

# Neural Spectro-polarimetric Fields

YOUNGCHAN KIM, POSTECH, South Korea

WONJOON JIN, POSTECH, South Korea

SUNGHYUN CHO, POSTECH, South Korea

SEUNG-HWAN BAEK, POSTECH, South Korea

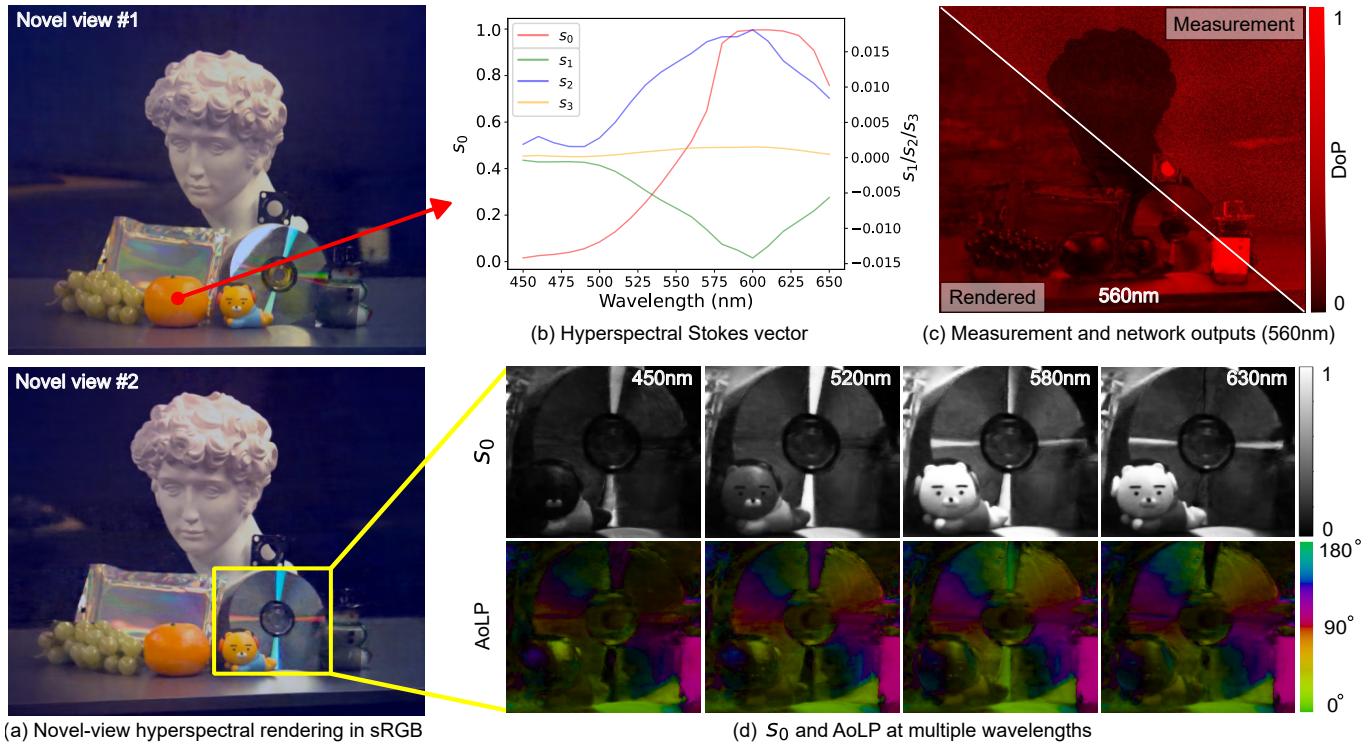


Fig. 1. We present neural spectro-polarimetric fields that allow for the rendering of a scene from novel views, not limited to the synthesis of (a) RGB radiance images. We can render (b) hyperspectral Stokes vectors for each individual light ray, thus providing a comprehensive description of its spectro-polarization property. Also, (c) it can inherently reduce noise in low-signal-to-noise ratio spectro-polarimetric measurements, as demonstrated in the degree of polarization (DoP). We recommend viewing this with a PDF reader for clarity. (d) We further show the analysis of spectro-polarimetric information for the CD that is otherwise invisible to the human eye, as illustrated by the radiance and angle-of-linear-polarization.

Modeling the spatial radiance distribution of light rays in a scene has been extensively explored for applications, including view synthesis. Spectrum and polarization – the wave properties of light – are often neglected due to their integration into three RGB spectral bands and their non-perceptibility to human vision. Despite this, these properties encompass substantial material and geometric information about a scene. In this work, we propose to model spectro-polarimetric fields, the spatial Stokes-vector distribution of any light ray at an arbitrary wavelength. We present Neural Spectro-polarimetric Fields (NeSpoF) – a neural representation that models the physically-valid Stokes vector at given continuous variables of position, direction, and wavelength. NeSpoF manages inherently noisy raw measurements, showcases memory efficiency, and preserves physically vital signals – factors that are crucial for representing the high-dimensional signal of a spectro-polarimetric

field. To validate NeSpoF, we introduce the first multi-view hyperspectral-polarimetric image dataset, comprised of both synthetic and real-world scenes. These were captured using our compact hyperspectral-polarimetric imaging system, which has been calibrated for robustness against system imperfections. We demonstrate the capabilities of NeSpoF on diverse scenes.

## 1 INTRODUCTION

Investigating the spatial trichromatic intensity distribution of light rays (position and direction) in a scene as a simplified plenoptic function [Bergen and Adelson 1991] has been extensively explored in various applications such as rendering [Mildenhall et al. 2020], display [Wetzstein et al. 2012], analysis [Mildenhall et al. 2019], and imaging [Kalantari et al. 2016; Levoy et al. 2006]. Spectrum and polarization, which are the wave properties of light, offer complementary information to the spatial distribution by disclosing the material and geometric properties of a scene. Consequently, these

Authors' addresses: Youngchan Kim, kyc618@postech.ac.kr, POSTECH, South Korea; Wonjoon Jin, jinwj1996@postech.ac.kr, POSTECH, South Korea; Sunghyun Cho, s.cho@postech.ac.kr, POSTECH, South Korea; Seung-Hwan Baek, shwbaek@postech.ac.kr, POSTECH, South Korea.

properties have been employed in applications such as skin analysis [Zhao et al. 2009], planet imaging in astronomy [Boccaletti et al. 2012], and mine detection [Cheng and Reyes 1995].

With the objective of harnessing multiple dimensions of light concurrently, recent methods have utilized both polarization and spatial dimensions. These have found applications such as 3D reconstruction with a polarized light stage [Ghosh et al. 2011] and multi-view capture with a hand-held polarization camera [Dave et al. 2022; Hwang et al. 2022]. Image segmentation leveraging polarization, spectrum, and spatial dimensions was demonstrated by Chen et al. [2022]. However, the exploitation of high-dimensional data still remains challenging.

Specifically, the representation of such high-dimensional visual information should facilitate physically-valid modeling of light properties without using excessive computational resources. Tensor representation [Baek and Heide 2021; Chen et al. 2022] has commonly been used to handle partial dimensions of light properties, assigning each light property to a distinct dimension of the tensor. However, the joint modeling of spectrum, polarization, position, and direction can lead to prohibitive memory requirements, potentially escalating to 58 GB [Karnewar et al. 2022]. Also, the interpolation of polarization properties for unseen position, direction, and wavelength can result in physically invalid polarization representation. These representations are also prone to measurement noise, which can easily arise due to the cumulative effect of spectral and polarization filters [Chen et al. 2022], and a low pixel count [Fan et al. 2022].

In this work, we propose to model spectro-polarimetric fields that describe the Stokes vector of a light ray, as a polarimetric representation [Collett 2005; Wilkie and Weidlich 2010], at a position, direction, and wavelength. We present Neural Spectro-polarimetric Fields, NeSpoF, the first neural representation specifically designed to represent physically-valid spectro-polarimetric fields. In addition to the modeling capability of physically-valid Stokes vectors, NeSpoF benefits from the regularization capability of implicit neural networks, enabling it to handle low-SNR measurements. Also, NeSpoF has a compact memory footprint of 13.6 MB compared to the tensor-based model of 58 GB. Refer to the Supplemental Document for the memory analysis. To evaluate NeSpoF on real-world scenes, we implement a hyperspectral-polarimetric imaging system and its multi-view capture procedure, for which we propose a calibration method to account for the physical imperfections of the acquisition system. Using the imaging system, we capture and release the first multi-view hyperspectral-polarimetric image datasets. We demonstrate the view-spectrum-polarization synthesis using NeSpoF.

## 2 RELATED WORK

### 2.1 Representation for Multi-dimensional Light Properties

Computational representation of multi-dimensional light properties is a critical consideration across visual computing applications. A prevalent method is the tensor-based approach, where each tensor dimension corresponds to a distinct light property. This approach spans the spatial tensor with two-plane methods and lumigraphs [Gortler et al. 1996; Levoy and Hanrahan 1996; Sitzmann et al. 2019], hyperspectral images [Kim et al. 2012], and multi-dimensional tensors [Baek and Heide 2021; Chen et al. 2022]. However, the tensor

representation for position, direction, spectrum, and polarization can impose an excessive memory burden due to the increased dimensionality. Moreover, it is vulnerable to the low SNR of hyperspectral-polarimetric measurements [Chen et al. 2022].

Recently, coordinate-based neural networks modeling the spatial distribution of RGB light intensity have exhibited promising performance in novel-view synthesis [Mildenhall et al. 2022, 2020; Suhaib et al. 2022]. PANDORA [Dave et al. 2022] utilizes polarization for robust neural 3D reconstruction of specular surfaces via a polarimetric BRDF model [Baek et al. 2018]. However, it does not directly model the spectro-polarimetric field of Stokes vectors under variable wavelengths, and it relies on the limited representational capacity of the polarimetric BRDF model. pCON [Peters et al. 2023] represents a polarization image based on singular-value-decomposition via a sinusoid-activation neural network, which considers frequency differences between intensity and polarimetric properties. However, it does not model the directional dimension and is restricted to trichromatic channels. In this work, for the first time, we propose to model a physically-valid spectro-polarimetric field using NeSpoF.

### 2.2 Applications using Multi-dimensional Light Properties

The individual dimensions of light properties have been used in various applications. The position and direction have been utilized for view synthesis and geometry reconstruction [Guo et al. 2022; Jin et al. 2005; Liu et al. 2022; Mildenhall et al. 2019, 2020; Penner and Zhang 2017]. The spectral dimension has been used for detection and segmentation [Aloupiogianni et al. 2022; Imamoglu et al. 2018; Trajanovski et al. 2020; Wang et al. 2021] and for estimating illumination spectrum [An et al. 2015; Li et al. 2021]. Polarization has been used for shape reconstruction [Ba et al. 2020; Baek et al. 2018; Ding et al. 2021; Fukao et al. 2021; Kadambi et al. 2015; Lei et al. 2022; Zou et al. 2020], acquiring appearance [Deschaintre et al. 2021; Kondo et al. 2020], removing reflections [Nayar et al. 1997; Wen et al. 2021; Yang et al. 2016], segmenting transparent objects [Kalra et al. 2020; Mei et al. 2022], seeing through scattering [Baek and Heide 2021; Liu et al. 2015; Zhou et al. 2021], and tone mapping [del Molino and Muñoz 2019]. Using multiple light properties could further enhance these capabilities such as shape and appearance reconstruction with the spatial and polarimetric dimensions [Baek and Heide 2021; Dave et al. 2022; Riviere et al. 2017]. Spectral-polarimetric analysis has been used for object recognition [Denes et al. 1998], skin analysis [Zhao et al. 2009], and dehazing [Xia and Liu 2016]. In this work, using NeSpoF, we demonstrate view-spectrum-polarization synthesis, which reveals various hidden scene properties.

### 2.3 Acquisition of Multi-dimensional Light Properties

Several methods have been proposed for simultaneously acquiring multiple dimensions of light. The positional and directional dimensions can be acquired using hand-held multi-view capture of images [Davis et al. 2012; Mildenhall et al. 2019, 2020] or multi-view camera arrays [Wilburn et al. 2004, 2005; Yang et al. 2002]. Capturing the positional, directional, and polarimetric dimensions has been practiced with light stages equipped with polarizers [Ghosh et al. 2011], hand-held polarization cameras and flashlights [Hwang et al. 2022], and polarization cameras mounted on goniometers [Dave

et al. 2022]. Light-field hyperspectral imaging systems [Cui et al. 2021; Manakov et al. 2013] and hyperspectral camera with a rotation stage [Kim et al. 2012] allow for capturing the directional and spectral dimensions. Hyperspectral-polarimetric imaging allows for capturing the spectral and polarimetric dimensions [Altaquai et al. 2021; Bai et al. 2021; Chen et al. 2022; Denes et al. 1998; Fan et al. 2022, 2020]. To test NeSpoF, we implement a scanning-based hyperspectral-polarimetric imaging system and propose calibrating the imperfections of the imaging system. Using the hyperspectral-polarimetric camera, we release the first real-world dataset of multi-view hyperspectral-polarimetric images that can be used for training NeSpoF and may spur further interest in multi-dimensional visual analysis.

### 3 BACKGROUND

#### 3.1 Neural Radiance Fields

The plenoptic function  $f^P(\cdot)$  is a multi-dimensional function that describes the spatial and temporal distribution of light in a 3D space by modeling the light intensity  $L$  as a function of a 3D position  $(x, y, z)$ , viewing direction  $(\theta, \phi)$ , wavelength  $\lambda$ , and time  $\tau$  [Adelson and Wang 1992]:  $L = f^P(x, y, z, \theta, \phi, \lambda, \tau)$ . Assuming static scenes and constant illumination allows for detaching the temporal dependency, resulting in the static plenoptic function:  $L = f^P(x, y, z, \theta, \phi, \lambda)$ .

Neural Radiance Field (NeRF) [Mildenhall et al. 2020] represents a simplified plenoptic function and density of a scene as a continuous volumetric field modeled with an MLP  $F_\Theta^{\text{NeRF}}$  as

$$\mathbf{L}, \sigma = F_\Theta^{\text{NeRF}}(x, y, z, \theta, \phi), \quad (1)$$

where  $\mathbf{L} = [L_R, L_G, L_B]^\top$  is the RGB radiance at the position  $(x, y, z)$  sampled from the direction  $(\theta, \phi)$ .  $\sigma$  is the volume density at the position  $(x, y, z)$ .  $\Theta$  is the network weights. Figure 3(a) depicts the RGB radiance of a ray. Rendering the RGB values of a pixel at the position  $\mathbf{p}$  amounts to casting rays and volumetrically integrating the learned radiance  $\mathbf{L}$  and density  $\sigma$ .

#### 3.2 Polarization

*Stokes Vector and Mueller Matrix.* Polarization is a wave property of light that describes the oscillation pattern of the electric field of light [Collett 2005; Wilkie and Weidlich 2010]. The Stokes-Mueller formalism is a mathematical framework that describes the polarization state of light and how it changes as it travels through a medium. The Stokes vector, denoted by  $\mathbf{s} = [s_0, s_1, s_2, s_3]^\top$ , describes the complete polarization state of light. The four elements of the vector represent different properties of the light.  $s_0$  represents the total radiance of the light.  $s_1$  and  $s_2$  represent the differences in the radiance of linearly-polarized light at  $0^\circ/90^\circ$  and  $45^\circ/-45^\circ$  respectively.  $s_3$  represents the difference in the radiance of right- and left-circularly polarized light. For instance, horizontal linearly-polarized light can be modeled as a Stokes vector  $\mathbf{s} = [1, 1, 0, 0]^\top$ . The Stokes vector  $\mathbf{s}$  is physically valid if the elements satisfy the condition  $s_0^2 \geq s_1^2 + s_2^2 + s_3^2$ . The Mueller matrix  $\mathbf{M} \in \mathbb{R}^{4 \times 4}$  describes the change of the polarization state of a light ray. To represent the change of a Stokes vector, the Mueller matrix is multiplied to a Stokes vector  $\mathbf{s}_{\text{in}}$ :  $\mathbf{s}_{\text{out}} = \mathbf{M}\mathbf{s}_{\text{in}}$ , where  $\mathbf{s}_{\text{out}}$  is the output Stokes vector.

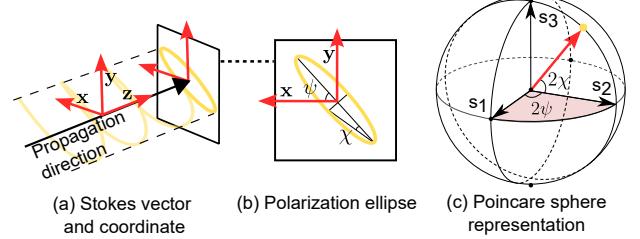


Fig. 2. (a) The Stokes vector is defined on a coordinate system  $\{x, y, z\}$ , where  $x, y$  can be set arbitrary to form an orthonormal coordinate with the propagation direction  $z$ . (b) The polarization state of light can be described as a projection of the oscillating electric field onto the tangent plane, which is called polarization ellipse, where  $\psi$  and  $\chi$  are the azimuth and ellipticity angles. (c) The Poincaré sphere visualizes the Stokes vector in 3D with the normalized Stokes-vector elements.

*Coordinate of a Stokes Vector.* A Stokes vector is associated with a coordinate system  $\{x, y, z\}$ , where  $z$  represents the direction of light propagation. The  $x$  and  $y$  can be chosen arbitrarily as long as they form an orthonormal coordinate system with  $z$ , as shown in Figure 2(a). This means that the polarization state of a light ray can be described differently with Stokes vectors with different elements lying at different coordinates. For instance, the Stokes vector  $[1, 1, 0, 0]^\top$  defined in the coordinate system of  $\{x, y, z\}$  describes the same polarization state with the Stokes vector  $[1, -1, 0, 0]^\top$  in the coordinate system of  $\{R_z^{90^\circ}x, R_z^{90^\circ}y, R_z^{90^\circ}z\}$ , where  $R_z^{90^\circ}$  is a rotation matrix by 90 degrees about the  $z$  axis.

*Polarization Ellipse and Poincaré Sphere.* The polarization ellipse describes the projected pattern of the oscillating electric field onto the tangent plane. Figure 2(b) shows the azimuth angle  $\psi$ , which is the angle of linear polarization, and the ellipticity  $\chi$  that determines the ratio between circularity and linearity. The Poincaré sphere, shown in Figure 2(c), depicts polarization in three-dimensional space with the first, second, and third Stokes-vector elements normalized by the total radiance:  $\{s_1/s_0, s_2/s_0, s_3/s_0\}$ .

*Visualization of Stokes Vector.* For visualizing Stokes vectors, we use degree of polarization (DoP), angle of linear polarization (AoLP), type of polarization (ToP), and chirality of polarization (CoP) [Wilkie and Weidlich 2010]. DoP describes the ratio of polarized light radiance compared to the total radiance, AoLP is the angle of the linearly-polarized component with respect to the  $x$  axis of the Stokes-vector basis, corresponding to  $\psi$ , ToP describes the ratio of linear and circular components corresponding to  $\chi$ , and CoP refers to the handedness of circularly polarized light corresponding to  $\chi$ .

### 4 NEURAL SPECTRO-POLARIMETRIC FIELD

*Spectro-polarimetric Field.* We define the spectro-polarimetric field  $f(\cdot)$ , which describes the Stokes vector of a light ray at a given position, direction, and wavelength:  $\mathbf{s} = f(x, y, z, \theta, \phi, \lambda)$ , where  $\mathbf{s}$  is the Stokes vector. Spectro-polarimetric field can be thought of as an extended parameterization of plenoptic function to account for polarization. Unlike the simplified plenoptic function used in NeRF [Mildenhall et al. 2020] shown in Figure 3(a), the spectro-polarimetric field incorporates wavelength as an input variable and the Stokes vector as an output, as depicted in Figure 3(b).

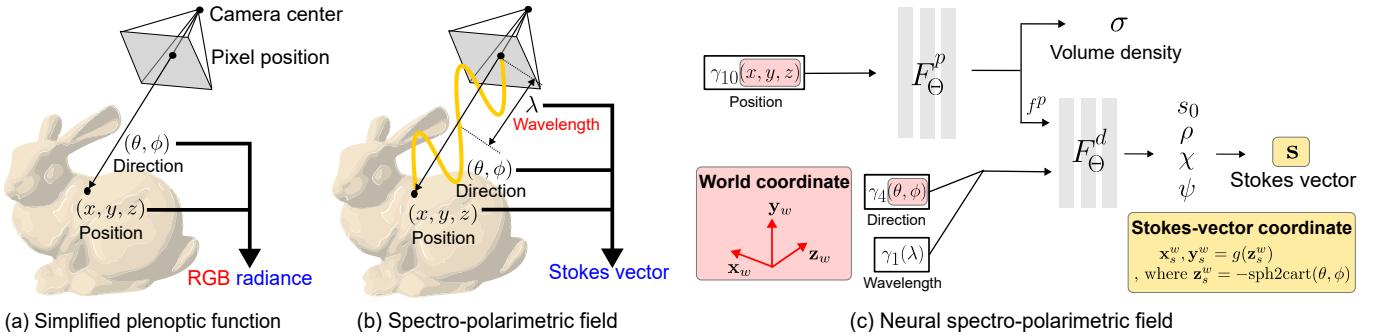


Fig. 3. (a) NeRF models a simplified plenoptic function to represent spatially-distributed RGB radiance. (b) Spectro-polarimetric field describes the polarization state and intensity of light as a Stokes vector per each wavelength  $\lambda$ , position  $x, y, z$ , and direction  $\theta, \phi$ . (c) NeSpoF, consisting of a positional MLP  $F_\Theta^p$  and a spectro-directional MLP  $F_\Theta^d$ , is a neural representation that describes the polarization state and radiance of spatially-distributed light at each wavelength. The inputs to the network are the wavelength  $\lambda$ , position  $(x, y, z)$  and direction  $\theta, \phi$ , which are both defined on the world coordinate system  $\{x_w, y_w, z_w\}$ . We apply positional encoding  $\gamma_k$  of the frequency  $k$  for each dimension. The outputs of the network are the volume density  $\sigma$  at the position  $(x, y, z)$  and polarization parameters ( $s_0, \rho, \chi$ , and  $\psi$ ). The polarization parameters are converted to the physically-valid Stokes vector  $s$ , defined on the Stokes-vector coordinate  $\{x_s^w, y_s^w, z_s^w\}$ .

*NeSpoF.* We propose modeling the spectro-polarimetric field  $f(\cdot)$  using NeSpoF, a neural representation that describes the Stokes vector  $s$  and volumetric density  $\sigma$  for the input variables of position, direction, and wavelength:

$$s, \sigma = F_\Theta(x, y, z, \theta, \phi, \lambda). \quad (2)$$

Using NeSpoF, we can render the Stokes vector  $s_{\text{rendered}}$  from a ray  $r$  emitted from a particular pixel at a wavelength  $\lambda$  by applying volumetric rendering as follows:

$$s_{\text{rendered}}(r, \lambda) = \int_{t_n}^{t_f} \underbrace{\exp \left( - \int_{t_n}^t \sigma(r(s)) ds \right)}_{\text{transmitted Stottess vector}} \underbrace{\sigma(r(t)) s(r(t), d, \lambda)}_{\text{accumulated transmittance}} dt, \quad (3)$$

where  $t_n$  and  $t_f$  are the near and far bounds. For details on accumulated transmittance and integral form, we refer to the linear differential formulation of volumetric rendering [Kajiya and Von Herzen 1984]. The ray is modeled as  $r(t) = o + td$  with respect to sample  $t$ .  $o$  is the center of the camera and  $d$  is the direction vector of the ray.

Note that this linear differential formulation has been previously applied to the radiance of light [Kajiya and Von Herzen 1984]. Here, we instead apply it to Stokes vectors with an assumption that the polarization state of light does not change during transmittance.

#### 4.1 Modeling Physically-valid Spectral Stokes Vector

We design NeSpoF with a positional MLP,  $F_\Theta^p$ , and a spectro-directional MLP,  $F_\Theta^d$ , as shown in Figure 3(c). Although the positional MLP is based on NeRF, we provide a brief description for clarity. The positional MLP estimates the volumetric density  $\sigma$  at the position  $(x, y, z)$  and extracts the positional Stokes-vector feature  $f^p$ . The positional encoding  $\gamma_k(x)$  [Tancik et al. 2020] is employed to learn high-frequency details of the Stokes-vector distribution with respect to the position:

$$\gamma_k(x) = [x, \sin(2^0 \pi x), \cos(2^0 \pi x), \dots, \sin(2^k \pi x), \cos(2^k \pi x)], \quad (4)$$

where  $k$  is a hyperparameter. For position,  $k = 10$  is used.

We now turn to model a physically-valid Stokes vector at a wavelength  $\lambda$  using the spectro-directional MLP. The spectro-directional MLP  $F_\Theta^d$  takes the positional feature  $f^p$ , directional features, and wavelength features and outputs intermediate polarimetric features. Below, we describe the key factors of spectro-directional MLP.

*Wavelength as input.* We use wavelength  $\lambda$  as an input to the spectro-directional MLP in addition to the direction variables  $\theta$  and  $\phi$ , unlike NeRF that takes only the direction variables as input and outputs as three RGB radiance values. In this way, we can query the Stokes vector from NeSpoF at an arbitrary wavelength  $\lambda$ , suitable for spectral analysis and measurements of the Stokes vectors. We apply the positional encoding of Equation (4) to the wavelength with the hyperparameter value  $k = 1$ . We can control  $k$  for representing higher frequency changes of the spectral Stokes vector.

*Physically-valid Stokes vector.* It is crucial to ensure that NeSpoF outputs *physically-valid* Stokes vectors. As described in Section 3, a Stokes vector is physically valid if the following condition is met:  $s_0^2 \geq s_1^2 + s_2^2 + s_3^2$ . As a naive approach of modeling the output of the spectro-directional MLP as Stokes-vector elements fails to guarantee the physical validity of the output Stokes vector, we propose to use intermediate polarimetric properties as outputs:  $X_0, X_1, X_2, X_3$ . We then map the values to the total intensity  $s_0$ , DoP  $\rho$ , ellipticity  $\chi$ , and azimuth angle  $\psi$  as follows:

$$s_0 = S(X_0), \quad \rho = S(X_1), \quad \chi = X_2, \quad \psi = X_3, \quad (5)$$

where  $S(\cdot)$  is the sigmoid activation function that bounds the intensity  $s_0$  and the DoP  $\rho$  from zero to one. Note that we do not apply bounding functions to the azimuth angle  $\psi$  and the ellipticity  $\chi$ , which naturally wrap within  $2\pi$  by sinusoidal functions. We then construct a physically-valid Stokes vector  $s$  as follows:

$$s_1 = s_0 \rho \cos 2\chi \cos 2\psi, \quad s_2 = s_0 \rho \cos 2\chi \sin 2\psi, \quad s_3 = s_0 \rho \sin 2\chi. \quad (6)$$

*Coordinate of Output Stokes Vector.* NeSpoF models a field of Stokes vectors, which must be associated with a Stokes-vector coordinate for each light ray. Given the position  $(x, y, z)$  and the direction  $(\theta, \phi)$  of a light ray defined on the world coordinate system  $\{x_w, y_w, z_w\}$ , we define the coordinate system of the Stokes vector, the output of the network, as  $\{\mathbf{x}_s^w, \mathbf{y}_s^w, \mathbf{z}_s^w\}$ , where  $\mathbf{z}_s^w$  is aligned with the reversed direction vector corresponding to  $(\theta, \phi)$ :  $\mathbf{z}_s^w = -\text{sph2cart}(\theta, \phi) \cdot \text{sph2cart}(\cdot)$ .  $\text{sph2cart}(\cdot)$  is the conversion function that maps a spherical coordinate to a Cartesian coordinate. In order to ensure that the coordinate system for the Stokes vector,  $\mathbf{s}$ , is well-defined, we compute the other two axes  $\mathbf{x}_s^w$  and  $\mathbf{y}_s^w$  deterministically to form an orthonormal coordinate system using an analytic method denoted as  $g$  [Duff et al. 2017]:  $\mathbf{x}_s^w, \mathbf{y}_s^w = g(\mathbf{z}_s^w)$ . This rule for determining the Stokes-vector coordinate enables us to use multi-view hyperspectral images of which Stokes vectors are represented in a local coordinate. Refer to the Supplemental Document for details. Figure 3(c) shows the coordinate scheme.

*Training with Polarization-weighted Loss.* To train NeSpoF, we cast rays  $\mathbf{r}$  and apply volumetric rendering as in Equation (3) for the Stokes vector  $\mathbf{s}^\lambda$  and density  $\sigma$ , minimizing the difference between the rendered and measured Stokes vectors:

$$\underset{\Theta}{\text{minimize}} \sum_{\mathbf{r} \in \mathcal{R}} \sum_{\lambda} \sum_{i=0}^3 w_i ([\mathbf{s}_{\text{meas}}(\mathbf{r}, \lambda)]_i - [\mathbf{s}_{\text{rendered}}(\mathbf{r}, \lambda)]_i)^2, \quad (7)$$

where  $\mathcal{R}$  is the set of rays in a training batch and  $[\mathbf{s}]_i$  retrieves the  $i$ -th element of the Stokes vector  $\mathbf{s}$ . We use the rendered Stokes vector  $\mathbf{s}_{\text{rendered}}$  for volumetric rendering of Equation (3). We propose an adaptive weight  $w_i$  for the  $i$ -th Stokes-vector element to account for the scale differences among the Stokes-vector elements:

$$w_i = \frac{\text{std.dev.}([\mathbf{s}_{\text{meas}}(\forall)]_i)}{\text{std.dev.}([\mathbf{s}_{\text{meas}}(\forall)]_i)}, \quad (8)$$

where  $\text{std.dev.}(\cdot)$  is the standard deviation operator. This strategy aims to learn all the Stokes-vector elements evenly considering their relative scales, as small-scale elements may convey physically significant meanings despite their absolute scales. In addition, we also apply the weight variance regularizer for training [Mildenhall et al. 2022].

## 5 MULTI-VIEW HYPERSPECTRAL-POLARIMETRIC IMAGING AND DATASET

To test NeSpoF on real-world scenes, we construct a portable imaging system. We propose a calibration method to address the spatially-varying imperfections of the experimental prototype. Using the imaging system, we capture and release the first real-world multi-view hyperspectral-polarimetric image dataset.

### 5.1 Hyperspectral-polarimetric Imaging

*Imaging Setup.* Our experimental prototype, shown in Figure 4, consists of a monochromatic sensor equipped with a 35 mm lens, a liquid crystal tunable filter (LCTF), and a quarter-wave plate (QWP) mounted on a motorized rotation stage. The LCTF can adjust spectral transmission. We placed a cut-off filter for the IR and UV wavelengths in front of the LCTF.

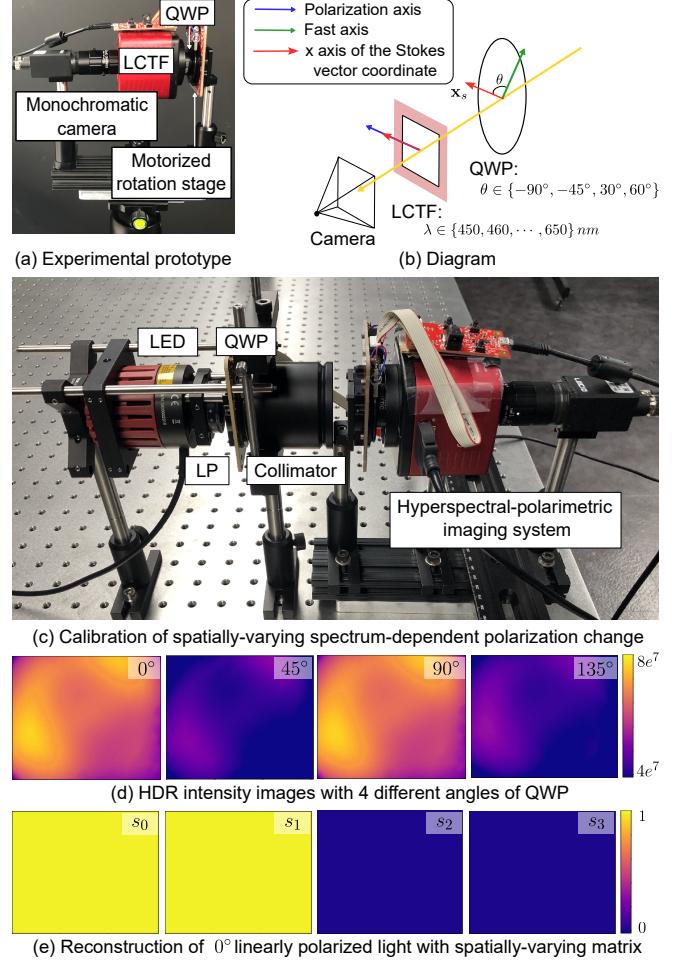


Fig. 4. (a) We built an experimental prototype with a monochromatic camera, LCTF, and QWP mounted on a rotation stage. (b) We capture images with the rotating QWP by varying the angle  $\theta$  at each target wavelength. (c) To calibrate the spatially-varying spectro-polarimetric variation of the prototype, we use 16 samples with known Stokes vectors made by the polarization-state generator. (d) The captured images with varying QWP angles clearly exhibit the spatially-varying spectro-polarimetric characteristics. (e) After calibration, we achieve accurate polarimetric reconstruction of the linearly-polarized at  $0^\circ$  degree.

*Image Formation.* Assume that light of a wavelength  $\lambda'$  coming from a scene with a Stokes vector  $\mathbf{s}(\lambda')$  enters the QWP mounted on a rotation stage, at an angle  $\theta$  as shown in Figure 4(b). This causes the Stokes vector to change to  $\mathbf{Q}(\theta, \lambda')\mathbf{s}(\lambda')$ , where  $\mathbf{Q}(\theta, \lambda')$  is the Mueller matrix of the QWP when its fast axis is at an angle  $\theta$ . The light then passes through the LCTF. At each target wavelength  $\lambda \in \{450, 460, \dots, 650\} \text{ nm}$ , we set the LCTF to maximize its transmission at the target wavelength  $\lambda$  and suppress the transmission at other wavelengths. We model the spectral transmission and polarization change by the LCTF with the first row of the unknown LCTF Mueller matrix as  $\mathbf{M}(\lambda'; \lambda) \in \mathbb{R}^{1 \times 4}$ . The optical cut-off filter, which has a spectral transmission of  $F(\lambda')$ , attenuates the radiance, and the monochromatic sensor, whose quantum efficiency is  $T(\lambda')$ , senses

the light intensity. In summary, we describe the image formation as:

$$I^{\lambda,\theta} = \int_{\lambda'} T(\lambda') F(\lambda') \mathbf{M}(\lambda'; \lambda) \mathbf{Q}(\theta, \lambda') \mathbf{s}(\lambda') d\lambda' \quad (9)$$

$$\approx T(\lambda) F(\lambda) \mathbf{M}(\lambda; \lambda) \mathbf{Q}(\theta, \lambda) \mathbf{s}(\lambda), \quad (10)$$

where the approximation in Equation (10) generally holds as the average bandwidth of the LCTF over the visible spectrum is 9.8 nm. We use the factory-calibrated quantum efficiency of the sensor,  $T(\lambda)$  and the transmission functions of the cut-off filter,  $F(\lambda)$ .

*Calibration of LCTF Modulation.* Even though we designed our imaging system using professional optical devices, the experimental prototype still presents deviation from a commonly-assumed model for the polarization modulation of LCTF, which has often been assumed to be an ideal linear polarizer [Fan et al. 2023]. To overcome this problem, we propose to optimize for spatially-varying matrices  $\mathbf{M}(\lambda, p; \lambda)$  that act as polarization modulation by the LCTF, where  $p$  is a pixel. To this end, we capture 16 samples with known Stokes vectors constructed with an LP, a QWP, and a collimated LED light source. We then solve for the matrix  $\mathbf{M}$  as follows:

$$\underset{\mathbf{M}(\lambda, p)}{\text{minimize}} \sum_{i=1}^N \sum_{k=1}^K \left( I_{\text{meas}, i}^{\lambda, \theta_k}(p) - T(\lambda) F(\lambda) \mathbf{M}(\lambda, p; \lambda) \mathbf{Q}(\theta_k, \lambda) \mathbf{s}_u \right)^2, \quad (11)$$

where  $I_{\text{meas}, i}^{\lambda, \theta_k}(p)$  is the intensity measurement of the  $i$ -th sample for the pixel  $p$  at the rotation angle  $\theta_k$  of the QWP.  $\mathbf{s}_u$  is the Stokes vector of unpolarized light. We used four uniformly-sampled  $\theta$  in the  $[0, \pi]$  range for this calibration. We refer to the Supplemental Document for its normal-equation formulation.

*Stokes-vector Reconstruction.* Once the matrix  $\mathbf{M}$  is obtained, we can reconstruct the Stokes vector  $\mathbf{s}_{\text{meas}}^{\lambda}$  for a pixel  $p$  of an arbitrary scene by solving the least-squares problem:

$$\mathbf{s}_{\text{meas}}(\lambda, p) = \underset{\mathbf{s}^{\lambda}}{\text{argmin}} \sum_{k=1}^K \left( I_{\text{meas}}^{\lambda, \theta_k}(p) - c(\lambda) \mathbf{M}(\lambda, p; \lambda) \mathbf{Q}(\theta_k, \lambda) \mathbf{s}(\lambda, p) \right)^2, \quad (12)$$

where  $c(\lambda) = T(\lambda) F(\lambda)$ . We refer to the Supplemental Document for its normal-equation formulation. Figure 4(c-e) demonstrates the calibration setup and reconstruction of the Stokes vector of 0° linearly-polarized light.

## 5.2 Multi-view Hyperspectral-polarimetric Dataset

*Real-world Scenes.* Using the experimental prototype, we acquired the first multi-view hyperspectral-polarimetric dataset of four real-world scenes. At each camera viewpoint, we capture raw measurements and reconstruct the per-pixel Stokes vector  $\mathbf{s}_{\text{meas}}^{\lambda}$  using Equation (12). It takes roughly 10 seconds to capture a hyperspectral-polarimetric image with 21 spectral channels at four QWP angles. We then perform local-to-world coordinate conversion to use it for NeSpoF. We obtain the geometric parameters of the multiple viewpoints and the camera intrinsic parameters using a structure-from-motion method, COLMAP [Schönberger and Frahm 2016], for which we use the RGB intensity images obtained by applying the spectrum-to-RGB conversion as well as the gamma correction.

We refer to the Supplemental Document for more details about the dataset, calibration, and coordinate conversion.

*Synthetic Scenes.* We render multi-view hyperspectral-polarimetric images of four synthetic scenes using Mitsuba3 [Jakob et al. 2022]. We manually assign the multispectral polarimetric BRDFs [Baek et al. 2020] to meshes [Bitterli 2016; Mildenhall et al. 2020]. Since only five spectral channels are available (450, 500, 550, 600, and 650 nm) in the BRDF dataset, we fit a fourth-order polynomial function at each rendered pixel along the spectrum.

## 6 ASSESSMENT

We train NeSpoF using multi-view hyperspectral polarimetric images for each scene with a batch of rays with the size 32×32×4 and 200k training iterations, which takes 10 hours on an NVIDIA GeForce RTX 3090 GPU. We use a learning rate of  $5 \times 10^{-4}$ .

### 6.1 View-spectrum-polarization Synthesis

*Qualitative Evaluation on Synthetic Scenes.* Figure 6(a) shows the rendered hyperspectral-polarimetric Stokes-vector images at two novel views of a synthetic scene. The synthesized results accurately match the ground-truth images as visualized in AoLP, DoP, and ToP. In particular, NeSpoF is capable of synthesizing unique spectro-polarimetric characteristics of the metallic dragon, spheres, and teapots made of different materials. Please see the Supplemental Document for additional synthetic-scene results.

*Quantitative Evaluation on Synthetic Scenes.* Figure 6(b) shows the quantitative results of NeSpoF on the test views of four synthetic scenes. In terms of wavelength, we observe a PSNR of 35 dB and an RMSE of 0.020 at a wavelength of 650 nm, with better reconstructions for other wavelengths. For each Stokes-vector element, the radiance component, which usually exhibits the most complex variation, has a PSNR of 33 dB and RMSE of 0.023, while the other elements demonstrate higher PSNRs and lower RMSEs. The scene-dependent quantitative analysis shows a minimum PSNR of 30.4 dB.

*Real-world Scenes.* Figure 10 presents the rendered images of NeSpoF on two real-world scenes. The first scene encompasses a laptop display and a mobile phone equipped with a protective film. In front of the mobile phone is a linear polarizer. While the laptop display emits linearly polarized light, the light from the mobile phone display interacts with the stress-affected protective film, leading to complex spectro-polarimetric patterns. The second scene features a CD demonstrating unique spectro-polarimetric characteristics attributed to diffraction caused by micro-scale surface structures, paired with a doll covered by a linear-polarizer film. As shown in the AoLP and ToP visualization at two distinct wavelengths, NeSpoF accurately synthesizes the invisible information, matching with the ground-truth data. Moreover, NeSpoF effectively regularizes low SNR measurements from hyperspectral-polarimetric images, resulting in high-fidelity synthesis of hyperspectral Stokes fields in real-world scenes. Due to the low SNR hyperspectral-polarimetric measurements, quantitative evaluation has been excluded. Figure 8 shows the rendered images with NeSpoF, exhibiting view-dependent hyperspectral-polarimetric information on the reflections on crystal and a baseball inside of a glass box. Figure 7 demonstrates novel

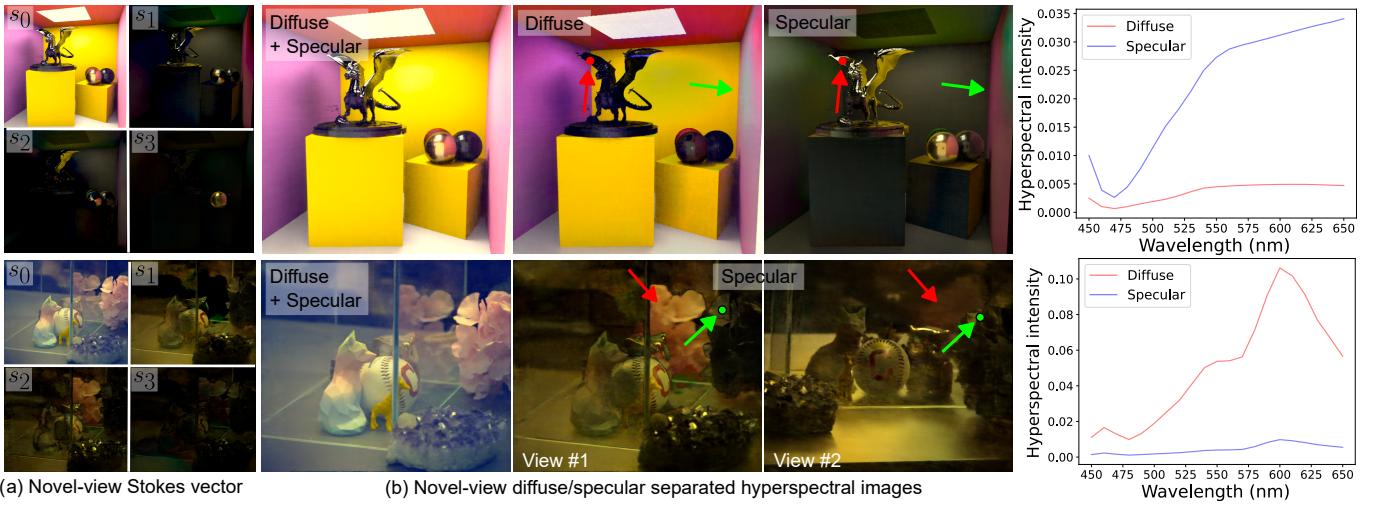


Fig. 5. (a) NeSpoF enables rendering of hyperspectral Stokes vectors from novel views and (b) facilitates the analysis of the hyperspectral intensity of unpolarized diffuse and polarized components, which include specular reflections and polarized inter-reflections. In the synthetic dragon scene, we analyze diffuse and specular intensity at each wavelength and observe polarized inter-reflections between walls. For the real-world scene, we examine the hyperspectral intensity of a flower and its reflection on glass, both showing different polarization states depending on reflection angles.

view synthesis by NeSpoF for an outdoor scene under sky lighting. This allows for analysis of the spectro-polarimetric properties of sky light, which is partially linearly polarized, as indicated by high values of  $s_1$  and  $s_2$ . The illumination spectrum of the sky can also be extracted, as depicted in Figure 7(b). This enables rendering of the hyperspectral intensity at a novel view and relighting by replacing the original illumination with the target illumination, here CIE D65 illuminant, shown in Figure 7(c).

*Diffuse, Specular, Inter-reflection, and Reflection Components.* Figure 5 shows the analysis of the diffuse and specular hyperspectral intensity with NeSpoF. Here, we modeled diffuse reflection as unpolarized intensity, while specular reflection is modeled as polarized intensity. This enables us to examine the hyperspectral intensity of each diffuse and specular component separately, at each wavelength. Within these separated hyperspectral diffuse and specular components, we can observe more complex light transport phenomena such as the polarized inter-reflection between walls for the dragon scene. For the real-world scene, it is observed that the diffuse component of the flower is unpolarized, and hence not visible in the specular image. However, its reflection on the glass is clearly visible in the specular image due to the strong polarization caused by Fresnel reflection near a Brewster angle. When rendering the frontal-view specular image of the glass, the strong specular signal of the flower on the glass is not visible, as the imaging geometry deviates from the Brewster-angle configuration.

## 6.2 Ablation Study

Being the first neural model to address the modeling of hyperspectral Stokes fields within a scene, we here focus on the analysis of NeSpoF. Comparative studies can be found in the Supplemental Document.

*Weight of the Stokes-vector Loss.* We test the weight of the loss function  $w_i$  for the  $i$ -th Stokes vector in Equation (8). Using the

mean-squared-error (MSE) loss with the uniform weights of  $w_i = 1$  results in unstable training for the Stokes-vector elements with low values, e.g. the last element  $[s]_3$ . Figure 9 shows that using our weighted loss of Equation (8) allows for accurate reconstruction of the original Stokes vector by balancing the scale difference between the Stokes-vector elements.

*Positional Encoding for Wavelength.* We test the impact of positional-encoding frequency  $k$  of Equation (4) for the input wavelength  $\lambda$ . Figure 9 shows that  $k = 1$  provides a high-fidelity plenoptic synthesis as visualized in the AoLP images.

## 7 DISCUSSION

NeSpoF interprets light as rays, thus does not encompass phase and amplitude of light [Goodman and Sutton 1996]. Also, NeSpoF demands hours of training time and tuning parameters that may benefit from recently-proposed neural representations. On the hardware front, our imaging system requires a lengthy capture time of 10 seconds for a single view. Developing a single-shot hyperspectral-polarimetric camera leaves as a future direction. Lastly, there is potential for further exploring the applications of NeSpoF in uncovering geometry, appearance, and material properties.

## 8 CONCLUSION

We propose NeSpoF, the first neural representation specifically designed for hyperspectral Stokes vector fields. Demonstrated across synthetic and real-world scenes captured via a calibrated hyperspectral-polarimetric imager, NeSpoF reveals hidden spectro-polarimetric-positional information of the scene outside the confines of human vision. We anticipate that NeSpoF spurs further interest in high-dimensional imaging, modeling, and analysis.

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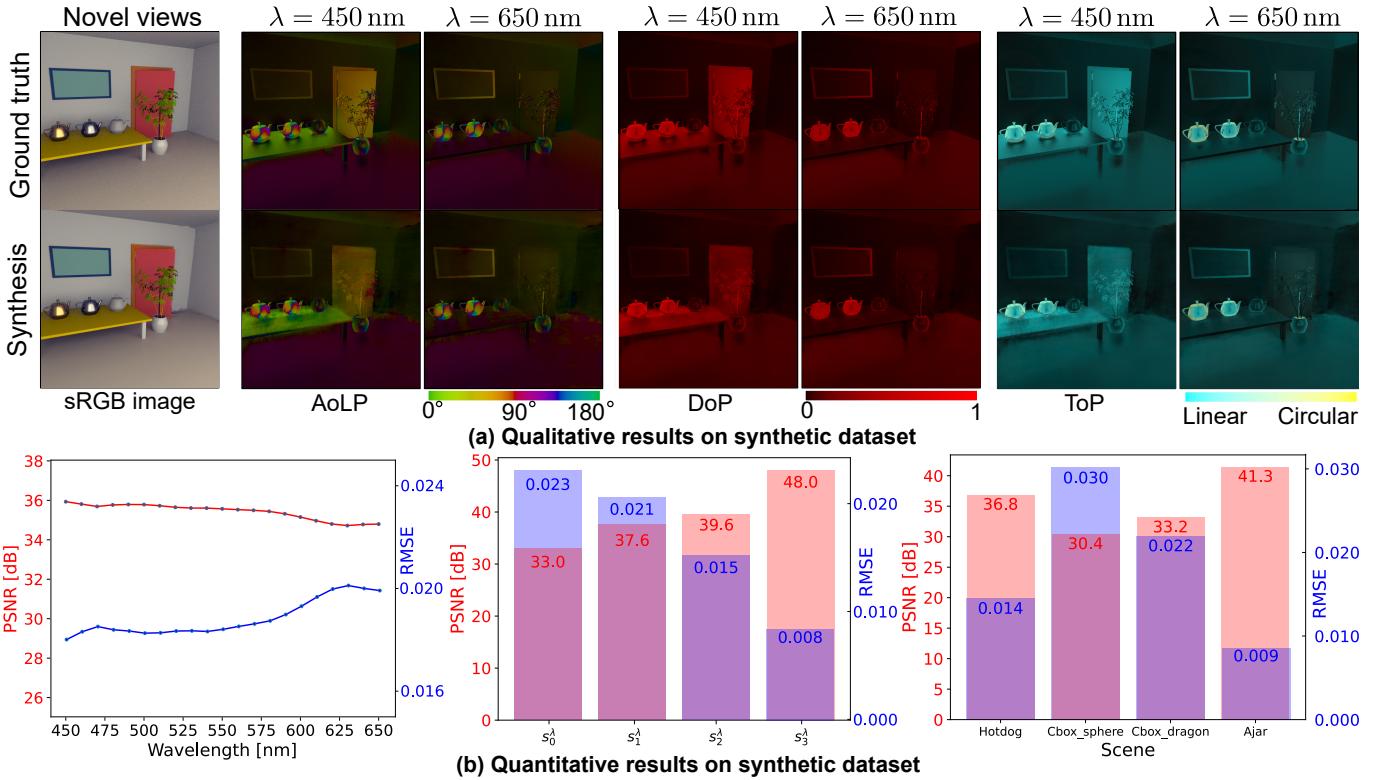


Fig. 6. Synthetic evaluation. NeSpoF achieves an accurate synthesis of hyperspectral Stokes vectors at novel views, evidenced in both (a) qualitative and (b) quantitative analyses. Two novel views are presented for the qualitative results, while the quantitative metrics are computed over all test views.

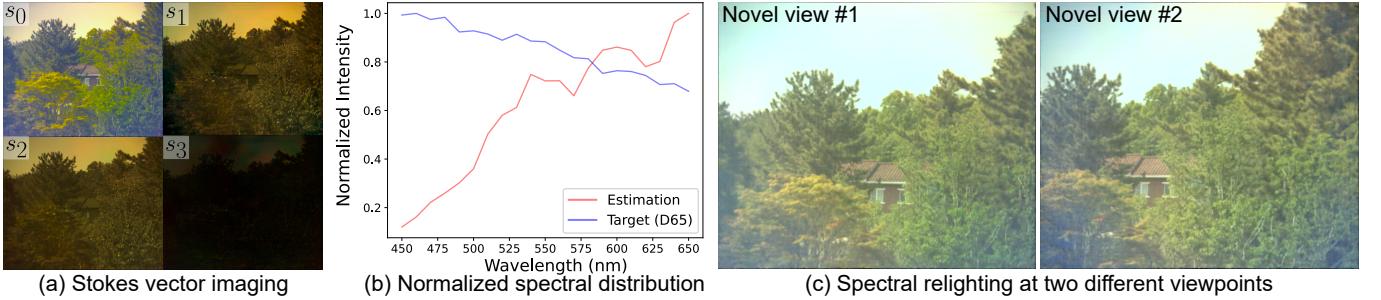


Fig. 7. (a) NeSpoF facilitates the rendering of hyperspectral-polarimetric images of an outdoor scene at a novel view, revealing the partially-linear polarization state of skylight. (b) We extract the hyperspectral intensity of the skylight and (c) use it to relight the scene from two novel views under D65 illumination.

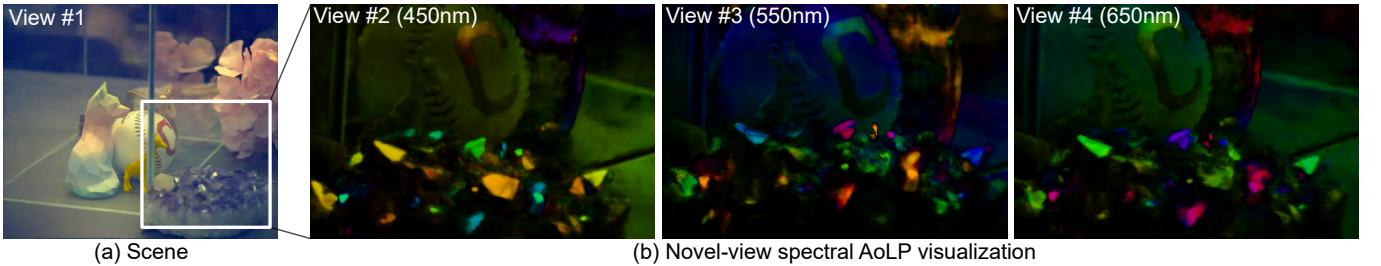
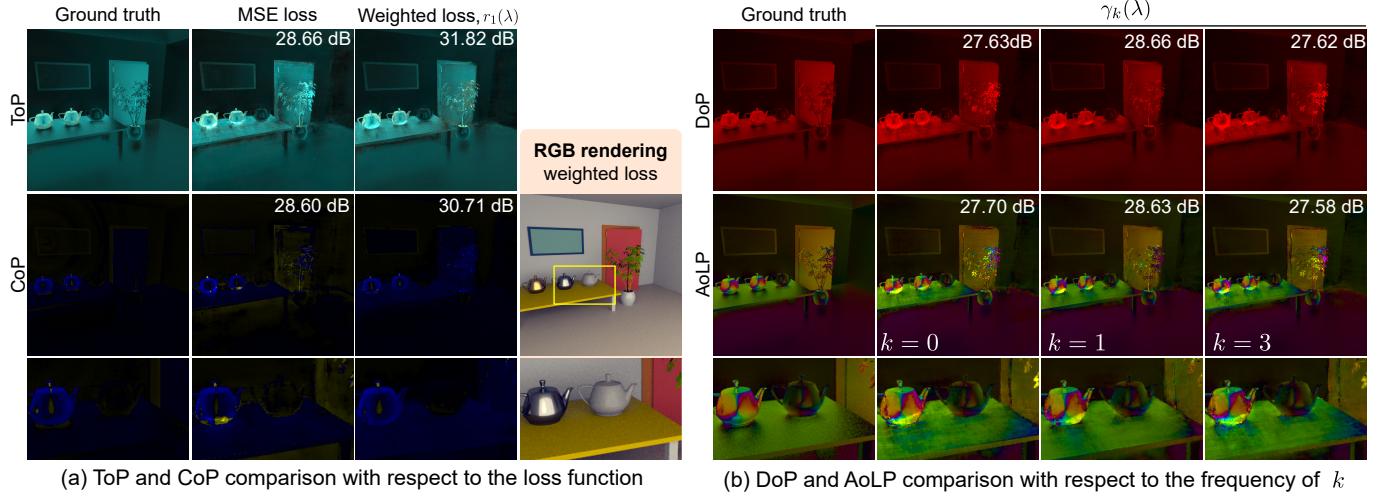


Fig. 8. NeSpoF allows for synthesizing view-dependent hyperspectral-polarimetric patterns of the crystal and a baseball.



(a) ToP and CoP comparison with respect to the loss function

(b) DoP and AoLP comparison with respect to the frequency of  $k$

Fig. 9. We evaluate the impacts of (a) the utilization of weighted loss and (b) the frequency  $k$  of the positional encoding for wavelength. Using the weighted loss and the frequency of  $k = 1$  enables better polarimetric reconstruction. We report PSNRs of the estimated ToP and CoP for the former, and DoP and AoLP for the later.

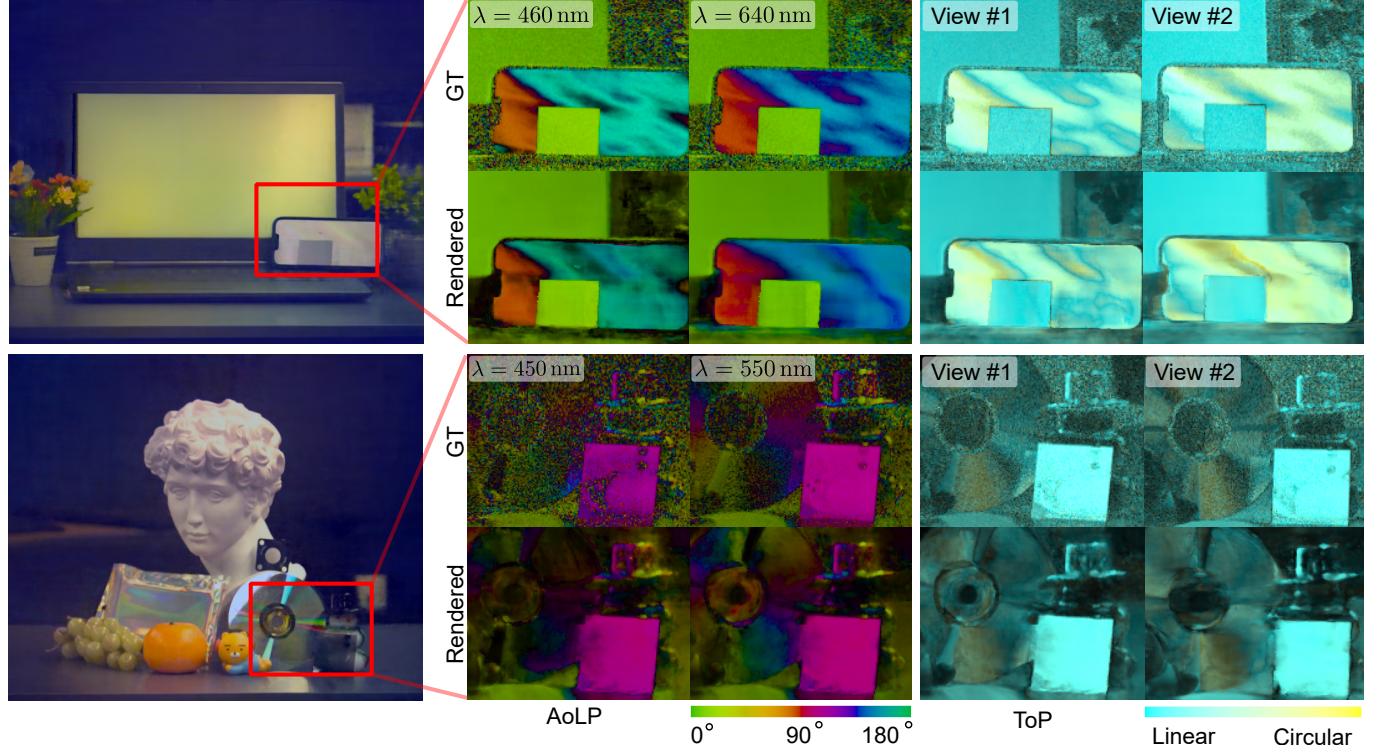


Fig. 10. We demonstrate the synthesis of view-spectrum-polarization using NeSpoF in two real-world scenes that display unique view-spectro-polarimetric characteristics, specifically a mobile display covered with film, a linear polarizer, and a CD. We visualize AoLP at two different wavelengths from a novel view, and ToP at different views.