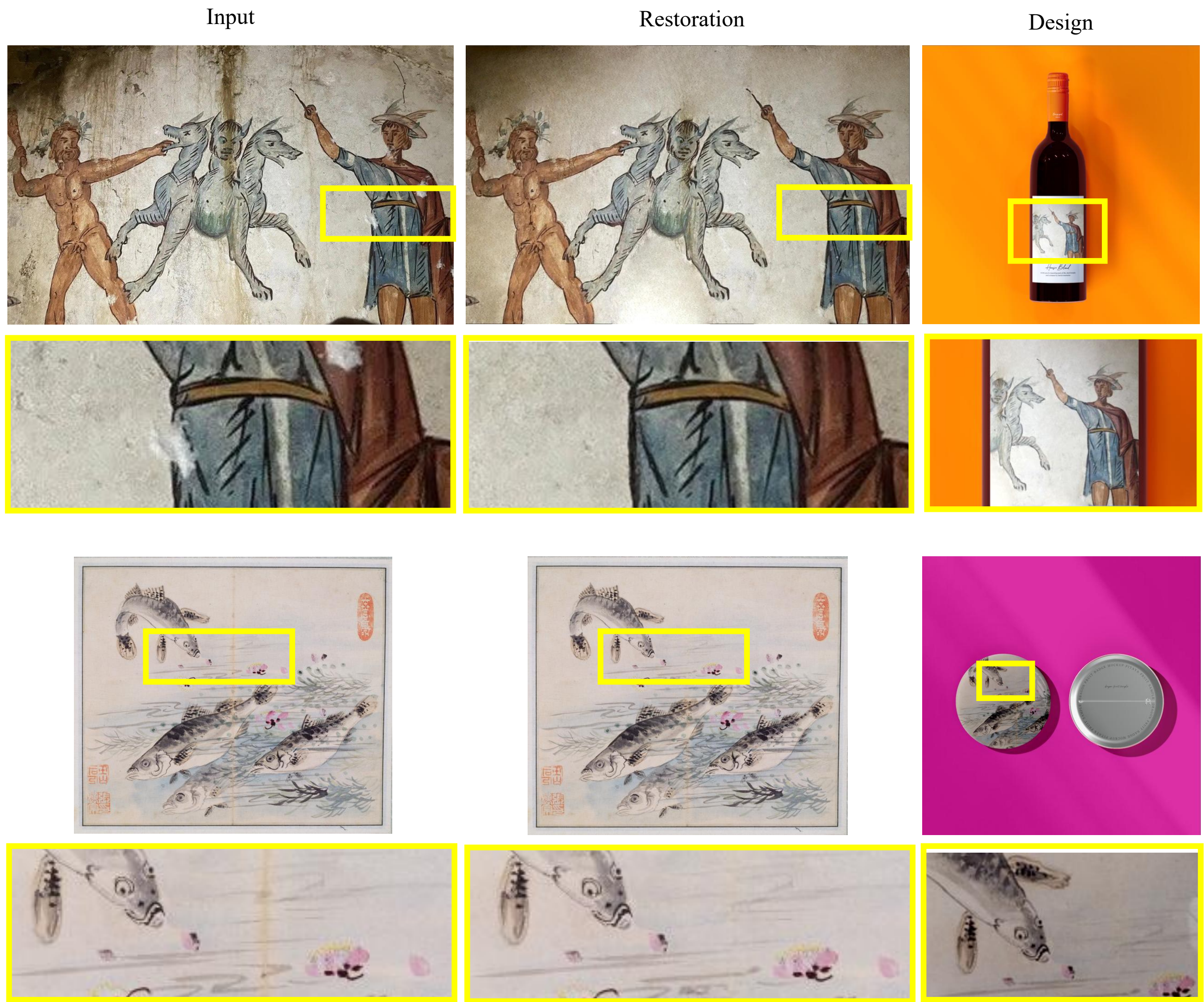

Figure 3. **Visual design results.**

4.1. Heritage Image Restoration

Fig. 3 presents the restoration results demonstrating effectiveness on two distinct cultural heritage types: traditional murals and folk paintings. The mural shows structural cracks in the wall substrate, paint layer loss in decorative areas, and extensive brown discoloration from contamination. Inpainting restoration eliminates structural cracks and perfectly reconstructs missing paint layers, restoring the original decorative patterns and color schemes. While complete removal of contamination proves challenging, the cleaning process significantly enhances visual clarity, achieving substantial improvement in overall image quality.

The folk painting exhibits deterioration along fold lines, creating visible damage that disrupts the artwork's visual continuity. The inpainting process completely removes fold-related deterioration, seamlessly reconstructing the affected areas without visible artifacts. The restoration preserves the original painting and maintains color harmony throughout the composition. Both cases demonstrate that inpainting effectively addresses various damage types while preserving the cultural authenticity and artistic integrity of the original works.

4.2. Design Application

Fig. 3 and Fig. 4 demonstrate commercial applications of restored cultural heritage images in three product categories. The restored mural adapts to wine bottle label design to create packaging that combines heritage aesthetics with mod-

w/o Restoration w/ Restoration

Figure 4. **Visual design comparison with and without restoration.**

ern commercial appeal. The folk painting transforms into badge designs, where the traditional imagery provides distinctive visual elements for commemorative applications. Dancheong architectural decoration undergoes pattern extraction to isolate lotus motifs, which designers then scale and arrange to create bathroom tile patterns that integrate traditional Korean decorative elements into contemporary interior design. The applications demonstrate the versatility of restored heritage images in generating commercially viable designs across diverse product categories while preserving cultural authenticity.

Comparative Analysis: Original Images vs. Restored Images We compare commercial design quality between products generated from damaged original images versus restored images using dancheong architectural decoration for bathroom tile pattern design. Fig. 4 presents the comparative results. Tile patterns generated from the damaged original image show quality degradation. Color loss and surface contamination directly transfer to the final design. In contrast, tile patterns from the restored image demonstrate superior design quality. The comparison demonstrates that restoration preprocessing significantly improves the commercial viability of heritage-inspired designs by eliminating damage-related artifacts and enhancing overall design quality.

5. Discussion

Our current method reveals several important limitations that warrant careful consideration. While the approach effectively maintains artwork structure and removes contamination, the inpainting process introduces modifications to original content that may compromise cultural authenticity when applied to pure heritage preservation contexts. Extensive inpainting areas pose additional risks when large portions of historical artwork require restoration, raising questions about the balance between restoration completeness and heritage preservation integrity.

Future research should address these limitations through several key directions. The method should evolve toward unified frameworks that seamlessly integrate restoration and design generation processes, developing end-to-end neural networks that perform both tasks in a single workflow. This integrated approach would optimize restoration parameters specifically for commercial design applications rather than pure preservation. Additionally, expansion to three-dimensional cultural heritage artifacts such as sculptures, architectural elements, and decorative vessels would unlock rich pattern sources that remain largely unexploited in contemporary design applications. Such developments would enhance both the efficiency and scope of heritage-inspired commercial design generation.

6. Conclusion

We present a method that applies digital restoration through inpainting to enhance visual design generation from cultural heritage images. Our findings confirm that restoration preprocessing improves design quality compared to using original images. The restoration of traditional murals, folk paintings, and dancheong architectural elements enables successful adaptation to diverse commercial applications, including packaging design, decorative accessories, and interior patterns. The method effectively addresses various damage types while preserving cultural authenticity, making heritage content accessible for modern creative workflows.

We contribute to the growing intersection of digital heritage preservation and commercial design, where restoration enhances both aesthetic quality and market viability of culturally-inspired products. This approach opens new possibilities for cultural institutions and designers to leverage heritage assets for contemporary applications while maintaining respect for original artistic intent. The demonstrated versatility across multiple heritage types and commercial applications suggests the broad applicability of our method. By transforming damaged cultural artifacts into high-quality design resources, this work establishes a foundation for sustainable cultural heritage commercialization that benefits both preservation efforts and creative industries.

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