

Radiance Fields from Photons

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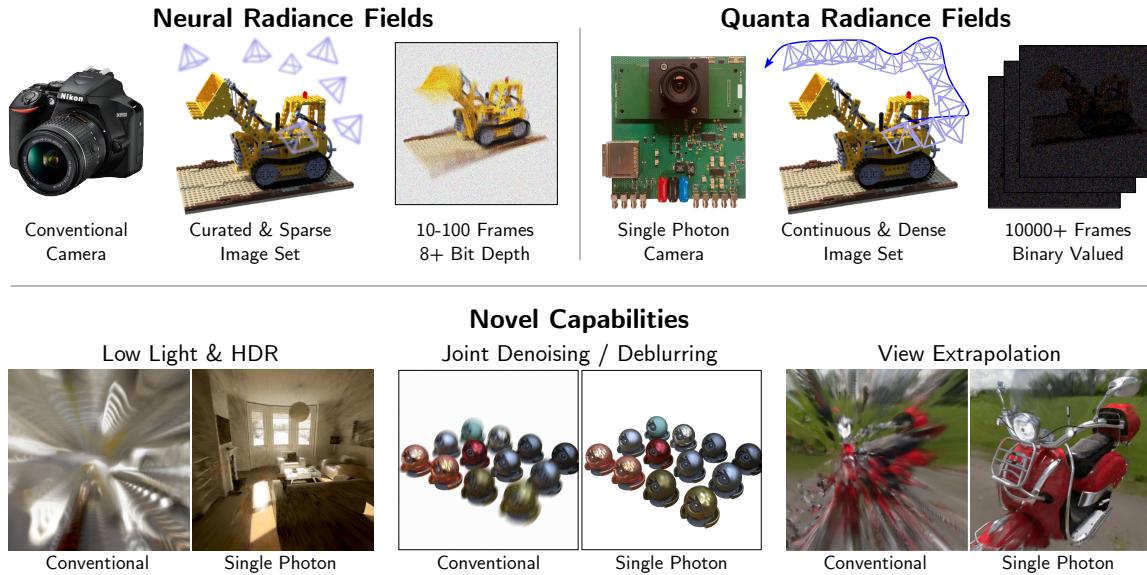


Fig. 1. Single Photon Radiance Fields: We introduce Quanta Radiance Fields (QRFs), neural radiance fields trained at the granularity of photons, which significantly mitigate common challenges conventional NeRFs face. They enable fast and continuous capture, enable faithful reconstructions in extremely low light and high dynamic range settings, effectively denoise and deblur training data without resorting to specialized techniques, and can produce novel view synthesis for a greater diversity of poses.

Neural radiance fields, or NeRFs, have become the de facto approach for high-quality view synthesis from a collection of images captured from multiple viewpoints. However, many issues remain when capturing images in-the-wild under challenging conditions, such as low light, high dynamic range, or rapid motion leading to smeared reconstructions with noticeable artifacts. In this work, we introduce *quanta radiance fields*, a novel class of neural radiance fields that are trained at the granularity of individual photons using single-photon cameras (SPCs). We develop theory and practical computational techniques for building radiance fields and estimating dense camera poses from unconventional, stochastic, and high-speed binary frame sequences captured by SPCs. We demonstrate, both via simulations and a SPC hardware prototype, high-fidelity reconstructions under high-speed motion, in low light, and for extreme dynamic range settings.

CCS Concepts: • Computing methodologies → Volumetric models; Shape representations; Appearance and texture representations; • Hardware → Emerging optical and photonic technologies.

Additional Key Words and Phrases: Neural Radiance Fields, Pose Estimation, Single Photon Cameras, SPADs, High-Speed Cameras, High Dynamic Range & Low-Light Imaging, Computational Imaging

1 Introduction

Whether they are used for autonomous navigation, localization, or augmented and mixed reality, a cornerstone of spatial intelligent systems is the ability to represent the world around us. Neural radiance fields [23], or simply NeRFs, have

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recently become an attractive choice for scene representations as they capture both appearance and geometry. NeRFs fundamentally operate on a set of pixel intensity measurements that are back-projected via inverse rendering into a neural volume. From there, volumetric radiance models learn a scene representation in the form of a view-dependent pointwise color and opacity function, which produces the input pixel values when integrated along light rays.

Under favorable imaging conditions, NeRFs can be built from a set of pixel measurements (collection of images) captured using conventional cameras and can enable high-fidelity scene reconstructions. However, in real-world scenarios, pixel intensities often suffer from artifacts such as motion or optical blur, strong noise in low-light settings, saturation in high-dynamic range scenes, and non-linearities due to proprietary image sensor processing pipelines. State-of-the-art NeRF techniques suffer dramatically – or even fail entirely – when the pixel data they consume contains such real-world imperfections. In fact, these issues are well-known and sufficiently important to have brought about long lines of work that aim to address each of these shortcomings individually [12, 13, 19, 22, 25].

We argue that many of these problems stem from the use of *pixels as the atomic measurement unit* of visual information. Since the imaging artifacts (noise, blur, saturation, non-linearities) occur when pixel values are captured, these imperfections get “baked-in” the learned radiance fields, making it extremely challenging, if not impossible, to mitigate them after the fact.

Building Radiance Fields, One Photon at a Time: Can we take a more granular approach, and build scene representations from individual photons – the finest granularity at which visual information can be captured? If we had access to every photon in a scene, then, by definition, we would have captured the perfect radiance field, avoiding the artifacts mentioned above. Such Quanta Radiance Fields (QRF) – radiance fields built one photon at a time – would faithfully capture the photometric information in the scene, from complex specularities to varying albedoes and intricate geometry. Fortunately, there is an emerging class of single-photon cameras that are capable of detecting and counting individual photons [4, 37] at ultra-high speeds, reaching up to 100 kHz. These cameras are starting to become widely available, including in recent consumer devices (e.g., Apple iPhones), making them ideally suited to capture quanta radiance fields.

As seen in Fig. 1, by using photons as the granular unit, QRFs considerably mitigate many of the common problems that plague traditional neural radiance fields, achieving high-quality reconstructions even under extreme imaging conditions such as large motion blur or strong camera noise in low-light and high dynamic range scenes. This is most notable in extremely low flux settings where conventional NeRF reconstructions are washed out due to the sensor’s read-noise being baked into the neural volume. For a given total capture time, high-speed single-photon cameras sample a denser set of viewpoints, resulting in higher fidelity scene geometry estimation. This greater generalizability, referred to as view extrapolation in Fig. 1, enables novel view synthesis for views that are far from the training data. In contrast, these added viewpoints are missed by conventional cameras due to their lower frame rates leading to the characteristic cloudy or ghost-like artifacts seen in some NeRFs which are a symptom of poorly constrained geometry. Finally, with single photon cameras, one can continuously sample the scene as the camera moves through space. The resulting QRF can use the entire data sequence as input, without needing careful curation. Practically, this means that the training data can be captured considerably faster, not only due to the high-speed nature of single-photon cameras but also because the user does not need to carefully plan or pause to take sharp images.

Why is it Challenging to Build QRFs? Although QRFs promise unprecedented scene representation capabilities, creating QRFs presents a unique set of challenges due to the unconventional image formation model of single-photon

cameras, which capture photons as a high-speed sequence of binary frames: a pixel is “on” if at least one photon is detected during the exposure time and “off” otherwise. Many algorithms on which neural representations rely, such as feature matching, photometric pose optimization, and volume rendering, are not directly compatible with individual binary images which suffer from severe noise and are not directly differentiable due to their discrete (binary) nature. One could integrate long sequences of binary frames over time to lower noise and quantization, but this comes at the cost of large motion blur, thus leading to a noise-vs-blur tradeoff. Our main observation is that it is possible to simultaneously avoid both blur and noise in QRFs by dense single-photon camera pose optimization, which allows aggregating information from a large collection of binary frames. We design a novel pose optimization regularizer tailored for high-speed single-photon cameras, which enables poses corresponding to hundreds of thousands of frames to be learned simultaneously. We also devise novel dataloading schemes to handle massive amounts of data captured by single-photon cameras (10s of thousands of frames, as compared to a few 10s of images in traditional NeRF methods) to build a representation that uses individual photons as basic building blocks.

Scope and Limitations: In this work, we take the first steps towards demonstrating that building scene representations at the granularity of individual photons enables high-fidelity view synthesis and 3D reconstructions in extremely challenging scenarios that were hitherto considered impossible. Even under normal conditions, we show that quanta radiance fields enable better reconstruction and view extrapolation as compared to their conventional counterparts. Finally, we show results both using simulations and captured using our prototype single-photon camera in a wide range of imaging scenarios.

Thinking about radiance fields at the photon level may simultaneously address many of the common problems faced by neural radiance representations, however, many challenges remain. While single-photon cameras are becoming more common, this technology is not yet fully mature. Notably, current-generation sensors have limited resolution, lack color filter arrays, and incur high memory requirements. Further, although the proposed pose optimization scheme improves the reconstruction quality, poses still need to be initialized using conventional techniques. In some settings, this could become a limiting factor as conventional structure-from-motion techniques may fail before single-photon sensing. Addressing these limitations is necessary before QRFs can be widely adopted, and therefore are important next steps.

2 Related Work

Reconstruction with Single Photon Cameras: While many technologies exist that enable detecting individual photons [18], cameras based on single photon avalanche diodes (SPADs) technology are becoming prevalent due to ease of manufacturing, low cost, and high speed capture. These sensors are often used with active illumination in time-of-flight settings such as solid-state LiDARs, or for 3D reconstruction [21], however, they can also be used passively. They have been shown to have large dynamic range [8, 16], enable fast motion compensation and reconstruction [9, 20], image ultra-wideband scenes [30], and enable low-light inference [5]. In this work, we use a passive SPAD-based single-photon camera to perform 3D reconstructions and novel view synthesis.

Neural Radiance Fields: NeRFs [23] enable view synthesis by learning the scene via inverse rendering. The scene is represented implicitly and estimated by minimizing the photometric error between the observed data and a rendering of the learned scene. Many subsequent works have addressed the original shortcomings of this method, by improving its speed with spatial datastructures [24, 32], its original reliance on external pose estimates [15], or even issues regarding

aliasing [1]. All these works consider a pixel as the atom of the visual representation, whereas we propose using a finer unit of visual information, the photon.

Radiance Fields for Challenging Scenes: Creating radiance fields *in-the-wild* under non-favorable imaging conditions remains challenging. Sensor noise and motion blur can result in poor reconstructions with a characteristic cloud-like appearance. Fast motion, low light, or high dynamic range can also significantly degrade reconstruction. Many methods have been developed to address these issues, although typically in a piecemeal manner. For example, a recent approach [22] trains NeRFs directly on the raw sensor data, improving low-light performance. Some methods focus on denoising by using learned priors to denoise an image sequence, treating radiance fields as a burst photography approach [25]. There are methods dedicated to deblurring, which work either by modeling motion blur as part of the inverse rendering step [13], or by using deformable kernels to correct for different types of blur [12, 19]. While these methods might be orthogonal, it is not clear if they are compatible with each other and whether they could be combined to handle multiple artifacts. Our goal is to demonstrate that, by building scene representations at the finest granularity that physics allows, QRFs can mitigate multiple challenging cases simultaneously.

3 Neural Radiance Fields: Background

Inverse Rendering: NeRFs learn the scene’s radiance, $\mathbf{L}(\mathbf{x}, d)$, and volume density, $\sigma(\mathbf{x})$, for any point in space, via inverse rendering, that is, they invert the process by which the scene’s radiance gets mapped to a camera pixel measurement. However, instead of integrating radiance over the solid angle subtended by each pixel and the pixel’s area, NeRFs often approximate this by taking a volumetric ray-tracing approach. The volume rendering equation used to render the expected radiant flux $\phi(\mathbf{r})$ incident upon a pixel parameterized by a camera ray $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$ with near and far bounds t_n and t_f is defined as [10, 23]:

$$\phi(\mathbf{r}) = \int_{t_n}^{t_f} T(t)\sigma(\mathbf{r}(t))\mathbf{L}(\mathbf{r}(t), \mathbf{d})dt, \text{ where } T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s))ds\right) \quad (1)$$

Directly solving for (σ, \mathbf{L}) from a set of ideal measurements ϕ_i and their poses is intractable and is done in practice via gradient descent.

Learning Radiance Fields from Pixels: The pixel brightness I of a conventional CMOS camera can be modeled as a function of scene radiance, consisting of two simple transformations [6]. First, light passes through the camera’s optical stack, which may present aberrations and various defects. While incorrect focusing or issues with shallow depth-of-field can occur and have been the topic of recent works [12, 19], we assume this transformation is linear, or equivalently that we use an in-focus camera with aberration-free optics. The image irradiance then hits the sensor and gets converted to image brightness via a complex, nonlinear function f which encapsulates the camera response curve, tonemapping, and proprietary image signal processing. In summary, we have $I = f(\phi)$.

The specific camera response function f can vary from manufacturer to manufacturer, yet most CMOS pixels will eventually saturate as they reach their full well capacity (FWC), leading to limited dynamic range. On top of this, many sources of noise exist denoted by \mathcal{N} , which affect the sensor’s low light performance. A simple model for this response function can be written as¹:

$$I = f(\phi) = f\left(\max\left(\int_{\tau} \phi dt, \text{FWC}\right) + \mathcal{N}\right). \quad (2)$$

¹For simplicity, various sources of noise, including photon noise, sensor read noise, fixed pattern and quantization noise, are absorbed into \mathcal{N} .

During training, the rendering equation Eq. 1 is computed numerically by sampling points along a ray and (σ, \mathbf{L}) are learned by minimizing a photometric loss between the rendered pixel color $\hat{\phi}$ and the observed pixel colors I :

$$\mathcal{L}_{\text{photo}} = \|\hat{\phi} - I\|_2 \quad (3)$$

In so doing, we recover radiance that has the nonlinear effects of the camera response function, pixel saturation, tonemapping, and noise, baked in, as they are captured by the pixel intensities. While using raw linear intensity pixels can help [22], many of these issues, notably saturation, blur, and noise, remain.

4 Building Radiance Fields, One Photon at a Time

Building radiance fields from conventional pixels is limiting in three fundamental ways. First, in low flux conditions, potentially severe noise N gets baked into the learned radiance field, washing out any reconstructions. This “white noise” phenomenon can be observed in the last row of Fig. 2. Second, in high flux settings, the pixels saturate, leading to poor contrast or clipped regions. Lastly, under rapid motion or long integration times τ , pixel measurements have large motion blur. Also, for a fixed total capture time, the number of measurements will be relatively low, thus limiting the diversity of viewpoints. In this section, we develop the theoretical foundations and practical methods for estimating quanta radiance fields, i.e., radiance fields built one photon at a time, and discuss how QRFs could address the limitations described above.

4.1 Quanta Radiance Fields

We start by describing the image formation model of SPAD-based single-photon cameras that we use for capturing QRFs. SPADs are digital photon counting devices, and as such they do not suffer from read noise, making them only fundamentally shot noise limited [3]. These capabilities enable high low-light sensitivity, high temporal resolution, and extremely large dynamic range.

Consider a SPAD pixel observing a scene with a radiant flux of ϕ . The number of incident photons k on a pixel during an exposure time τ follows a Poisson distribution given by:

$$P(k) = \frac{(\phi\tau)^k e^{-\phi\tau}}{k!}. \quad (4)$$

However, a SPAD pixel resets after each photon detection. During this “dead” time, the pixel cannot detect any more photons. Thus the measurement, B , of a SPAD pixel is binary (1 if the pixel records one or more photons during exposure time τ , 0 otherwise) and follows a Bernoulli distribution given by:

$$P(B=0) = P(k=0) = e^{-\phi\tau}, \quad P(B=1) = P(k \geq 1) = 1 - e^{-\phi\tau}. \quad (5)$$

Notice how this imaging model is different from the one described by Eq. 2. There is no read-noise or full well capacity, and τ is usually in the tenths of microseconds range as opposed to the tenths of millisecond range.

Neural radiance fields from SPAD measurements: We train neural radiance fields directly on the binary measurements B_i captured with an array of SPAD pixels by defining a photometric loss term on binary measurements:

$$\mathcal{L}_{\text{quanta}} = \|\hat{\phi} - B_i\|_2. \quad (6)$$

Blur-Noise Tradeoff: The key challenge with estimating the radiance field directly from the above-defined loss function is the highly quantized and noisy nature of the raw binary measurements captured by SPADs. One idea is to add a series of consecutive binary frames to generate “virtual exposures” [9] to mitigate noise and quantization.

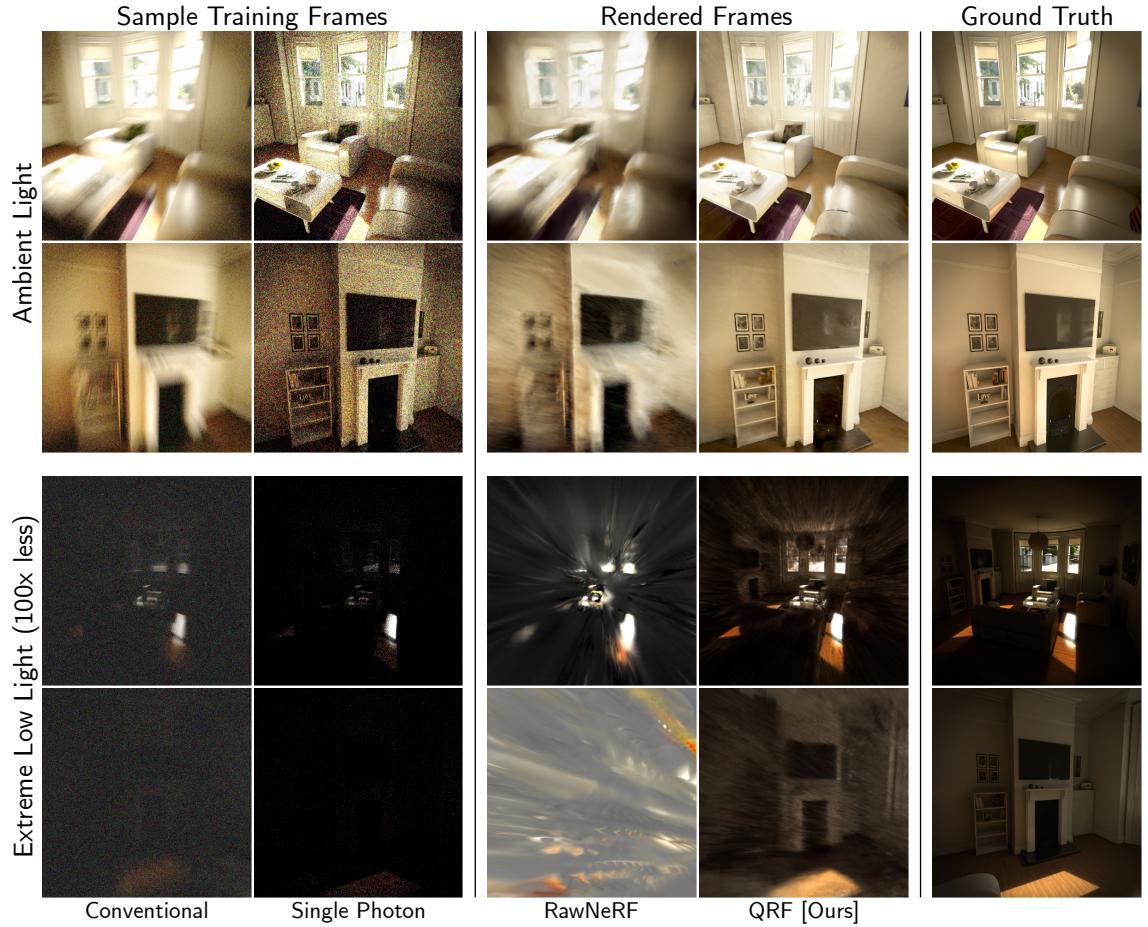


Fig. 2. Reconstruction under challenging scenario: We simulate a single photon and conventional camera flying through a high dynamic range scene, with a dynamic range of 16 stops, at a high speed of $\sim 72\text{km/h}$. We train a conventional NeRF with the raw, linear intensity, conventional images like in [22], and a QRF with binary frames from the simulated single-photon camera.

For dynamic scenes, however, this approach runs into the fundamental noise-vs-blur tradeoff. Just like a conventional camera image, if the total exposure time $n\tau$ of a virtual exposure produced by aggregating a sequence of n binary frames is large compared to the camera or scene motion, the resulting virtual exposure image will be blurred. Unlike a conventional image, however, the parameter n can be reduced post-capture by changing the exposure time after-the-fact, trading off motion blur and noise.

Instead of settling for an operating point on this blur-vs-noise tradeoff space and preprocessing groups of binary frames, we leverage the robustness to noise that optimizers provide and aggregate measurements directly in the neural volume. This can be done by using the relative pose between neighboring binary frames to reproject individual photon detections into the learned radiance field. Even though the measurements are quantized, the continuous-valued photometric loss in Eq. 6, and continuous estimated flux values, ensure the differentiability of the resulting optimization problem. When using the binary frames directly, not only can each observation be considered blur-free due to the high-speed nature of single photon cameras, but we also benefit from the largest number of differing viewpoints, which greatly helps constrain geometry.

Estimating Radiance from Quanta Measurements: Typically, NeRFs are trained using images that have been processed on-device using a complex – and often proprietary – pipeline. Previous work [22] has shown that learning a radiance field using raw, mosaicked, linear intensity images and only post-processing the re-rendered images results in cleaner denoised images and a larger dynamic range. Single photon cameras enable us to push this idea to its limit: instead of training using linear intensity images, which can be achieved using virtual exposures, we learn a radiance field directly from binary frames.

The induced change of domain on the learned radiance field means that the network learns the spatially varying, view-dependent, probability \widehat{P} that at least one photon is detected. Similarly to previous works, what is learned by the network still isn’t true radiance. However, we can trivially invert the SPAD’s camera response (Eq. 5) and get a good estimate of scene radiance:

$$\widehat{\phi} = -\frac{1}{\tau} \ln(1 - \widehat{P}) \quad (7)$$

Note that this is similar to the maximum likelihood estimator of ϕ for a static scene [31], except here, the photon detection probability \widehat{P} is estimated by the network instead of by the average of many binary frames. Using Eq. 7, we can effectively estimate the scene’s flux and render tonemapped images. Learning the photon detection probability directly avoids having to average binary frames, which might introduce motion blur and numerical instabilities that can occur in Eq. 7, and does not require any preprocessing of the raw binary data.

4.2 Data deluge & Practical Considerations

The extremely high-speed capture enabled by single photon cameras can easily strain the available bandwidth and memory of a system as a large quantity of data gets acquired rapidly. For example, a current SPAD-based single-photon camera [37] has a modest resolution of 512×512 and can run at 100kHz, resulting in a bandwidth of 24.4 Gbps, more than two orders of magnitude more than the 0.1 Gbps needed for a conventional camera with similar specs running at 60 fps. This data deluge problem has been the subject of many recent works [7, 17, 27], however, these usually compress the data in a lossy way and cannot be directly used in our context for building neural scene representations.

Further, neural representations are trained on mini-batches of pairs of rays and pixel values. The implication is that at each step, a random sample of pixels must be drawn uniformly from all the training data. For conventional images this is feasible since a few hundred images can be decoded and cached on GPU as one big tensor. However, this is infeasible for binary frames due to the prohibitively large amounts of data, thus posing an acute technical challenge.

To solve both these problems, we bit-pack the binary frames, which provides an 8× compression, and memory-map the whole bit-packed array. Our dataloader is then responsible for loading binary pixel data directly from the disk, decompressing and extracting the individual bits on the fly, and sending them to the GPU. Despite training on potentially hundreds of thousands of frames, we find that, with modern solid-state drives, this data-loading scheme is only about 10% slower than when training with around a hundred conventional images that are preloaded and cached on the GPU. However, when using slower conventional hard disks the training time can easily double. Bit-packing the array does not significantly impact training time, rather it makes the dataset’s disk footprint more manageable and might contribute to better cache locality.

4.3 Novel Capabilities of Quanta Radiance Fields

Low Light and High Dynamic Range: The excellent low light and high dynamic range characteristics of single-photon cameras enable the creation of neural radiance fields in challenging scenarios that are impossible to capture with conventional cameras. In Fig. 2, we simulate a conventional camera (50fps) and single photon camera (10 kHz

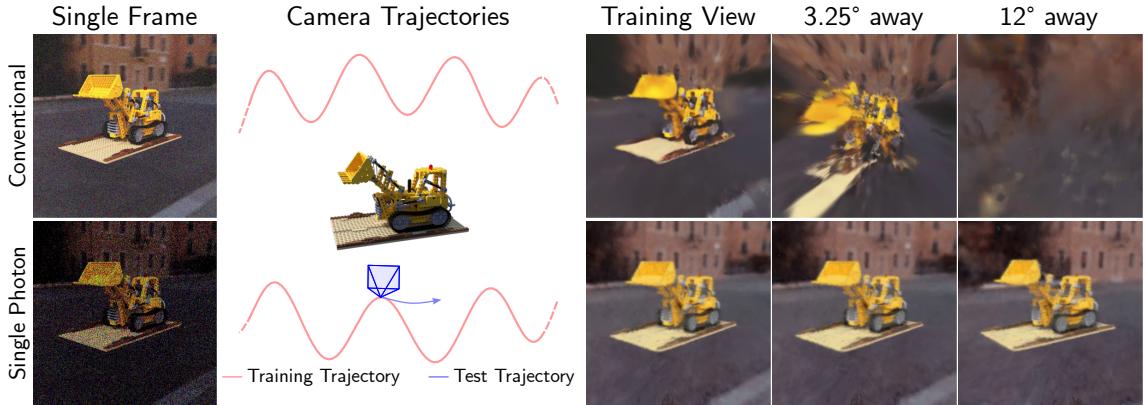


Fig. 3. View Extrapolation: Radiance fields trained using single photon data perform better view extrapolation and degrade more gracefully than ones trained with conventional frames, given the same total capture time. We attribute this behavior to the denser sampling of viewpoints provided by single photon cameras, which better constrains the scene’s geometry.

SPAD) zipping through a scene with extremely high dynamic range ($\sim 61,000$). We show RawNeRF [22] and QRF reconstructions, as well as raw frames, for both cameras. In both cases, the trajectory and total capture time is held constant.

Under ambient light, the reconstruction trained using conventional camera frames struggles to properly reconstruct the scene due to camera motion and high dynamic range. Despite substantial noise in the single-photon input frames, the reconstruction is high-fidelity, with sharp reflections on the hardwood floor and clearly discernible books on the shelf.

Under extremely low light (100X lower than ambient light), the raw frames from both sensors are almost entirely dark, with less than 0.01 photons per pixel detected by the single photon camera. At these light levels, the read noise from the conventional camera completely overwhelms the training process, leading to distorted highlights at best, and featureless gray reconstructions at worst (last row, conventional). In contrast, the single photon reconstruction degrades much more gracefully – significant noise can be seen throughout, but the scene remains recognizable despite the extremely challenging conditions.

Denoising and Deblurring: NeRFs have been shown to be excellent general-purpose denoisers, beating even state-of-the-art one-shot denoisers, when accurate camera poses can be estimated [22]. With quanta cameras, we can take this idea to its physical limit, where the denoising and deblurring capabilities are only limited by the fundamental shot noise of photon arrival.

We demonstrate these capabilities in Fig. 2, where again, in all cases the total capture time and camera trajectories are held constant for a fair comparison. Already at medium light levels, the conventional reconstructions start to suffer from motion artifacts and blown-out highlights. With 16 stops less light, reconstructions made using raw conventional camera frames are washed out due to the inherent noise in the measurements. This bias at low flux is not seen when using single photon cameras as they are only shot noise limited.

View Extrapolation: While neural radiance fields excel at novel view synthesis under ideal conditions, imperfections – such as camera noise or blur – cause typical methods to fail when the desired view is not close to a training view. We show that by using frames from a single-photon camera, which are individually noisier but can be captured at faster frame rates, enabling denser sampling and higher diversity of viewpoints, we can perform *view extrapolation* and not

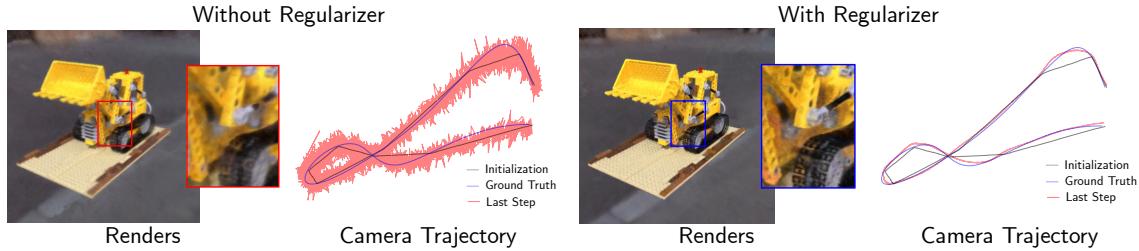


Fig. 4. **Camera Pose Optimization:** The trajectory of the camera is co-optimized with the radiance field. Due to the large number of camera poses to optimize and the noisy binary measurements, a strong smoothing regularizer on the poses is needed.

merely view interpolation. In Fig. 3, we learn a NeRF of a Lego truck with simulated frames for a fast conventional RGB camera (at 200fps) and a single photon camera (at 80KHz). In all cases, the total capture time and the camera’s trajectory are held constant. The training poses are drawn from a sinusoidal trajectory that encircles the object. Once trained, we render frames from a validation trajectory which starts on the training trajectory and slowly gets further along a circular arc centered on the truck. Notice that with a small perturbation of the pose of only a few degrees, the reconstruction quality for the NeRF trained with conventional frames degrades rapidly, and completely fails thereafter.

The training viewpoints in both cases span the same trajectory, that is, both datasets have the same pose diversity, however, the denser sampling provided by the single photon camera better constrains the scene’s geometry leading to significantly improved reconstructions.

5 Pose Optimization with Quanta Cameras

Thus far, we have assumed known camera poses, however, poses are often initialized using estimates obtained from either a structure-from-motion preprocessing step such as COLMAP [26] or from an IMU chip. As these initial estimates often suffer from noise and drift, camera poses need to be co-optimized alongside the radiance field. While most modern NeRF variants perform this optimization by default, it is not feasible when directly using binary frames. The problem is twofold: i) each individual frame is too noisy, leading to noisy optimized poses that are prone to get stuck in local minima, and ii) the number of poses that need to be optimized is greatly increased, from a few hundred to a few hundred thousand, which makes the optimization intractable.

Pose Optimization & Smoothing: Optimizing poses of conventional cameras is an already notoriously difficult and non-convex problem, which gets considerably harder when every image is binary valued as the photometric loss becomes noisy and unreliable. Our key enabling observation is that, due to the high sampling rate of single-photon cameras and known frame ordering, we can leverage a simple but powerful prior: neighboring frames should have similar poses. Specifically, the “pose trajectory” should be smooth. To formalize this insight, we devise a Fourier-domain smoothing regularizer and apply it to the pose optimization.

We first encode poses as 9-dimensional vectors consisting of a translation component $\vec{t} = [x, y, z]^T$, and a rotational component [34]. The rotational mapping is not unique, as it is overparameterized, yet it is smooth, invertible, and easily computable. The resulting tensor, \mathcal{P} , has dimensions $N \times 9$ where N is the number of poses (number of binary frames in the captured sequence).

These components are then individually smoothed using a lowpass filter in the Fourier domain, transformed back, and compared to their non-smoothed counterparts, resulting in the following total loss:

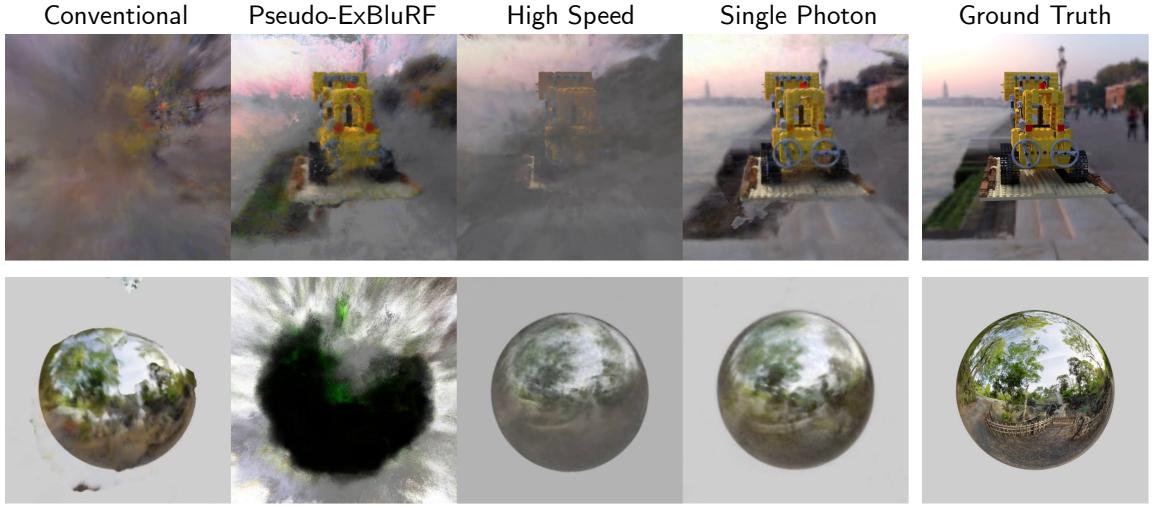


Fig. 5. Robustness to Motion Blur: (Column 1) Traditional NeRF reconstructions suffer considerably when the data it has been trained on contains motion blur. (Column 2) Some methods, such as [13], address this by incorporating the formation of image blur into the forward rendering model. (Column 3) A high-speed camera running at 1000fps can be used to capture more views with less motion blur, however, the colors look washed out due to the read noise being baked into the learned radiance field. (Column 4) We show that, despite much noisier individual frames, training using binary data obtained from a single photon camera achieves visually superior reconstructions.

$$\hat{\mathcal{P}} = \mathcal{F}^{-1}(\mathcal{F}(\mathcal{P}) \cdot H_{\text{lowpass}})$$

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{quanta}} + \lambda \sum_j \|\mathcal{P}_j - \hat{\mathcal{P}}_j\|^2 \quad (8)$$

Where λ controls the regularizer strength, \mathcal{F} is the 1D Fourier transform (which is applied only along the first dimension of the pose embedding), and H_{lowpass} is the transfer function of a lowpass filter. This smoothing is performed on the 9-dimensional vectors representing camera poses. As seen in Fig. 4, a strong smoothing regularizer is imperative to get visually pleasing results when training NeRFs with high-speed binary data. With the regularizer ensuring that the overall trajectory is well-behaved, the high-speed SPAD sampling can recover fine tremors and high-frequency motion.

This frequency-based reasoning is enabled by the high sampling rate of SPADs, and is not easily applicable to conventional cameras. In fact, notice that this loss naturally degrades to the standard NeRF loss when used with conventional cameras. The total loss, $\mathcal{L}_{\text{total}}$, will equal $\mathcal{L}_{\text{photo}}$ when the cutoff frequency of lowpass filter H_{lowpass} is larger than the Nyquist rate of the camera, which is often the case when using slow conventional RGB cameras.

Framing the regularizer in this manner allows us to think about camera shake in a natural way, using frequencies. Specifically, it enables smoothing of high-frequency motion which is mostly composed of noise. This cutoff frequency can be tuned if needed, or if any priors want to be incorporated. More complex filtering regimes are also possible, for instance, a notch filter can prove useful for filtering out specific frequencies such as vehicle resonant frequencies for vehicle-mounted cameras or handshake jitter for handheld cameras.

Deblurring as Pose Optimization: Despite potential issues caused by blurry images when optimizing for pose, for conventional cameras, motion blur and pose estimation are generally considered as two distinct issues. This is not the case for quanta radiance fields. While each individual binary frame can be assumed to have no inherent motion blur due to its extremely small exposure time, poor pose estimates will cause the learned radiance to appear blurry, while good estimates will enable a sharp reconstruction (Fig 4).

Intuitively, motion blur occurs because the inter-frame motion is not compensated. For conventional cameras, this motion cannot be easily compensated for after the fact. To circumvent this issue, modern smartphones take multiple short exposures and fuse them based on a local motion model such as optical flow [14]. We take this idea to its logical limit with extremely short exposures of single-photon imaging. With quanta radiance fields, *motion blur and pose optimization are tightly interleaved issues*, and the Fourier-regularizer introduced above helps us tackle both simultaneously.

Motion Blur Mitigation in Conventional NeRFs: Creating radiance fields out of blurry conventional images remains a challenging problem. ExBluRF [13], a state-of-the-art approach that addresses motion blur, does so by modeling blur as part of the inverse rendering process. They spawn virtual cameras into the scene and enforce that the average value seen by consecutive cameras within a certain window corresponds to the observed blurry image in the training set. Finally, they promote smooth camera movements by utilizing a Bezier curve-based regularizer term on the camera trajectory.

As this method has not yet been made publicly available, we reimplement its key features with minor modifications to perform comparisons. Specifically, we replaced their Bezier regularizer with our Fourier smoothing regularizer (Eq. 8) as they both achieve the same effect with the exception that the proposed Fourier smoothing regularizer scales to hundreds of thousands of virtual cameras. This enables a direct comparison between our method and this modified baseline, which we call pseudo-ExBluRF.

In Fig. 5, we train the pseudo-ExBluRF method with simulated 50fps images from a conventional camera and spawn 20 additional virtual cameras per training frame (corresponding to a blur kernel of 21). Camera poses are initialized to their corresponding ground truth pose, or an interpolation of them for the virtual cameras. We train our method on the equivalent dataset which would be captured by a single photon-camera capturing 40k binary frames per second, and initialize camera poses in the same way, that is, only the cameras corresponding to a 50 fps conventional camera get initialized with their true poses; every other one is initialized with an interpolated pose. Both methods use the same hyperparameters, and all camera poses are co-optimized with the radiance field. Finally, due to the slow sampling rate of the 50fps camera, the low-pass cutoff used in our regularizer is lowered to 25Hz. While one might expect a lowpass cutoff which corresponds to the Nyquist rate of the camera to not perform any filtering, this is not the case as the regularizer is applied to the virtual cameras as well which have a combined sampling rate of $50 \times 21 = 1050$ Hz.

While pseudo-ExBluRF outperforms the conventional method for the Lego truck (first row of Fig. 5), it fails to recover the mirror sphere, likely due to the specularities and lack of environment map. Better still are the reconstructions with a simulated high-speed camera, which can capture specularity, yet are washed-out due to read noise. The proposed QRFs outperform these baselines and recover accurate geometry and photometric effects, even in these challenging conditions with rapid motion and high-frequency specular reflectance.

Implementation Details: We use Nerfstudio’s implementation of Instant-NGP [24] as a backbone architecture. We use Blender [35] and Eq. 5 to simulate binary frames. Unless otherwise noted, we use a lowpass cutoff of 500Hz and a λ of 0.1. For more implementation details and code please see the supplement.

6 Real World Experimental Results

We use a SwissSPAD2 [37] single-photon camera, which can be seen in Fig. 1, to validate our findings using real hardware. This SPAD-based camera is capable of reaching frame rates of 97KHz at a resolution of 512×512 . By averaging multiple consecutive binary frames, we can emulate a conventional camera running at any arbitrary slower

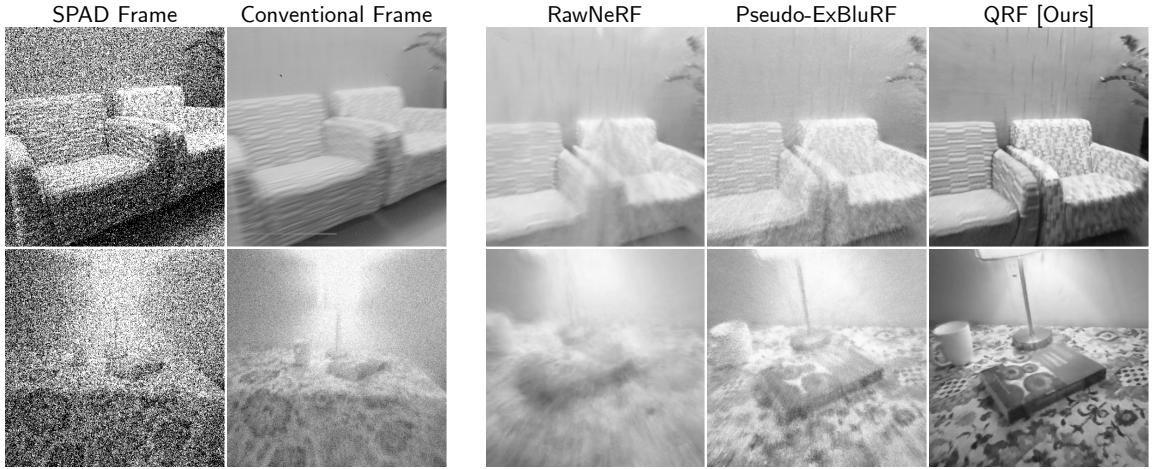


Fig. 6. Qualitative results on real-world captures: We capture a room-scale and tabletop scene with a single photon camera in about 8 seconds and show reconstructions made using emulated raw conventional frames at 30fps [22], a blur-specific baseline [13], and with quanta radiance fields. Overall QRFs exhibit fewer artifacts and better reconstruction quality than baseline methods.

frame rates, thus enabling direct comparisons between methods. We captured multiple scenes using this camera, two of which are shown in Fig. 6. These were taken in ~ 8 seconds at 40 kHz, the first was in ambient light while the second was only illuminated using a small nightstand lamp. From this, we emulated raw-intensity 30fps conventional frames and reconstructed the scene using multiple techniques. Again, we see higher-quality reconstruction with QRF, with other baselines having washed-out colors and noticeable artifacts.

Note that these results are in grayscale because our hardware prototype does not include a color filter array; this is a limitation of this specific device and not fundamental to SPADs. Please refer to the supplement for more details about the hardware setup and implementation details, as well as video results.

7 Discussion and Future Work

In this work, we show that learning radiance fields at the granularity of single photons has many advantages, including better view extrapolation and reconstruction quality. However, many challenges remain. Specifically, a key limitation of this approach is that, while camera poses are finetuned during training, a good initial estimate is still required. While this limitation is not unique to our method, we highlight it here as currently, this is the key limiting factor for extreme low light, in-the-wild QRFs, that must be addressed in future work.

Many improvements to neural radiance fields have been proposed, and many more will follow. New advances in NeRFs, from faster training and inference [11], to surface rendering approaches [29], or deep priors [33], could all benefit from using photons instead of pixels as their basic building blocks. These advances are orthogonal directions that will cross-pollinate with the proposed concept and systems of quanta radiance fields.

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Supplementary Document for “Radiance Fields from Photons”

S.1 Simulating Single Photon Cameras

We use Blender [35] to render out ground truth RGB images of a scene for a camera moving along a spline. To save on rendering time, we only render ground truth frames at a simulated 10kHz and interpolate these to the speeds achieved by single photon cameras using [36]. This setup enables us to render a sequence in about 8 hours using a single RTX 3090.

These RGB frames are then sampled using Eq. 5 to create binary frames, or Eq. 2 to create conventional RGB frames with realistic camera blur and noise.

S.2 Experimental Setup

Our experimental setup consists of a SwissSPAD2 [37] single-photon camera along with two Opal Kelly FPGAs, one for each half of the sensor array, and a C-Mount varifocal lens. This sensor is capable of capturing 97 thousand frames per second at a resolution of 512×512 .

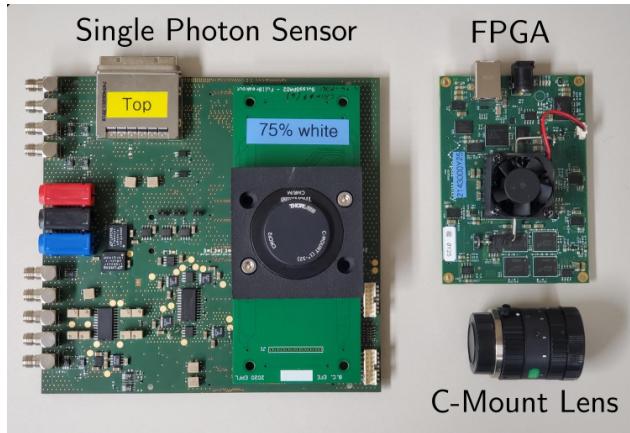


Fig. 1. Hardware Setup

In practice, we often run this sensor at slightly slower frame rates as it greatly improves the readout reliability. Using it at its maximum framerate limits the total capture time to about two seconds as the memory buffers fill up faster than the two USB 3.0 interfaces can read off.

Further, we preprocess the raw data read off this sensor by applying simple filters. First, the two half arrays are read out separately (one FPGA and USB per side), so we must recombine them after the capture is complete. Second, many pixels are dead or always on, so we apply dead-pixel and hot-pixel corrections by simply inpainting these pixels based on their neighbor's values.

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