Computer-aided Approaches to Cultural Heritage Restoration

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Abstract. For the sustainable preservation of cultural heritages, this paper summarizes computer-aided approaches to cultural heritages restoration, discusses the content, features, principles and advantages of these approaches in detail. Relevant cases are also introduced in this paper. Researchers are welcome to choose appropriate methods and technologies in this paper to conduct restoration work of cultural heritages.

Keywords: restoration of cultural heritages; computer simulation; computer graphics; artificial intelligence

1 INTRODUCTION

The preservation and restoration of cultural heritages are confronted with complex and challenges due to the passage of time and environmental changes. Traditionally, these tasks were manually conducted with extensive expertise, experiences, professional ethics, physical stamina, and craftsmanship, which leads to low efficiency and high risks of damage during restoration. With the advent of information technology, digital empowerment has emerged as a leading approach in cultural heritage conservation, striking a balance between traditional preservation, restoration practices, and innovative applications. Computer-aided restoration not only reduces the risk of failed restoration but also enhances the efficiency and quality of the restoration process.

Digital empowerment in cultural heritage restoration is primarily realized through computer-aided heritages restoration. The restoration of heritages can be classified into two main categories: (1) Restoring the missing graphics, patterns, textures, and emblazonries all based on two-dimensional data. (2) The reconstruction and restoration of three-dimensional structures based on three-dimensional data. The followings are the primary steps:

Step1: Restoration modeling based on digital models. This involves creating high-resolution digital models from optical and X-ray scanning. Utilizing computer graphics and artificial intelligence specifically deep learning, and incorporating the historical

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and cultural context of the artifact, missing parts are reconstructed both in two and three dimensions, and make indistinct patterns and textures clearer.

Step2: Designing restoration schemes using computer simulation technology. Upon obtaining the restored model, according to various restoration techniques, experts design the schemes of computer simulation and evaluate them to select the most practical and viable one.

2 METHODS OF CULTURAL HERITAGE RESTORATION BASED ON DIGITAL MODELS

2.1 Classification of Digital Restoration Models of Cultural Heritages

(1) Two-dimensional modeling, which is commonly referred to as two-dimensional image acquisition (digital photography), operates within a 2D plane and is primarily used for the restoration of patterns and textures. This technique is considered a relatively simple and foundational approach to digital modeling. Utilizing the optical characteristics of the artifact’s surface, high-resolution digital cameras, infrared cameras, and CT scanners are employed to capture the image features (such as lines, contours, and colors) of the artifact’s patterns and textures. In instances where the cultural heritage lacks optical features, CT scanners can be used to construct images based on the distribution and structural characteristics of materials on the surface.

(2) Three-dimensional (3D) modeling, which primarily focuses on capturing the 3D shape characteristics of heritages, aiding in their structural restoration. The technology for collecting and modeling 3D data has become highly developed and popular. Three prevailing methods are widely used:

①Interactive human-computer modeling. It involves designers using 3D modeling software to manually create models based on the artifact's shape. This method, among the earliest forms, is prone to inaccuracies and is time-intensive. Currently, it is rarely employed on its own except in cases of extremely simple or highly standardized structures.

②Modeling based on scanned point clouds. This technique uses laser scanning to gather data on the external form of artifacts, generating point cloud data, which is then used with computer modeling software to create a 3D model. This method is characterized by high sampling accuracy and a high level of automation, making it ideal for objects of medium size or smaller, irrespective of their shape regularity. It is a prevalent technique for 3D modeling of artifacts today. However, it is expensive and comes with high operational costs.

③Modeling based on close-range photogrammetry. This is a traditional and frequently used method for collecting 3D shape data of heritages. It does not require a 3D scanner. Usually, a digital camera is enough to photograph the heritages from multiple angles. Specialized software such as Reality Capture or Agisoft is then used to construct a 3D digital model by stitching images together. The accuracy of the model largely depends on the type of measurement data, the degree of missing and fragmentation of heritages, and the geometric features and complexity of the surfaces. Compared to point cloud scanning, this method is more cost-effective. For the restoration of damaged cultural heritages, it is a method with lower operational complexity [1].

2.2 Digital Model Restoration Technology Based on Two-Dimensional Data of Cultural Heritages

The Computer Graphics-Based Restoration Technology. When restoring patterns and textures on images, the central concept of it is to leverage information from known sections to reconstruct unknown sections, so that the restored image closely approximates [2]. Currently, there are the two main types of image restoration technologies in this field.

(1) Image Inpainting Algorithms with Non-Textured Structures

The primary categories of image inpainting algorithms encompass those based on total variation models and those utilizing partial differential equations (PDEs) [3], with the latter being more widely adopted. Notable examples of these techniques include the BSCB, curvature-driven diffusion (CDD), and total variation (TV) models. The fundamental concept is propagating edge information from the periphery of the damaged area towards its center. The selection and application of diffusion algorithms are critical areas of ongoing research aimed at optimizing both the efficiency and quality of the repair process. When dealing with excessively large damaged areas, the limited availability of data within the region, coupled with increased diffusion distances, necessitates more iterations and imposes greater computational demands, thus prolonging the repair duration. Restoration outcomes are often influenced by smoothing principles, leading to a certain degree of blurriness in the restored image. As a result, non-textured structure-based image restoration techniques are most effective for addressing small-scale damages in digital images, such as cracks and scratches. These methods yield relatively ideal results when applied to smaller repair areas. However, they are not advisable for repairing regions characterized by texture information, extensive damage, or large-scale missing parts.

(2) Image Inpainting Algorithms with Texture Structures

These algorithms are designed for the restoration of image textures and are particularly suitable for repairing large-scale damage in digital images. They can be primarily categorized into two types.

①Sample-Based Texture Synthesis Technique techniques. These techniques also referred to as image completion techniques, rely on block-matching texture synthesis. These approaches involve defining a block template of a specific size along the edges of the damaged area and then filling in the unknown pixel information according to predefined matching principles. These principles typically take into account both the linear and edge structural information, as well as the detailed texture information. A widely recognized algorithm in this category is Criminisi's method.

②Image decomposition-based restore techniques. These techniques involve decomposing the damaged image into structural and textural parts. Initially, an image decomposition algorithm is applied to separate the image into its structural and textural parts. Subsequently, different methods are used to repair each component individually before recombining them. For the structural component, non-textured structure-based image inpainting algorithm (typically those based on partial differential equations) is employed, while texture synthesis methods are used for the textural component. The final restoration is achieved through the integration of these two types of repair algorithms.

Restoration Techniques with Deep Learning. With the recent proliferation and advancement of deep learning technologies, deep learning has demonstrated remarkable performance in the restoration of images with "large-scale missing" areas [4]. Depending on the model architecture, deep learning-based restoration techniques can be categorized into three main classes.

(1) Image restoration method based on self-coding. As a cutting-edge technology in image processing, generative models demonstrate remarkable potential in addressing image defects and damage. Leveraging powerful image generation capabilities, these methods, including deep convolutional generative adversarial networks (DCGANs) and progressive growing GANs (Progressive-GANs), achieve high-fidelity restoration and creative filling of image details. They capture and learn both global and local features, generating content that is consistent with the original style and naturally seamless.

(2) Image restoration method based on network structure. Leveraging the inherent capabilities of deep generative networks (DGNs) to accurately fit complex image data distributions, this method achieves image restoration. Its uniqueness lies in using only the network structure as prior knowledge, eliminating the need for additional data sources or complex preprocessing steps. Through iterative processes, the network can reverse-engineer and reconstruct the missing or damaged parts. This novel and ingenious approach demonstrates exceptional results in restoring scarce image resources.

(3) Image Inpainting Methods Based on Generative AI. As a cutting-edge technology in image processing, generative AI shows exceptional potential in addressing image defects and damage due to their powerful generation capabilities. It relies on generative models such as deep convolutional generative adversarial networks (DCGANs) and progressive growing GANs (Progressive GANs). Through complex neural network architectures and algorithmic optimizations, generative model-based inpainting methods can achieve high-fidelity restoration and creative filling of image details, capturing and learning both global and local features. This enables the generation of content that is consistent with the original style and naturally seamless [5-8].

3 COMPUTER SIMULATION-BASED RESTORATION SCHEME DESIGN

Computer simulation technology offers advantages such as high efficiency, cost-effectiveness, flexibility, safety, and non-destructiveness, and is not constrained by external conditions such as climate, location, or time. This technology has been widely applied in fields such as military, industry, education, scientific research, aerospace, and biomedicine. Currently, computer simulation methods are also gaining popularity in the field of artifact restoration. The main workflow includes the following steps:

(1) Selecting engineering material parameters from a materials library based on the data from the restoration prosthetics. These materials include prosthetics and auxiliary

materials (such as adhesives and structural components). Relevant parameters cover physical properties (material, color, density, hardness, aging, fading, etc.) and chemical properties (antioxidation, corrosion resistance, etc.). Environmental data, including temperature, humidity, wind speed, light exposure, dust, noise, vibration, and air composition, must also be collected.

(2) Developing mechanical models for the junctions of different restoration schemes, chemical aging models for the prosthetics, and models for the physical, chemical, and biological conditions of the environment where the heritage is located.

(3) Running the established models in a computer environment and observing changes in indicators over a specified time period, such as color, texture, gloss, and the bonding strength at the junctions. Then Collecting relevant data throughout this process.

(4) Analyzing the outcomes of the simulations to evaluate the economic viability, operational feasibility, effectiveness, and potential risks of each scheme. Professionals ultimately choose the optimal and most reasonable solution to ensure that the restoration meets aesthetic standards, historical value, economic criteria, and physical and chemical metrics.

4 RESTORATION PRACTICES

Case 1: The restoration of the Vajra Cave at the Longmen Grottoes. Ma Chaolong's team innovatively merged 3D printing with simulation restoration technology to tackle traditional restoration challenges at the Vajra Cave in the Longmen Grottoes. Traditional materials, such as natural limestone and fiberglass, were found to add unnecessary weight and complicate the process during collapse restoration. Instead, the team utilized advanced methods including: (1) comprehensive data collection on deficiencies and cracks; (2) restoration model design using color 3D scanning, colorimeters, and Geomagic software; (3) model optimization via light and temperature field simulations; and (4) final printing, assembly, coloring, and artistic style verification. This approach has significantly enhanced the efficiency and precision of the restoration process.

Case 2: The restoration of fragmented bronze artifacts. Bronze artifacts are vulnerable to damage and deformation due to underground conditions. Professor Zhou Mingquan utilizes computer technology to explore their digitization and virtual restoration. The restoration process includes:(1) Digitization: Acquiring multi-view images via laser scanning and enhancing precision through non-rigid registration. (2) Preprocessing: Smoothing and noise reduction, and hole filling using template registration. (3) Deformation Recovery: Implicit surface techniques for minor deformations and interactive editing for severe cases. (4) Fragment Matching: Ranking fragments by contour features and manual adjustment for accuracy. (5) Fragment Joining: Repairing cracks and joining fragments. Those technology leverages advanced computing methods to tackle key restoration challenges, enhancing efficiency and safety, and offering a new approach to preserving bronze artifacts.

Case 3: The restoration of paintings and calligraphy. The Palace Museum integrates traditional techniques with modern technologies, including 3D modeling, multispectral and infrared imaging, and X-ray fluorescence scanning, to analyze and restore paintings and calligraphy, revealing artists' methods and providing a scientific basis for conservation.

5 CONCLUSION

Due to the complexity of heritages damage, various techniques exhibit clear advantages but also significant drawbacks. Traditional image inpainting methods based on non-textured and textured structures perform well for small areas with simple structures and textures. In contrast, computer graphics and deep learning-based techniques excel in restoring large-scale damage and possess superior high-level semantic perception compared to traditional methods.

However, image feature-based restoration methods should also consider additional constraints and corrections based on cultural and material factors. Due to the complexity and variability of heritage restoration, there may be extreme cases where technical or financial limitations prevent restoration efforts. In such cases, digital virtual restoration techniques are introduced to present the original appearance of the heritage via digital models, effectively showcasing its original condition.

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