



THE UNIVERSITY OF
SYDNEY



ROBOTIC
IMAGING
LAB

Robotic Imaging: From Photons to Actions



ACFR
AUSTRALIAN CENTRE
FOR FIELD ROBOTICS

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RVSS
2024 · Feb · 09

Why don't objects appear dimmer as we move away from them?

Should we expect them to?

Yes, further = less energy into lens

Inverse square law

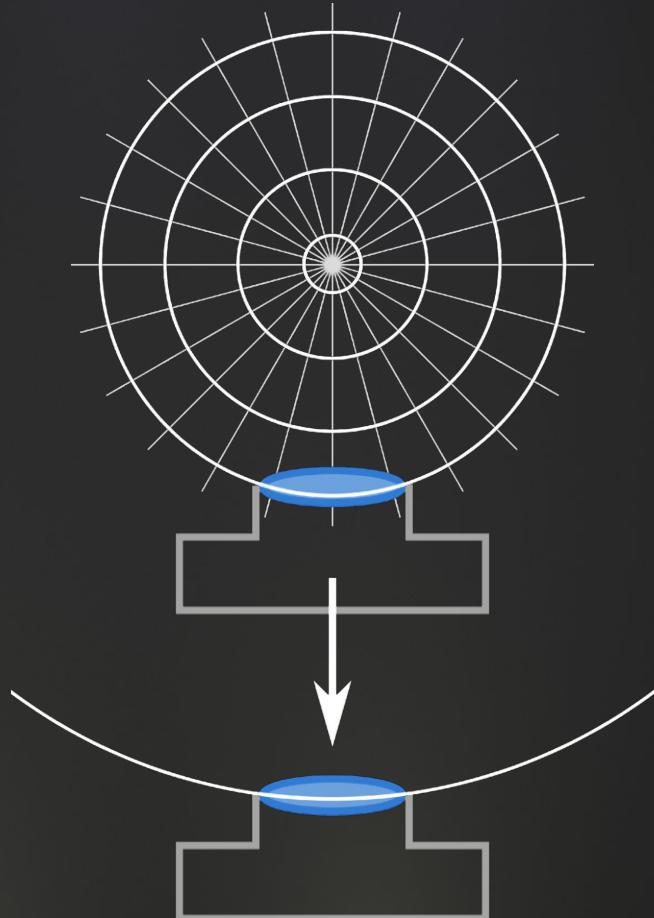
True for isotropic point sources

$$I \propto \frac{S}{\pi r^2}$$

I = measured intensity

S = lens area

r = distance to source



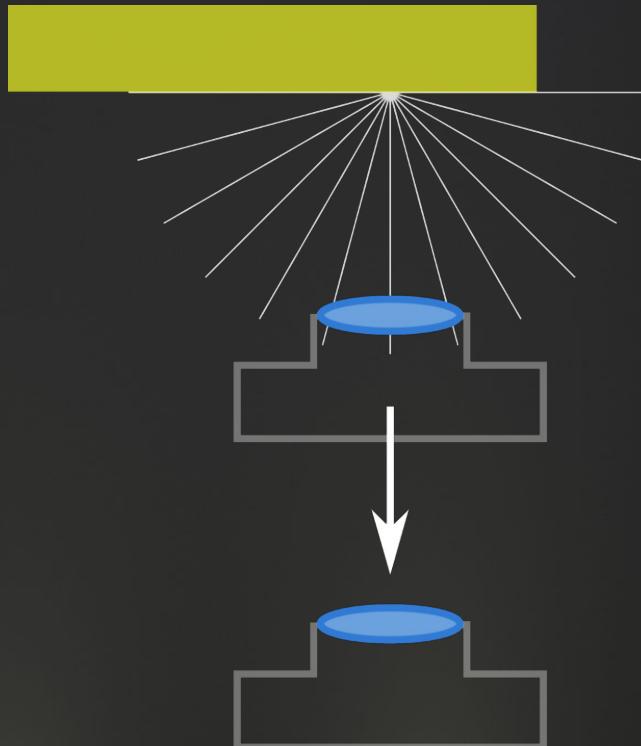
Surfaces are collections of points

Model surface as superposition of points

This doesn't help, still follows inverse square falloff

Hint: What have we missed about the scene?

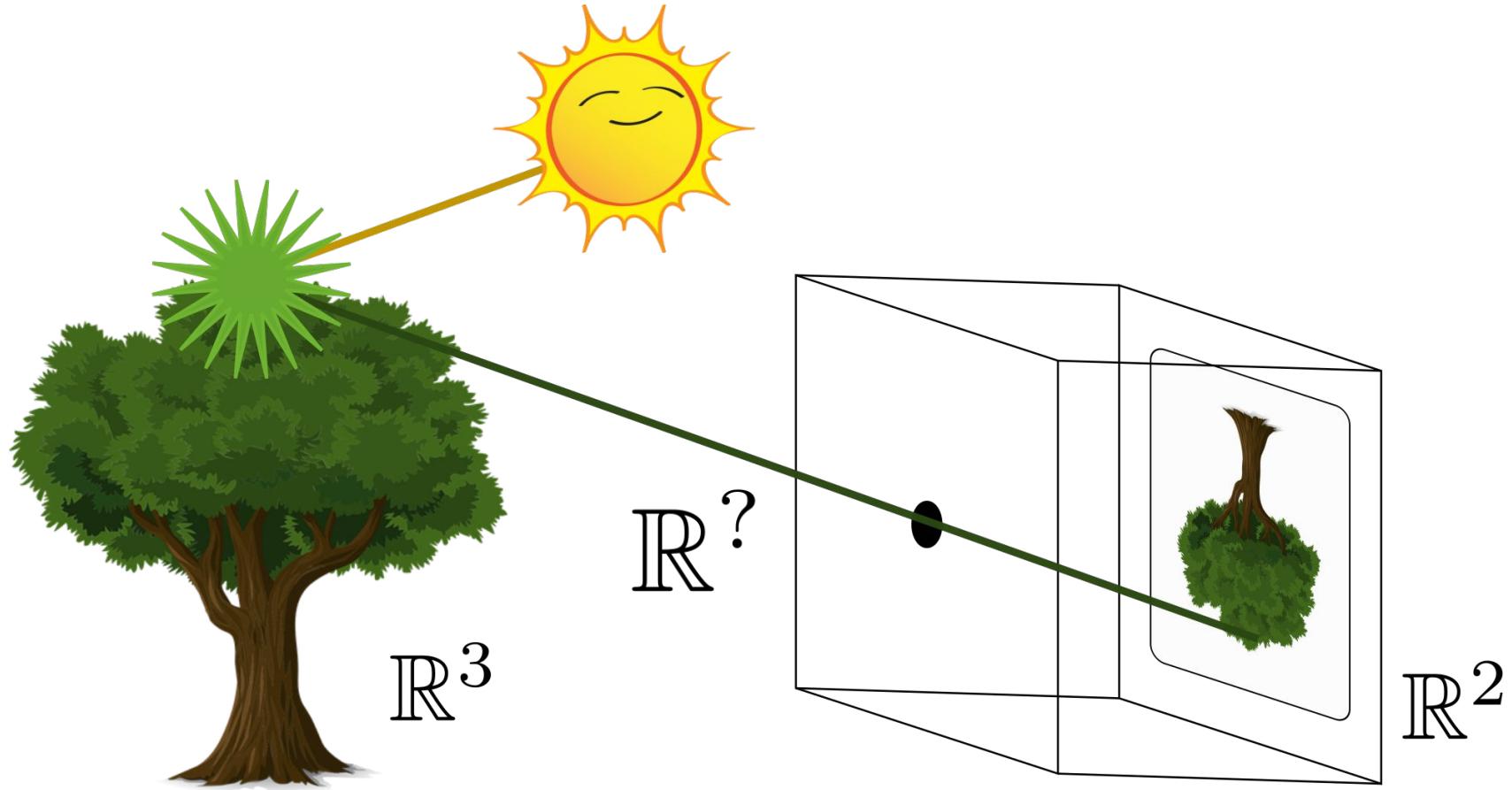
$$I \propto \frac{S}{\pi r^2}$$



Today's Talk

1. Designing a camera for robots
2. Automating integration of new cameras
3. Making the most of existing cameras
4. Emerging challenges

What Do Cameras Measure?



Light as a Field



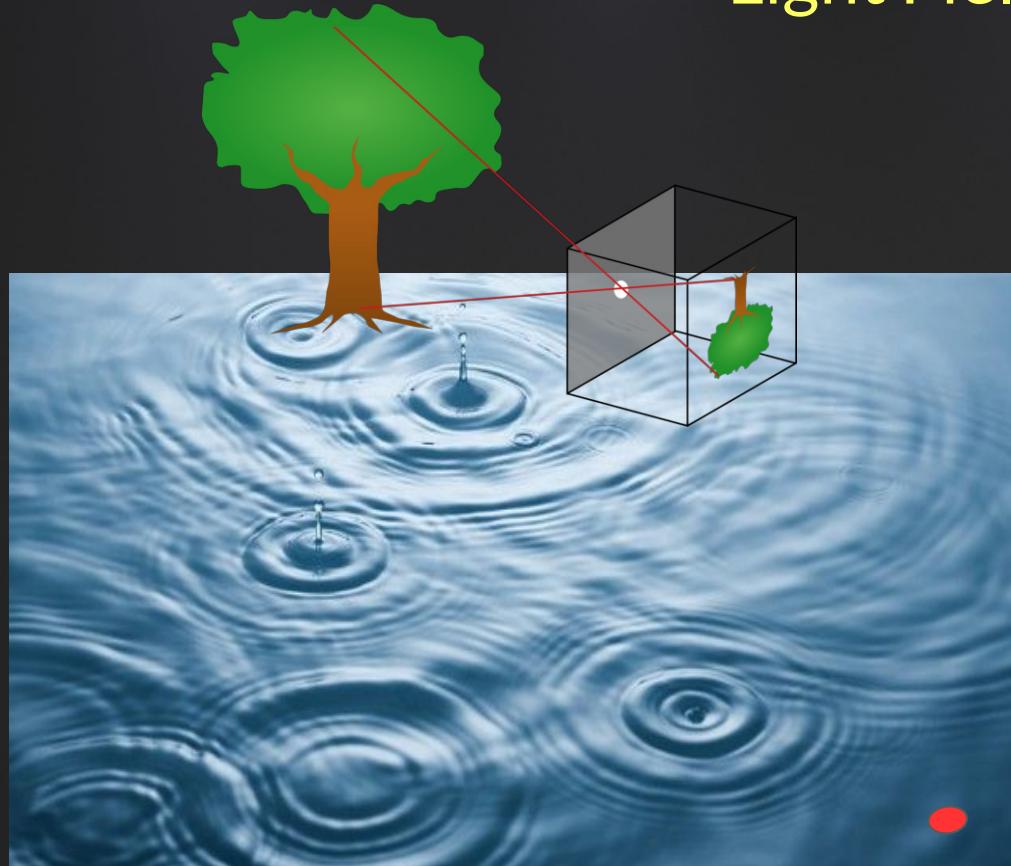
Cameras sample from a *field of light*

Caused by matter / photon interactions *in the scene*

Cameras measure light *at the lens*

An analogy: measuring ripple height at some point in a pond
We measure the ripples, not the drops

Light Field Cameras



Cameras measure waves arriving *at a point*



Light field cameras measure waves arriving *at a surface*

Light Field as Subset of Plenoptic Function

Plenoptic Function $\mathcal{L}(.)$

Position x,y,z

Direction u,v

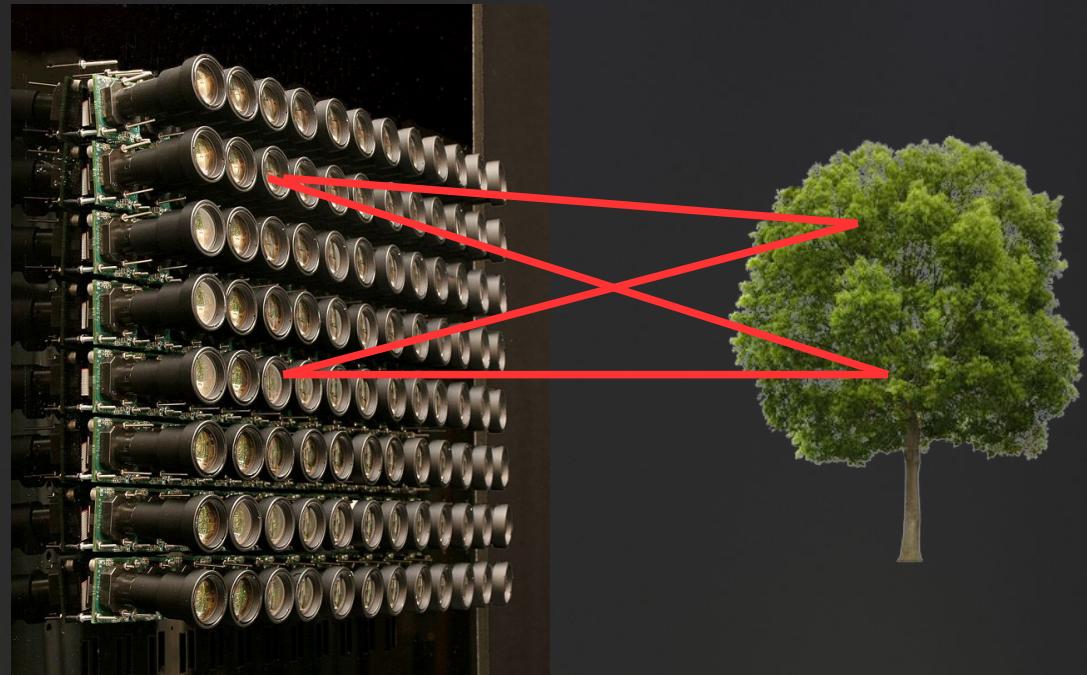
Time

Wavelength

Polarization

Camera: $\mathcal{L}(u,v)$

NeRF: $\mathcal{L}(x,y,z, u,v)$



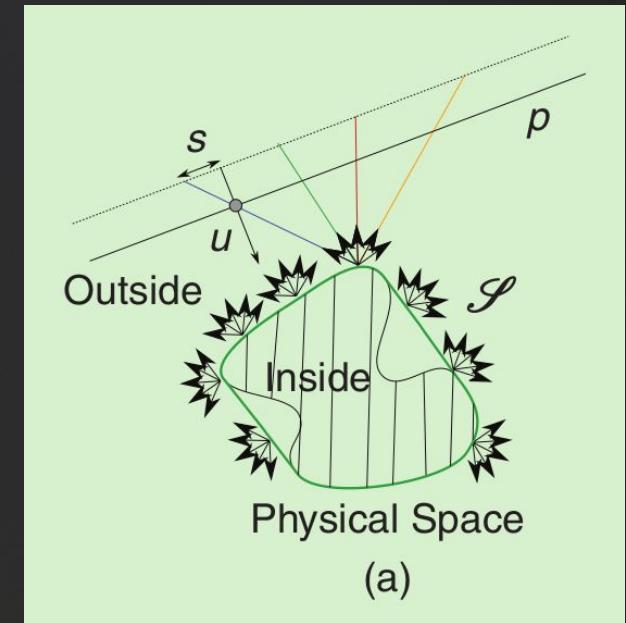
Light Field: $\mathcal{L}(x,y, u,v)$

4D is a Sweet Spot for Light Rays

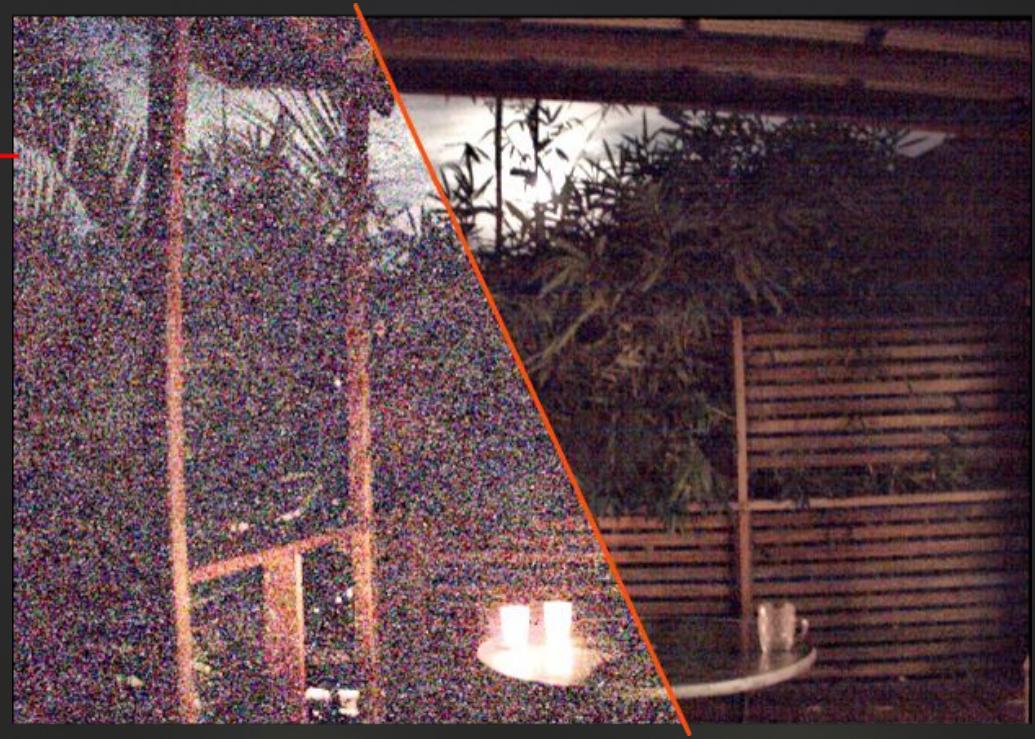


Complete description of light in a volume
1D less than the obvious 5D

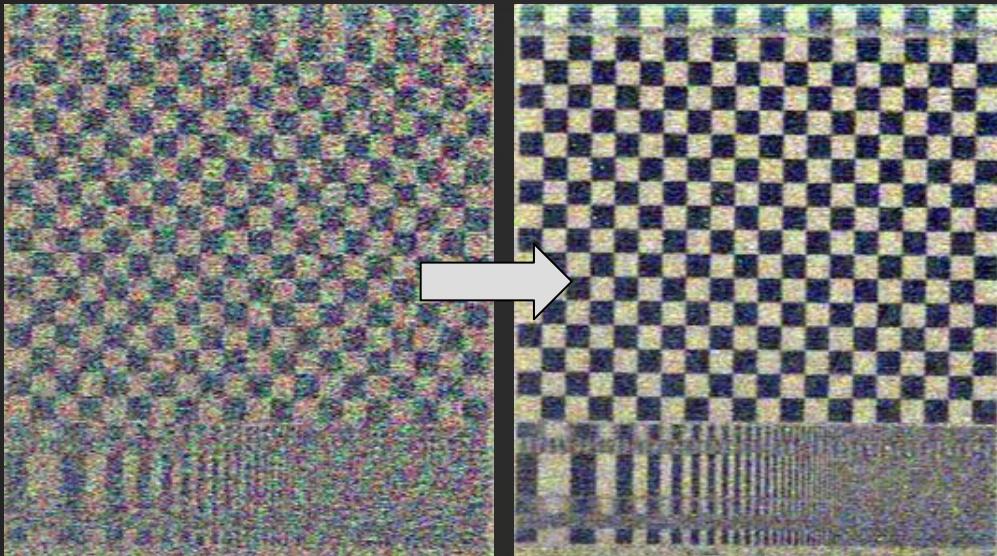
Assumes : non-participating medium,
Viewers remain outside the volume



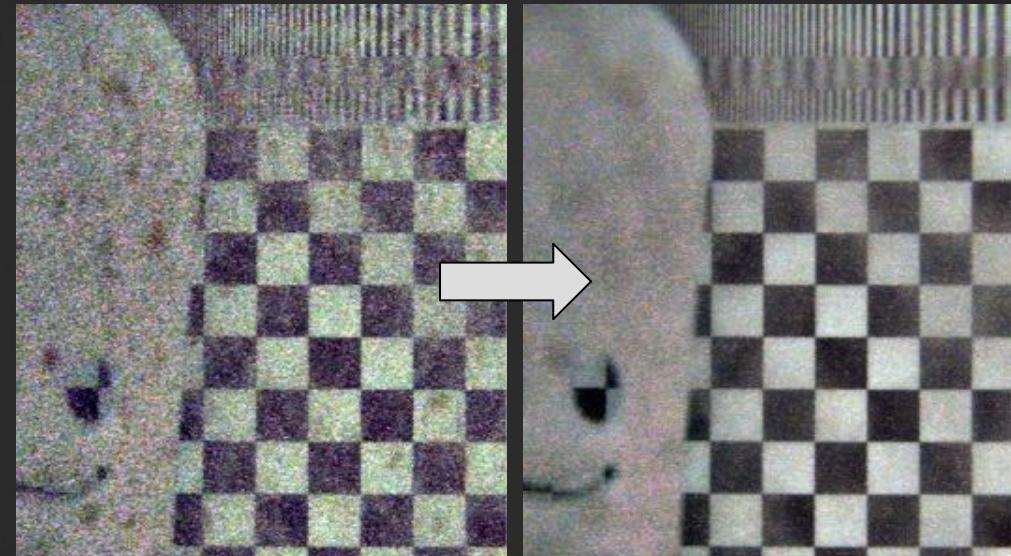
Light Field Capabilities: Seeing in the Dark



Seeing through Haze and Around Particulate

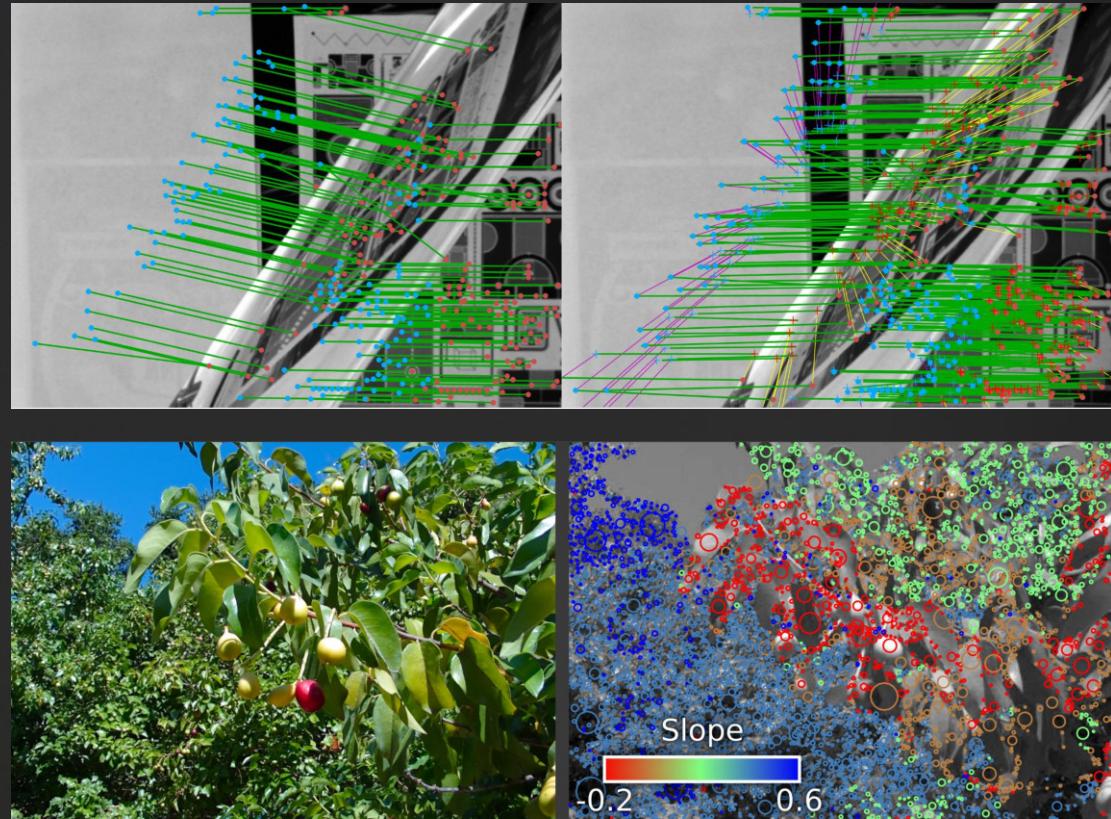


Backscatter (noise-limited)

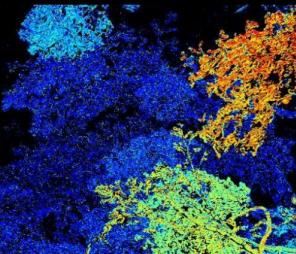
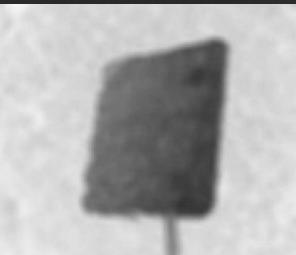


Particulate / occluders

Native Transparency and Dense Structures

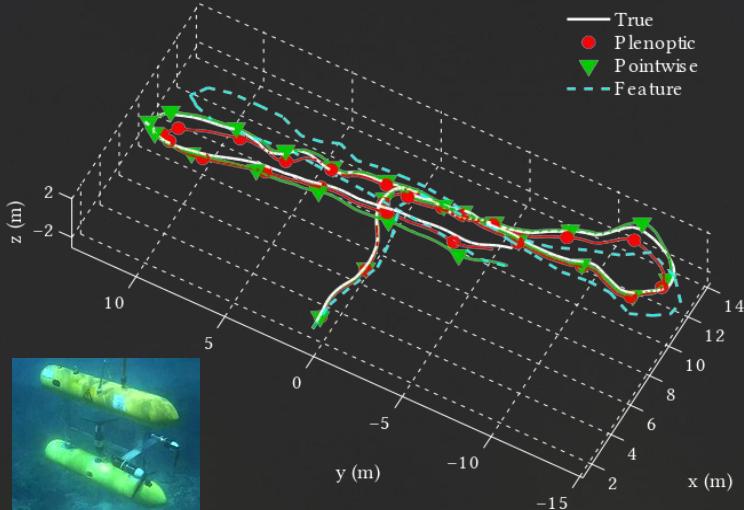


3D is Easier in 4D



Fast Depth Estimation

[dansereau2004]



Fast 6D Motion Estimation

[dansereau2011]



Fast 3D Change Detection

[dansereau2015]

Designing a Camera for Robots: Wide-FOV LF Camera

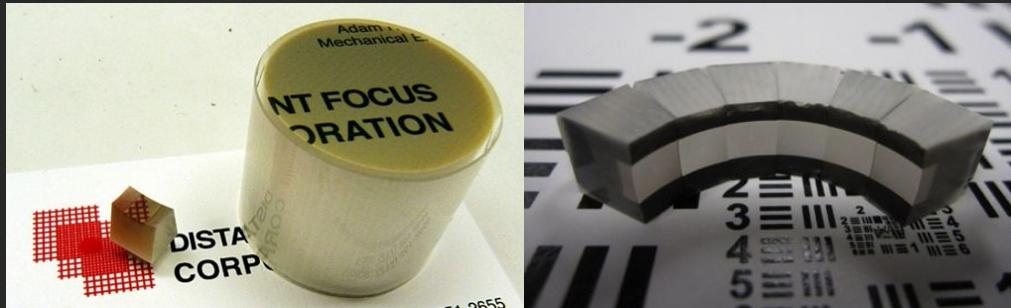
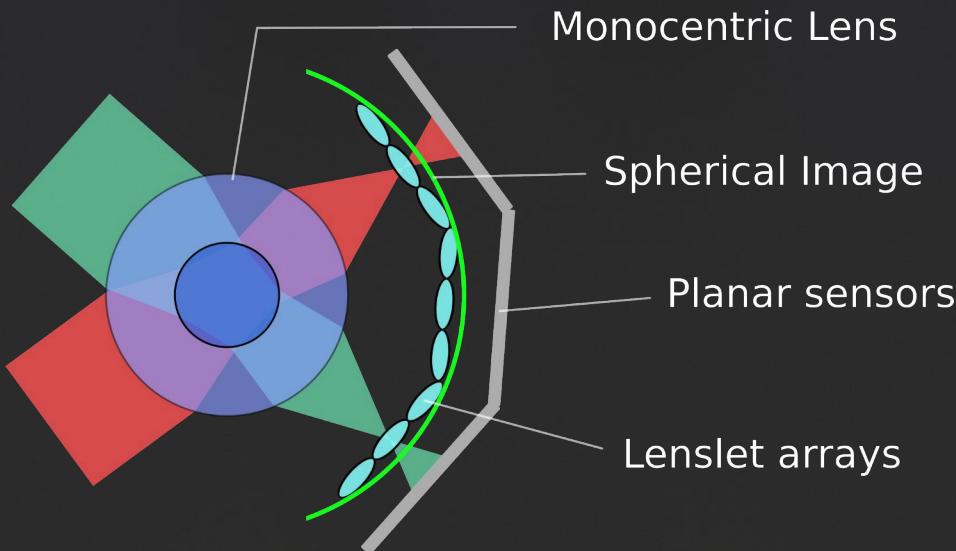
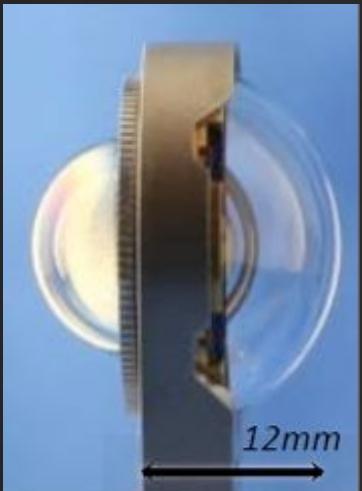
Gordon Wetzstein
Joseph Ford
Glenn Schuster

OpEx 2019
CVPR 2017

Low-latency, low-power, hardware-friendly vision

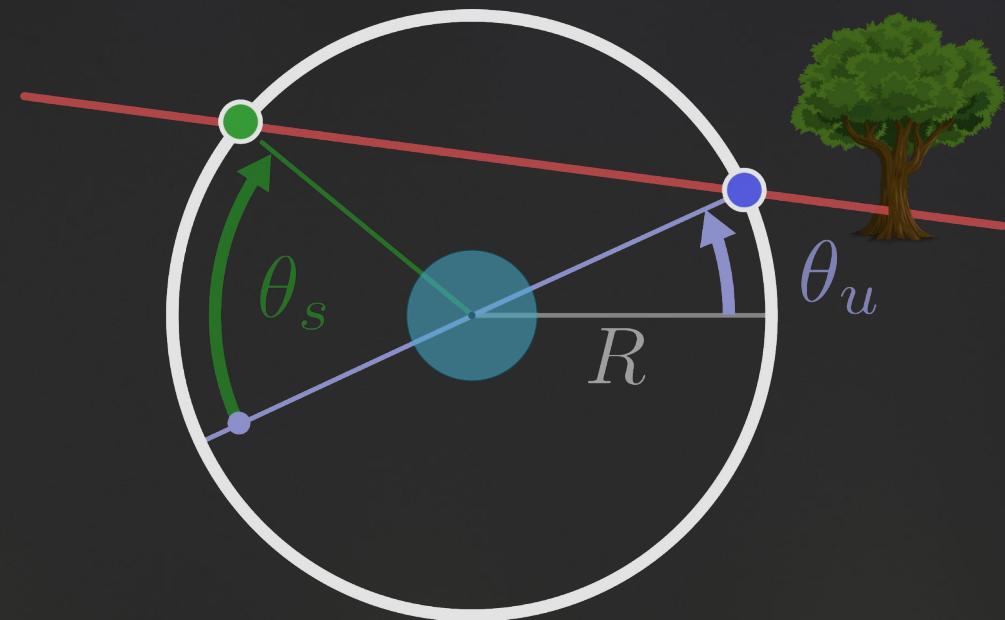
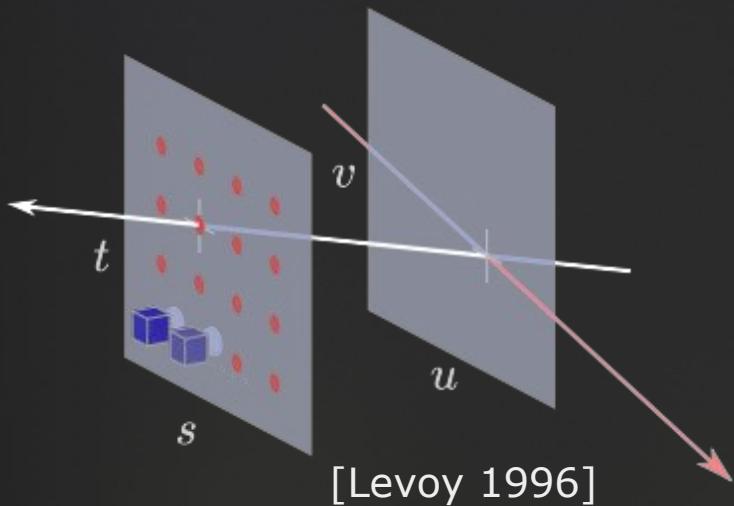


Monocentric-Lens LF Camera



Fiber Bundles
→ Replace with LF processing

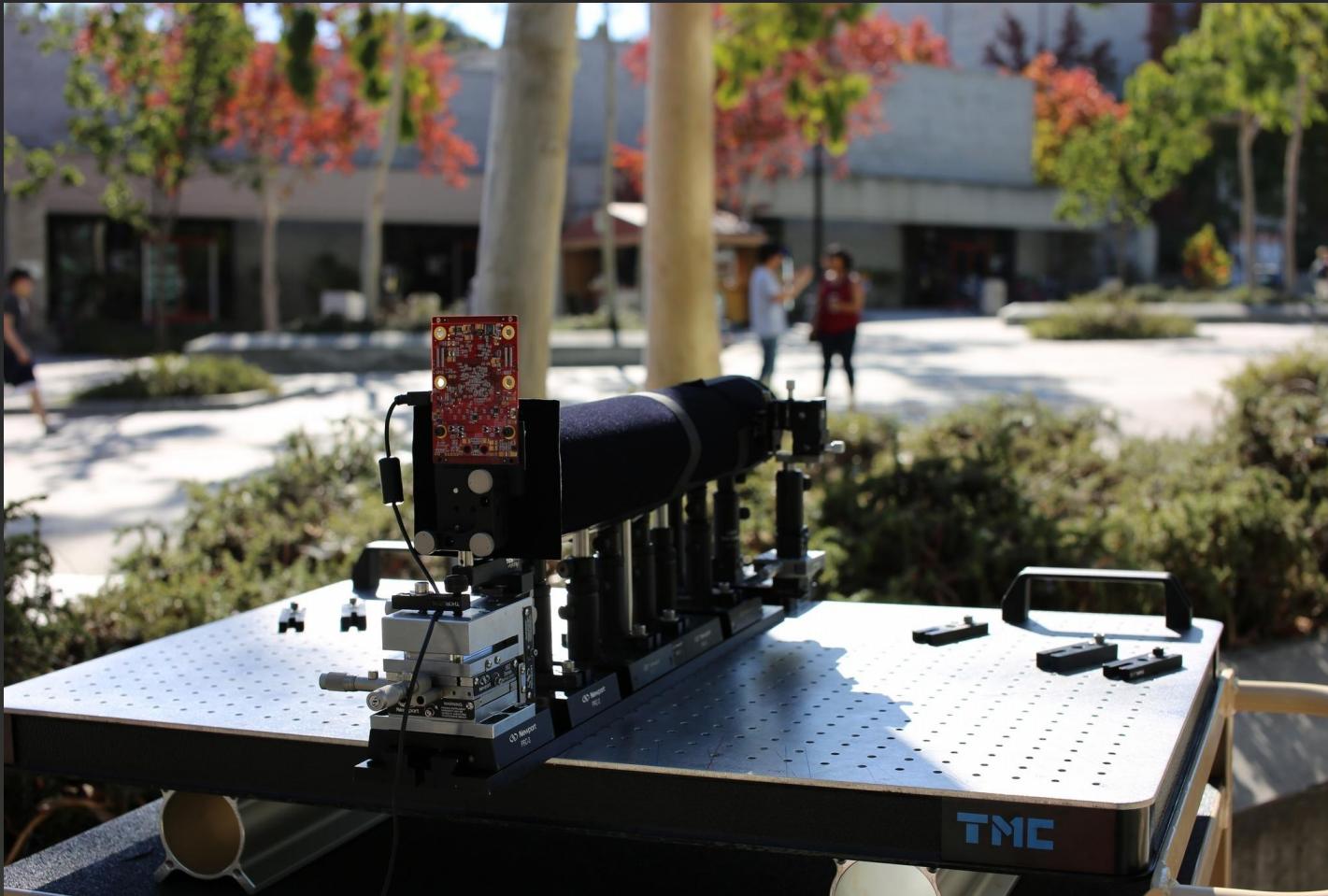
Spherical Parameterization



$R = \text{foc dist}$

Locally 2pp-compatible
Existing tools work!

1st Prototype



Panoramas



$15 \times 15 \times 1600 \times 200$ (72 MPix) 138° FOV

Refocus:



Panoramas

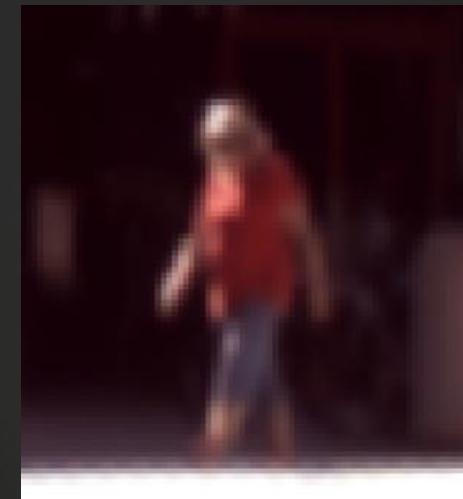


$15 \times 15 \times 1600 \times 200$ (72 MPix) 138° FOV

Refocus:



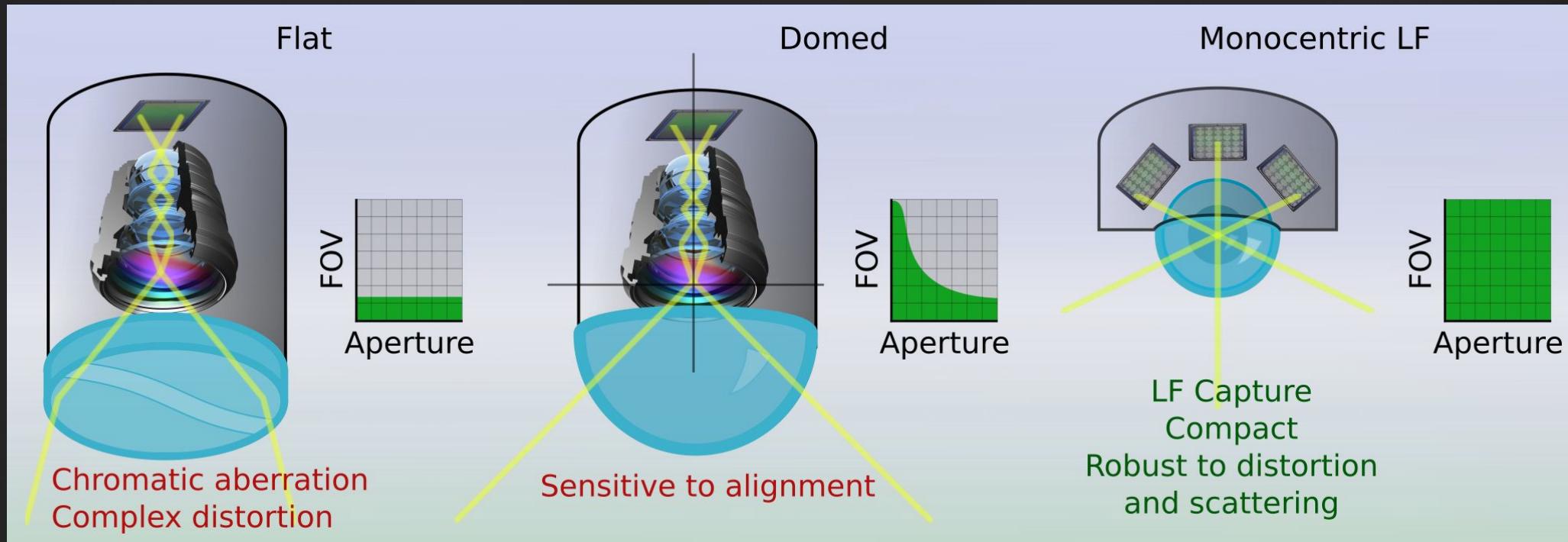
Super-resolution:



Compact Prototype



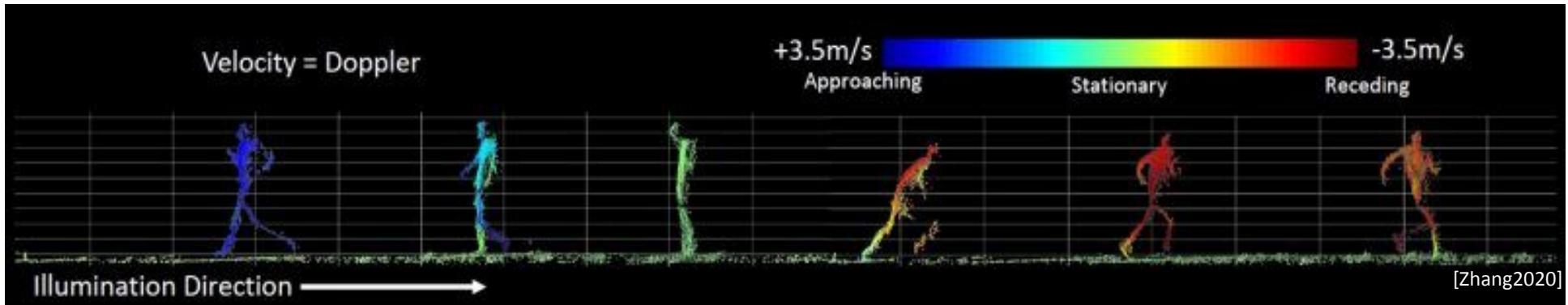
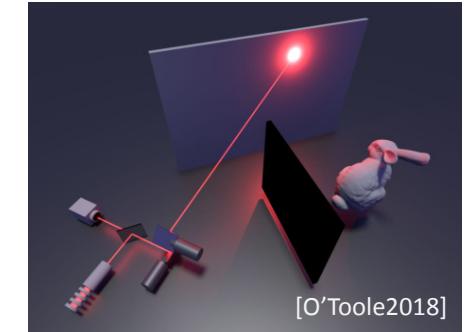
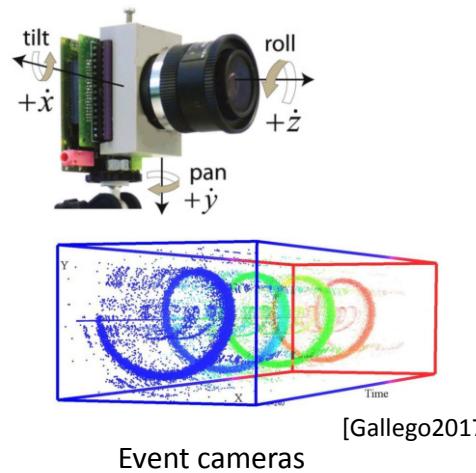
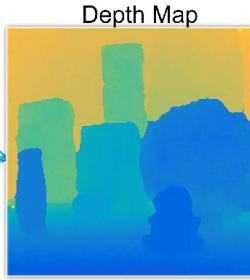
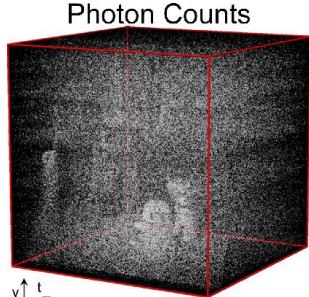
Next Steps: Underwater



Today's Talk

1. Designing a camera for robots
2. **Automating integration of new cameras**
3. Making the most of existing cameras
4. Emerging challenges

New Cameras = New Ways of Seeing, But...



Automating Integration of New Cameras

[Teja Digumarti
Joe Daniel
Avie Ravendran
Ryan Griffiths
Jack Naylor
ICRA 2023
IROS 2021]

IROS 2021 : Odometry and 3D from LF cameras



Lenslet-based cameras



[K|Lens]



[Bajpayee2018]

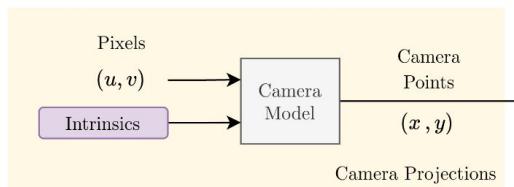


[EPIImaging LLC]



[Pelican Imaging]

ICRA 2023: Automating calibration “NOCaL”



Data-driven
freeform distortion model

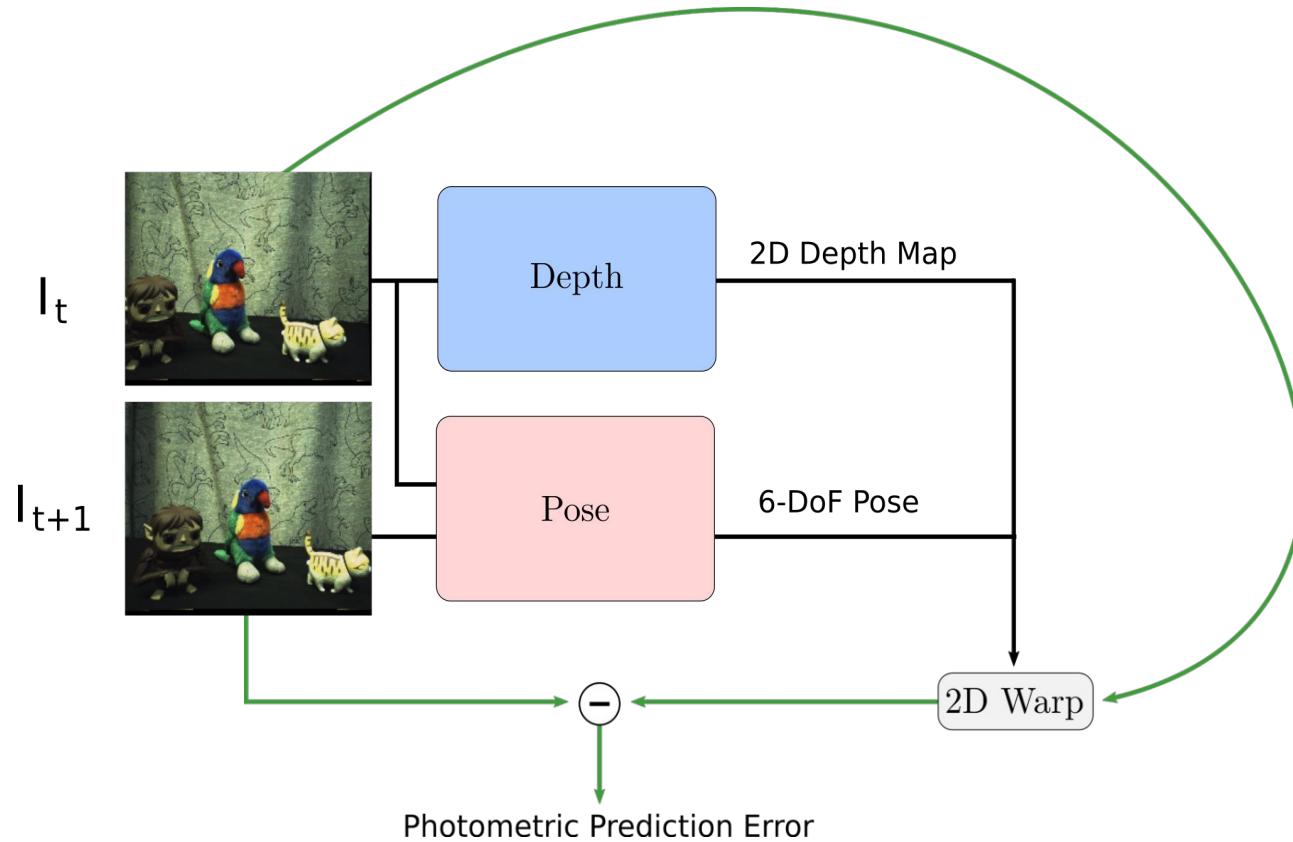


Odometry



Novel View Synthesis

Prediction as Supervisory Signal



[Zhou2017] : Prediction as supervision

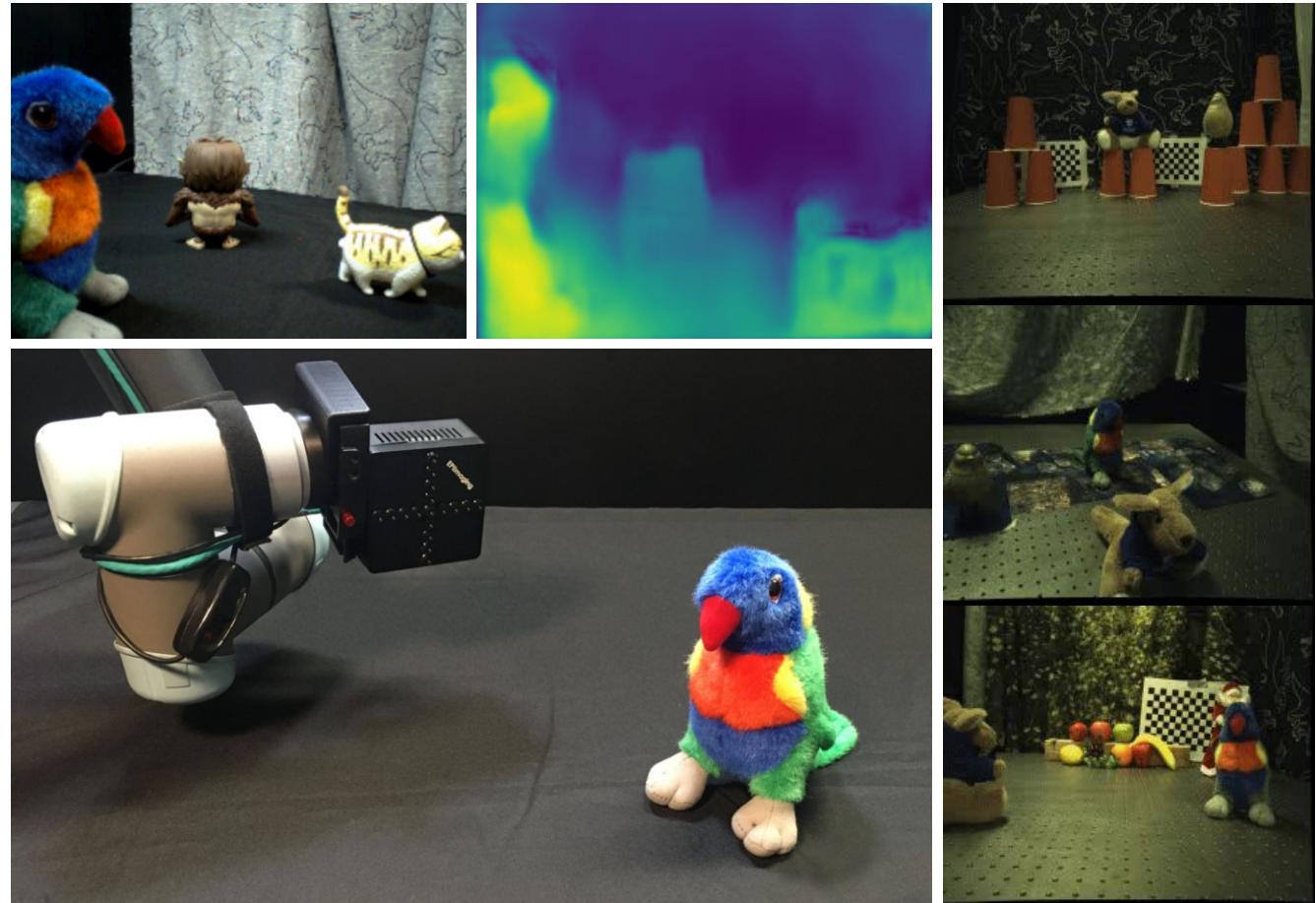
[Zhan2018, Dharmasiri2018] : Learning from Stereo

Adapting to Sparse Light Field Cameras

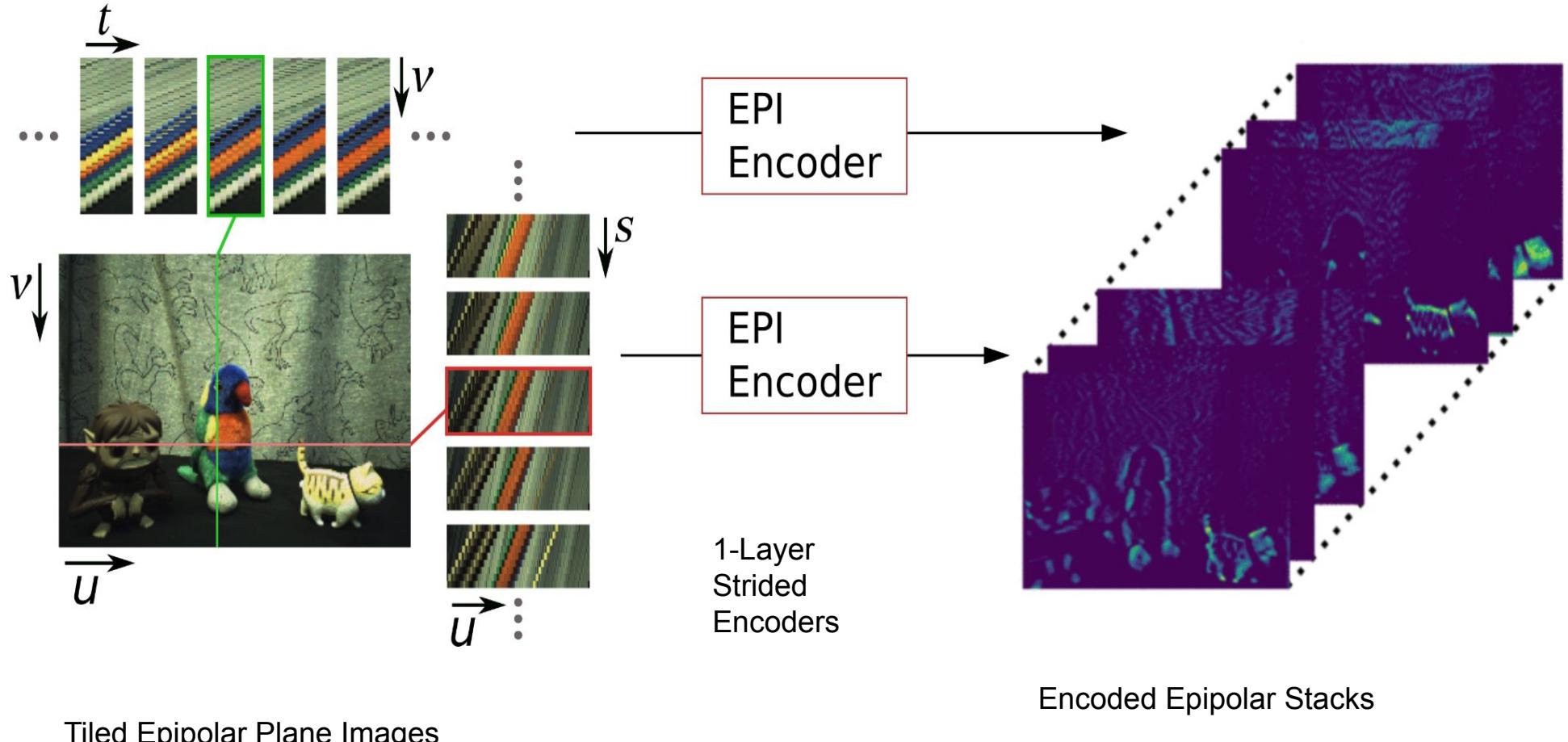
RoboticImaging.org/Projects/LearnLFOdo/



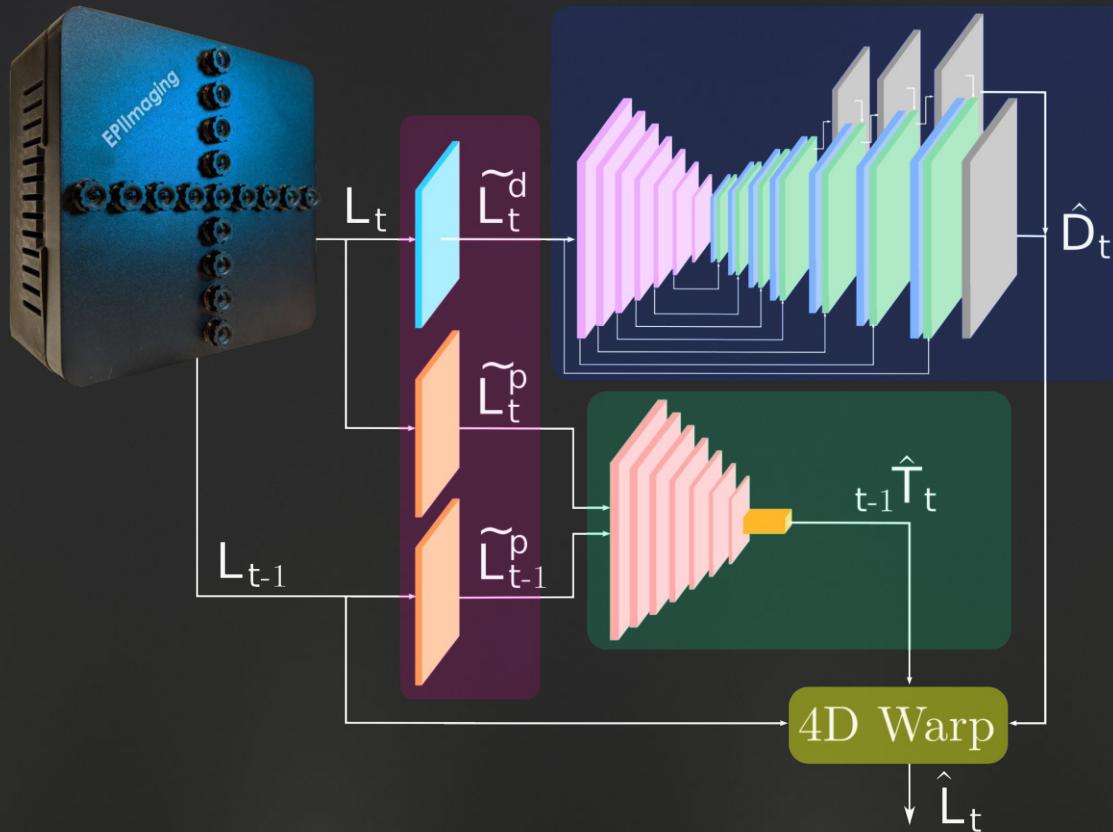
Sparse LF Video
8298 x 17-views
Arm-mounted



A General LF Encoder

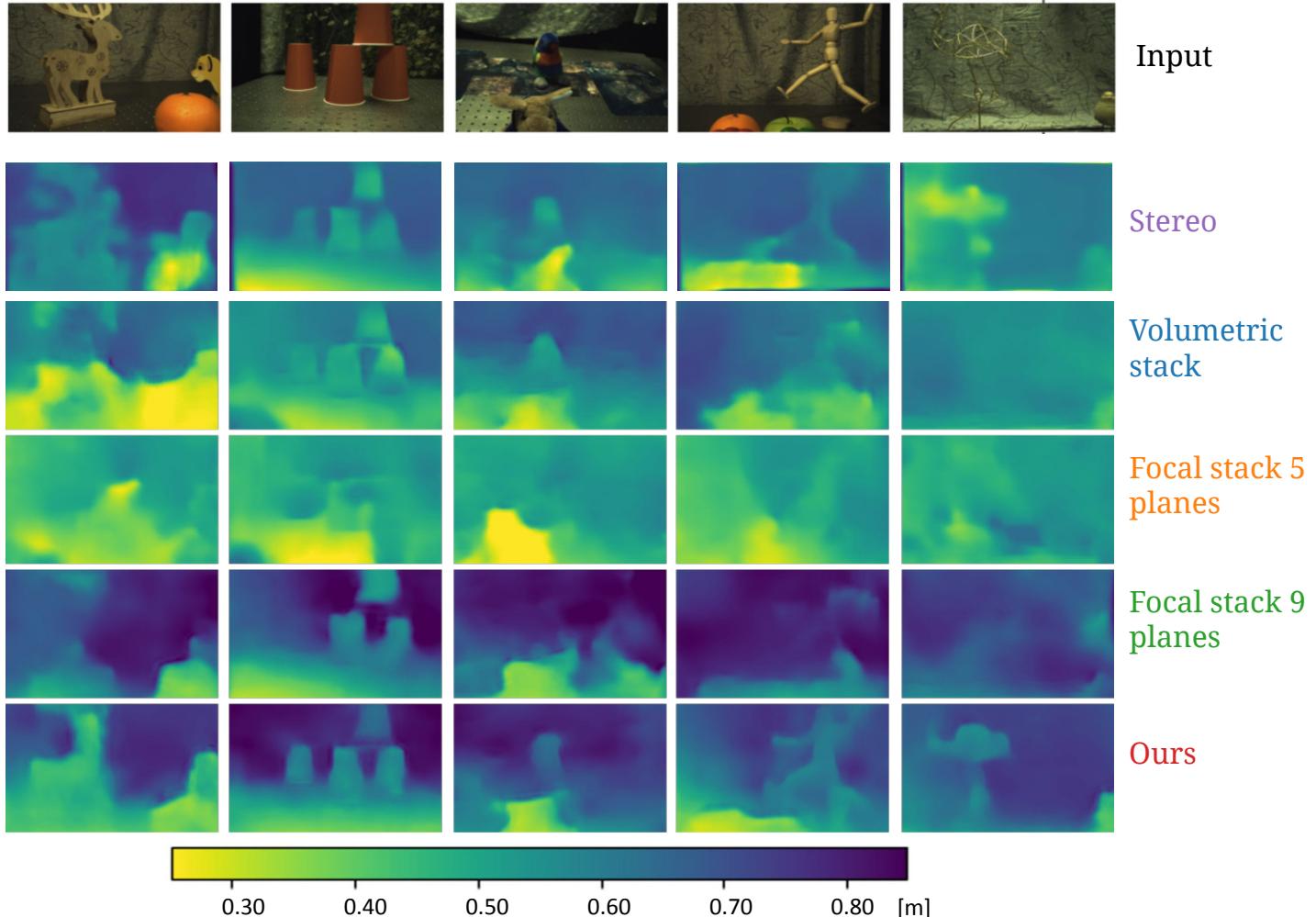


Self-Supervised Odometry and Depth



Results

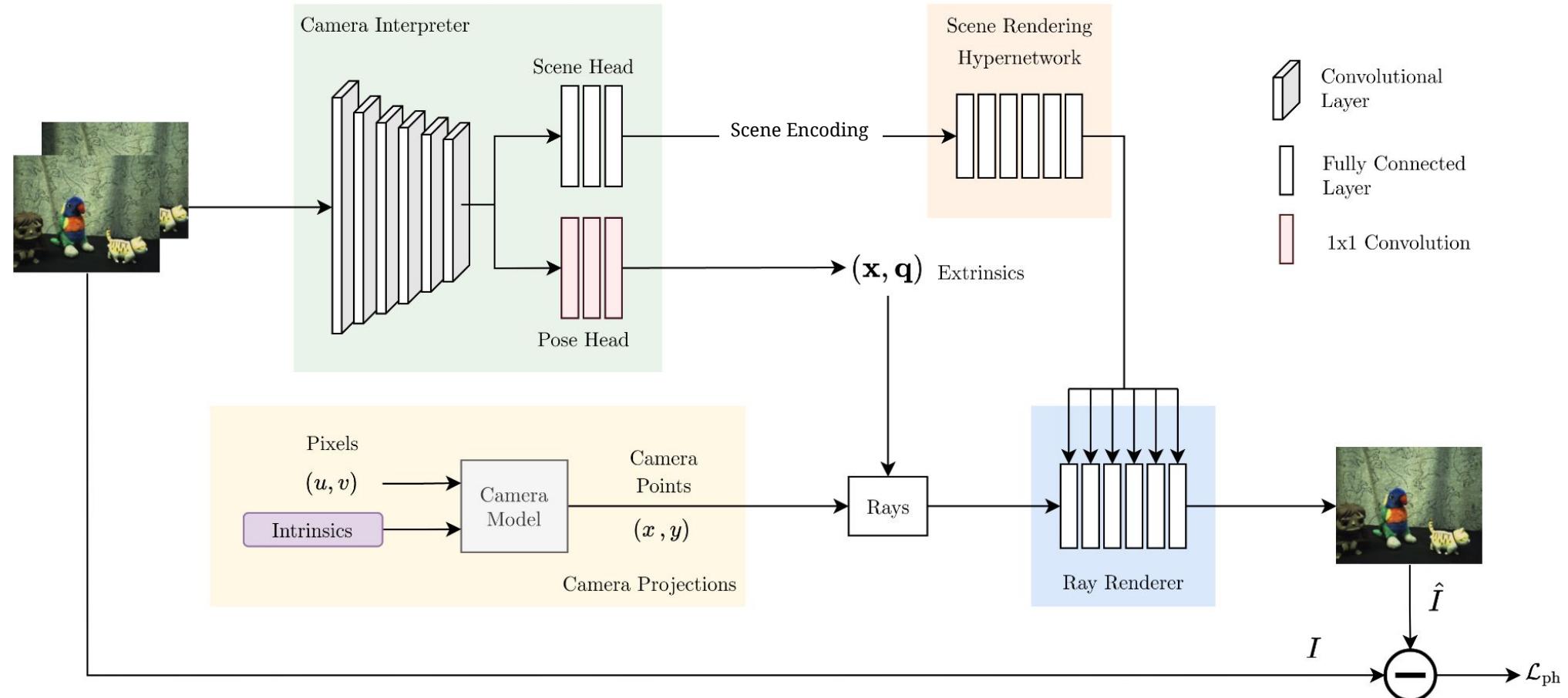
Results: Depth



Results: Odometry

	Monocular	Relative pose error in translation [m]		Relative pose error in rotation [deg]	
		Mean	Std.dev	Mean	Std.dev
Single-warp	Volumetric stack	0.029	0.016	1.522	0.969
	Focal stack – 5	0.028	0.015	1.453	0.880
	Focal stack – 9	0.030	0.015	1.439	0.883
	Ours	0.030	0.016	1.452	0.912
	Volumetric stack	0.026	0.016	1.302	0.885
	Focal stack – 5	0.024	0.016	1.366	0.802
	Focal stack – 9	0.031	0.017	1.457	0.779
	Stereo	0.035	0.017	1.585	0.868
	Ours	0.028	0.015	2.413	1.655
		0.023	0.017	1.282	1.311
Multi-warp	Volumetric stack	0.029	0.016	1.522	0.969
	Focal stack – 5	0.028	0.015	1.453	0.880
	Focal stack – 9	0.030	0.015	1.439	0.883
	Ours	0.030	0.016	1.452	0.912
	Volumetric stack	0.026	0.016	1.302	0.885
	Focal stack – 5	0.024	0.016	1.366	0.802
	Focal stack – 9	0.031	0.017	1.457	0.779
	Stereo	0.035	0.017	1.585	0.868
	Ours	0.028	0.015	2.413	1.655
		0.023	0.017	1.282	1.311

Generalising the Camera with LF Meta-Rendering



LF Rendering Novel Views & Novel Cameras

Input Pair



Novel Views



Novel Camera Geometries



Odometry & Calibration Results

Odometry

Method	Labelled Images	Unlabelled Images	Translation Error [m]			Rotation Error [degrees]		
			Mean	STD	RMSE	Mean	STD	RMSE
Odometry accuracy on captured indoor imagery								
Fully supervised	800	0	0.025	0.009	0.027	1.553	1.847	2.414
Unlabelled calibrated	0	8000	0.029	0.016	0.033	1.522	0.969	1.808
NOCaL (ours)	800	7200	0.020	0.008	0.022	0.412	0.295	0.505
Ablation study using rendered indoor imagery with camera distortion								
Ours no intrinsics or distortion	100	900	0.157	0.060	0.168	8.026	9.180	12.194
Ours no distortion	100	900	0.147	0.053	0.156	4.790	2.209	5.275
Ours full	100	900	0.145	0.054	0.154	4.024	1.971	4.481

Calibration

Camera	Initial		NOCaL (ours)		COLMAP [1]	
	f [px]	Error $\overline{\Delta r}$	f [px]	Error $\overline{\Delta r}$	f [px]	Error $\overline{\Delta r}$
Focal: 600px, no distortion	640.0	0.0225	601.1	0.0008	599.4	0.0003
Focal: 600px, large distortion	640.0	0.0440	595.3	0.0186	602.1	0.0010

Next Steps

More Sensors, Modes

IMUs



Mr Potato Head:
Plug-and-play
more imaging technologies

Today's Talk

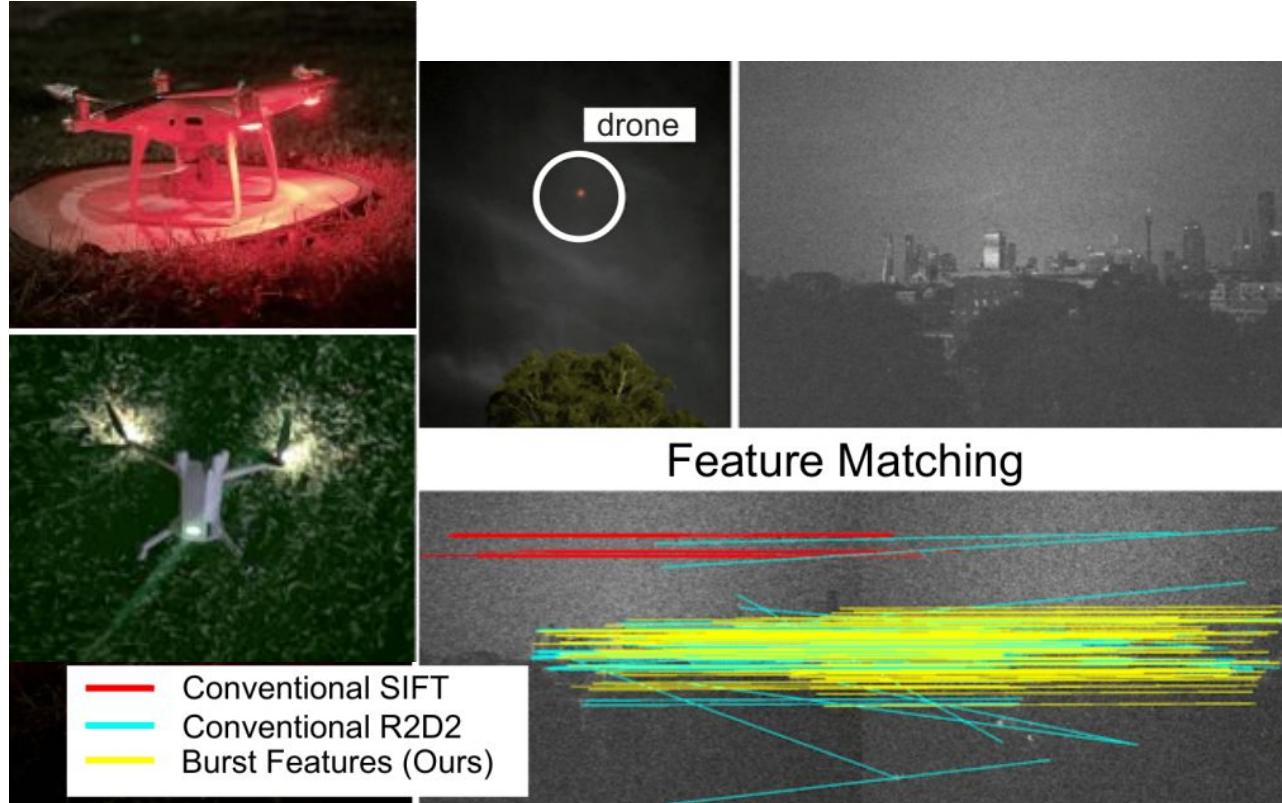
1. Designing a camera for robots
2. Automating integration of new cameras
3. **Making the most of existing cameras**
4. Emerging challenges

Making the Most of Cameras: Burst

[Avie Ravendran
Mitch Bryson]

Seeing in mLux conditions
Exploiting statistics of platform dynamics and image formation

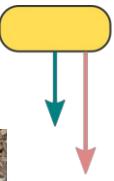
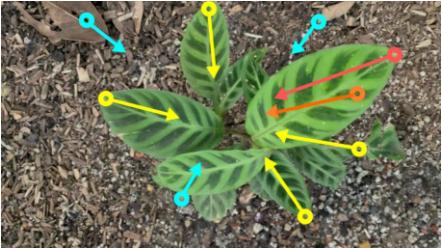
RA-L/ICRA 2024
ICRA 2022



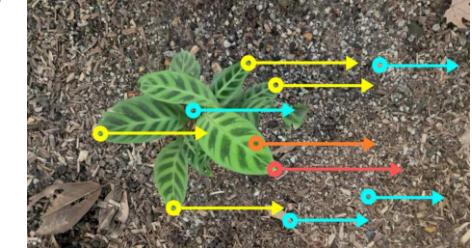
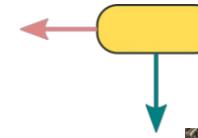
Burst Imaging in Low Light



Platform Motion in a Burst

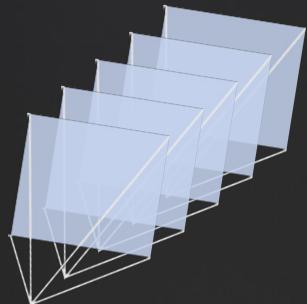


Platform inertia
→ local linear apparent motion
Not all the time
... but much of the time

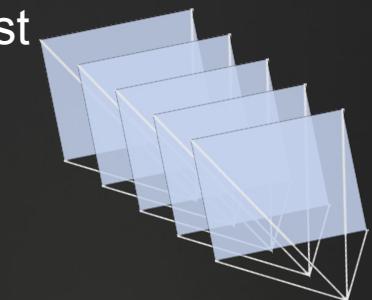
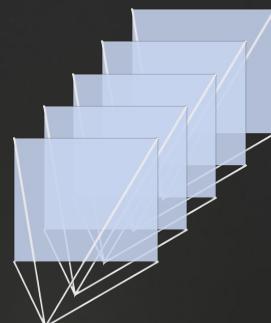


Approach: Hybrid Dense + Sparse

Within burst: 2D+T feature detection, no merging
Exploits visual coherence, platform dynamics

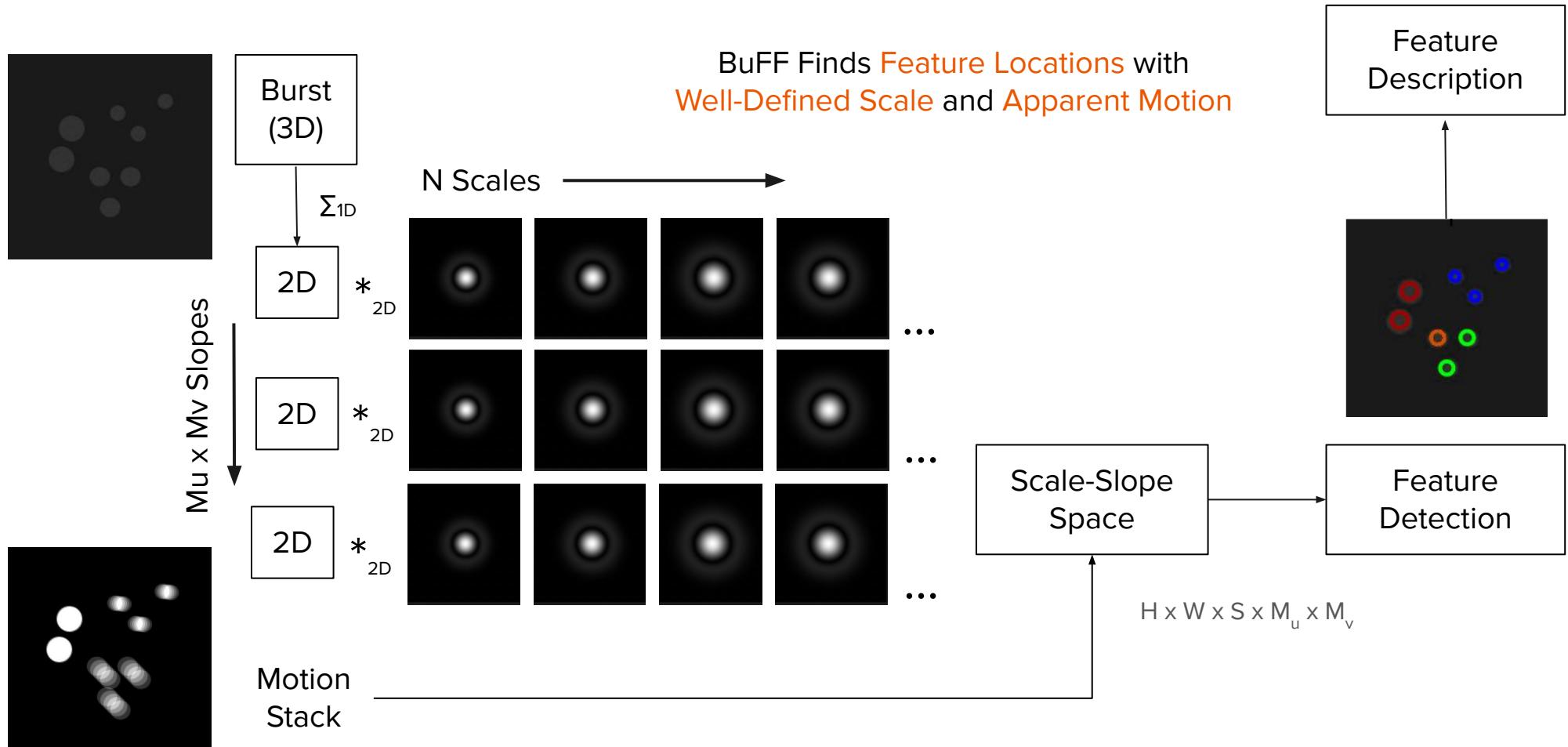


Between bursts: Sparse feature matching
Tolerates appearance changes, fast

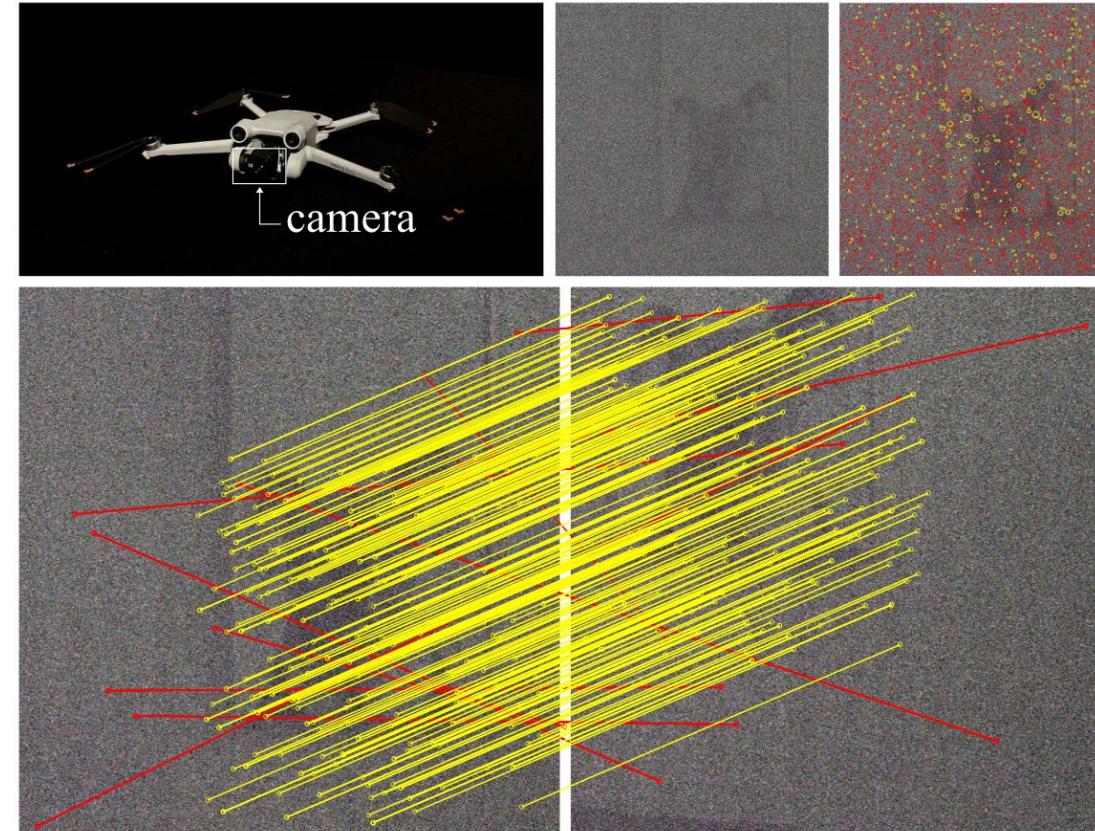


Moderate compute / bandwidth
Large signal gains

Hand-Crafted Burst Feature

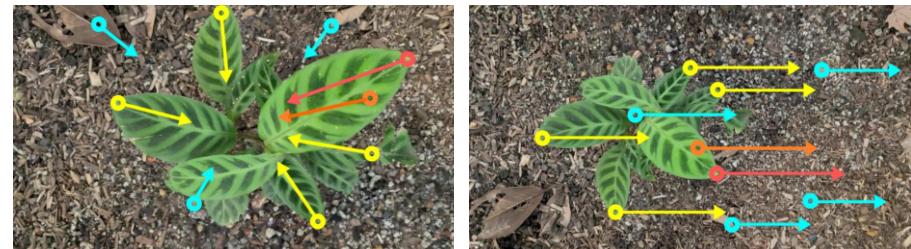
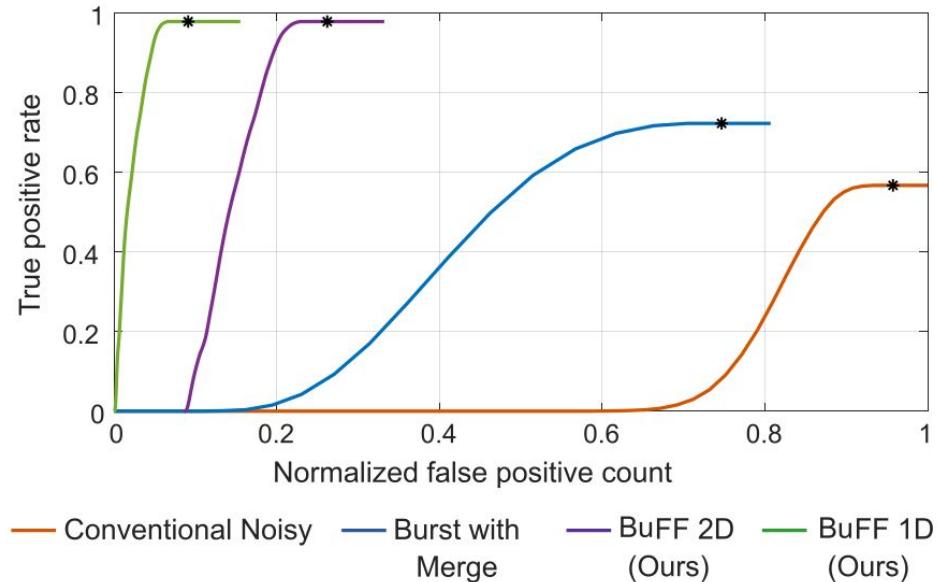


Hand-Crafted Burst Feature



red: SIFT

yellow: ours



Drone Flight by Moonlight: mLux conditions

Images at 0.05 - 0.12 lux



DJI Mini 3 Pro



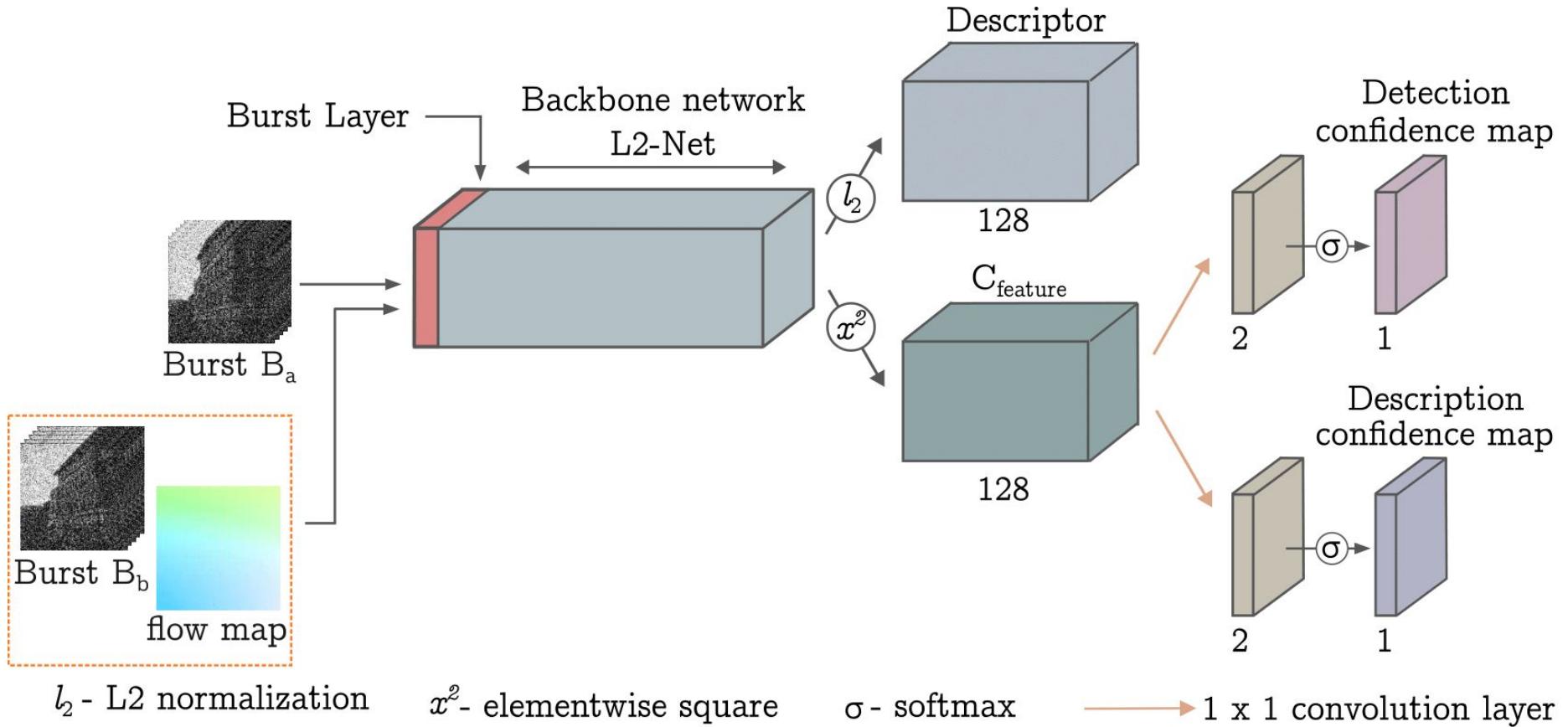
Images at 0.02 - 0.08 lux



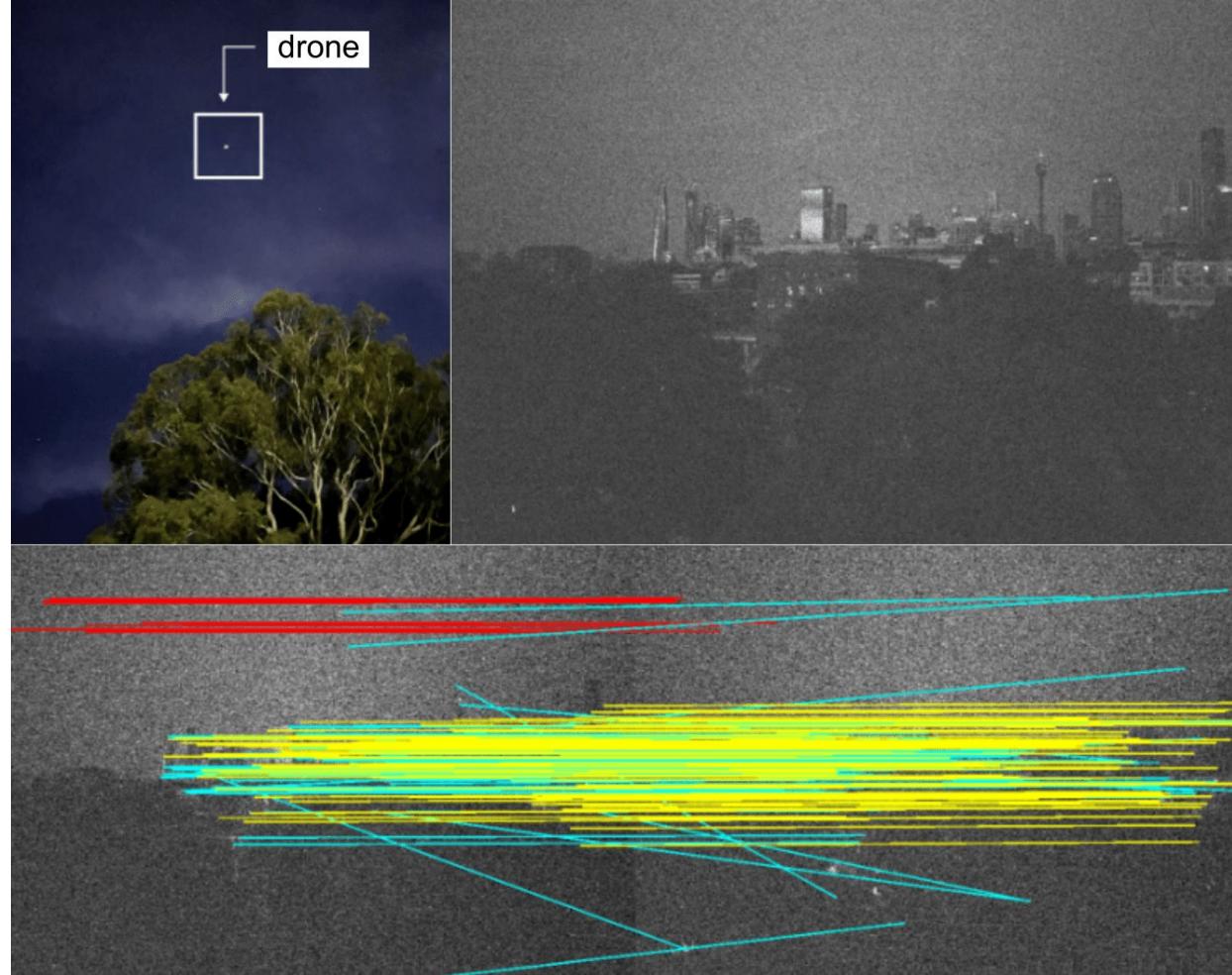
DJI Phantom 4



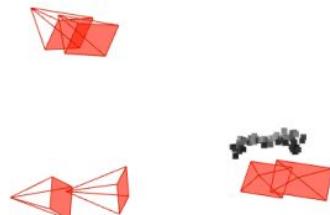
Learning-Based Burst Feature



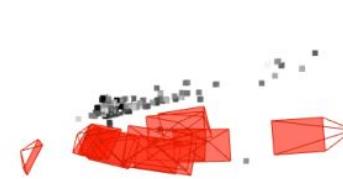
Learning-Based Burst Feature



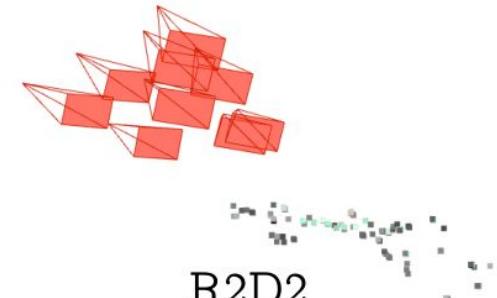
Reconstruction



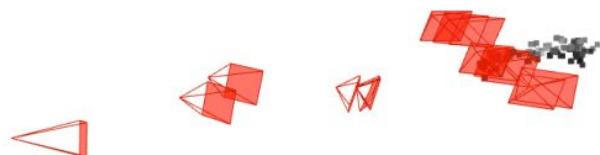
SIFT



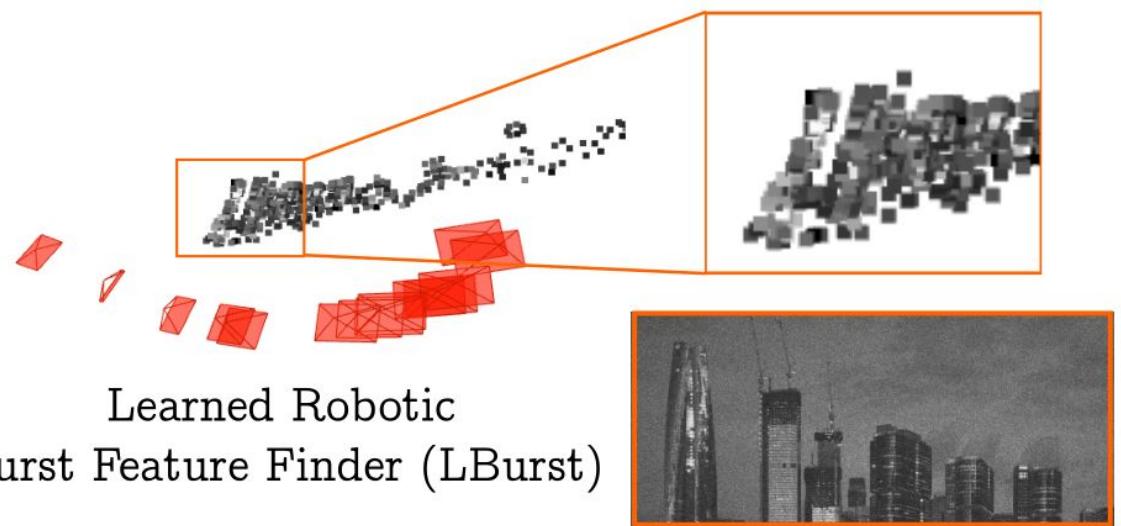
SuperPoint



R2D2



Robotic Burst Feature Finder
(BuFF)



Learned Robotic
Burst Feature Finder (LBurst)

Reconstruction Performance

Average Performance Over 5 Scenes Each with 20 Bursts using COLMAP (Schönberger, et al., 2016)

Apparent Motion	Method	Convergence Rate	% of Images Pass	Match Ratio	Match Score	Precision	3D Points/ Image
2D	Gold Standard	1.0	100.0	3.89	3.87	0.99	305.5
	SIFT	0.0	0.0	0.00	0.00	0.86	0.0
	Conventional Noisy	SuperPoint	0.0	0.0	0.01	0.00	0.00
		R2D2	0.0	0.0	0.65	0.10	0.15
		SIFT	0.8	77.0	0.18	0.95	32.2
	Burst with Merge	SuperPoint	0.4	19.0	0.24	0.07	0.24
		R2D2	0.4	41.0	0.62	0.10	0.16
	BuFF	1.0	98.0	0.26	0.26	0.98	47.2
	LBurst	1.0	100.0	0.44	0.43	0.97	73.1

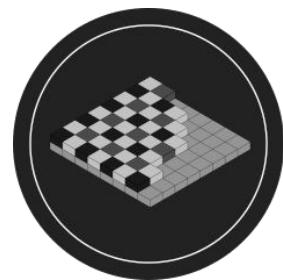
Next Steps



Adaptive Sampling



Sensor Fusion / IMU



Direct RAW input

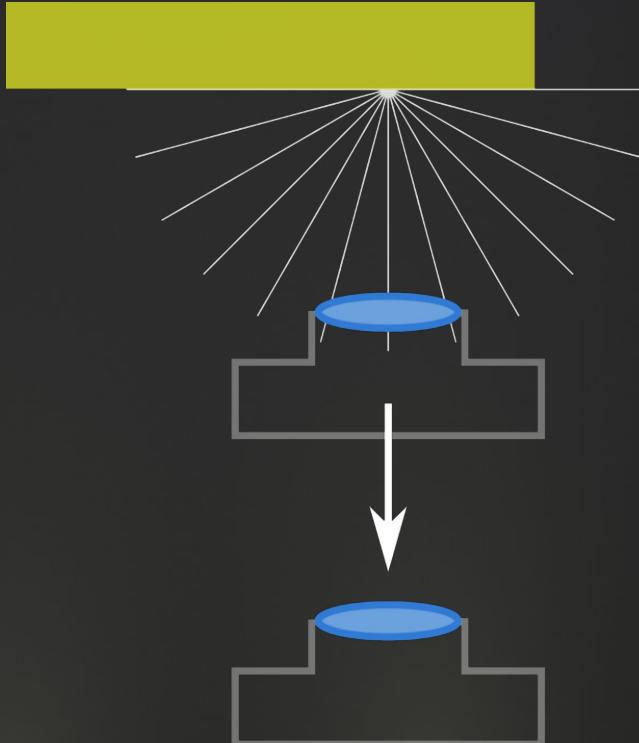


Imaging Physics
Beyond Burst

Why don't objects appear dimmer as we move away from them?

Hint: What have we missed about the scene?

$$I \propto \frac{S}{\pi r^2}$$



Why don't objects appear dimmer as we move away from them?

Hint: What have we missed about the scene?

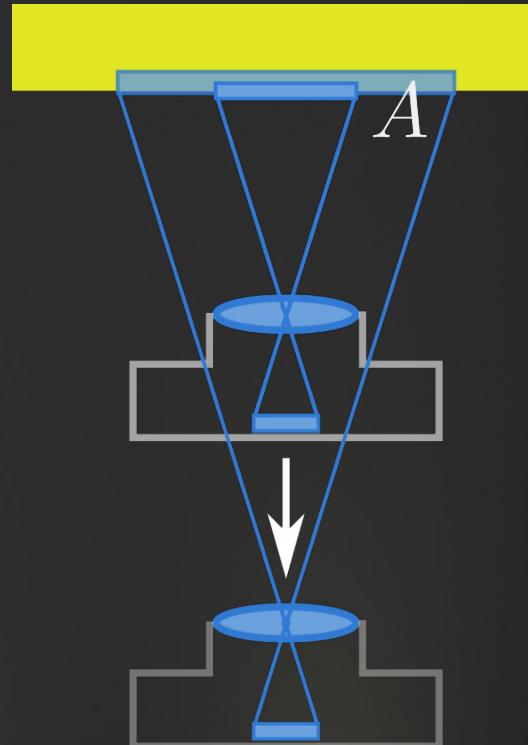
The camera!

Projected pixel area grows with r^2

The r^2 cancel

→ Constant apparent intensity

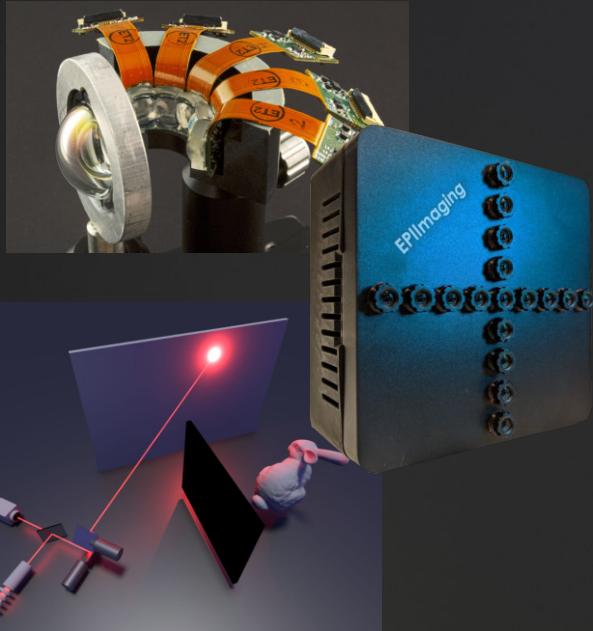
$$I \propto \frac{S}{\pi r^2}$$



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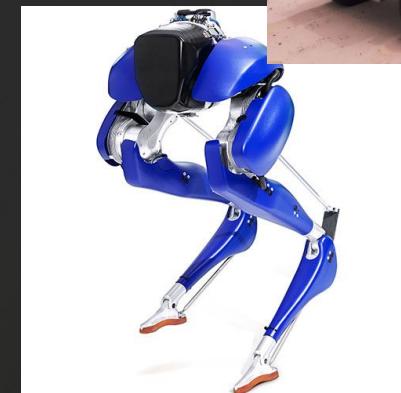
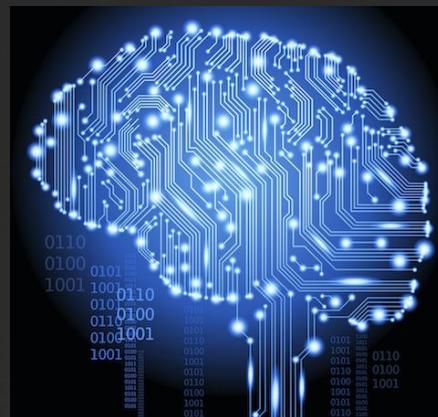
Representations for Eyes, Brains, and Bodies



Light:
NeRFs,
Gaussian Splats,
LFs

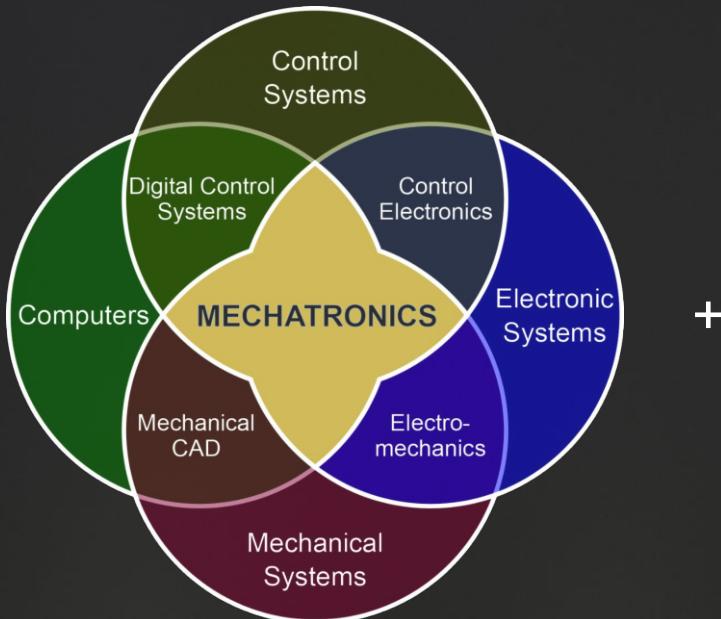
Geometry,
Semantics,
Uncertainty

Language, Vision,
Action & Interaction



Automating Perception System Design...

Co-designing optics, sensing, embodiments, and algorithms
to let robots work in new ways



+





Robotic Imaging Lab



Dr Don Dansereau



Bina Rajan



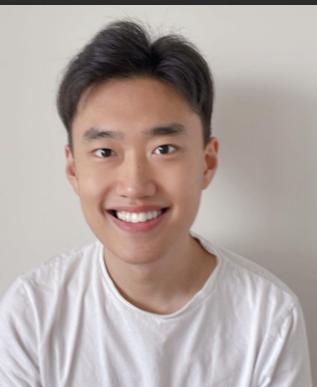
Jack Naylor



Ryan Griffiths



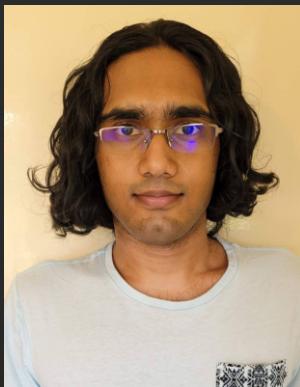
Nikolai Goncharov



Oliver Yan



Alex Cardaillac



Bhargava Gowda



Dr Ahalya Ravendran

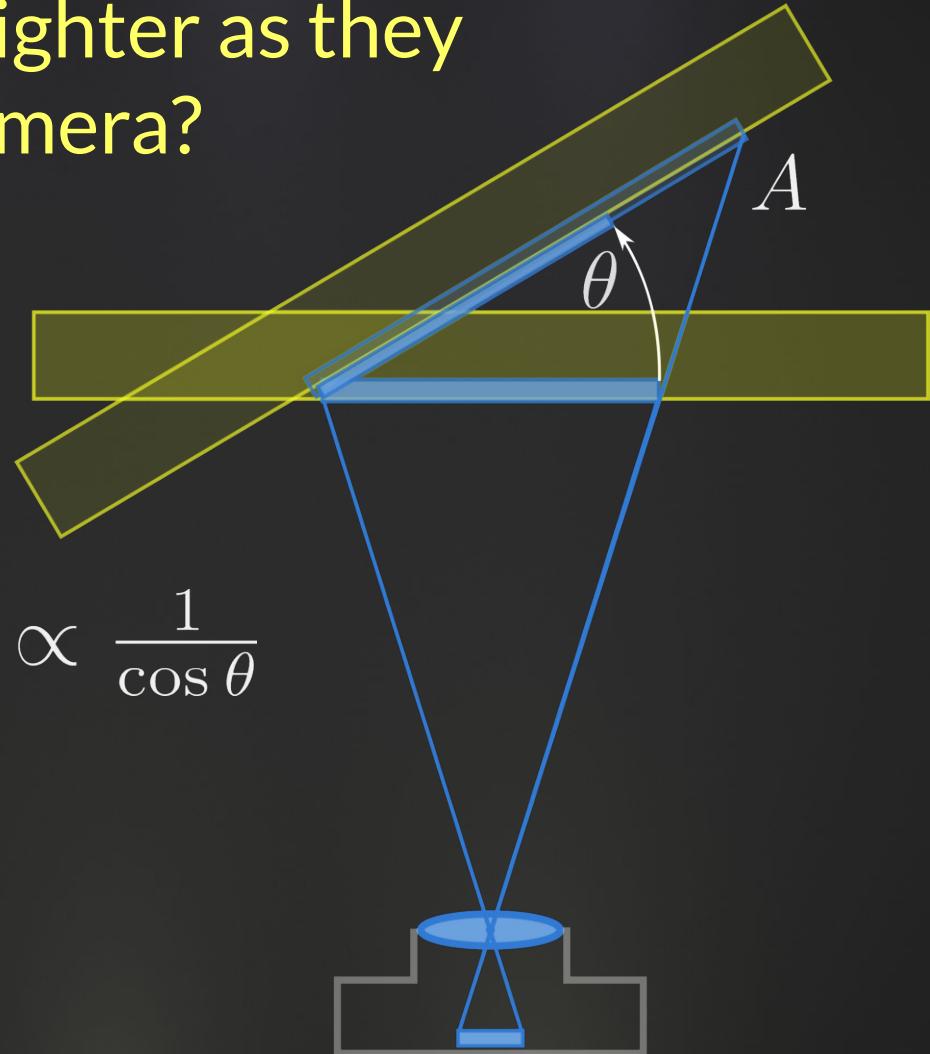


Dr Teja Digumarti

Why don't surfaces appear brighter as they turn away from the camera?

Should we expect them to?

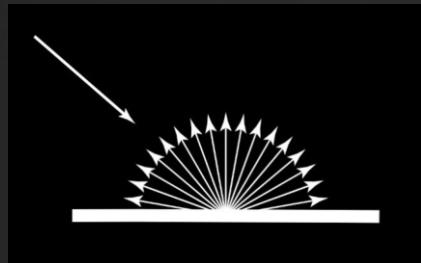
Yes, more angle = more projected pixel area
= more energy into the lens



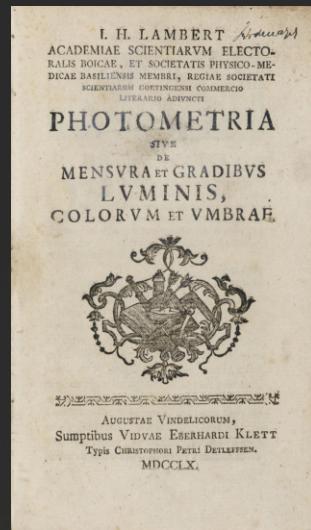
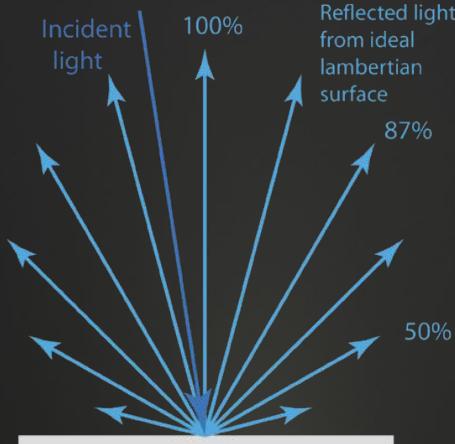
$$I \propto A \propto \frac{1}{\cos \theta}$$

Why don't surfaces appear brighter as they turn away from the camera?

Hint: this is useful but wrong
(or at least misleading):



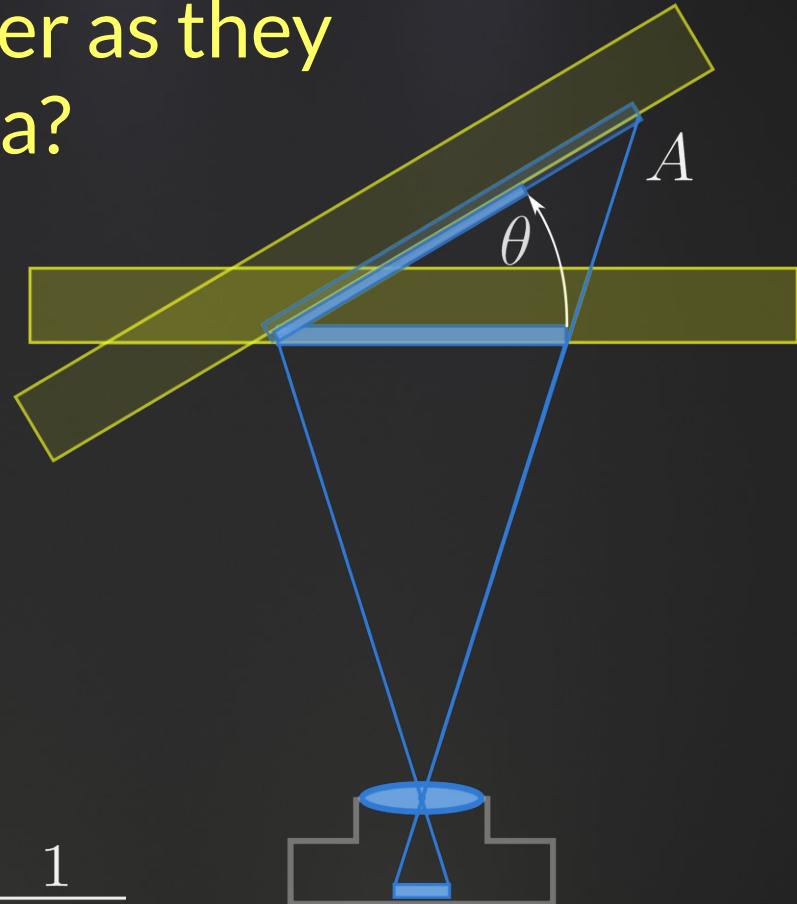
Lambert cosine law:



[lambert1760]

$$I \propto A \propto \frac{1}{\cos \theta}$$

$$I \propto \cos \theta$$



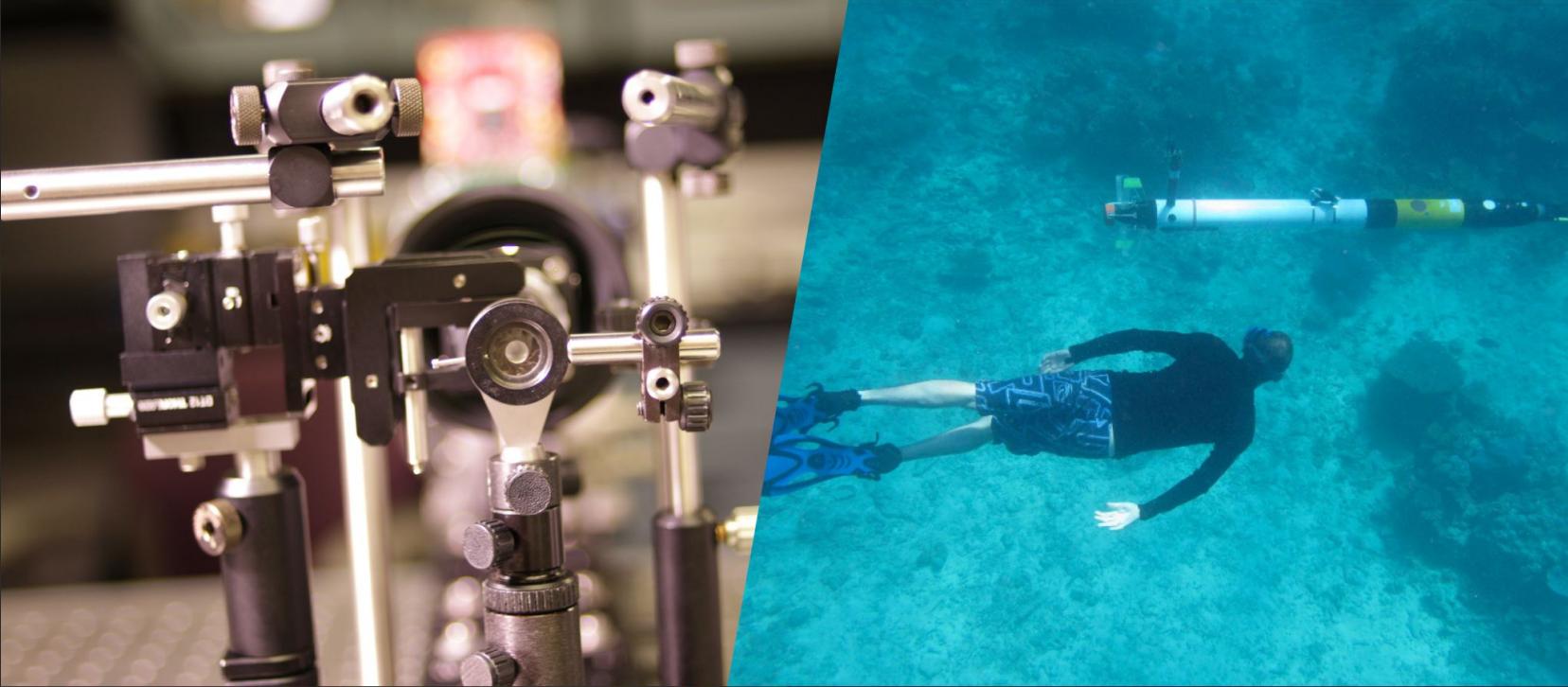
To Ponder:
Is our moon Lambertian? How would you prove it?





ROBOTIC
IMAGING
LAB

RoboticImaging.org



Australian Robotic Inspection & Asset Management Hub (ARIAM)

USyd, QUT, ANU +10 industry partners

5-year ARC Research Hub

Fundamental Problems in Sensing, Perception & Control

Autonomy to Manage Infrastructure & Assets

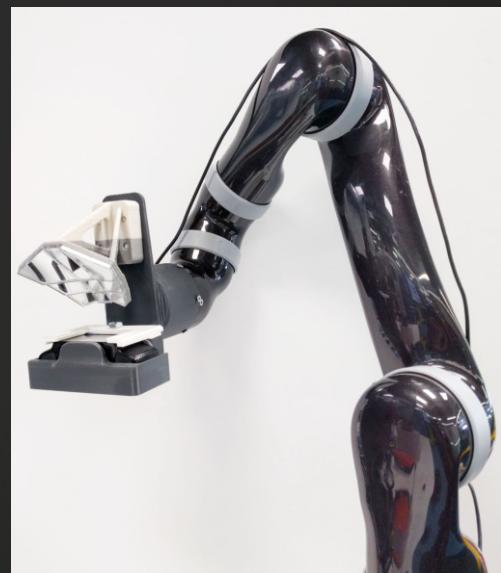
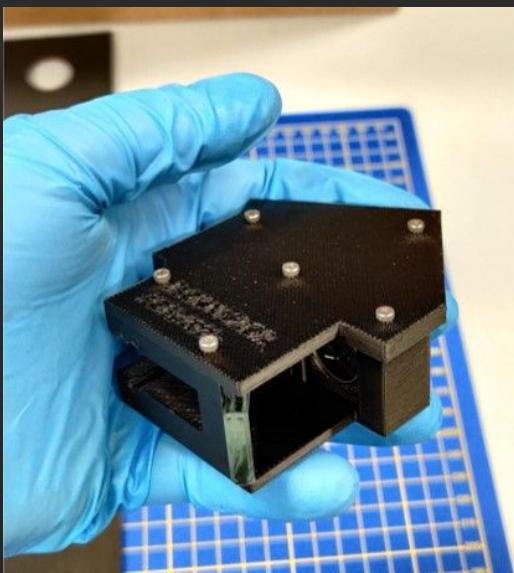
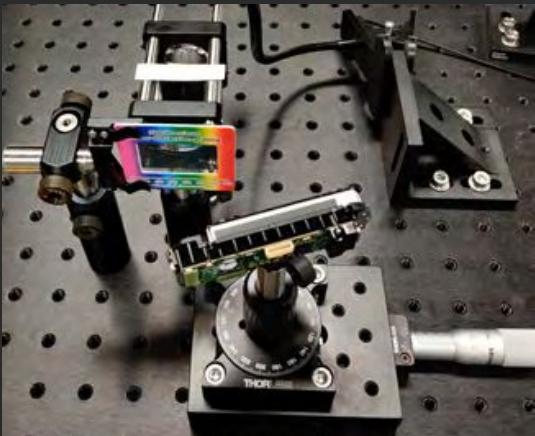
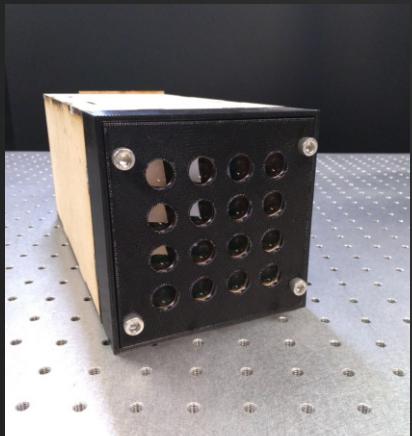
Underwater, Ground, Air

Multiple PhD & Postdoc Roles Open

<https://ariamhub.com/>



Robotic Imaging Lab @ ACFR



New Cameras, Representations & Algorithms...



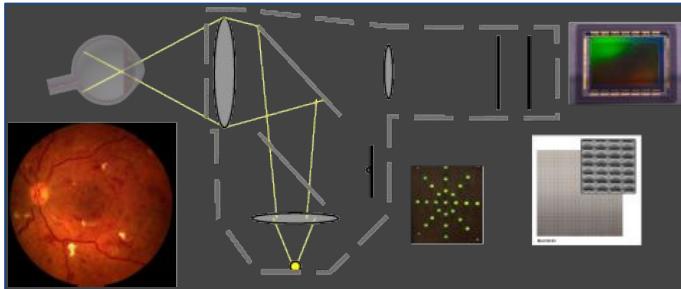
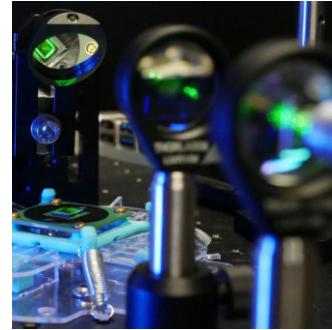
Spherical-lens light field (LF)
w/UCSD, Stanford



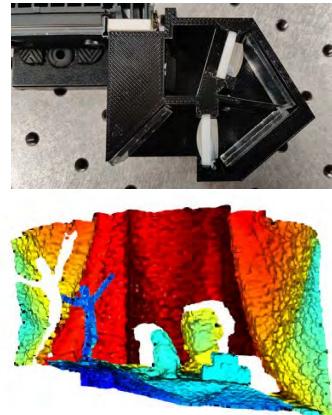
Sparse LF
w/EPIImaging LLC



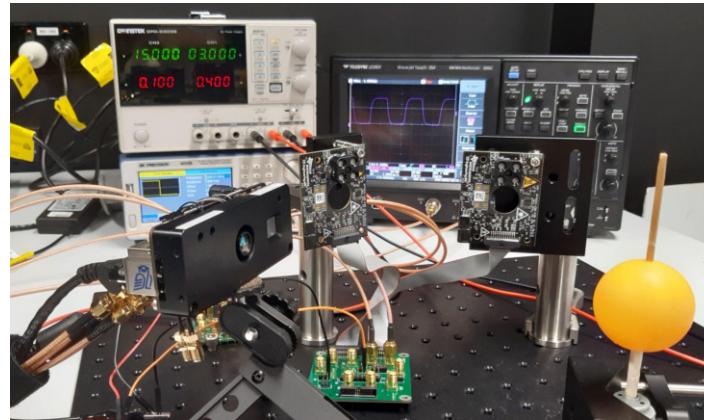
Open-source LF adapters,
Light Field Toolbox



Medical Fundus LF imager
w/QUT, Spun out as Integral
Scopes



Hyperspectral 3D
Adapter



Emerging technologies:
Doppler, Single-photon, Vision-on-chip

... to Make Machines Smarter



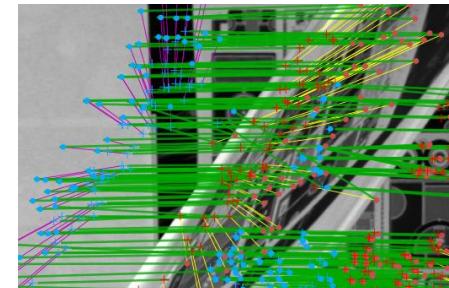
Underwater
Robotics



Vision for the Blind



All-Weather Autonomous
Driving



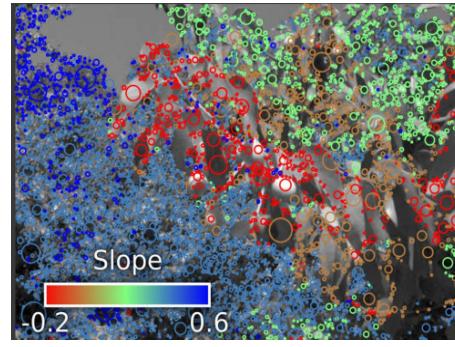
Automation around
Transparency



Night-time Operation



VR, AR, MR

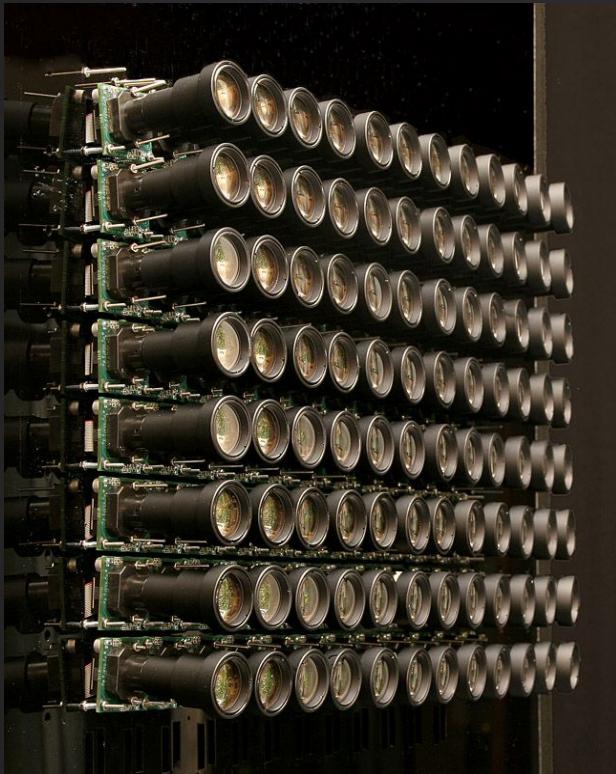


Natural Environments

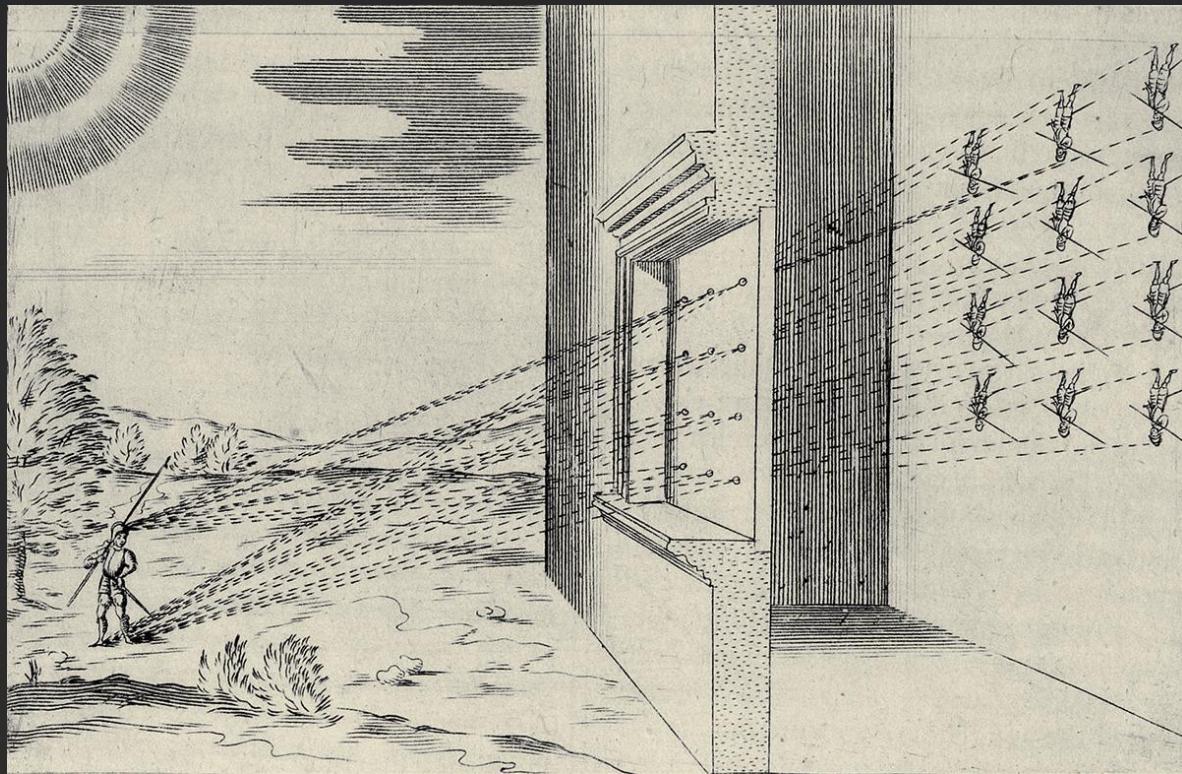


Privacy-Enhanced
Robotic Vision

Light Field Cameras

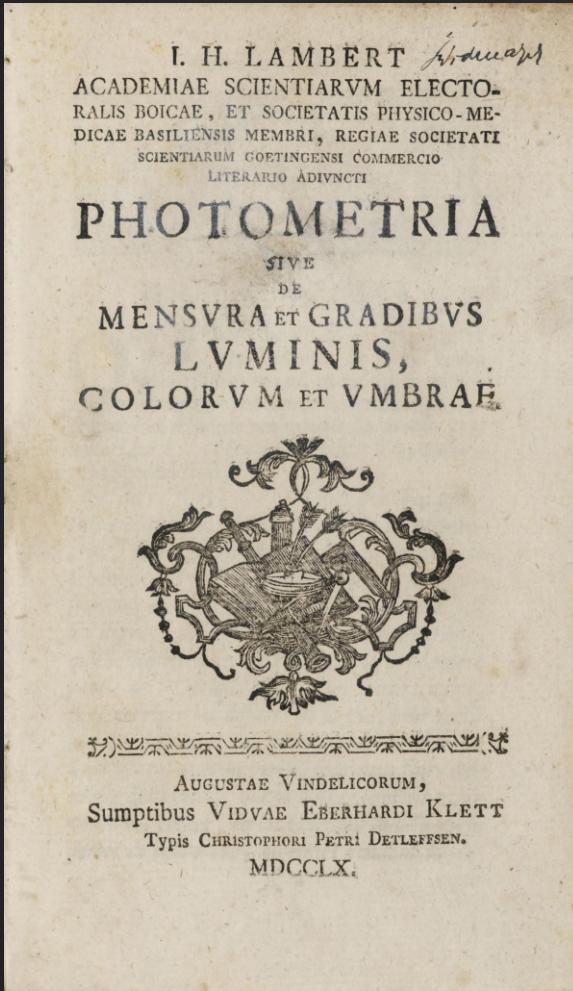


Stanford camera array
2005



Bettini 1642

Thinking About Light



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  year = {1760},
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“Photometry, or the measure and gradation of light, colour, and shadow”