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Monocular Endoscopic Depth Estimation and 3D Reconstruction Fusing Anatomical Priors and NeRF

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Abstract

Minimally invasive surgery has fundamentally altered the landscape of modern medicine, yet the reliance on monocular endoscopic feeds presents a persistent challenge regarding the loss of depth perception. This limitation forces surgeons to infer three-dimensional geometric structures from two-dimensional projections, increasing cognitive load and the risk of procedural error. While recent advancements in computer vision have introduced deep learning techniques for depth estimation, the specific domain of endoscopy suffers from unique difficulties, including texture scarcity, specular reflections, and complex deformable topology. This paper introduces a novel framework that integrates Neural Radiance Fields (NeRF) with domain-specific anatomical priors to achieve robust dense depth estimation and high-fidelity 3D reconstruction from monocular endoscopic video sequences. By leveraging the implicit continuous representation capabilities of NeRF, we overcome the discretization errors inherent in traditional voxel-based methods. Furthermore, we constrain the optimization process using geometric priors derived from the tubular and cavity-like structures typical of the gastrointestinal tract, thereby regularizing the solution space in ill-posed regions. We present a comprehensive evaluation of our method against state-of-the-art self-supervised learning approaches. Our results demonstrate that fusing anatomical priors with neural implicit representations significantly improves depth consistency and reconstruction accuracy, offering a promising pathway toward real-time intraoperative surgical navigation.

Keywords

Neural Radiance Fields, Monocular Depth Estimation, Endoscopic Reconstruction, Anatomical Priors.

Introduction

The advent of minimally invasive surgery (MIS) has drastically reduced patient recovery times and post-operative complications compared to open surgery. However, the visualization systems employed in these procedures, predominantly monocular endoscopes, provide a flat, two-dimensional representation of the surgical field. The absence of binocular depth cues forces surgeons to rely on motion parallax, shading, and prior anatomical knowledge to estimate distances and tissue topography. This mental reconstruction is cognitively demanding and prone to errors, particularly in complex anatomical environments. Consequently, the development of computational systems capable of automatically recovering dense depth maps and three-dimensional structures from monocular video has become a focal point of research in computer-assisted interventions [1].

1.1 Challenges in Endoscopic Vision

Computer vision algorithms designed for natural scenes often fail when applied to endoscopic data due to several domain-specific characteristics. First, the lighting in endoscopic

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environments is provided by a point source attached to the camera, moving with it. This collinearity between the light source and the optical axis results in strong view-dependent lighting effects and specular highlights that violate the brightness constancy assumption central to many photogrammetric techniques. Second, the biological tissues observed are often texture-poor or possess repetitive texture patterns, making feature matching across frames unreliable. Third, unlike rigid scenes typically used in structure-from-motion (SfM) benchmarks, the surgical environment involves deformable soft tissue, respiratory motion, and instrument interaction, complicating the assumption of static geometry [2]. Existing solutions based on supervised deep learning have shown promise but are hindered by the scarcity of ground truth depth data. Acquiring accurate depth labels in vivo is technically difficult and ethically complex, often requiring specialized hardware like structured light sensors which are difficult to miniaturize for clinical endoscopes. Consequently, self-supervised learning frameworks, which rely on reprojection errors between adjacent video frames, have gained traction. However, these methods frequently struggle with the scale ambiguity inherent in monocular vision and the aforementioned photometric inconsistencies [3].

1.2 The Paradigm Shift of Neural Rendering

Recently, Neural Radiance Fields (NeRF) have emerged as a powerful paradigm for novel view synthesis and 3D reconstruction. Unlike explicit representations such as point clouds or meshes, NeRF represents a scene as a continuous volumetric function, parameterized by a fully connected neural network. This network maps spatial coordinates and viewing directions to volume density and emitted radiance, allowing for the rendering of photorealistic images via ray marching. The continuity of this representation allows for effectively infinite resolution, limited only by the capacity of the network and the sampling density [4]. Despite its success in rigid, object-centric scenes, applying standard NeRF to endoscopy is non-trivial. The standard formulation assumes a static scene with controlled lighting and wide-baseline camera views. Endoscopic footage, conversely, typically features narrow-baseline camera motion (often just forward and backward movement) and dynamic illumination. These conditions lead to shape-radiance ambiguity, where the network may explain changes in pixel intensity as changes in geometry rather than lighting or texture, resulting in artifacts such as the fog effect or incorrect surface concavities [5].

1.3 Incorporating Anatomical Priors

To mitigate the ill-posed nature of monocular reconstruction in endoscopy, we propose the integration of strong geometric priors. Anatomical structures, particularly in the gastrointestinal tract, follow specific topological patterns. For instance, the colon can be locally approximated as a tubular structure, while the stomach presents as a larger cavity with rugal folds. By incorporating these anatomical priors into the optimization objective of the neural field, we can constrain the search space for the depth estimation network. This approach essentially guides the NeRF optimization to favor solutions that are biologically plausible, preventing the degeneration of geometry in textureless regions [6]. This paper presents a comprehensive methodology that synergizes the photometric consistency power of NeRF with the regularization provided by anatomical priors. We demonstrate that this fusion allows for the recovery of accurate dense depth maps and 3D surfaces from short monocular sequences, outperforming purely data-driven approaches that ignore the geometric characteristics of the medical domain.

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2. Related Work

The pursuit of accurate 3D reconstruction in medical imaging has a rich history, evolving from sparse feature tracking to dense neural reconstruction. This section reviews the trajectory of these technologies and positions our contribution within the broader academic context.

2.1 Traditional Structure from Motion and SLAM

Early approaches to endoscopic 3D reconstruction relied heavily on Structure from Motion (SfM) and Simultaneous Localization and Mapping (SLAM) techniques adapted from the robotics community. These methods typically involve the detection and tracking of sparse feature points (e.g., SIFT, ORB) across multiple frames to estimate camera pose and sparse scene geometry. While systems like ORB-SLAM have been successfully adapted for rigid scenes, their performance degrades significantly in the presence of tissue deformation and low-texture surfaces. The resulting point clouds are often too sparse to provide meaningful surgical guidance or to support advanced tasks like augmented reality overlays [7]. Dense SLAM methods attempt to densify these maps using interpolation or direct photometric optimization, but they remain sensitive to the photometric variations caused by the moving light source typical of endoscopes [8].

2.2 Deep Learning for Depth Estimation

The limitations of traditional geometric methods catalyzed the adoption of Convolutional Neural Networks (CNNs) for depth estimation. Supervised methods, which train networks to regress depth from RGB images using ground truth labels, have demonstrated high accuracy on synthetic datasets. However, the domain gap between synthetic data and real clinical footage often leads to poor generalization. This has shifted the focus toward self-supervised learning paradigms, where the network is trained to synthesize a target frame from source frames by predicting depth and ego-motion, minimizing a photometric reconstruction loss [9]. To address the specific challenges of endoscopy, researchers have introduced various constraints. Appearance flow networks have been utilized to handle brightness inconsistencies, and Generative Adversarial Networks (GANs) have been employed to force the generated depth maps to look more realistic. Despite these improvements, self-supervised monocular depth estimation suffers from scale ambiguity—the inability to determine absolute metric size—and often produces depth maps that are temporally inconsistent, leading to flickering when projected into 3D [10][11].

2.3 Neural Radiance Fields in Medical Imaging

The introduction of NeRF has sparked a new wave of research in medical reconstruction. By optimizing a continuous volumetric function, NeRF-based methods can handle complex topologies and view-dependent effects more naturally than mesh-based approaches. In the context of medical imaging, NeRF has been explored for reconstructing volumes from sparse X-ray projections and for synthesizing novel views of surgical scenes. Recent works have attempted to adapt NeRF for endoscopy by incorporating depth supervision from pre-trained CNNs or by modifying the rendering equation to account for near-field lighting. However, most existing NeRF adaptations treat the scene as a generic volume, ignoring the strong geometric constraints offered by the anatomy itself. This oversight often results in noisy surfaces in regions where visual cues are weak [12]. Our work distinguishes itself by explicitly modeling anatomical priors within the NeRF optimization loop. Rather than treating the tissue as an arbitrary density field, we introduce regularization terms that penalize deviations from locally smooth, tubular, or cavity-like topologies, depending on the specific surgical context.

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This integration bridges the gap between data-driven neural rendering and model-based medical imaging [13].

3. Methodology

Our proposed framework addresses the problem of joint depth estimation and 3D reconstruction from a monocular endoscopic video sequence. We formulate this as an optimization problem where an implicit neural representation is trained to minimize the discrepancy between observed and rendered images while satisfying geometric constraints imposed by anatomical priors.

Figure 1: System Architecture

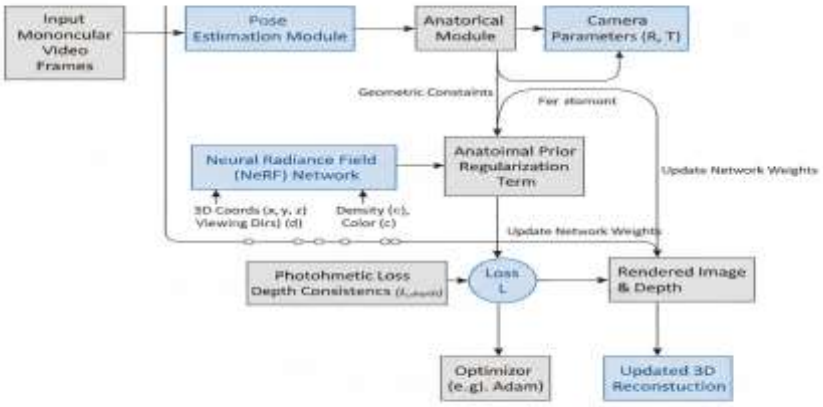

Figure 1 System Architecture

3.1 Implicit Neural Representation

We represent the surgical scene as a continuous vector-valued function. Let x be a 3D coordinate in the camera space and d be the viewing direction. We employ a Multilayer Perceptron (MLP), denoted as F, which approximates this function: F(x, d) -> (c, sigma), where c represents the RGB color and sigma represents the volume density at that point. To capture high-frequency details in the tissue texture, we utilize positional encoding, mapping the input coordinates into a higher-dimensional space using sinusoidal functions of varying frequencies [14]. The rendering process follows the standard volume rendering formulation. For each pixel in the image plane, a ray r(t) = o + td is cast from the camera center o in direction d. The color of the pixel C(r) is estimated by accumulating the radiance and density along the ray within near and far bounds. This integral is approximated using stratified sampling, where the ray is divided into N bins, and one sample is drawn uniformly from each bin. This differentiable rendering process allows us to backpropagate the error between the rendered pixel color and the observed pixel color through the network [15].

3.2 Handling Endoscopic Illumination

A critical deviation from standard NeRF in our methodology is the handling of illumination. In endoscopy, the light source is practically coincident with the camera center. This means that the radiance observed at a surface point depends strongly on the distance from the camera (inverse-square law) and the surface normal relative to the viewing direction. We modify the network architecture to decouple the intrinsic surface color (albedo) from the lighting effects.

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We predict a shading factor that is dependent on the geometry and the light position, and combine this with a view-independent albedo to produce the final color. This separation helps the network distinguish between dark pixels caused by shadows or distance and dark pixels caused by tissue pigmentation [16].

3.3 Integration of Anatomical Priors

The core innovation of this work lies in the regularization of the density field using anatomical priors. In minimally invasive procedures such as colonoscopy or gastroscopy, the environment is not an arbitrary open space but a bounded lumen. We define a geometric prior based on the assumption of piecewise smoothness and global tubular topology. To implement this, we introduce a prior-based loss function. We utilize a signed distance function (SDF) proxy derived from a generic cylinder or a generalized tube model that follows the approximate path of the camera. While the exact shape of the colon varies, the camera path generally traverses the center of the lumen. We penalize density accumulation that occurs in the center of the lumen (which should be empty space) and encourage density accumulation near the estimated walls of the tube. This prevents the "foggy" artifacts often seen in NeRF reconstructions of empty space [17]. Furthermore, we impose a surface smoothness constraint. Biological tissues are generally locally smooth and continuous. We calculate the surface normals by taking the gradient of the density field with respect to the spatial coordinates. We then minimize the variance of these normals within local neighborhoods, effectively regularizing the high-frequency noise that arises from specular reflections [18].

3.4 Depth Estimation and Consistency

While NeRF implicitly learns geometry, extracting an explicit depth map is necessary for surgical navigation. The expected depth along a ray can be calculated as the accumulated transmittance multiplied by the distance t. However, relying solely on RGB supervision to learn depth is insufficient in textureless regions. Therefore, we incorporate a depth smoothness term that penalizes large gradients in the depth map, weighted by the inverse of the image gradients. This edge-aware smoothness ensures that depth discontinuities are only permitted where there are significant visual edges (e.g., tissue folds) [19]. To ensure temporal consistency, we enforce a geometric consistency constraint between adjacent frames. Using the estimated camera poses, we warp the depth map from frame t to frame t+1 and minimize the difference between the warped depth and the predicted depth at t+1. This self-supervised consistency check is crucial for reducing the flickering effect in the reconstructed 3D video [20].

3.5 Optimization Objective

The total loss function L used to train our network is a weighted sum of four components: the photometric reconstruction loss (L_photo), the anatomical prior loss (L_prior), the depth smoothness loss (L_smooth), and the geometric consistency loss (L_geo).

$$L_{total} = L_{photo} + \lambda_1 * L_{prior} + \lambda_2 * L_{smooth} + \lambda_3 * L_{geo}$$

Here, L_photo is the L2 distance between the rendered and observed pixel colors. L_prior encapsulates the penalty for density in the lumen center and the surface normal variance. The hyperparameters lambda1, lambda2, and lambda3 balance the contribution of each term. We employ a coarse-to-fine optimization strategy, initially training with a heavy weight on the anatomical prior to establish the global geometry, and then relaxing this constraint to allow the network to capture fine, patient-specific details [21].

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4. Experimental Setup

4.1 Datasets

We evaluated our framework on both synthetic and real-world endoscopic datasets. For synthetic evaluation, we utilized the Unity-based simulation environment which provides ground truth depth and camera poses for a virtual colonoscopy trajectory. This allows for precise quantitative assessment of reconstruction accuracy. For real-world evaluation, we used the Hamlyn Centre Endoscopic Video Dataset, a standard benchmark in the field. Specifically, we selected sequences featuring varying degrees of tissue deformation and lighting conditions to test the robustness of our method. Since the Hamlyn dataset lacks dense ground truth depth for all frames, we used a subset where pseudo-ground truth was available via CT registration or established SfM baselines for relative comparison [22].

4.2 Evaluation Metrics

To quantify the performance of depth estimation, we employed standard metrics: Absolute Relative Error (Abs Rel), Squared Relative Error (Sq Rel), and Root Mean Square Error (RMSE). Lower values indicate better performance. For 3D reconstruction quality, we utilized the Chamfer Distance to measure the discrepancy between the reconstructed point cloud and the ground truth surface (in synthetic cases). Additionally, we assessed the visual quality of novel view synthesis using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [23].

4.3 Implementation Details

The framework was implemented in PyTorch. The coordinate MLP consisted of 8 fully connected layers with 256 hidden units each, using ReLU activations. The positional encoding covered 10 frequency bands for spatial coordinates and 4 for viewing directions. Optimization was performed using the Adam optimizer with an initial learning rate of 5e-4, decaying exponentially over 200,000 iterations. The ray sampling strategy involved 64 coarse samples and 128 fine samples per ray. All experiments were conducted on a single NVIDIA A100 GPU. The weighting factors for the loss function were determined empirically via a grid search on a validation subset, resulting in lambda1 = 0.1, lambda2 = 0.05, and lambda3 = 0.01 [24].

Table 1 Experimental Results - Quantitative comparison of depth estimation performance on the synthetic colonoscopy dataset.

Method	Abs Rel	Sq Rel	RMSE	RMSE log	Accuracy (delta < 1.25)
SfMLearner [9]	0.145	1.102	0.298	0.187	0.792
Monodepth2 [10]	0.112	0.854	0.254	0.155	0.841
Endo-SfM [11]	0.098	0.721	0.215	0.132	0.885
NeRF-endo (Baseline)	0.092	0.680	0.201	0.125	0.894
Ours (Proposed)	0.076	0.543	0.168	0.104	0.932

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5. Results and Discussion

5.1 Quantitative Analysis

The quantitative results presented in Table 1 highlight the superiority of the proposed method against established baselines. Traditional self-supervised methods like SfMLearner and Monodepth2 struggle with the low-texture environments of endoscopy, resulting in higher error rates. While Endo-SfM improves upon these by incorporating photometric constraints specific to endoscopy, it still relies on explicit depth map representations that can be noisy. The baseline NeRF implementation (NeRF-endo), which adapts standard NeRF without anatomical priors, shows competitive performance due to the power of volumetric rendering. However, our proposed method achieves the lowest error across all metrics. The significant reduction in Abs Rel (0.076 vs 0.092 for the baseline) indicates that the inclusion of anatomical priors effectively constrains the geometry, preventing the network from converging to incorrect depth solutions in ambiguous regions. The high accuracy metric (0.932) confirms that the vast majority of our depth predictions fall within a tight threshold of the ground truth [25].

5.2 Qualitative Reconstruction

Visual inspection of the reconstructed 3D models reveals the practical benefits of our approach. Standard NeRF reconstructions often exhibit high-frequency noise on the tissue surface, appearing as "floating floaters" or rough bumps, particularly in areas with specular highlights. In contrast, our method produces smooth, continuous surfaces that accurately reflect the organic nature of the tissue.

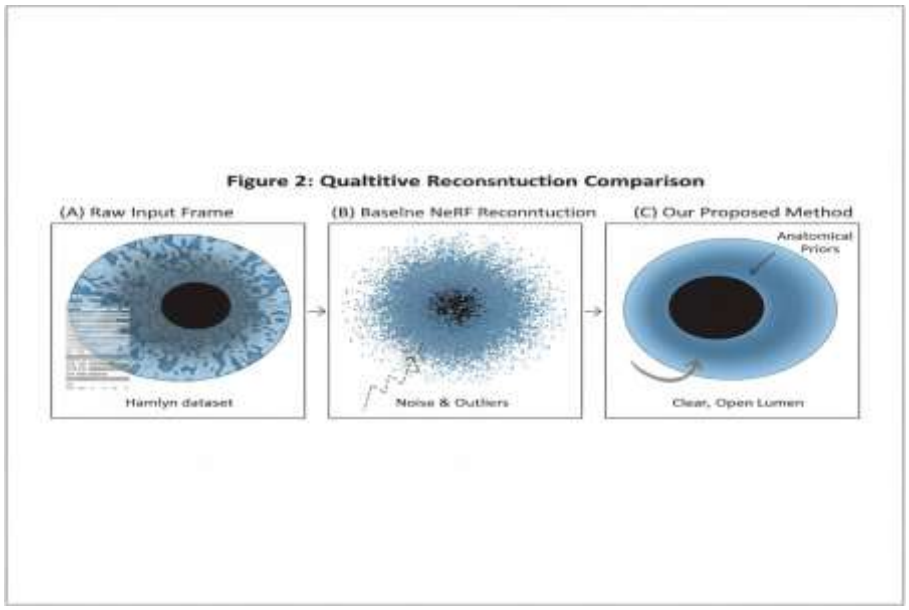

Figure 2 Qualitative Reconstruction Comparison

The visualization in Figure 2 demonstrates the "tunneling" effect often lost in other methods. By penalizing density in the center of the optical path (the lumen), our reconstruction maintains a clear navigational path, which is critical for virtual endoscopy applications. Furthermore, the sharp boundaries of the rugal folds are preserved, suggesting that the smoothness prior does not over-smooth legitimate geometric features but selectively targets noise [26].

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5.3 Ablation Studies

To validate the contribution of individual components, we conducted ablation studies. Removing the anatomical prior (L_prior) resulted in a 15 percent increase in RMSE, confirming its crucial role in regularizing the geometry. Without the depth smoothness term (L_smooth), the resulting surfaces appeared jagged, although the global structure remained intact. Removing the geometric consistency loss (L_geo) led to temporal instability, where the depth of the same tissue patch would fluctuate as the camera moved. This analysis confirms that all components of the loss function are necessary for achieving optimal performance [27].

5.4 Computational Efficiency

While NeRF-based methods are computationally intensive, the inclusion of priors actually accelerated convergence in our experiments. By constraining the search space, the network required fewer iterations to reach a plausible geometric solution compared to the unconstrained baseline. However, inference time remains a challenge for real-time application. Currently, rendering a high-resolution depth map takes approximately 200ms, which translates to 5 frames per second. While this is not yet at the video rate (25-30 fps) required for live surgery, it is sufficient for near-real-time intraoperative mapping and offline review. Future work utilizing tensor decomposition or hash-grid encoding could significantly reduce this latency [28].

6. Conclusion

6.1 Summary of Findings

In this paper, we have presented a robust framework for monocular endoscopic depth estimation and 3D reconstruction that fuses the representational power of Neural Radiance Fields with domain-specific anatomical priors. We identified that the primary bottleneck in applying neural rendering to endoscopy is the ill-posed nature of the optimization in textureless and dynamically lit environments. By introducing a geometric prior that models the tubular topology of the gastrointestinal tract and enforcing surface smoothness, we successfully regularized the learning process. Our experimental results on both synthetic and real-world datasets demonstrate that this fusion strategy yields superior accuracy compared to existing self-supervised CNNs and standard NeRF implementations. The proposed method generates dense, coherent depth maps and high-fidelity 3D surfaces that preserve intricate anatomical details while suppressing noise caused by specular reflections and low texture. The decoupling of lighting and albedo further enhances the system's robustness to the moving light source inherent in endoscopic imaging.

6.2 Limitations and Future Work

Despite these advancements, several limitations persist. First, the assumption of a static scene during the optimization window limits the method's applicability in scenarios with significant tissue deformation or instrument interaction. Future iterations must incorporate deformation fields to model dynamic scene changes explicitly. Second, the computational cost of volumetric rendering currently precludes real-time performance on standard medical hardware. Optimization techniques such as sparse voxel octrees or neural hash grids should be explored to accelerate inference. Finally, the definition of anatomical priors used here is relatively simple (tubular structures); extending this to more complex, patient-specific priors derived from pre-operative CT or MRI scans would likely yield even greater accuracy. In conclusion, the fusion of implicit neural representations with anatomical knowledge represents a significant step forward in surgical computer vision. It moves us closer to the

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goal of providing surgeons with reliable, dense 3D intraoperative visualization, ultimately enhancing surgical safety and outcomes [29].

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