

Combining Multispectral Imaging and Holographic Projection for Non-Contact Color Restoration of Dunhuang Murals: A Review and Conceptual Framework

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Abstract

The historically significant murals of the Dunhuang Mogao Grottoes exhibit severe fading and discoloration resulting from over a millennium of physicochemical deterioration. This study proposes a novel conceptual framework for non-contact visual restoration that synergistically integrates multispectral imaging, deep learning, and computer-generated holography (CGH). The proposed workflow begins with multispectral imaging to capture the spectral signatures of residual pigments. Subsequently, deep learning models—specifically, an invertible neural network for color restoration and generative adversarial networks for image inpainting, potentially fine-tuned with domain-specific constraints for cultural heritage—are employed to infer the original colors. In the final stage, CGH algorithms transform the digitally restored image into a phase-only hologram, enabling its projection onto the mural surface. The results demonstrate that multispectral data constitute the essential foundation for color inference, while deep learning enables effective restoration, and optimized CGH facilitates high-fidelity projection. The seamless integration of these technologies thus establishes a feasible perception-computation-presentation pipeline for non-contact visual restoration. Collectively, this work reviews the state of the art and presents an innovative, interdisciplinary paradigm for cultural heritage conservation, offering a safe, controllable alternative with significant potential for both preservation and public engagement.

Keywords

Dunhuang murals, non-contact restoration, multispectral imaging, deep learning, computer-generated holography

1. Introduction

The Dunhuang Mogao Grottoes, a UNESCO World Heritage Site, house an unparalleled collection of Buddhist mural art spanning a millennium. These irreplaceable cultural treasures, however, suffer from severe fading and discoloration due to long-term exposure to environmental factors, leading to irreversible physicochemical degradation. Traditional physical restoration methods, while sometimes necessary, inherently

involve direct contact with the artifact and carry the risk of further damage, which conflicts with the core conservation principle of “minimal intervention.” Therefore, there is a pressing need to develop safe, effective, and completely non-invasive techniques capable of visually restoring the original colors of these murals—a critical, unmet challenge in modern preservation science.

To address this challenge, this paper proposes an innovative **technical framework** for non-contact visual restoration. This framework is built upon the synergistic integration of three core technologies: multispectral imaging, deep learning-based color inference, and computer-generated holographic (CGH) projection. The core objective is to project reconstructed light fields onto the mural surface to precisely restore the visual appearance of colors compromised by long-term aging, all without any physical contact. It is important to clarify that the present work is primarily a **theoretical exposition and review**, synthesizing state-of-the-art techniques from multiple fields to construct a novel, feasible pipeline. It serves as a foundational proposal and roadmap for future empirical research and system development in digital heritage conservation.

2. Overall Technical Architecture and Workflow

The proposed methodology is architected as a “Non-contact Mural Color Restoration System,” which consists of three functionally dedicated and logically sequential modules: Multispectral Information Acquisition, Intelligent Color Reasoning, and Holographic Color Projection. These modules are integrated to form a cohesive, closed-loop pipeline encompassing the core stages of Perception, Computation, and Presentation. A critical aspect of system integration involves the spatial calibration between the multispectral camera and the Spatial Light Modulator (SLM). This ensures that the digitally restored image, generated from the multispectral data coordinate system, can be accurately mapped and projected onto the mural's corresponding physical region. Techniques such as fiducial marker-based registration or feature point matching between the captured visible-band image and the SLM's projection plane may be employed to achieve this alignment.

2.1 Multispectral Data Perception Layer

The multispectral imaging module initiates the pipeline. This module captures high-fidelity reflectance data from the mural surface across a series of discrete, narrow spectral bands. These measurements are consolidated into a three-dimensional data structure known as a spectral cube, or hyperspectral image, in which each pixel is associated with a continuous reflectance spectrum. This data structure critically extends the information content beyond the limits of the conventional visible RGB spectrum. Consequently, the output of this stage transcends a conventional image; it constitutes a detailed spectral fingerprint that is uniquely characteristic of the chemical composition and state of the residual pigments. This fingerprint thereby provides the essential scientific dataset for the subsequent inference of the mural's original color gamut [1-3].

2.2 Intelligent Color Reasoning Layer

Serving as the computational core of the system, this layer employs deep learning models. The primary task of these models is to learn a complex, non-linear mapping function that translates the acquired “current spectral features” of the mural into estimates of its “original color space.” To achieve this, the models are designed to analyze both the spectral signatures of specific pigments (e.g., minium, azurite) and their degradation byproducts [2], and to integrate auxiliary structural information, such as preparatory line drawings and surface texture, which provide crucial contextual constraints [4]. Through this multifaceted analysis, the models generate a high-fidelity digital image that represents a scientifically informed hypothesis of the mural's original colors [5-7]. This step effectively translates physical spectral data into a coherent visual reconstruction.

2.3 Holographic Color Presentation Layer

The final stage of the pipeline employs computer-generated holography (CGH) algorithms to encode the inferred digital image into a phase-only hologram [8, 9]. This computed hologram is then loaded onto a spatial light modulator (SLM), which acts as a programmable diffraction optical element. When illuminated by a coherent light source, the SLM modulates the incoming wavefront to reconstruct a target light field. This reconstructed light field carries the restored color information and is precisely projected onto the mural surface. Crucially, this approach relies on modulating the phase of light to shape the projection, rather than directly

illuminating the surface with colored light. Consequently, it achieves a pure visual restoration perceptible to an observer, fulfilling the core requirement of zero physical contact with the artifact [10].

3. Multispectral Imaging for Mural Information Acquisition

As a fundamental, non-invasive diagnostic tool, multispectral imaging has established itself as a cornerstone of scientific analysis of cultural heritage, particularly of mural paintings. Early foundational work by Fischer and Kakoulli [1] systematically detailed its potential, underscoring its unique capability to reveal subsurface and spectral information beyond the visible range, which is critical for non-destructive pigment identification and condition assessment. This perspective was later complemented by Liang [2], who emphasized the power of spectral reflectance analysis for not only identifying pigments but also for distinguishing them from their alteration products—a key to understanding degradation pathways.

Building on this international foundation, significant recent contributions by Chinese researchers have focused on advancing the practical application and algorithmic sophistication of multispectral imaging for mural conservation. Notably, collaborative research led by Professor Wang Huiqin and the Shaanxi Provincial Institute of Cultural Relics Protection has pioneered the integration of multispectral optical imaging with artificial intelligence (AI) for end-to-end conservation solutions [3]. Their work on cases like the Dule Temple murals has demonstrated the identification of pigment compositions and the mapping of deterioration patterns. Parallel to this, Xu Kunzhu's research within this framework focuses on the intelligent identification and quantitative assessment of specific mural deterioration types, such as flaking and craquelure, by developing automated image analysis pipelines based on multispectral data [3]. A key challenge in applying these technologies to ancient murals is the highly degraded condition of the surfaces. Addressing the fundamental challenge of extracting preparatory sketches (sinopia) from such surfaces, Zhang Huanhuan et al. [4] proposed a novel computational imaging method that synergistically combines optimal band selection derived from multispectral data with a specially designed pixel difference convolution (PDC) network, proving effective in retrieving clearer line drawings from images heavily affected by fading and complex noise. This underscores the need for **customized algorithmic approaches** that account for the unique degradation patterns and data characteristics of cultural heritage artifacts, rather than the direct application of generic image-processing techniques.

4. Deep Learning for Mural Color Restoration and Inpainting

4.1 The Mechanism and Challenge of Spectral-Color Mapping

The effectiveness of deep learning for color restoration stems from its capacity to learn the complex mapping function between multispectral reflectance data and a standard color space. This need arises because pigment fading and discoloration are direct manifestations of physicochemical alterations, which fundamentally modify their spectral reflectance curves. Therefore, the core computational task is formulated as learning an optimal mapping function f that satisfies $f(\mathbf{R}(\lambda)) \rightarrow (R_{orig}, G_{orig}, B_{orig})$, where $\mathbf{R}(\lambda)$ denotes the measured multi-band reflectance vector and $(R_{orig}, G_{orig}, B_{orig})$ represents the vector of inferred original tristimulus values [2].

However, learning this mapping constitutes a severely ill-posed inverse problem, exacerbated by the scarcity of large-scale, accurately paired training data specific to Dunhuang murals and the complex, non-linear nature of the degradation processes themselves. When adapting state-of-the-art models for this domain, specific modifications are often necessary. Contemporary methods mitigate these challenges by incorporating physical constraints (e.g., spectral libraries of historical pigments), employing specialized network architectures for lossless or structurally-aware feature transformation, and implementing mechanisms to integrate non-local and multi-scale contextual information. For mural restoration, this might involve tailoring network inputs to accept multispectral data cubes directly, incorporating loss functions that penalize deviations from known pigment reflectance properties, or designing attention mechanisms that prioritize regions with surviving artistic details.

4.2 State-of-the-Art Approaches

Representative of the strategy focusing on specialized architectures, Li et al. [5] proposed a color restoration method centered on an Invertible Neural Network (INN). Their framework employs a reference selection module and processes core features through a Reversible Residual Network (RevNet), an INN variant designed to ensure theoretically lossless feature transformation, thereby preserving critical image details crucial for artifact fidelity. A final unbiased color transfer module performs the restoration. In the context of mural restoration, the reversibility property of INNs could be leveraged not only to restore color but also to model or simulate the degradation process in reverse, providing physical insight. This approach demonstrated significant improvements in structural similarity metrics.

In a separate approach that addresses both intricate texture synthesis and contextual reasoning, Zhou Qixue et al. [6] introduced a deep learning network for mural inpainting that employs a novel Involution cascade attention mechanism. A key innovation is replacing standard convolution with involution, which dynamically generates kernel weights specific to each spatial location. This allows the network to capture better the irregular, non-repetitive texture patterns characteristic of hand-painted murals—a domain-specific adaptation crucial for maintaining artistic authenticity. Complementing this, a cascade attention module effectively aggregates contextual information across multiple scales, enabling coherent repair.

Hu Sheng et al. [7] developed a Generative Adversarial Network (GAN) framework emphasizing multi-scale information fusion. Their generator employs two pathways: a multi-branch dilated convolutional network to capture detailed local features and contextual information across various receptive fields, and a Fast Fourier Convolution (FFC) branch to integrate global image-wide context in the frequency domain efficiently. This generator is trained adversarially against a PatchGAN discriminator that assesses local patch realism, driving the synthesis of visually coherent, high-fidelity inpainted content. For mural inpainting, the adversarial training in such GANs must be carefully regularized, perhaps with perceptual or style losses derived from intact mural regions, to prevent the generation of anachronistic or semantically inconsistent content while driving the synthesis of visually coherent results.

5. Computer-Generated Holography Algorithm Optimization

The holographic projection stage is fundamentally concerned with encoding a 2D image into a controllable optical wavefront. A cornerstone algorithm is the Gerchberg-Saxton (GS) algorithm [8], an iterative phase-retrieval method that operates by recursively enforcing known constraints in both spatial and Fourier domains. To address specific demands, such as speckle noise reduction for high-quality displays, Fan Shuang et al. [9] developed an enhanced GS variant based on a layered angular spectrum method, demonstrating significant suppression of speckle noise, a finding directly relevant to achieving clear visual restoration in projection.

Beyond reconstruction quality, computational efficiency for complex or dynamic content is critical for a practical system. The benchmarking study by Gupta et al. [10] provides vital guidance, analyzing the computational efficiency of polygon-based CGH across diverse programming languages, hardware platforms (CPU/GPU), and algorithmic implementations. Their findings offer crucial insights for selecting configurations to achieve practical, potentially real-time hologram computation. For projecting onto non-planar mural surfaces, the standard GS and related algorithms require significant adaptation. Future work must integrate 3D surface geometry data (e.g., from laser scanning) into the CGH computation to enable dynamic geometric alignment and adaptive optical phase compensation, ensuring the reconstructed light field accurately conforms to the curved, irregular target surface rather than assuming an ideal plane.

6. Discussion and Challenges

This review and proposed framework collectively underscore the significant integrated potential of combining multispectral imaging with holographic projection for the non-contact restoration of Dunhuang murals. The analysis confirms that multispectral imaging is indispensable for acquiring essential spectral data [1-4], that contemporary deep learning architectures demonstrate considerable efficacy in learning the required nonlinear mappings [5-7], and that advancements in CGH algorithms provide a robust foundation for high-fidelity projection [8-10].

Despite this promising convergence, several formidable challenges must be overcome to translate this integrated framework into a robust, practical system. First, the accuracy of multispectral data acquisition is constrained by hardware limitations and, more critically, by the complex, non-planar geometry of mural surfaces, which can introduce shading variations and perspective distortions that corrupt spectral signatures. Second, the performance of deep learning models remains heavily contingent upon access to large-scale, high-quality training datasets, which are exceedingly scarce for Dunhuang murals. Future research could explore data-efficient approaches such as few-shot learning, meta-learning, or physics-based simulation to generate synthetic yet physically plausible training data. Third, holographic projection techniques are predominantly developed for ideal, planar surfaces. Their application to the non-ideal, deteriorated, and often curved surfaces of ancient murals necessitates the development of advanced computational techniques for dynamic geometric alignment and adaptive optical phase compensation. A concrete experimental direction could involve first validating the projection subsystem on high-fidelity physical replicas of mural fragments with controlled curvature and texture, before in-situ trials. Finally, the perceptual efficacy of the projection—that is, how convincingly a viewer perceives the restored colors—is significantly influenced by ambient lighting conditions. The interaction between the projected light field and existing illumination requires systematic study to optimize viewing conditions.

Addressing these challenges will define the trajectory of future research. Key priorities include developing more data-efficient or unsupervised learning algorithms, creating robust phase compensation and geometric calibration methods tailored to irregular surfaces, conducting fundamental studies of the photometric interaction between projected and ambient light, and rigorously validating the entire pipeline through high-fidelity physical replicas or controlled, non-destructive field trials.

7. Conclusion

This study systematically reviewed the state of the art and presented a novel technical framework for the non-contact color restoration of Dunhuang murals. The framework is built upon the synergistic integration of three pivotal technologies: multispectral imaging, deep learning, and computer-generated holography (CGH).

Our analysis substantiates that multispectral imaging effectively captures the essential spectral signatures of residual pigments. It further demonstrates that advanced deep learning models can infer and restore original colors with high fidelity. Finally, it confirms that optimized CGH algorithms furnish the critical technical foundation for accurate projective display. The principal contribution of this work lies in the coherent integration of these technologies into a functional “perception-computation-presentation” pipeline. This integrated pipeline establishes a novel methodological approach for the non-contact visual restoration of immovable cultural heritage, thereby proposing a new paradigm to address the persistent challenge of visually restoring degraded heritage without physical intervention.

This work underscores the significant potential of converging optical imaging, artificial intelligence, and advanced display technologies to generate innovative solutions for complex conservation scenarios. The transition from this conceptual framework to a practical system necessitates focused future work. This includes tackling the identified technical challenges—particularly in data efficiency, projection onto complex surfaces, and ambient light integration—and advancing towards rigorous validation through physical prototype development and controlled in-situ testing.

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Conflicts of Interest

The authors declare no conflict of interest.

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