

Neural Visibility Field for Uncertainty-Driven Active Mapping

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Abstract

This paper presents Neural Visibility Field (NVF), a novel uncertainty quantification method for Neural Radiance Fields (NeRF) applied to active mapping. Our key insight is that regions not visible in the training views lead to inherently unreliable color predictions by NeRF at this region, resulting in increased uncertainty in the synthesized views. To address this, we propose to use Bayesian Networks to composite position-based field uncertainty into ray-based uncertainty in camera observations. Consequently, NVF naturally assigns higher uncertainty to unobserved regions, aiding robots to select the most informative next viewpoints. Extensive evaluations show that NVF excels not only in uncertainty quantification but also in scene reconstruction for active mapping, outperforming existing methods. More details can be found at <https://sites.google.com/view/nvf-cvpr24/>.

1. Introduction

Active 3D reconstruction plays a pivotal role in robotics. The challenge lies in enabling the robot to precisely reconstruct a target using the fewest views possible. Consider the example, illustrated in Figure 1, where the agent’s objective is to thoroughly explore an unknown object (the Hubble telescope). To achieve this, the robot assesses the uncertainty of potential views, choosing actions that significantly diminish this uncertainty. A crucial aspect of this process is the representation of the scene. It should not only facilitate high-quality reconstruction but also be cognizant of uncertainties.

Recently, implicit scene representations, notably NeRF [30] have shown remarkable ability in high-quality scene reconstructions. The result has motivated applying NeRF for active reconstruction [33, 49, 51]. However, due to the opaque nature of neural networks, estimating the uncertainty of NeRF remains challenging. Previous works have developed various proxy measurements to represent the uncertainty in NeRF, in which they aim to maximize the NeRF’s reconstruction accuracy and geometric faithfulness to the scene. However, these approaches neglect a crucial

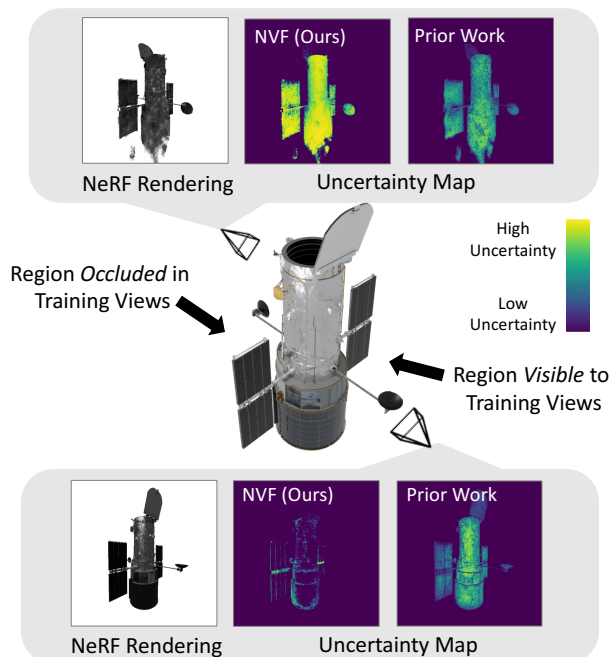


Figure 1. Neural Visibility Field (NVF) is an uncertainty estimation framework for NeRF that accounts for *visibility*: whether a region is covered by the training views of a NeRF. Visible regions should have low uncertainty (bottom row), and unobserved should have high uncertainty (top row). In this paper, we show that many existing methods in NeRF uncertainty quantification can be viewed as special cases of our framework, and NVF outperforms them empirically in uncertainty quantification and active mapping tasks.

factor to optimize for, namely, visual coverage.

In active reconstruction, an agent makes a tradeoff between exploring new areas of a scene and revisiting previously explored ones. Since NeRF is a multiview reconstruction method, a natural strategy is to explore regions that have not been observed by previous views and have these regions hold a high degree of uncertainty. Surprisingly, prior methods have largely failed to account for visibility and instead focus on estimating uncertainty via density or NeRF-predicted position-based RGB variance. Another gap in prior research is the integration of position-based uncertainty factors (e.g., emitted color, opacity, and visibility) into ray-based obser-

vation uncertainty. Previous approaches typically employ a simple (weighted) average or sum of position-based uncertainties to approximate the observation uncertainty. However, these methods often lack a solid theoretical foundation and can underperform in complex scenarios.

To address these challenges, we propose Neural Visibility Field (NVF). Our key insight is that if a region has never been visible in the training views, the color prediction for this point by NeRF is unreliable. To effectively integrate this location-based uncertainty into ray-based camera observations, we view NeRF through the lens of a Bayesian Network. Within this framework, the distribution of a color along a ray can be interpreted as a Gaussian mixture Model. Subsequently, we calculate the entropy of the GMM and employ it as a cost function, guiding the agent to select the next best view for active mapping. We observed that all previous methods can be interpreted as specific approximations within our proposed theoretical framework, yet, they consistently overlook a crucial aspect, namely, visibility.

Our evaluation of the proposed approach is multi-faceted and spans a range of environments, encompassing objects, indoor rooms, and spaces. We illustrate how our method offers a superior metric for assessing uncertainty in NeRF. We also apply our approach to active mapping tasks. Specifically, we demonstrate that employing our metric in Next-Best-View (NBV) planning facilitates the planning of trajectories that not only enhance reconstruction quality but also maximize visual coverage of the scene. As a result, our proposed method demonstrates significant improvements over these prior approaches in experimental evaluations. To summarize, our main contributions are:

- We propose a principled uncertainty estimation method for NeRF that takes into account visibility, called Neural Visibility Field (NVF).
- We provide a unified lens of prior methods in uncertainty estimation for NeRF using NVF.
- We apply the NVF framework to active mapping tasks demonstrating superior performance compared to the existing state-of-the-art methods.

2. Related Work

Active Mapping. Research on active mapping or NBV selection is a long-studied problem [1, 2] with the goal of searching for observation poses to create an optimal reconstruction of an environment. Scott et al [40] categorizes these approaches as model-based approaches, which utilize knowledge of the geometry and appearance of a scene [11, 39], and model-free approaches, which use information extracted from data gathered online [1, 2, 4]. More relevant are view-point selection strategies, including frontier-based [6, 9], sampling-based [7, 12, 37], and uncertainty based [41, 42]. In particular, our method is inspired by the line of work that uses probabilistic volumetric occupancy to facilitate vis-

ibility operations [16, 20], which employs the concept of entropy to estimate uncertainty.

Implicit Scene Representation. Implicit neural fields [28, 34, 48] represent 3D scenes as a continuous differentiable signal parameterized via a neural network. The seminal work of Neural Radiance Fields (NeRFs) [29] learns a density and a radiance field supervised by multiview 2D images. New views can be queried from a trained NeRF through volumetric rendering. Along this direction, significant progress has been made in novel view rendering [27, 29, 45], 3D reconstruction [3, 22], 3D generation [17, 36] and videos [10, 23, 24, 35, 47]. Despite their success, the quality of representation hinges on using a large number of well-posed images which limits their applicability in real-time applications. To counter these problems, recent work has focused on few-shot neural rendering [5, 8, 32, 50], handling unknown or noisy camera pose estimates [25, 46], using heuristic camera placement strategy [19], or adding a notion of uncertainty [18, 21, 26, 42] to quantify information gain for next-best-view selection.

Uncertainty Estimation for NeRF. This work focuses on quantifying the epistemic uncertainty of a NeRF model to determine the next best view for improving its reconstruction. Direct approaches such as ensemble-based methods [44] are conceptually simple but computationally expensive or require prior data collection [14, 18]. Our method improves upon and unifies a recent line of work [21, 33, 38, 42, 49, 51]. ActiveNerf [33] and NeurAR [38] model RGB color distribution at a specific spatial point as a Gaussian distribution, and directly use NeRF to predict its variance. However, the predicted variance tends to be inaccurate in instances where a region has never been visible from the training views. In comparison, [21, 42, 49, 51] ignore the spatial RGB uncertainty, and approximating the entropy through the probability of occupancy by using NeRF’s density prediction. In particular, [21] treats the sampled points in volumetric rendering that are displayed by pixels as discrete random variables and computes the entropy based on it. In [49, 51], the entropy is approximated by utilizing the probability of a ray being occluded at a point. However, it is worth noting that a remaining gap exists in all previous methods as they lack theoretical grounding for bridging the position-based uncertainty or occupancy uncertainty with ray-based observation uncertainty. In our work, we proposed a theoretically principled method based on Bayesian Network to address this challenge. Moreover, a crucial aspect of uncertainty estimation is that if a region is never visible by any of the previous views, the NeRF prediction at this region is not reliable, and high uncertainty should be associated with these regions, yet this aspect is overlooked by all relevant previous works. Our proposed theoretical framework enables us to properly model this aspect through visibility, and all previous work could

be viewed as special cases under our proposed framework while lacking certain key aspects.

3. Method

Active mapping aims to reduce uncertainties in the reconstructed map and achieve visual coverage of the entire scene. This is achieved by assessing the current uncertainties in the reconstructed map and predicting the potential information gained from proposed viewpoints. However, the challenge arises when utilizing NeRF for active mapping. The opaque and complex nature of neural networks presents significant challenges for accurately quantifying uncertainty within NeRF. Although several methods have been proposed to approximate uncertainty in NeRF, they often lack a theoretical foundation and may underperform in complex scenarios. Our key insight is that if a region has never been visible in the training views, the color prediction for this point by NeRF is inherently unreliable. To effectively incorporate this position-based uncertainty into camera observations, we propose to use a Bayesian network. This allows for the seamless integration of uncertainty from the implicit field into the observed image’s uncertainty. In this section, we will start with a review of NeRF, followed by a detailed explanation of how to model NeRF’s volume rendering process using a Bayesian network. Subsequently, we will delve into the integration of visibility aspects within the framework. Finally, we will discuss the application of this framework to active mapping.

3.1. Problem Formulation

A NeRF [30] is defined as an implicit function $F_{\Theta} : (x, d) \rightarrow (c, \sigma)$, where x represents the 3D position, $d = (\theta, \phi)$ the viewing direction, c the emitted RGB color at x , and σ the volume density at x . The volume density function $\sigma(x)$ is a differentiable measure of the probability that a ray is occluded at position x . Considering a ray $r(t) = o + td$ with near and far bounds t_n, t_f , the observed color at the ray’s origin is given by:

$$C(r) = \exp \left(- \int_{t_n}^{t_f} T(t) \sigma(r(t)) c(r(t), d) dt \right) \quad (1)$$

$$T(t) = \exp \left(- \int_{t_n}^t \sigma(r(s)) ds \right) \quad (2)$$

where $T(t)$ is the transmission probability from t_n to t without occlusion. Empirically, the algorithm approximates the integral with N discrete samples $\{t_i\}_{i=0}^{N-1}$ along the ray, where t_0 denotes the ray’s origin where the camera is located. Consequently, Eq. (1) becomes:

$$\hat{C}(r) = \sum_i w_i c(t_i), \text{ where } w_i = \alpha_i \prod_{j=0}^{i-1} (1 - \alpha_j), \quad (3)$$

where $s_i = t_{i+1} - t_i$ denotes the distance between two adjacent sampled points along the ray, $\alpha_i = 1 - \exp(-s_i \sigma(t_i))$

is the alpha value in alpha composition, which can also be viewed as the probability of occlusion at the i th point.

3.2. Volume Rendering as Bayesian Network

While NeRF synthesizes novel views, NeRF cannot estimate the uncertainty in the views. We introduce a method that composites position-based uncertainty into ray-based uncertainty using a probabilistic graphical model. This framework enables the integration of visibility factors into the uncertainty estimation process (see Sec. 3.3). We consider the observed color along a ray, $C(r)$, as a random variable instead of a constant. In this subsection, we detail the computation of this variable’s distribution by using a Bayesian network to model the volume rendering process. We use a binary random variable D_i to denote whether the ray is occluded in the interval $[t_i, t_{i+1}]$ ($D_i = 1$ for occluded, $D_i = 0$ for transparent). The continuous random variable C_i then represents the emitted color at t_i in the direction d , and Z_i is a continuous random variable for the observed color at t_i . Here, Z_0 corresponds to the camera’s observed color at the origin, and hence, the goal is to compute $p(z_0)$. Notice that, although both C_i and Z_i represent colors, their difference lies in the objects they represent: C_i represents the color distribution associated with a specific position in $\mathbb{R}^3$, whereas Z_i corresponds to the color distribution of a camera observation, associated with a particular ray. For simplicity, we omit the ray index r for D_i , C_i , and Z_i in Sections 3.2 and 3.3 below.

Note that the value of Z_i only depends on D_i , C_i , and Z_{i+1} . Specifically, if the interval $[t_i, t_{i+1}]$ occludes the ray, Z_i assumes the emitted color C_i ; otherwise, Z_i equals Z_{i+1} , as the interval is transparent. The conditional probability $p(z_i | D_i, c_i, z_{i+1})$ is thus:

$$p(z_i | D_i, c_i, z_{i+1}) = \begin{cases} \delta(z_i - c_i), & \text{if } D_i = 1, \\ \delta(z_i - z_{i+1}), & \text{otherwise,} \end{cases} \quad (4)$$

where $\delta(\cdot)$ is the Dirac delta function. Thus, the volume rendering process could be modeled as a hybrid Bayesian network (illustration included in the Appendix). Moreover, we can express the marginal probability of z_i using the following recursion:

$$p(z_i) = \alpha_i p(c_i) + (1 - \alpha_i) p(z_{i+1}). \quad (5)$$

Note that this formulation utilizes the relationship $P(D_i = 0) = 1 - \alpha_i = \exp(-\sigma_i s_i)$, where α_i was previously defined as the probability of occlusion at the i th point along the ray. If we assume $p(c_i)$ is a Gaussian distribution with mean μ_{c_i} and covariance Q_{c_i} , as predicted by the NeRF model (see Sec. 3.4 for details), by using recursion Eq. (5), the marginal probability of z_0 is computed as a Gaussian mixture model (GMM):

$$p(z_0) = \sum_i w_i \mathcal{N}(\mu_{c_i}, Q_{c_i}), \quad (6)$$

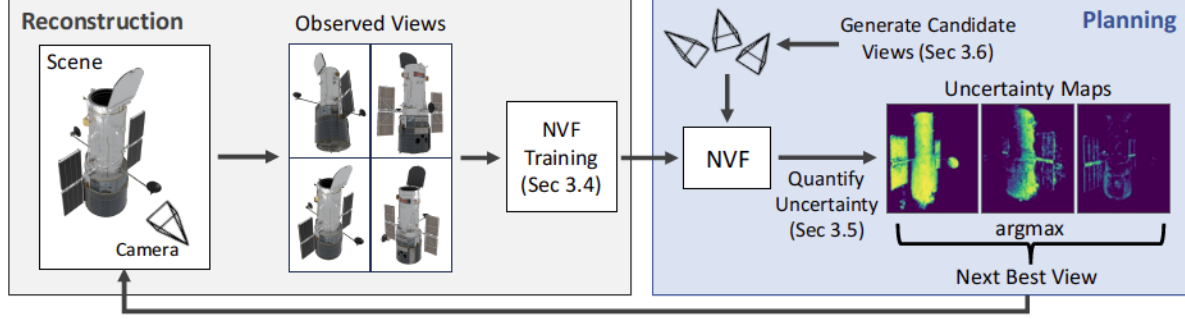


Figure 2. **Active Mapping with NVF.** Starting with a small set of initial views, a trained NVF is used to quantify uncertainties among sampled candidate views and chooses the view with maximum uncertainty as the next view to be observed by the agent.

with $w_i = \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j)$. The distribution of the camera's observation, $p(z_0)$, implies that $E[z_0] = \sum_i w_i \mu_{c_i}$ which aligns with the original NeRF's volume rendering expression (Eq. (3)).

So far, we have developed a framework based on a probabilistic graphical model to bridge position-based uncertainty with ray-based observational uncertainty. In the following subsection, we will discuss the integration of the visibility factor into this framework.

3.3. Uncertainty with Visibility

With the Bayesian network formulation, we can now add visibility into the uncertainty estimation. Let a binary random variable V_i represent whether point i is visible to any camera in the training set. When a point is visible ($V_i = 1$), we can rely on NeRF's output for RGB and its variance. If a point is unobserved ($V_i = 0$), the NeRF's output at this point becomes unreliable, and we assign a prior color distribution $\mathcal{N}(\mu_0, Q_0)$ to it, as follows:

$$p(c_i|V_i) = \begin{cases} \mathcal{N}(\mu_{c_i}, Q_{c_i}), & \text{if } V_i = 1, \\ \mathcal{N}(\mu_0, Q_0), & \text{otherwise.} \end{cases} \quad (7)$$

Moreover, for invisible points, density prediction may also lack accuracy. Therefore, we define the conditional probability table for $P(D_i|V_i)$ as follows

Visibility V_i	Occlusion D_i	
	1	0
1	$\exp(-\sigma_i s_i)$	$1 - \exp(-\sigma_i s_i)$
0	ρ_i	$1 - \rho_i$

(8)

where $\rho_i = (1 - \beta) \exp(-\sigma_0 s_i) + \beta \exp(-\sigma_i s_i)$, and the hyperparameter β represents the accuracy of occlusion prediction, specifically indicating the likelihood that a prediction about occlusion is correct for points that are invisible. In situations where the occlusion prediction is incorrect, we resort to using a constant prior density σ_0 to estimate the occlusion probability. This approach helps in adjusting our

model's predictions on density, particularly for points not visible to any camera in the training set.

By combining Eqs. (2), (7), (8), the marginal probability of z_i satisfies the recursive formula similar to Eq. (5): $p(z_i) = \alpha_i^* \mathcal{N}(\mu_{c_i}, Q_{c_i}) + (1 - \alpha_i^*) \mathcal{N}(\mu_0, Q_0)$, where $\alpha_i^* = (v_i + (1 - v_i)\beta)(1 - \exp(-\sigma_i s_i)) + (1 - \beta)(1 - v_i)(1 - \exp(-\sigma_0 s_i))$, and $v_i = P(V_i = 1)$ is the probability of point i being visible to at least one camera in the training set. The marginal probability of $p(z_0)$ can be computed similarly as follows

$$p(z_0) = \sum_i w_i^* v_i \mathcal{N}(\mu_{c_i}, Q_{c_i}) + \mathcal{N}(\mu_0, Q_0) \sum_i w_i^* (1 - v_i), \quad (9)$$

resulting in a GMM as well, where $w_i^* = \alpha_i^* \prod_{j=1}^{i-1} (1 - \alpha_j^*)$.

3.4. Neural Visibility Field

So far, we have established a framework that bridges position-based uncertainty with ray-based observation uncertainty, while also incorporating visibility factors. Next, we discuss a method to determine visibility v_i , which is the probability that a point x_i is visible to at least one camera in the training set. Let $\mathcal{P} = \{p_1, p_2, \dots\}$ be the set of camera poses in the training set. If point x_i is within the field of view of a camera p in $\mathcal{P}$, the visibility of x_i to camera p can be expressed as $v_p(x_i) = T_p(t_i^p)$, where $x_i = o_p + t_i^p d_p$ is on a ray from camera p , and $T_p(t_i^p)$ denotes the probability of the ray being transmitted from o_p to t_i^p without occlusion, as defined in Eq. (2). Therefore, the probability that point x_i is visible to at least one camera in the set $\mathcal{P}$ is given by:

$$v_{\mathcal{P}}(x) = 1 - \prod_{p \in \mathcal{P}} (1 - v_p(x_i)). \quad (10)$$

However, directly computing Eq. (10) during volume rendering is impractical. For each point along a ray r , it would require generating an additional ray r_p from camera p and sampling points along this ray to determine the point's visibility to camera p . Doing this for all existing views is computationally expensive. To address this, we propose to amortize the cost by training an implicit model to predict the visibility.

We introduce Neural Visibility Field (NVF), an augmented NeRF that outputs both color uncertainty and visibility. The enhanced model is defined as $F_\Theta : (x, d) \rightarrow (\sigma, \mu_c, Q_c, v)$, where v represents the visibility with respect to the training views, and μ_c and Q_c denote the mean and covariance of the color vector, respectively. The parameters μ_c and σ are trained with Mean Square Error loss as in [29]. To train Q_c , we employ the Negative Log-Likelihood Loss as follows:

$$\mathcal{L}_{cov} = - \sum_{r \in \mathcal{R}} \log \left(\sum_i w_i \mathcal{N}(C_g(r); \mu_{c_i}, Q_{c_i}) \right), \quad (11)$$

where $\mathcal{R}$ denotes the set of rays in each batch, and $C_g(r)$ represents the ground truth color of ray r . For training, we randomly sample points within the scene. The ground truth visibility, derived using Eq. (10), is then utilized to train the visibility head, using cross-entropy loss. Further details on training and network architecture are provided in Supp.

3.5. Active Mapping with NVF

In this section, we apply the PDF of ray color, derived from Sec. 3.4, for active mapping purposes. Let Z_p^{mn} be the color of the ray corresponding to pixel index m, n from camera pose p . The PDF of Z_p^{mn} , denoted as $p(z_p^{mn})$, can be obtained using the formulation provided in Eq. (9). We define Z_p as a random variable in $\mathbb{R}^{H \times W \times 3}$, representing the collective observation of all pixels in an image with height H and width W .

The goal of active mapping is to identify a camera pose, denoted as p^* , that maximizes the entropy of the observation Z at that pose. This is formally expressed as:

$$p^* = \arg \max_p \mathcal{H}(Z_p). \quad (12)$$

Note that we can deduce Eq. (12) from the information gain or mutual information $\mathcal{I}(Z_p; M) = \mathcal{H}(Z_p) - \mathcal{H}(Z_p|M)$, where M represents the random variable of the entire map. This assumes that $\mathcal{H}(Z_p|M)$ is constant, specifically, that measurement noise remains constant given a known map.

To compute $\mathcal{H}(Z_p)$, we initially assume that the color of each pixel is independent of the others. Under this assumption, the entropy of Z_p can be calculated as $\mathcal{H}(Z_p) = \sum_{m,n} \mathcal{H}(Z_p^{mn})$. However, this assumption of independence may not always hold true. For instance, when the camera is in close proximity to an object, the pixels in the image are often strongly correlated, particularly since they are measuring points that are spatially close. To account for this spatial correlation, we introduce a correction term:

$$\mathcal{H}(Z_p) = \sum_{m,n} \left(\mathcal{H}(Z_p^{mn}) - f_{\text{corr}}(\mathcal{H}(Z_p^{mn}); d_p^{mn}) \right) \quad (13)$$

Here, $f_{\text{corr}}(\mathcal{H}(Z_p^{mn}); d_p^{mn})$ incorporates spatial correlation based on the expected depth d_p^{mn} . Furthermore, we use the

upper bound as proposed in [15] to closely approximate the entropy of the GMM $\mathcal{H}(Z_p^{mn})$, as it is known that there is no analytical solution for the entropy of GMM [15]. Further details on $f_{\text{corr}}(\mathcal{H}(Z_p^{mn}); d_p^{mn})$ and entropy computation are included in supp material.

Within our theoretical framework for estimating uncertainty in NeRF and active mapping, all prior works, to our best knowledge, can be viewed as special cases. Specifically, if we drop the visibility factor, each prior work can be viewed as a specific approximation of our method. For instance, Lee et al [21] focuses only on the discrete random variable, computing the Shannon entropy with $-w_i \log w_i$, which can be regarded as a simplified version of ours, albeit excluding the differential entropy term. Similarly, [33, 38] uses the weighted average of position-based color variance to approximate the rays-based observation variance, which lacks theoretical grounding and ignores the visibility factor in weight computation. In addition, Zhan et al [51] approximate the entropy of ray-based observation by directly summing the position-based entropy of occlusion, whereas, similarly, Yan et al [49] use the weighted average of position-based entropy of occlusion to approximate the ray-based observation entropy.

3.6. Active Mapping Pipeline

Here we briefly describe the active mapping pipeline using NVF (illustrated in Fig. 2). Please refer to Supp. material for more details. The process starts with training the NVF on a small batch of initial views. We employ two strategies for next view selection. In the sampling-based strategy, we sample N views from a prior distribution, estimate their uncertainty using Eq. (12), and select the view with maximum uncertainty. The gradient-based strategy is implemented by adjusting the selected pose through gradient-based optimization, aimed at maximizing entropy, leveraging the inherent differentiability of our uncertainty estimation method. Lastly, the agent proceeds to collect and integrate the new observations into the training views to re-train the NVF model and plan the next view.

4. Experiments

In this section, we seek to verify our hypothesis that (a) NVF outperforms existing methods in both uncertainty quantification and active mapping both quantitatively and qualitatively; and (b) the visibility term plays a vital role in this result.

Simulation Environments and Learning Setup. We conduct experiments on three datasets of varying difficulty levels for active mapping: all assets from the original NeRF dataset [30], the Hubble Space Telescope, and a custom synthetic indoor Room scene. In particular, the Room scene consists of two spaces divided by a wall. Successfully mapping the scene requires traversing both spaces. We assume access to a coarse bounding box that contains the region of

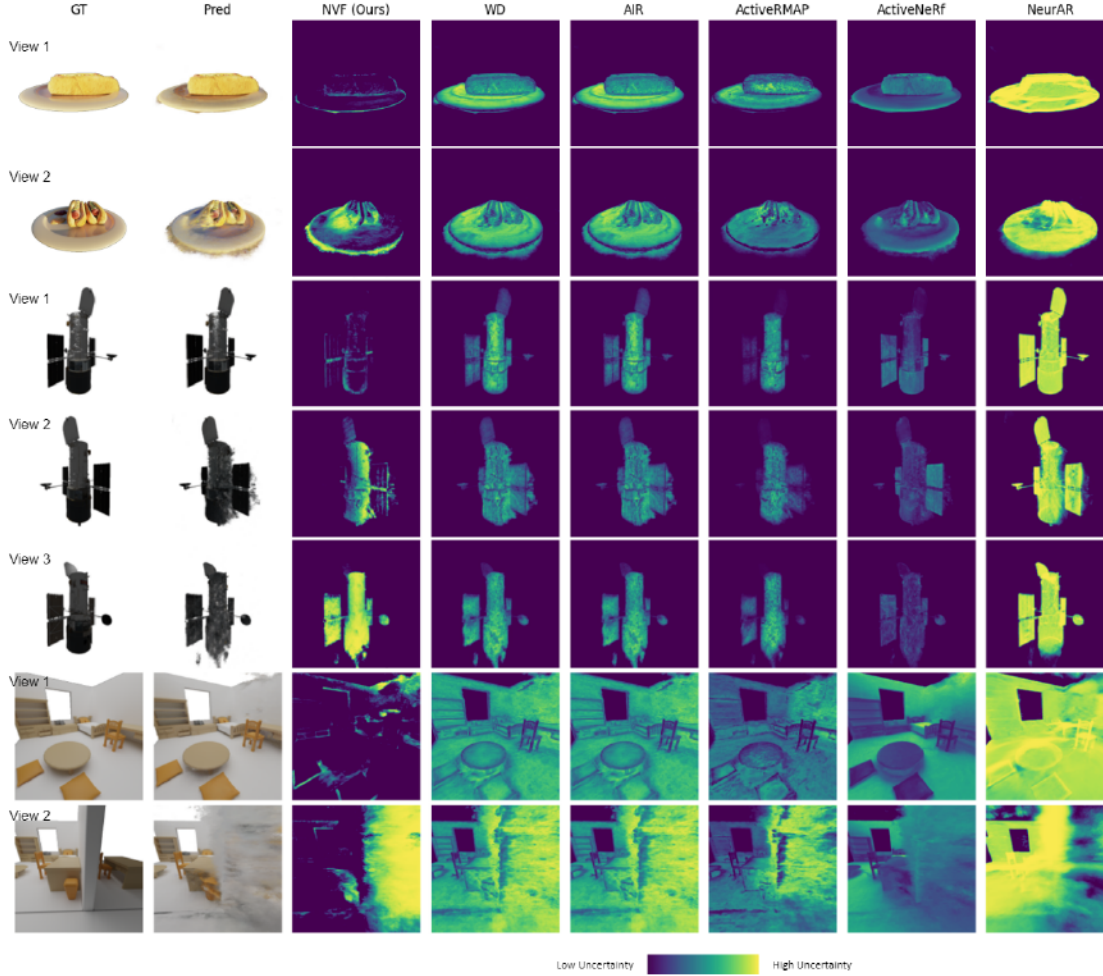


Figure 3. **Qualitative results of entropy estimation:** NVF assigns a higher entropy to previously unobserved regions while the baselines do not distinguish between the observed (View 1) and unobserved regions (View 2/3). Schematic illustrations of the poses of View 1, 2, and 3 can be found in supp. material. Note that within each method and scene, all rendered views share the same color bar.

interest. All ground truth images used for training NeRF and assessing reconstruction quality were rendered using Blender at a resolution of 512×512 . We utilized Instant-NGP [31] as an efficient backbone for all uncertainty estimation methods. All NeRF models were trained for 5,000 iterations. For NVF, it first trains the Instant-NGP backbone, freezes its weights, and then trains variance and visibility heads, to ensure the performance improvements are attributed to better entropy estimation instead of a change in the loss function.

Baselines. We compared our method with state-of-the-art NeRF uncertainty quantification and active mapping methods. This includes the weight distribution-based entropy approximation (WD) [21]; occlusion-based entropy approximation (ActiveRMAP) [51]; weighted occlusion-based entropy approximation - ActiveImplicitRecon (AIR) [49], and spatial RGB variance-based uncertainty estimation ActiveNeRF [33] and NeurAR [38]. As discussed earlier, all of these works can be viewed as a special case of our method, while

missing key aspects that NVF introduces. In addition, we include an agent that randomly selects views from the candidate poses (Random).

4.1. Uncertainty Estimation

Setup. We qualitatively compare the uncertainty (entropy) maps produced by our method and the baselines given a set of training views. For each scene, we design scenarios where only certain regions are visible in the training views. We then train all methods on the same training views and query for uncertainty estimation at an unseen test view. An effective uncertainty estimation method should be able to differentiate regions unobserved in the training set, as reconstruction in these areas is noisy and inaccurate. For the “Hotdog” scene from the original NeRF dataset, we randomly sample 20 training views from a 90-degree sector above the plate. In the Hubble scene, we sample 20 training views from a 90-degree sector on one side, keeping the opposite side of the

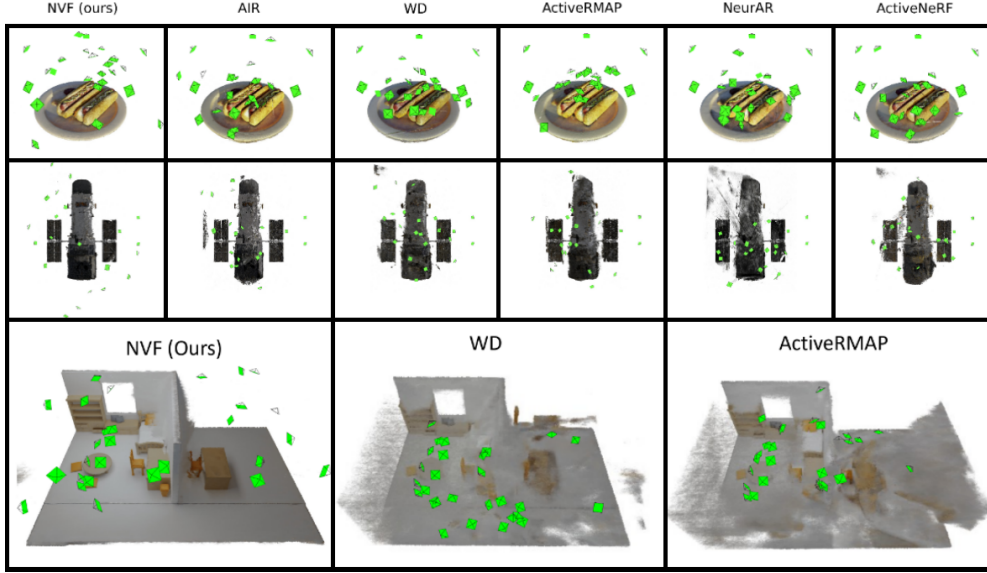


Figure 4. **Reconstruction results and camera view distribution:** NVF demonstrates superior reconstruction and scene coverage across all datasets in comparison to baselines. For room scene, only comparable baselines are presented, full results are provided in supp. material.

Hubble out of view. For the Room scene, we sample 30 training views oriented toward the back wall, the common wall, and the floor of one of the rooms, ensuring that the other room is unobserved.

Results. In the Hubble and Hotdog scenes, as illustrated in Fig. 3, all baseline methods fail to accurately capture the uncertainty in the unobserved areas of the scenes. Several baselines assign greater or similar uncertainty to the observed views as compared to the unobserved ones. A notable example is the Room scene. The first view focuses on the room observed in the training view, while the second view targets the common wall between the two rooms. The result indicates that our method differentiates between the uncertainties in regions seen in training views and unseen regions by modeling their visibilities. In Hubble and Hotdog, ActiveNeRF and NeurAR estimate a similar level of uncertainty for both unobserved and observed regions. However, in the Room scene, the uncertainty in the unobserved region is estimated to be lower than the observed. This shows that in complex scenarios, the uncertainty formulations of ActiveNeRF and NeurAR are ineffective, and such formulation alone is insufficient as guidance to explore unobserved regions.

4.2. Active Mapping

Setup. We deploy active mapping agents with the pipeline described in Sec. 3.6 with different uncertainty estimation methods. To ensure a fair comparison, all methods are evaluated under the same conditions during the comparison, to ensure that the planning is driven solely by the uncertainty estimation. Specifically, all candidate views are uniformly sampled within the space, without any prior constraints (such as the hemisphere constraint employed in ActiveNeRF). This

approach ensures that a more accurate uncertainty estimation method will enable the robot to achieve more precise mapping results. For all original NeRF assets and Hubble scenes, we utilize 3-5 initial views covering only a portion of the scene, to realistically simulate active mapping scenarios. The Room scene presents the greatest challenge, with nine initial views sampled from one room, leaving the second room entirely unexplored. All agents start without knowledge of the second room’s existence and are expected to discover it through uncertainty estimation and reconstruct the scene in 20 steps. Please refer to Supp. material for more details.

Evaluation metric. Our evaluation employs three types of metrics. For novel view synthesis quality, evaluations are performed at fixed testing viewpoints. We compare views synthesized by NeRF with ground truth renderings. The errors are quantified using Peak Signal-to-Noise Ratio (PSNR), Perceptual Image Patch Similarity (PIPS), Learned Perceptual Image Patch Similarity (LPIPS) [52], and RGB loss. For reconstructed mesh quality, we quantitatively evaluate the geometric accuracy of the scene reconstructions. We employ the metrics, Accuracy (Acc), Completion (Comp), and Completion Ratio (CR) as proposed in [43]. For visual coverage (Vis), we assess the proportion of faces in the ground truth mesh observed without occlusion during the experiments over all faces. The visibility of each face in the mesh is tracked using the ground truth mesh and a rasterizer.

Results. In Table 1, we show the quantitative results of our approach in comparison to other baselines. For the original NeRF Assets, we only include the average of the results across all scenes due to space limitation, detailed results are provided in supp. material. Our method significantly outperforms baseline methods achieving higher-quality re-

Table 1. Evaluation of Reconstructed Models Using Different Methods for Active Mapping

Scene	Method	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	RGB $\downarrow$	Acc. $\downarrow$	Comp $\downarrow$	CR $\uparrow$	Vis $\uparrow$
NeRF Assets (Avg.)	Random	17.63	0.766	0.264	0.0193	0.0426	0.0401	0.348	0.225
	WD	19.91	0.807	0.227	0.0121	0.0311	0.0204	0.479	0.466
	ActiveRMAP	20.03	0.807	0.219	0.0118	0.0292	0.0184	0.510	0.471
	AIR	19.86	0.807	0.230	0.0118	0.0290	0.0195	0.494	0.453
	ActiveNeRF	18.78	0.771	0.281	0.0157	0.0301	0.0238	0.433	0.415
	NeurAR	19.58	0.755	0.286	0.0134	0.0347	0.0251	0.452	0.424
	NVF (Ours)	23.90	0.890	0.106	0.0045	0.0193	0.0111	0.685	0.532
Hubble	Random	21.76	0.778	0.265	0.0113	0.0734	0.0262	0.329	0.291
	WD	24.15	0.855	0.184	0.0039	0.0297	0.0184	0.471	0.571
	ActiveRMAP	23.34	0.835	0.205	0.0048	0.0282	0.0162	0.465	0.570
	AIR	24.63	0.862	0.182	0.0035	0.0249	0.0140	0.525	0.586
	ActiveNeRF	23.33	0.824	0.250	0.0047	0.0355	0.0201	0.442	0.552
	NeurAR	25.19	0.772	0.265	0.0030	0.0480	0.0170	0.416	0.537
	NVF (Ours)	27.99	0.919	0.100	0.0016	0.0225	0.0110	0.651	0.681
Room	Random	12.95	0.800	0.378	0.0563	0.1837	0.5468	0.338	0.397
	WD	13.42	0.792	0.387	0.0533	0.2893	0.5415	0.317	0.428
	ActiveRMAP	13.91	0.786	0.412	0.0411	0.2233	0.4646	0.317	0.450
	AIR	15.19	0.829	0.386	0.0307	0.2710	0.3153	0.343	0.498
	ActiveNeRF	10.69	0.733	0.434	0.0853	0.1847	0.8181	0.292	0.338
	NeurAR	12.23	0.584	0.508	0.0599	0.3948	1.2647	0.178	0.375
	NVF (Ours)	22.83	0.943	0.156	0.0053	0.1132	0.1997	0.464	0.586

Table 2. Ablation Studies for Active Mapping with NVF

Ablations	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	Vis $\uparrow$
w/o Vis.	21.11	0.844	0.187	0.382
w/o Var.	23.77	0.897	0.113	0.551
Ind. Rays	20.32	0.822	0.236	0.482
Loose	22.54	0.881	0.137	0.504
NVF (Ours)	24.42	0.902	0.108	0.546

construction and improved visual coverage. This is especially evident in challenging scenarios such as the Hubble and Room scenes, where our method successfully explores the entire scene and excels across all metrics. In contrast, baseline methods failed to fully explore these scenes, often revisiting previously explored areas (see Fig. 4) due to inadequate uncertainty estimation that overlooks visibility.

4.3. Ablation studies

We ablate key components in NVF to examine their role. First, we negate the visibility factor by presuming all sampled points as visible to the camera, setting the visibility head output to 1 for any input. Second, we disregard the spatial color variance estimation from NeRF, assuming a constant small uncertainty for all sampled points. Third, we omit the correlation correction factor, treating all rays as independent. Lastly, for entropy computation, we substitute the upper bound proposed by [15] with a looser bound, treating multiple Gaussians as a single Gaussian following [13]. The average results across all scenes are shown in Table 2,

highlighting the crucial role in the visibility factor, removing it significantly drops the performance. We also observe that the correction of independence in Eq. (13) ("Ind. Rays." in Tab. 2), and a tighter upper bound ("Loose") positively impact performance. However, the position-based color uncertainty directly predicted by NeRF ("w/o Var.") plays a less important role, underscoring visibility as the most critical factor in uncertainty estimation for active mapping.

5. Conclusion

In this work, we present Neural Visibility Field, a principled approach that accounts for visibility in uncertainty quantification and provide a unifying view of prior research in this direction. We empirically demonstrated that NVF significantly outperforms baselines in reconstruction quality and visual coverage across three scenes with varying levels of complexity. A limitation of our current active mapping pipeline is that it does not account for the constraints imposed on the planned trajectory of an agent. A possible future direction is to integrate NVF with cost-aware path planning.

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