

Novelty Assessment Report

Paper: HDR-4DGS: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

PDF URL: <https://openreview.net/pdf?id=9ZrjgzlAuh>

Venue: ICLR 2026 Conference Submission

Year: 2026

Report Generated: 2025-12-30

Abstract

We introduce HDR-4DGS, the first system for reconstructing renderable 4D high dynamic range (HDR) scenes from unposed monocular low dynamic range (LDR) videos captured with alternating exposures. To tackle such a challenging problem, we present a unified framework with two-stage optimization approach based on Gaussian Splatting. The first stage learns a video HDR Gaussian representation in orthographic camera coordinate space, eliminating the need for camera poses and enabling robust initial HDR video reconstruction. The second stage transforms video Gaussians into world space and jointly refines the world Gaussians with camera poses. Furthermore, we propose a temporal luminance regularization strategy to enhance the temporal consistency of the HDR appearance. Since our task has not been studied before, we construct a new evaluation benchmark using publicly available datasets for HDR video reconstruction. Extensive experiments demonstrate that HDR-4DGS significantly outperforms alternative solutions adapted from state-of-the-art methods in both rendering quality and speed.

Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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Core Task Landscape

This paper addresses: **Reconstructing 4D High Dynamic Range Scenes from Unposed Monocular Alternating-Exposure Videos**

A total of **6 papers** were analyzed and organized into a taxonomy with **6 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Gaussian Splatting-Based 4D HDR Reconstruction**
- **Learning-Based HDR Video Reconstruction**
- **Monocular 4D Dynamic Scene Reconstruction**

Complete Taxonomy Tree

- Reconstructing 4D High Dynamic Range Scenes from Unposed Monocular Alternating-Exposure Videos Survey Taxonomy
- Gaussian Splatting-Based 4D HDR Reconstruction
 - Unposed Monocular Alternating-Exposure 4D HDR ★ (2 papers)
 - [0] HDR-4DGS: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos (Anon et al., 2026) [View paper](#)
 - [1] Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos (Liu, 2025) [View paper](#)
- Learning-Based HDR Video Reconstruction
 - Pixel-Level Exposure Sampling and Synthesis (1 papers)
 - [2] Pix2HDR-A pixel-wise acquisition and deep learning-based synthesis approach for high-speed HDR videos (Caixin Wang, 2024) [View paper](#)
 - Multi-Stage Alignment and Fusion Networks (1 papers)
 - [5] Multi-Attention Guided SKFHDRNet For HDR Video Reconstruction (Ehsan Ullah, 2023) [View paper](#)
 - Generative Adversarial HDR Video Synthesis (1 papers)
 - [6] HDRVideo-GAN: deep generative HDR video reconstruction (Mrinal Anand, 2021) [View paper](#)
- Monocular 4D Dynamic Scene Reconstruction
 - View Augmentation Through Video Inpainting (1 papers)
 - [3] Vivid4D: Improving 4D Reconstruction from Monocular Video by Video Inpainting (Huang Jia-xin, 2025) [View paper](#)
 - Neural 4D Decomposition for Stationary Cameras (1 papers)
 - [4] DRSM: Efficient Neural 4D Decomposition for Dynamic Reconstruction in Stationary Monocular Cameras (Weixing Xie, 2024) [View paper](#)

Narrative

Core task: Reconstructing 4D high dynamic range scenes from unposed monocular alternating-exposure videos. This emerging field sits at the intersection of dynamic scene reconstruction, HDR imaging, and camera pose estimation. The taxonomy reveals three main branches that reflect different methodological emphases. Gaussian Splatting-Based 4D HDR Reconstruction leverages explicit 3D Gaussian representations to model both geometry and radiance in dynamic scenes, enabling efficient rendering and HDR fusion from alternating exposures. Learning-Based HDR Video Reconstruction focuses on neural network architectures that directly synthesize HDR frames from low dynamic range input sequences, often relying on temporal consistency and exposure bracketing patterns; representative works include SKFHDRNet[5] and HDRVideo-GAN[6], which employ deep learning to merge multi-exposure frames. Monocular 4D Dynamic Scene Reconstruction addresses the broader challenge of recovering time-varying geometry and appearance from single-camera video, with methods like Vivid4D[3] and DRSM[4] tackling motion, deformation, and view synthesis without requiring known camera poses.

Within the Gaussian splatting branch, a small handful of works specifically target the unposed monocular alternating-exposure setting, combining pose estimation with HDR radiance modeling in a unified framework. HDR-4DGS[0] exemplifies this direction, jointly

optimizing camera trajectories and 4D Gaussian representations to reconstruct high dynamic range dynamic scenes from raw alternating-exposure video. Its closest neighbor, Mono4DGS-HDR[1], shares the same technical foundation but may differ in how exposure alignment or temporal regularization is handled. Compared to learning-based approaches like Pix2HDR[2], which rely on training data to hallucinate HDR content, the Gaussian splatting methods offer more explicit geometric control and can adapt to novel scenes without retraining. The main open questions revolve around robustness to rapid motion, scalability to longer sequences, and the trade-off between reconstruction fidelity and computational cost when jointly solving for pose, geometry, and radiance.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

Authors: Liu, Jinfeng, Kong Lingtong, Jinfeng Liu, Zhou Mi, et al. (12 authors total) | **Year/Venue:** 2025 | **URL:** [View paper](#)

Abstract

We introduce Mono4DGS-HDR, the first system for reconstructing renderable 4D high dynamic range (HDR) scenes from unposed monocular low dynamic range (LDR) videos captured with alternating exposures. To tackle such a challenging problem, we present a unified framework with two-stage optimization approach based on Gaussian Splatting. The first stage learns a video HDR Gaussian representation in orthographic camera coordinate space, eliminating the need for camera poses and enabling robust initial...

△ Similarity Notice

These papers appear to be the same work or very closely related variants. Both have nearly identical titles (HDR-4DGS vs. Mono4DGS-HDR), describe the same two-stage Gaussian Splatting optimization approach for reconstructing 4D HDR scenes from unposed monocular alternating-exposure videos, use identical methodology including video Gaussians in orthographic space followed by world Gaussian refinement, propose the same temporal luminance regularization strategy, and report the same experimental results on the same benchmark datasets. The core technical contributions, system architecture, and evaluation are essentially identical.

Contributions Analysis

Overall novelty summary. The paper introduces HDR-4DGS, a system for reconstructing 4D high dynamic range scenes from unposed monocular videos with alternating exposures using Gaussian Splatting. It resides in the 'Unposed Monocular Alternating-Exposure 4D HDR' leaf, which contains only two papers total (including this work). This indicates a highly sparse research direction within the broader taxonomy of 4D HDR reconstruction. The sibling paper, Mono4DGS-HDR, shares the same technical foundation, suggesting this specific problem formulation—joint pose estimation, dynamic scene modeling, and HDR synthesis from alternating exposures—is still in its early stages.

The taxonomy reveals three main branches: Gaussian Splatting-Based 4D HDR Reconstruction (where this paper sits), Learning-Based HDR Video Reconstruction (including multi-stage alignment networks and GAN-based synthesis), and Monocular 4D Dynamic Scene Reconstruction (focused on geometry without HDR). The paper's approach diverges from learning-based methods like SKFHDRNet and HDRVideo-GAN, which rely on trained networks for exposure fusion, by using explicit Gaussian representations for joint optimization. It also differs from broader monocular 4D methods like Vivid4D and DRSM, which do not address HDR synthesis or alternating-exposure input.

Among the three contributions analyzed, each was examined against a limited candidate pool: the core HDR-4DGS system (10 candidates, 1 refutable), the two-stage optimization framework (3 candidates, 1 refutable), and temporal luminance regularization (7 candidates, 1 refutable). The analysis is based on 20 total candidates from semantic search and citation expansion. The statistics suggest that while each contribution has at least one overlapping prior work among the examined candidates, the majority of candidates (9 out of 10 for the core system, 2 out of 3 for the framework, 6 out of 7 for regularization) do not clearly refute the novelty.

Given the sparse taxonomy leaf (only 2 papers) and the limited search scope (20 candidates), the work appears to occupy a relatively unexplored niche. The presence of one sibling paper and scattered refutable candidates suggests incremental refinement over closely related methods rather than a completely new problem formulation. However, the analysis does not cover exhaustive literature review, and the true novelty may depend on technical details not captured in the abstract-level comparison.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: HDR-4DGS system for 4D HDR reconstruction from unposed monocular alternating-exposure videos

Description: The authors present the first system capable of reconstructing 4D HDR scenes from monocular LDR videos with alternating exposures and unknown camera parameters. This addresses a previously unexplored challenging task in HDR novel view synthesis.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Compressive Sensing-Based HDR-Like Image Encryption and Artifact-Mitigated Reconstruction

URL: [View paper](#)

Brief Assessment

Compressive HDR Encryption[20] focuses on HDR-like image encryption using compressive sensing and multi-exposure fusion (MEF), not on 4D scene reconstruction from monocular videos with unknown camera parameters.

2. Diffusion-Promoted HDR Video Reconstruction

URL: [View paper](#)

Brief Assessment

Diffusion HDR Video[22] focuses on HDR video reconstruction from alternating-exposure LDR frames using diffusion models, not on 4D scene reconstruction with novel view synthesis from unposed monocular videos. The candidate addresses a 2D video reconstruction task, while the original tackles 4D spatial-temporal reconstruction with camera pose estimation.

3. Hdrflow: Real-time hdr video reconstruction with large motions

URL: [View paper](#)

Brief Assessment

HDRflow[15] focuses on real-time HDR video reconstruction from alternating-exposure sequences but does not address 4D scene reconstruction, novel view synthesis, or camera pose estimation—core components of the original paper's contribution.

4. High-Speed HDR Video Reconstruction from Hybrid Intensity Frames and Events

URL: [View paper](#)

Brief Assessment

High-Speed Events HDR[18] focuses on HDR video reconstruction from hybrid intensity frames and event camera data, not from monocular alternating-exposure videos with unknown camera poses. The technical approaches and input modalities are fundamentally different.

5. HDR video reconstruction from events and LDR frames via spatiotemporal attention and exposure compensation

URL: [View paper](#)

Brief Assessment

Events LDR HDR[19] focuses on HDR video reconstruction from event cameras and LDR frames using spatiotemporal attention, not on 4D scene reconstruction from monocular alternating-exposure videos with unknown camera poses.

6. Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

URL: [View paper](#)

Prior Art Analysis

Mono4DGS-HDR[1] demonstrates that the same task of reconstructing 4D HDR scenes from unposed monocular LDR videos with alternating exposures has been addressed. Both papers present systems for this identical problem setup, use the same input format (alternating-exposure monocular videos), and target the same output (4D HDR scene reconstruction). The candidate paper explicitly states it is 'the first system for reconstructing renderable 4D high dynamic range (hdr) scenes from unposed monocular low dynamic range (ldr) videos captured with alternating exposures,' which directly challenges the original paper's novelty claim of being the first to explore this task.

Evidence

Evidence 1 - **Rationale:** Both papers claim to be 'the first system' for the identical task of reconstructing 4D HDR scenes from unposed monocular LDR videos with alternating exposures, using nearly identical wording. This demonstrates that Mono4DGS-HDR[1] addresses the same previously unexplored problem. - **Original:** we introduce hdr-4dgs, the first system for reconstructing renderable 4d high dynamic range (hdr) scenes from unposed monocular low dynamic range (ldr) videos captured with alternating exposures. - **Candidate:** We introduce mono4dgs-hdr, the first system for reconstructing renderable 4d high dynamic range (hdr) scenes from unposed monocular low dynamic range (ldr) videos captured with alternating exposures.

Evidence 2 - **Rationale:** The identical problem statement and claim that 'no existing method has yet explored this challenging task' appears verbatim in both papers, indicating they address the exact same unexplored problem space. - **Original:** this work focuses on recovering 4d hdr scenes from alternating-exposure monocular ldr videos with unknown camera parameters, as demonstrated in fig. 1(a). to the best of our knowledge, no existing method has yet explored this challenging task. - **Candidate:** this work focuses on recovering 4d hdr scenes from alternating-exposure monocular ldr videos with unknown camera parameters, as demonstrated in fig. 1(a). to the best of our knowledge, no existing method has yet explored this challenging task.

Evidence 3 - **Rationale:** The identical technical formulation of the input setup, including notation and exposure patterns, confirms both papers work on the same problem with the same input specifications. - **Original:** in our monocular 4d hdr reconstruction setup, the input is an unposed monocular video consisting of alternating-exposure ldr frames $\{l_t\}_{t=1}^f$, where f is the frame number. consider 2-exposure case, $\{l_1, l_3, \dots\}$ are captured with a short exposure Δt_s and $\{l_2, l_4, \dots\}$ with long exposure Δt_l . - **Candidate:** in our monocular 4d hdr reconstruction setup, the input is an unposed monocular video consisting of alternating-exposure ldr frames $\{l_t\}_{t=1}^f$, where f is the frame number. consider 2-exposure case, $\{l_1, l_3, \dots\}$ are captured with a short exposure Δt_s and $\{l_2, l_4, \dots\}$ with long exposure Δt_l .

7. DeepHS-HDRVideo: Deep high speed high dynamic range video reconstruction

URL: [View paper](#)

Brief Assessment

DeepHS-HDRVideo[17] focuses on HDR video reconstruction from alternating-exposure frames using video interpolation techniques, not on 4D scene reconstruction with novel view synthesis capabilities or camera pose estimation from unposed videos.

8. Single-Image HDR Reconstruction Assisted Ghost Suppression and Detail Preservation Network for Multi-Exposure HDR Imaging

URL: [View paper](#)

Brief Assessment

Ghost Suppression HDR[21] focuses on multi-exposure HDR imaging from static captures with ghost suppression, not on 4D dynamic scene reconstruction from monocular videos with unknown camera poses and alternating exposures.

9. Deep HDR video from sequences with alternating exposures

URL: [View paper](#)

Brief Assessment

Deep Alternating HDR[16] focuses on reconstructing HDR videos from alternating-exposure sequences but assumes known camera poses and does not address 4D scene reconstruction or novel view synthesis from unposed monocular videos.

10. HDRVideo-GAN: deep generative HDR video reconstruction

URL: [View paper](#)

Brief Assessment

HDRVideo-GAN[6] focuses on HDR video reconstruction from alternating-exposure LDR sequences using optical flow alignment and GANs, but does not address 4D scene reconstruction, novel view synthesis, or camera pose estimation - the core contributions of the original paper's HDR-4DGS system.

Contribution 2: Two-stage optimization framework with video-to-world Gaussian transformation

Description: The authors introduce a novel two-stage optimization approach where the first stage learns HDR Gaussians in orthographic camera coordinate space without requiring camera poses, and the second stage transforms these to world space and jointly refines world Gaussians with camera parameters. This includes a video-to-world Gaussian transformation strategy based on 2D covariance invariance.

This contribution was assessed against **3 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Two-Stage Gaussian Splatting Optimization for Outdoor Scene Reconstruction

URL: [View paper](#)

Brief Assessment

Two-Stage Gaussian Outdoor[14] focuses on outdoor scene reconstruction with foreground/background separation using spherical shells, not video-to-world transformation for dynamic HDR scenes from unposed monocular videos.

2. Pseudo-View-Driven Gaussian Optimization for Sparse Novel View Synthesis

URL: [View paper](#)

Brief Assessment

Pseudo-View Gaussian[13] focuses on sparse novel view synthesis using pseudo-view generation techniques, not on HDR reconstruction from alternating-exposure videos with video-to-world Gaussian transformation strategies.

3. Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

URL: [View paper](#)

Prior Art Analysis

Mono4DGS-HDR[1] presents the same two-stage optimization framework where the first stage learns HDR Gaussians in orthographic camera coordinate space without camera poses, and the second stage transforms these to world space with joint refinement. The candidate paper includes the identical video-to-world Gaussian transformation strategy based on 2D covariance invariance. The technical approach, including the orthographic camera model in stage one and the transformation methodology, is described in nearly identical terms.

Evidence

Evidence 1 - **Rationale:** The identical description of the two-stage optimization framework, including the specific stages and their purposes, demonstrates that Mono4DGS-HDR[1] employs the same architectural approach. - **Original:** we propose a unified framework with a two-stage optimization procedure that learns video gaussians in the first stage, transfers the gaussians to world space, and then optimizes world gaussians along with camera poses in the second stage. - **Candidate:** we propose a unified framework with a two-stage optimization procedure that learns video gaussians in the first stage, transfers the gaussians to world space, and then optimizes world gaussians along with camera poses in the second stage.

Evidence 2 - **Rationale:** The identical technical description of the first stage, including the orthographic camera model and elimination of camera pose requirements, shows both papers use the same methodology. - **Original:** in the first stage, inspired by sav (sun et al., 2024), we optimize dynamic hdr gaussians in a 3d canonical space with an orthographic camera model, which can eliminate the need for camera poses, making hdr training video reconstruction easier and better. - **Candidate:** in the first stage, inspired by sav (sun et al., 2024), we optimize dynamic hdr gaussians in a 3d canonical space with an orthographic camera model, which can eliminate the need for camera poses, making hdr training video reconstruction easier and better.

Evidence 3 - **Rationale:** The identical description of the 2D covariance invariance strategy for video-to-world transformation confirms both papers employ the same technical innovation for Gaussian transformation. - **Original:** to obtain initial world gaussians with rational scales, we propose to re-fit gaussian scaling based on the invariance of 2d covariance, which is motivated by the fact that the projected 2d gaussians should have consistent shapes and sizes before and after transformation. - **Candidate:** to obtain initial world gaussians with rational scales, we propose to re-fit gaussian scaling based on the invariance of 2d covariance, which is motivated by the fact that the projected 2d gaussians should have consistent shapes and sizes before and after transformation.

Contribution 3: Temporal luminance regularization strategy for HDR temporal consistency

Description: The authors propose a temporal luminance regularization strategy using flow-guided photometric loss to align per-pixel HDR irradiance between consecutive frames. This ensures temporally consistent HDR appearance across the reconstructed video, particularly for dynamic content.

This contribution was assessed against **7 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Spatiotemporal variance-guided filtering: real-time reconstruction for path-traced global illumination

URL: [View paper](#)

Brief Assessment

Variance-Guided Filtering[10] focuses on spatiotemporal variance estimation for denoising path-traced rendering, not HDR reconstruction from alternating-exposure videos. The temporal stability mechanisms serve different purposes in distinct problem domains.

2. Capturing Stable HDR Videos Using a Dual-Camera System

URL: [View paper](#)

Brief Assessment

Dual-Camera HDR[12] addresses temporal flicker through a dual-stream paradigm with dual-camera hardware and exposure-adaptive fusion, not through flow-guided photometric loss for per-pixel HDR irradiance alignment as in the original paper's temporal luminance regularization.

3. Temporally consistent atmospheric turbulence mitigation with neural representations

URL: [View paper](#)

Brief Assessment

Turbulence Neural Mitigation[8] addresses temporal consistency in atmospheric turbulence mitigation using flow-guided photometric loss for video restoration, not HDR reconstruction. The technical domains and applications are fundamentally different.

4. Spatiotemporally consistent hdr indoor lighting estimation

URL: [View paper](#)

Brief Assessment

Spatiotemporal HDR Indoor[7] focuses on indoor lighting estimation from LDR images/videos for AR applications, not on HDR video reconstruction from alternating-exposure captures. The temporal consistency mechanism in [7] uses RNNs for progressive lighting refinement across video frames, which is fundamentally different from the original paper's flow-guided photometric loss for aligning per-pixel HDR irradiance in dynamic scene reconstruction.

5. Infrared Video Dynamic Range Compression Based on Global and Local Temporal Coherence

URL: [View paper](#)

Brief Assessment

Infrared Temporal Coherence[11] addresses temporal coherence in infrared video dynamic range compression (converting HDR to LDR for display), not HDR reconstruction from LDR inputs. The original paper reconstructs HDR scenes from alternating-exposure LDR videos, while the candidate compresses HDR infrared video to LDR format—fundamentally different tasks with opposite data flows.

6. Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

URL: [View paper](#)

Prior Art Analysis

Mono4DGS-HDR[1] proposes the same temporal luminance regularization strategy using flow-guided photometric loss to align per-pixel HDR irradiance between consecutive frames. The technical formulation, including the normalization approach and the purpose of ensuring temporal consistency in HDR appearance, is described identically in both papers. The candidate paper presents this as a novel contribution for addressing temporal inconsistency in dynamic HDR scenes.

Evidence

Evidence 1 - **Rationale:** The identical description of the temporal luminance regularization strategy, including its flow-guided photometric loss mechanism and purpose, demonstrates both papers propose the same technical solution. - **Original:** we propose a temporal luminance regularization strategy, including a flow-guided photometric loss aligning per-pixel hdr irradiance between consecutive frames, which ensures the temporal stability of hdr reconstruction and rendering. - **Candidate:** we propose a temporal luminance regularization strategy, including a flow-guided photometric loss aligning per-pixel hdr irradiance between consecutive frames, which ensures the temporal stability of hdr reconstruction and rendering.

Evidence 2 - **Rationale:** The identical technical formulation of the temporal luminance regularization, including the warping mechanism and notation, confirms both papers implement the same approach. - **Original:** to address this issue, we propose temporal luminance regularization using flow-guided photometric loss to align per-pixel hdr luminance between consecutive frames. given two adjacent timestamp-1andt, we can warp the hdr rendering eht-1 to timetusing optical flow, generating eht-1→t. - **Candidate:** to address this issue, we propose temporal luminance regularization using flow-guided photometric loss to align per-pixel hdr luminance between consecutive frames. given two adjacent timestamp-1andt, we can warp the hdr rendering eht-1 to timetusing optical flow, generating eht-1→t.

7. Lan-hdr: Luminance-based alignment network for high dynamic range video reconstruction

URL: [View paper](#)

Brief Assessment

Lan-HDR[9] focuses on temporal consistency through a temporal loss that enforces difference maps between consecutive tonemapped outputs to match ground truth, rather than flow-guided photometric loss for per-pixel HDR irradiance alignment. The technical approaches differ fundamentally in their regularization mechanisms.

Appendix: Text Similarity Detection

Textual similarity detection checked 18 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos

Detected in: Core Task (sibling), Contribution: contribution_1, Contribution: contribution_2, Contribution: contribution_3

△ **Note:** This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] HDR-4DGS: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos [View paper](#)
- [1] Mono4DGS-HDR: High Dynamic Range 4D Gaussian Splatting from Alternating-exposure Monocular Videos [View paper](#)
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- [8] Temporally consistent atmospheric turbulence mitigation with neural representations [View paper](#)
- [9] Lan-hdr: Luminance-based alignment network for high dynamic range video reconstruction [View paper](#)
- [10] Spatiotemporal variance-guided filtering: real-time reconstruction for path-traced global illumination [View paper](#)
- [11] Infrared Video Dynamic Range Compression Based on Global and Local Temporal Coherence [View paper](#)
- [12] Capturing Stable HDR Videos Using a Dual-Camera System [View paper](#)
- [13] Pseudo-View-Driven Gaussian Optimization for Sparse Novel View Synthesis [View paper](#)
- [14] Two-Stage Gaussian Splatting Optimization for Outdoor Scene Reconstruction [View paper](#)
- [15] Hdrflow: Real-time hdr video reconstruction with large motions [View paper](#)
- [16] Deep HDR video from sequences with alternating exposures [View paper](#)
- [17] DeepHS-HDRVideo: Deep high speed high dynamic range video reconstruction [View paper](#)
- [18] High-Speed HDR Video Reconstruction from Hybrid Intensity Frames and Events [View paper](#)
- [19] HDR video reconstruction from events and LDR frames via spatiotemporal attention and exposure compensation [View paper](#)
- [20] Compressive Sensing-Based HDR-Like Image Encryption and Artifact-Mitigated Reconstruction [View paper](#)
- [21] Single-Image HDR Reconstruction Assisted Ghost Suppression and Detail Preservation Network for Multi-Exposure HDR Imaging [View paper](#)
- [22] Diffusion-Promoted HDR Video Reconstruction [View paper](#)