

# Simulation technologies for image systems engineering

Professor Brian A. Wandell  
Stanford University

Stanford Center for Image Systems Engineering  
Wu Tsai Neurosciences Institute  
Stanford Center for Cognitive and Neurobiological Imaging

QUANTITATIVE MEASUREMENTS



COMPUTATIONAL MODELS



CHECK AND SHARE

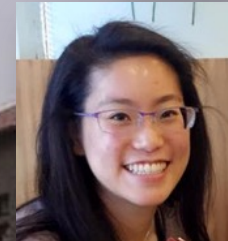
Joyce Farrell



Zhenyi Liu



Trisha Lian



Zheng Lyu



Henryk Blasinski



Andy Lin



Thomas Goossens



Haomiao Jiang

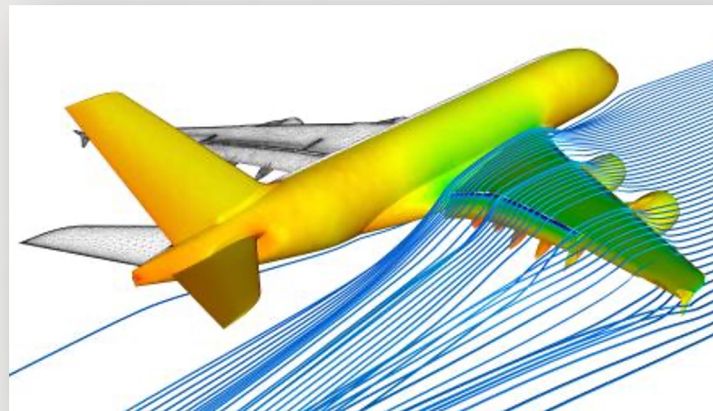


Thanks to Meta, Ford and Google

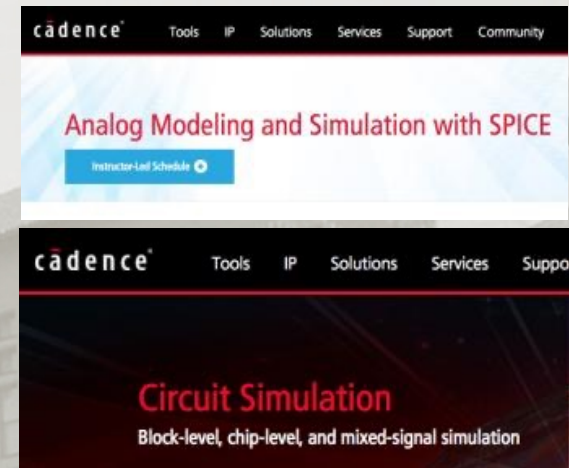
# Systems simulation (digital twin) is important in many mature industries



**ECU (Electronic Control Unit) Simulation for Automobiles**



**Numerical flow simulation on an Airbus A380**



**Integrated circuitry**

# Physics-based image systems simulation: Our origins

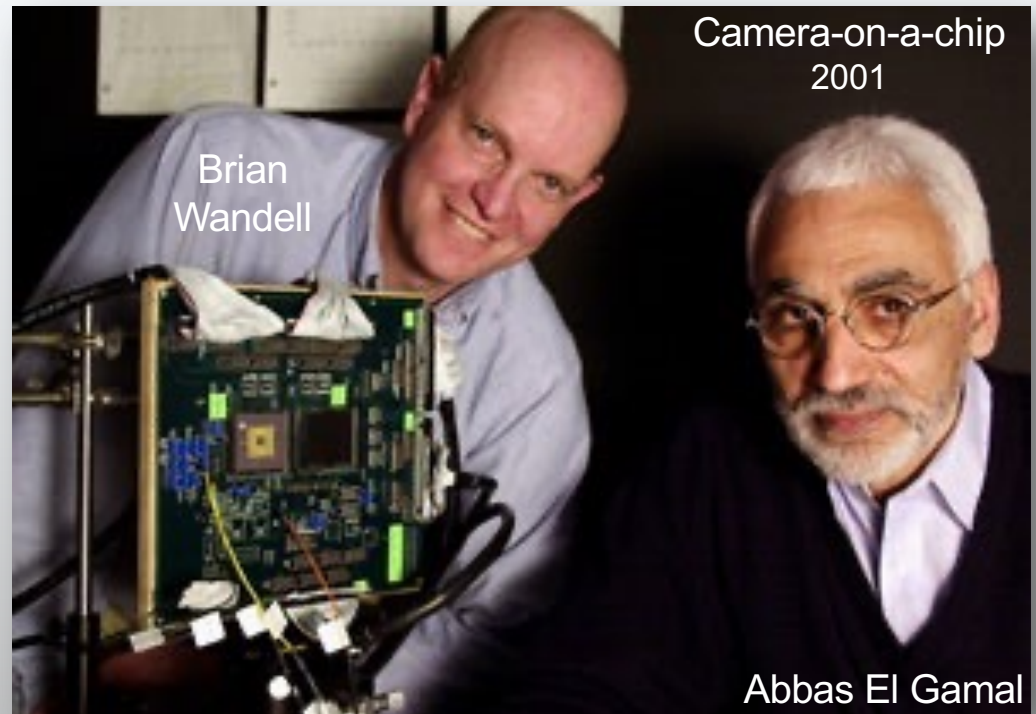
Ting Chen



Peter Catrysse



Joyce Farrell



Brian  
Wandell

Camera-on-a-chip  
2001

Abbas El Gamal

## 2003: We developed a 2D imaging systems simulation (physical units)

### Image Systems Engineering Toolbox for cameras (**ISETCam**)

- End-to-end simulation (radiance to sensor)
- Physical units (photons to electrons)



Optics



Sensor



Display

# Imaging Systems Engineering Toolbox (ISETCam)

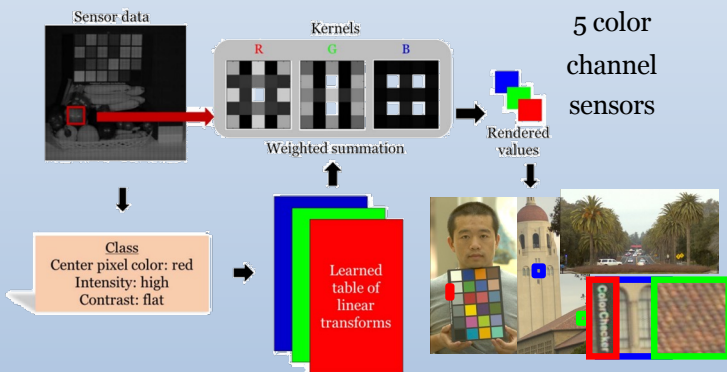
More than 500 users in  
80 companies,  
9 research institutes,  
65 universities,  
in 24 countries

Open Sourced on GitHub  
in 2018

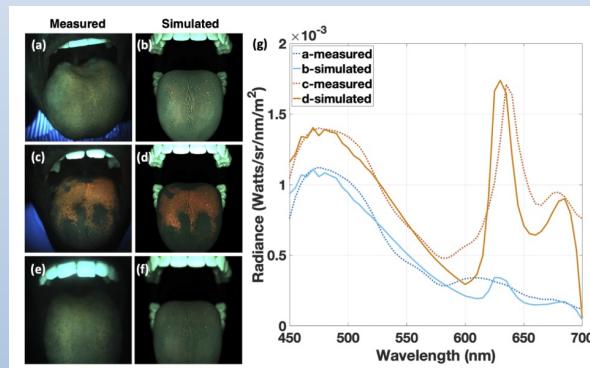


# Applications: ISP pipeline, optics, biomedical

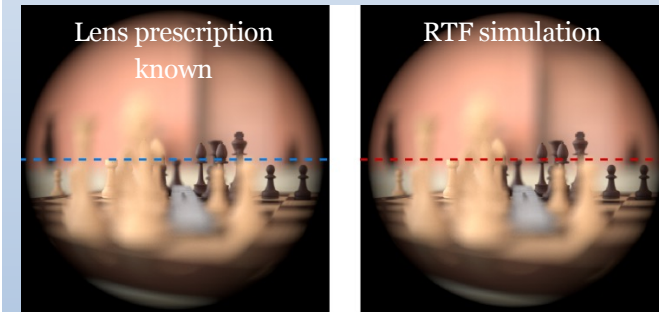
Learning the image processing pipeline (IEEE Transactions on image processing, 2017)  
H. Jiang, Q. Tian, J. Farrell, B. Wandell



Simulations of fluorescence imaging in the oral cavity (Biomedical Optics Express, 2021)  
Z. Lyu, H. Jiang, F. Xiao, J. Rong, T. Zhang, B. Wandell, J. Farrell



Ray-transfer functions for camera simulation of 3D scenes with hidden lens design (Optics Express, 2022)  
Z. Lyu, H. Jiang, F. Xiao, J. Rong, T. Zhang, B. Wandell, J. Farrell



# Automotive systems simulations

## ISETHDR: A Physics-based Synthetic Radiance Dataset for High Dynamic Range Driving Scenes

Zhenyi Liu, Devesh Shah, and Brian A. Wandell

## Neural Network Generalization: The Impact of Camera Parameters

ZHENYI LIU<sup>1,2</sup>, TRISHA LIAN<sup>2</sup>, JOYCE FARRELL<sup>2</sup>, AND BRIAN A. WANDELL<sup>2</sup>

<sup>1</sup>State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun 13000, China

<sup>2</sup>Department of Electrical Engineering, Stanford University, Stanford, CA 94305, USA

Corresponding author: Zhenyi Liu (zhenyiliu27@gmail.com)

This work was supported by the Jilin University.

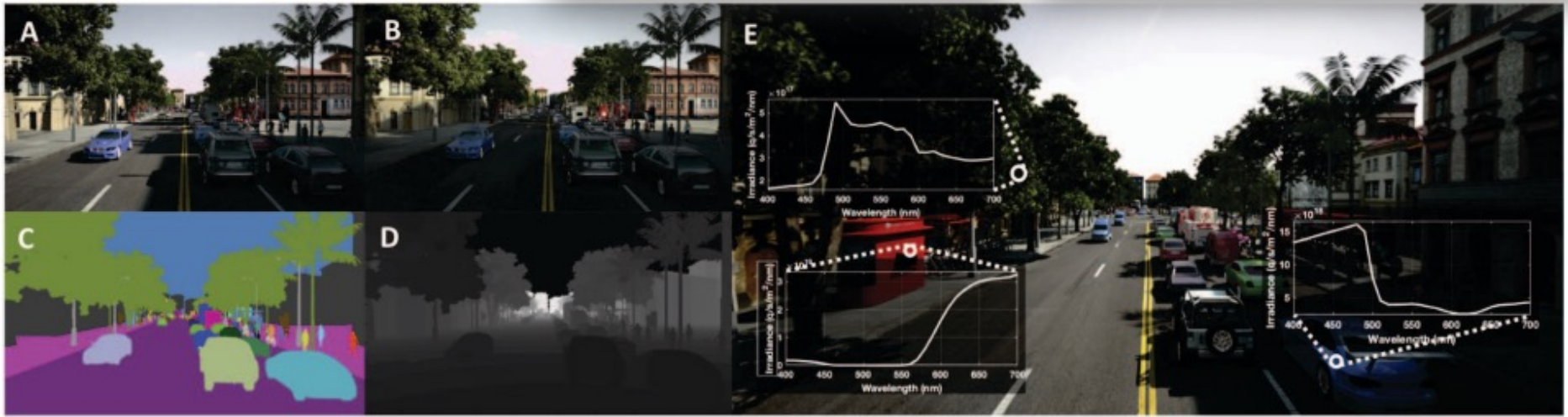
## ISETAuto: Detecting vehicles with depth and radiance information

ZHENYI LIU<sup>1</sup>, JOYCE FARRELL<sup>2</sup> AND BRIAN WANDELL<sup>2</sup>

<sup>1</sup>State Key Laboratory of Automotive Simulation and Control, Jilin University (e-mail: zhenyiliu27@gmail.com)

<sup>2</sup>Stanford University (e-mail: jfarrell, wandell@stanford.edu)

Corresponding author: Zhenyi Liu (e-mail: zhenyiliu27@gmail.com)



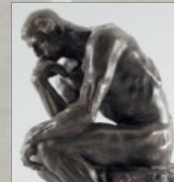
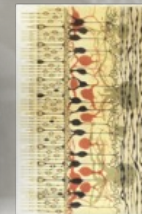
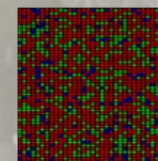
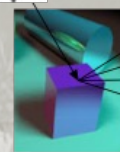
Imaging systems are increasingly used as input to convolutional neural networks (CNN) for object detection; we would like to design cameras that are optimized for this purpose. It is impractical to build different cameras and then acquire and label the necessary data for every potential camera design; creating software simulations of the camera in context (soft prototyping) is the only realistic approach. We implemented soft-prototyping tools that can quantitatively simulate image radiance and camera designs to create realistic images that are input to a convolutional neural network for car detection. We used these methods to quantify the effect that critical hardware components (pixel size), sensor control (exposure algorithms) and image processing (gamma and demosaicing algorithms) have upon average precision of car detection. We quantify (a) the relationship between pixel size and the ability to detect cars at different distances, (b) the penalty for choosing a poor exposure duration, and (c) the ability of the CNN to perform car detection for a variety of post-acquisition processing algorithms. These results show that the optimal choices for car detection are not constrained by the same metrics used for image quality in consumer photography. It is better to evaluate camera designs for CNN applications using soft prototyping with task-specific metrics rather than consumer photography metrics.

## First point

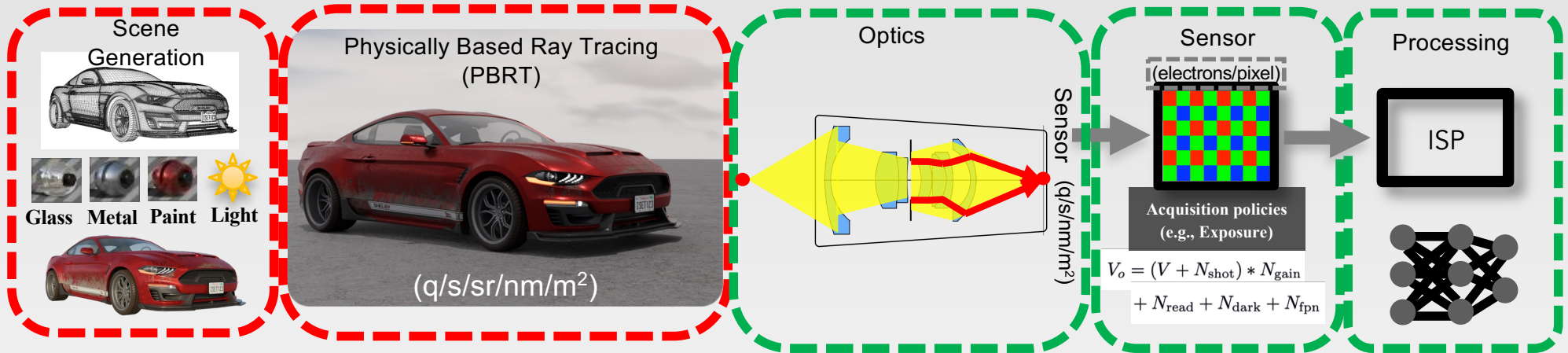
Image systems simulation software that is trusted by key stakeholders in industry and academia can speed the development of next generation image sensors, camera arrays and displays.

## Image systems engineering tools (ISET) – What is it?

- **ISETCam** is a Matlab toolbox that computes the image sensor response from the sensor irradiance; it also includes many industrial tools for evaluation of color (CIE standards) and spatial resolution (ISO standards)
- **ISET3d** is a Matlab toolbox that uses **Physically Based Rendering Tools (PBRT)** to calculate three-dimensional scene spectral radiance and sensor irradiance for certain lenses and complex scenes
- **ISETBio** is a Matlab toolbox that builds on ISET3d and ISETCam to compute the human visual system's encoding



# ISSET computational pipeline



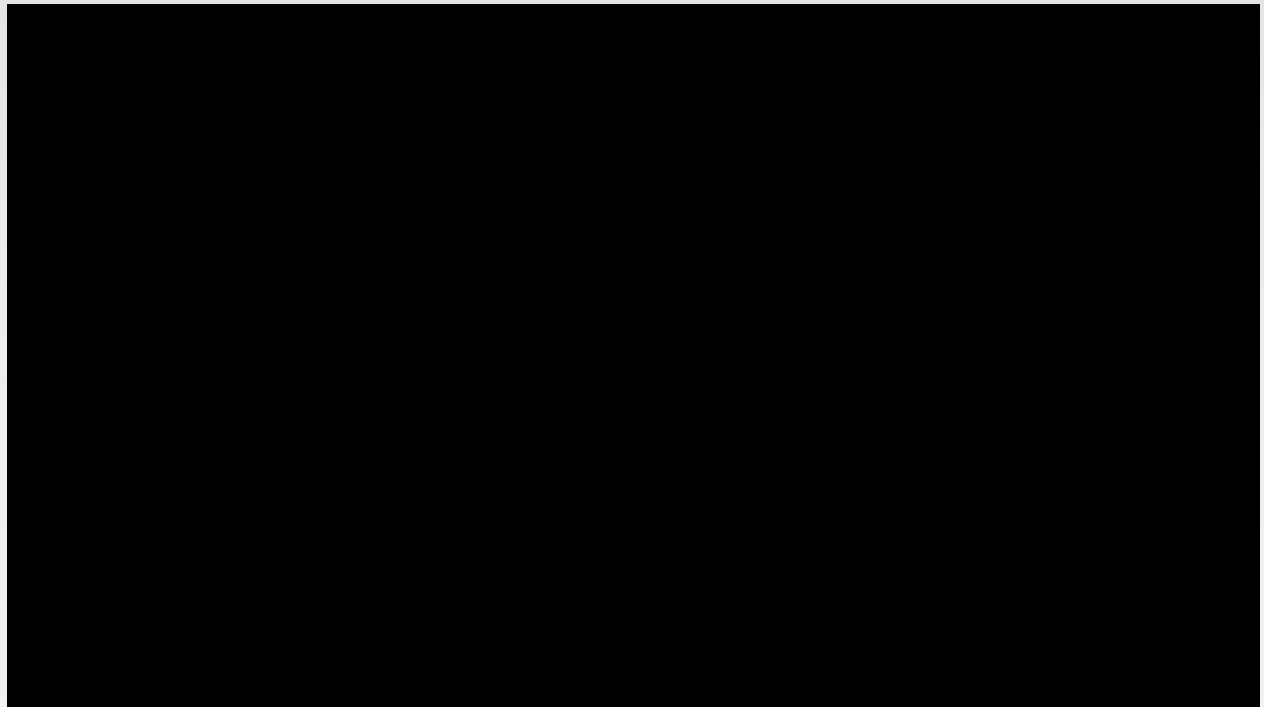
**ISSET3d** – Matlab toolbox that uses PBRT-V4 to calculate the sensor spectral irradiance of complex scenes

**ISSETCam** – Matlab toolbox that computes the image sensor response from the sensor spectral irradiance; it includes many evaluation tools for color and spatial resolution

## Scene generation: Quantitative computer graphics

- Progress in computer graphics enables us to create synthetic and yet highly realistic input data.
- For digital twins we need simulations with **physical units**; quantitative computer graphics
- PBRT uses path tracing from the sensor, through multi-element optics, into the scene spectral radiance.
- PBRT is open-source and well documented, enabling us to add custom features
- N.B. This is not Generative AI of RGB

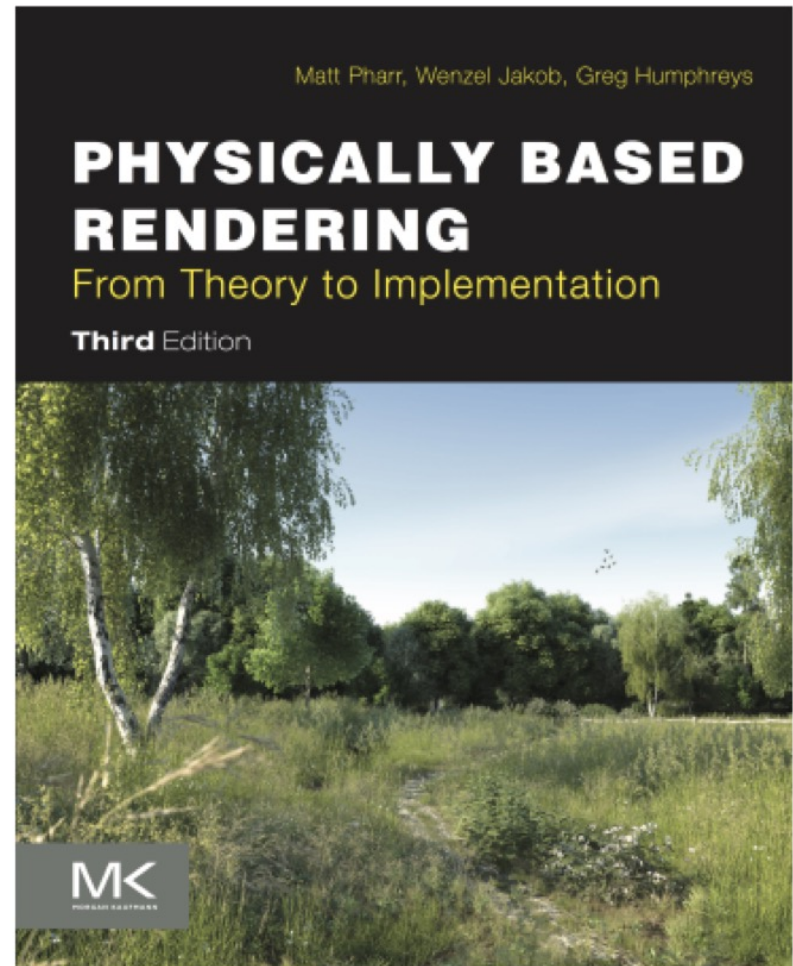
Spectral ray tracing examples (PBRT, ISET3d)



# Scene generation: Quantitative computer graphics

We added ISET methods to PBRT-V4 in order to compute

- Diffraction
- Human eye models
- Aspherical lenses
- Microlens arrays
- Linear models of texture maps to control surface spectral reflectance
- Fluorescence (Medical imaging)
- Participating media (Underwater)
- Flare (aperture, scratches)
- Computational imaging (CNN, Ideal observer)



# Optics simulation

Wide Angle 56 Deg



FishEye 87 Deg



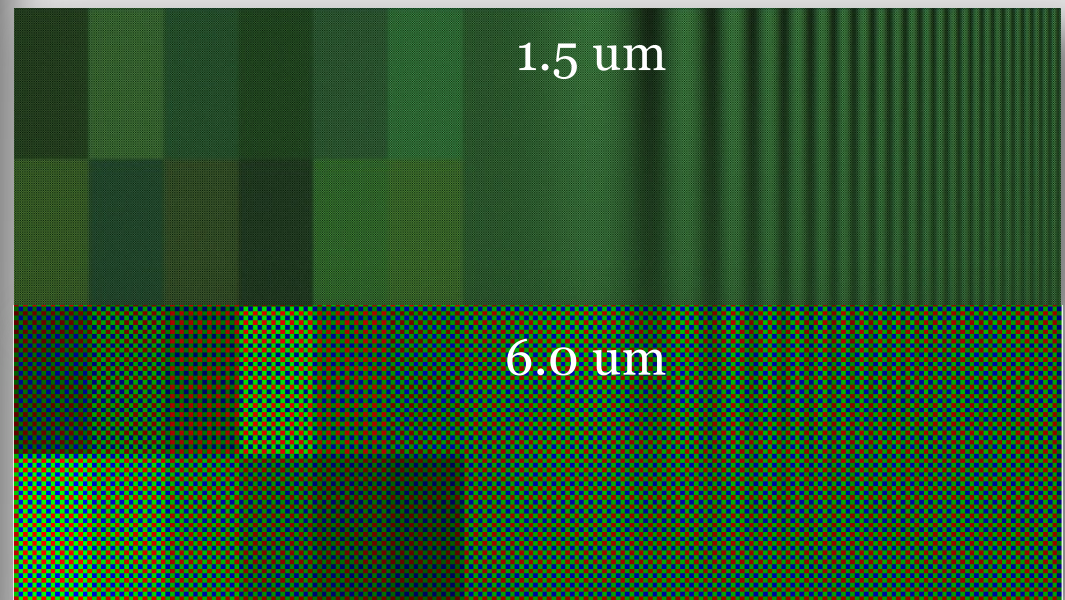
Light Field Camera  
Main lens: Double Gauss 22 Deg  
Microlens: 1.2 mm with 10 x 10 pixels



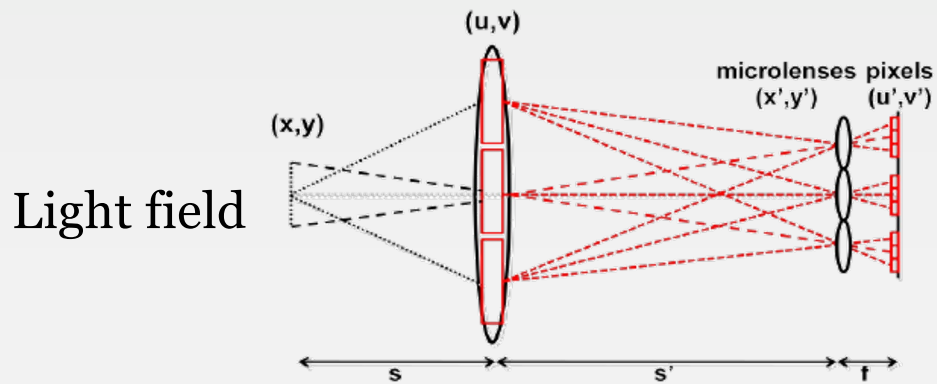
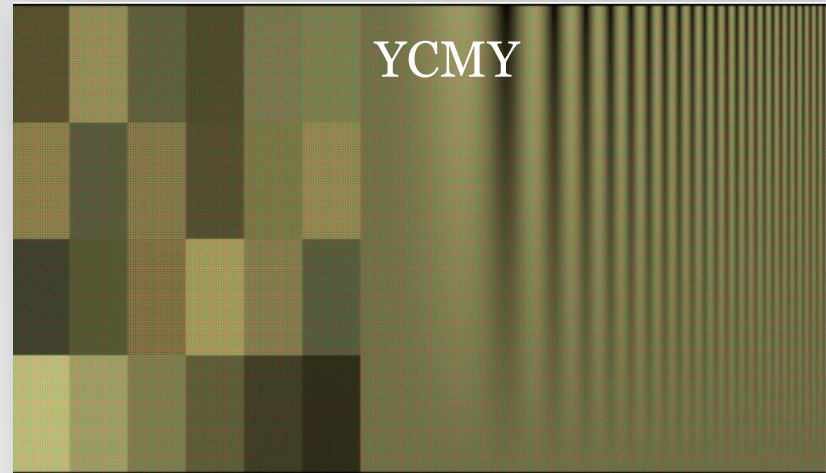
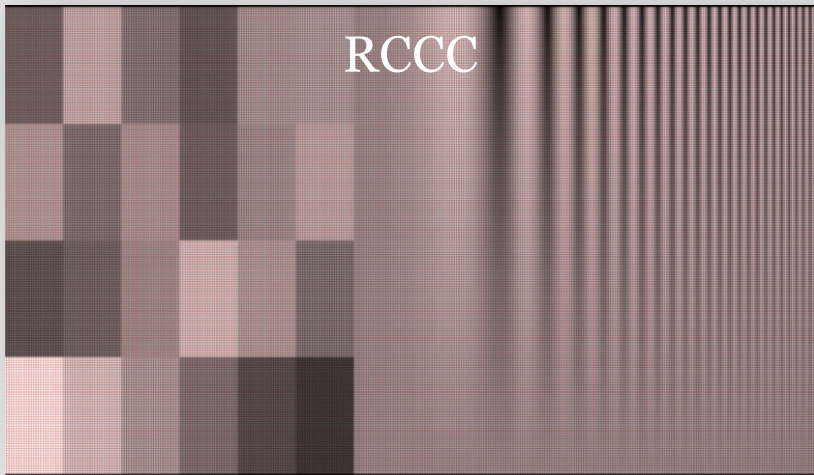
All used 12.5 mm focal length

# System modeling: Sensor properties (ISETCam)

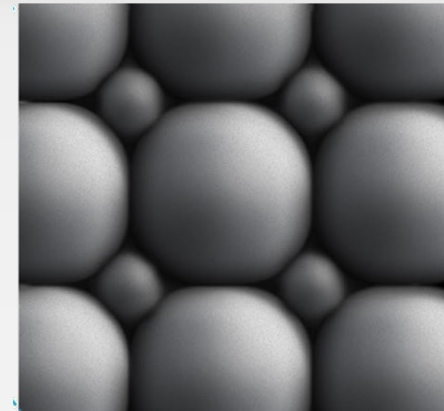
ISET Parameter Table for a Sensor		
Property	Value	Units
Name	IMX363	
Size	0.786 1.36	mm
Rows and Columns	524 908	
Horizontal FOV	20	deg
Horizontal Res / dista...	1.5	um
Horizontal Res / degre...	0.022	deg/pixel
Exposure time	0.0020219	s
DSNU	0	V
PRNU	0.7	%
Analog gain	0.204	
Analog offset	0.00585	V
-----	----- Pixel -----	-----
Width & height	1.5	um
Fill factor	0.871	
Dark voltage (V/sec)	0	V/sec
Read noise (V)	0.000383	V
Conversion Gain (V/e-)	7.65e-05	V/e-
Voltage Swing (V)	0.459	V
Well Capacity (e-)	6e+03	e-

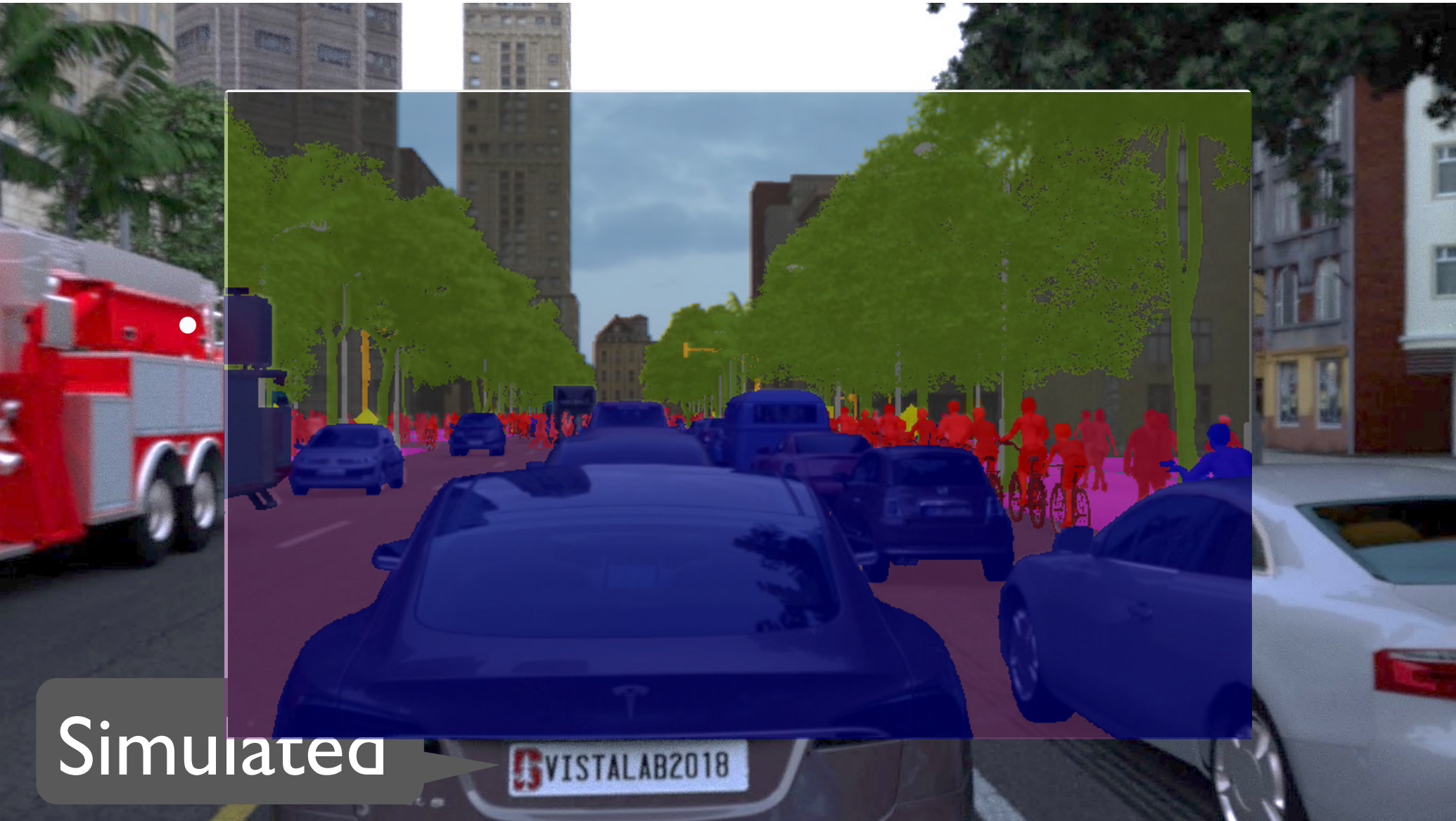


# ISETCam: Advanced sensor simulations



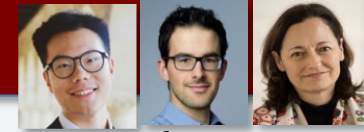
Split pixel





Simulated

# Evaluation of the simulation accuracy



Zheng  
Lyu

Thomas  
Goossens

Joyce  
Farrell



IEEE SENSORS JOURNAL, VOL. XX, NO. XX, XXXX 2022

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## Validation of Physics-Based Image Systems Simulation with 3D Scenes

Zheng Lyu, Thomas Goossens, Brian Wandell and Joyce Farrell



## Validation tests: Cornell Box Construction

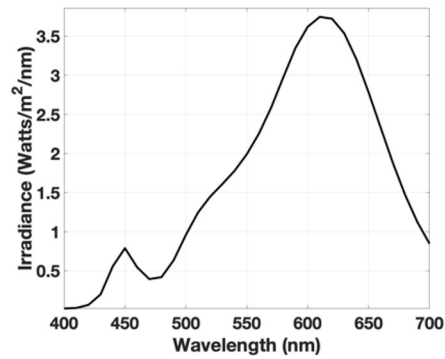
- The Cornell Box has been widely used to evaluate the **accuracy of computer graphics rendering**
- We use it to quantitatively test end-to-end simulation of **3D scenes, optics, and image sensors**



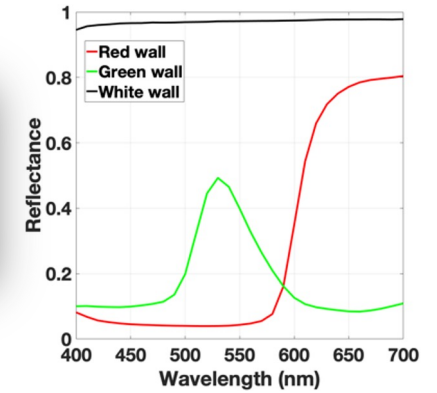
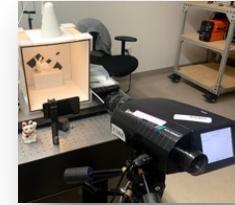
- Goral, Torrance, Greenberg, and Battaile, "Modeling the Interaction of Light Between Diffuse Surfaces," *Computer Graphics (Proc. SIGGRAPH 84)*, Vol. 18, No. 3, July 1984, pp. 213-222
- Meyer, Rushmeier, Cohen, Greenberg, and Torrance, "An Experimental Evaluation of Computer Graphics Imagery" *ACM Transactions on Graphics*, Vol. 5, No. 1, January 1986, Pages 30-50

## We built one (the 3D scene)

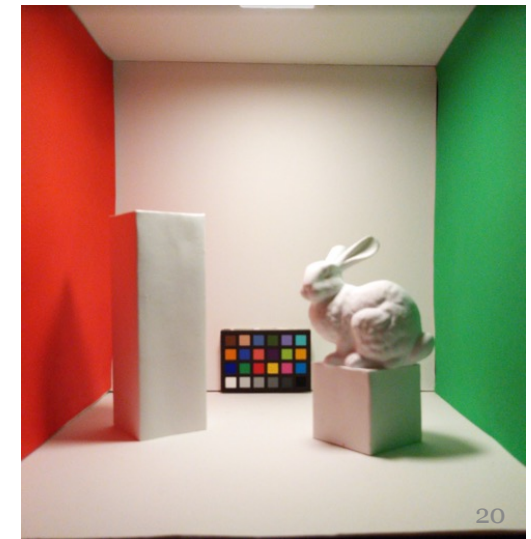
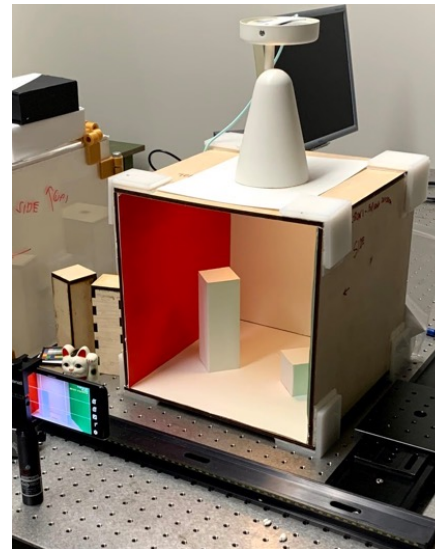
- We measured the asset sizes and scene geometry, surface reflectance, illuminant spectral power distribution



Illuminant SPD

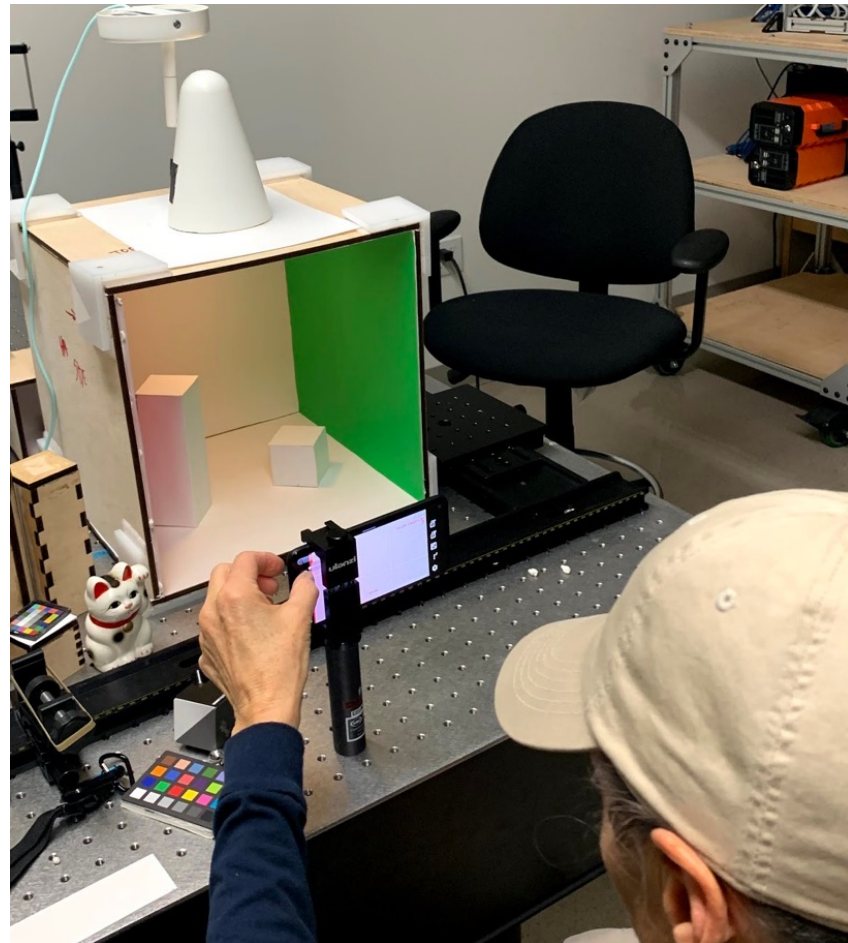
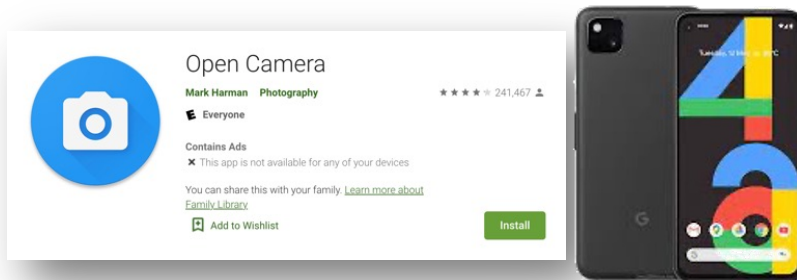


Surface spectral reflectance



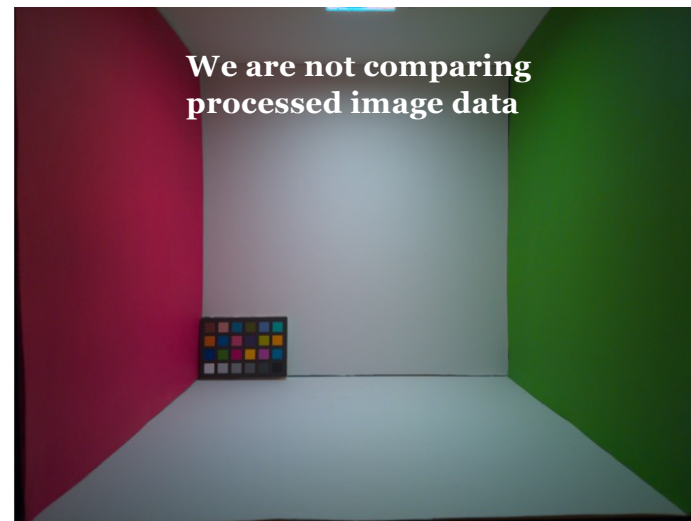
## Validation test: Raw sensor data from the camera

- We used a Google Pixel 4a and the OpenCamera app to acquire **relatively raw data**



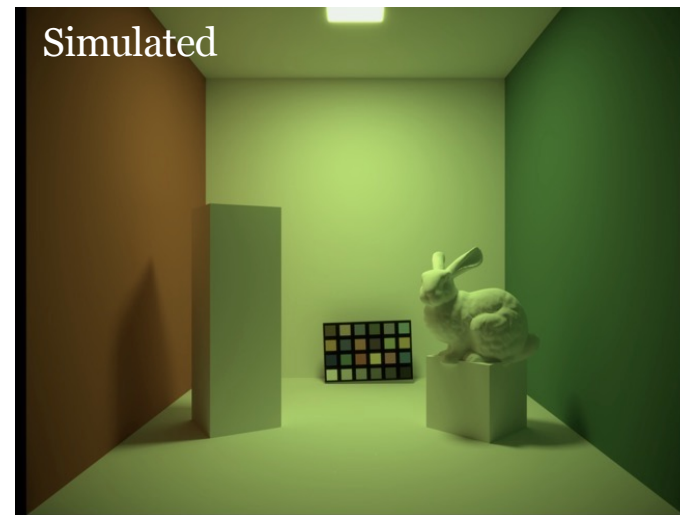
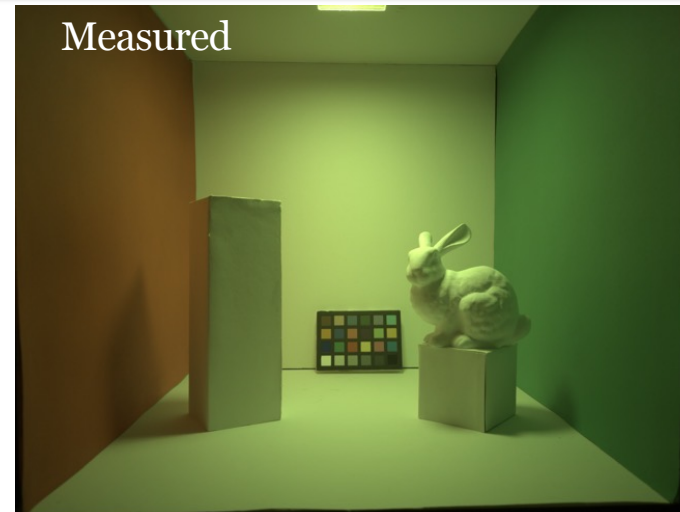
## Sensor renderings

- Our goal is to match the **digital sensor values**, not the processed data
- The renderings we show are **simulated or measured sensor data**, with only bilinear demosaicking



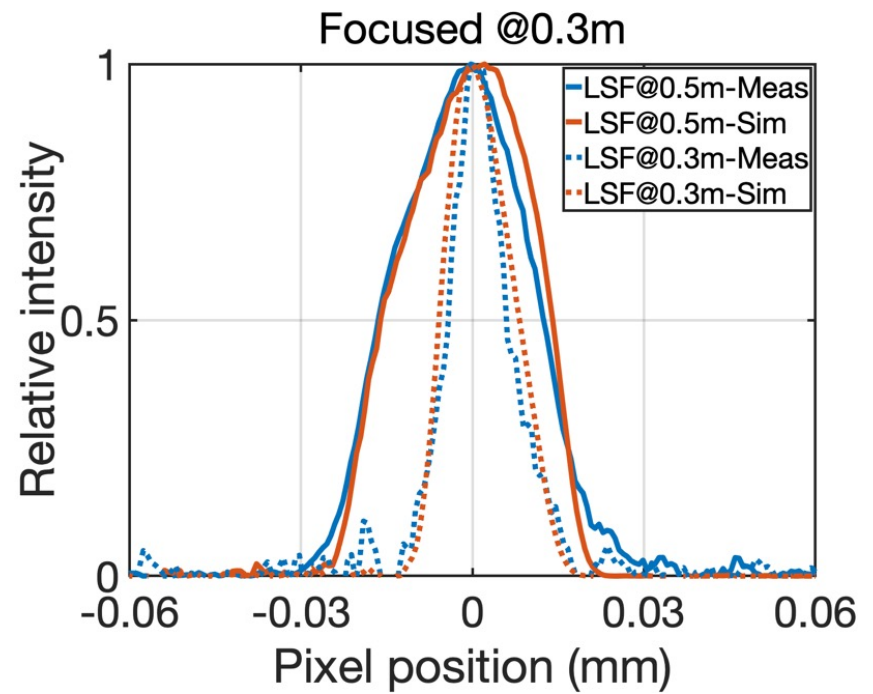
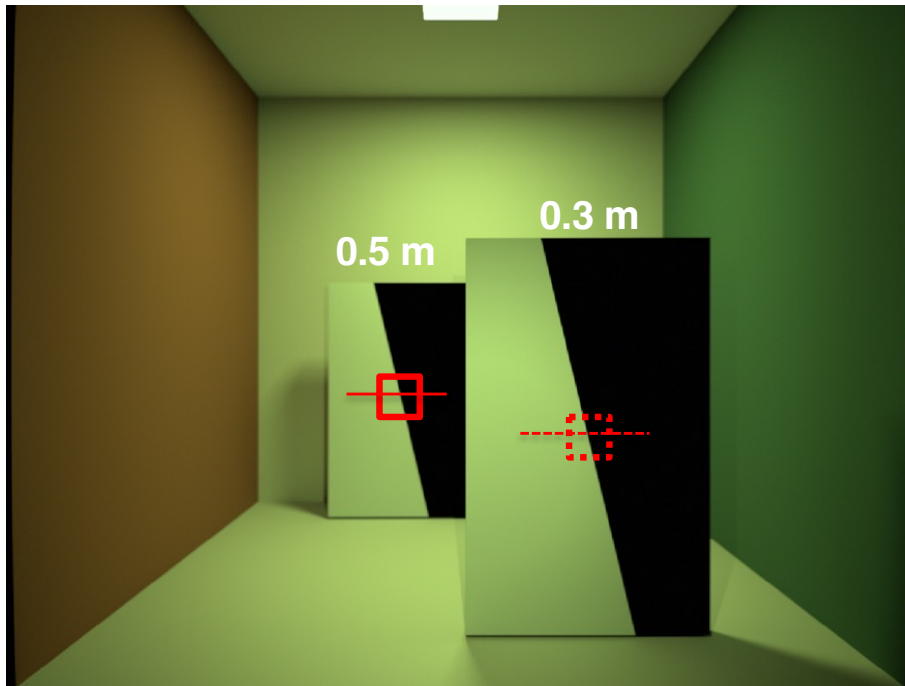
## Quick check based just on appearance

- Overall similarity is good
- High dynamic range
- Shadows
- Color interreflections (sides of the box reflect light from the wall)
- If you are designing hardware, this check is far from adequate: quantify!



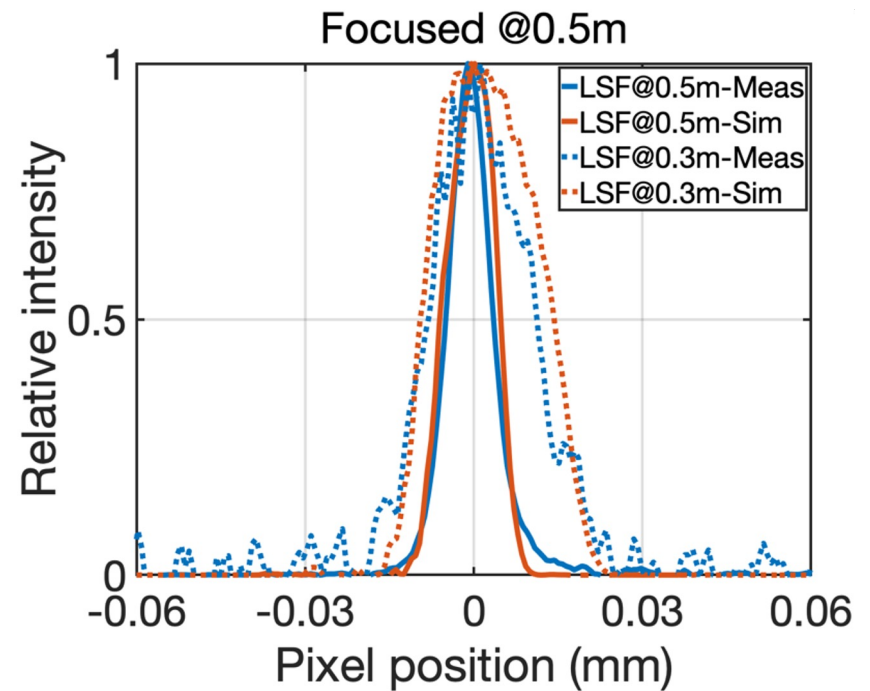
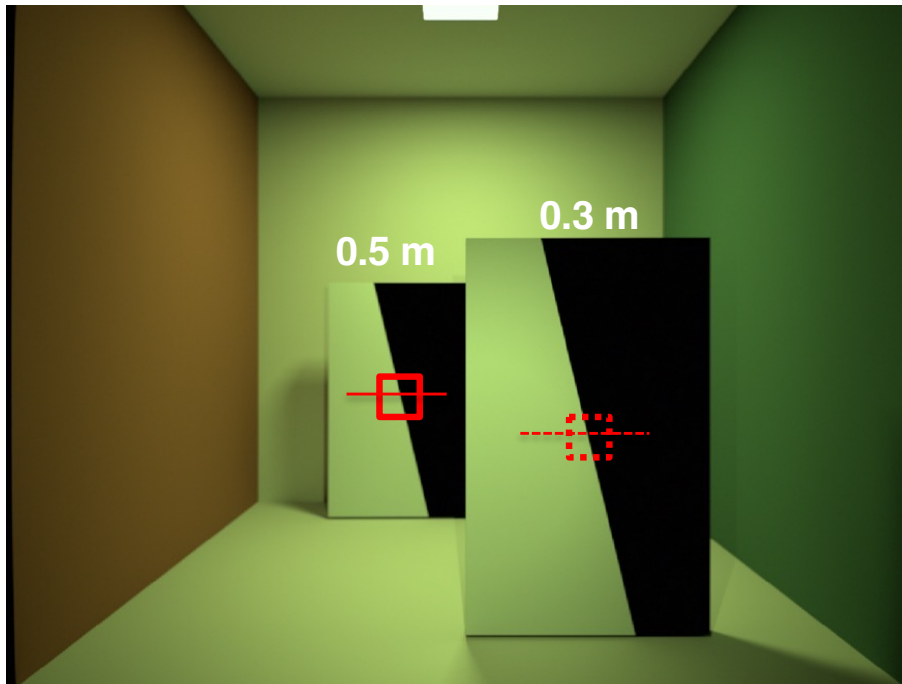
# Optics validation: Resolution and depth of field

Focused at 0.3 meters



## Focus-dependent LSF/MTF (depth of field)

Focused at 0.5 meters



# Mention Goossens Ray Transfer Function Extension

Since then, we have improved our optics modeling



Research Article

Vol. 30, No. 13/20 Jun 2022 / Optics Express 24031

Optics EXPRESS

## Ray-transfer functions for camera simulation of 3D scenes with hidden lens design

THOMAS GOOSSENS,<sup>1,\*</sup> ZHENG LYU,<sup>1</sup> JAMYUEN KO,<sup>2</sup> GORDON C. WAN,<sup>2</sup> JOYCE FARRELL,<sup>1</sup> AND BRIAN WANDELL<sup>1</sup>

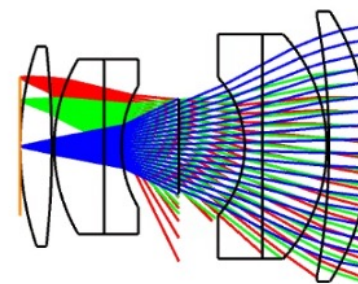
<sup>1</sup>Stanford Center for Image Systems Engineering, Stanford University, Stanford, California 94305, USA

<sup>2</sup>Google, Mountain View, California 94043, USA

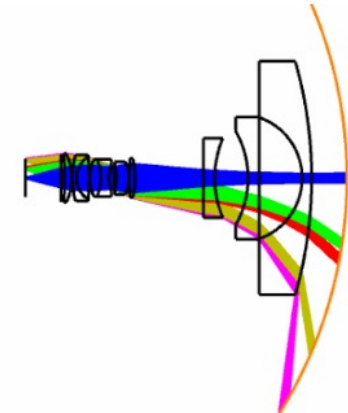
\*contact@thomasgoossens.be

**Abstract:** Combining image sensor simulation tools with physically based ray tracing enables the design and evaluation (soft prototyping) of novel imaging systems. These methods can also synthesize physically accurate, labeled images for machine learning applications. One practical limitation of soft prototyping has been simulating the optics precisely: lens manufacturers generally prefer to keep lens design confidential. We present a pragmatic solution to this problem using a black box lens model in Zemax; such models provide necessary optical information while preserving the lens designer's intellectual property. First, we describe and provide software to construct a polynomial ray transfer function that characterizes how rays entering the lens at any position and angle subsequently exit the lens. We implement the ray-transfer calculation as a camera model in PBRT and confirm that the PBRT ray-transfer calculations match the Zemax lens calculations for edge spread functions and relative illumination.

(a) Double Gauss 28deg.

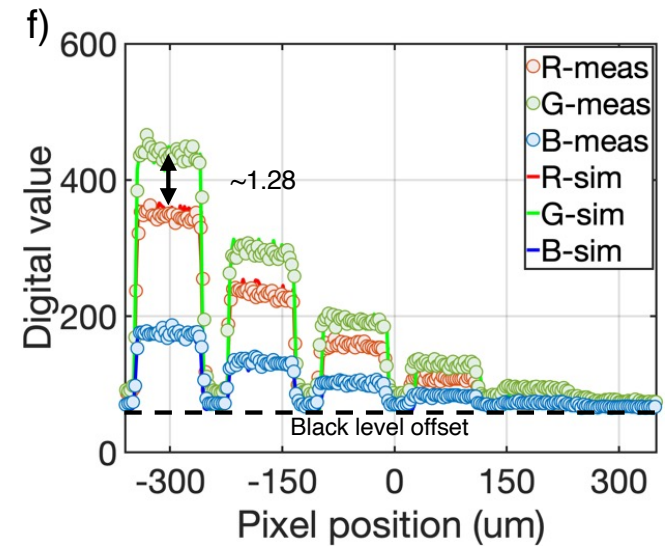
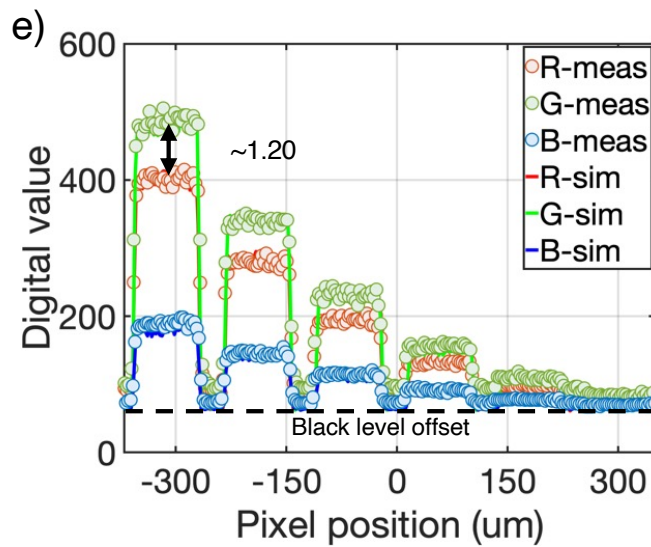
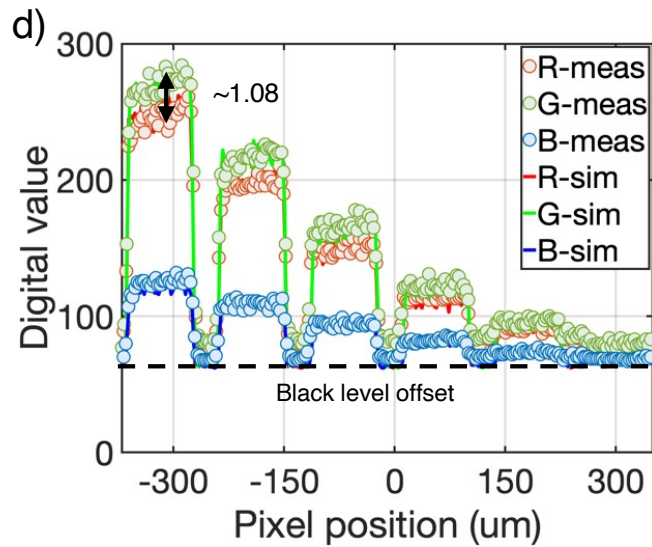
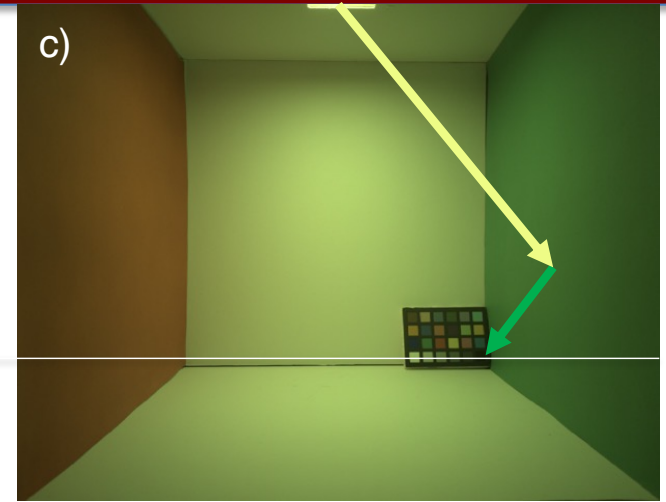
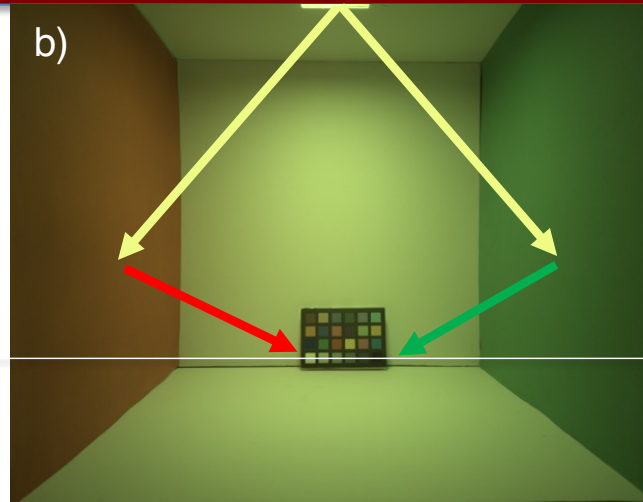
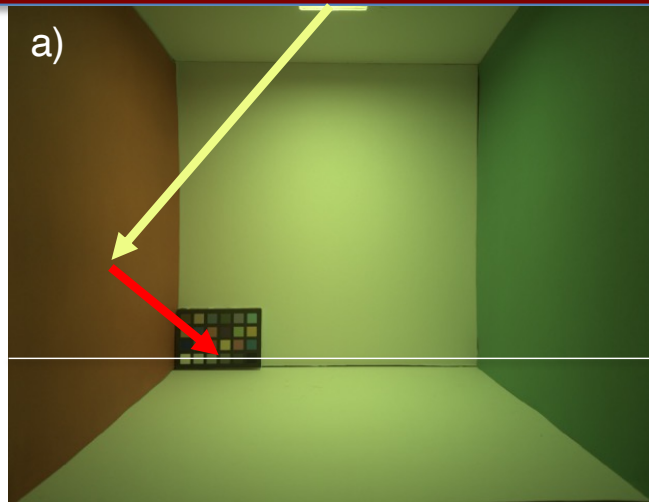


(b) Wide angle lens 200deg.



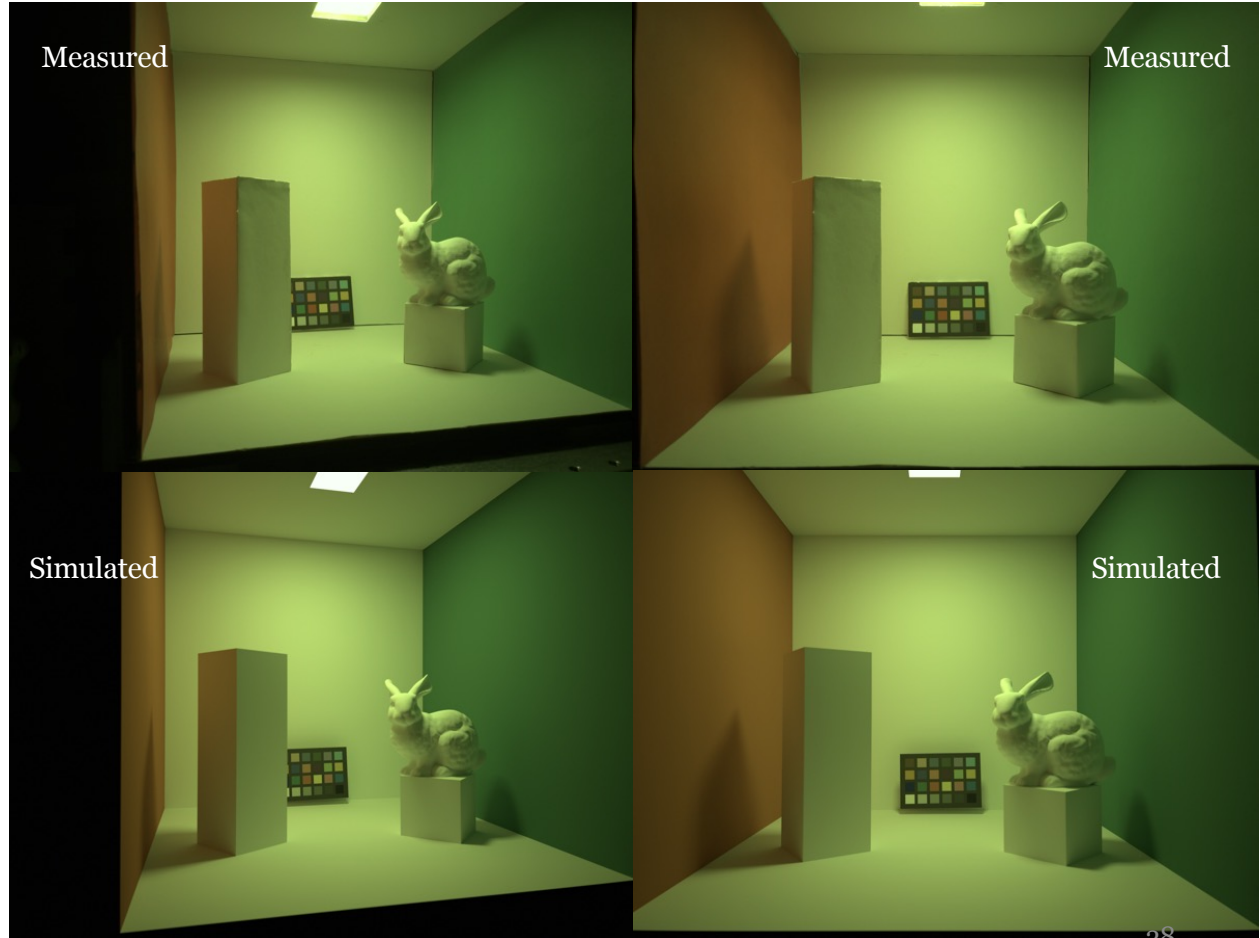
**Fig. 2.** Illustration of the Ray Transfer Function (RTF). (a) The Double Gauss lens can be accurately simulated with rays represented on an input and output plane. (b) The wide angle lens can be accurately simulated with input rays on a plane and output rays on a spherical surface. Because of the high degree of bending near the aperture edge, certain rays would not intersect any output plane to the right of the final vertex.

# Surface inter-reflections and electronic sensor noise



## Image system simulation evaluation using 3D scenes

- ✓ Surface inter-reflections
- ✓ Depth of focus
- ✓ Vignetting
- ✓ Sensor quantum efficiency
- ✓ Sensor noise



## Second point

- Image systems simulations can accurately create physical descriptions of realistic scenes and compute the expected sensor response
- We are working to expand the range of conditions – particularly HDR - and to validate quantitative, spectral simulations

# ISETHDR: Data set for nighttime driving sensor evaluation

- HDR nighttime data


IEEE Sensors Council IEEE SENSORS JOURNAL, VOL. XX, NO. XX, XXXX 2022 1

## ISETHDR: A Physics-based Synthetic Radiance Dataset for High Dynamic Range Driving Scenes

Zhenyi Liu, Devesh Shah, and Brian A. Wandell

**Abstract**—This paper presents a physics-based simulation that models the complete imaging pipeline from scene radiance to final rendered image. We use this simulation to evaluate sensor designs optimized for high dynamic range (HDR) environments, such as driving through daytime tunnels or in nighttime conditions. The work makes three main contributions: (1) A synthetic, labeled dataset of HDR driving scenes with instance segmentation and depth information; (2) Open-source simulation software with validated performance; and (3) A comparative analysis of two single-shot sensor designs optimized for HDR imaging. Both the dataset ((ISETHDR)) and simulation software (ISETHDRSensor) are made publicly available and can be used to evaluate sensor designs for high dynamic range environments, such as nighttime driving scenes.

**Index Terms**—Image system engineering, high dynamic range, digital twins, open source dataset, automotive imaging, nighttime driving



## Prior work: daytime images



## A nighttime scene (Real Image)

- High dynamic range (HDR).
- Lots of bright lights.
- Low SNR.
- Image labeling is hard.



# Modeling flare in the pupil function

We implemented methods for simulating **two sources** of flare

- Aperture shape
- Lens dust and scratches
- We model lens wavefront phase aberrations

We have not yet found an efficient representation for inter-reflections

Point Spread Function is  
Fourier Transform of the Pupil Function

$$I(x, y) = |\mathcal{F}\{P(u, v)\}|^2$$



Pupil Function is represented by  
amplitude transmission function  
and phase shift function

$$P(u, v) = A(u, v) \cdot e^{i\phi(u, v)}$$

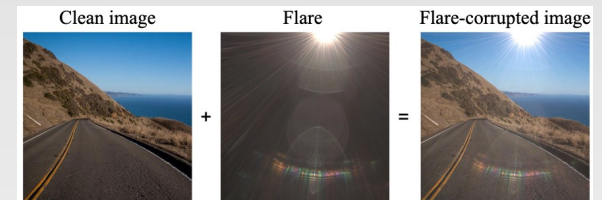


The phase shift function is  
represented using Zernike Polynomials

$$P(u, v) = A(u, v) \cdot e^{i\sum_{n,m} a_{nm} Z_{nm}(u, v)}$$

N.B. We point out imperfections in the methods of prior papers concerning flare

Wu, et al. (2021, ICCV)



Dai, et al. (2022, NeurIPS)



Wu, Yicheng, Qiurui He, Tianfan Xue, Rahul Garg, Jiawen Chen, Ashok Veeraraghavan, and Jonathan T. Barron. "How to train neural networks for flare removal." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 2239-2247. 2021.

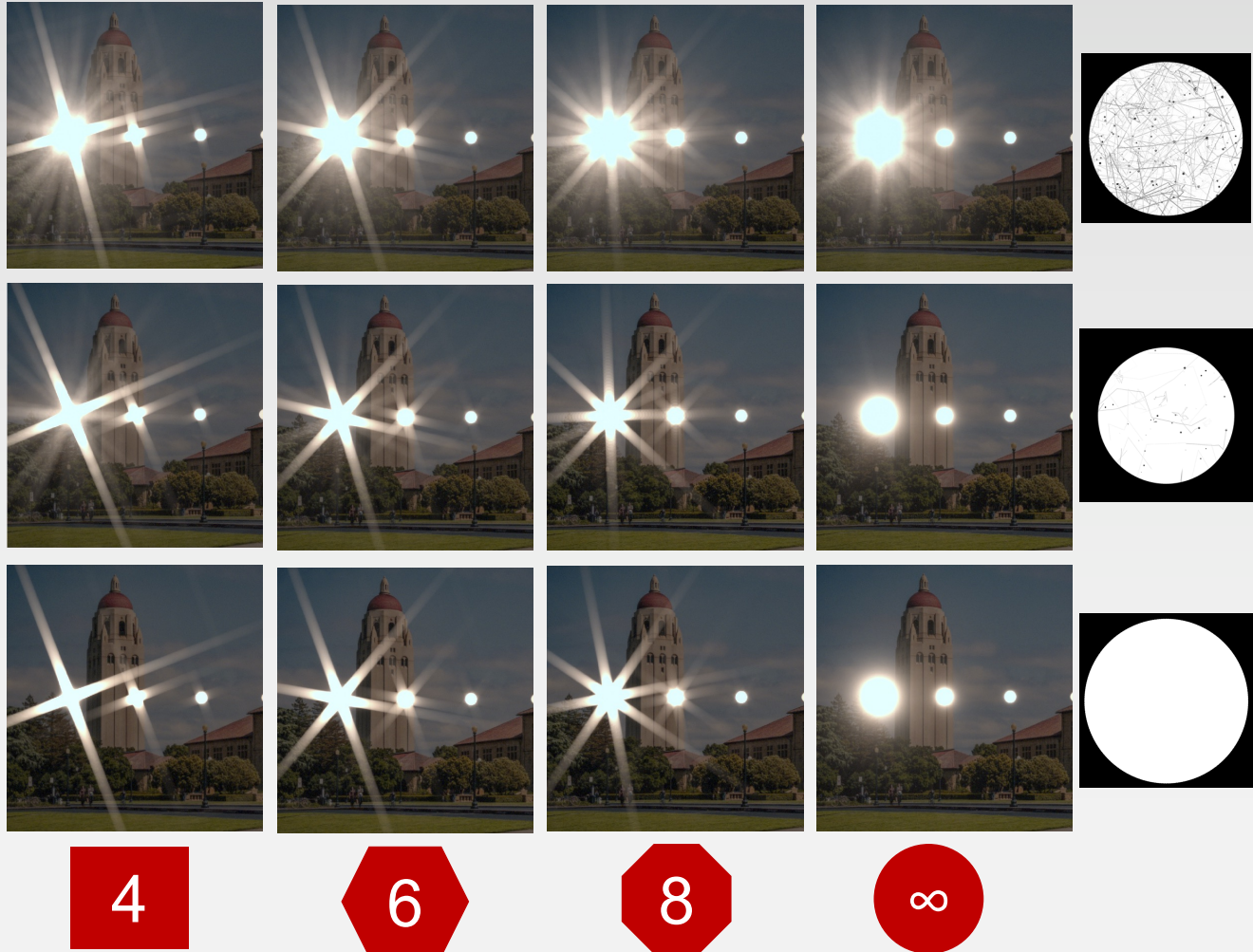
Dai, Yuekun, Chongyi Li, Shangchen Zhou, Ruicheng Feng, and Chen Change Loy. "Flare7k: A phenomenological nighttime flare removal dataset." Advances in Neural Information Processing Systems 35 (2022): 33926-3937.

## Flare due the aperture shape and scratches (apodization)

We implemented methods for simulating **two sources** of flare

- Aperture shape
- Lens dust and scratches
- We model lens wavefront phase aberrations

We have not yet found an efficient representation for inter-reflections



# Daytime images – flare not important

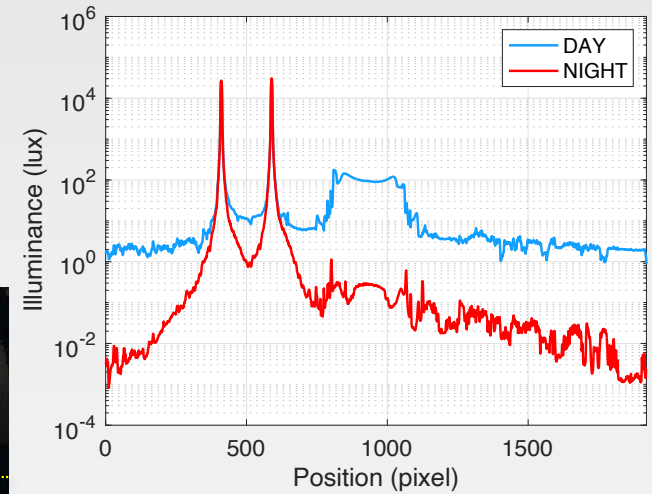


# Nighttime HDR images – flare becomes important



# ISETHDR – Light group concept

Four renderings with different lighting models  
(2000 scenes at <https://purl.stanford.edu/zg292rq76o8>)



## ISET HDR Driving scene light groups

ISET HDR Driving scene light groups

16828 files 

File Name	Size	
▼ ISETScene_001_renderings		
1112153442_headlights.exr	76.47 MB	<a href="#">Download</a>
1112153442_instancelD.exr	6.3 MB	<a href="#">Download</a>
1112153442_otherlights.exr	22.39 MB	<a href="#">Download</a>
1112153442_skymap.exr	90.33 MB	<a href="#">Download</a>
1112153442_streetlights.exr	66.36 MB	<a href="#">Download</a>
1112153830_headlights.exr	76.47 MB	<a href="#">Download</a>
1112153830_instancelD.exr	6.3 MB	<a href="#">Download</a>
1112153830_otherlights.exr	22.39 MB	<a href="#">Download</a>

## Abstract/Contents

## Abstract

The dataset comprises 2000 driving scenes, each defined by four spectral radiance maps representing illumination by the sky, headlights, streetlights, and other light sources (e.g., tail lights, bicycle lights). To simulate various lighting conditions, the four maps are combined with different weights. The ISETCam (<https://github.com/ISET/isetcam/wiki>) and isethrsensor (<https://github.com/ISET/isethrsensor>) GitHub repositories contain software to read the light groups and select the appropriate weights for achieving the desired dynamic range and low-light conditions.

## Description

**Type of resource** Dataset, still image

**Publication date** October 3, 2024

## Creators/Contributors

**Author**

Wandell, Brian	<a href="https://orcid.org/0000-0002-2974-1836">https://orcid.org/0000-0002-2974-1836</a> (unverified)
Liu, Zhenyi	<a href="https://orcid.org/0000-0002-2673-3734">https://orcid.org/0000-0002-2673-3734</a> (unverified)

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## Preferred citation

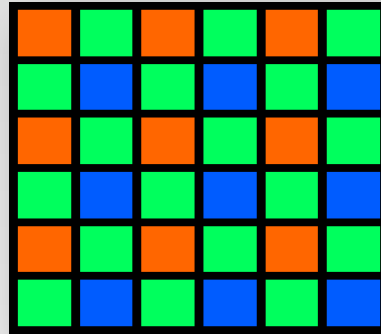
Wandell, B. and Liu, Z. (2024). ISET HDR Driving scene light groups. Stanford Digital Repository. Available at <https://purl.stanford.edu/zg292rq7608>. <https://doi.org/10.25740/zg292rq7608>.

## Collection

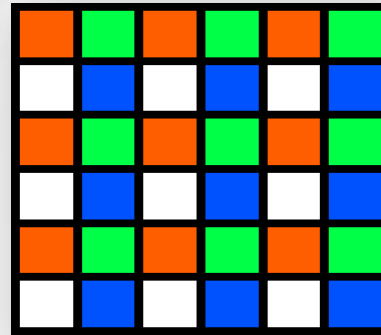
- 2000 Highway and country road driving scenes
- Spectral radiance light groups
- Depth maps, pixel-level object ids
- Freely available for download using methods in ISETCam

# Experiments with HDR sensor designs

- Split photodiode
- RGBW sensor

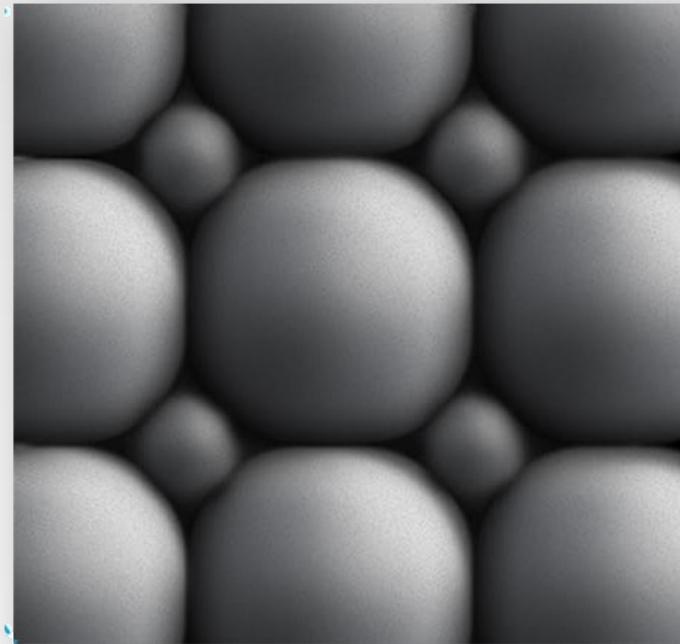
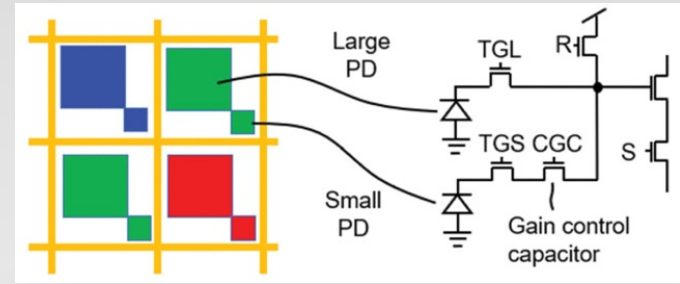


Bayer



RGBW

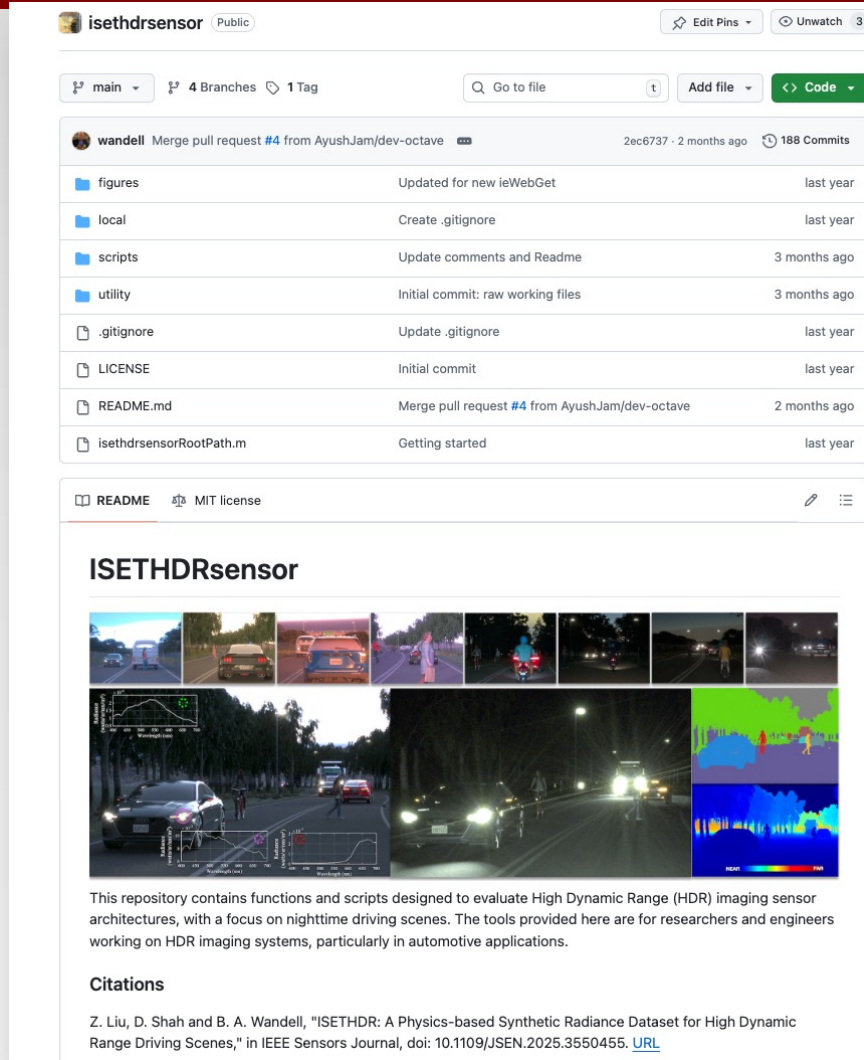
low-light sensitivity  
dynamic range<sup>39</sup>



# ISET HDR sensor computational methods

- Reproducible software repositories
- Two types of experiments
  1. Split photodiode model
  2. RGBW CFA model

<https://github.com/ISET/isethdrsensord>  
<https://github.com/ISET/isethdrsensord/wiki>



**isethdrsensord** Public

main 4 Branches 1 Tag


Go to file Add file Code

wandell Merge pull request #4 from AyushJam/dev-octave 2ec6737 · 2 months ago 188 Commits

File	Commit Message	Time
figures	Updated for new ieWebGet	last year
local	Create .gitignore	last year
scripts	Update comments and Readme	3 months ago
utility	Initial commit: raw working files	3 months ago
.gitignore	Update .gitignore	last year
LICENSE	Initial commit	last year
README.md	Merge pull request #4 from AyushJam/dev-octave	2 months ago
isethdrsensordRootPath.m	Getting started	last year

README MIT license

## ISETHDRsensor



This repository contains functions and scripts designed to evaluate High Dynamic Range (HDR) imaging sensor architectures, with a focus on nighttime driving scenes. The tools provided here are for researchers and engineers working on HDR imaging systems, particularly in automotive applications.

### Citations

Z. Liu, D. Shah and B. A. Wandell, "ISETHDR: A Physics-based Synthetic Radiance Dataset for High Dynamic Range Driving Scenes," in IEEE Sensors Journal, doi: 10.1109/JSEN.2025.3550455. [URL](#)

LPD-LG



LPD-HG



SPD-LG

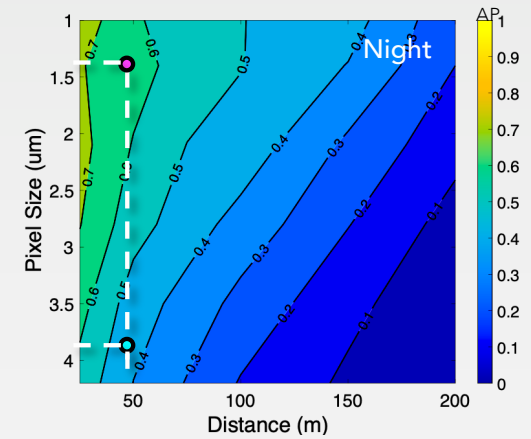
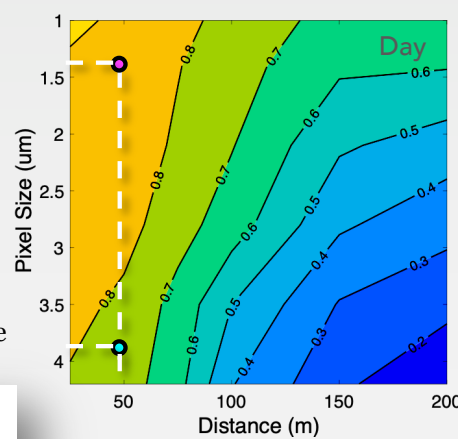
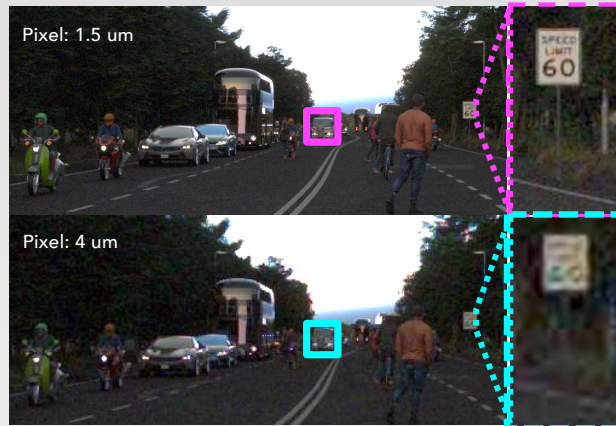


Combined



# Machine learning applications: Evaluation

- We used the simulated data to evaluate performance with different sensors (pixel size) under different conditions
- These provide global assessments of the design tradeoffs



Liu, Zhenyi, Devesh Shah, Alireza Rahimpour, Devesh Upadhyay, Joyce Farrell, and Brian Wandell. "Using simulation to quantify the performance of automotive perception systems." *Electronic Imaging* 35 (2023): 1-8.

Using simulation to quantify the performance of automotive perception systems

Autonomous driving • Image systems simulation • Automotive perception system • Neural network

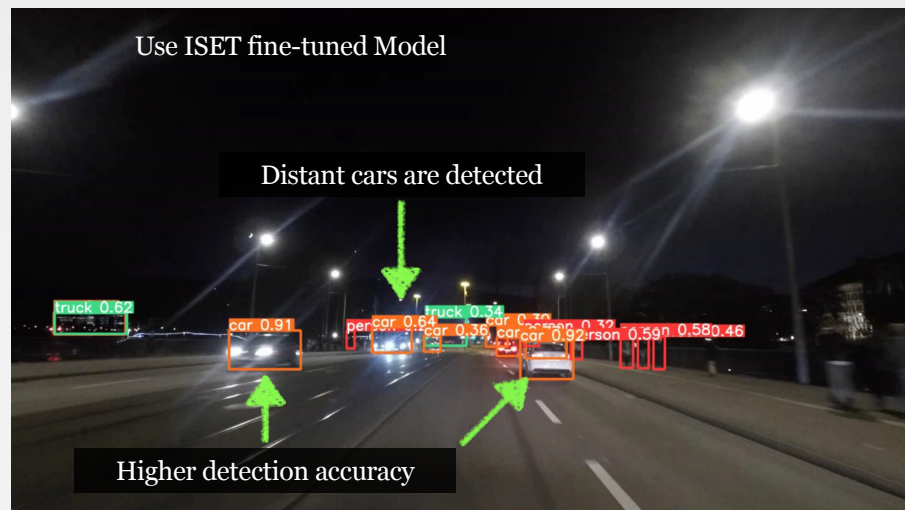
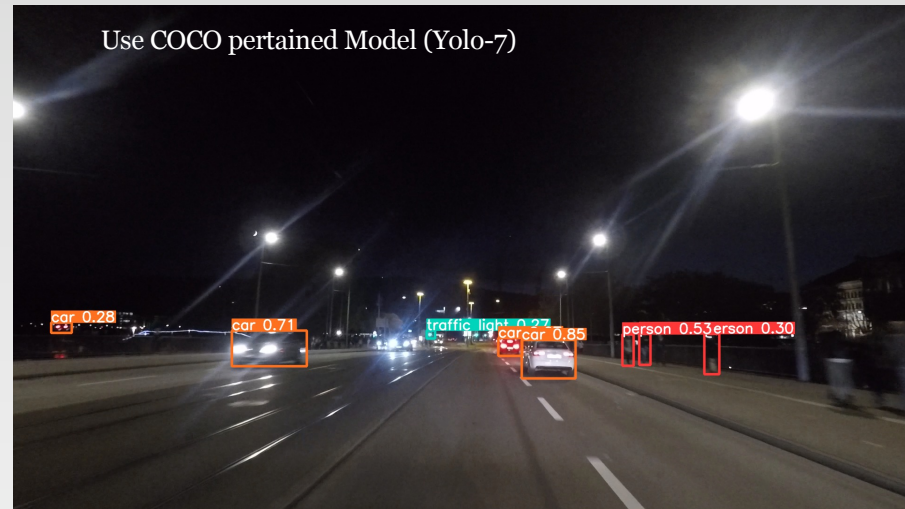
Zhenyi Liu, Devesh Shah, Alireza Rahimpour, Devesh Upadhyay, Joyce Farrell, Brian Wandell

DOI: 10.2352/EI.2023.35.16.AVM-118 | Published Online: January 2023



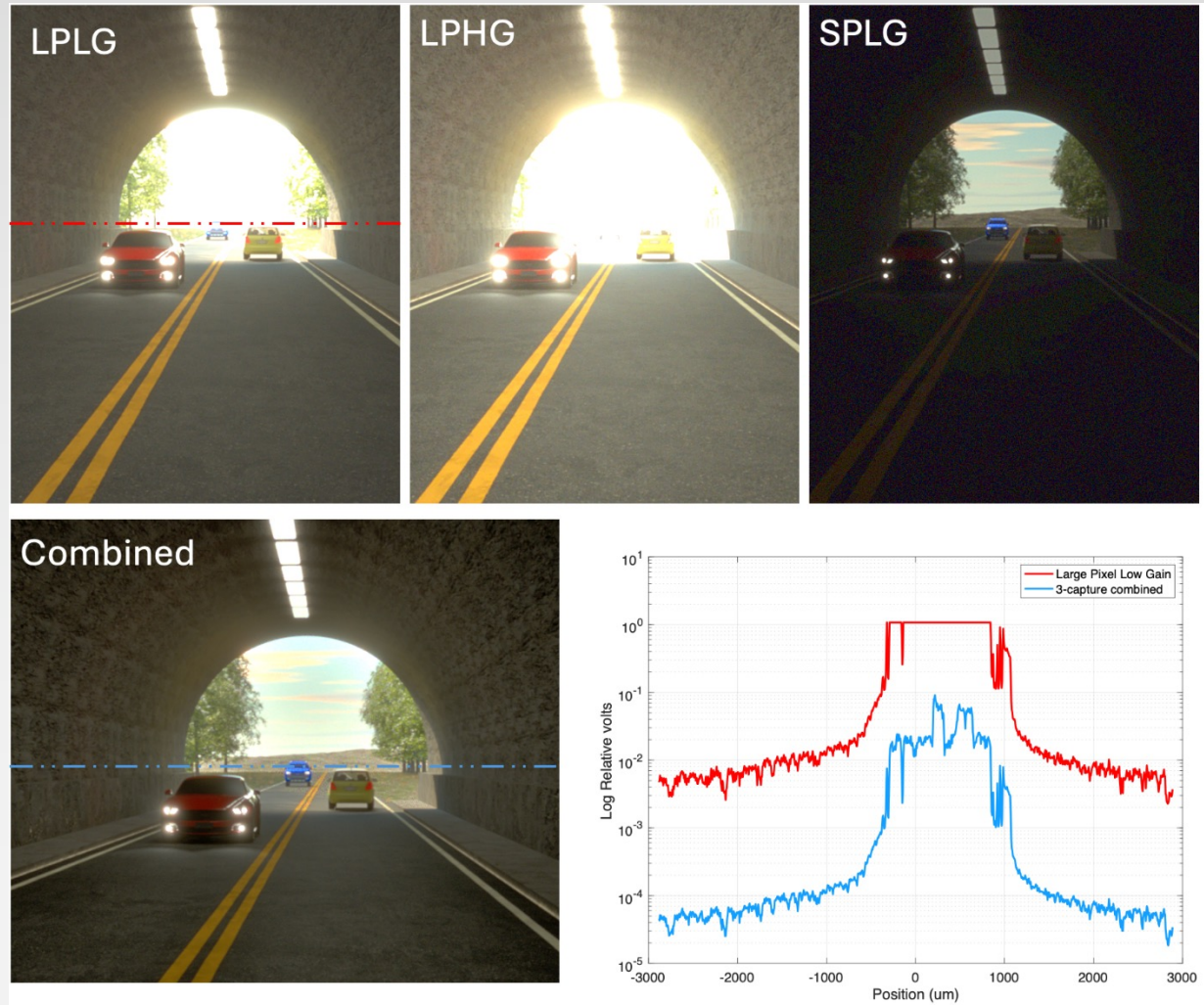
# Machine learning application

- We used the simulated data for fine-tuning pretrained models (in this case Yolo-7)
- Using the ISETHDR flare data set improved the model performance

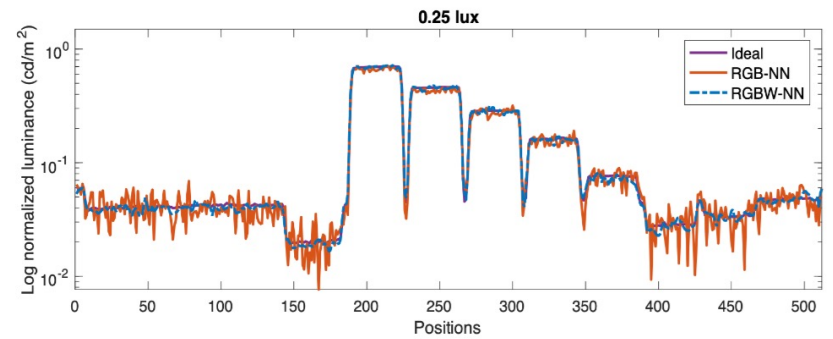
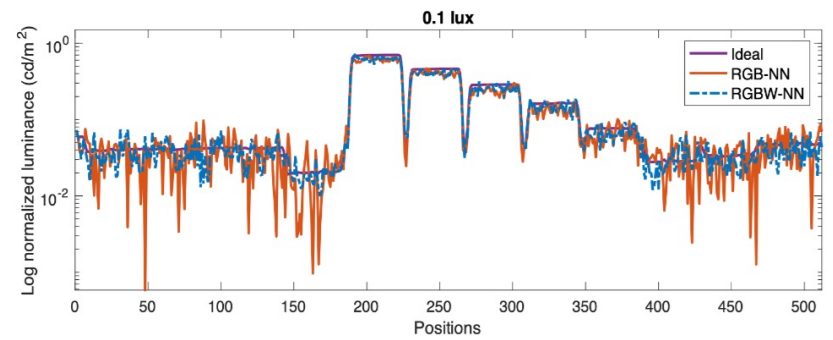
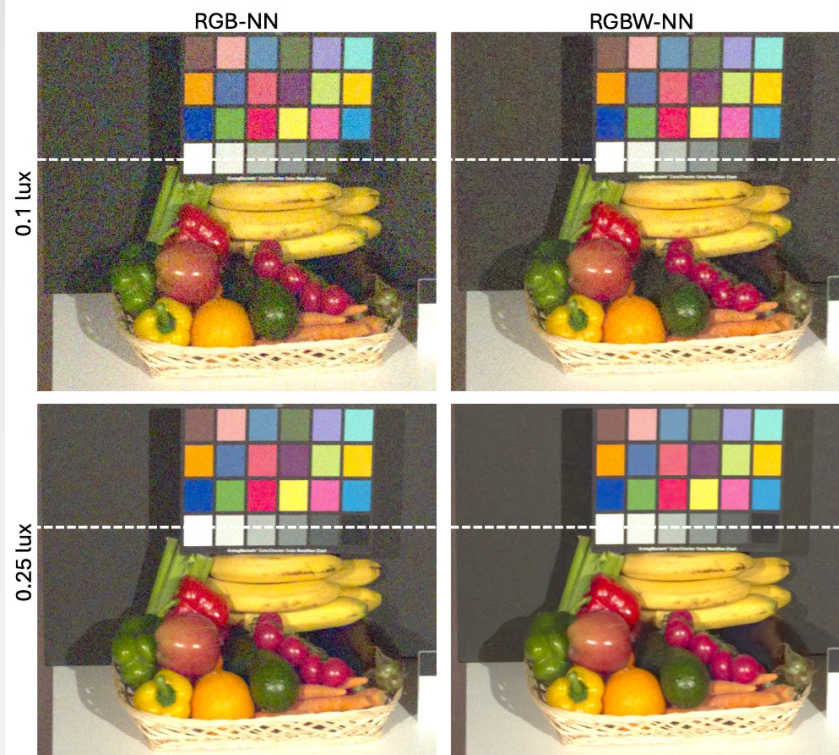


## The value of designed case analysis compared to group analysis

- We used the simulated data to investigate edge-cases
- This is an example of how the split photodiode improves the rendering of a classic driving performance issue

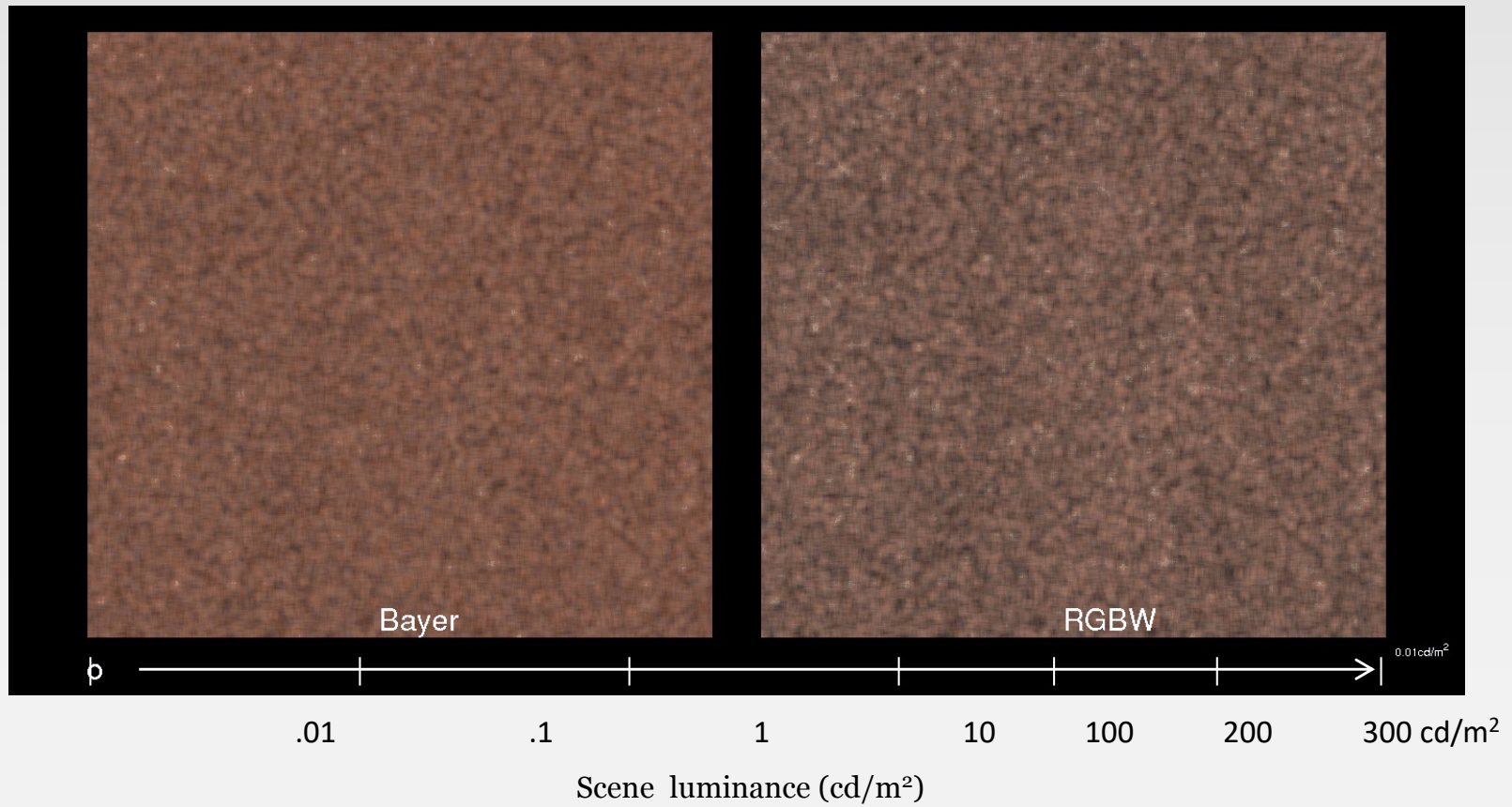


# Experiments with RGB and RGBW sensors



## RGBW compared to Bayer

RGBW: better in low light & same in high light



## Third point

- There are opportunities for digital twinning novel sensor and optics configurations
- Digital twin data and be used for network training and end-to-end system evaluation

# Simulation technologies for image systems engineering

Professor Brian A. Wandell  
Stanford University

Stanford Center for Image Systems Engineering  
Wu Tsai Neurosciences Institute  
Stanford Center for Cognitive and Neurobiological Imaging

QUANTITATIVE MEASUREMENTS



COMPUTATIONAL MODELS



CHECK AND SHARE

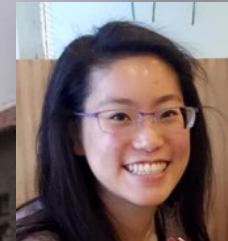
Joyce Farrell



Zhenyi Liu



Trisha Lian



Zheng Lyu



Henryk Blasinski



Andy Lin



Thomas Goossens



Haomiao Jiang



Thanks to Meta, Ford and Google