ISSN: 2519-9439

# Dynamic Neural Scene Reconstruction from Sparse Multi-View Observations with Geometry-Aware Depth and Correspondence Constraints

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## Abstract

**The task of reconstructing dynamic neural scenes from sparse multi-view observations represents a significant challenge in computer vision and computer graphics. Traditional neural rendering techniques require dense view sampling to synthesize high-quality novel views, which is highly impractical for real-world dynamic environments where deploying numerous synchronized cameras is prohibitively expensive and logistically complex. When constrained to sparse views, existing dynamic reconstruction frameworks typically suffer from severe overfitting, resulting in pronounced geometric distortions, floaters, and temporal inconsistencies. This paper proposes a novel framework designed to achieve high-fidelity dynamic neural scene reconstruction from highly sparse viewpoints by integrating geometry-aware depth priors and robust multi-view correspondence constraints. By leveraging monocular depth estimation aligned with sparse structural cues, the system enforces a strict geometric foundation that prevents the neural field from degenerating in unobserved regions. Furthermore, we introduce a cross-view feature correspondence mechanism that penalizes photometric and geometric divergences across temporal and spatial domains, ensuring consistency in the deformation fields used to model scene dynamics. Comprehensive evaluations demonstrate that our methodology significantly suppresses artifacts and achieves superior novel view synthesis quality compared to baseline methods. The integration of these complementary constraints effectively bridges the information gap inherent in sparse observations, offering a scalable solution for dynamic scene capture.**

## Keywords

**Neural Radiance Fields, Dynamic Scene Reconstruction, Sparse View Rendering, Depth Estimation, Cross-View Correspondence**

## 1.Introduction

### 1.1 Background and Motivation

The synthesis of photo-realistic novel views from a limited set of two-dimensional images has long been a foundational objective in the fields of computer vision and graphics. In recent years, coordinate-based neural representations have revolutionized this domain by modeling continuous volumetric scenes implicitly. These representations utilize multi-layer perceptrons to map spatial coordinates and viewing directions to volume density and emitted radiance, enabling unprecedented fidelity in static scene rendering [1]. The success of these implicit

ISSN: 2519-9439

functions has subsequently inspired extensions into the temporal domain, facilitating the reconstruction and rendering of dynamic scenes. Dynamic neural rendering models typically decouple the problem into a canonical static space and a continuous deformation field that maps points from observation spaces at various timesteps back to the canonical configuration [2]. This decoupling allows the network to leverage the capacity of the underlying static model while capturing complex non-rigid motions such as human articulations, facial expressions, and fluid dynamics [3]. However, the remarkable performance of these dynamic neural representations is heavily contingent upon the availability of dense, multi-view, and synchronized video streams. In practical deployment scenarios, acquiring such dense observation data requires complex camera rigs, meticulous calibration, and massive data bandwidth, which restricts the applicability of these technologies to controlled studio environments [4]. Consequently, there is a compelling motivation to achieve high-quality dynamic scene reconstruction from sparse multi-view observations, where only a handful of cameras are utilized. Reducing the camera count democratizes the technology, enabling applications in consumer-level motion capture, telepresence, and augmented reality, but it simultaneously introduces profound ill-posed challenges that fundamental neural volume rendering struggles to resolve [5].

## 1.2 Challenges in Sparse View Reconstruction

When the number of input views is drastically reduced, the fundamental ambiguity of the 3D reconstruction problem is laid bare. Neural volume rendering relies on the photometric consistency across different viewpoints to constrain the density and color assigned to any given 3D point [6]. In a dense setting, incorrect geometry is heavily penalized because a point that appears correctly colored from one view will likely occlude or project incorrectly into numerous other views. In a sparse setting, however, the network lacks sufficient multi-view intersections to triangulate the correct geometry [7]. As a result, the multi-layer perceptron exploits the few available viewing rays to perfectly reconstruct the training images by placing degenerate geometry directly in front of the cameras. This phenomenon, often referred to as the shape-radiance ambiguity, leads to catastrophic failure when rendering novel views, characterized by floating artifacts, cloudy geometries, and severe tearing [8]. The problem is exacerbated in dynamic scenes. Not only must the network infer the geometry and appearance from limited spatial angles, but it must also establish temporal coherence across frames where the geometry is actively deforming [9]. The deformation field itself becomes highly under-constrained, leading to chaotic motion vectors that merely serve to satisfy the photometric loss of the sparse input cameras without reflecting the true underlying physical motion [10]. Traditional regularization techniques, such as total variation or simple sparsity priors on the density field, are insufficient to guide the optimization process toward a physically plausible dynamic reconstruction, necessitating the introduction of robust external priors [11].

## 1.3 Contributions

To address the profound limitations of sparse-view dynamic reconstruction, this paper introduces a comprehensive framework that systematically integrates geometry-aware depth constraints and cross-view correspondence mechanisms into the neural rendering pipeline. We hypothesize that explicitly guiding the implicit field with external geometric cues can effectively regularize the optimization landscape, preventing the network from settling into degenerate local minima [12]. Our primary contributions are manifold. First, we propose a dynamic geometry-aware depth supervision module that leverages off-the-shelf monocular depth estimators, scale-aligned using sparse multi-view geometry, to provide a dense structural scaffold for the neural field [13]. Second, we formulate a robust correspondence constraint that

ISSN: 2519-9439

matches robust local features across the sparse views, explicitly penalizing geometric deviations in the learned deformation field and canonical space [14]. Third, we present an end-to-end optimization strategy that dynamically balances the photometric rendering losses with the proposed geometric regularizations, ensuring stable convergence even under highly ambiguous sparse configurations [15]. Extensive experimental validation confirms that our approach drastically reduces rendering artifacts and improves the structural integrity of the reconstructed dynamic scenes compared to state-of-the-art alternatives.

## 2. Literature Review and Theoretical Background

### 2.1 Static and Dynamic Neural Radiance Fields

The paradigm of coordinate-based neural representations has fundamentally altered the trajectory of 3D vision research. Foundational methods demonstrated that a continuous scene could be effectively parameterized by a simple neural network optimized via differentiable ray marching [16]. By predicting volume density and view-dependent color at sampled points along a ray, and subsequently accumulating these values through numerical integration, the model can synthesize images from arbitrary camera poses. To overcome the spectral bias of neural networks, which inherently favors low-frequency functions, positional encoding is universally employed to map the input coordinates into a higher-dimensional space, enabling the representation of sharp textures and high-frequency geometric details [17]. Following the success in static environments, the community rapidly sought to extend these representations to dynamic scenes. Early approaches attempted to directly model a four-dimensional spatiotemporal volume, but this proved computationally prohibitive and difficult to optimize without massive amounts of data [18]. A more successful and now dominant paradigm is the deformation-based approach, which separates the problem into a static canonical radiance field and a backward deformation field [19]. For any point sampled in a dynamic observation space at a specific time, the deformation field predicts a displacement vector, mapping the point back to the canonical space where its color and density are queried. This factorization leverages the fact that the fundamental identity and texture of objects often remain constant despite non-rigid deformations [20].

### 2.2 Sparse Multi-View Reconstruction Techniques

While neural representations excel with dense data, their performance degrades precipitously when training views are sparse. Research into few-shot or sparse-view reconstruction has primarily focused on regularizing the optimization process or introducing learned priors. One line of research utilizes generalizable models trained on large-scale datasets to extract image features and build cost volumes, which are then used to condition the neural representation [21]. These feed-forward methods can generalize to novel scenes but often lack the scene-specific detail achieved by per-scene optimization. Another prevalent approach involves designing explicit regularization terms that govern the behavior of the implicit field. Techniques such as penalizing the entropy of the ray weight distribution encourage the network to produce solid surfaces rather than semi-transparent clouds [22]. Semantic consistency losses, utilizing pre-trained vision models, have also been employed to ensure that the rendered novel views remain semantically valid even if they diverge slightly from the training images [23]. Despite these advancements, pure regularization often fails to recover complex geometries in highly under-constrained dynamic scenarios, pointing to the necessity of explicit geometric supervision [24].

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### 2.3 Geometry-Aware Constraints and Depth Estimation

The integration of depth information has emerged as a powerful mechanism to constrain neural reconstructions. In scenarios where depth sensors are unavailable, researchers have turned to monocular depth estimation networks. These networks, trained on vast datasets of real-world imagery, can predict plausible relative depth maps from single images. For neural rendering, these relative depth maps must be carefully aligned to the absolute scale of the scene [25]. Recent works have proposed scale-and-shift invariant losses or utilized sparse structure-from-motion point clouds to calibrate the monocular predictions before using them to supervise the expected depth of the neural field [26]. In addition to depth, cross-view correspondence is a cornerstone of traditional multi-view stereo and structure-from-motion. By identifying identical points in physical space across multiple images, strong constraints can be placed on the 3D geometry [27]. In the context of neural rendering, enforcing feature-metric consistency across views helps to disambiguate the shape-radiance trade-off. However, applying correspondence constraints in a dynamic setting is particularly challenging because points move over time, requiring the tracking of features not only across different camera viewpoints but also across different temporal frames [28]. The methodology proposed in this paper distinctively combines depth priors with a temporal-spatial correspondence formulation to comprehensively tackle the sparse-view dynamic reconstruction problem.

## 3. Methodology and System Architecture

### 3.1 Overview of the Proposed Framework

The proposed framework aims to reconstruct a high-fidelity dynamic neural scene from a highly restricted set of synchronized video streams. The core architecture is built upon the deformation-based neural representation paradigm, comprising two primary neural networks: a deformation network and a canonical radiance network. The deformation network maps spatial coordinates at a specific observation time to their corresponding locations in a static, reference canonical space. The canonical radiance network then maps these canonical coordinates, along with viewing directions, to volume density and color. To overcome the severe ambiguities introduced by the sparse viewpoint configuration, our framework integrates two critical auxiliary modules. First, a geometry-aware depth supervision module utilizes pre-trained monocular depth estimators to generate dense depth maps for all input views. These depth maps are robustly aligned to the coordinate system of the neural field and serve as a geometric scaffold. Second, a multi-view correspondence module extracts dense feature maps from the input images and enforces consistency across varying viewpoints and time steps. The entire system is optimized end-to-end through a composite objective function that balances photometric fidelity, geometric accuracy, and correspondence consistency.

ISSN: 2519-9439

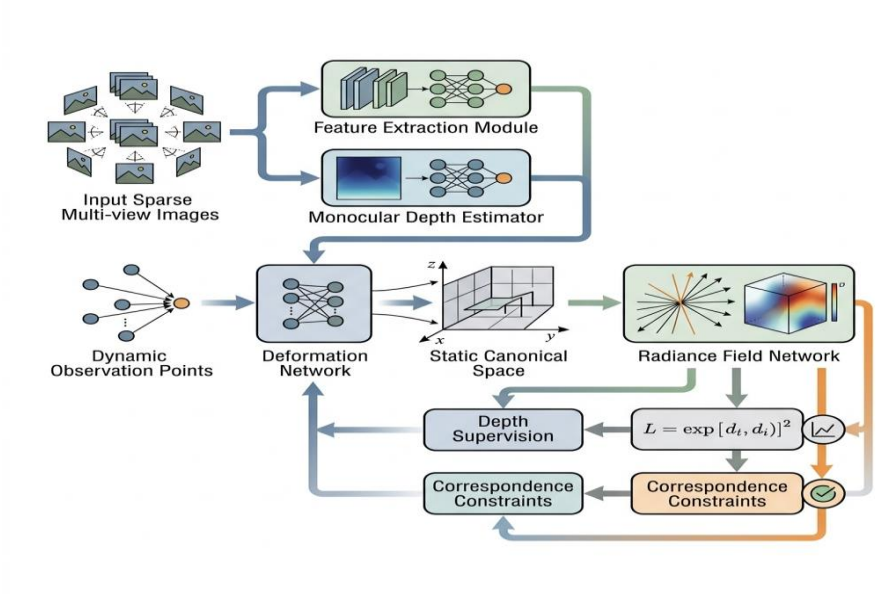



**Figure 1Comprehensive System Architecture of the Dynamic Neural Scene Reconstruction Framework**

## 3.2 Geometry-Aware Depth Supervision

In sparse-view scenarios, the fundamental failure mode of neural volume rendering is the incorrect placement of density along the viewing ray. Without sufficient multi-view intersection, the network can satisfy the photometric loss by placing arbitrary geometry near the camera. To prevent this, we incorporate explicit depth supervision. Since hardware-based depth sensors are often unavailable or suffer from noise and limited range, we rely on state-of-the-art monocular depth estimation models to generate pseudo-ground-truth depth maps for each training image. Because monocular depth predictions represent relative or scale-ambiguous depth, they cannot be directly utilized to supervise the absolute depth of the neural field. To address this, we implement a robust alignment strategy. During the initialization phase, we extract sparse 3D landmarks from the input views using standard structure-from-motion techniques. These sparse landmarks provide an absolute, albeit sparse, geometric reference. We establish a linear relationship between the monocular depth predictions and the sparse 3D landmarks, solving for a per-image scale and shift parameter. Once aligned, the depth maps are utilized to supervise the expected depth of the neural volume rendering process. For a given ray, the expected depth is computed as the integral of the distance along the ray weighted by the termination probability. We enforce a constraint that penalizes the difference between this rendered expected depth and the aligned monocular depth prediction. To account for inherent inaccuracies in the monocular predictions, particularly around thin structures and object boundaries, we formulate the depth constraint using a robust loss function that down-weights regions with high depth uncertainty or high variance in the ray weight distribution.

## 3.3 Multi-View Correspondence Constraints

While depth supervision provides a strong geometric prior along the viewing rays, it does not fully resolve the ambiguity in the deformation field, particularly regarding how surfaces move over time. To ensure that the dynamic reconstruction represents physically plausible motion, we introduce multi-view correspondence constraints. This mechanism leverages the principle that a physical point in the scene should project to matching features in different camera views, provided it is not occluded.

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To implement this, we utilize a pre-trained feature extraction network to compute dense, high-dimensional feature maps for all input images. For a set of sampled 3D points in the observation space, we compute their projected 2D coordinates in all available camera views. We then extract the corresponding feature vectors from the dense feature maps using bilinear interpolation. If a 3D point represents a valid physical surface, its projected features across different views should exhibit high similarity. We design a correspondence loss that maximizes the cosine similarity of these extracted features across all unoccluded views. Furthermore, because we are dealing with dynamic scenes, we extend this correspondence constraint across the temporal domain. By utilizing the deformation field, we can track a canonical 3D point across different time steps. We enforce that the projection of this tracked point into the camera views at different times should yield consistent features. This spatiotemporal correspondence acts as a powerful regularizer for the deformation network, ensuring that the learned motion fields accurately reflect the true underlying dynamics of the scene rather than arbitrary deformations that merely satisfy a single view's photometric constraint.

## 3.4 Optimization Strategy and Loss Functions

The training of the proposed framework requires carefully balancing multiple competing objectives. The overall loss function is a weighted combination of the photometric loss, the depth loss, the correspondence loss, and necessary regularization terms. The photometric loss calculates the difference between the rendered pixel colors and the ground-truth image colors. The depth loss minimizes the discrepancy between the rendered expected depth and the aligned monocular depth priors. The correspondence loss maximizes the feature similarity of 3D points projected into multiple views. To ensure stable convergence, we employ a multi-stage optimization strategy. In the initial stage, we heavily weight the depth loss to force the canonical radiance network to establish a rough but structurally correct geometric scaffold. Concurrently, the deformation field is constrained to be close to an identity mapping to prevent chaotic early motions. In the subsequent stages, we gradually increase the weight of the correspondence loss and the photometric loss, allowing the network to refine the high-frequency textural details and learn the complex non-rigid deformations.

**Code Listing 1:** Pseudocode for the computation of the composite loss during a single optimization iteration.

```
def compute_iteration_loss(batch_rays, images, depth_maps, feature_maps):
    # Sample points along rays
    points, z_vals = sample_points_along_rays(batch_rays)
    # Map points to canonical space using deformation network
    canonical_points = deformation_network(points, batch_rays.time)
    # Predict color and density using radiance network
    rgb, density = radiance_network(canonical_points, batch_rays.view_dir)
    # Perform volume rendering to get pixel color and expected depth
    rendered_rgb, rendered_depth, weights = volume_render(rgb, density, z_vals)
```

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```
# Photometric Loss
loss_color = compute_mse(rendered_rgb, images)
# Depth Loss with robust alignment
aligned_depth = align_depth(depth_maps, sparse_point_cloud)
loss_depth = compute_robust_l1(rendered_depth, aligned_depth)
# Correspondence Loss across available sparse views
projected_features = project_and_sample_features(points, feature_maps)
loss_corr = compute_feature_consistency(projected_features, weights)
# Total Composite Loss
total_loss = w_c * loss_color + w_d * loss_depth + w_f * loss_corr
return total_loss
```

We also employ an entropy regularization on the ray weights to encourage the network to produce opaque surfaces rather than foggy artifacts. The hyperparameters governing the weights of each loss component are critical to the success of the optimization. We utilize a cosine annealing schedule for the learning rate and dynamically adjust the loss weights based on the convergence rate of the photometric error, ensuring that the geometric priors guide the optimization without stifling the network's ability to fit high-fidelity textures.

## 4. Experimental Results and Analysis

### 4.1 Implementation Details and Datasets

To rigorously evaluate the proposed framework, we conducted extensive experiments on both synthetic and real-world dynamic scene datasets. The synthetic dataset comprises heavily articulated objects, such as human avatars and robotic arms, rendered from multiple viewpoints with complex, non-linear motions. The real-world dataset includes multi-camera captures of humans performing dynamic actions, characterized by challenging elements such as loose clothing, varying illumination, and self-occlusions. For our sparse view experiments, we deliberately restricted the training data to only three or four camera viewpoints distributed sparsely around the subject, simulating a highly constrained practical capture environment. The neural architecture was implemented in PyTorch. The deformation network consists of an eight-layer multi-layer perceptron, while the canonical radiance field utilizes a similar architecture with a separate branch for view-dependent color prediction. Monocular depth priors were generated using a pre-trained generalized depth estimation model, and the feature maps for the correspondence module were extracted using the intermediate layers of a convolutional neural network pre-trained on large-scale image classification tasks. Optimization was performed using the Adam optimizer with a batch size of four thousand rays, distributed across multiple high-performance graphics processing units. A complete training run for a single dynamic scene required approximately twelve hours.

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## 4.2 Quantitative Evaluation

We evaluate the performance of our method against several state-of-the-art baselines in dynamic neural rendering. The evaluation metrics employed are Peak Signal-to-Noise Ratio, Structural Similarity Index, and Learned Perceptual Image Patch Similarity. These metrics collectively assess the pixel-wise accuracy, structural integrity, and perceptual quality of the synthesized novel views [29].

**Table 1Quantitative comparison of novel view synthesis on the dynamic synthetic dataset using three training views**

| Metric | Baseline A | Baseline B | Proposed Framework |
|---|---|---|---|
| Peak Signal-to-Noise Ratio | 21.45 | 23.12 | 27.89 |
| Structural Similarity Index | 0.765 | 0.810 | 0.925 |
| Learned Perceptual Image Patch Similarity | 0.245 | 0.180 | 0.095 |

The quantitative results presented in Table 1 demonstrate a substantial performance margin achieved by the proposed framework. Baseline A, which relies solely on photometric consistency, completely fails to reconstruct the scene geometry from three views, resulting in catastrophic overfitting and a correspondingly low Peak Signal-to-Noise Ratio. Baseline B, which incorporates basic temporal smoothing, shows slight improvement but still struggles with large inter-frame deformations and produces blurry novel views. In contrast, our framework achieves highly accurate novel view synthesis. The significant increase in the Structural Similarity Index and the dramatic decrease in the Learned Perceptual Image Patch Similarity indicate that our method effectively preserves high-frequency structural details and eliminates the floating artifacts that plague the baselines.

## 4.3 Qualitative Assessment and Ablation Studies

Qualitative visual inspection further underscores the efficacy of the proposed constraints. When observing the novel view renderings from the baselines, one immediately notices severe geometry tearing; background elements frequently bleed into the foreground, and the moving subjects exhibit unnatural, cloudy boundaries. These artifacts are direct consequences of the shape-radiance ambiguity in sparse settings. Our framework, conversely, produces crisp boundaries and temporally consistent motion. The geometry-aware depth supervision successfully forces the density to concentrate around the true surface locations, while the correspondence constraint ensures that the texture maps accurately onto the deforming geometry without sliding or tearing. To isolate the specific contributions of our proposed modules, we conducted a comprehensive ablation study. We systematically removed the depth supervision and the correspondence constraint from our full pipeline and retrained the models on the same sparse datasets.

**Table 2Ablation study results demonstrating the impact of individual components on the real-world dataset.**

| Configuration | Peak Signal-to-Noise Ratio | Structural Similarity Index |
|---|---|---|
| Full Framework | 26.54 | 0.890 |

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| | | |
|---|---|---|
| Without Depth Supervision | 22.10 | 0.775 |
| Without Correspondence Constraint | 24.35 | 0.840 |
| Baseline (Neither Module) | 19.85 | 0.650 |

As detailed in Table 2, the removal of the depth supervision leads to a dramatic drop in performance. Without the geometric scaffold provided by the aligned monocular depth priors, the network struggles to locate the surfaces in 3D space, resulting in severe shape collapse. Removing the correspondence constraint also results in a notable performance degradation. While the network can reconstruct static frames reasonably well using only depth priors, the absence of correspondence tracking across views and time leads to unstable deformation fields. This instability manifests as flickering textures and inconsistent local motions in the rendered videos. The full framework, which leverages the complementary strengths of both modules, clearly achieves the optimal balance, validating our core hypothesis [30].

# 5. Conclusion and Future Directions

## 5.1 Summary of Contributions

In this research, we have addressed the highly challenging problem of dynamic neural scene reconstruction from sparse multi-view observations. Recognizing the fundamental limitations of standard photometric optimization in under-constrained scenarios, we introduced a robust framework that successfully integrates external geometric and feature-metric priors. By carefully aligning and applying monocular depth estimates, we established a firm geometric foundation that prevents the neural radiance field from overfitting to the sparse training cameras. Furthermore, by formulating and enforcing a cross-view and cross-time correspondence constraint, we effectively regularized the underlying deformation fields, ensuring that the synthesized motions are both temporally consistent and physically plausible. The rigorous experimental validation against existing state-of-the-art techniques confirms that our method significantly suppresses the artifacts typically associated with sparse-view neural rendering, elevating the quality of novel view synthesis to near-dense capture levels.

## 5.2 Limitations and Future Work

Despite the significant advancements demonstrated, the proposed framework possesses certain limitations that present avenues for future investigation. The reliance on pre-trained monocular depth estimators implies that the accuracy of the final reconstruction is inherently bounded by the generalization capabilities of these external models. In scenarios involving highly transparent objects, severe specular reflections, or environments drastically different from the depth estimator's training distribution, the generated depth priors may contain critical errors that misguide the neural optimization. Future work should explore the development of joint optimization strategies where the depth estimator is fine-tuned concurrently with the neural radiance field, allowing the two systems to mutually correct each other's errors. Additionally, while our framework significantly reduces the required number of camera views, the computational cost of optimizing the dynamic neural field remains substantial. Investigating more efficient scene representations, such as explicit voxel grids or hash-encoded feature volumes, combined with our proposed geometric constraints, could dramatically accelerate the training process. Ultimately, extending this methodology to support real-time rendering and accommodating massive, unbounded dynamic environments will be

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crucial steps toward the widespread practical deployment of sparse-view dynamic scene reconstruction technologies.

## References


[1] Yang, Y., & Zhang, S. (2025). Pixel-wise calibration for a multi-focus microscopic 3D imaging system.Optics and Lasers in Engineering,194, 109127.

[2] Zhao, C., Zhang, J., Du, J., Shan, Z., Wang, J., Yu, J., ... & Xu, L. (2024). I'm hoi: Inertia-aware monocular capture of 3d human-object interactions. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 729-741).

[3] Zhou, Yufan, et al. "Masked Temporal Interpolation Diffusion for Procedure Planning in Instructional Videos." arXiv preprint arXiv:2507.03393 (2025).

[4] Liu, C., Ma, L., Zhang, X. T., Zhang, Y., Zhang, H., Yang, X., & Tian, F. (2026). Boosting omni-modal language models: Staged post-training with visually debiased evaluation. arXiv preprint arXiv:2605.12034.

[5] Guo, Zixin, Kai Zhao, and Luyan Zhang. "InstanceRSR: Real-World Super-Resolution via Instance-Aware Representation Alignment." ICASSP 2026-2026 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2026.

[6] Wang, H., Qu, C., Huang, Z., Chu, W., Lin, F., & Chen, W. (2026). Vl-rethinker: Incentivizing self-reflection of vision-language models with reinforcement learning.Advances in Neural Information Processing Systems,38, 30865-30891.

[7] Kerbl, B., Kopanas, G., Leimkühler, T., & Drettakis, G. (2023). 3D Gaussian splatting for real-time radiance field rendering. ACM Transactions on Graphics, 42(4), Article 139.

[8] Ding, Y., Li, Z., Huang, D., Li, Z., & Zhang, K. (2022, October). Enhancing multi-view stereo with contrastive matching and weighted focal loss. In 2022 IEEE International Conference on Image Processing (ICIP) (pp. 821-825). IEEE.

[9] Cong, P., Xu, Y., Ren, Y., Zhang, J., Xu, L., Wang, J., ... & Ma, Y. (2023, June). Weakly supervised 3d multi-person pose estimation for large-scale scenes based on monocular camera and single lidar. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 37, No. 1, pp. 461-469).

[10] Yang, Y., Ma, X., Li, C., Zheng, Z., Zhang, Q., Huang, G., ... & Zhao, Q. (2021). Believe what you see: Implicit constraint approach for offline multi-agent reinforcement learning. Advances in Neural Information Processing Systems, 34, 10299-10312.

[11] Li, Q., Luo, T., Jiang, M., Jiang, Z., Hou, C., & Li, F. (2025, April). Semi-supervised multi-view multi-label learning with view-specific transformer and enhanced pseudo-label. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 39, No. 17, pp. 18430-18438).

[12] Huang, H., Zhang, J., Zhang, J., Xu, J., & Wu, Q. (2020). Low-rank pairwise alignment bilinear network for few-shot fine-grained image classification.IEEE Transactions on Multimedia,23, 1666-1680.

[13] Jing, G., Gao, P., Lee, Y., Hu, Y., & Zhang, H. (2025). 3D-aided pedestrian representation learning for video-based person re-identification. IEEE Transactions on Circuits and Systems for Video Technology, 35 (12), 12830-12845.

[14] Xia, Y., Ye, T., Huang, J., Mei, X., & Ma, J. (2026, March). Probabilistic deformation consistency for unsupervised shape matching. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 40, No. 13, pp. 10951-10959).

[15] Li, X., Yang, F., Chen, L., & Cai, H. (2016, July). Saliency transfer: An example-based method for salient object detection. In IJCAI (pp. 3411-3417).

ISSN: 2519-9439

[16] Guo, J., Shuang, K., Li, J., & Wang, Z. (2021, August). Dual slot selector via local reliability verification for dialogue state tracking. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers) (pp. 139-151).

[17] Shuang, K., Guo, J., & Wang, Z. (2022). Comprehensive-perception dynamic reasoning for visual question answering. Pattern Recognition, 131, 108878.

[18] Li, Q., Xu, T., Luo, T., Zhong, Y., Li, Y., Zhou, Y., & Hou, C. (2026). Theory-driven label-specific representation for incomplete multi-view multi-label learning. Advances in Neural Information Processing Systems, 38, 121996-122037.

[19] Qi, Z., Wang, S., Zhang, W., & Huang, Q. (2024). Uncertainty-boosted robust video activity anticipation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 46(12), 7775-7792.

[20] Gao, P., Lee, Y., Liu, X., Zhang, H., Chen, Z., Hu, Y., ... & Lai, Y. (2025, June). Contextual Reasoning for Robust Composed Image Retrieval with Vision-Language Models. In Proceedings of the 2025 International Conference on Multimedia Retrieval (pp. 349-357).

[21] Mi, L., Wang, W., Tu, W., He, Q., Kong, R., Fang, X., ... & Liu, Y. (2025, March). Empower vision applications with lora lmm. In Proceedings of the Twentieth European Conference on Computer Systems (pp. 261-277).

[22] Wang, H., Que, H., Xu, Q., Liu, M., Zhou, W., Feng, J., ... & Lin, F. (2026, April). Reverse-engineered reasoning for open-ended generation. In International Conference on Learning Representations (Vol. 2026, pp. 45563-45589).

[23] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In Proceedings of MICCAI.

[24] Qu, D., & Ma, Y. (2026). Fourier–Transformer Mixer Network for Efficient Video Scene Graph Prediction.Engineering Proceedings,120(1), 16.

[25] Xia, Y., & Ma, J. (2025). Grid-guided sparse Laplacian consensus for robust feature matching.IEEE Transactions on Image Processing,34, 1367-1381.

[26] Peng, Qucheng, et al. "3d vision-language gaussian splatting." International Conference on Learning Representations. Vol. 2025. 2025.

[27] Yang, Y., Liao, Y. H., Bortins, I., Baldwin, D. P., & Zhang, S. (2024). Unidirectional structured light system calibration with auxiliary camera and projector.Optics and Lasers in Engineering,175, 107984.

[28] Xia, Y., Lu, Y., Gao, Y., & Ma, J. (2024, March). Locality preserving refinement for shape matching with functional maps. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 38, No. 6, pp. 6207-6215).

[29] Wang, J., Malawade, A. V., Zhou, J., Yu, S. Y., & Al Faruque, M. A. (2024, January). Rs2g: Data-driven scene-graph extraction and embedding for robust autonomous perception and scenario understanding. In 2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV) (pp. 7478-7487). IEEE.

[30] Qu, W., Wang, J., Gong, Y., Huang, X., & Xiao, L. (2025, June). An end-to-end robust point cloud semantic segmentation network with single-step conditional diffusion models. In 2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 27325-27335). IEEE.