NeRF and Gaussian-Based Relighting Advances

Naveen Meena
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Abstract

Neural Radiance Fields (NeRF) have emerged as a groundbreaking framework for **novel view synthesis**, enabling the generation of highly realistic 3D reconstructions from 2D images. However, **NeRF struggles with relighting**, as it encodes both geometry and illumination into a single implicit representation, preventing the modification of scene lighting. This limitation has driven extensive research into **relightable NeRF variants**, focusing on disentangling material properties, surface normals, and environmental illumination.

The introduction of **3D Gaussian Splatting (3DGS)** has revolutionized neural scene representations by providing an **efficient and real-time** alternative to NeRF. Unlike NeRF, which relies on implicit multi-layer perceptrons (MLPs), **Gaussian splatting models scenes as explicit point-based primitives**, enabling faster rendering and better support for **physically-based relighting**. This shift has enabled advanced relighting techniques that leverage **BRDF-based material estimation**, **environment illumination modeling**, and **differentiable light transport simulation**.

The motivation behind this survey is to explore the **evolution of relighting techniques** in neural rendering, comparing how different approaches tackle **illumination estimation**, **material decomposition**, and **global light transport**. Our objective is to analyze key advancements in **relightable NeRF** and **Gaussian splatting-based methods**, studying how they have progressively improved in **realism**, **efficiency**, and **robustness**.

In this survey, we systematically examine the **timeline of relighting research**, focusing on major contributions from 2020 to 2025. We compare **each relighting approach** in terms of its **methodology**, **improvements over predecessors**, and **practical applications**. Key topics covered include **BRDF decomposition**, **inverse rendering**, **differentiable light transport**, **global illumination modeling**, and **Gaussian-based relighting frameworks**. This analysis provides a comprehensive understanding of how neural scene representations are transitioning from **static appearance models** to **fully editable and relightable scene representations**, bridging the gap between traditional **physically-based rendering** and **neural rendering**.

Contents

1 Introduction

NeRF has fundamentally transformed novel view synthesis, but its limitation in **relighting** motivated researchers to extend its capabilities. Over the years, multiple papers introduced methods to **factorize lighting and material properties** for relightable NeRF models. Recent approaches leverage **Gaussian splatting**, enabling efficient scene decomposition.

2 Methodology

The report follows a chronological structure, summarizing key relighting papers from **2020 to 2025**. Each paper is explained in detail, focusing on **high-level insights**, without mathematical formulations. Papers are compared against their predecessors, highlighting significant advancements in **relighting accuracy**, **material separation**, **lighting manipulation**, and **computational efficiency**.

3 Timeline of Research in Relightable NeRF and Gaussian Splatting

3.1 2021: Initial Steps Towards Relightable NeRF

NeRFactor [1] introduced factorization of NeRF into surface-based components, enabling estimation of albedo, normal maps, and BRDF parameters. This method allowed for relighting under novel illumination conditions but suffered from limited indirect illumination modeling, restricting realistic shadow and global lighting effects.

Neural Light Transport [2] relighting and novel view synthesis by learning a 6D light transport function. light-material interactions, enabling realistic relighting under novel lighting conditions. NLT separates diffuse base rendering and non-diffuse residuals

NeRV [3] differs from other NeRF-based relighting research by introducing Neural Visibility Fields (NVFs), which efficiently approximate scene visibility and indirect illumination, making it significantly more scalable to complex lighting conditions. Unlike earlier methods like NeRFactor and Neural Light Transport that struggled with global illumination due to computational costs, NeRV trains a neural network to approximate visibility, enabling realistic relighting under arbitrary lighting.

3.2 2022: Improving Global Illumination and Outdoor Relighting

NeRF-OSR [4] was the first NeRF-based approach tailored for outdoor scene relighting. It separated albedo and illumination, enabling realistic manipulation of sunlight and shadows. Compared to NeRFactor, it handled dynamic lighting conditions but still struggled with complex material reflectance.

NeILF [5] introduced a 5D neural incident light field for improved material and illumination estimation. Unlike earlier works that relied on precomputed lighting, NeILF could model interreflections and occlusions without requiring multi-bounce ray tracing, pushing neural relighting closer to physically-based rendering.

3.3 2023: Advanced NeRF-Based Relighting And The Emergence of Gaussian Splatting

GS-IR [6] extended Gaussian Splatting for inverse rendering by incorporating material estimation. This allowed normal, albedo, roughness, and metallic properties to be stored per Gaussian, bridging the gap between NeRF's material separation and Gaussian Splatting's efficiency.

GaussianShader [7] marked the beginning of relightable Gaussian Splatting by introducing BRDF-based shading functions. Unlike NeRF approaches that relied on ray marching, GaussianShader utilized point-based representations for efficient relighting, but it lacked indirect light modeling.

ReNeRF [8] improved intrinsic decomposition using OLAT-based supervision, making relighting more accurate. Unlike NeRF-OSR, it captured nearfield lighting effects, enabling realistic rendering of specular highlights and shadowing.

IBL-NeRF [9] introduced a novel neural representation called prefiltered radiance fields to efficiently model spatially varying illumination in complex indoor scenes. Unlike previous methods (NeRFactor, NeRV) that require Monte Carlo sampling and environment map approximations, IBL-NeRF achieves superior results through efficient image-based lighting approximation and implicit neural representations.

NeILF++ [10] builds upon its predecessor NeILF by significantly improving the modeling of complex illumination and inter-reflections through a unified neural incident light field representation. It explicitly captures detailed interactions between surfaces, enabling precise separation of material properties from intricate lighting. Unlike earlier approaches, NeILF++ incorporates a highly effective mechanism for estimating spatially varying illumination from multi-view images, resulting in more accurate relighting of scenes with complex global illumination and detailed material properties.

LLNeRF [11] introduces an unsupervised method for relighting low-light scenes by decomposing the NeRF into view-dependent (lighting) and view-independent (intrinsic color) components. It enhances illumination, corrects colors, and reduces noise directly within the NeRF optimization process, enabling high-quality novel view synthesis from low-light sRGB images without ground truth supervision.

ReLight My NeRF [12] introduces the ReNe dataset, the first publicly available real-world dataset specifically for joint novel view synthesis and relighting of complex objects under diverse illumination conditions. Unlike prior works that primarily relied on synthetic scenes or limited setups with minimal shadows, this dataset utilizes a sophisticated dual-robotic-arm system for precise camera and lighting pose control, enabling comprehensive modeling of challenging shadows and intricate lighting effects.

3.4 2024: Real-Time Relightable Gaussian Splatting

Relightable 3D Gaussians [13] introduced BVH-based point ray tracing for occlusion handling in Gaussian Splatting. Unlike GaussianShader, this approach improved accuracy in shadow computation and material estimation.

BiGS [14] Separates diffuse, direct, directional scattering, and indirect transport components for each Gaussian. Uses spherical harmonics based light transport modeling to efficiently represent direct and indirect lighting. Introduces BSH to model light-dependent appearance functions that capture both surface and volumetric materials. One-Light-At-a-Time datasets to train an inverse rendering framework that captures complex material-light interactions. Outperforms GaussianShader in preserving subsurface scattering and fur details

LumiGauss [15] brought Gaussian Splatting to outdoor relighting by incorporating 2D Gaussian representations for inverse rendering. Unlike NeRF-OSR, which relied on volumetric density, LumiGauss used spherical harmonics to estimate environment lighting, significantly improving efficiency for real-world relighting tasks.

3iGS [16] Factorized tensorial illumination model for 3DGS to improve viewdependent effects, material estimation, and relighting. Gaussian-specific BRDF representation to capture specular highlights and roughness variations.Unlike GaussianShader, which relies on precomputed cube maps, 3iGS learns a dynamic illumination field to adapt to complex light interactions. Unlike NeRF-based inverse rendering, which requires ray tracing, 3iGS achieves similar relighting quality with significantly lower computation

Ref- Gaussian [17] pixel-level BRDF properties, Gaussian-grounded interreflection, a novel technique that uses efficient ray-tracing on an extracted mesh to compute indirect lighting

GI-GS [18] introduced global illumination decomposition in Gaussian Splatting, enabling indirect light transport modeling. Unlike earlier methods such as GS-IR, which only modeled direct lighting, GI-GS leveraged an efficient path tracing approach to handle multi-bounce light effects, pushing Gaussian Splatting closer to physically-based rendering.

ReCap [19] cross-environment captures as multi-task supervision, optimization friendly shading function based on a variant of the split-sum approximation and applies physically appropriate post-processing to maintain a linear HDR lighting space. ReCap outperforms prior methods (such as GShader, 3DGS-DR, GS-IR, and R3DG) in achieving more realistic, robust, and consistent relighting results across both diffuse and specular surfaces.

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