

Simulation technologies for image systems engineering

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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

From Cameras to Retinas: Open Source Tools for Image Systems Simulation

Brian A. Wandell

Stanford Center for Image Systems Engineering

Department of Psychology

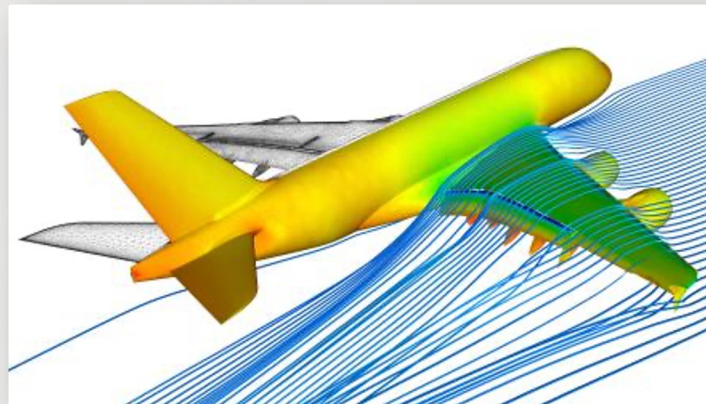
Modern imaging systems are ubiquitous - from smartphones to medical devices to self-driving cars. These technologies, increasingly integrated with artificial intelligence, require extensive data for training and validation. This reality has made soft prototyping ("digital twins") indispensable for both design and evaluation.

I will introduce three complementary open-source MATLAB toolboxes - ISETCam, ISETBio, and ISET3d - that enable comprehensive imaging system simulation. These tools support end-to-end modeling from scene to sensor: physically realistic scene simulation (spectral light fields), multi-element optics, and final image encoding. I will present three key studies: validation of the simulation accuracy, optimization of CMOS sensor design for high dynamic range imaging, and modeling of retinal encoding (physiological optics and cone sampling) to reveal fundamental limits of human visual resolution.

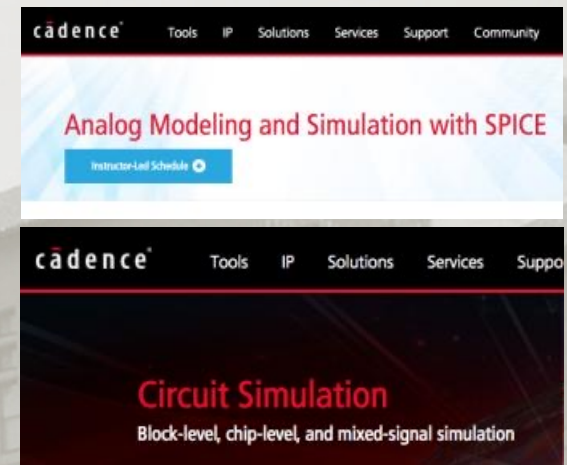
Systems simulation (digital twin) is important in many mature industries



ECU (Electronic Control Unit) Simulation for Automobiles



Numerical flow simulation on an Airbus A380



Integrated circuitry

Physics-based image systems simulation: Our origins

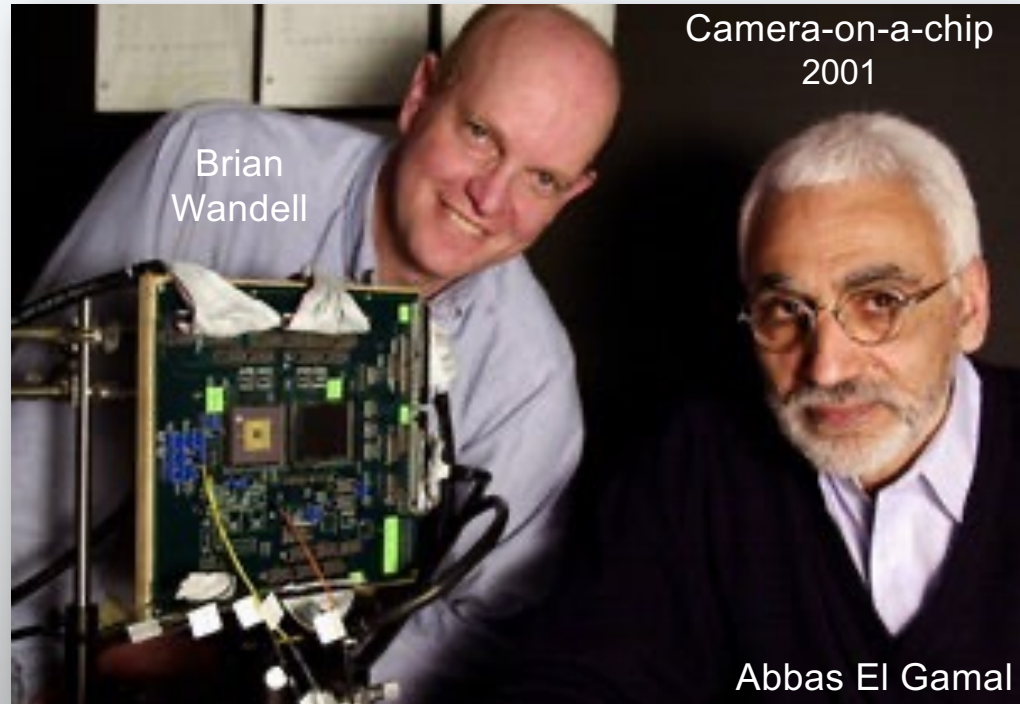
Ting Chen



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

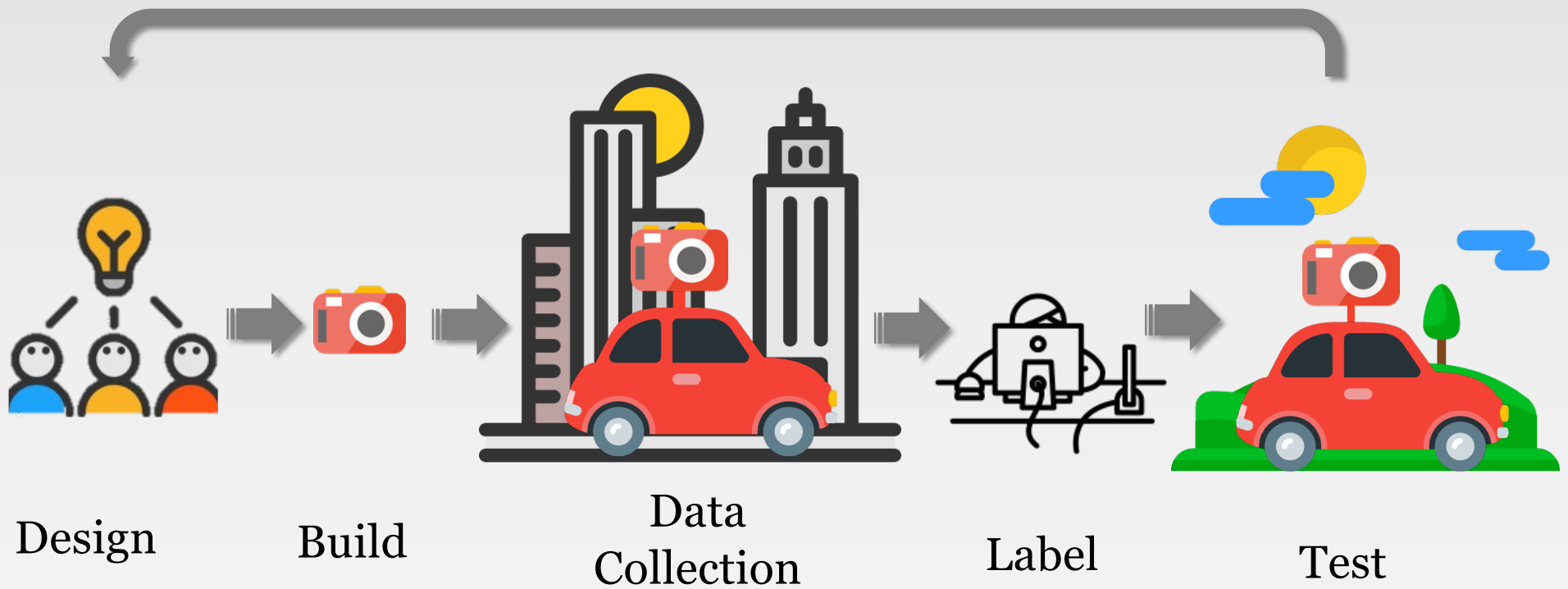
Imaging Systems Engineering Toolbox (ISETCam)

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

Open Sourced on GitHub
in 2018



The value of soft prototyping (digital twin)

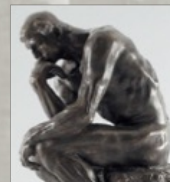
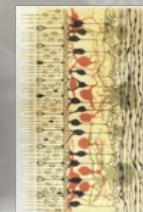
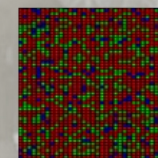
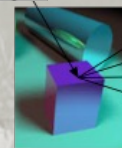


First point

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) for digital twinning

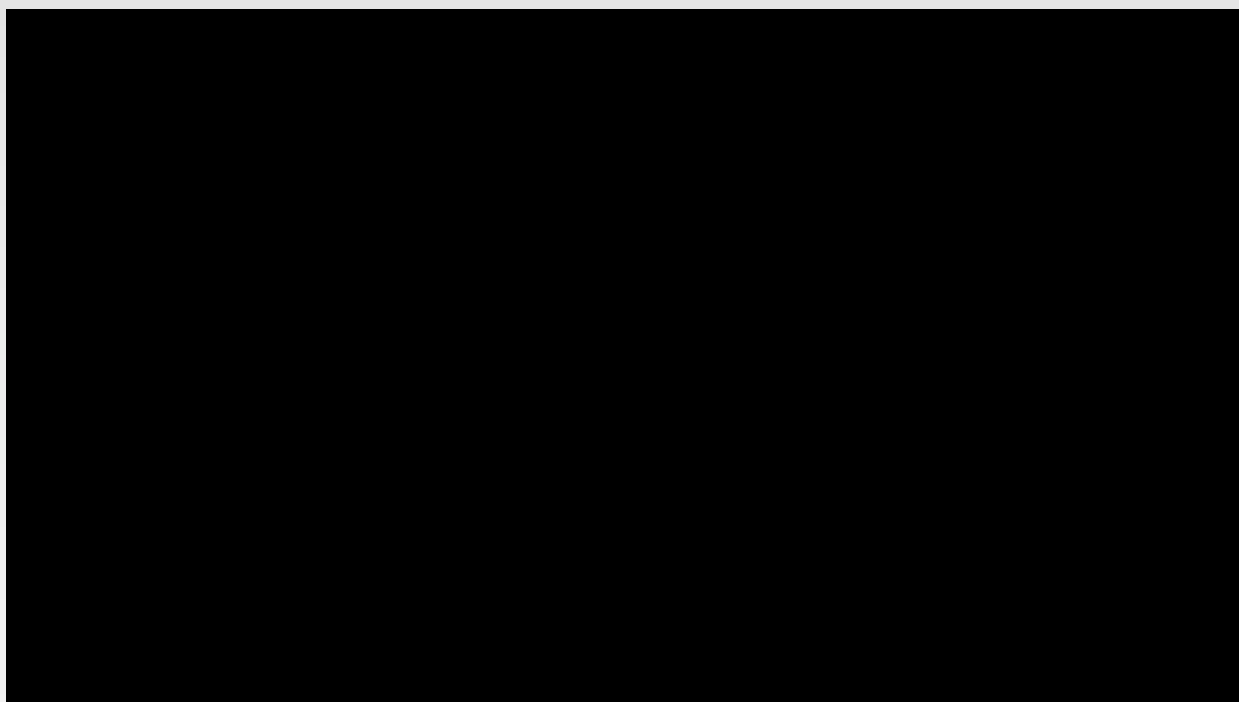
- **ISET3d** is a Matlab toolbox that uses **PBRT** to calculate three-dimensional scene spectral radiance and sensor irradiance of complex scenes
- **ISETCam** is a Matlab toolbox that computes the image sensor response from the sensor irradiance; it also includes many industrial tools for evaluation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



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

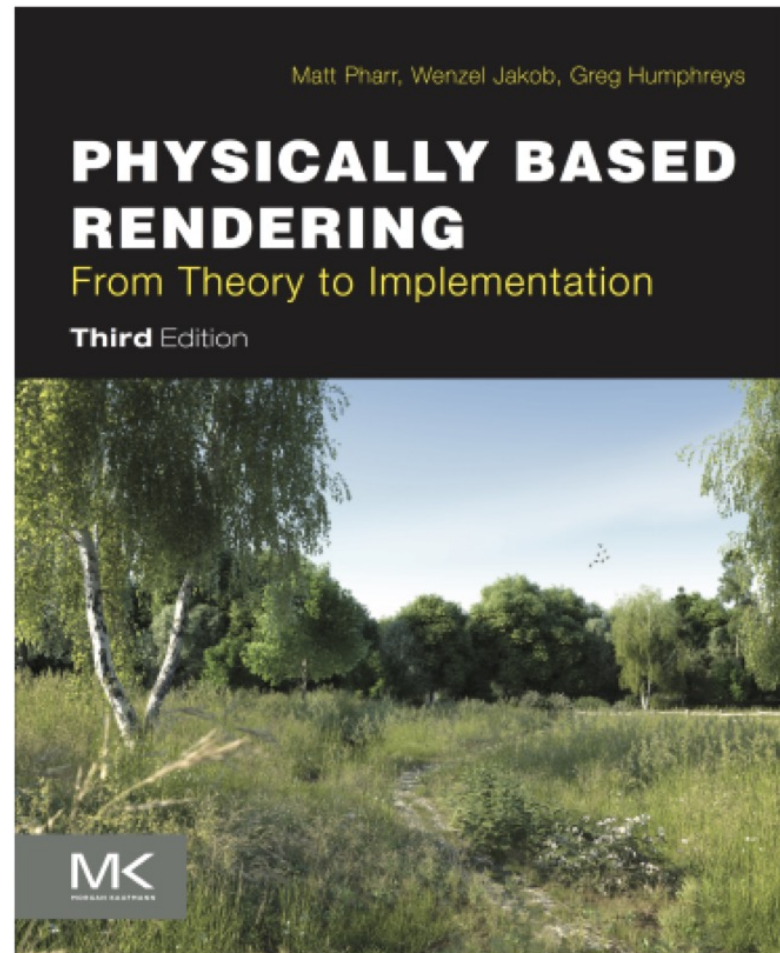
Spectral ray tracing examples (PBRT, ISET3d)



Scene generation: Quantitative computer graphics

We added methods to model and 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)
- Computational imaging (CNN, Ideal observer)



System modeling: optics

Sensor: 7.5mm diagonal

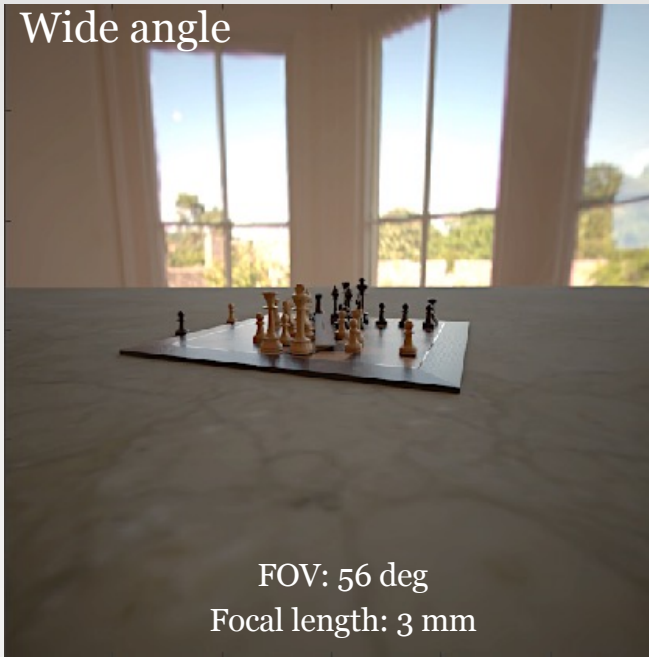
Spectral ray tracing

Double Gauss



FOV: 22 deg
Focal length: 3 mm

Wide angle



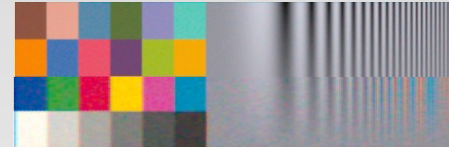
FOV: 56 deg
Focal length: 3 mm

Fisheye

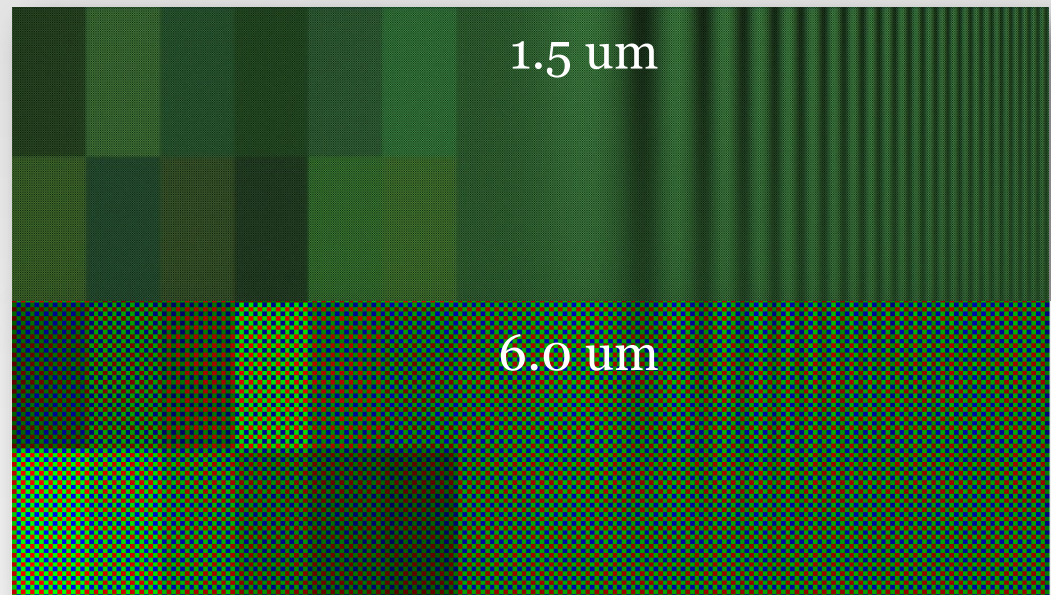


FOV: 87 deg
Focal length: 3 mm

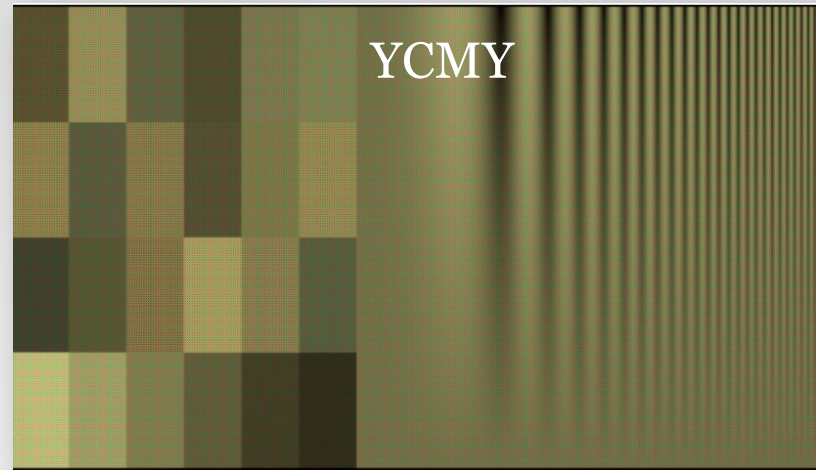
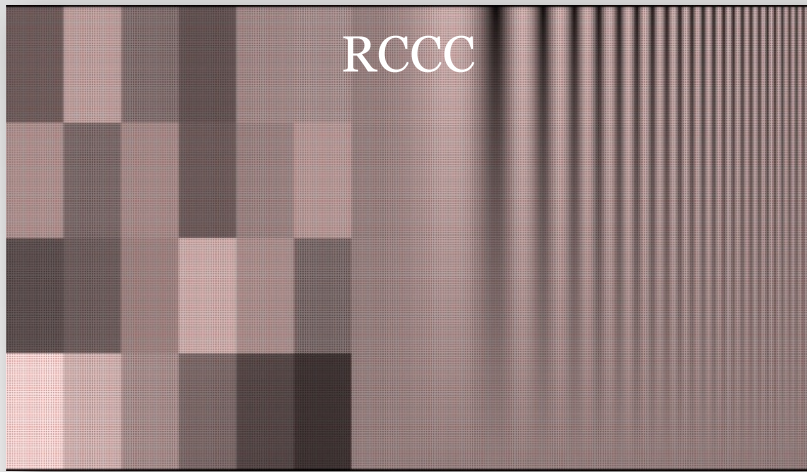
System modeling: Sensor properties (ISETCam)



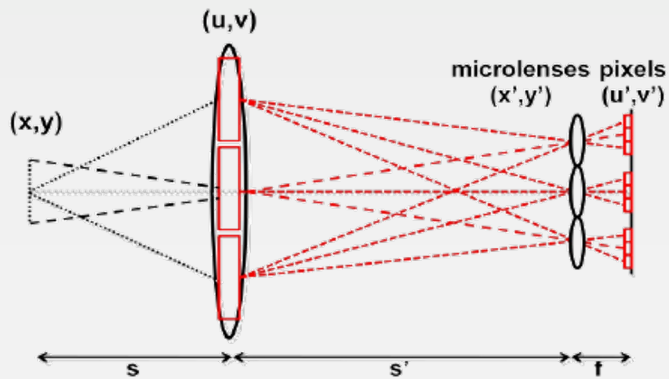
Property	Value	Units
Name	IMX363	
Size	0.786 1.36	mm
Rows and Columns	524 908	
Horizontal FOV	20	deg
Horizontal Res / dista...	1.5	um
Horizontal Res / degre...	0.022	deg/pixel
Exposure time	0.0020219	s
DSNU	0	v
PRNU	0.7	%
Analog gain	0.204	
Analog offset	0.00585	v
----- Pixel -----		
Width & height	1.5	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-



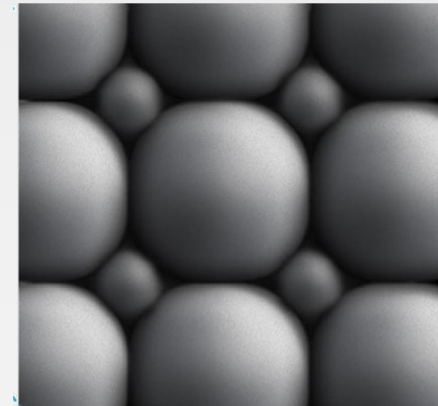
ISETCam: Advanced sensor simulations



Light field



Split pixel



Empirical evaluation of the simulation accuracy



Zheng
Lyu

Thomas
Goossens

Joyce
Farrell



Validation tests: Cornell Box Construction

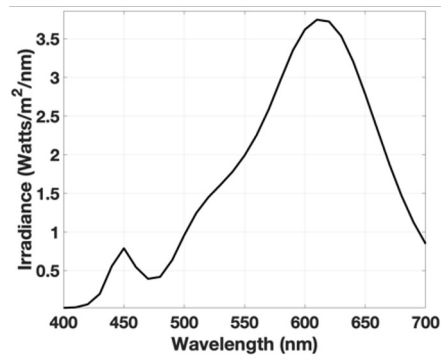
- The Cornell Box has been widely used to evaluate the **accuracy of computer graphics rendering**
- We use it to quantitatively test end-to-end simulation of **3D scenes, optics, and image sensors**



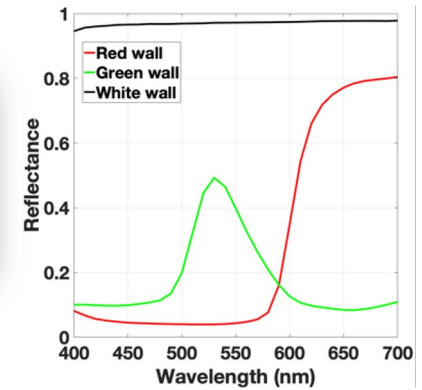
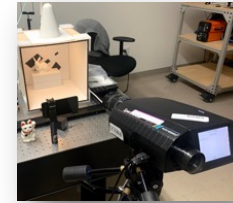
- Goral, Torrance, Greenberg, and Battaile, "Modeling the Interaction of Light Between Diffuse Surfaces," Computer Graphics (Proc. SIGGRAPH 84), Vol. 18, No. 3, July 1984, pp. 213-222
- Meyer, Rushmeier, Cohen, Greenberg, and Torrance, "An Experimental Evaluation of Computer Graphics Imagery" ACM Transactions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

We built one (the 3D scene)

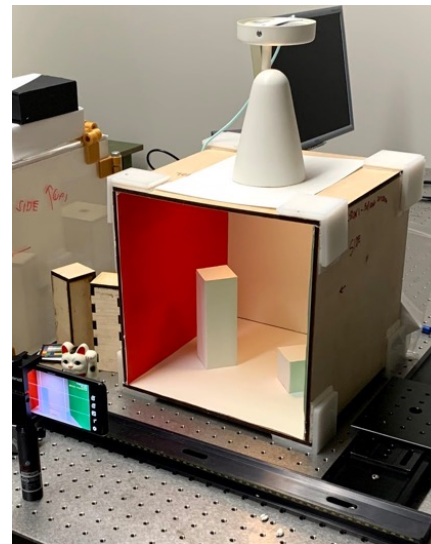
- We measured the asset sizes and scene geometry, surface reflectance, illuminant spectral power distribution



Illuminant SPD

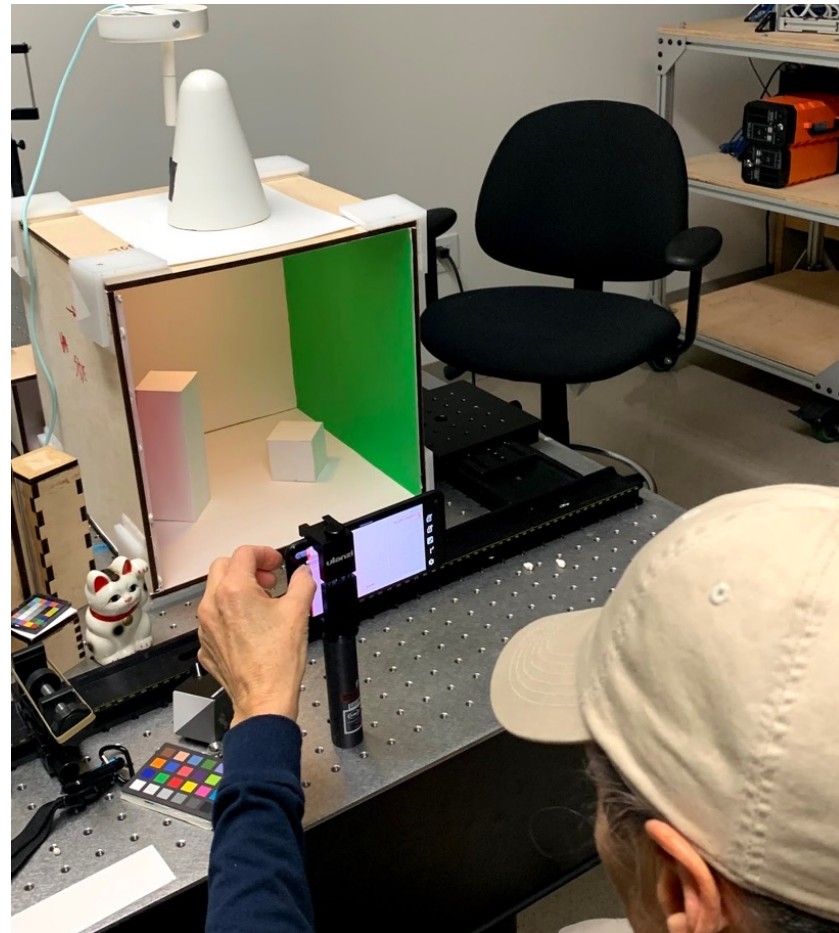
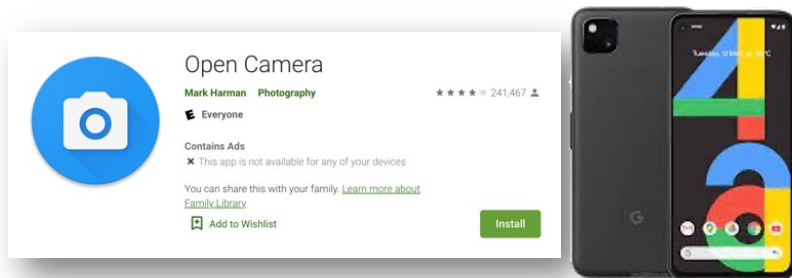


Surface spectral reflectance



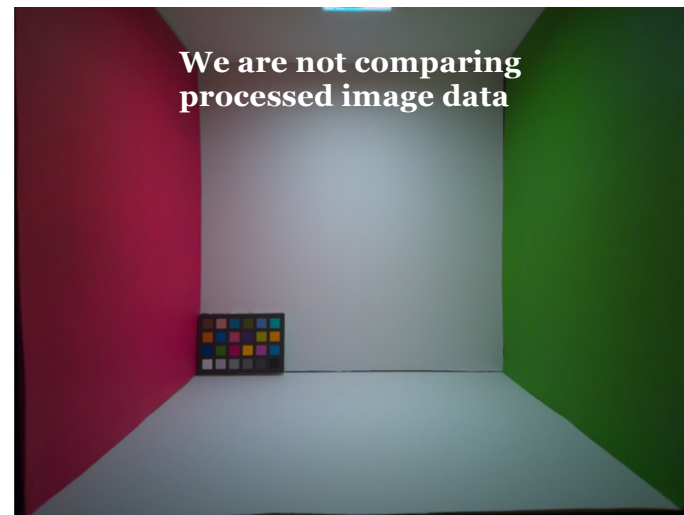
Validation test: Raw sensor data from the camera

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



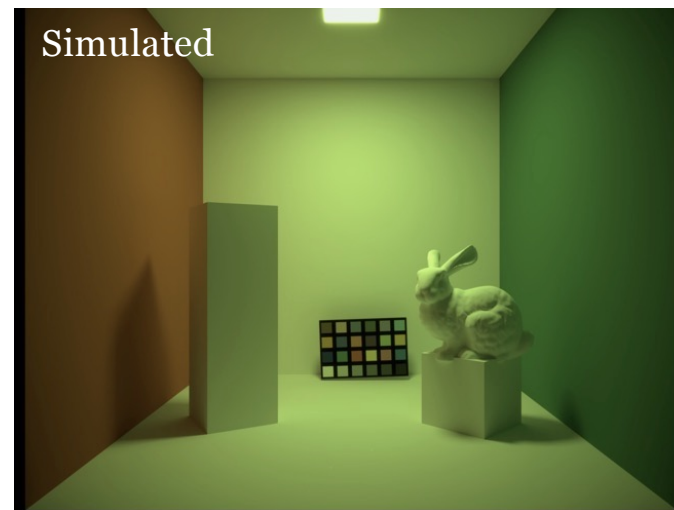
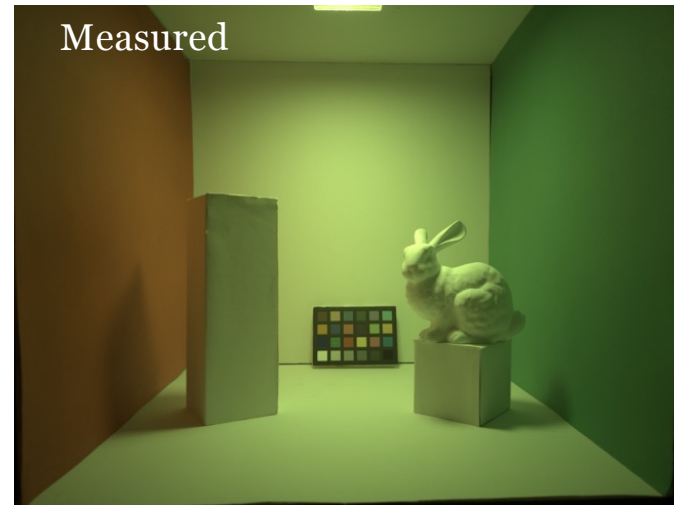
Sensor renderings

- 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



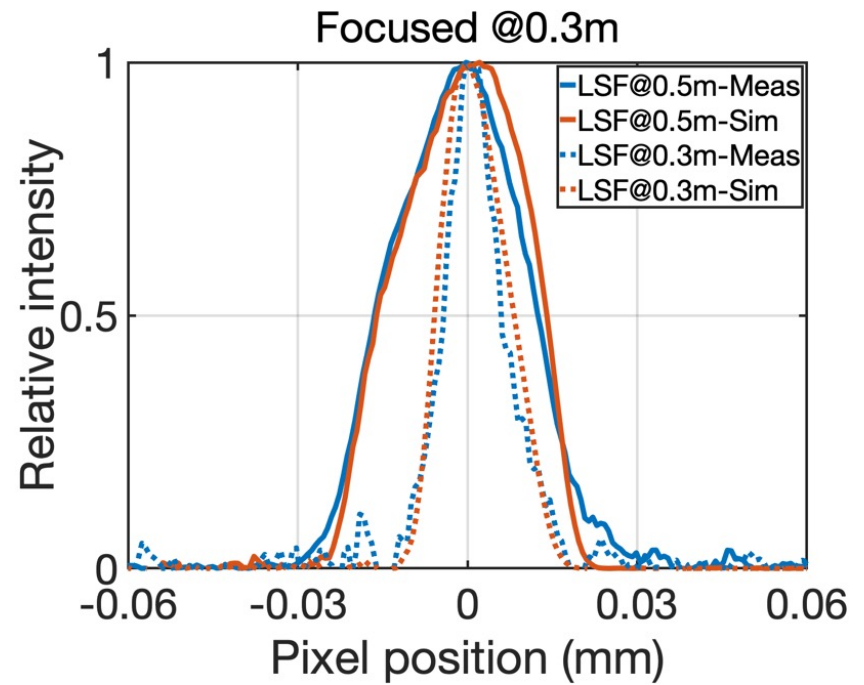
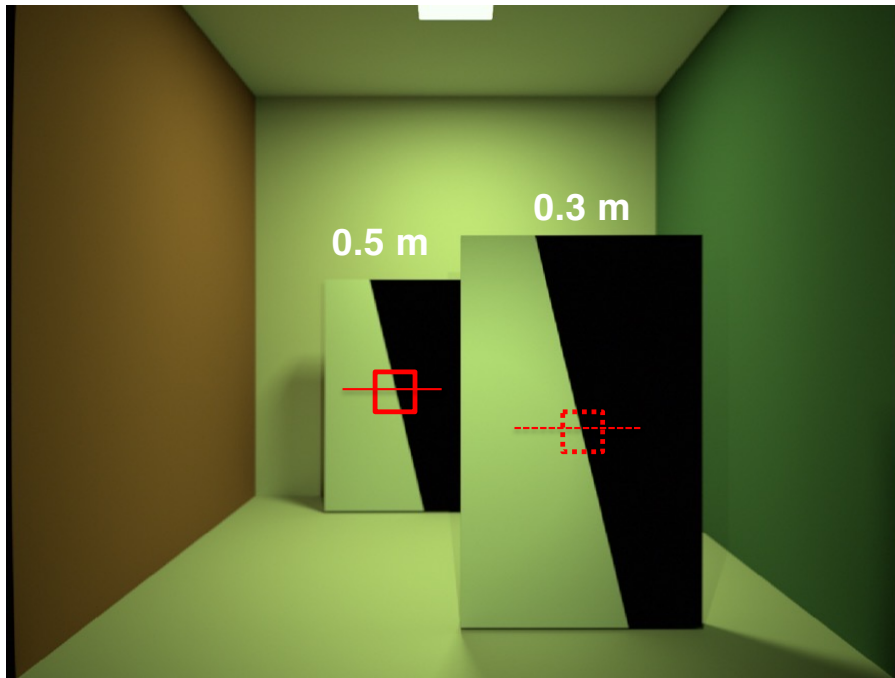
Quick check based just on appearance

- 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!



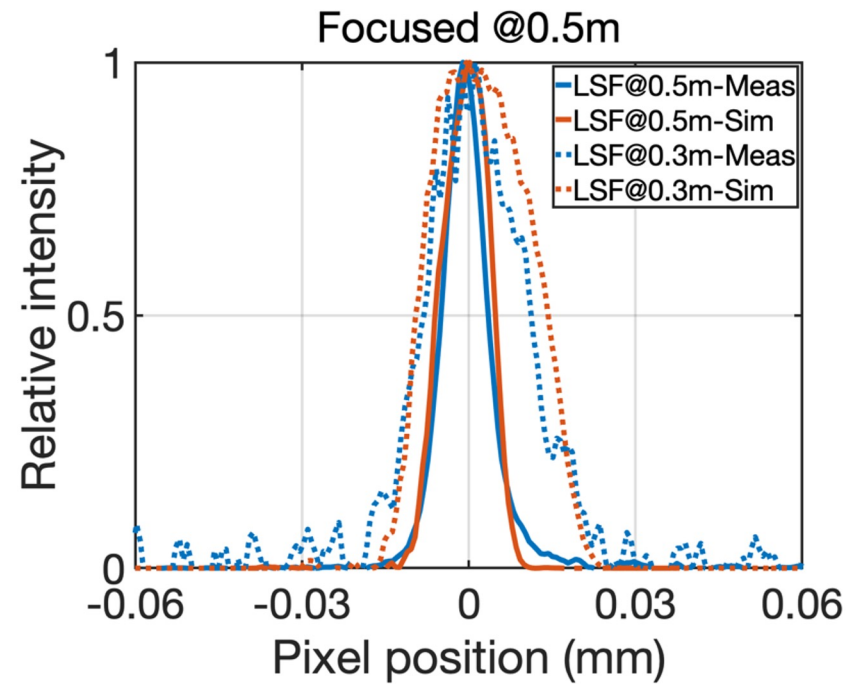
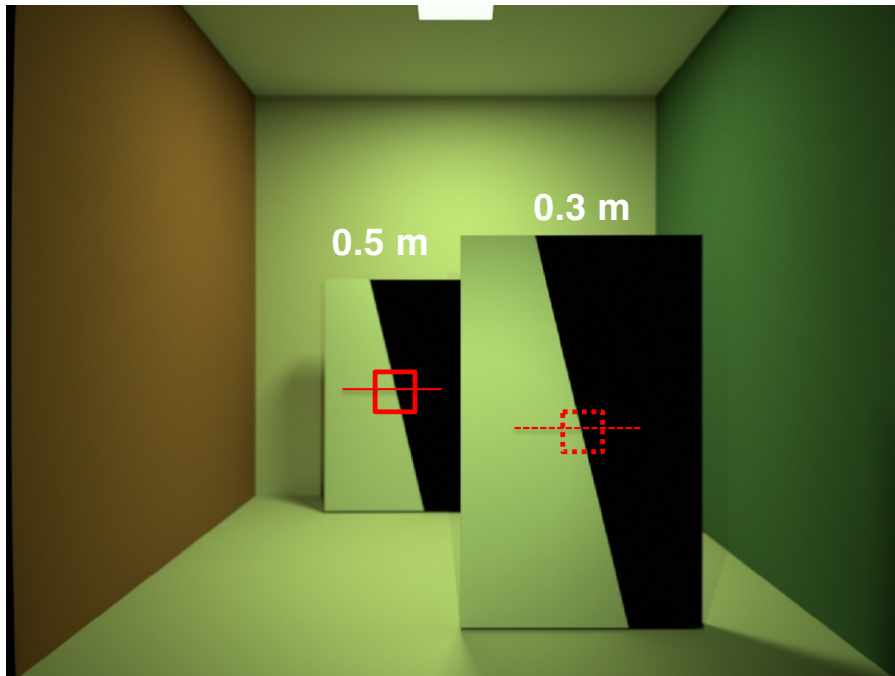
Optics validation: Resolution and depth of field

Focused at 0.3 meters



Focus-dependent LSF/MTF (depth of field)

Focused at 0.5 meters



Surface inter-reflections and electronic sensor noise

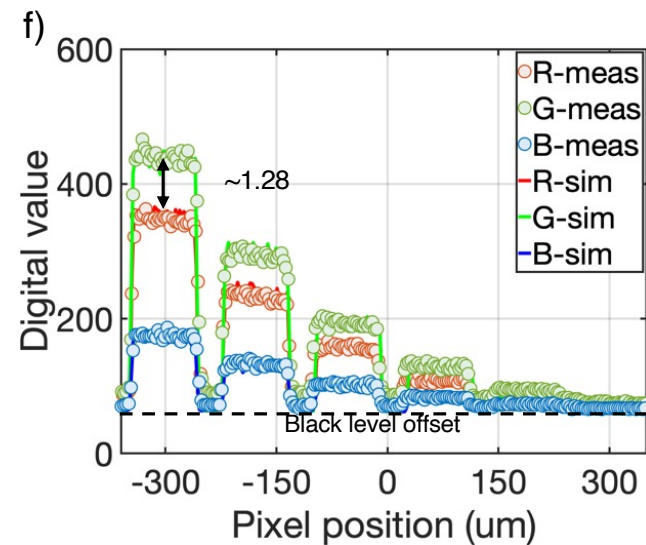
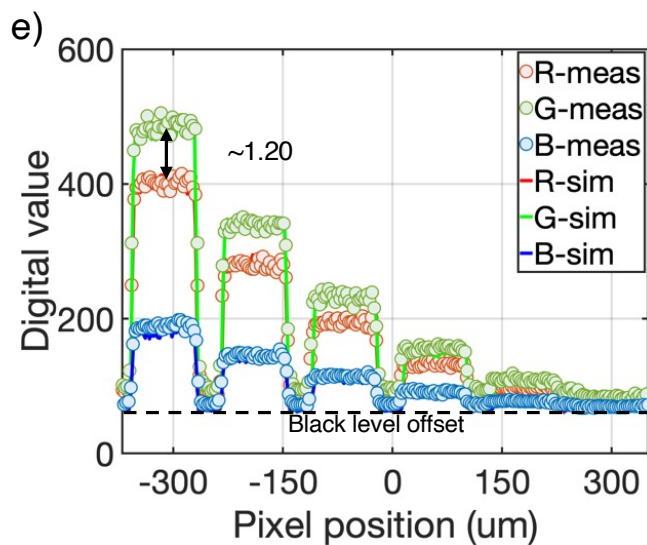
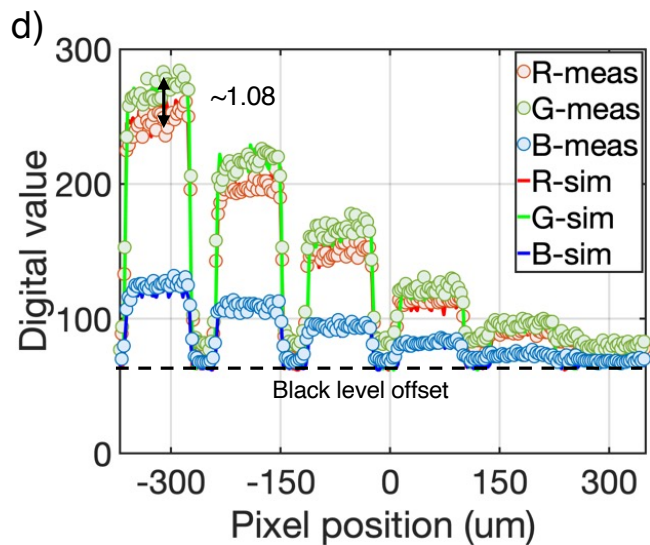
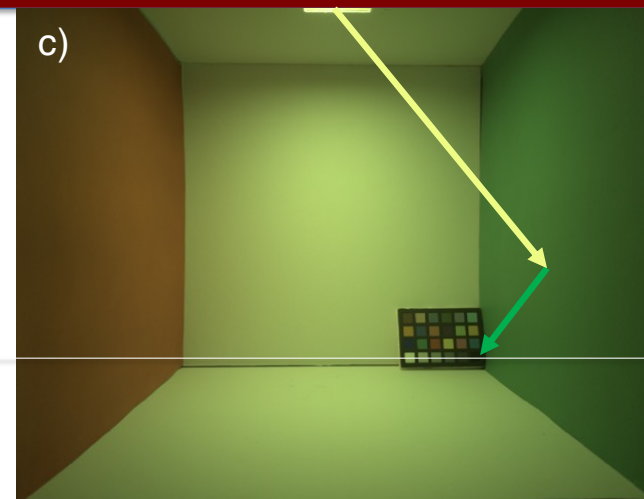
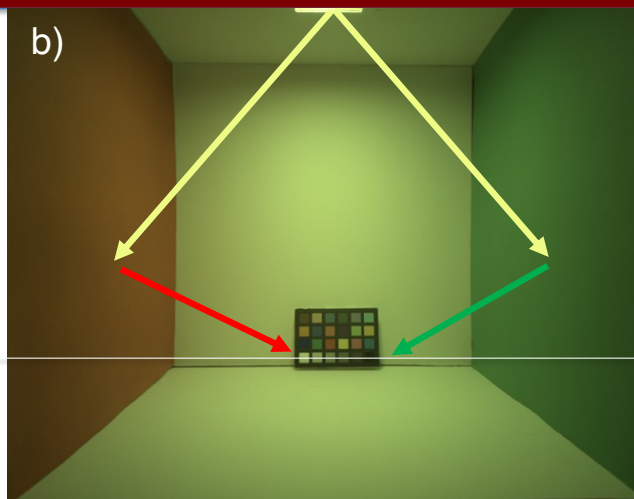
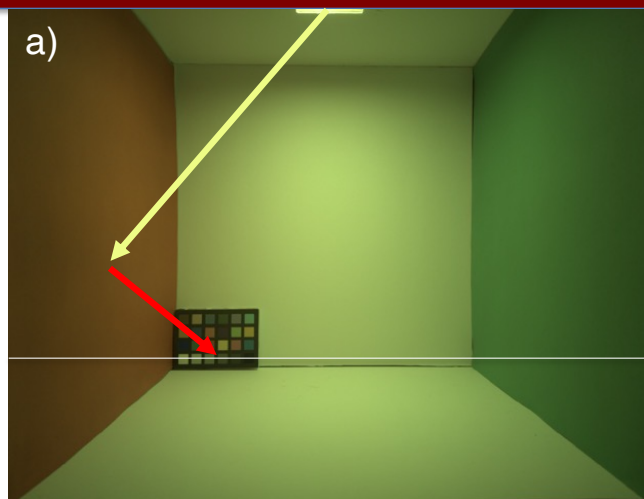
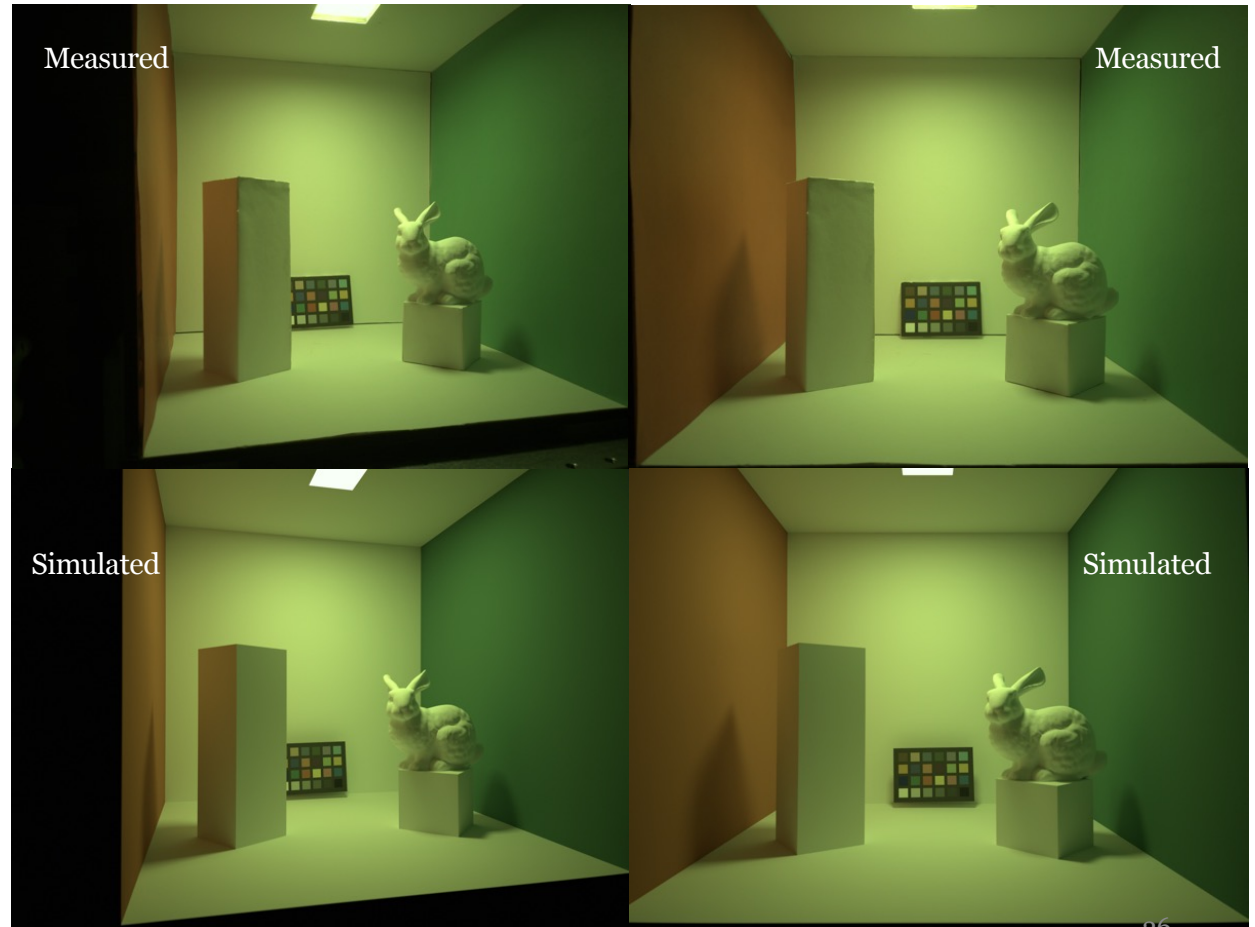


Image system simulation evaluation using 3D scenes

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



Second point: Empirical validation

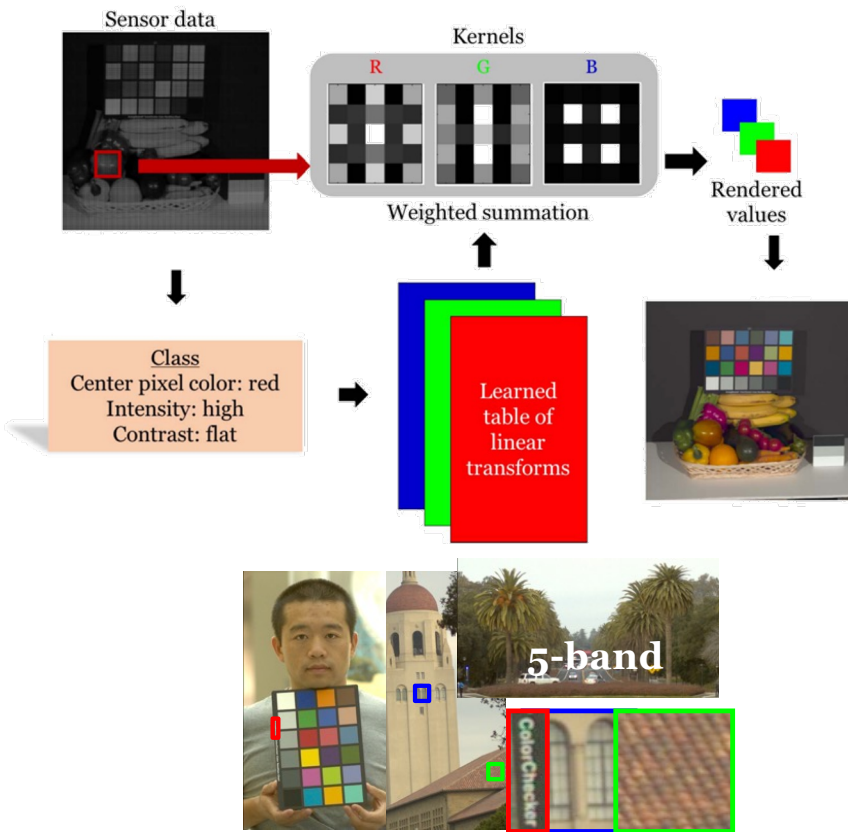
- Image systems simulations can accurately create many scenes, and compute the expected sensor response
- We are working to expand the range of conditions – particularly HDR - and to validate quantitative, spectral simulations

Device Applications: Sensor, optics and pipeline modeling

IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 26, NO. 10, OCTOBER 2017

Learning the Image Processing Pipeline

Haomiao Jiang, Qiyuan Tian, Joyce Farrell, and Brian A. Wandell



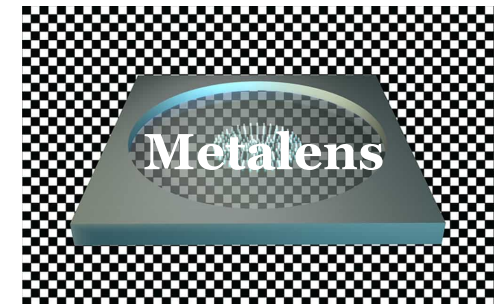
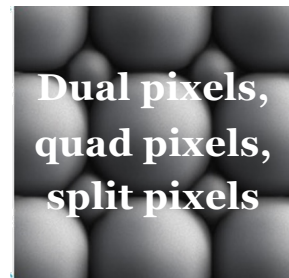
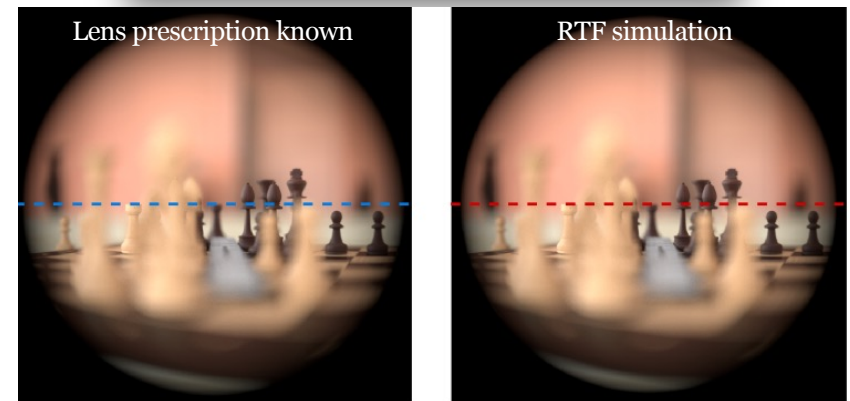
Ray-transfer functions for camera simulation of 3D scenes with hidden lens design

THOMAS GOOSSENS,^{1,*} ZHENG LYU,¹ JAMYUEN KO,² GORDON C. WAN,² JOYCE FARRELL,¹ AND BRIAN WANDELL¹

¹Stanford Center for Image Systems Engineering, Stanford University, Stanford, California 94305, USA

²Google, Mountain View, California 94043, USA

*contact:thomasgoossens.be

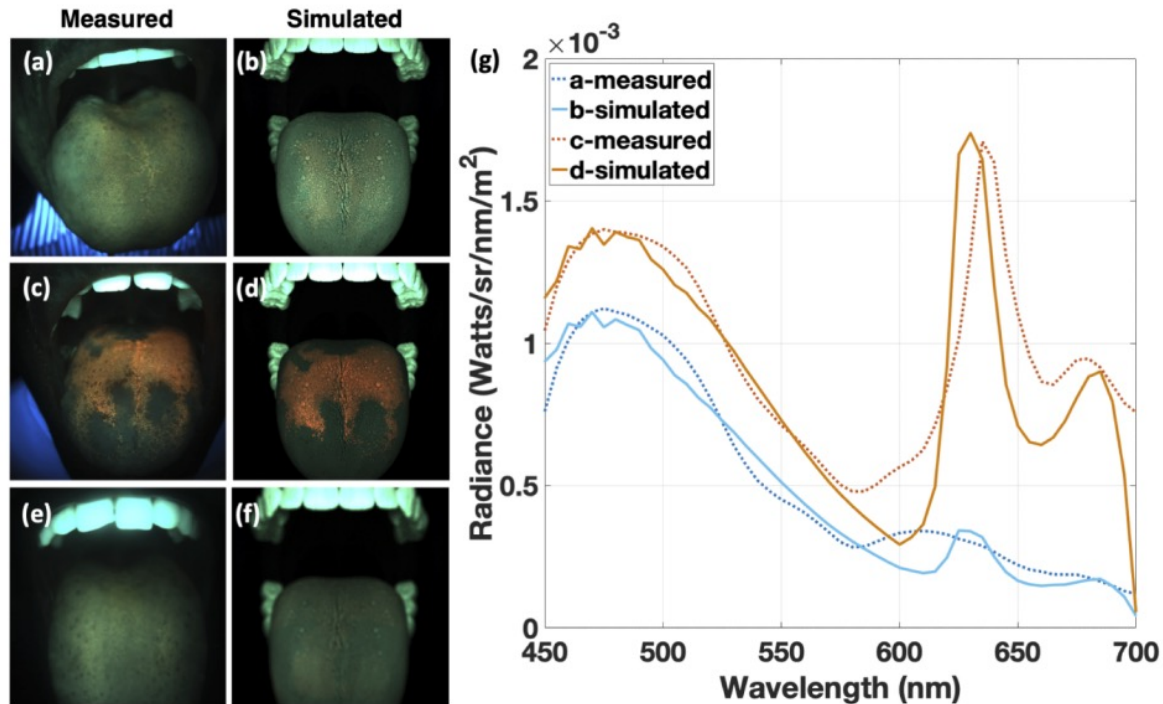


Medical imaging applications

Tissue fluorescence,
blood, bacterial
fluorescence

Simulations of fluorescence imaging in the oral cavity

ZHENG LYU,^{1,2} HAOMIAO JIANG,³ FENG XIAO,⁴ JIAN RONG,⁴
TINGCHENG ZHANG,⁴ BRIAN WANDELL,^{1,5} AND JOYCE FARRELL^{1,2,*}



Engineering applications: Automotive systems



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

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^{1,2}, TRISHA LIAN², JOYCE FARRELL², AND BRIAN A. WANDELL²

¹State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun 13000, China

²Department of Electrical Engineering, Stanford University, Stanford, CA 94305, USA

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

This work was supported by the Jilin University.

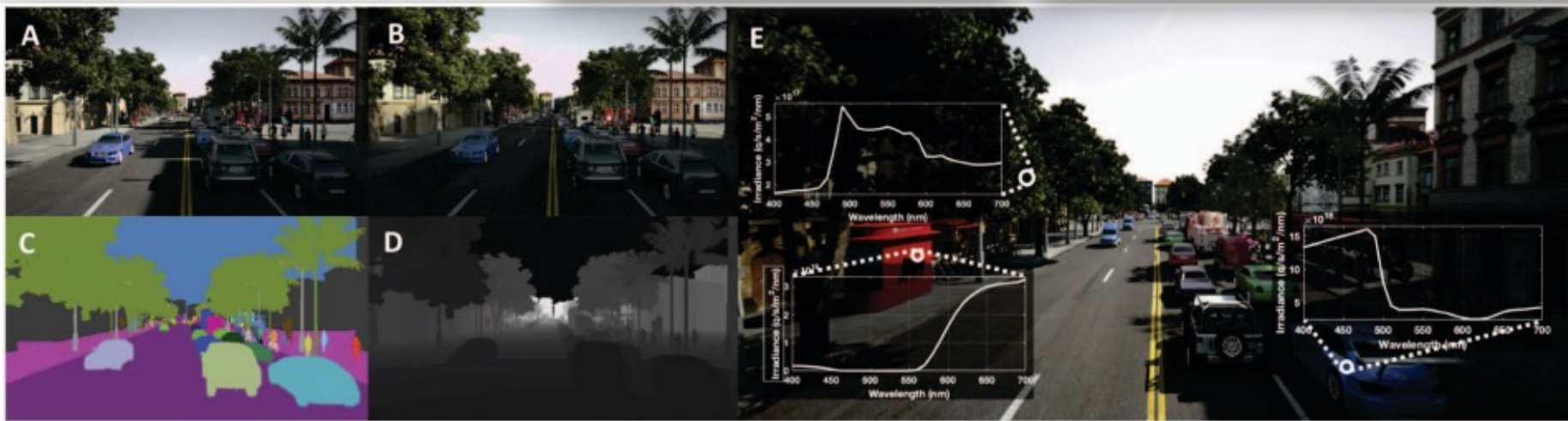
ISETAuto: Detecting vehicles with depth and radiance information

ZHENYI LIU¹, JOYCE FARRELL² AND BRIAN WANDELL²

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

²Stanford 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.

ISETHDR: Data set and split photodiode simulation

- HDR nighttime data
- Split-photodiode for single-shot HDR imaging

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

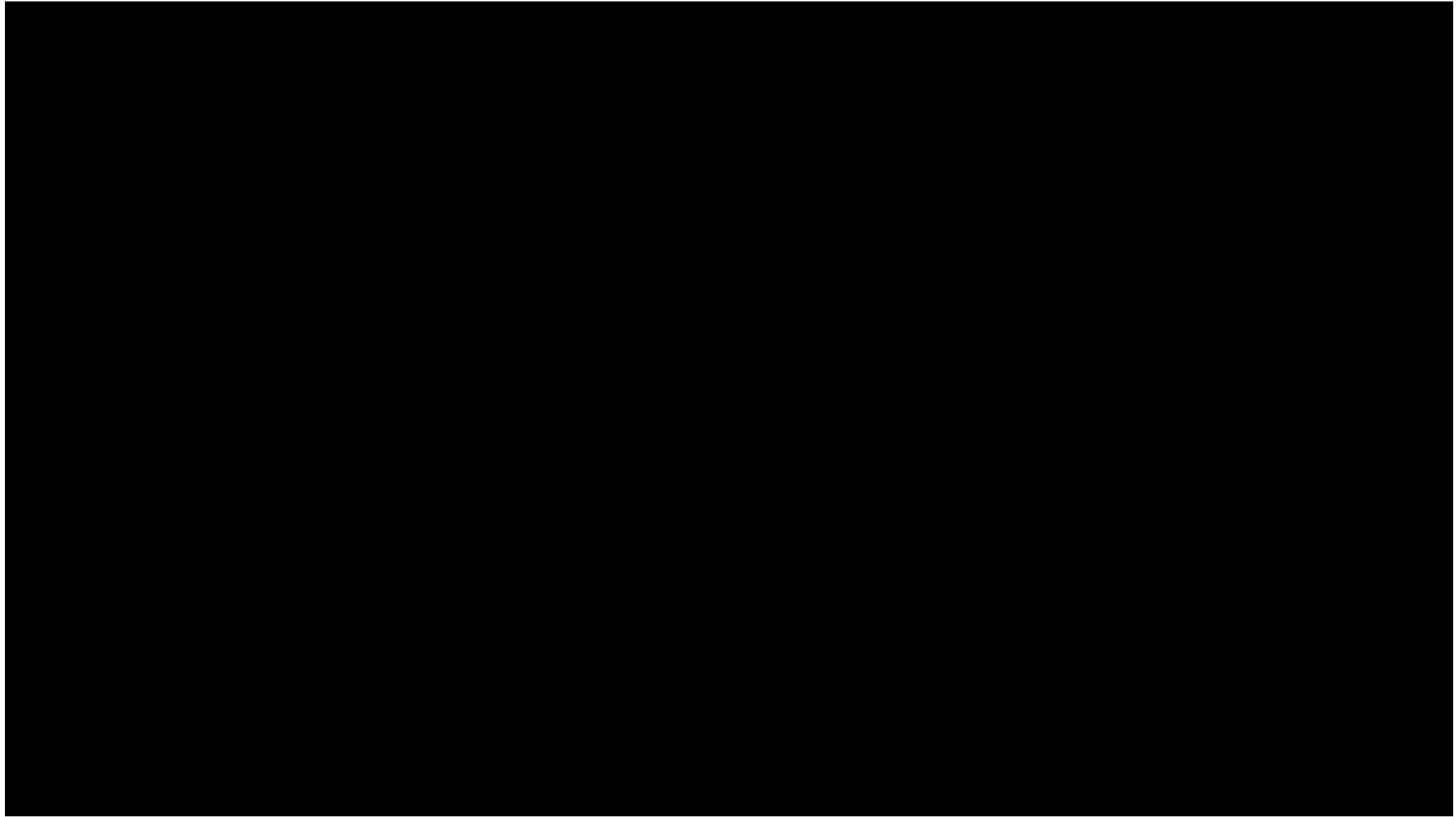
Zhenyi Liu, Devesh Shah, and Brian A. Wandell

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.



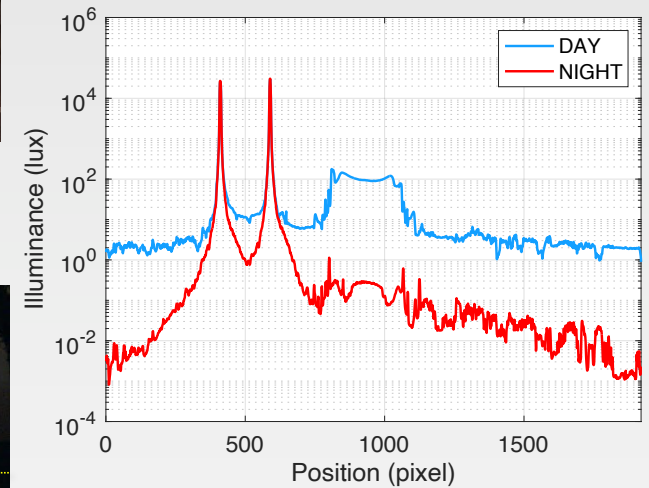
Index Terms—Image system engineering, high dynamic range, digital twins, open source dataset, automotive imaging, nighttime driving





ISETHDR – Light group concept

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



- Spectral radiance light groups
- Highway and country road driving scenes

Stanford Digital Repository

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	Download
1112153442_instanceID.exr	6.3 MB	Download
1112153442_otherlights.exr	22.39 MB	Download
1112153442_skymap.exr	90.33 MB	Download
1112153442_streetlights.exr	66.36 MB	Download
1112153830_headlights.exr	76.47 MB	Download
1112153830_instanceID.exr	6.3 MB	Download
1112153830_otherlights.exr	22.39 MB	Download

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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 <https://orcid.org/0000-0002-2974-1836> (unverified)

Liu, Zhenyi <https://orcid.org/0000-0002-2673-3734> (unverified)

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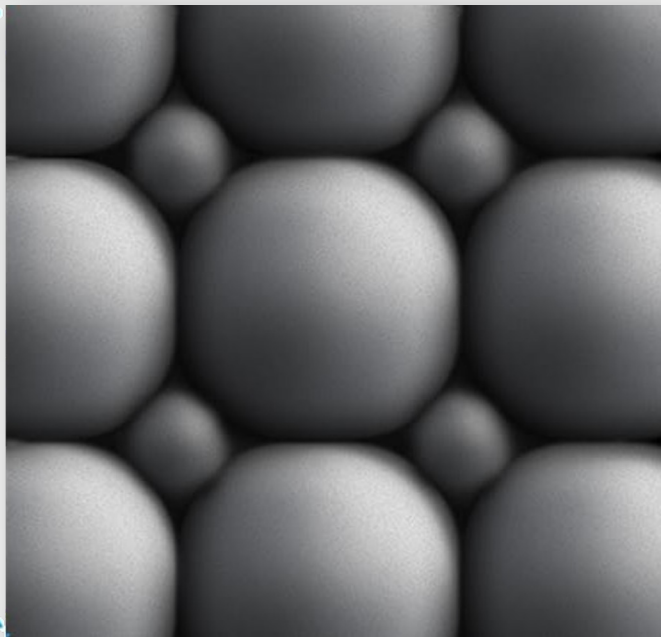
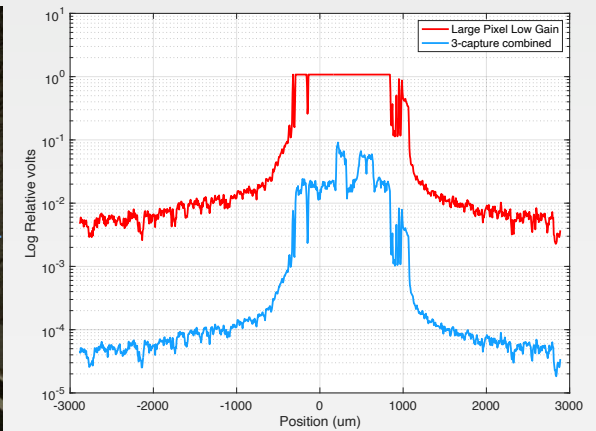
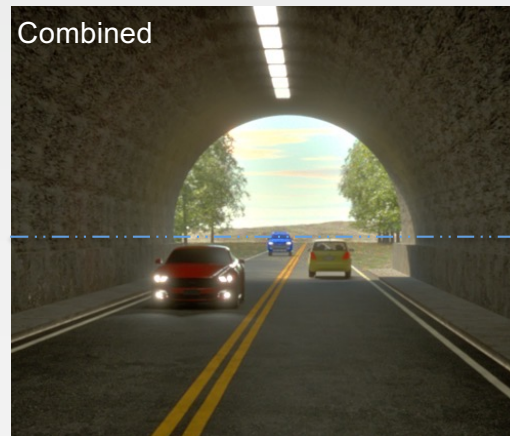
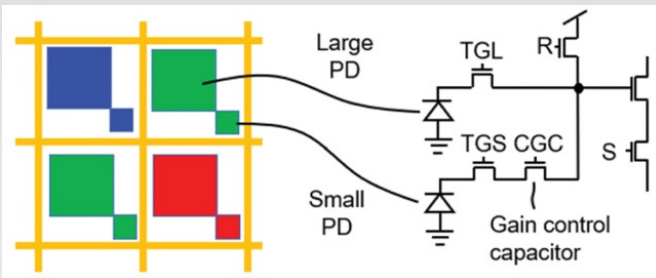
Preferred citation

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

ISETHDR – evaluation in a complex HDR scene

(<https://github.com/ISET/isethdrsensord>)



ISETHDRSensor

- Optical flare
- Split photodiode sensor
- RGBW sensor

The screenshot shows the GitHub repository for ISETHDRSensor. At the top, it indicates the current branch is 'main', with 4 branches and 1 tag. A search bar and 'Add file' button are visible. Below this is a table of repository files and folders:

File/Folder	Description	Last Update
figures	Updated for new ieWebGet	4 months ago
local	Create .gitignore	4 months ago
scripts	add dirGet & use it to patch hsSkyBrightness	4 months ago
utility	add dirGet & use it to patch hsSkyBrightness	4 months ago
.gitignore	Update .gitignore	4 months ago
LICENSE	Initial commit	8 months ago
README.md	Update README.md	4 months ago
isethdrsensordRootPath.m	Getting started	8 months ago

The main content area displays the README for ISETHDRsensor. It features a collage of images showing various driving scenes, including daytime and nighttime views, and a heatmap visualization. Below the images, the text reads: "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." A link to the Arxiv paper is provided: "Arxiv ISETHDR: A Physics-based Synthetic Radiance Dataset for High Dynamic Range Driving Scenes". A note at the bottom suggests looking at the repository's Wiki for scripts that create the images.

The right sidebar contains repository statistics and metadata:

- About:** Test ideas about sensor architectures for HDR imaging. Includes links to Readme, MIT license, Activity, Custom properties, 6 stars, 3 watching, 0 forks, and Report repository.
- Releases:** 1 tag. Includes a link to Create a new release.
- Packages:** No packages published. Includes a link to Publish your first package.
- Contributors:** 3 contributors: wandell Brian Wandell, Zhenyi-Liu Zhenyi Liu, and digital-pro David Cardinal.
- Languages:** HTML 99.7%, Other 0.3%.
- Suggested workflows:** Based on your tech stack. Includes a workflow for "Jekyll using Docker image" with a Configure button.

Third point: Soft prototyping in academia

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

What goes into an image systems simulation for the human eye



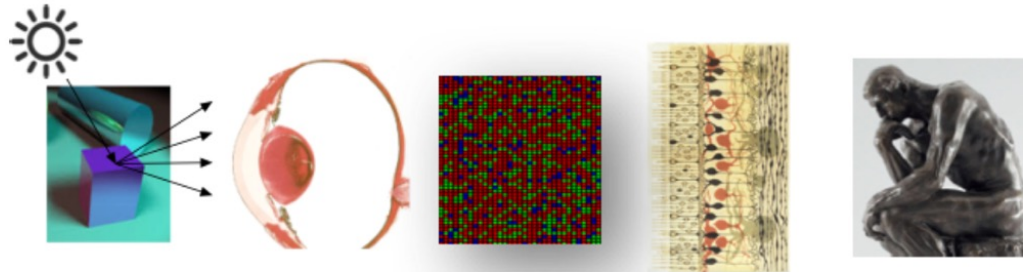
Nicolas Cottaris



Joyce Farrell



David Brainard



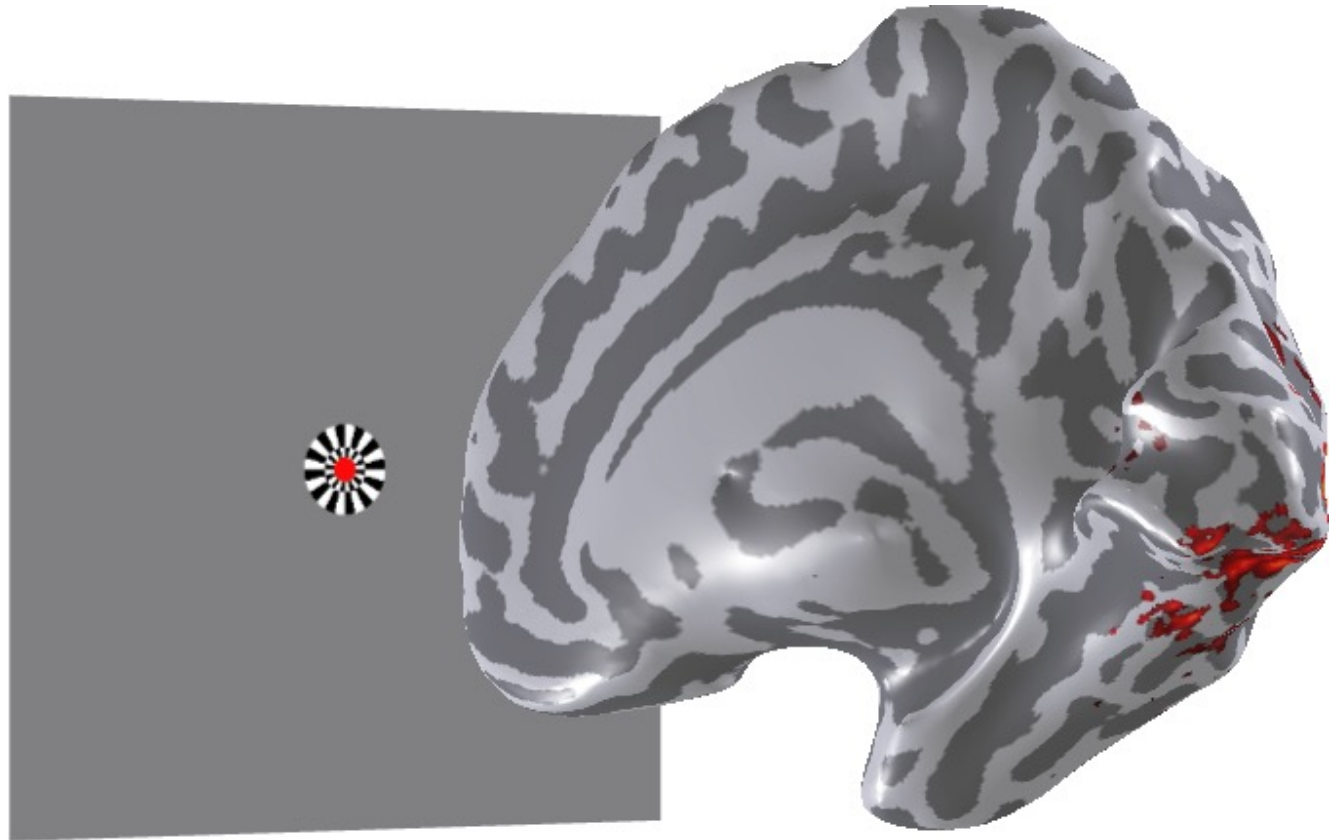
<https://github.com/isetbio/isetbio/wiki>

The Image System Engineering Toolbox for Biology (ISETBio) supports vision science calculations. The Matlab software enables you to create spectral radiance scenes and use these scenes as input to estimate the effects of human optics, eye movements, cone absorptions and photocurrent, and retinal cell properties. We hope to expand the software to model visual responses in thalamus and cortex. We have recorded some that introduce various aspects of ISETBio, and also that introduce basic vision science concepts. These may be found under the Videos menu item to the right.

Motivation: Understanding human vision



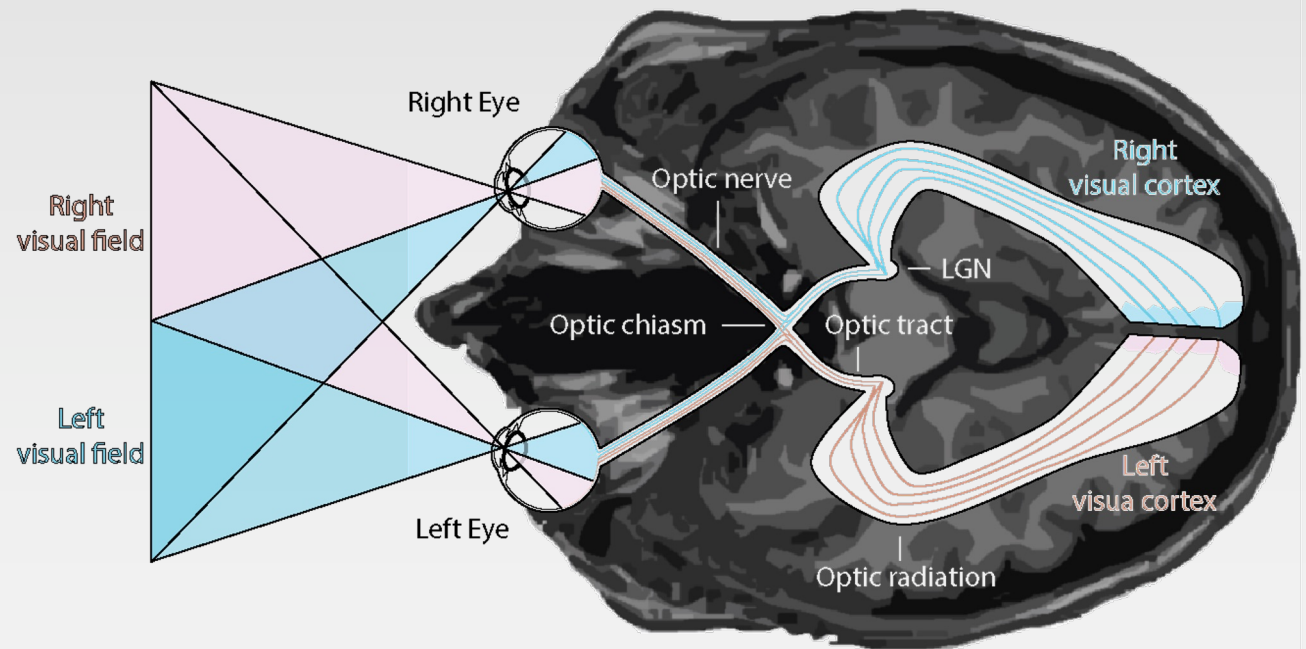
- Human visual neuroscience, in this example functional MRI, measures signals in visual cortex
- We don't know which response features are explained by cortex and which by the inputs to cortex
- The same can be said about single unit measurements



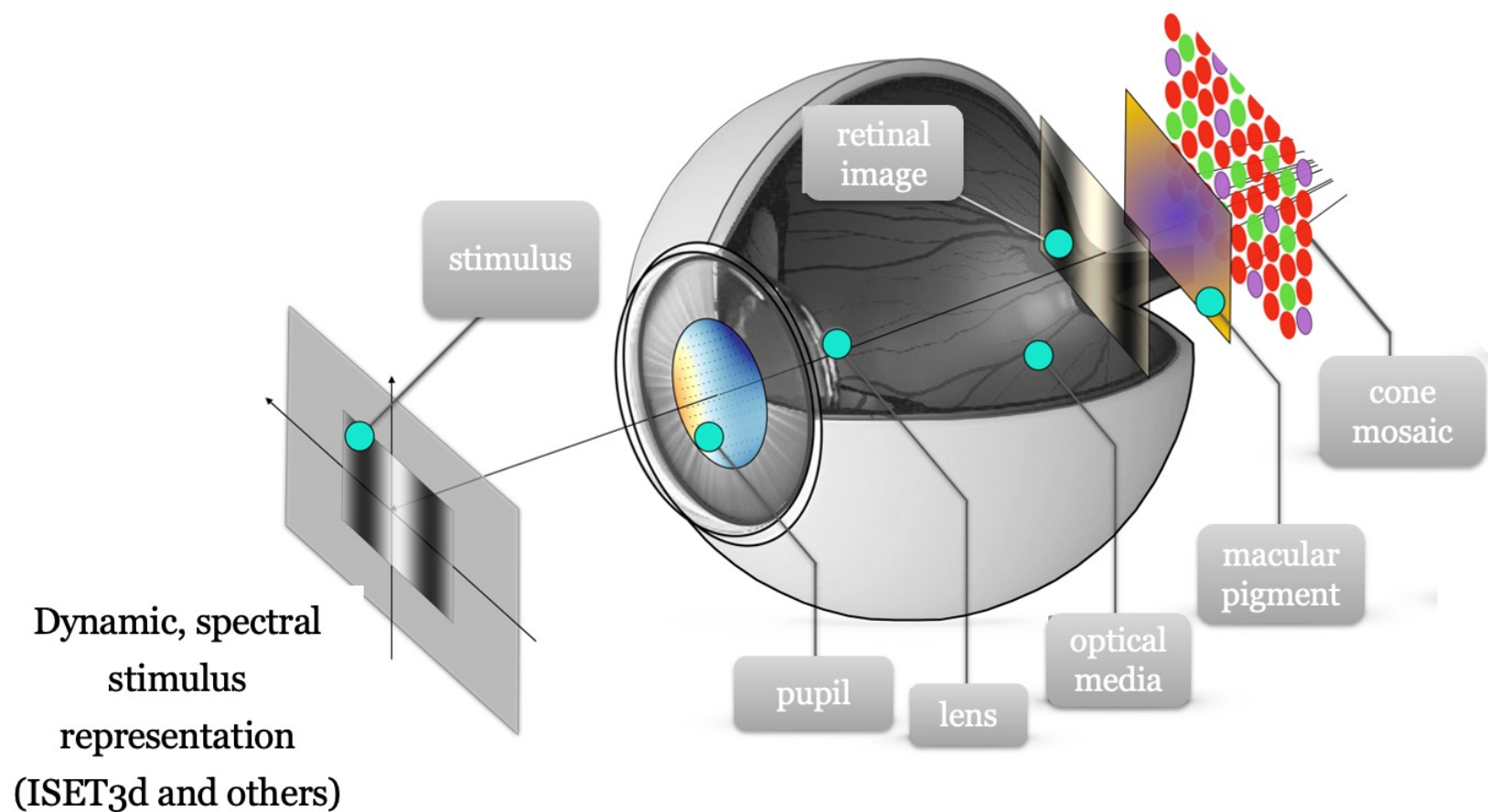
- Segmented and inflated brain surface
- Gray/white are sulci/gyri

The pathway from light to visual cortex contains many steps

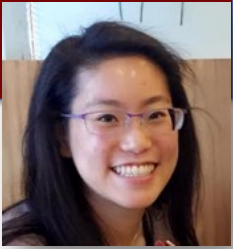
- The pathway from light to visual cortex contains many components
- A great deal is known about most of these components, but in a scattered literature
- ISETBio brings that knowledge together in a computable form
- We use ISETBio for biologically based calculations of the initial encoding



First steps: Image computable models of neural mosaics



Comparison of eye models: 3D renderings

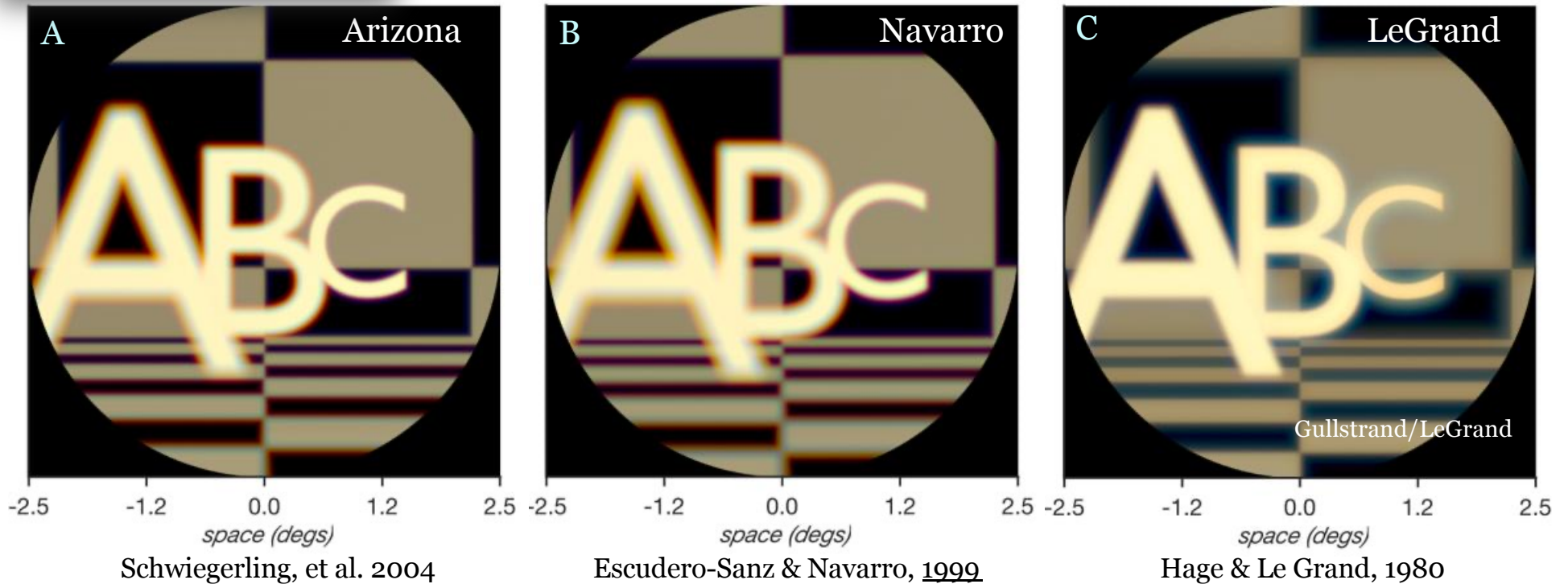


Trisha Lian

The PBRT-ISET3d code implements three major human eye models (Lian et al. 2019, Journal of Vision).

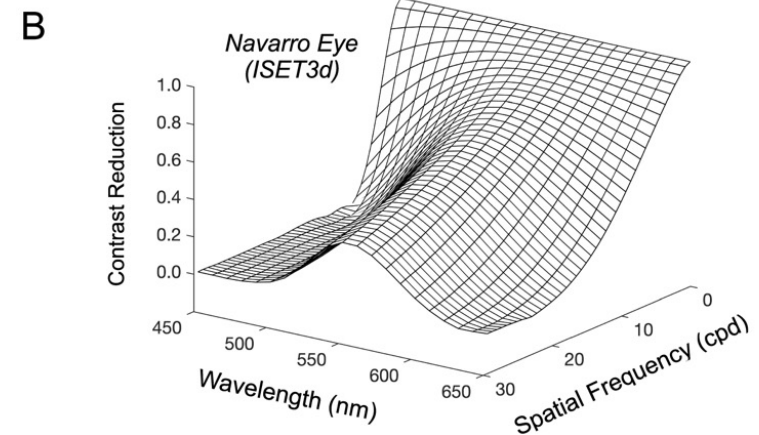
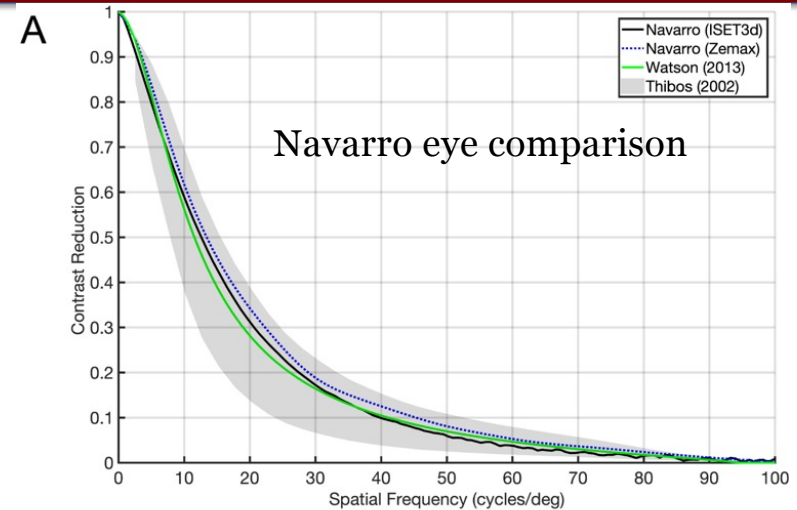
OPEN ACCESS
Article | October 2019
Ray tracing 3D spectral scenes through human optics models
Trisha Lian; Kevin J. MacKenzie; David H. Brainard; Nicolas P. Cottaris; Brian A. Wandell
+ Author Affiliations
Journal of Vision October 2019, Vol. 19, 23. doi:https://doi.org/10.1167/19.12.23

Remember: these images represent underlying spectral irradiance



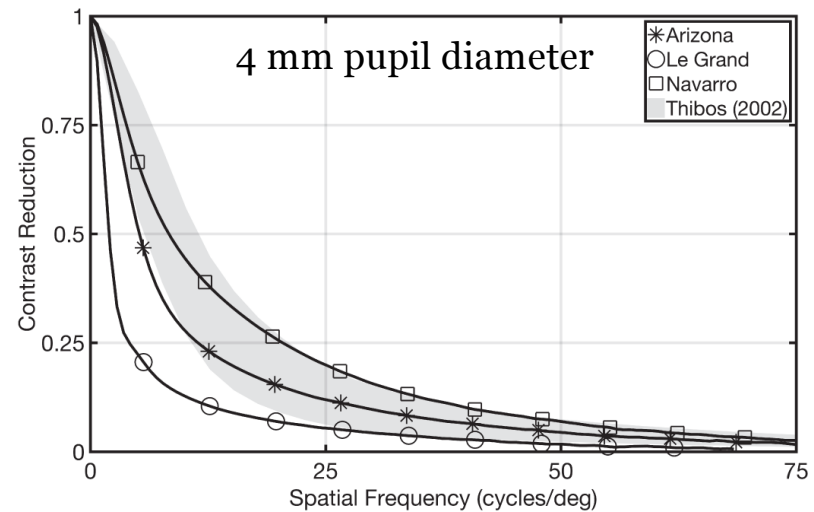
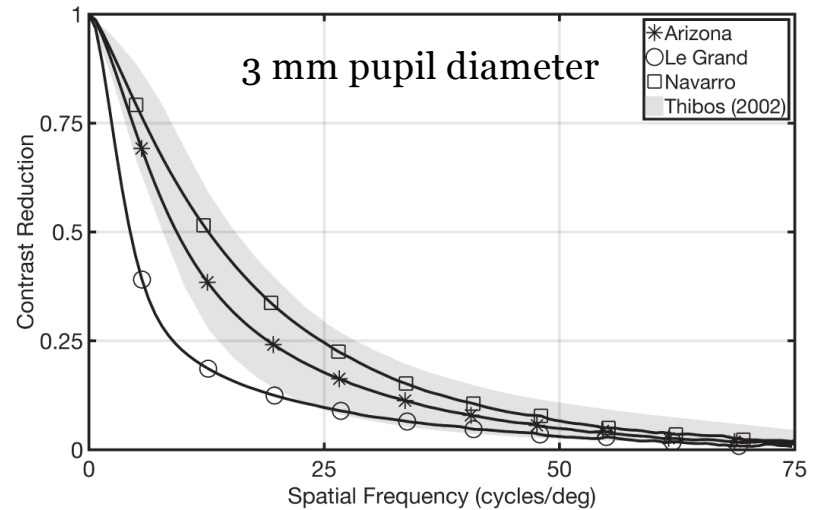
Validation of the ray tracing methods

- The PBRT implementation matches the Zemax calculations for these models
- We compared with L. Thibos' wavefront aberration data from many eyes (shaded) – which is the basis of the Watson (green) CSF summary as well
- We calculated as a function of wavelength, too – note huge chromatic aberration



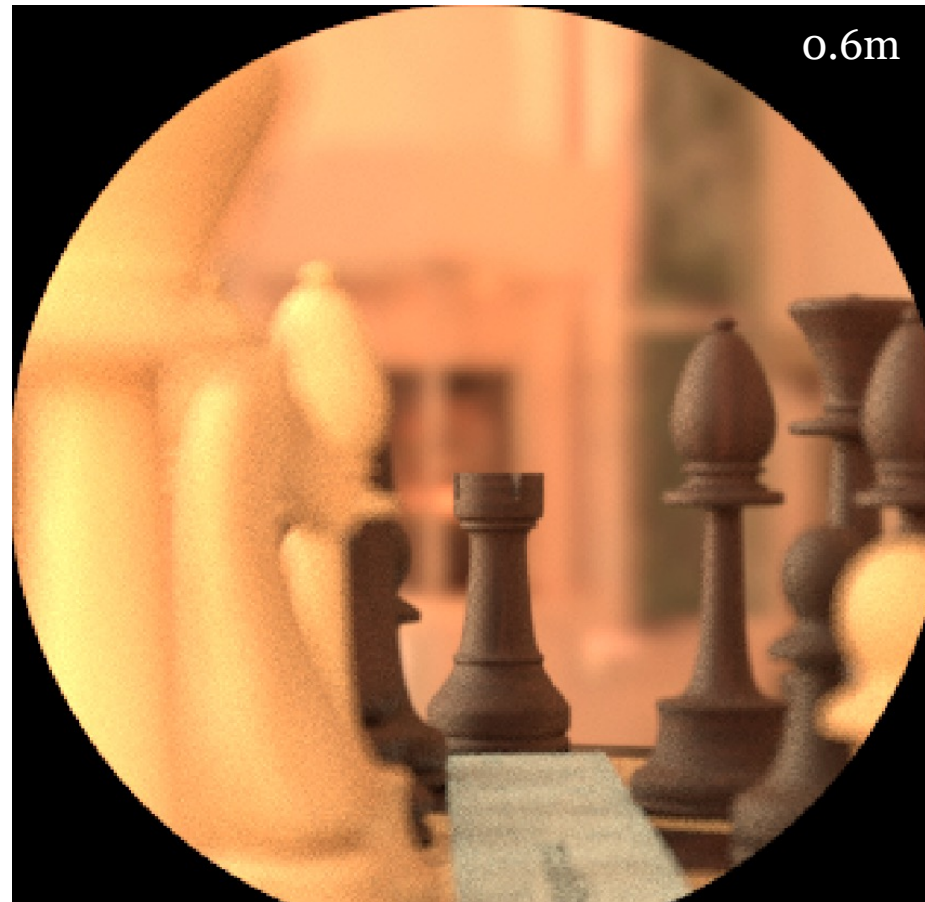
Human eye model comparisons

- There are quantitative differences between the models
- The LeGrand extension of the Gullstrand eye – is out of compliance with modern MTF measurements
- We can implement a range of eye parameters to match population distributions



Depth of field and accommodation (5 mm pupil)

- The eye models enable us to model the change of accommodation (focus) for the human eye using complex scenes – or simple scenes!!



- The eye models enable us to model the change of accommodation (focus) for the human eye using complex scenes – or simple scenes!!
- And to calculate the excitations at the cone mosaic



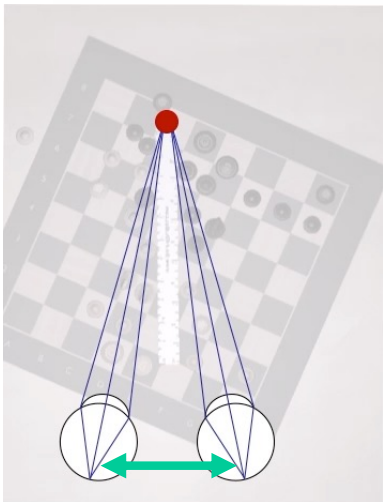
And to model vergence and accommodation

Where the eye (or eyes) is looking is controlled
thisEye.set('to',loc)

1.66 D (Left)



1.66 dpt (Right)

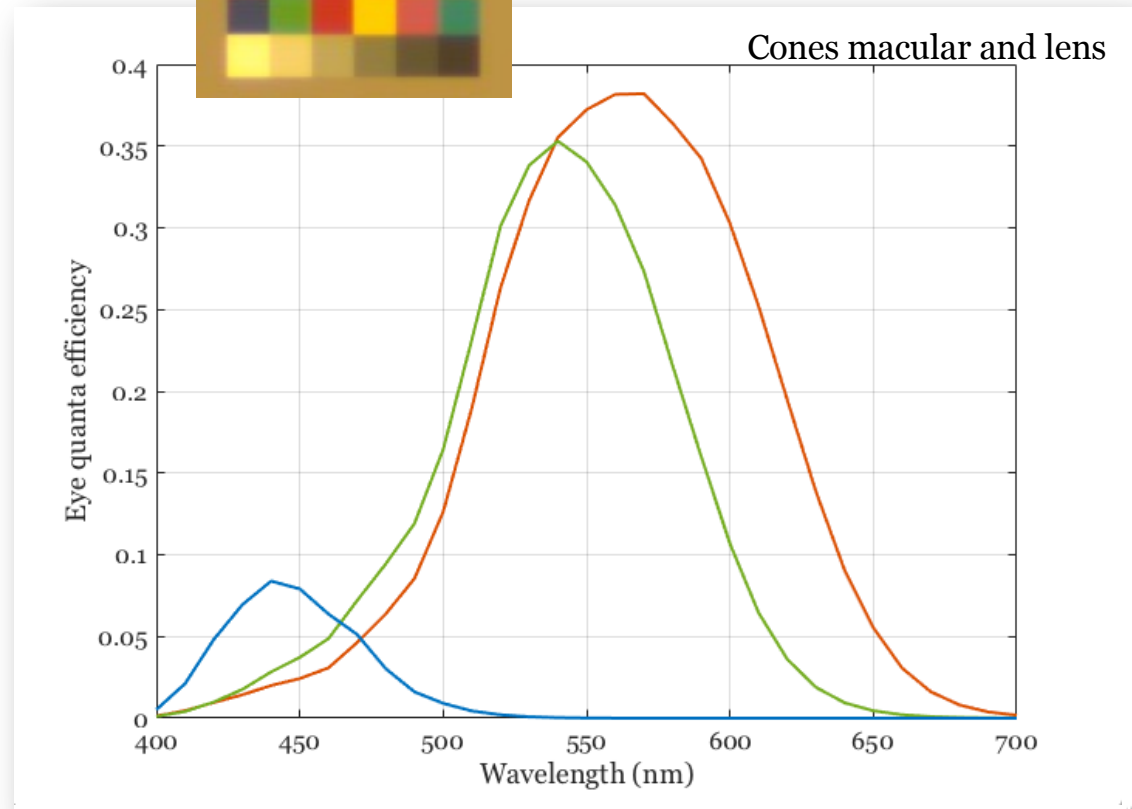
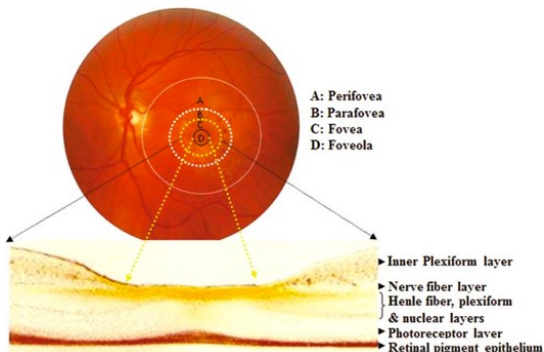
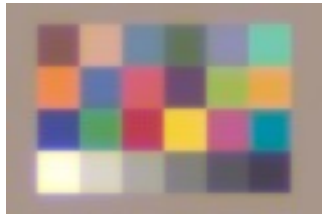


64 mm

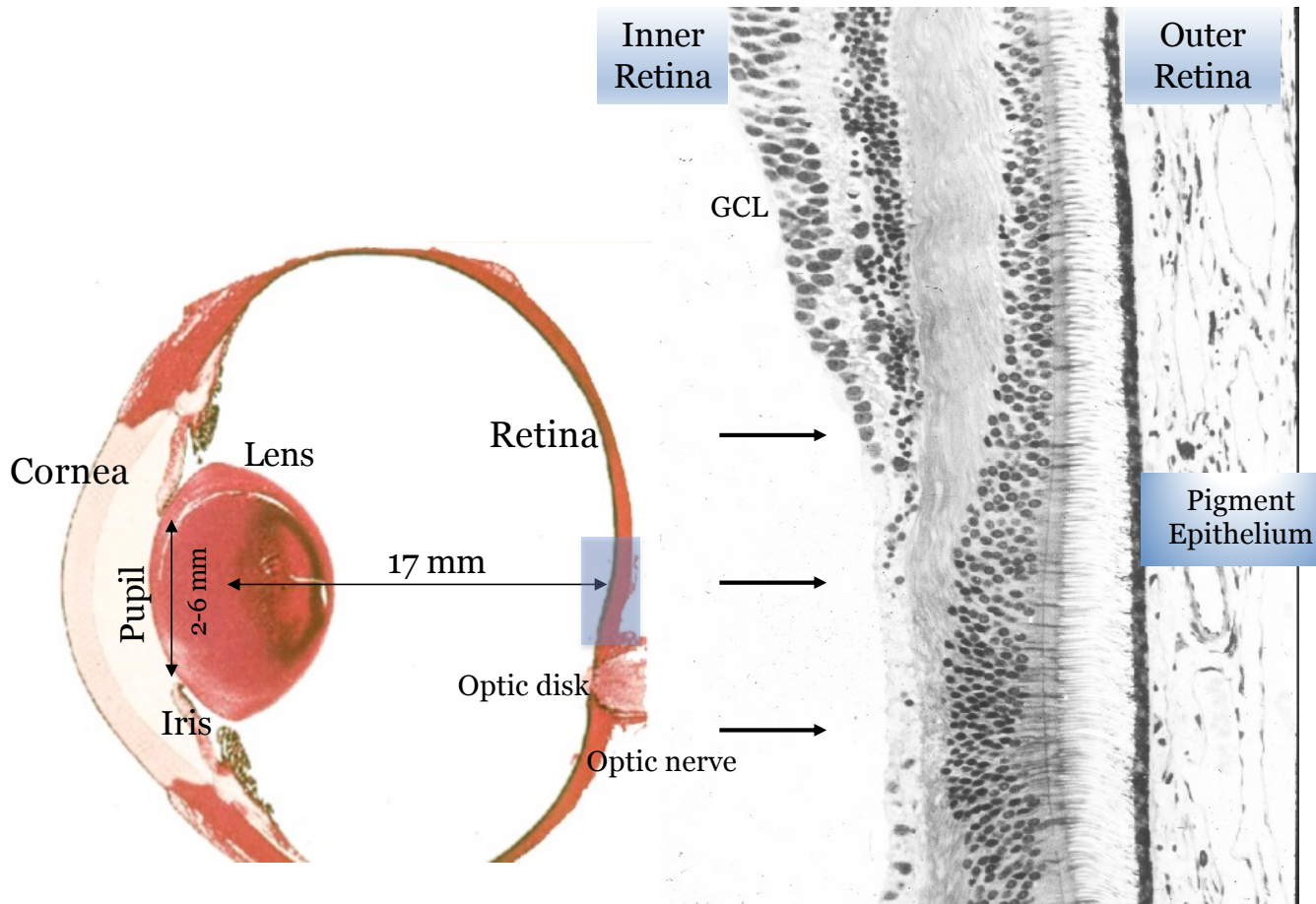
Remember: these images represent underlying spectral irradiance

Human wavelength absorptions depend on a several factors

- Cone photopigments (L,M,S) absorption efficiency for standard pigment density
- These curves are input referenced; they include the effect of the lens and macular pigments



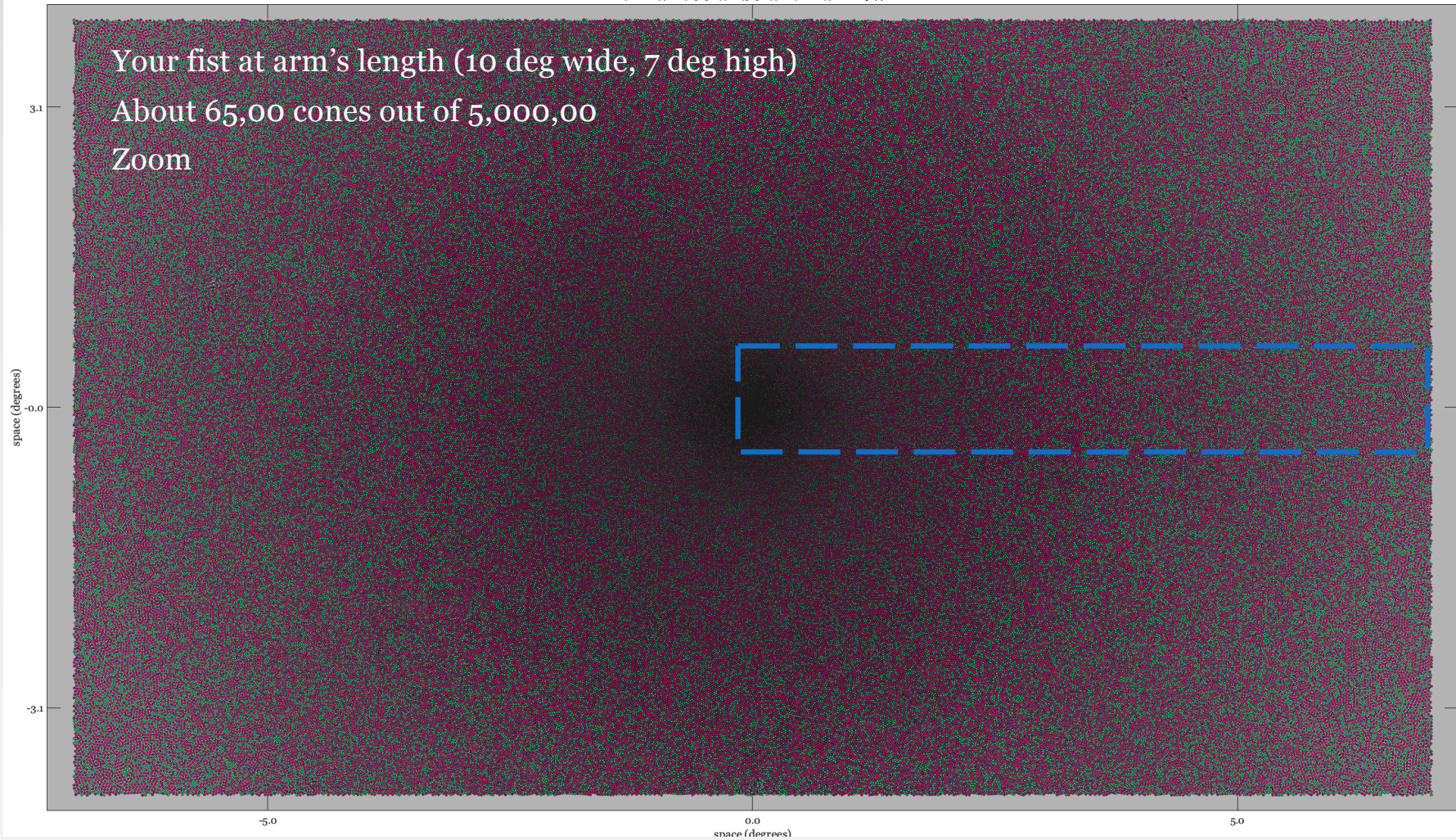
The retina: spatial inhomogeneity



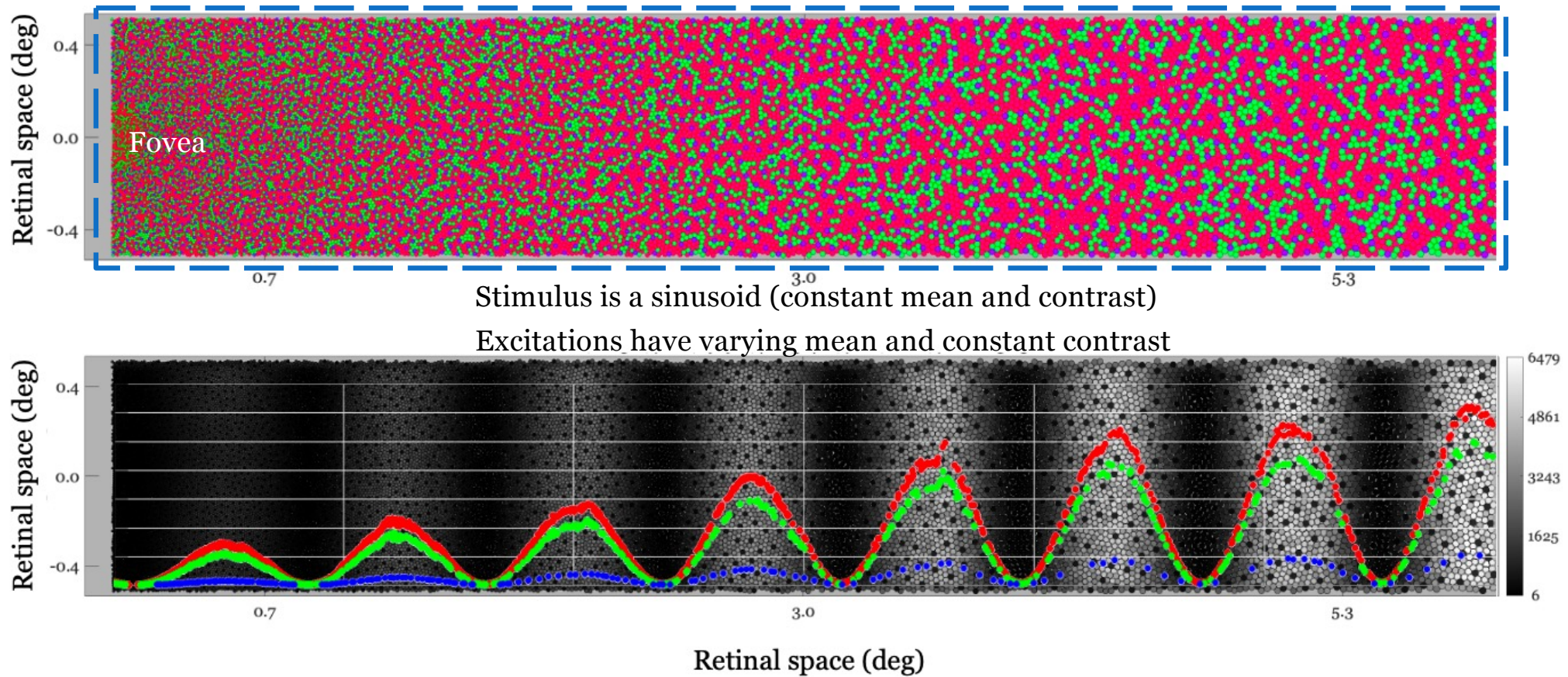
- 5×5 cm, 0.4 mm thick
- 5×10^6 cones
- 10^8 rods
- Foveal cone: $1 \mu\text{m}^2$
- Contacts per cone: 250
- 10^6 optic nerve fibers

Hard to represent large amounts of the retina

L (60.1%), M (29.9%), S (9.9%), K (0.0%), N = 241778

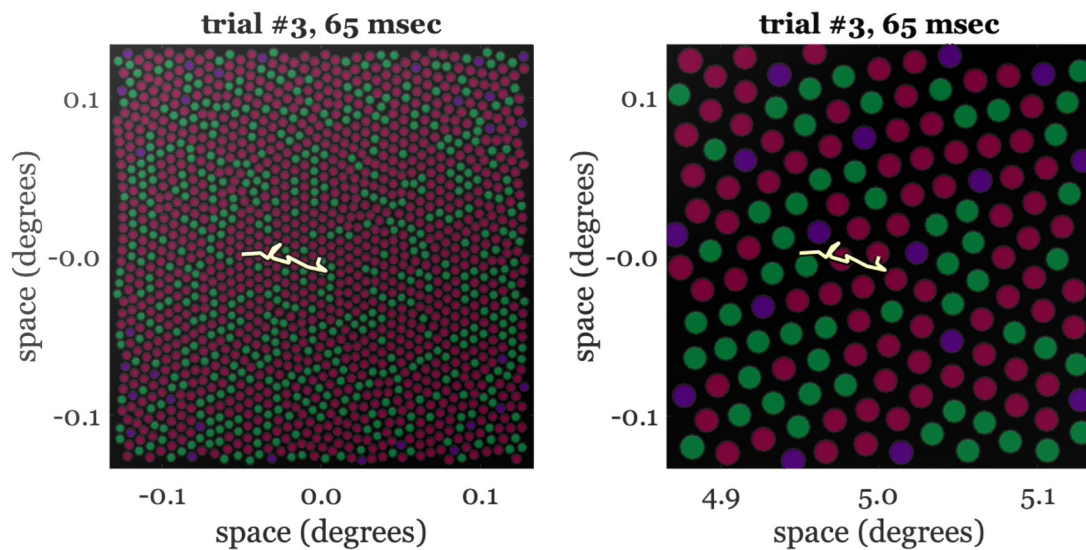


Cone excitations: sinusoidal stimulus of constant contrast



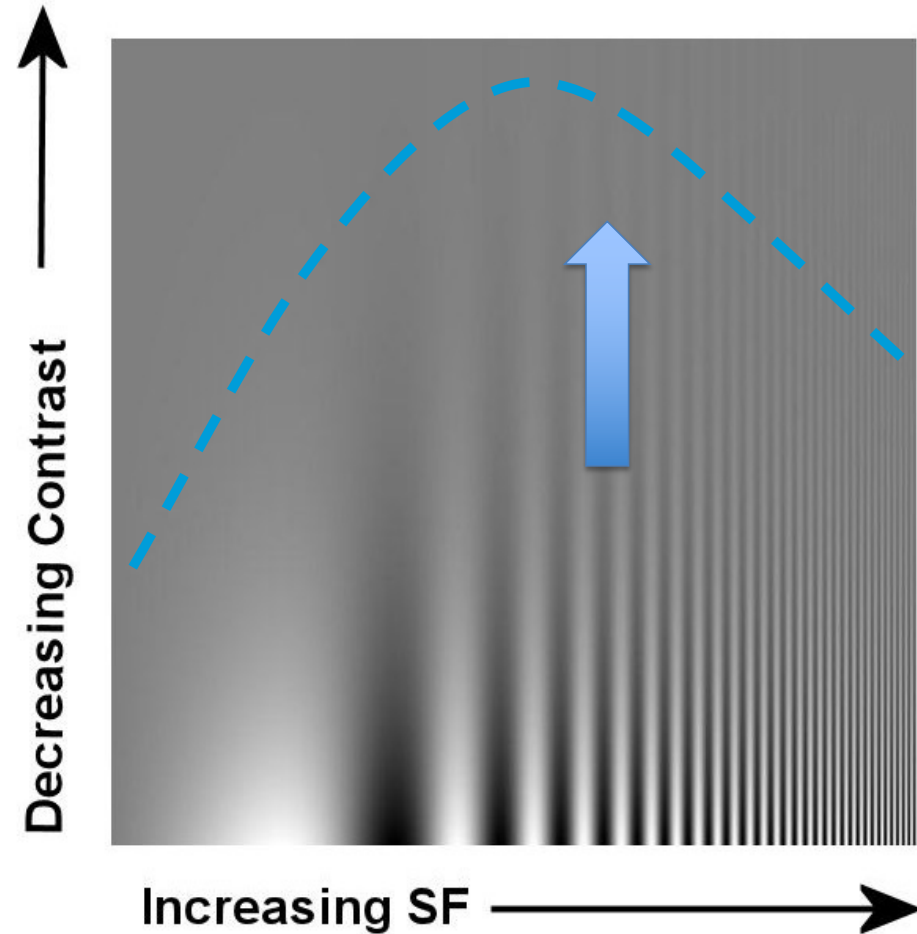
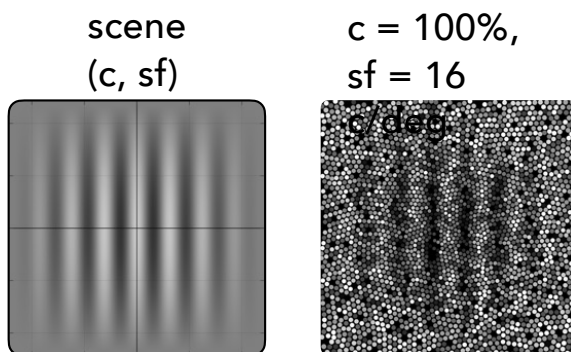
Eye movements and the space-varying cone mosaic

- The different sampling density across the array means that eye movements have different impacts on the fovea and periphery
- How the brain compares images after eye movements is an interesting neuroscience question



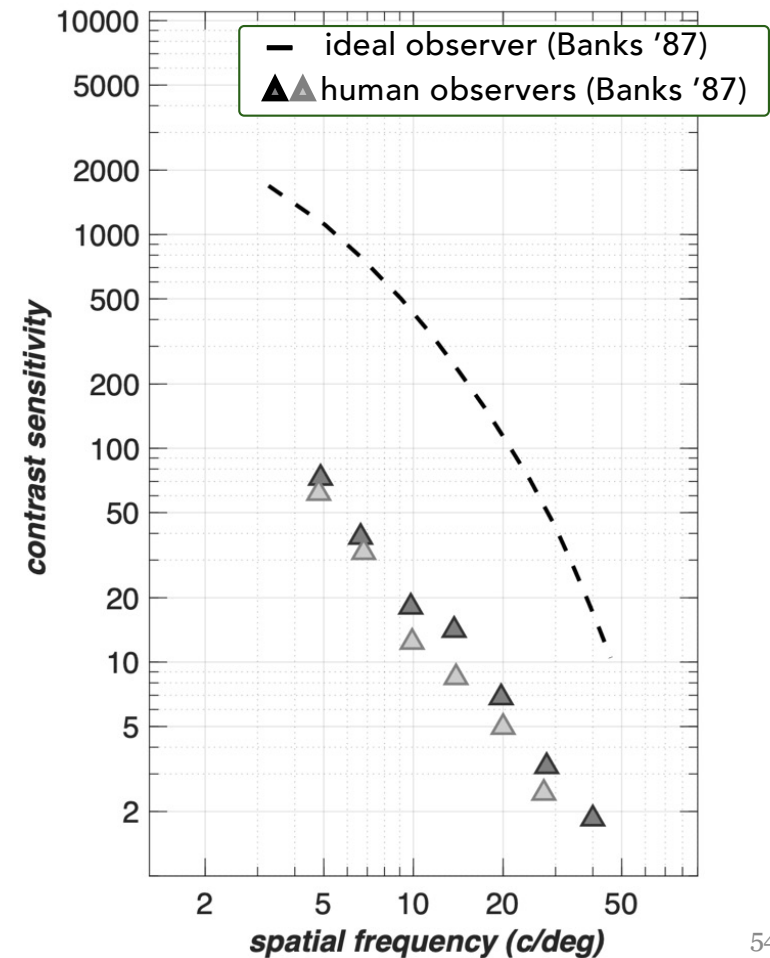
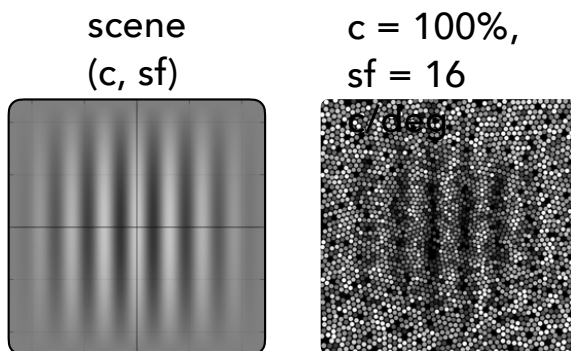
Putting it together: Analyzing the system spatial frequency contrast sensitivity

- The original work from Banks et al. (1987) compared the high frequency roll-off predicted using an ideal observer and measured with a few real observers
- The predictions were based on formulae and various simplifying assumptions about the mosaic



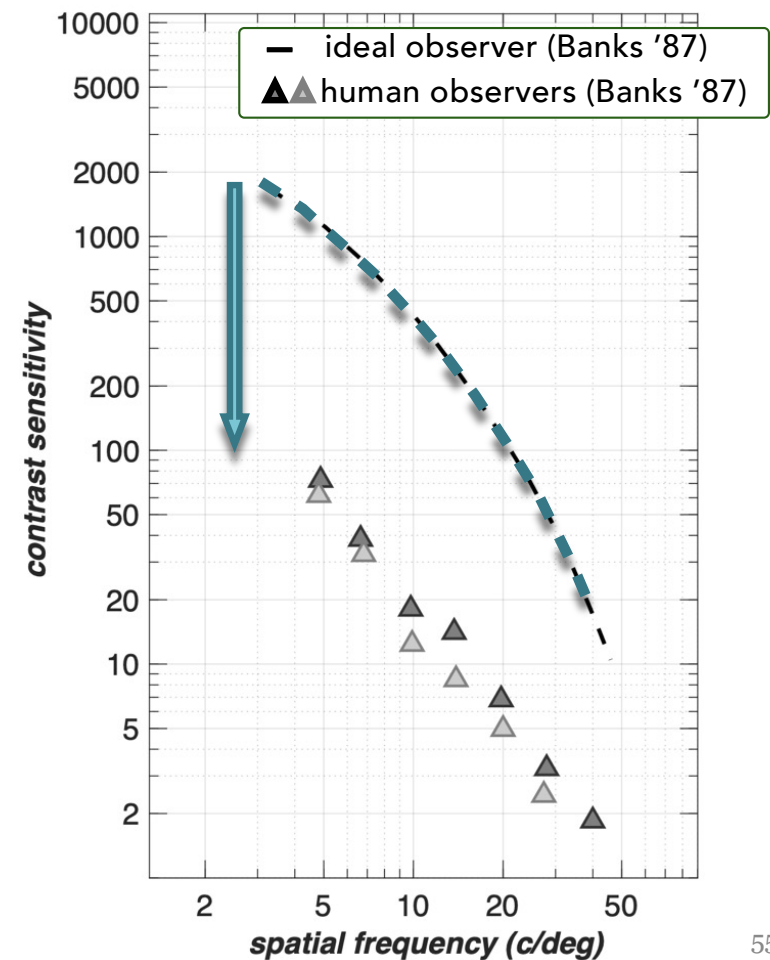
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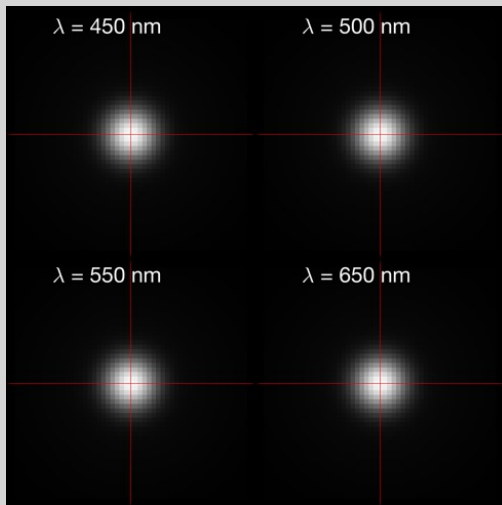
Ideal observer accounts for shape of CSF roll-off at increasing SF

- The original work from Banks et al. (1987) compared the high frequency roll-off predicted using an ideal observer and measured with a few real observers
- The predictions were based on formulae and various simplifying assumptions about the mosaic
- The shapes were in good alignment



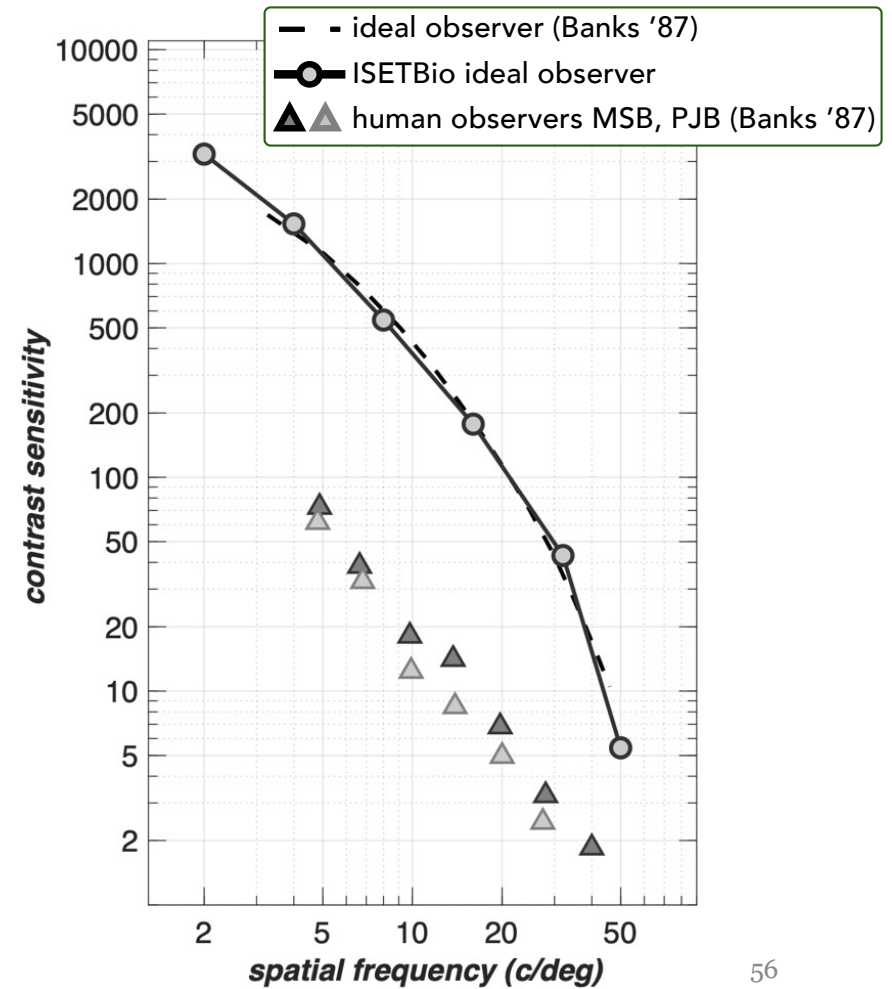
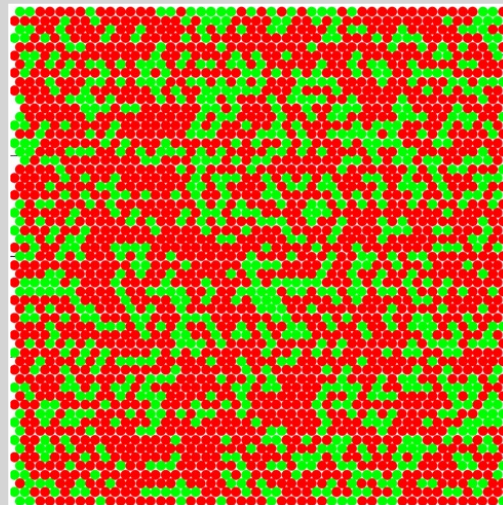
ISETBio validation: reproduce earlier ideal observer calculation

point spread function -
based optics



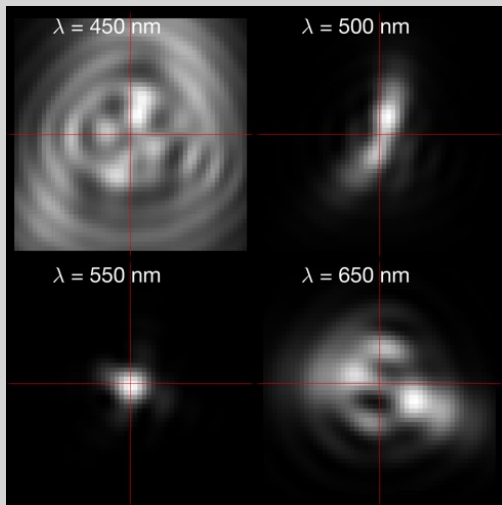
(based on Campbell & Gubisch '66)

constant cone
density mosaics



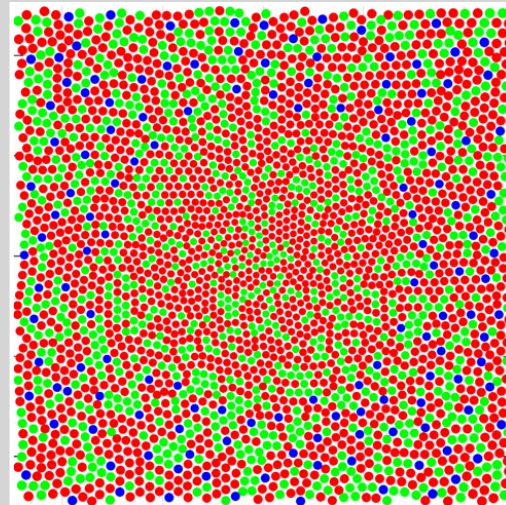
Accounting for absolute sensitivity: modern estimates of optics/mosaic

Wavefront aberration - based optics

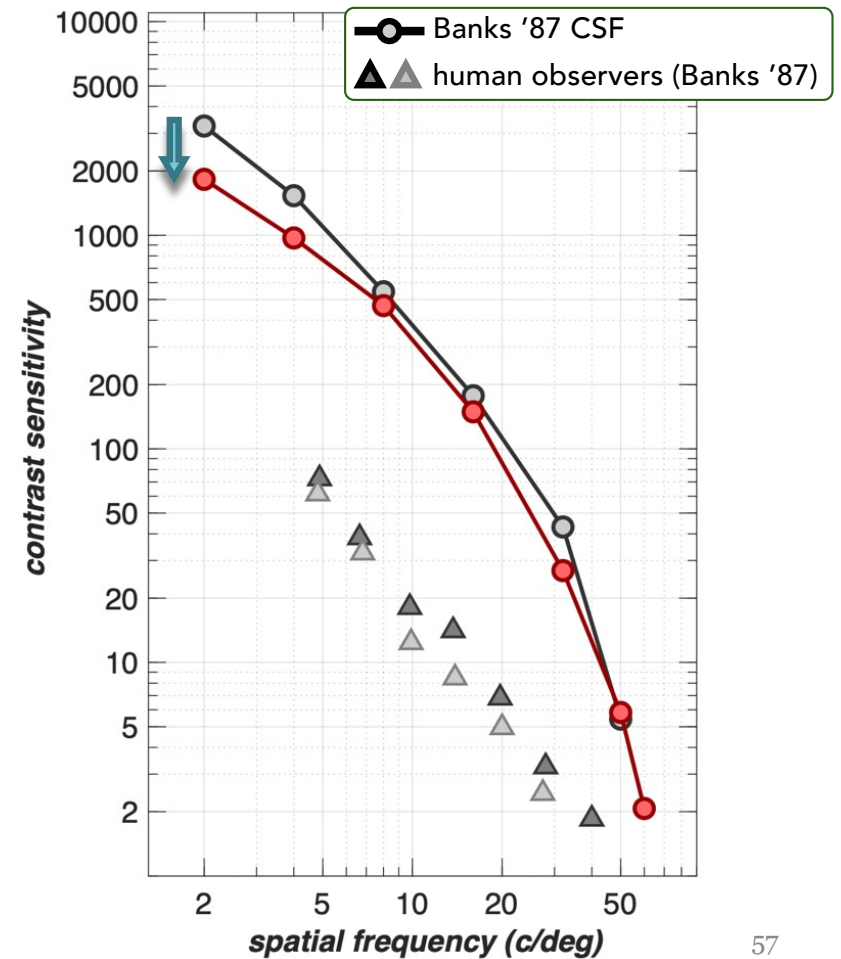


(from Thibos et al. '92)

Eccentricity-dependent density mosaics

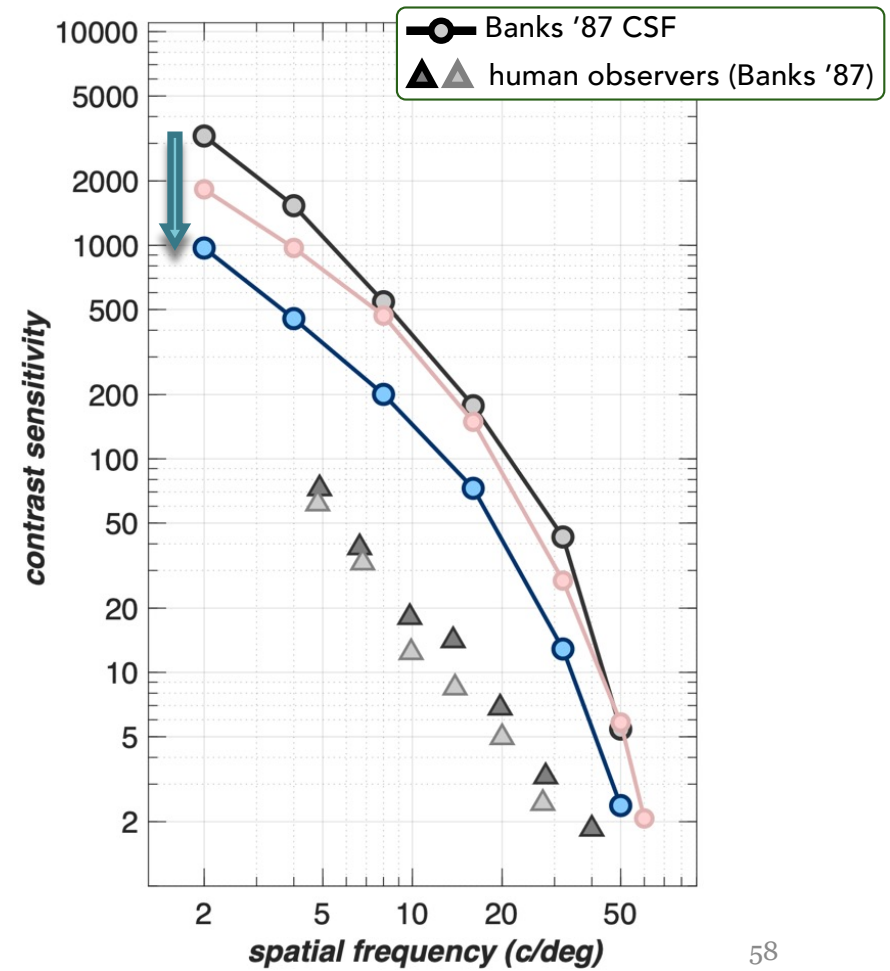
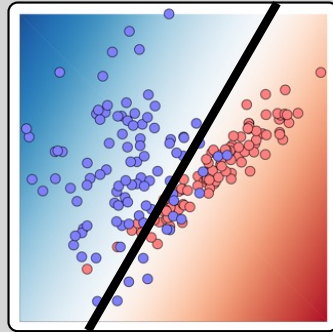
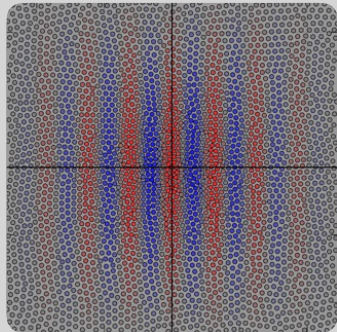
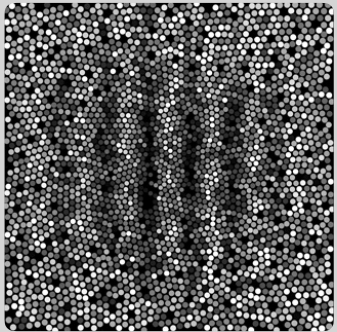


(based on Curcio et al. '90)

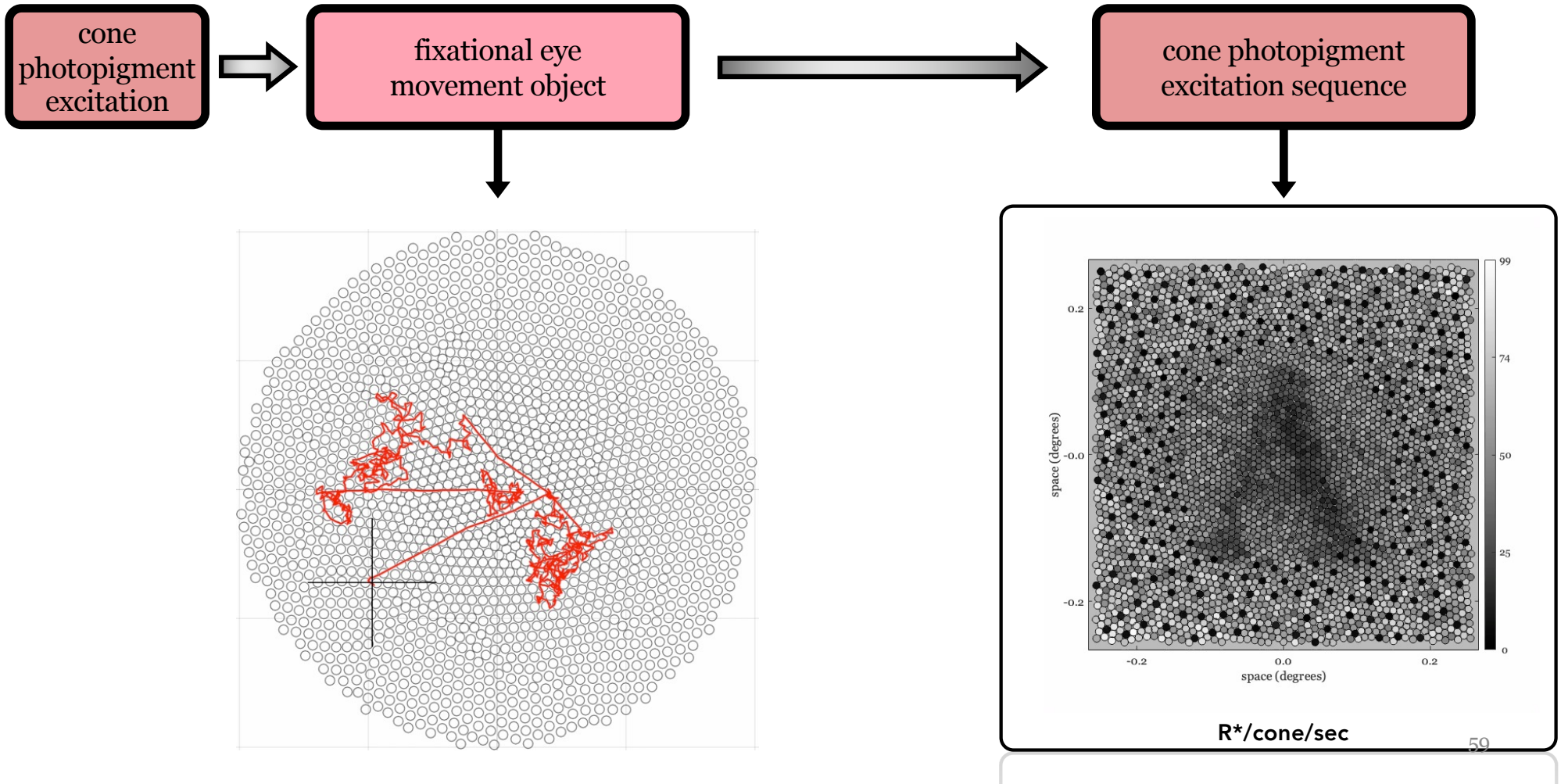


Accounting for absolute sensitivity: imperfectly learned classifier

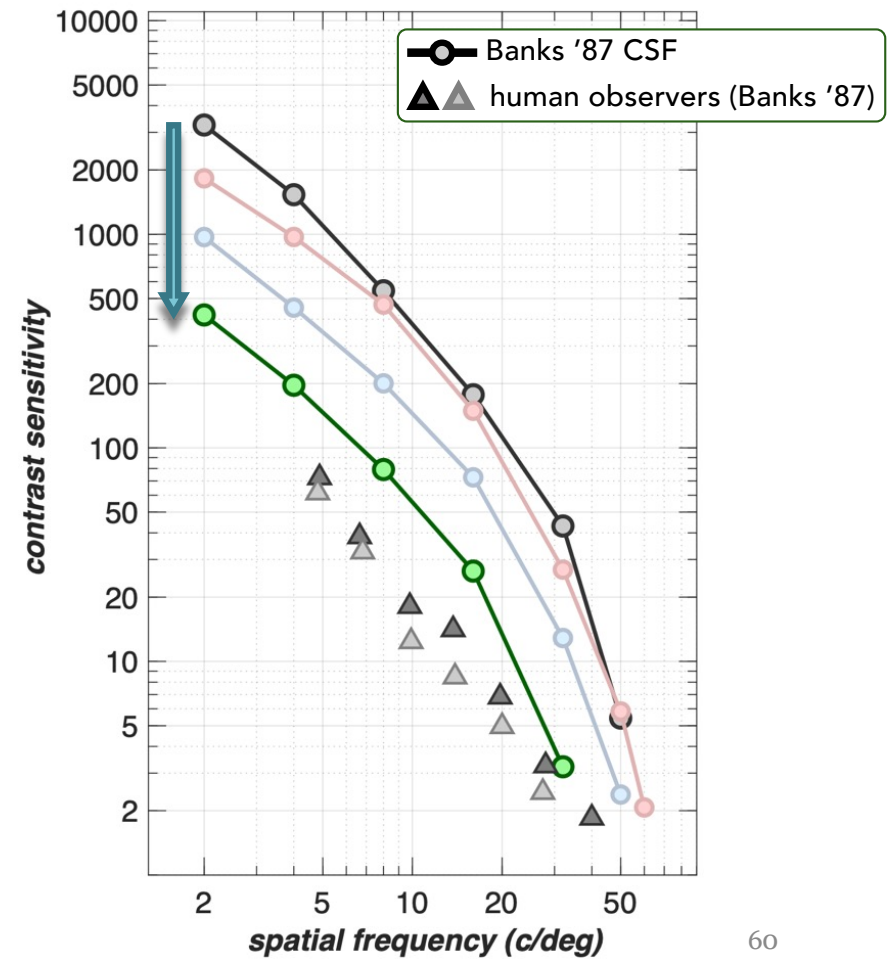
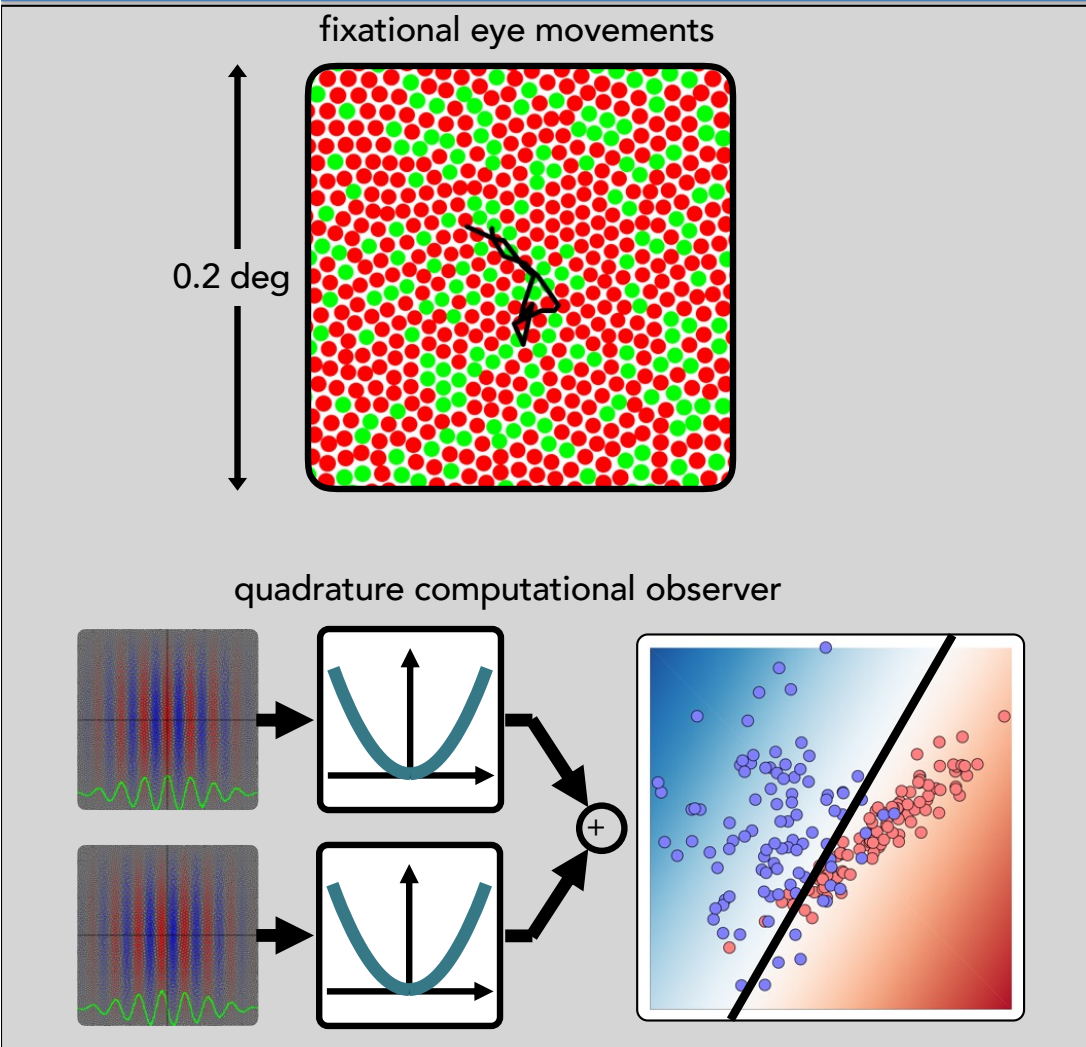
Computational observer: Support vector machine



Accounting for absolute sensitivity: fixational drift (Engbert and Kliegl, 2004)

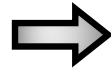


Energy computations (quadrature filters) reduce the impact of fixational drift

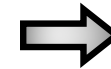


Time: Photocurrent transduction (Angueyra & Rieke, 2013)

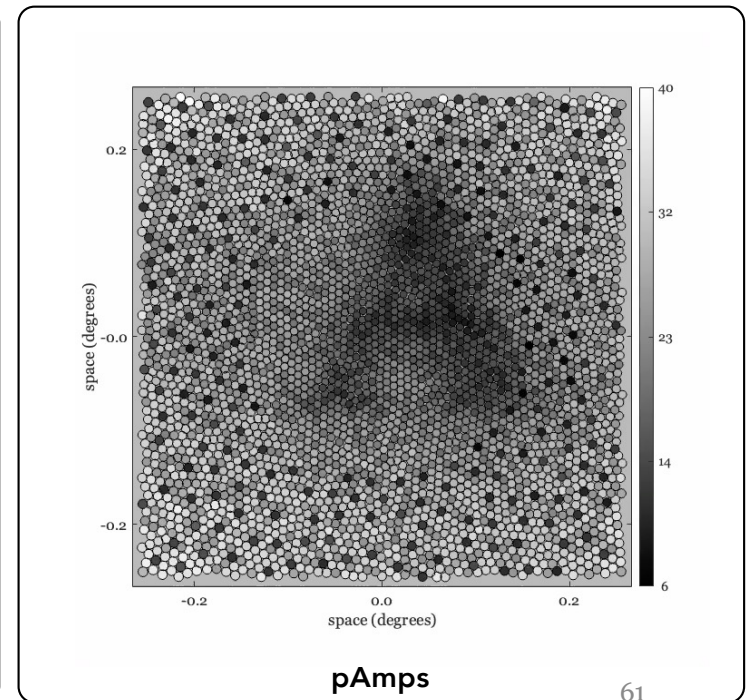
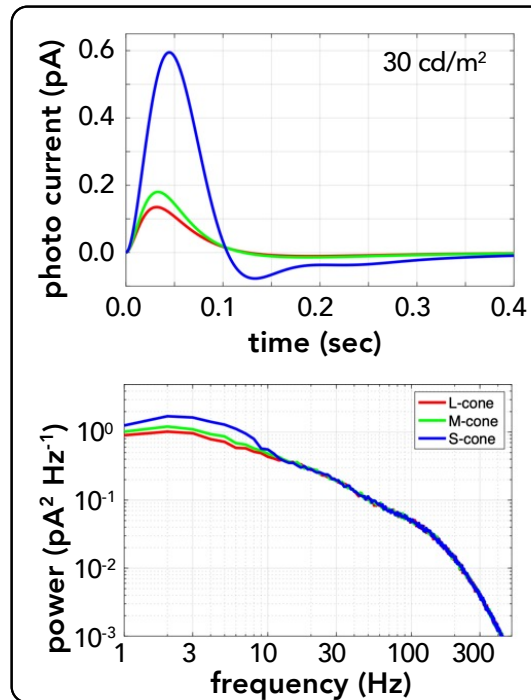
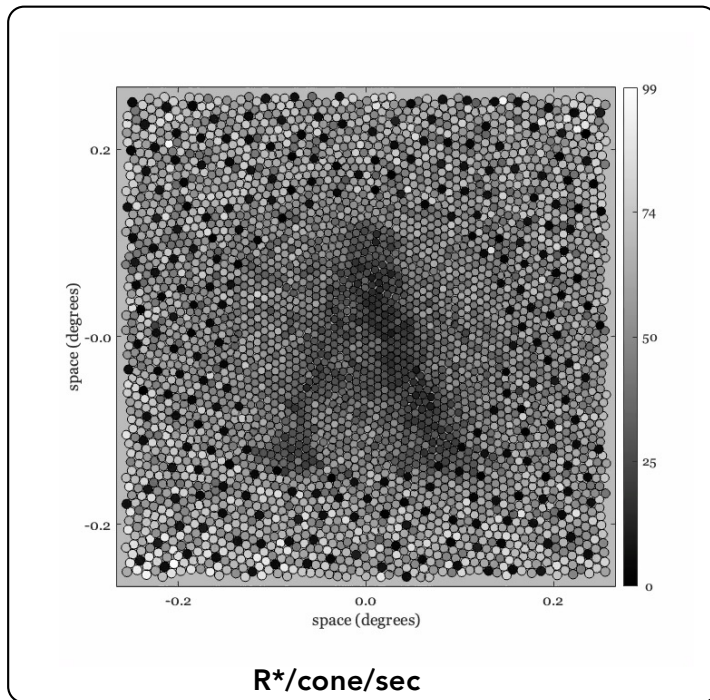
cone photopigment
excitation sequence



outer segment
object



cone outer-segment
photocurrent response



Accounting for absolute sensitivity: photocurrent transduction

1. **Updated optics & cone mosaic** modeling has a minor impact relative to the Banks '87 estimate (factor of 1.7 at 2 c/deg),
2. **Computational observers**, which learn visual tasks by observing neural responses, result in a significant sensitivity drop across the entire spatial frequency range (accumulated factor of 2-3).
3. Inclusion of **fixational eye movements**, requires non-linear computational observers, and further reduces sensitivity across the entire spatial frequency range (accumulated factor: 7-10).
4. Inclusion of **photocurrent encoding** further reduces sensitivity approaching psychophysical limits (accumulated factor: 18-30).

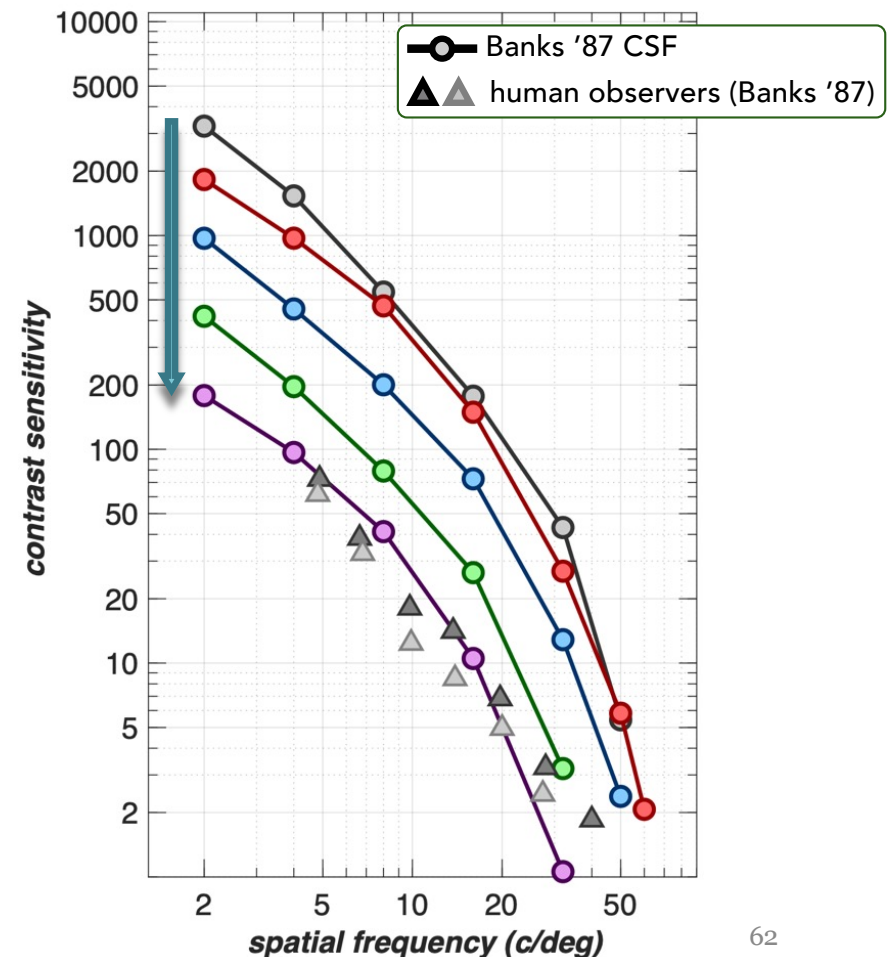
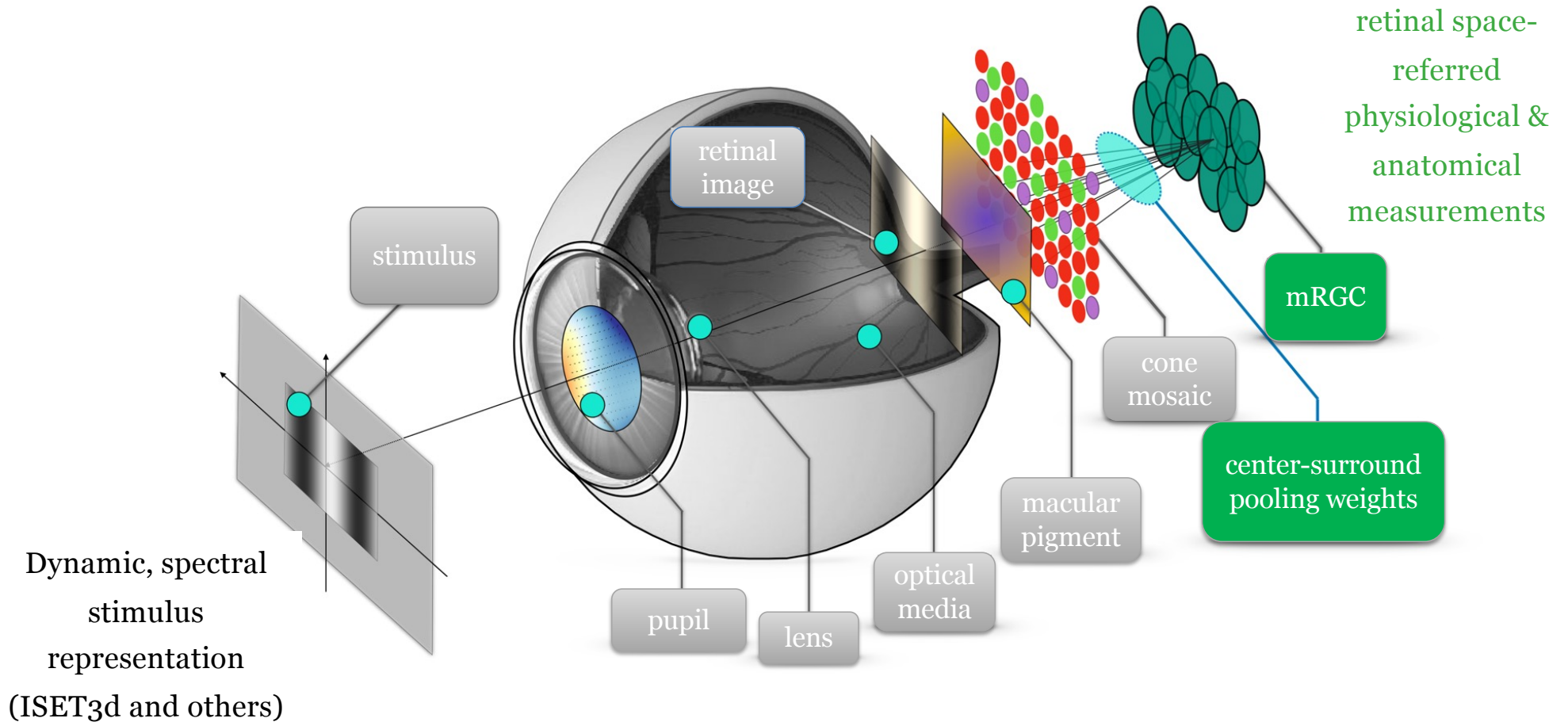


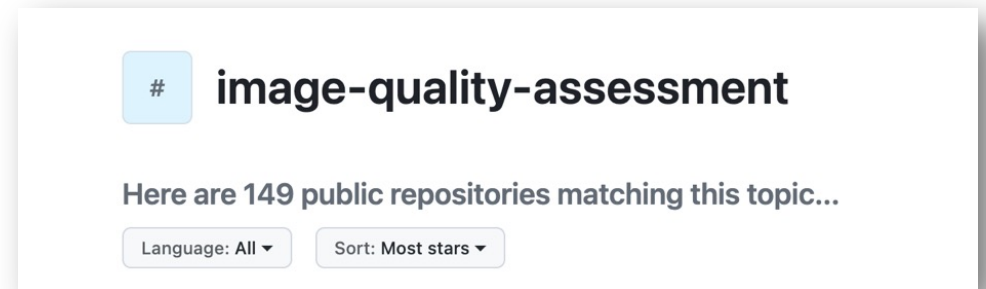
Image computable models of neural mosaics: mRGC



Motivation: Next generation image quality models

- Display design requires a model of the receiver, particularly for advanced displays
- Image quality metrics (SSIM, FSIM, Multiscale SSIM, LPIPS*, PSNR) all have an implicit human vision model
- There are many metrics, and we often fail to understand why they do or don't work
- Digital twinning of the human visual encoding provides a way to create a metric based on biological foundations; this will matter for display design decisions

<https://github.com/topics/image-quality-assessment>



LPIP

The Unreasonable Effectiveness of Deep Features as a Perceptual Metric

Richard Zhang¹ Phillip Isola^{1,2} Alexei A. Efros¹ Eli Shechtman³ Oliver Wang³
¹UC Berkeley ²OpenAI ³Adobe Research

*“agrees surprisingly well with humans”

Fourth point: Vision simulations

- Visual pathway simulations can clarify how multiple biological components combine and impact how we see
- These simulations may lead to well-grounded tools for image quality, useful in the design of displays

Simulation technologies for image systems engineering and biology

Brian A. Wandell

Stanford Center for Image Systems Engineering

Wu Tsai Neurosciences Institute
Stanford Center for Cognitive and
Neurobiological Imaging

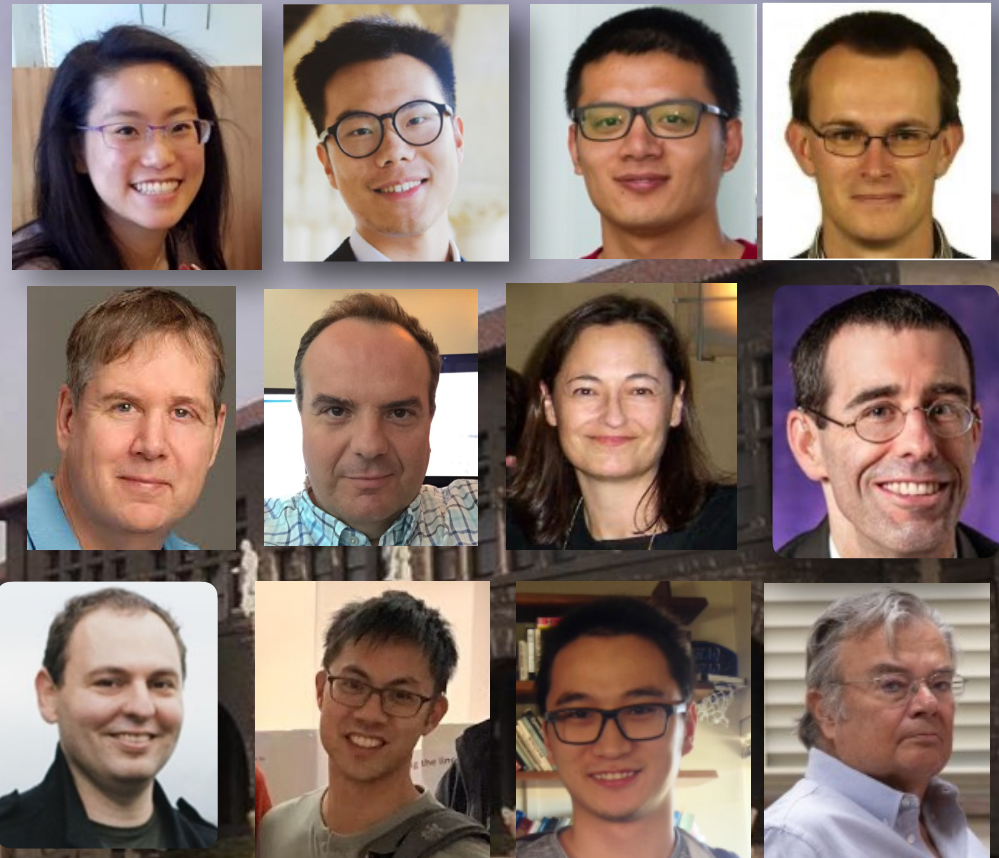
QUANTITATIVE MEASUREMENTS



COMPUTATIONAL MODELS



CHECK AND SHARE



Supported by the Simons Foundation, Facebook research