ISET Camera Simulation and Evaluation of PSF Estimation

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Abstract

In this project, a simulation of a stereo camera was built. The main components of this simulation were the sensor module and the optics module. To simulate the sensor module we estimated the spectral and noise characteristics of the sensor. Noise from various sources including read noise, dark voltage, DSNU and PRNU were considered. For the optics module, the optical properties of the camera lens were derived using Zemax. These were combined to form a complete simulation using ISET, a MATLAB toolbox. The simulation was used to explore the performance of a blur kernel estimation method, thus demonstrating one potential use of the camera simulation model.

1. Introduction

The image processing pipeline refers to the steps involved from the acquisition of a scene to the rendering of an image. The components of the pipeline capture, process and store an image [6]. A lot of effort has been spent on modeling the individual components or subcomponents of an imaging process pipeline including the camera, camera optics and sensor noise [7],[3]. However, by modeling only the system subcomponents, a narrow view of the imaging processing pipeline is captured.

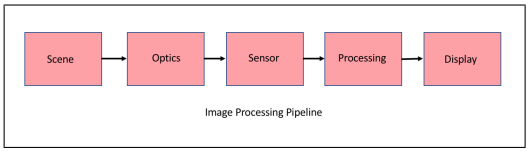

Figure 1. Image Processing Pipeline

There is great interest in not only modeling individual components but also simulating the entire imaging pipeline [5]. This simulation could serve as a useful tool that can assist better understanding of the system, enable cost-efficient and rapid prototyping, guide development of sensor components, and provide predictions of performance in settings that are difficult to measure.

The steps followed to create the simulation were the following: (1) follow established methods to estimate spectral and noise characteristics of the camera sensor [4], (2) create and validate a sensor simulation using ISET with the estimated values, (3) extract optical properties from the manufacturer-provided lens file using Zemax, (4) construct and validate an optics simulation using the ray tracing functions in the Image Systems Evaluation Toolbox (ISET).

We explored one potential application of the simulation in this project. A state-of-the-art blur kernel estimation method was implemented [2]. The performance of the algorithm was tested with (1) a simple evaluation of the optimization that they perform in the paper, (2) a comparison of ground-truth PSFs derived from Zemax with PSFs derived by capturing images with the camera and (3) by deriving PSFs using simulated images. Custom optics with known PSFs were used for the simulation in this case.

2. Methods

2.1. Estimation of sensor spectral characteristics

The sensor spectral quantum efficiency is the relative efficiency of detection of light as a function of wavelength. It results from a combination of the effects of lens transmittance, color filter arrays and photodiode quantum efficiency [5].

To measure the spectral quantum efficiencies we captured images of a set of narrowband lights with constant exposure and calculate R,G and B values from the image.We measured the spectral power distribution (spd) of the narrowband light using spectroradiometer. These quantities are related by the equation $C = S * L$, where S is the spectral sensitivity, C is the RGB values and L is the spd. We found S by inverting L using linear least squares fitting with Tikhonov regularization [5].

2.2. Estimation of sensor noise characteristics

The sensor noise introduced by various sources were considered in the model, including read noise, dark voltage, DSNU and PRNU. The read and reset operations on a sensor are inherently noisy processes and lead to read noise. Dark current is a source of noise that arises from increases photon counts due to thermal energy.

Noise also arises from irregularities across the sensor surface. There exists a linear relationship between a pixel value and the exposure duration. PRNU refers to the variance in the slope of pixel value versus exposure duration across different pixels in a pixel array. DSNU refers to the variability in dark noise across pixels in a pixel array.

Images taken with no illumination (dark field) with constant exposure were used to estimate read noise and DSNU. Images taken with uniform illumination (light field) with varying exposure were used to estimate PRNU. Figure 2 summarizes the data collected for sensor noise estimation.

Noise type	Image type acquired	Exposure duration	No. images acquired (per sensor)
Dark voltage	Zero intensity (Dark frame)	Varying: 125 µs - 30 ms	150
photoreceptor nonuniformity (PRNU)	Uniform light field (Light frame)	Varying: 125 µs - 30 ms	142 Deleted photos that were: • dominated by noise at short exposure durations • Saturated at high exposure durations
Dark nonuniformity (DSNU)	Dark frame	Constant: 125 µs	149
Read noise	Dark frame	Constant: 125 µs	

Figure 2. Noise measurements

2.3. Derivation of optical properties

The lens file provided by the manufacturer was used to derive the required optical properties of the camera. A macro written in Zemax was used to extract relative illumination, geometric distortion and point spread functions [1].

The PSFs were sampled at 33 wavelengths, varying from 400nm to 720nm in steps of 10nm. The PSFs were also sampled at 21 different field heights, starting from the centre of the sensor area and moving to the edge. The PSFs are sampled in the way described because the ISET raytracing module is designed to interpolate PSFs assuming that radial symmetry conditions hold.

2.4. PSF estimation

The PSF estimation method described by Mosleh et al. have two components: Alignment and PSF Estimation. Images of four targets are captured: a white target, a black target, a checkerboard pattern and a bernoulli noise pattern. These images are captured such that there is no relative motion between captures. To ensure this targets shown on a high resolution screen [2].

In the alignment phase, the ideal noise pattern is warped to be in the same space as the captured noise pattern (b). This warping is done with local bilinear interpolation using the checkerboard pattern as reference. The image is then corrected to account for lens vignetting using the captured images of white and black targets. The warped, color corrected noise pattern (u) is shown in the figure 3

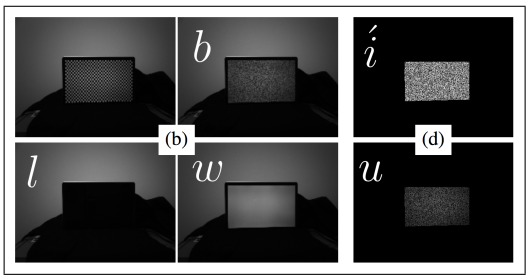

Figure 3. Alignment

Using the aligned ideal noise target u and the captured blurry noise target b as input, and optimization is performed to estimate kernel k. The optimization objective is shown in the figure 4.

$$min_k E(k) = \underbrace{\|\hat{u}k - \hat{b}\|^2}_{\text{Data fidelity term}} + \underbrace{\lambda\|k\|^2}_{\text{sparsity prior}} + \underbrace{\mu\|\Delta k\|^2}_{\text{smoothness prior}} + \underbrace{\gamma\||\mathcal{F}(k)| - |\mathcal{F}(k')|\|^2}_{\text{prior on PSF}}, \text{ s.t } \underbrace{k > 0}_{\text{PSF constrained to be positive}}$$

Figure 4. Optimization

3. Results

3.1. Sensor characteristics

The estimated spectral quantum efficiency curves are shown in the figure 5. The curves have been normalized to lie between [0,1]. They are in close agreement with the manufacturer's curves which are shown as the dashed line. At higher frequencies the curves diverge due to the effect of the IR filter.

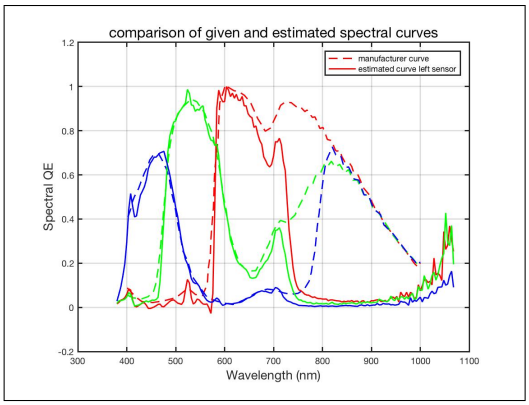

Figure 5. Spectral quantum efficiencies

The estimated noise values are shown in figure 6. To build the sensor simulation we included the specifications provided by the manufacturer, including pixel width, CFA pattern, focal length, f-number, dark voltage, fill factor and conversion gain.

Parameter	Left image sensor vcap0	Right image sensor vcap1
Noise		
PRNU	2.2897 %	2.4100 %
DSNU	0.2536 mV	0.2727 mV
Read-noise	1.3884 mV	1.5619 mV

Figure 6. Estimated noise parameters

3.2. Validation of sensor module

The Macbeth ColorChecker was used as a target to validate the sensor module. An image of it was captured under uniform illumination using the stereo camera. This served as the measurement.

To simulate the Macbeth ColorChecker a scene was created using the reflectance properties of each of the 24 patches. This scene was processed assuming diffraction-limited optics and sent to the sensor module. Here the effects of spectral and noise properties of the sensor were applied and a predicted RAW image was obtained.

From both the measured image and predicted image, boxes were drawn to identify the 24 patches, and R,G and B values were extracted. There values were found to be in agreement. Figure 7 shows a qualitative comparison of the two sets of values, and figure 8 shows a quantitative comparison.

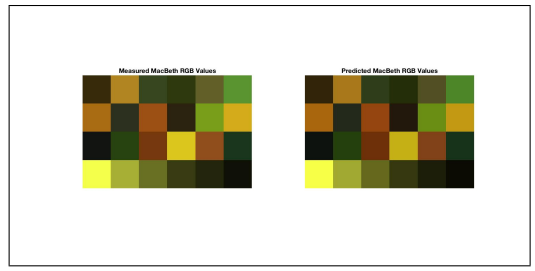

Figure 7. Qualitative comparison

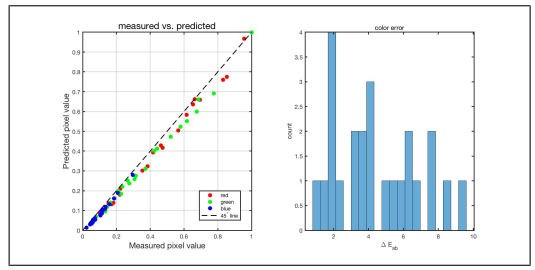

Figure 8. Quantitative comparison

3.3. Validation of optics module

A slanted line target with a slope of 2.6 was used to validate the optics module as shown in figure 9. An image of the slanted line target served as the measurement. The effect of the estimated optical parameters - geometric distortion, relative illumination and blur were simulated using in-built ISET ray-tracing functions.

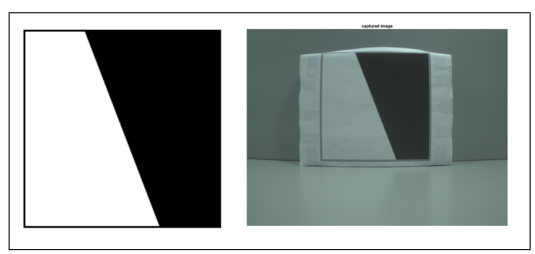

Figure 9. Slanted line target

To validate the optics, a central part of the image was selected and the gradient corresponding to the slanted line was found. The rows of the were aligned with respect to the gradient, and the line spread function was found. Using this line spread function, the modulation transfer function (MTF) was derived.

We compared the MTF for the measured and predicted images as shown in figure 15. The two MTF curves do

not match, but we hypothesize this may be because of the presence of an anti-aliasing filter. Further analysis is required to understand why the curves differ.

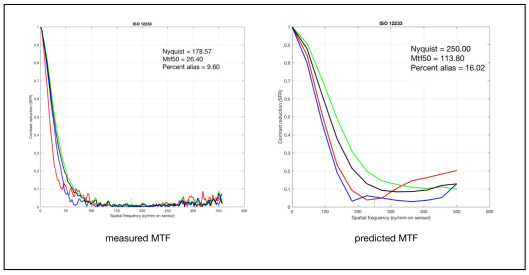

Figure 10. Comparison of MTF

3.4. Evaluation of PSF estimation

We evaluate the PSF estimation method using different methods, as discussed below.

3.4.1 Evaluation of Optimization

Mosleh et al., perform a simple validation of the optimization. They blur the noise target with a Gaussian PSF and discuss the effect of tuning the parameters of their optimization [2].

We implemented and analyzed the optimization similarly. We find the PSNR between the ground truth PSF and the estimated PSF. The values were 46.81, 46.96,47.60,30.93 and 26.61 respectively for the examples shown below. The PSNRs are higher for the Gaussian PSFs used in the first three examples, and drop for the non-Gaussian cases. We note that since the optimization has smoothness and sparsity priors, its performance is poorer for non-smooth PSFs such as the fourth and fifth example in figure 11.

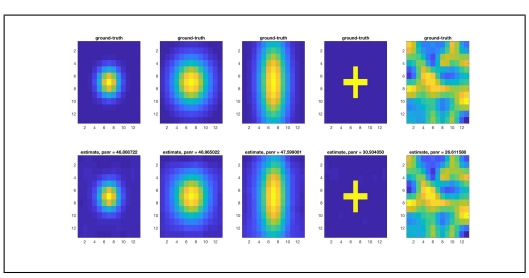

Figure 11. Evaluation of optimization

3.4.2 Comparison of Zemax PSFs and measured PSFs

Measurements were taken to estimate the PSF using the stereo camera. The PSFs estimated using the captured images were compared to the PSFs derived using Zemax for two cases - at the centre and near the edge.

The PSF estimation was done separately for each color channel, and the resulting combined PSF is displayed as an RGB image. For the ground truth Zemax PSFs I used the PSFs derived at 450nm, 550nm and 600nm as proxies for the blue, green and red PSFs respectively.

The PSFs at the centre are shown in figure 12. The PSNR of the estimated PSF with respect to ground truth is 35.2957. The PSFs at the edge are shown in figure 13, and have PSNR 35.0213. This is lower than the PSNR obtained using the simple validation described above. The PSFs also appear to have some chromatic artifacts which is not captured in the basic analysis.

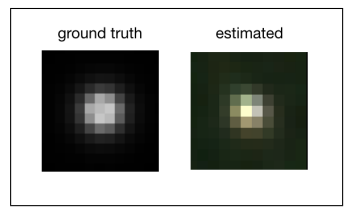

Figure 12. Comparison of PSF at centre

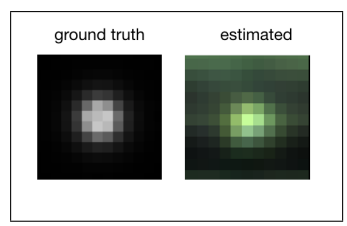

Figure 13. Comparison of PSF at edge

3.4.3 Evaluation using ISET Simulation model

We used the camera simulation model described in the previous sections to simulate the output of a hypothetical camera. Sensor parameters were set to be the same as the estimated sensor parameters, in order to have realistic values. Custom optics were added into the simulation. In the case discussed a simple shift-invariant Gaussian model was used.

The simulation took in a target image, processed it first through the optics module, then the sensor module, applied basic image processing and provided a linear sRGB image as output. This process is shown in figure 14. The output from the simulation was used to perform the PSF estimation.

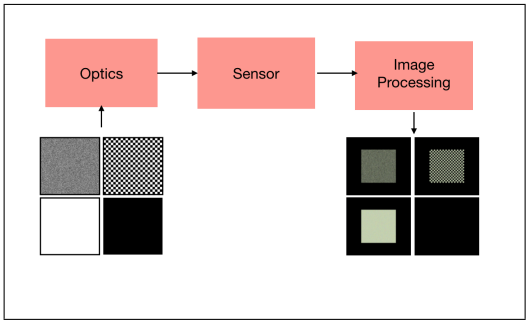

Figure 14. ISET simulation

Figure 15 shows the ground truth PSF set as the input to the optics simulation on the left, and the PSF estimated using the simulated images on the right. The PSNR of the estimate with respect to ground truth is 43.9273. The PSNR is lower than the first case, perhaps because the simulation adds noise corresponding to various noise sources.

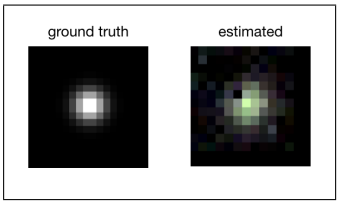

Figure 15. Comparison of MTF

4. Discussion

To model the stereo camera accurately the optics simulation needs to be improved upon. Further analysis using Zemax may provide insight on why the MTF curves do not match.

Currently the ISET ray tracing method assumes that radial symmetry applies to the distribution of PSFs, and interpolates them accordingly. Based on this the PSFs estimated from Zemax were chosen along a single axis. Hence comparisons between only the centre and edge PSFs were made. The radial symmetry assumption may not hold, and the interpolation might need modification.

The simulation was useful for a more rigorous validation the PSF estimation method since the simulation includes a realistic amount of noise from various sources. The optics are easily customizable, and it can be used to test the performance of the method on a range of PSFs. It also takes a fraction of the time compared to capturing images in the lab.

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