RGB Photometric Model for Optical/Neural Network Co-Design

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Marius Dufraisse,[1,*] Pauline Trouvé-Peloux,[1] Jean-Baptiste Volatier,[2] and Frédéric Champagnat[1]

[1] *DTIS, ONERA - Université Paris-Saclay, F-91123, Palaiseau, France*
[2] *DOTA, ONERA - Université Paris-Saclay, F-91123, Palaiseau, France*
[*] *marius.dufraisse@onera.fr*

Abstract: We propose to relate a photometric model of imaging sensors to optical parameters, including sensor noise and non-linearities in optics/neural-network co-design. We apply it in extension of the depth of field examples.

1. Introduction

Imaging systems consist of a lens and processing, usually designed separately. Co-design methods aim at optimizing both components simultaneously. Joint optimization of neural network parameters and a phase plate on the diaphragm of a lens has been shown to improve depth of field extension, super-resolution, and depth estimation [3, 6]. Co-design can also optimize a complete lens and neural network [4, 7, 8]. Optimizing simultaneously a neural network and optics relies on differentiable optical simulation based on Fourier optics or ray tracing. Generally, it simulates only the impact of optical parameters on aberrations but not their effects on light intensity.

However, some optical parameters, including the aperture, have a direct influence on the amount of light that passes through the lens: closing the diaphragm reduces aberrations but lowers the amount of light reaching the sensor at the expense of noise. The best possible compromise will depend on the processing's ability to denoise or deblur, so it is interesting to integrate aperture optimization into co-design to find its optimal value. This was first done by considering the aperture as a hyperparameter and testing several values [5]. To optimize it directly, we have already shown how to link Schottky noise to optical parameters [1] rather than simply adding a fixed variance Gaussian noise as most co-design works do.

We propose here an improved image formation pipeline that incorporates a more complete sensor model with multiple noise sources and non-linearities. It remains fully differentiable and as such can be used for co-design. We validate this pipeline with experiments on the extension of the depth of field (EDOF) and highlight the influence of the scene illumination on the co-design results.

2. Image formation pipeline

Our image formation pipeline first models the focusing of light by the lens before modifying the image intensity depending on the entrance pupil diameter and applying the sensor model. It is shown in Figure 1.

2.1. Optical model

The effect of a lens on an image is described by its Point Spread Function (PSF): the image I_o formed by the lens is obtained by convolving the PSF with the sharp ground truth image I_{gt}: $I_o = I_{gt} * PSF$.

Several models exist for calculating the PSF and its gradient [2]. Fourier optics is suitable for phase masks, but not for off-axis objects and multi-element lenses. Ray tracing solves these issues by describing a lens as a series of surfaces and using Snell's law to trace light rays through them. We use the Formidable[1] library, which performs differentiable ray tracing (DRT) to compute ray trajectories and their jacobian with respect to the optical parameters. Using DRT we trace rays from a given point so that they uniformly sample the diaphragm. Following the path of these rays we obtain their intersection with the sensor plane which gives us a discrete approximation of the energy received by each pixel. To obtain the value of the PSF in each pixel and take into account diffraction, we integrate the convolution between the discrete distribution obtained by DRT and an Airy disk. Indeed, reducing the aperture reduces aberrations but can introduce diffraction. The Airy disk radius is computed in a differentiable manner using DRT tools.

These tools can compute the PSF for objects placed at different distances on and off the optical axis. They simulate how a scene would be projected on the sensor by the lens.

[1] Freeform optics ray tracer with manufacturable imaging design capabilities: https://gitlab.space-codev.org/formidable

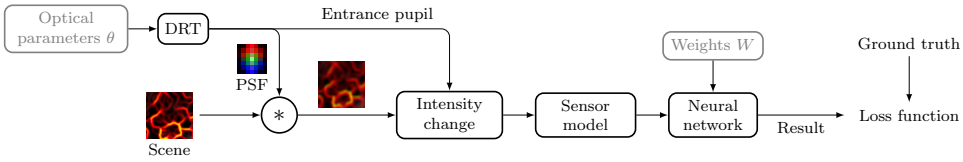

Fig. 1. Our image formation pipeline.

2.2. *Radiometric sensor model*

The PSF is normalized: it only takes into account the influence of optical parameters on the blur of the image but not on its dynamic range. However, some optical parameters, especially the aperture, have a direct influence on the amount of light passing through the lens: closing the aperture reduces aberrations but decreases the amount of light reaching the sensor at the expense of more noise. Our co-design pipeline models the effects of aperture, which is fixed in the literature, in two steps: an intensity change and a sensor simulation.

The intensity change is proportional to the square of the entrance pupil diameter which is the image of the physical aperture stop, as seen through the front of the lens. We use DRT to compute the image of the physical aperture stop and thus get the radius of the entrance pupil as well as its gradient with respect to the optical parameters. As such the intensity change is fully differentiable.

The sensor model adds noise sources and non-linearities. We first used a simple model which only adds Schottky noise to demonstrate the validity of our two step approach [1]. Now we simulate more noise sources (dark current and readout noise) and non-linearities (saturation of the photo-receptors and quantification of the signal) described in [8]. We also expanded the scope of our experiments with RGB images and off-axis objects.

3. Application to EDOF

We propose several experiments in which we apply our image formation model to an image quality enhancement task. Indeed, neural networks have the ability to deblur or denoise and thus, can have two distinct modes of operation when jointly optimized with aperture. Initially, we study a system with objects on the axis at a fixed distance to validate our model. Then we consider EDOF by varying the distance of objects. Finally, we include off-axis objects. We carried an ablation study to compare the importance of the multiple noise sources. In our experiments, the added sensor noise sources lead to similar optical system but the co-design process benefits from having 3 wavelength with 3 different focus distances to reconstruct the image. We also study how the optimized systems differ based on the level of illumination.

4. Conclusion

Our differentiable image formation pipeline incorporates the effects of lens parameters on the PSF but also on the image acquisition by the sensor. We applied it to the task of EDOF. We can now more accurately simulate the behavior of imaging systems and we plan to use our co-design methods to a range of imaging problems.

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