# Computational Approaches to Cameras

11/14/13

Magritte , *The False Mirror* (1935)

Computational Photography

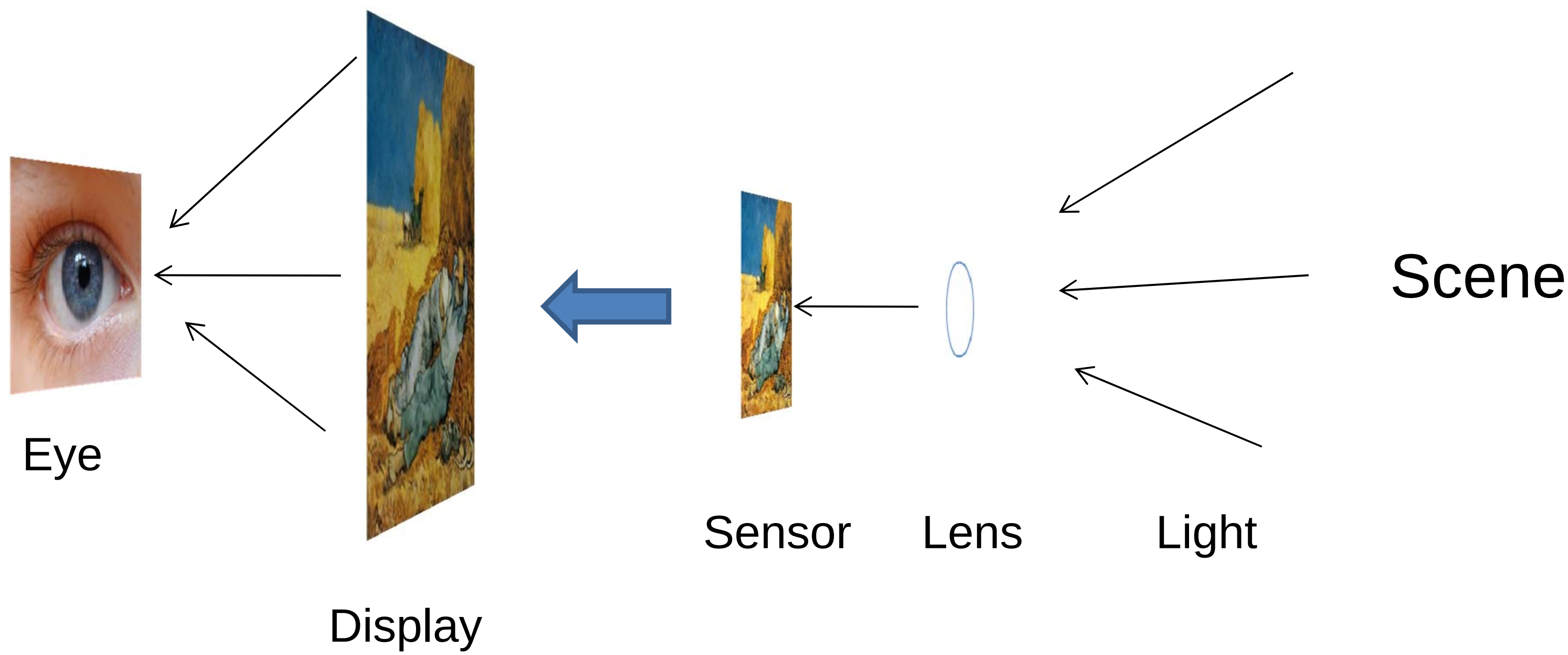
Derek Hoiem, University of Illinois

# Announcements

- Final project proposal due Monday (see links on webpage)

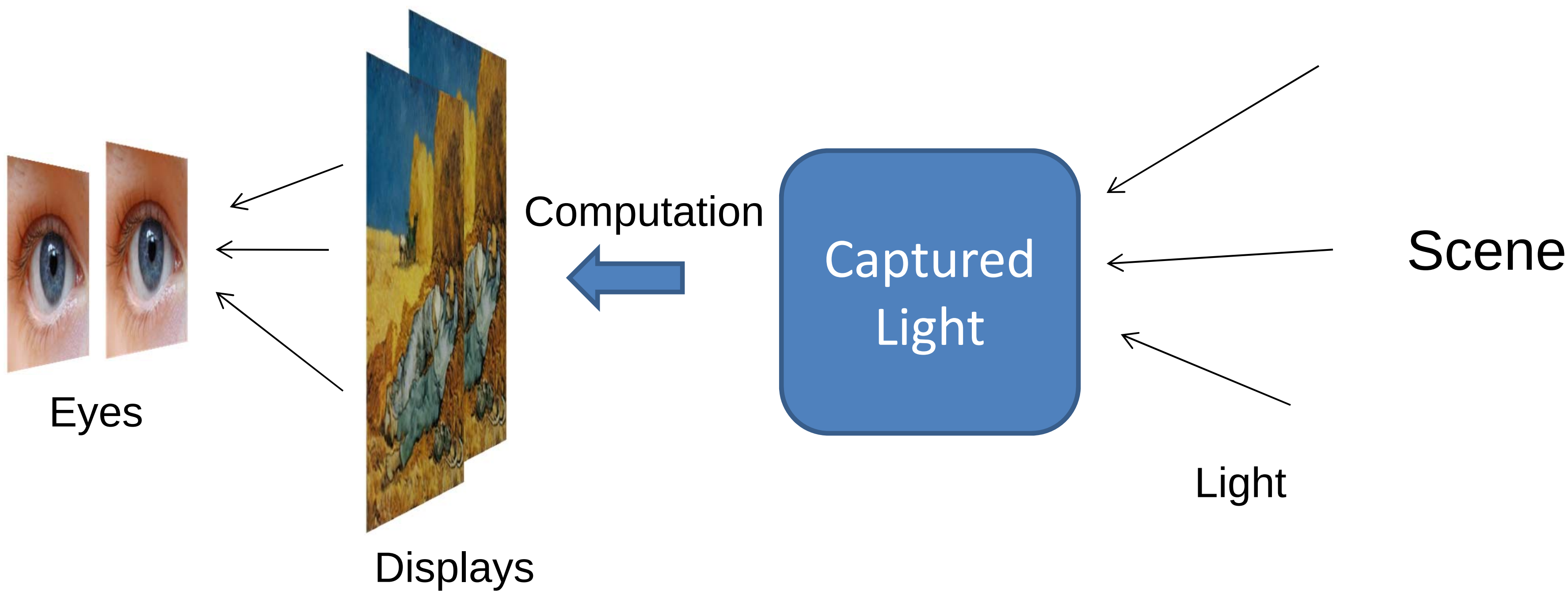
# Conventional cameras

- Conventional cameras are designed to capture light in a medium that is directly viewable



# Computational cameras

- With a computational approach, we can capture light and then figure out what to do with it



# Questions for today

- How can we represent all of the information contained in light?

- What are the fundamental limitations of cameras?

- What sacrifices have we made in conventional cameras?  For what benefits?

- How else can we design cameras for better focus, deblurring, multiple views, depth, etc.?

How can we represent all of the information contained in light?

# Representing Light: The Plenoptic Function

Figure by Leonard McMillan

Q: What is the set of all things that we can ever see?

A: The Plenoptic Function (Adelson & Bergen)

Let's start with a stationary person and try to parameterize <u>everything</u> that he can see…

Slides from Efros

# Grayscale snapshot

$$P(\theta,\phi)$$

is intensity of light

- Seen from a single view point
- At a single time
- Averaged over the wavelengths of the visible spectrum

(can also do *P(x,y),* but spherical coordinate are nicer)

# Color snapshot

$$P(\theta,\phi,\lambda)$$

is intensity of light

- Seen from a single view point
- At a single time
- As a function of wavelength

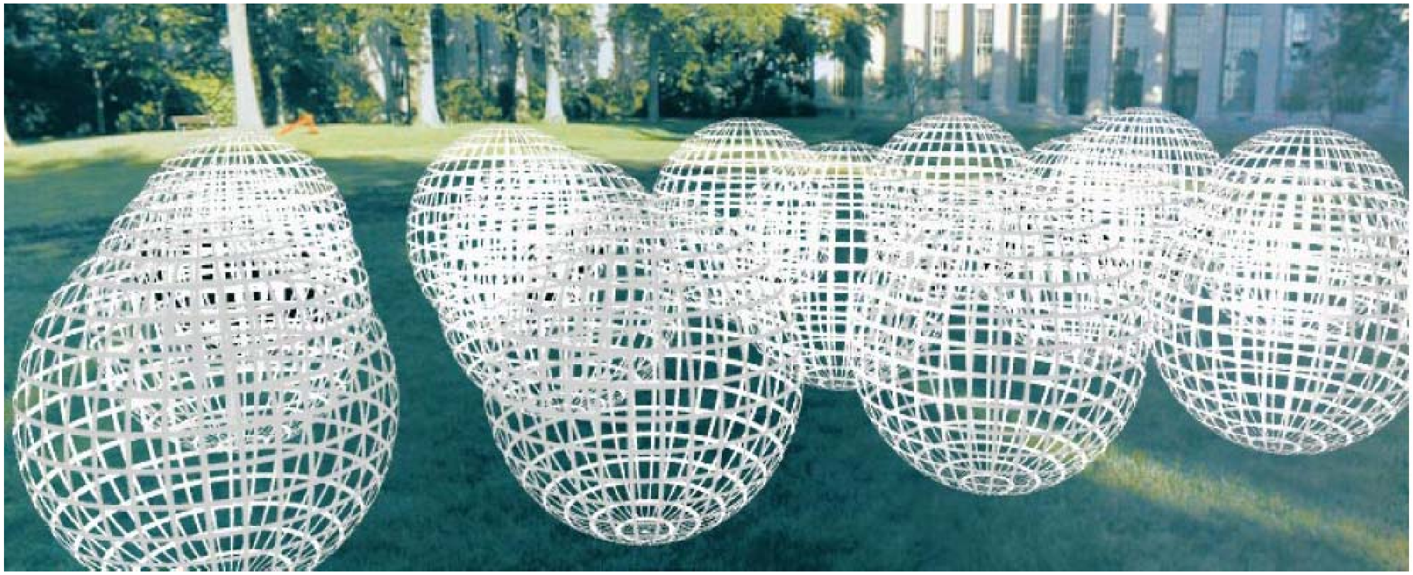
# A movie

$$P(\theta,\phi,\lambda,t)$$

is intensity of light

- Seen from a single view point
- Over time
- As a function of wavelength

# Holographic movie

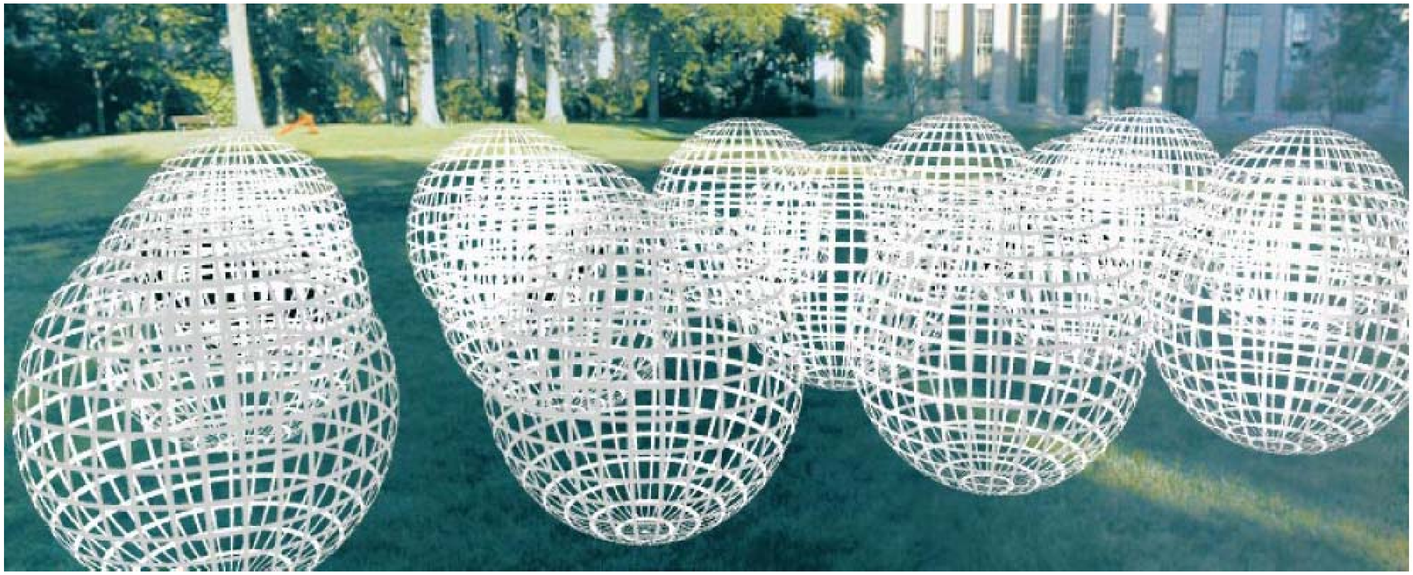


$$P(\theta,\phi,\lambda,t,V_X,V_Y,V_Z)$$

is intensity of light

- Seen from ANY viewpoint
- Over time
- As a function of wavelength

# The Plenoptic Function



$$P(\theta,\phi,\lambda,t,V_X,V_Y,V_Z)$$

- Can reconstruct every possible view, at every moment, from every position, at every wavelength
- Contains every photograph, every movie, everything that anyone has ever seen!

# Full Plenoptic Camera

Records position and orientation of each ray at each time and wavelength

$$P(V_X, V_Y, V_Z, \theta, \phi, t, \lambda)$$

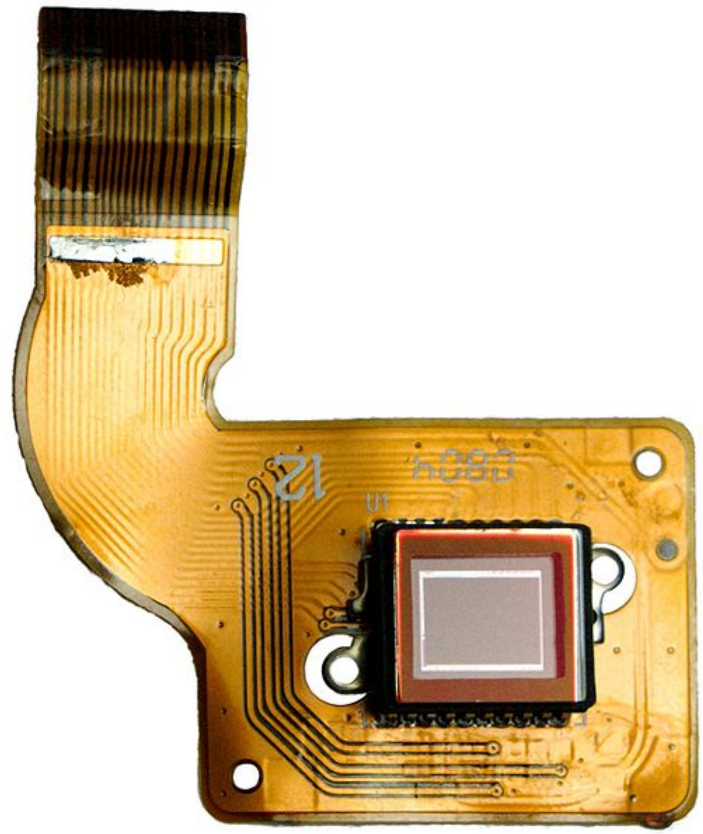
# What fundamentally limits cameras?

# Representing light

The atomic element of light: ~~a pixel~~ **a ray**

# Fundamental limitations and trade-offs

- Only so much light in a given area to capture
- Basic sensor accumulates light at a set of positions from all orientations, over all time
- We want **intensity** of light at **a given time** at **one position** for a **set of orientations**
- Solutions:
  - funnel, constrain, redirect light
  - change the sensor



CCD inside camera

What sacrifices does the conventional camera make? For what gains?

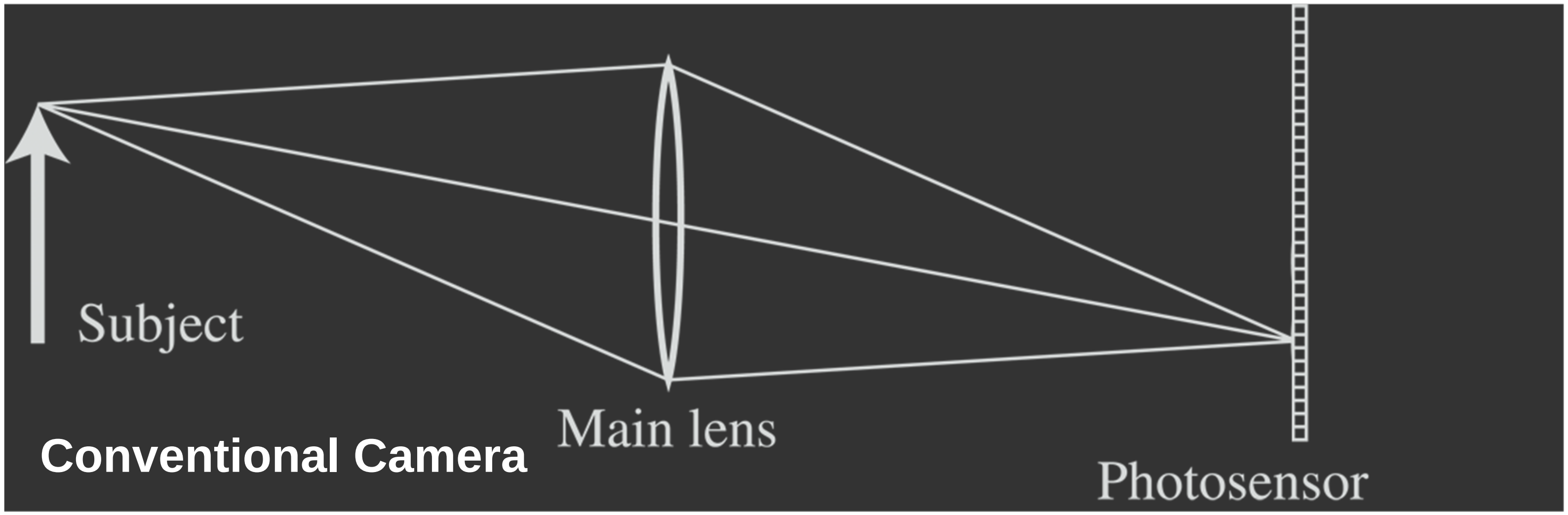
# Trade-offs of conventional camera

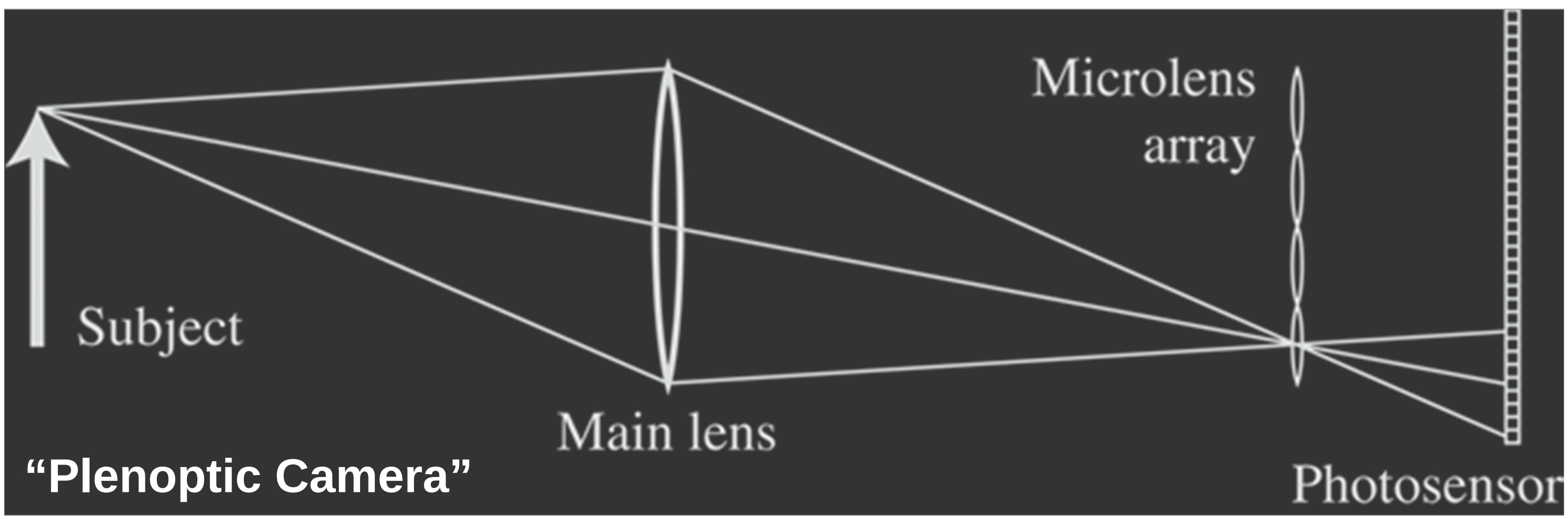
- Add a pinhole
  - ✓ Pixels correspond to small range of orientations at the camera center, instead of all gathered light at one position
  - ✗ Much less light hits sensor
- Add a lens
  - ✓ More light hits sensor
  - ✗ Limited depth of field
  - ✗ Chromatic aberration
- Add a shutter
  - Capture average intensity at a particular range of times
- Increase sensor resolution
  - ✓ Each pixel represents a smaller range of orientations
  - ✗ Less light per pixel
- Controls: aperture size, focal length, shutter time

How else can we design cameras?

What do they sacrifice/gain?

# 1. Light Field Photography with “Plenoptic Camera”



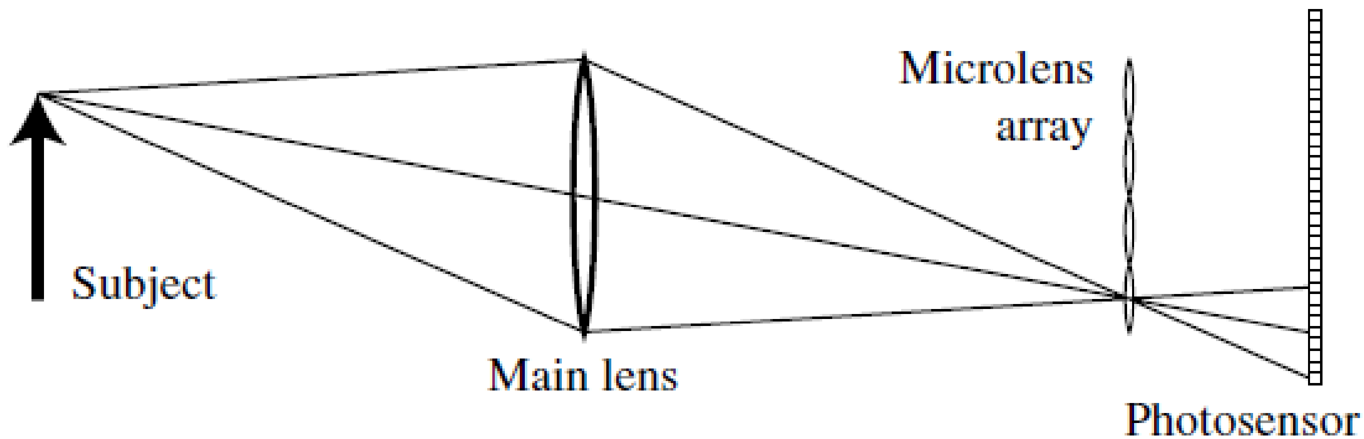



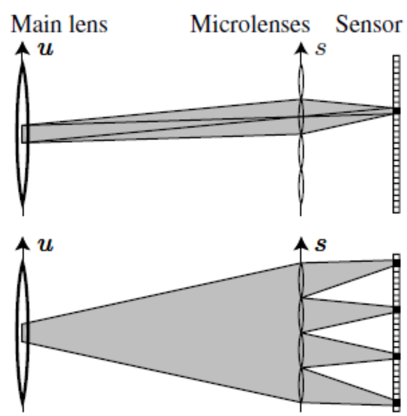

Adelson and Wang 1992

Ng et al. Stanford TR, 2005

# Light field photography

- Like replacing the human retina with an insect compound eye
- Records where light ray hits the lens

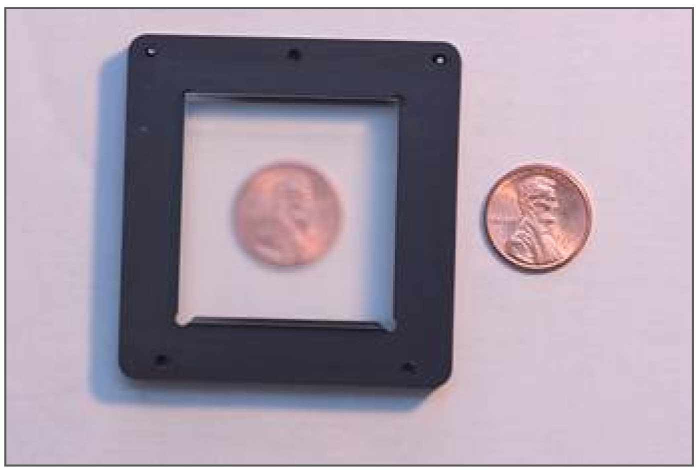


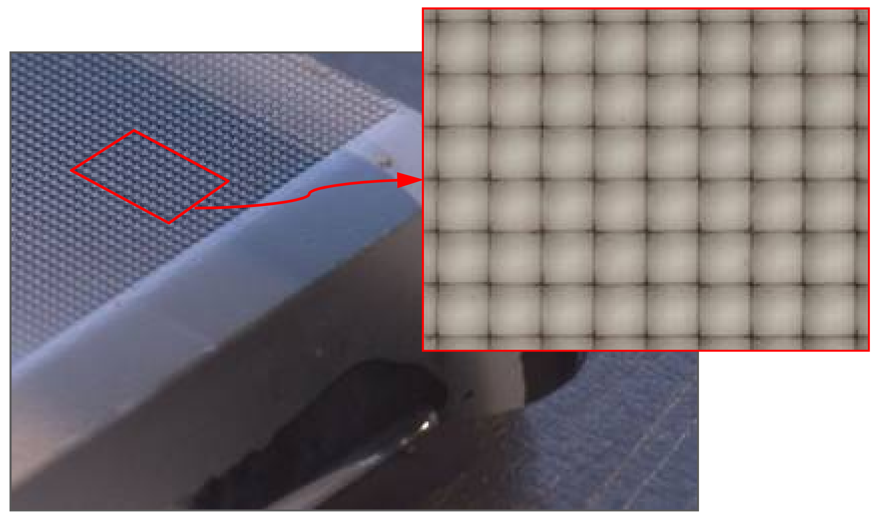



# Stanford Plenoptic Camera [Ng et al 2005]

Contax medium format camera

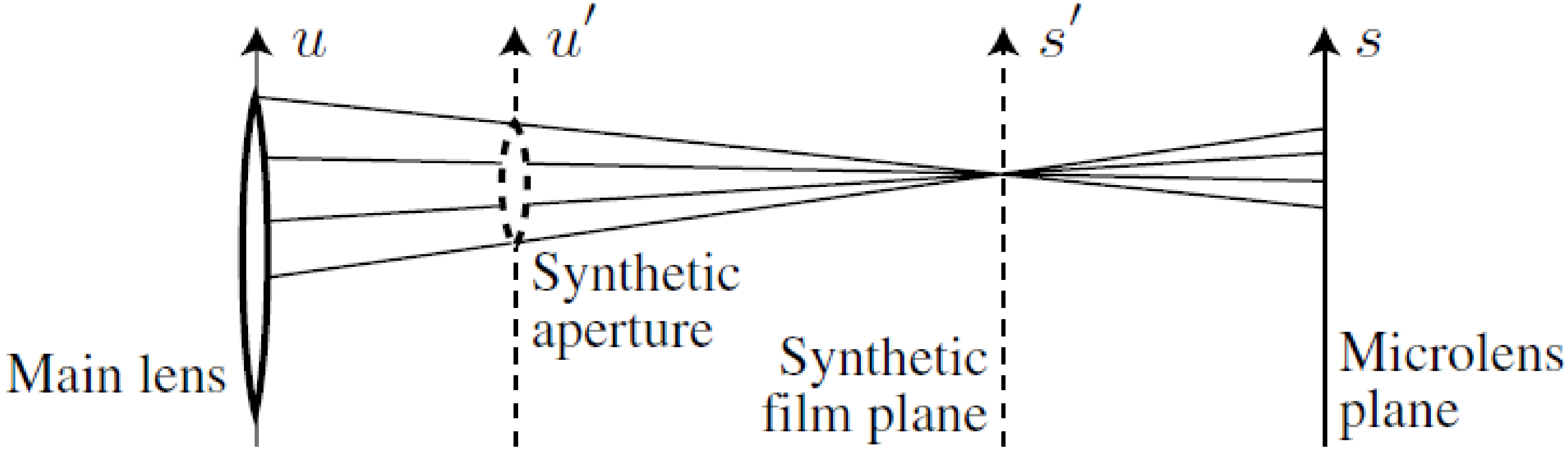

Kodak 16-megapixel sensor


Adaptive Optics microlens array

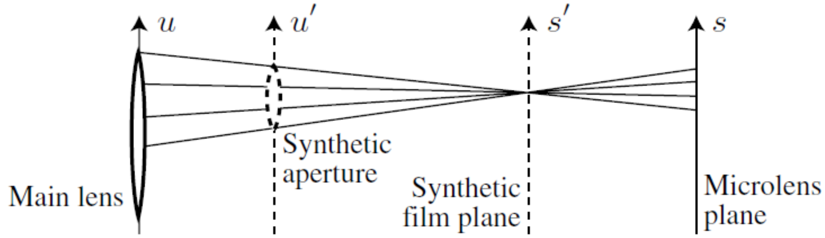

125μ square-sided microlenses

*4000 × 4000 pixels ÷ 292 × 292 lenses = 14 × 14 pixels per lens*

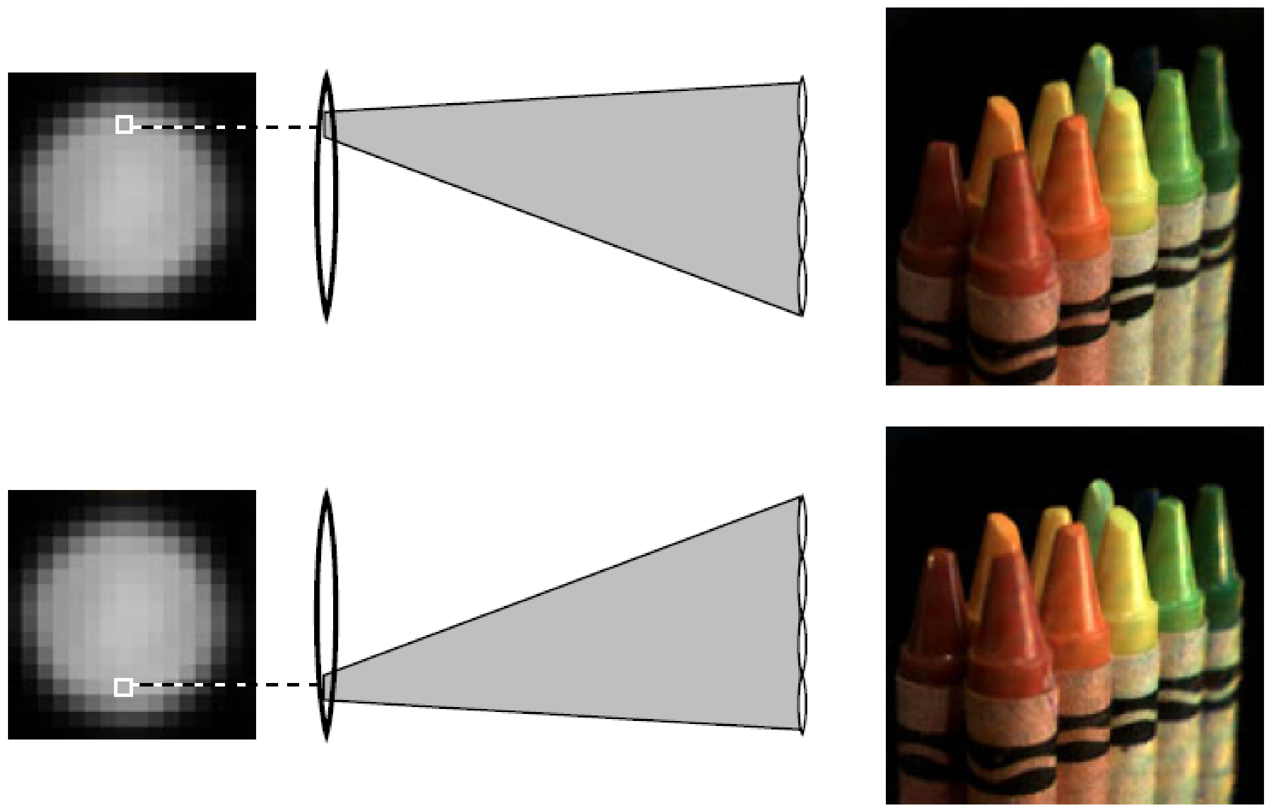
# Light field photography: applications



# Light field photography: applications



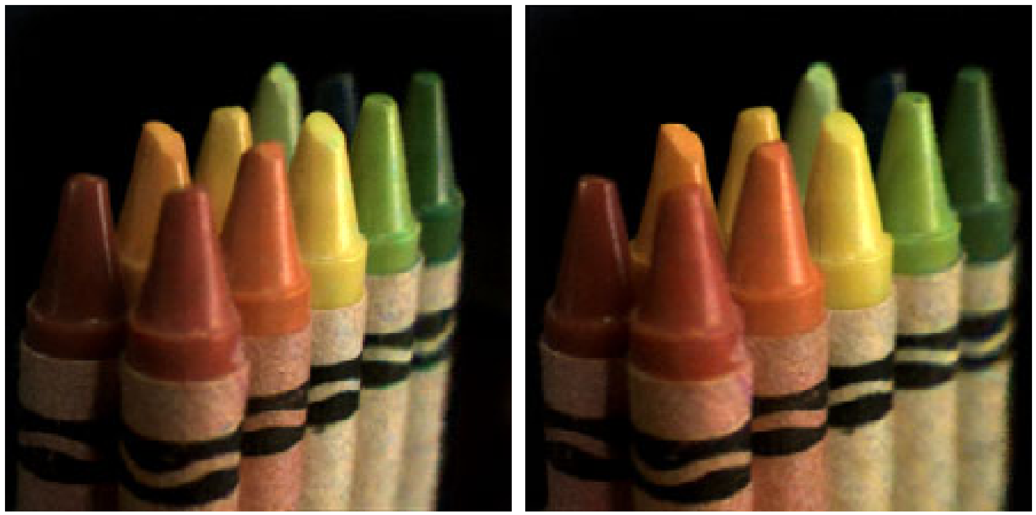

Change in viewpoint



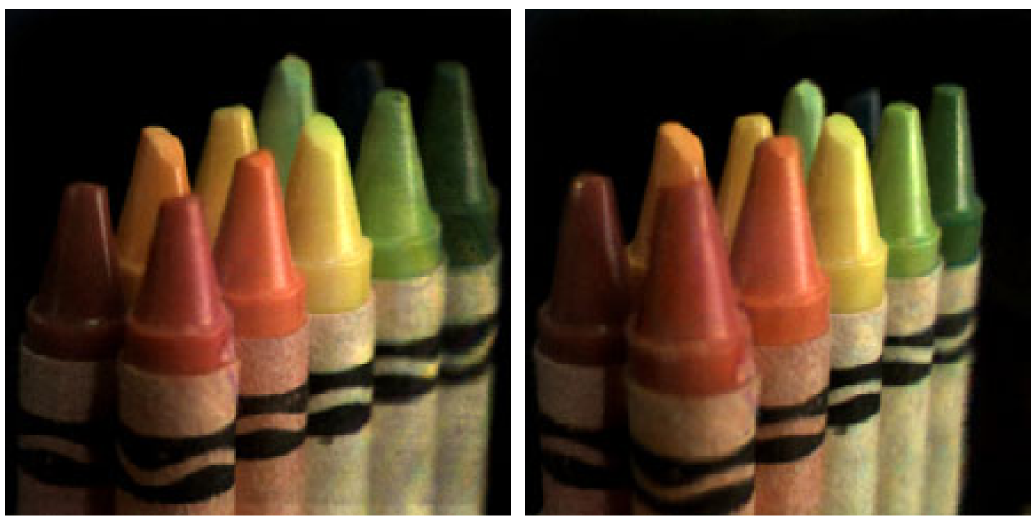
# Light field photography: applications

## Change in viewpoint

Lateral



Along Optical Axis



# Digital Refocusing

# Light field photography w/ microlenses

- We gain
  - Ability to refocus or increase depth of field
  - Ability for small viewpoint shifts

- What do we lose (vs. conventional camera)?

# 2. Coded apertures

# Image and Depth from a Conventional Camera with a Coded Aperture

**Anat Levin, Rob Fergus,**
**Frédo Durand, William Freeman**

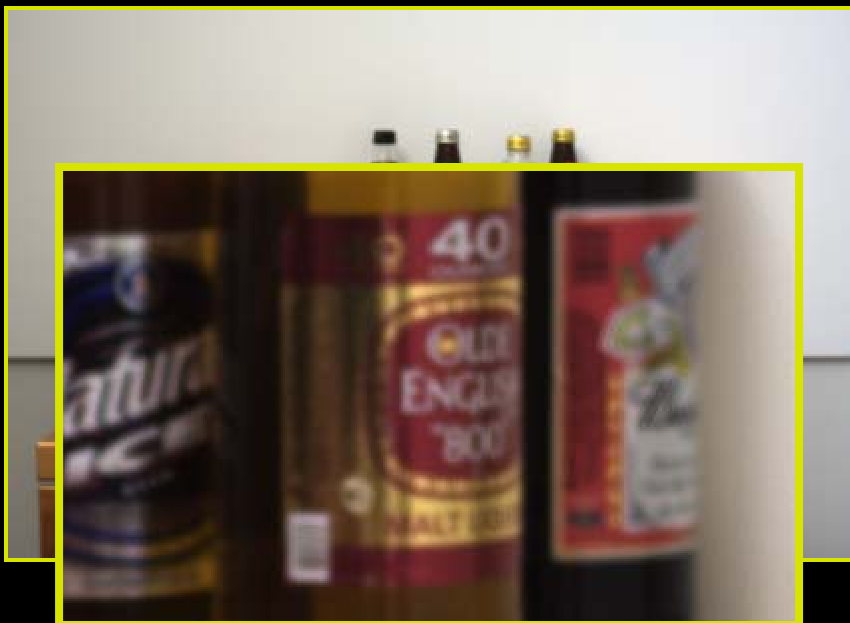
**MIT CSAIL**

Sliides from SIGGRAPH Presentation

Output #1: Depth map

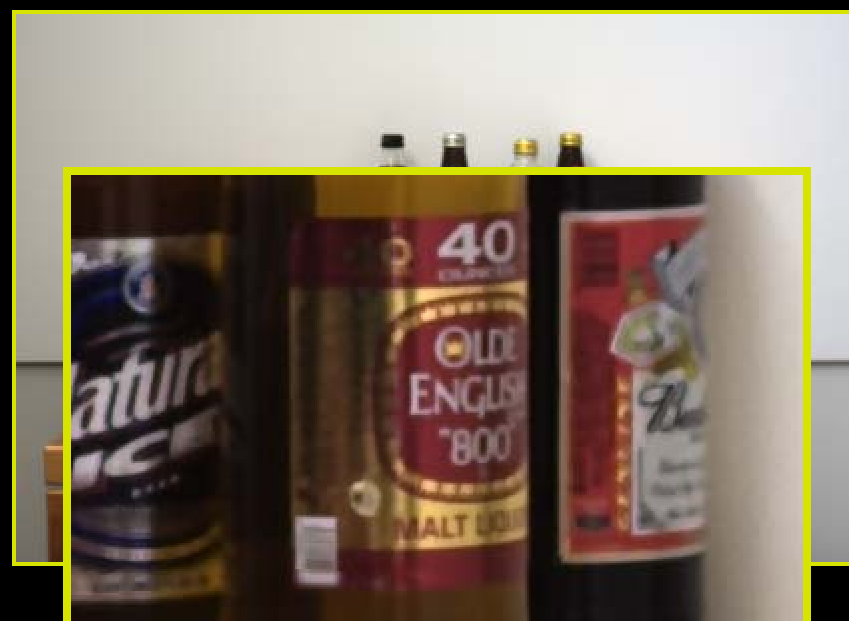
Single input image:

**Single input image:**



**Output #1: Depth map**

**Output #2: All-focused image**



# Lens and defocus

Lens' aperture

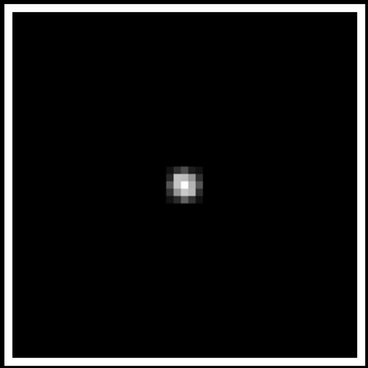
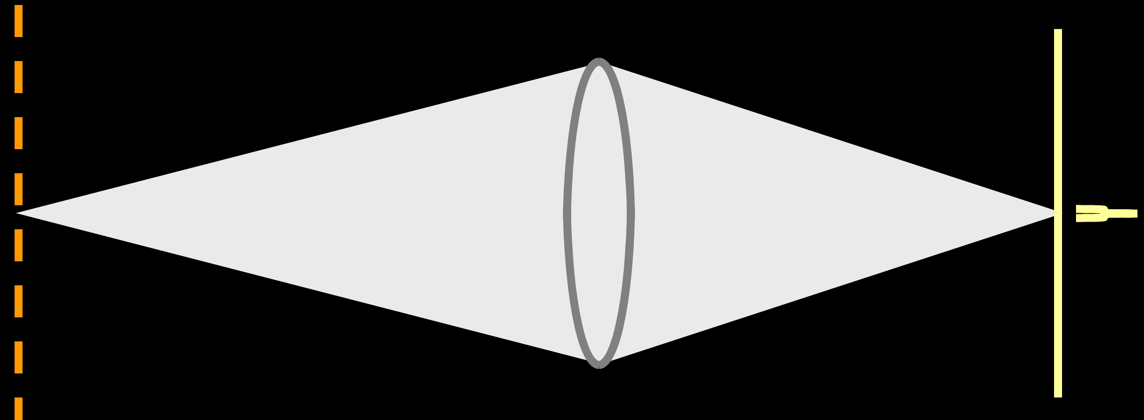


Image of a point light source



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Lens’ aperture

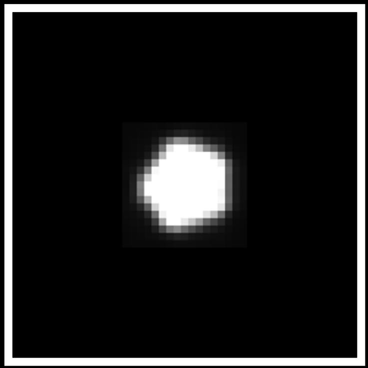
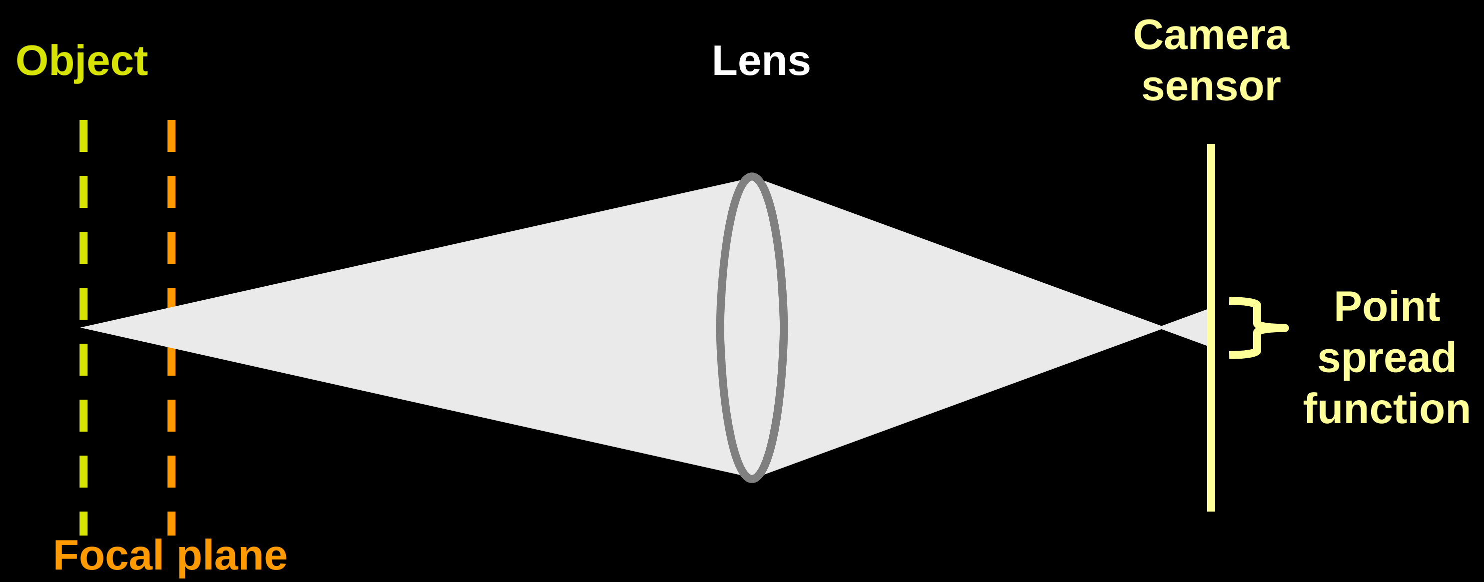


Image of a defocused point light source



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Lens' aperture

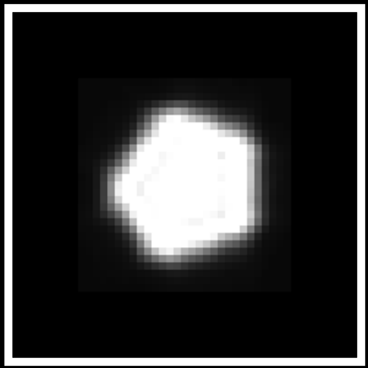
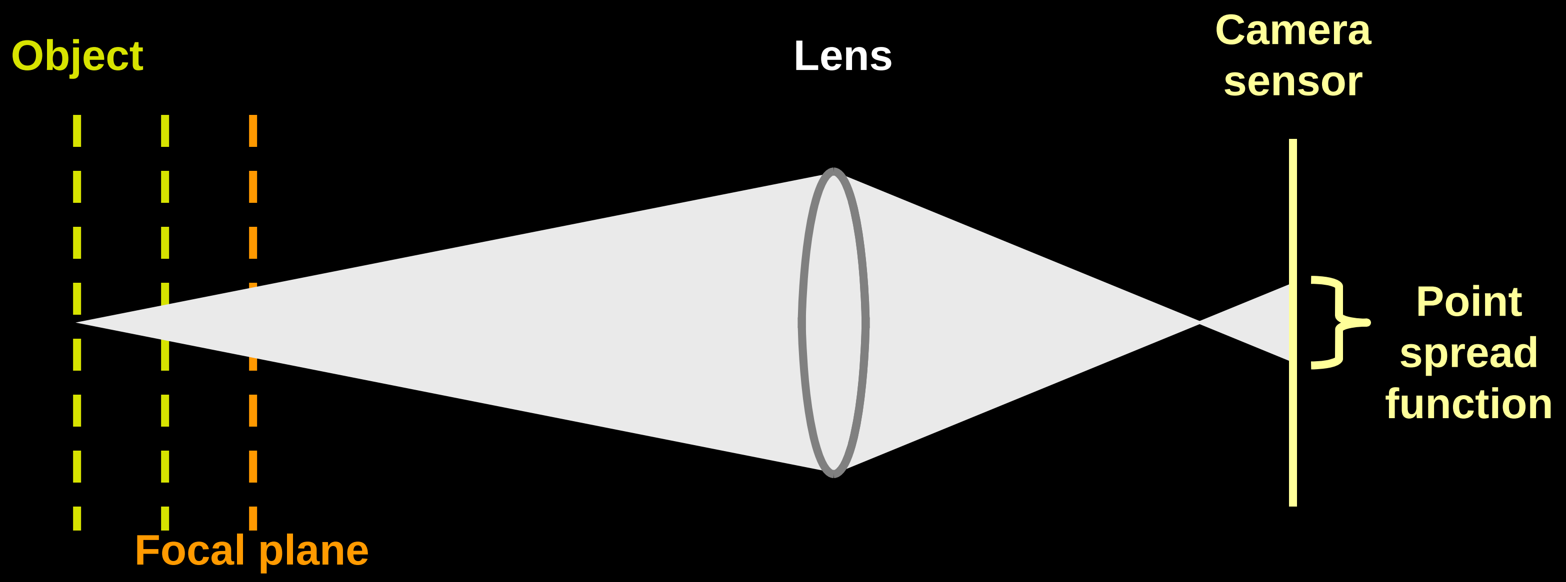


Image of a defocused point light source



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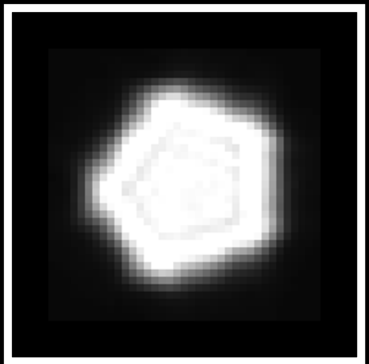
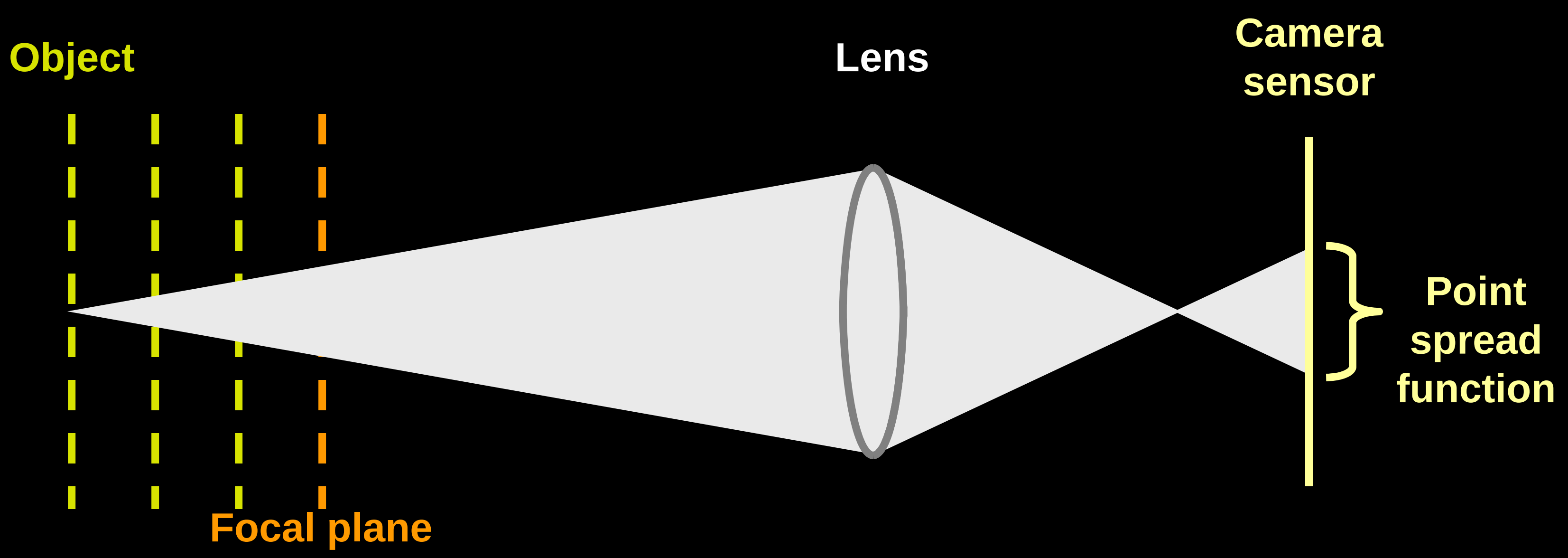


Image of a defocused point light source



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Lens' aperture

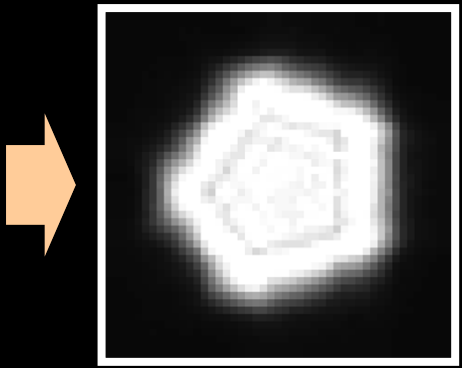
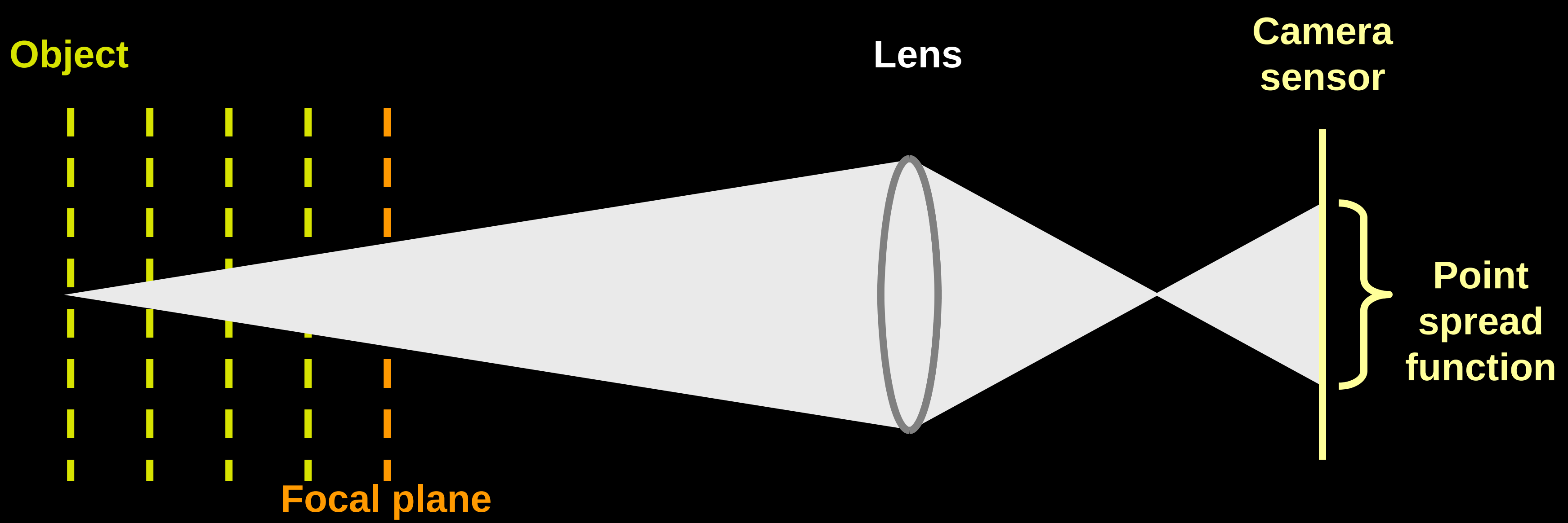


Image of a defocused point light source



# Depth and defocus


ill posed

**Depth from defocus:**

Infer depth by analyzing local scale of defocus blur

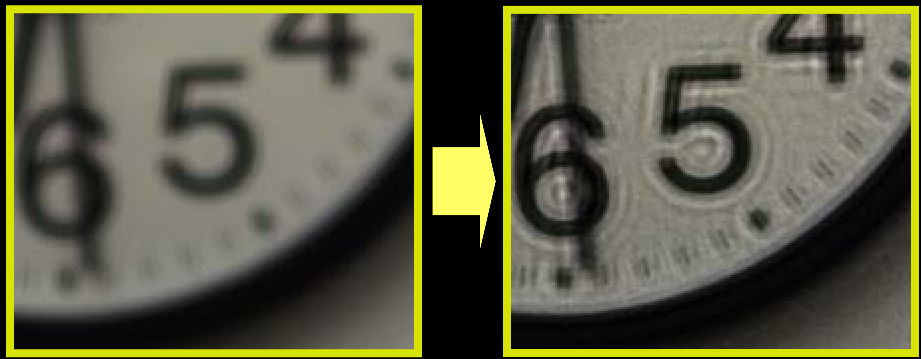
# Challenges

- Hard to discriminate a smooth scene from defocus blur

?

Out of focus

- Hard to undo defocus blur



Input

Ringing with conventional deblurring algorithm

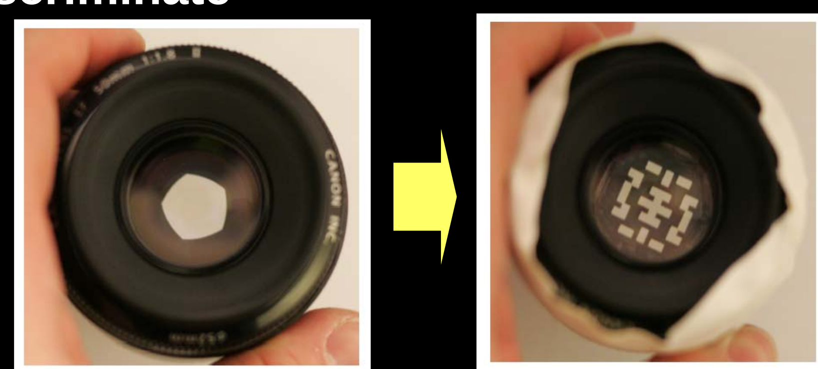
# Key ideas

- Exploit prior on natural images
  - Improve deconvolution
  - Improve depth discrimination

Natural

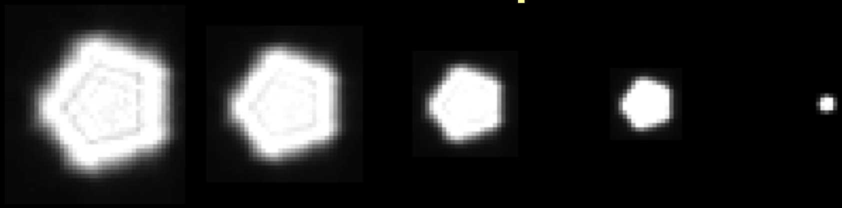
Unnatural

- Coded aperture (mask inside lens)
  - make defocus patterns different from natural images and easier to discriminate



# Defocus as local convolution


Calibrated blur kernels at different depths



# Defocus as local convolution


$$y = f_k \otimes x$$

Local sub-window

Calibrated blur kernels at depth $k$

Sharp sub-window

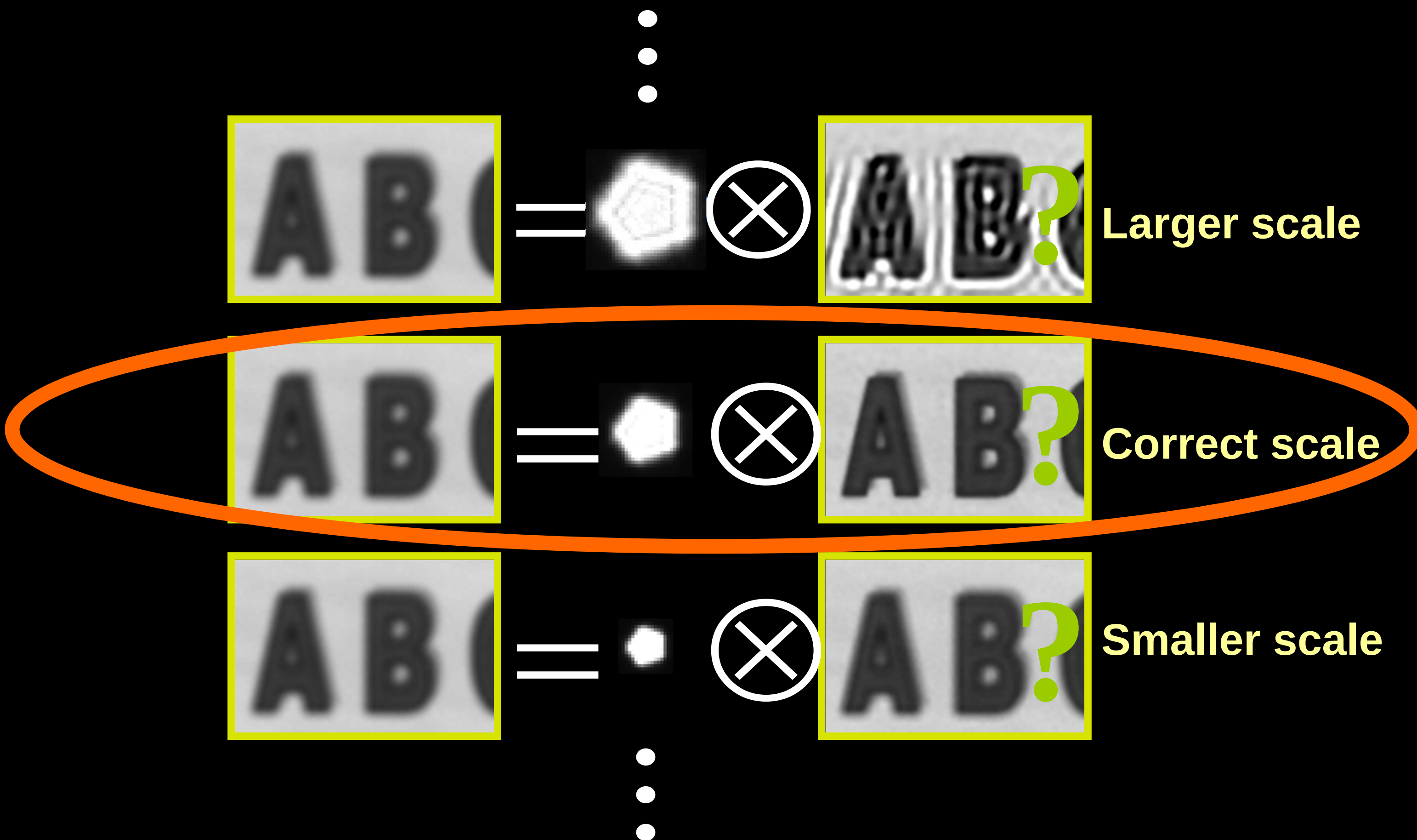
Depth $k$=1:

Depth $k$=2:

Depth $k$=3:

# Overview

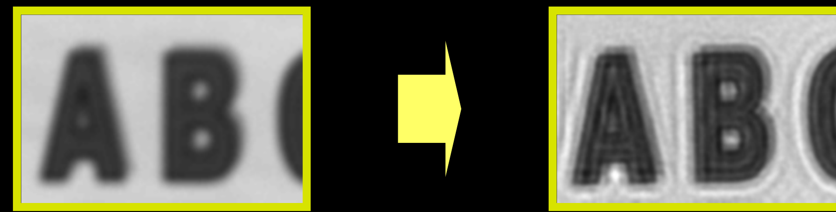
Try deconvolving local input windows with different scaled filters:




Somehow: select best scale.

# Challenges

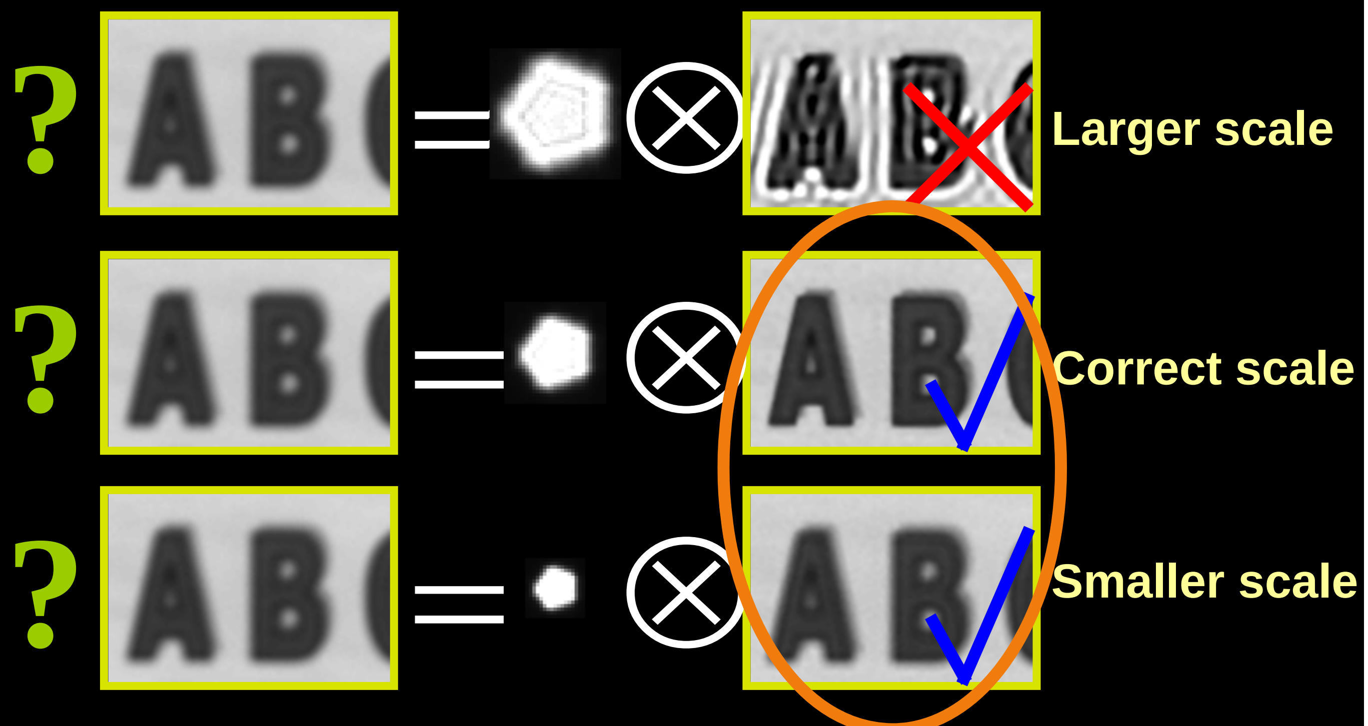
- Hard to deconvolve even when kernel is known



Input

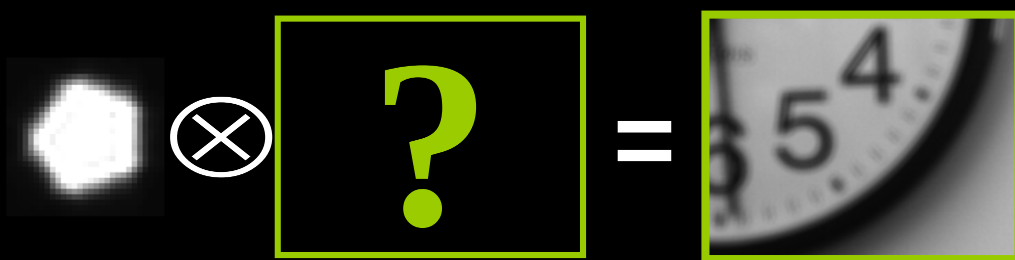
Ringing with the traditional Richardson-Lucy deconvolution algorithm

- Hard to identify correct scale:



# Deconvolution is ill posed

$$f \otimes x = y$$



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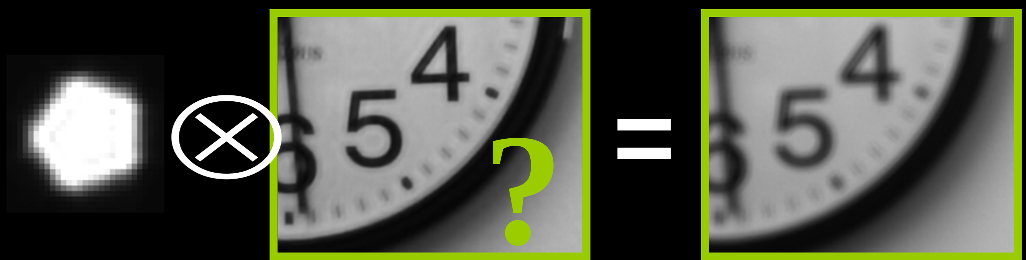
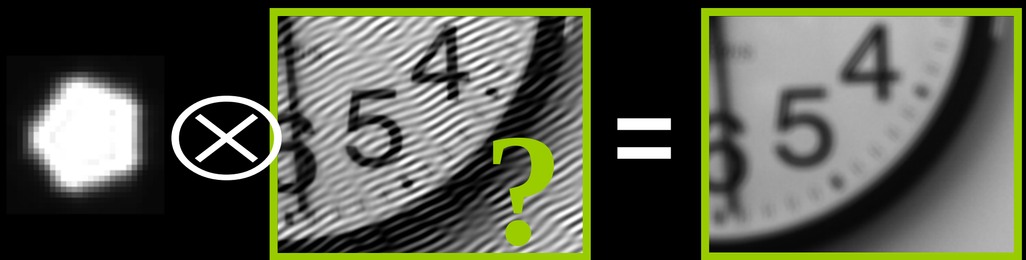
$$f \otimes x = y$$

**Solution 1:**



**Solution 2:**



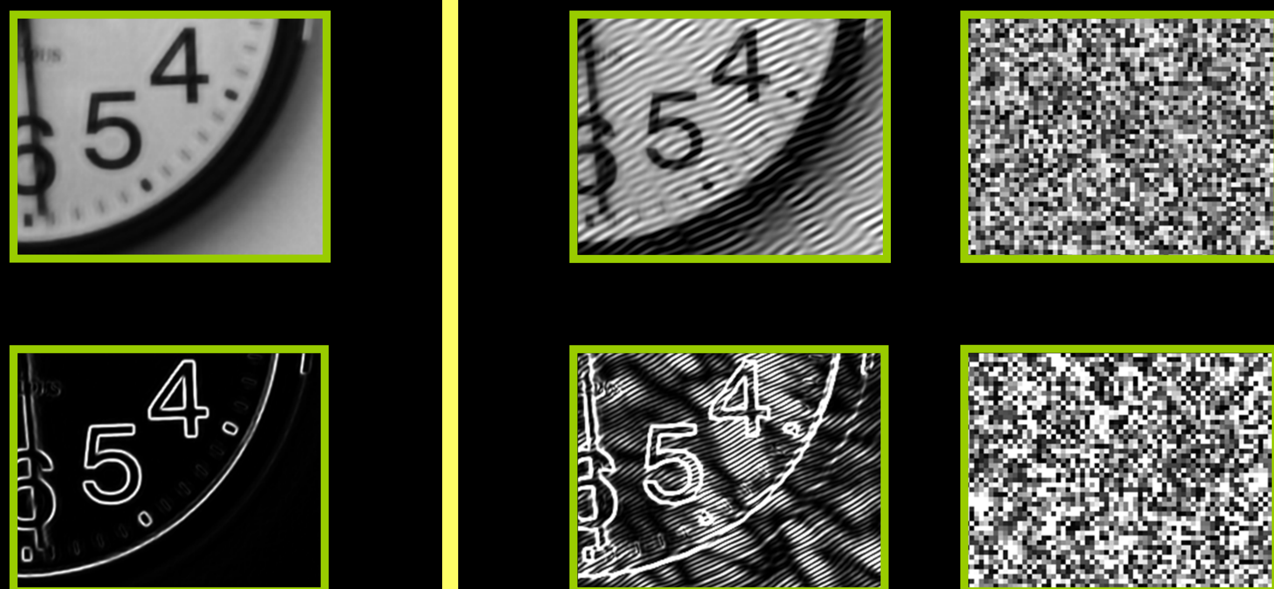
# Idea 1: Natural images prior

## What makes images special?

Natural | Unnatural

Image

gradient

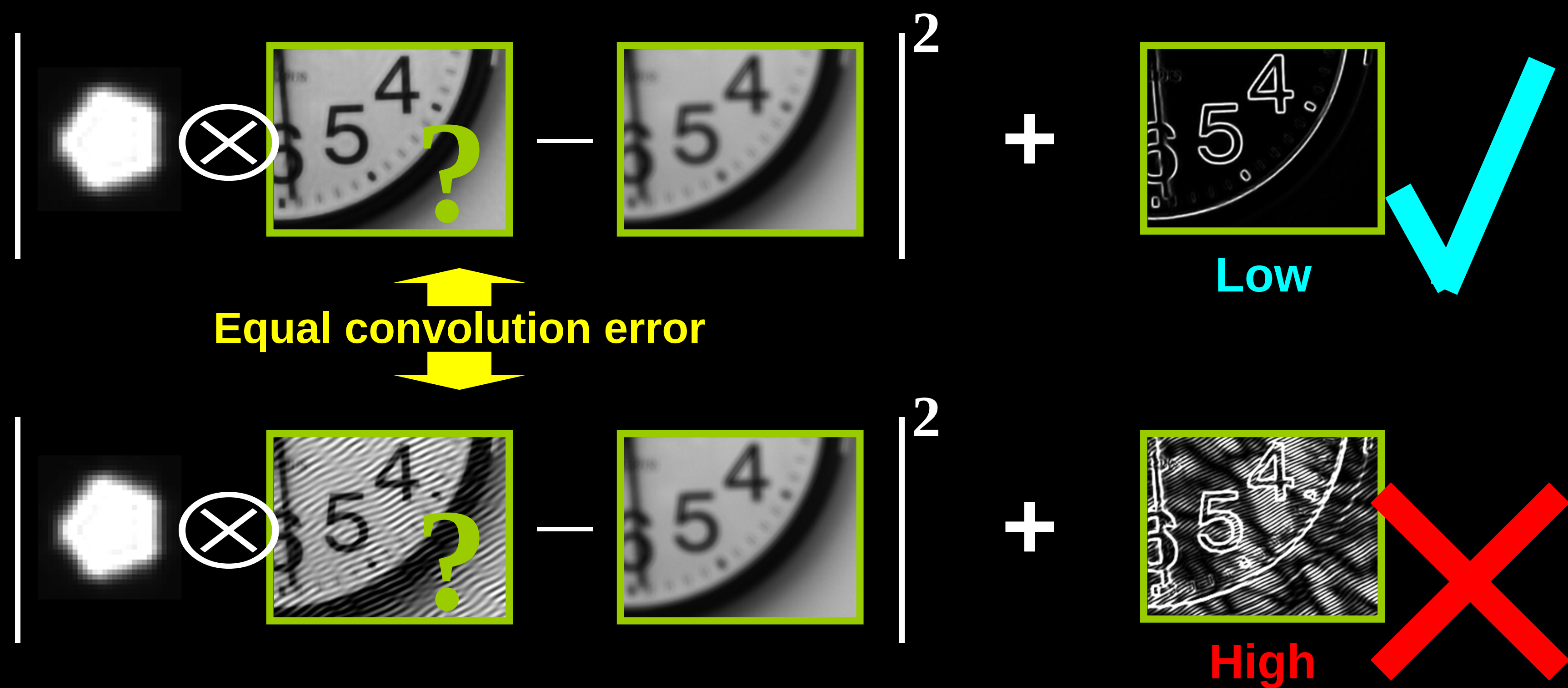


**Natural images have sparse gradients**

**put a penalty on gradients**

# Deconvolution with prior

$$x = \arg\min \underbrace{| f \otimes x - y |^2}_{\text{Convolution error}} + \lambda \underbrace{\sum_i \rho(\nabla x_i)}_{\text{Derivatives prior}}$$



# Comparing deconvolution algorithms

(Non blind) deconvolution code available online:
http://groups.csail.mit.edu/graphics/CodedAperture/

Input

$$\rho(\nabla x) = \left\|\nabla x\right\|^2$$

"spread" gradients

$$\rho(\nabla x) = \left\|\nabla x\right\|^{0.8}$$

"localizes" gradients

Richardson-Lucy

Gaussian prior

Sparse prior

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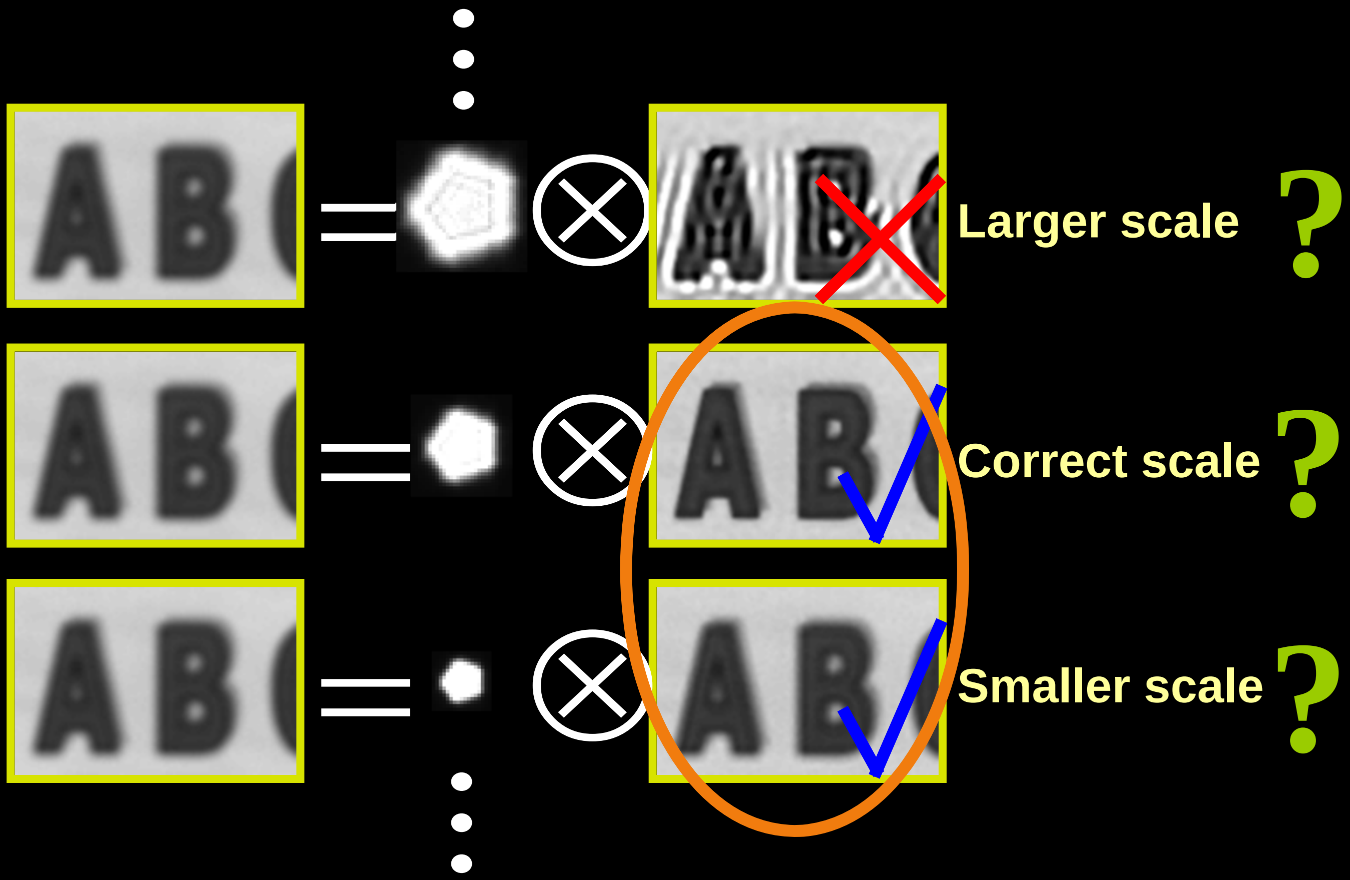
Sparse prior

# Recall: Overview

Try deconvolving local input windows with different scaled filters:



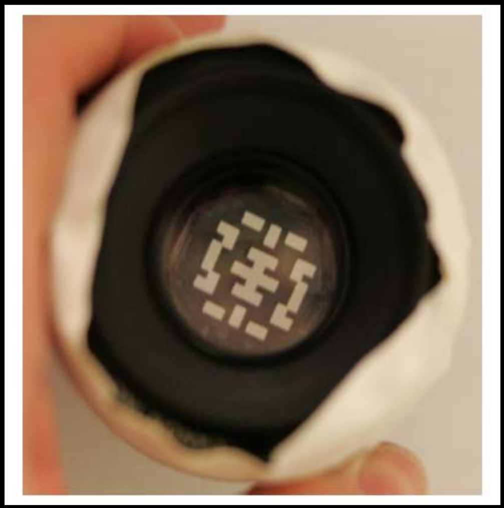

Somehow: select best scale.

Challenge: smaller scale not so different than correct

# Idea 2: Coded Aperture

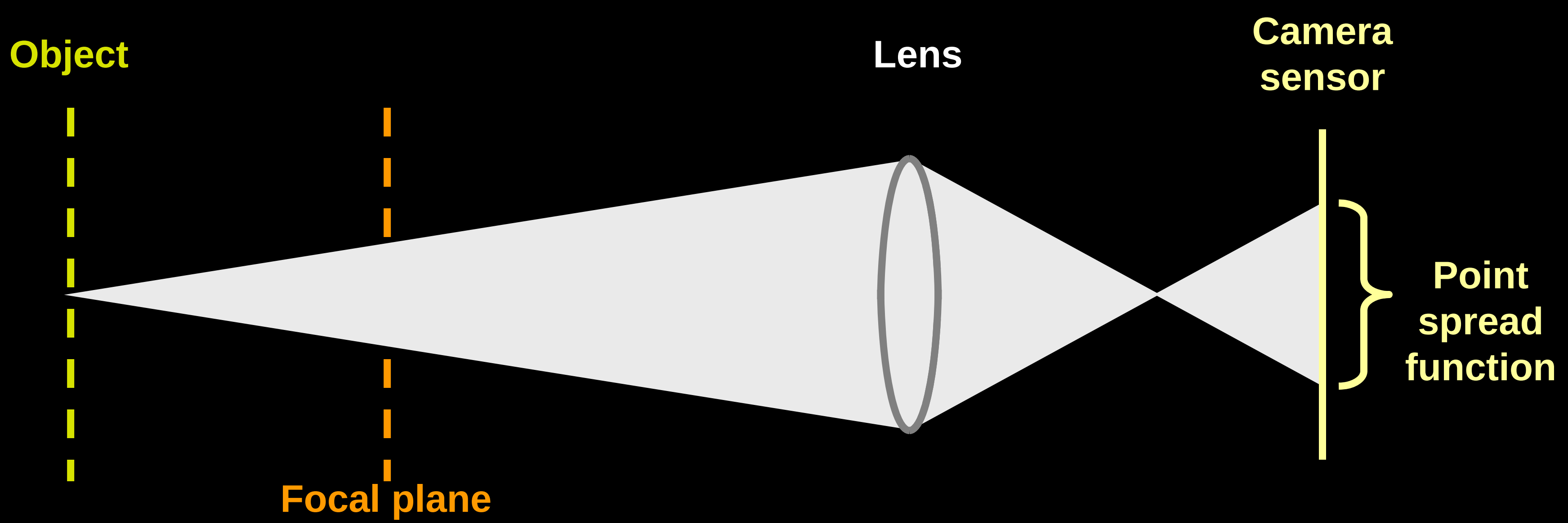
- Mask (code) in aperture plane
  - make defocus patterns different from natural images and easier to discriminate


Conventional aperture



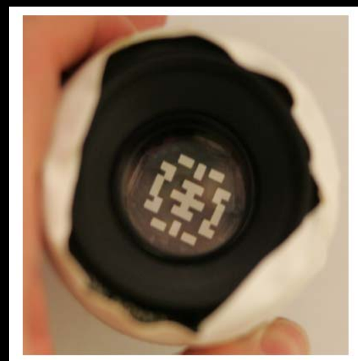
Our coded aperture

# Solution: lens with occluder



# Solution: lens with occluder

Aperture pattern



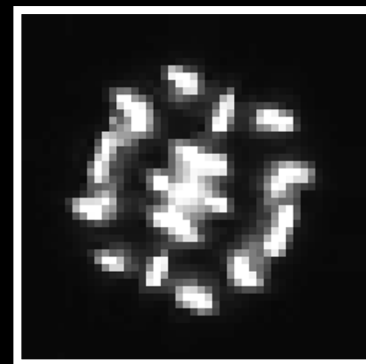
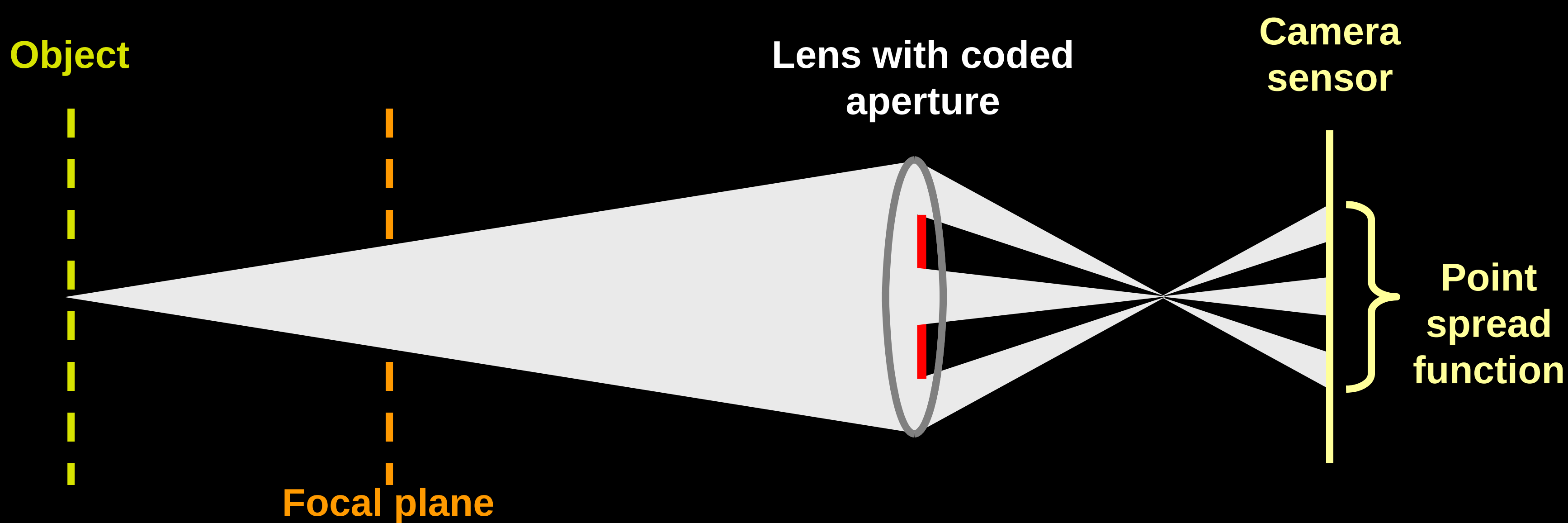


Image of a defocused point light source



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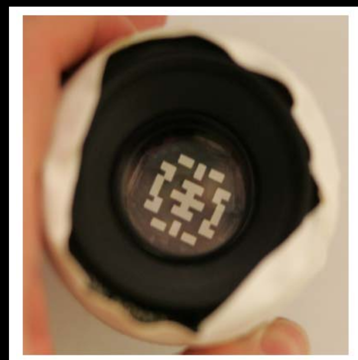

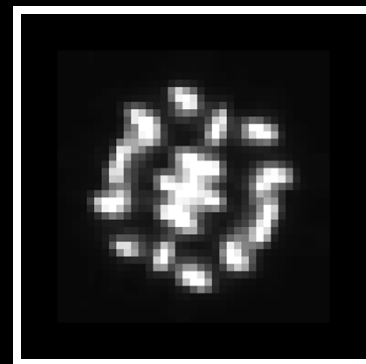

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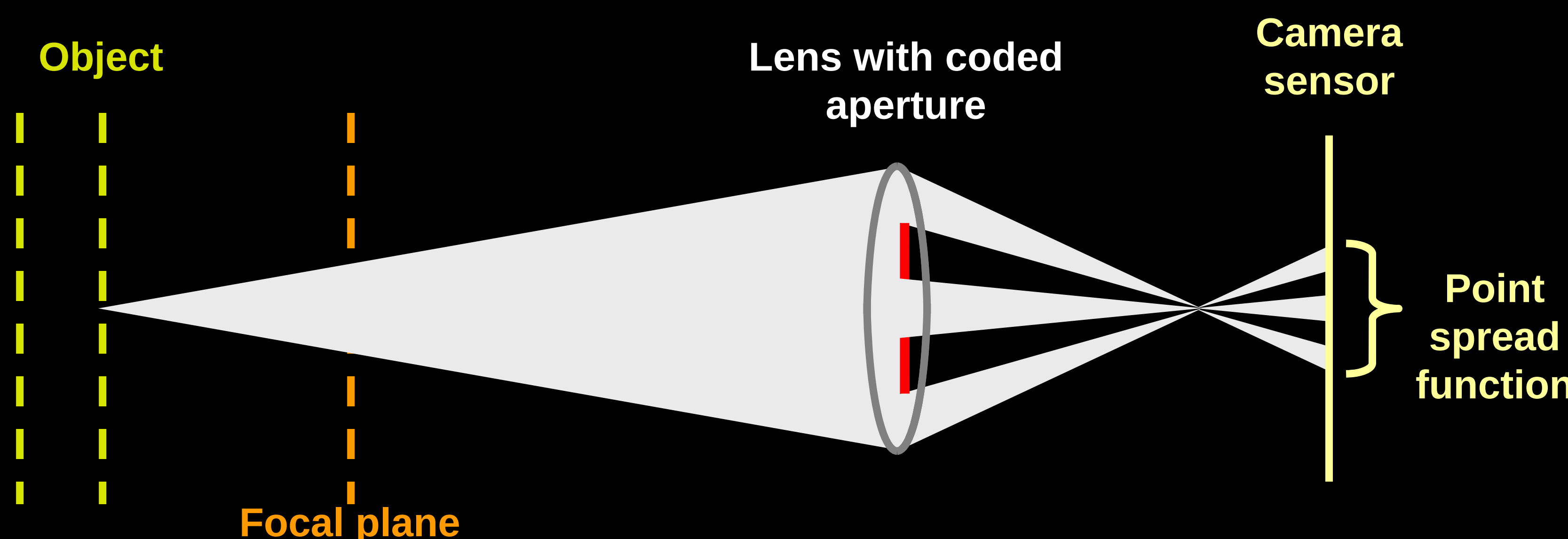

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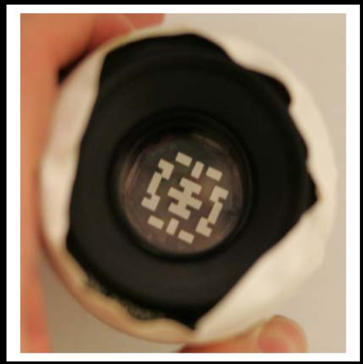

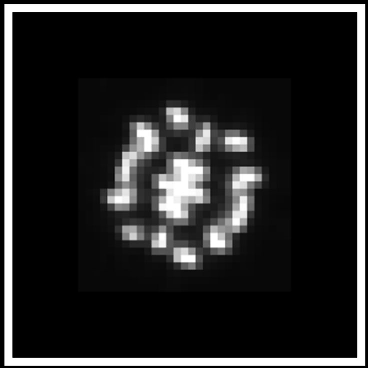

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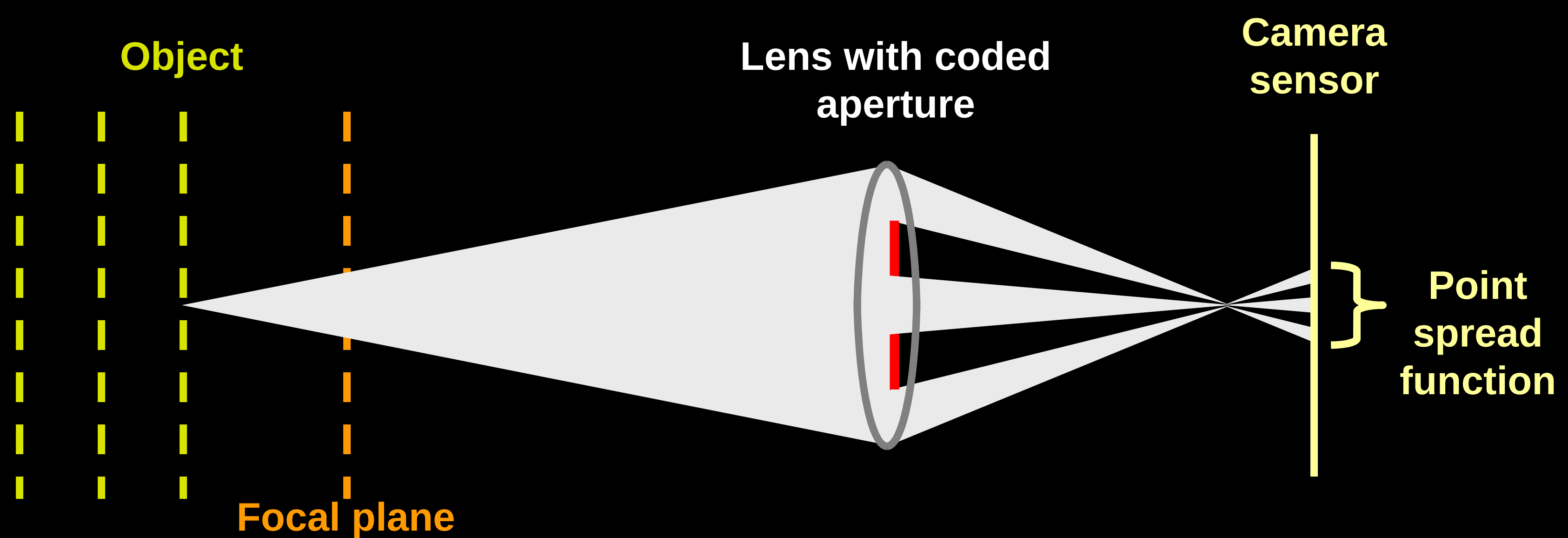

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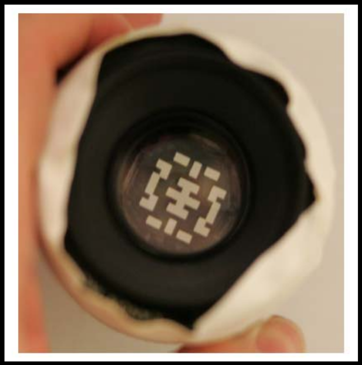
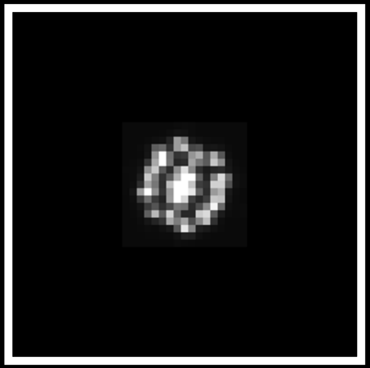
Aperture pattern





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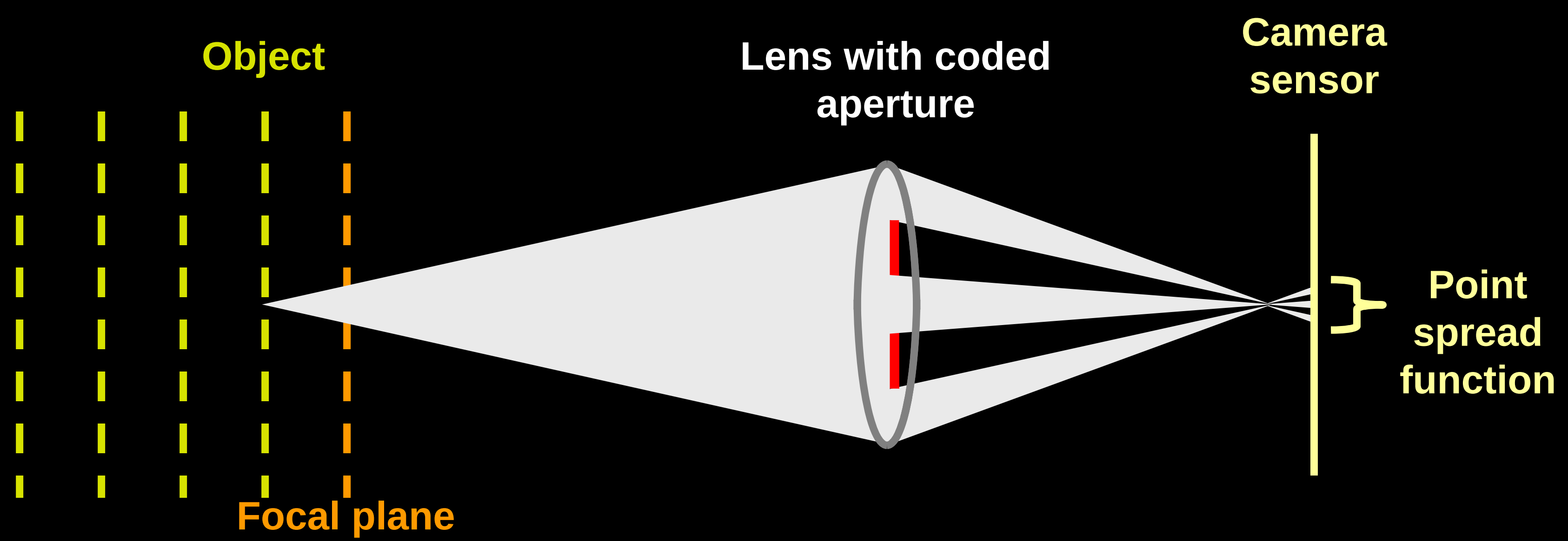

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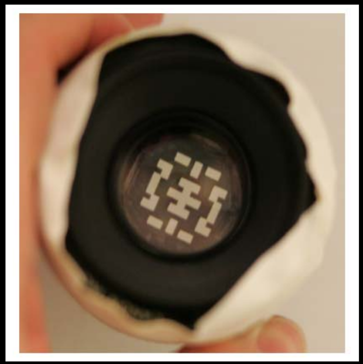


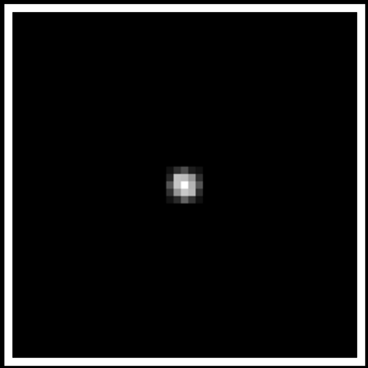
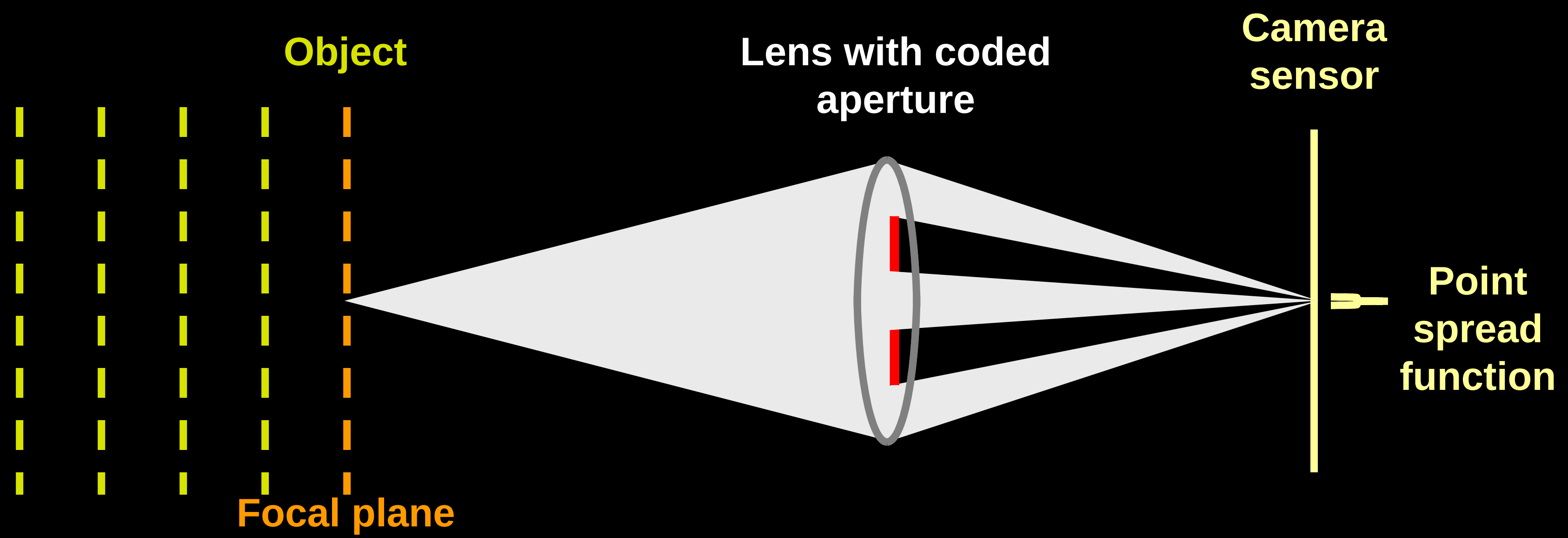
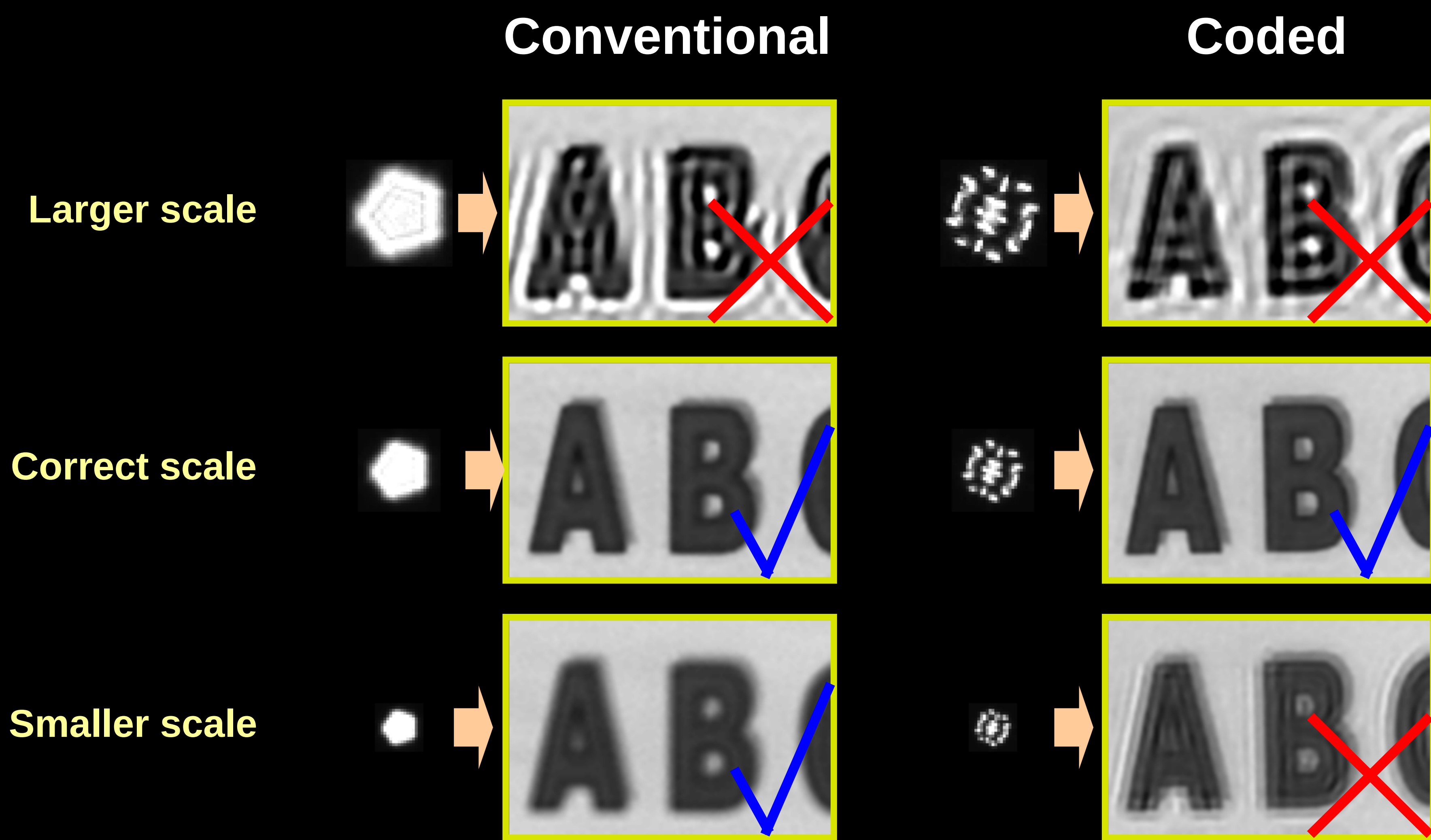


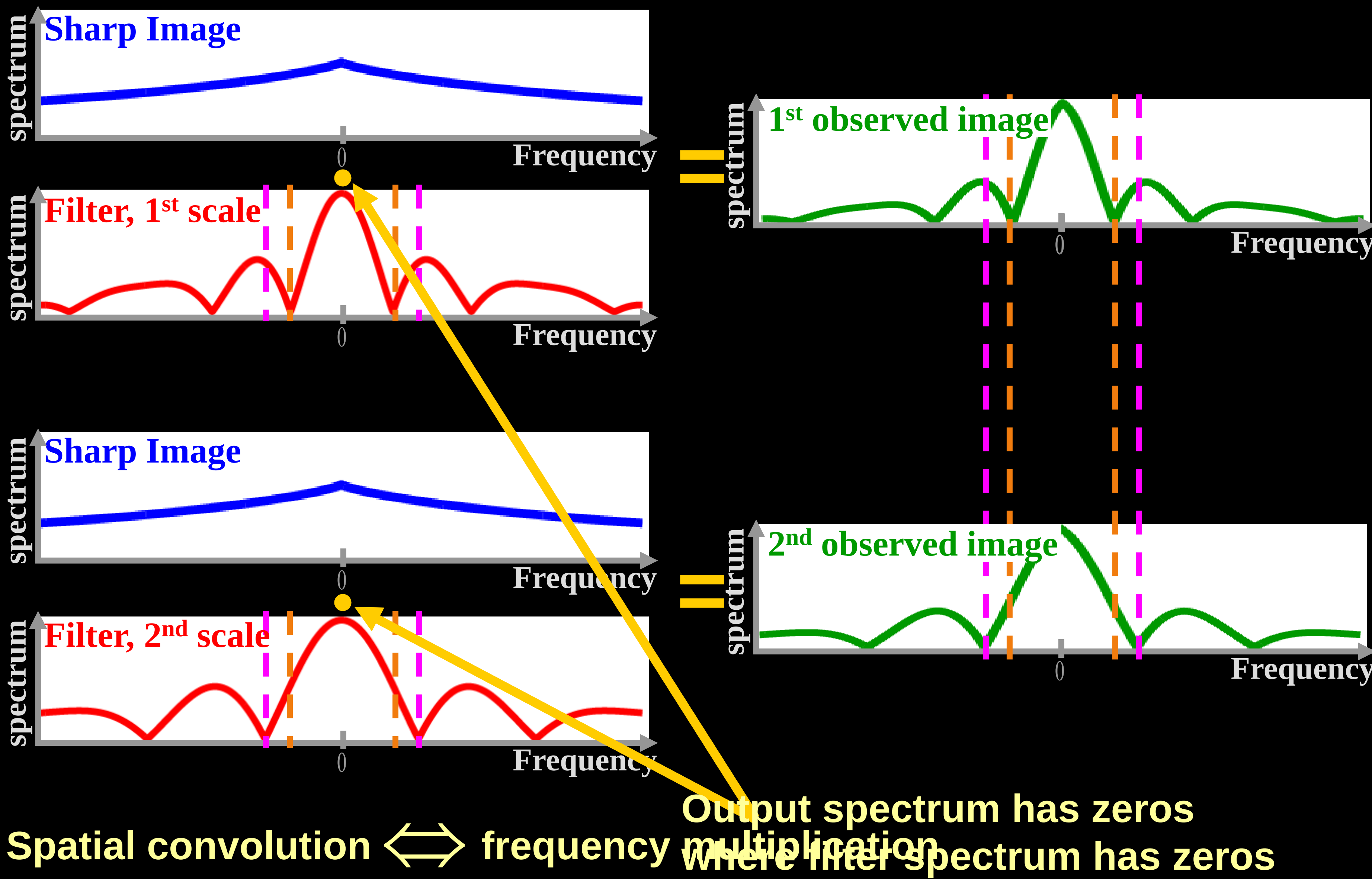
Image of a defocused point light source



# Coded aperture reduces uncertainty in scale identification

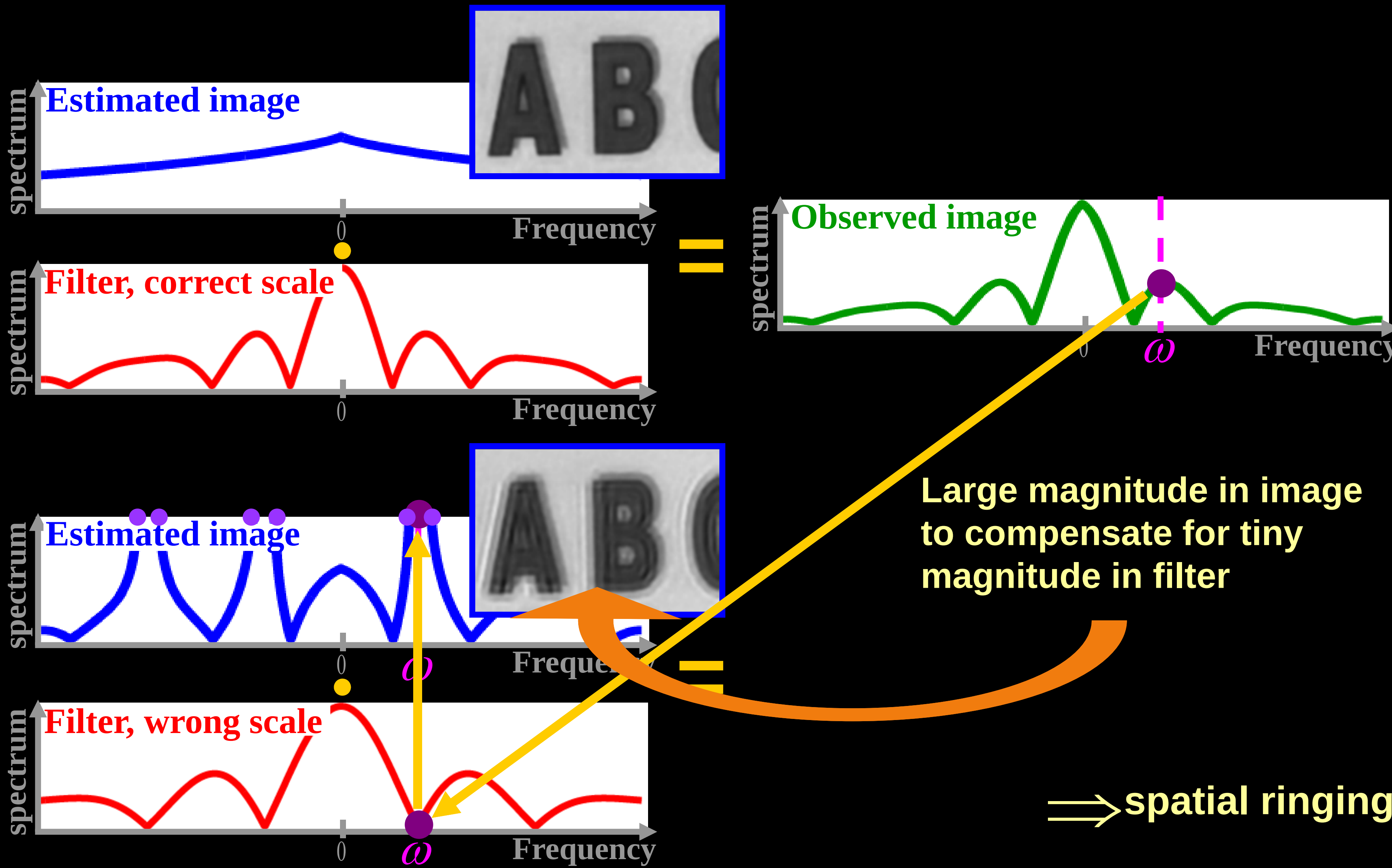


# Convolution- frequency domain representation




Spatial convolution ⟺ frequency multiplication

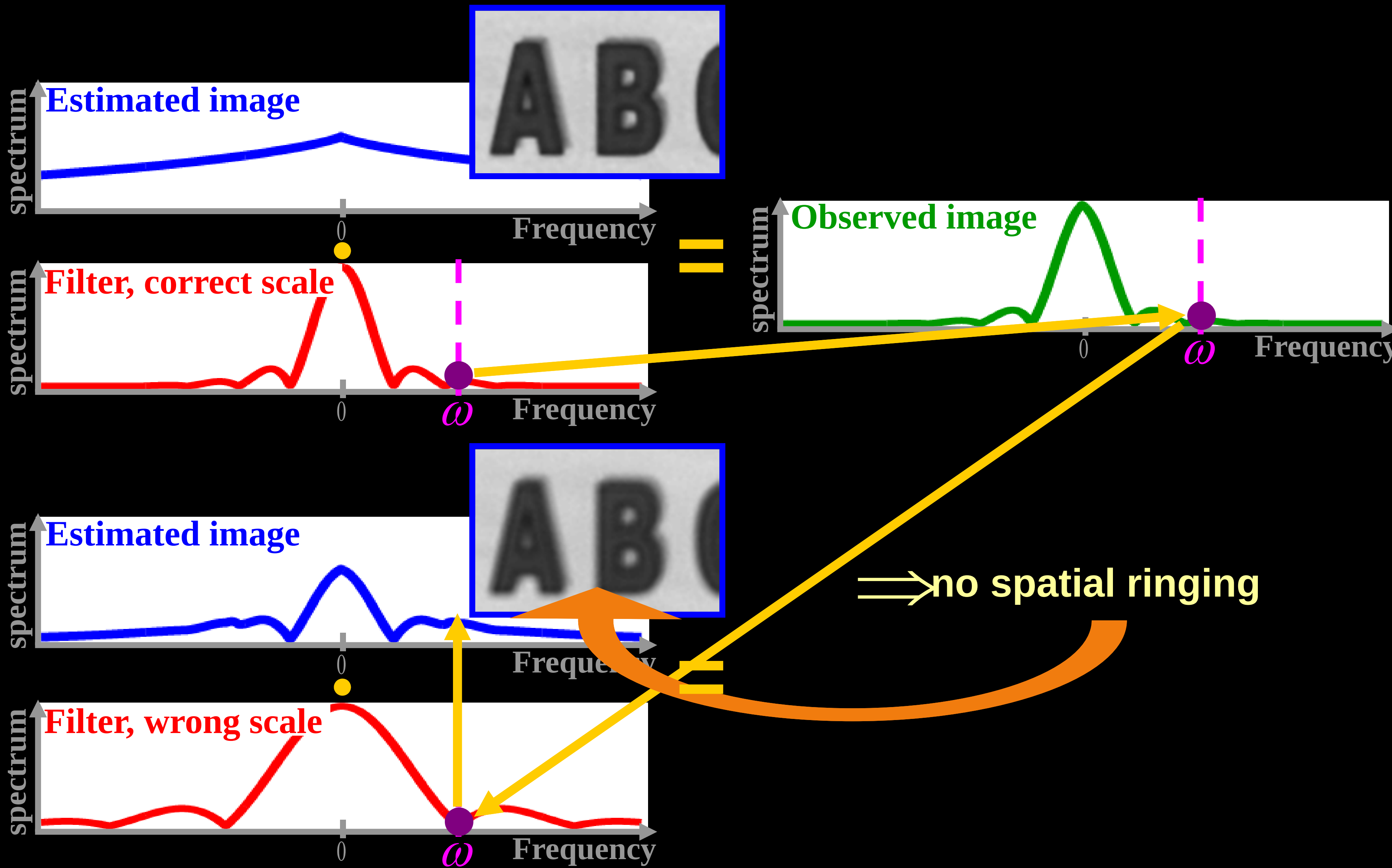
# Coded aperture: Scale estimation and division by zero




Large magnitude in image to compensate for tiny magnitude in filter

$\Longrightarrow$ spatial ringing

# Division by zero with a conventional aperture?

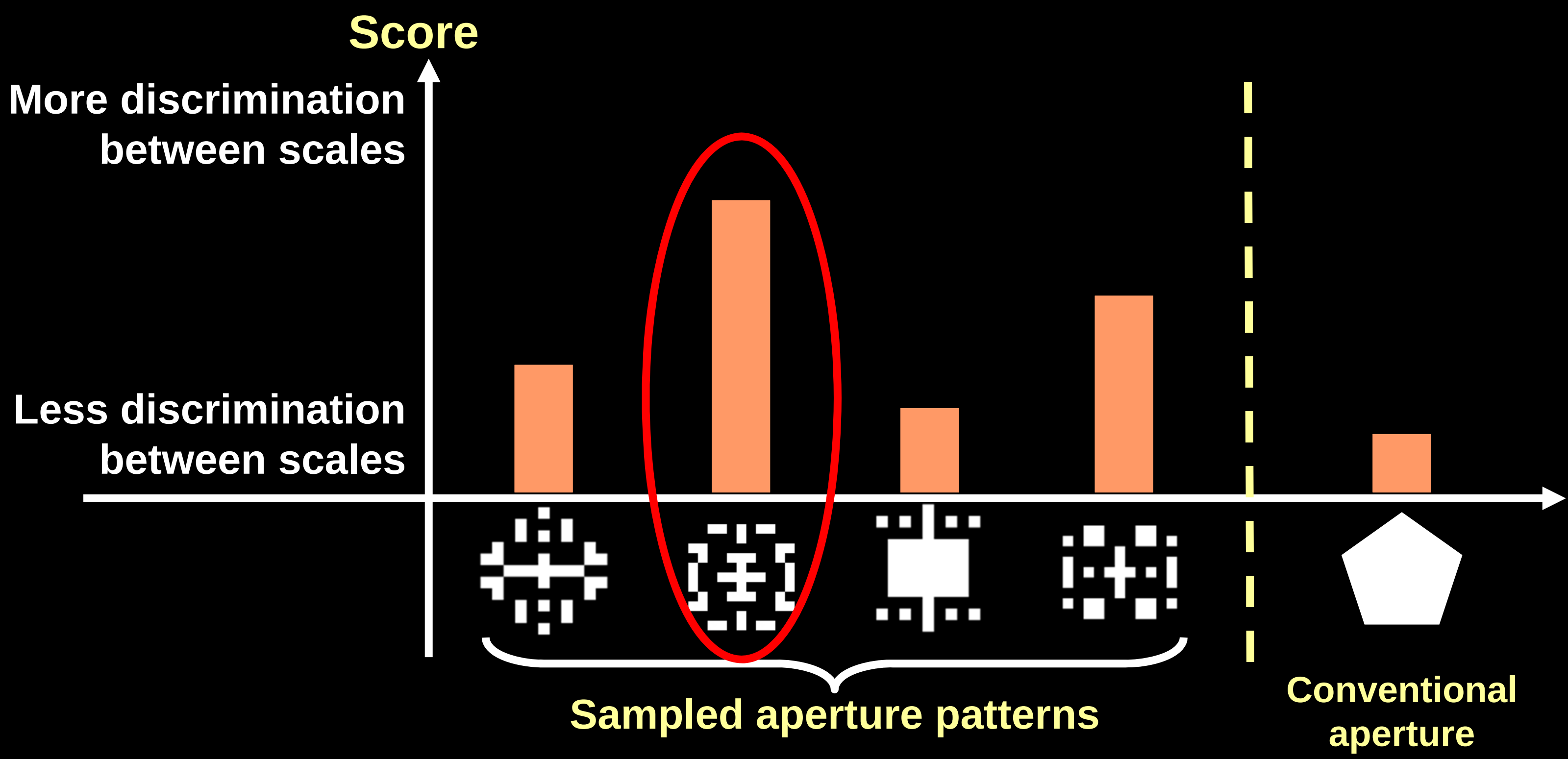



$\Longrightarrow$ no spatial ringing

# Filter Design

**Analytically search for a pattern maximizing discrimination between images at different defocus scales (*KL-divergence)***

**Account for image prior and physical constraints**

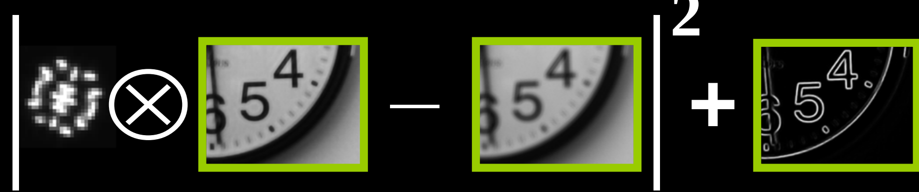


# Depth results

# Regularizing depth estimation

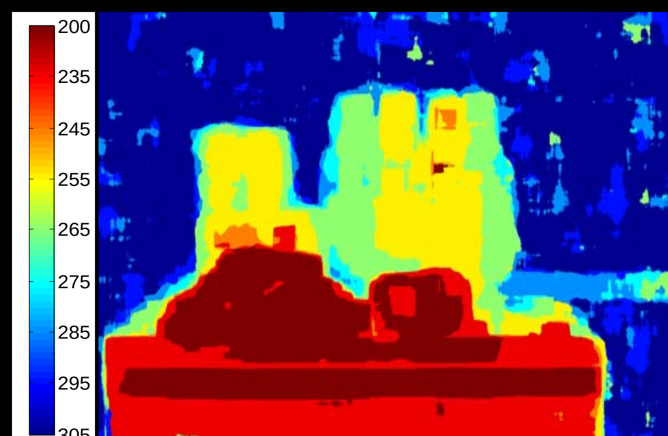
**Try deblurring with 10 different aperture scales**

$$x = \arg\min \underbrace{|f \otimes x - y|^2}_{\text{Convolution error}} + \underbrace{\lambda \sum_i \rho(\nabla x_i)}_{\text{Derivatives prior}}$$

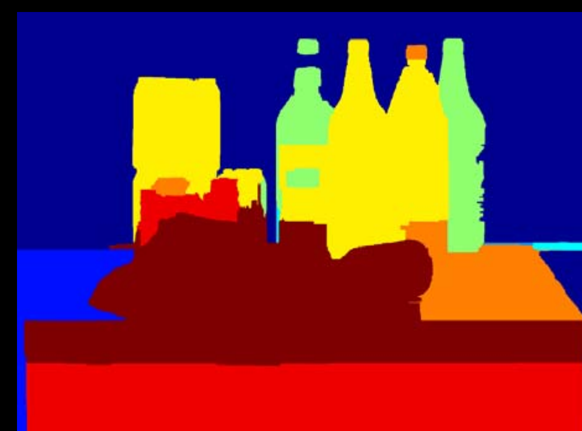


**Keep minimal error scale in each local window + regularization**

**Input**



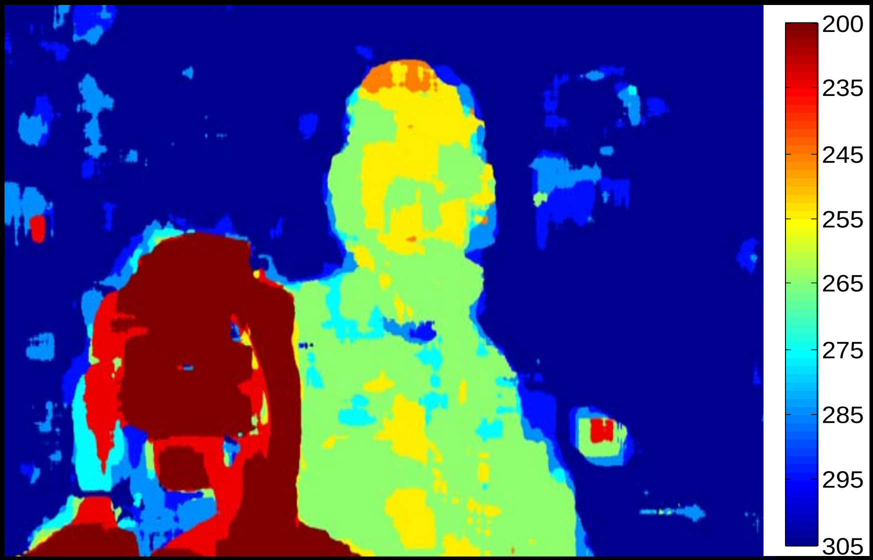

**Local depth estimation**



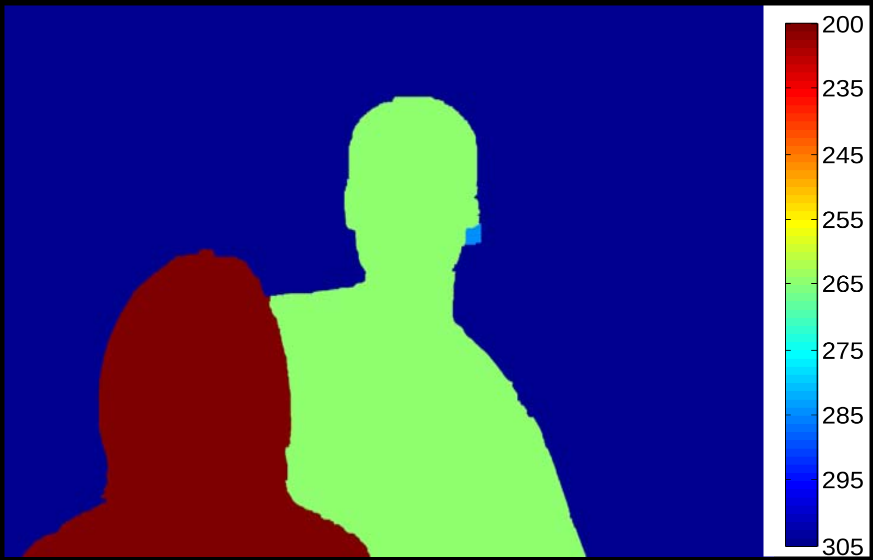
**Regularized depth**

# Regularizing depth estimation

Input



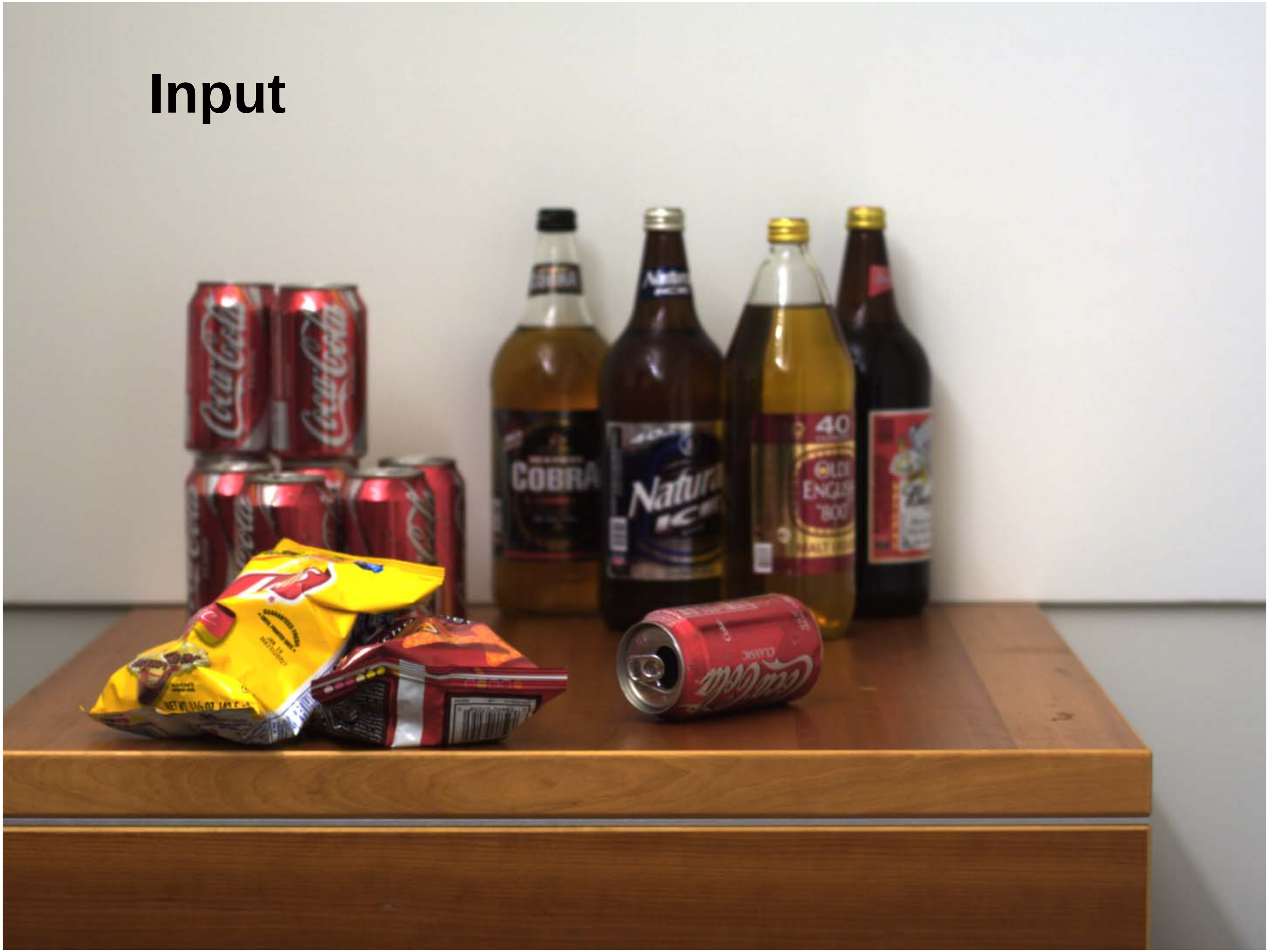

Local depth estimation



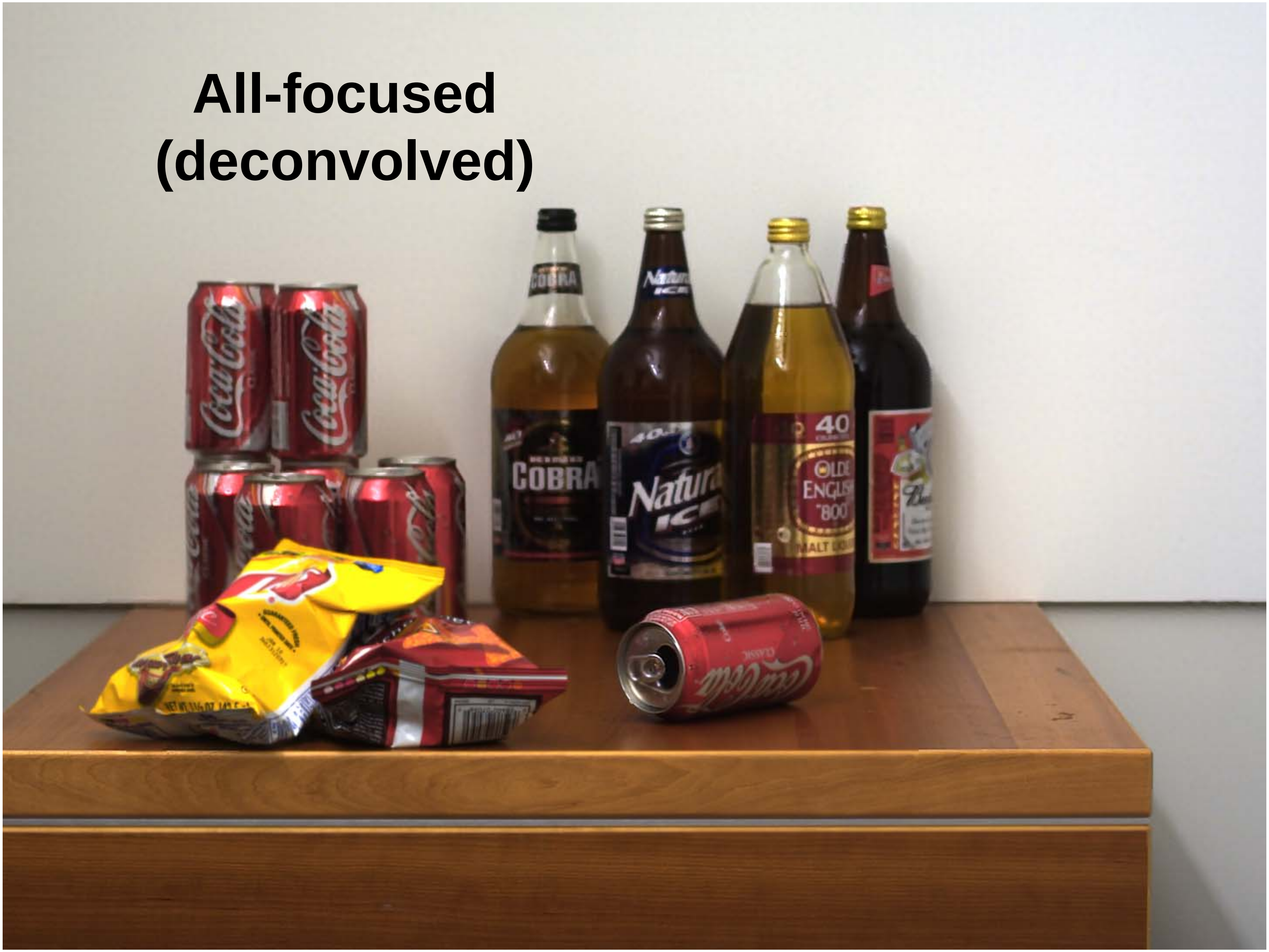

Regularized depth

# All focused results

# Input



# All-focused (deconvolved)



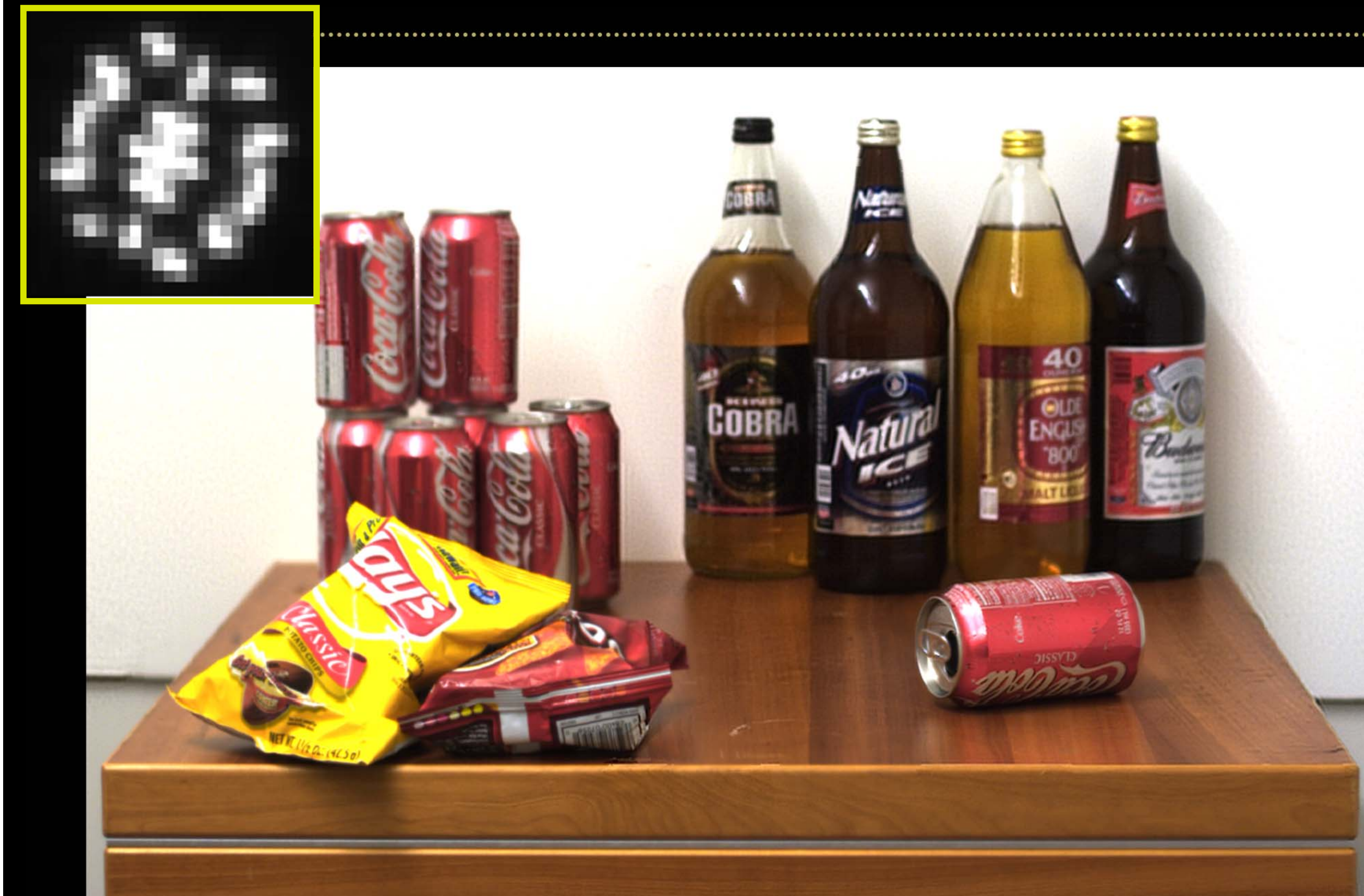
# Close-up

**Original image**


**All-focus image**

# Comparison- conventional aperture result

# Comparison- coded aperture result




Input


All-focused
(deconvolved)

# Close-up

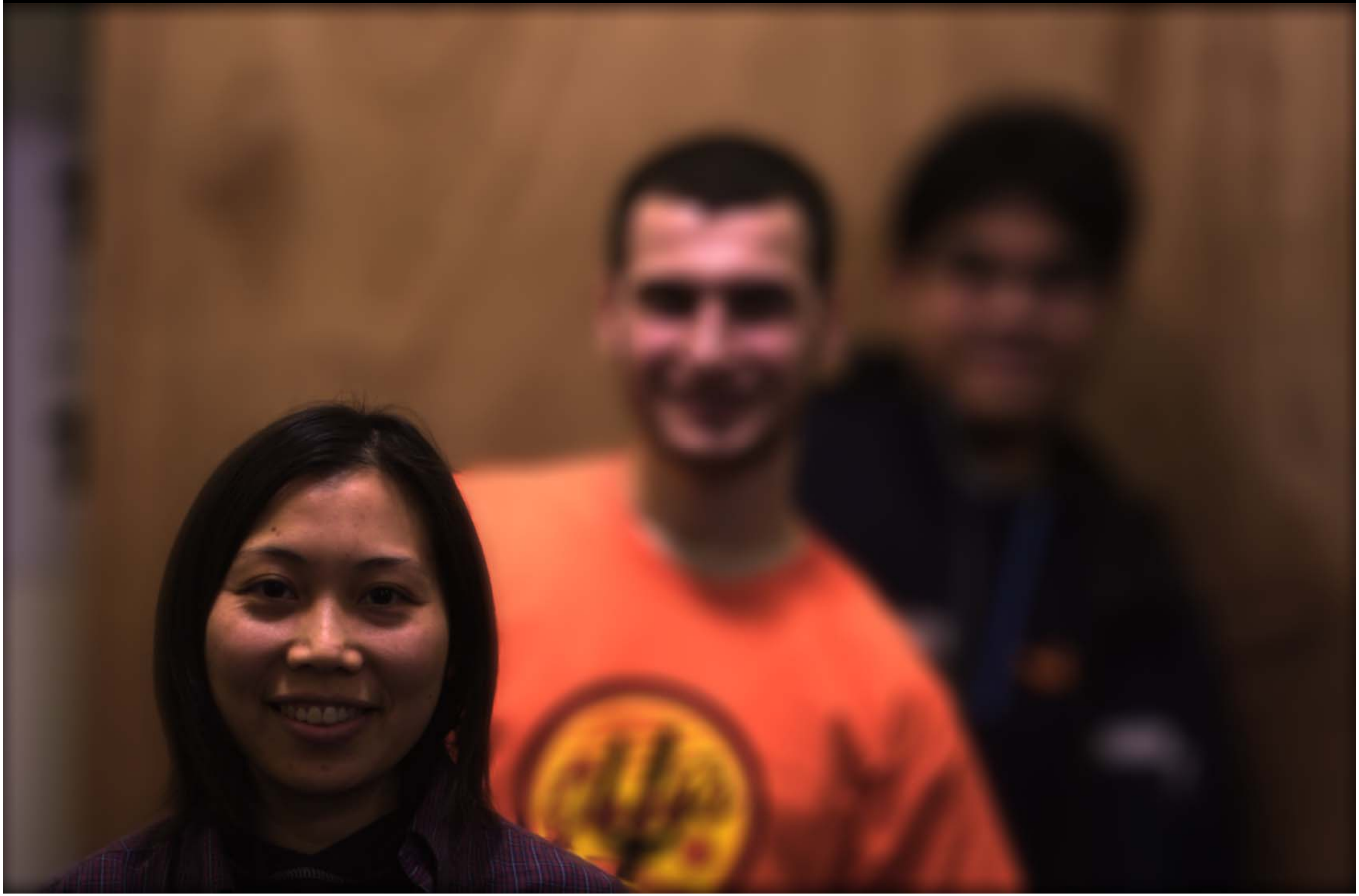
Original image

All-focus image

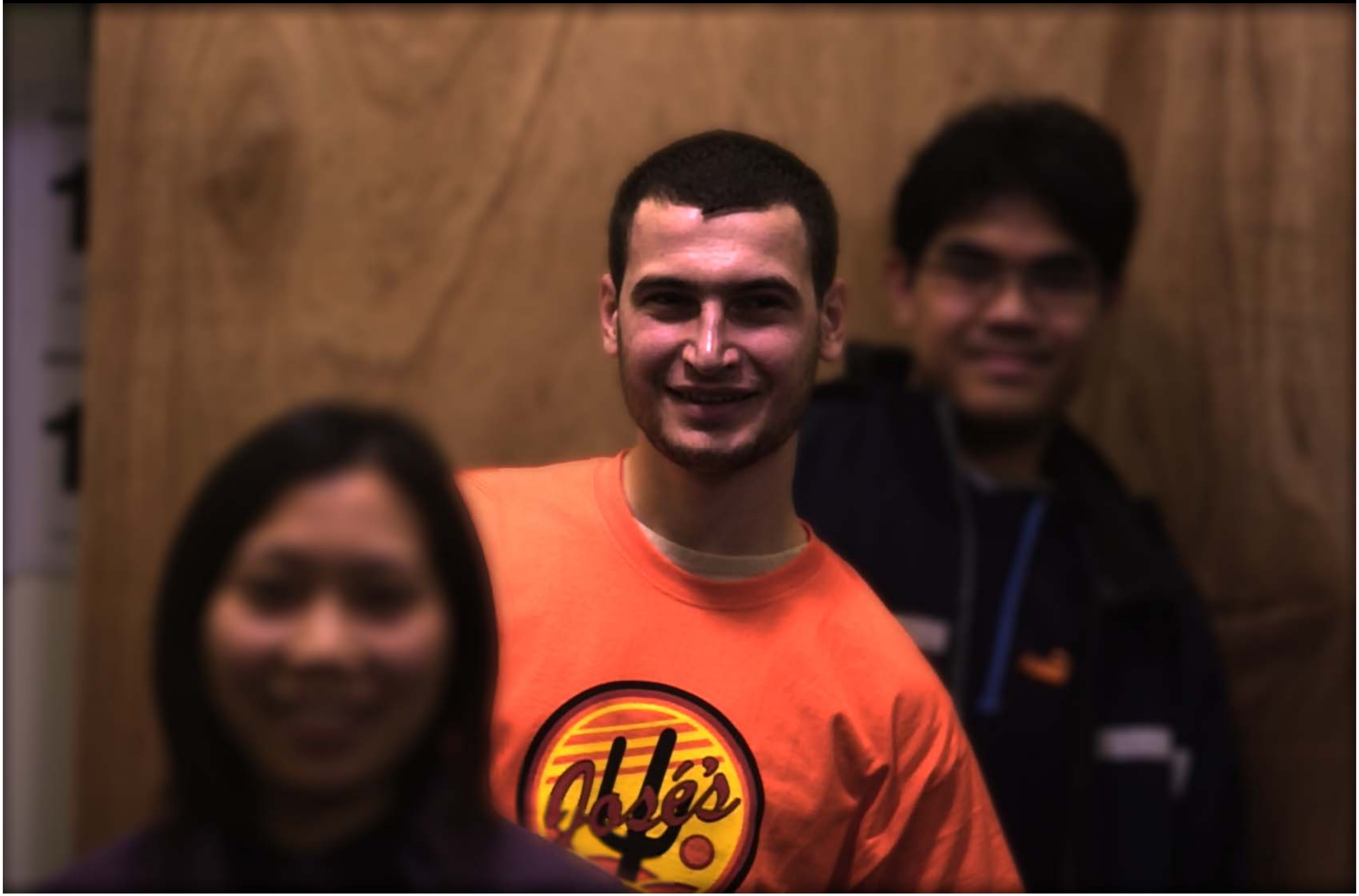
Naïve sharpening

# Application: Digital refocusing from a single image

# Application: Digital refocusing from a single image



# Application: Digital refocusing from a single image



# Application: Digital refocusing from a single image

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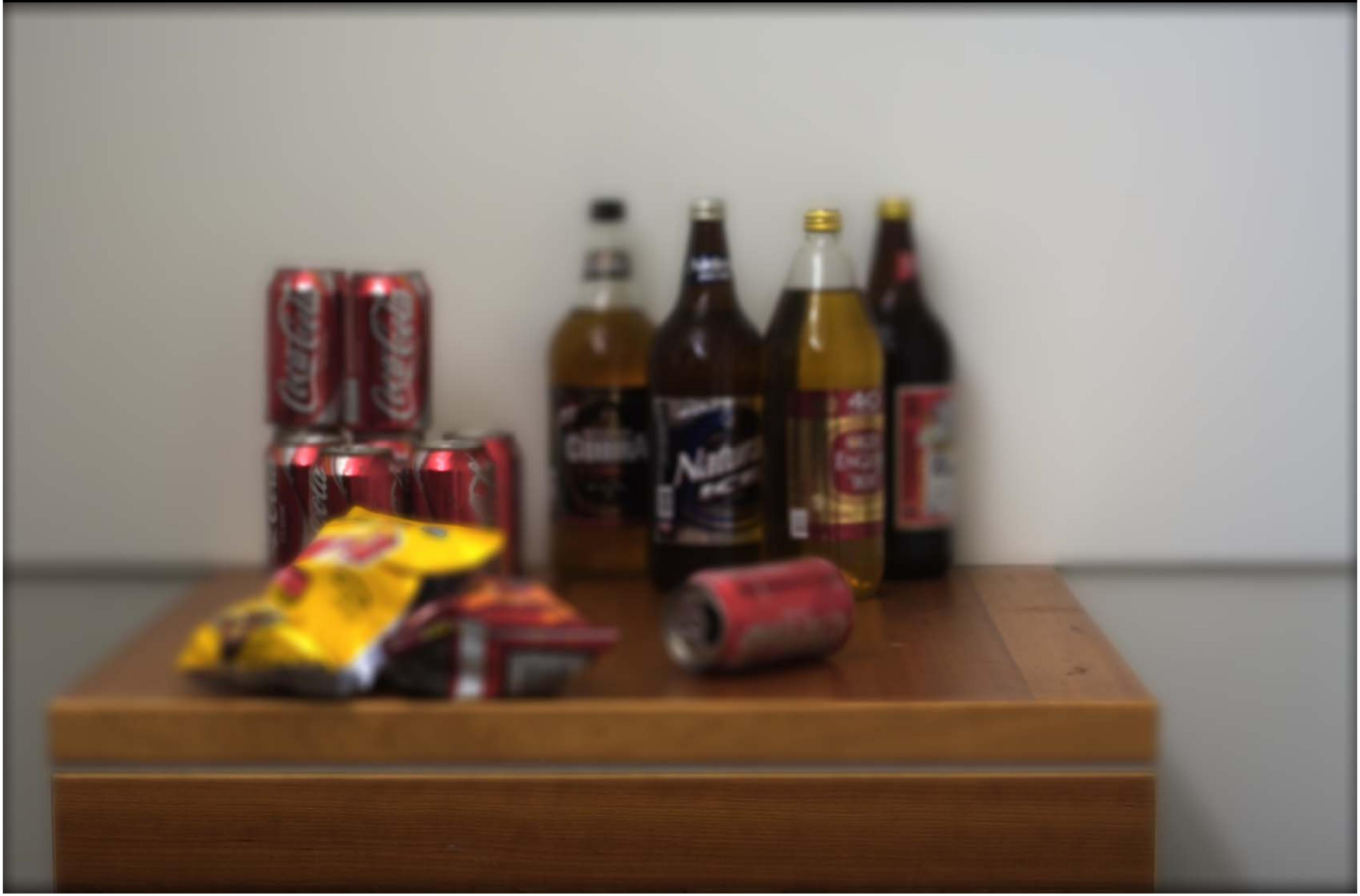
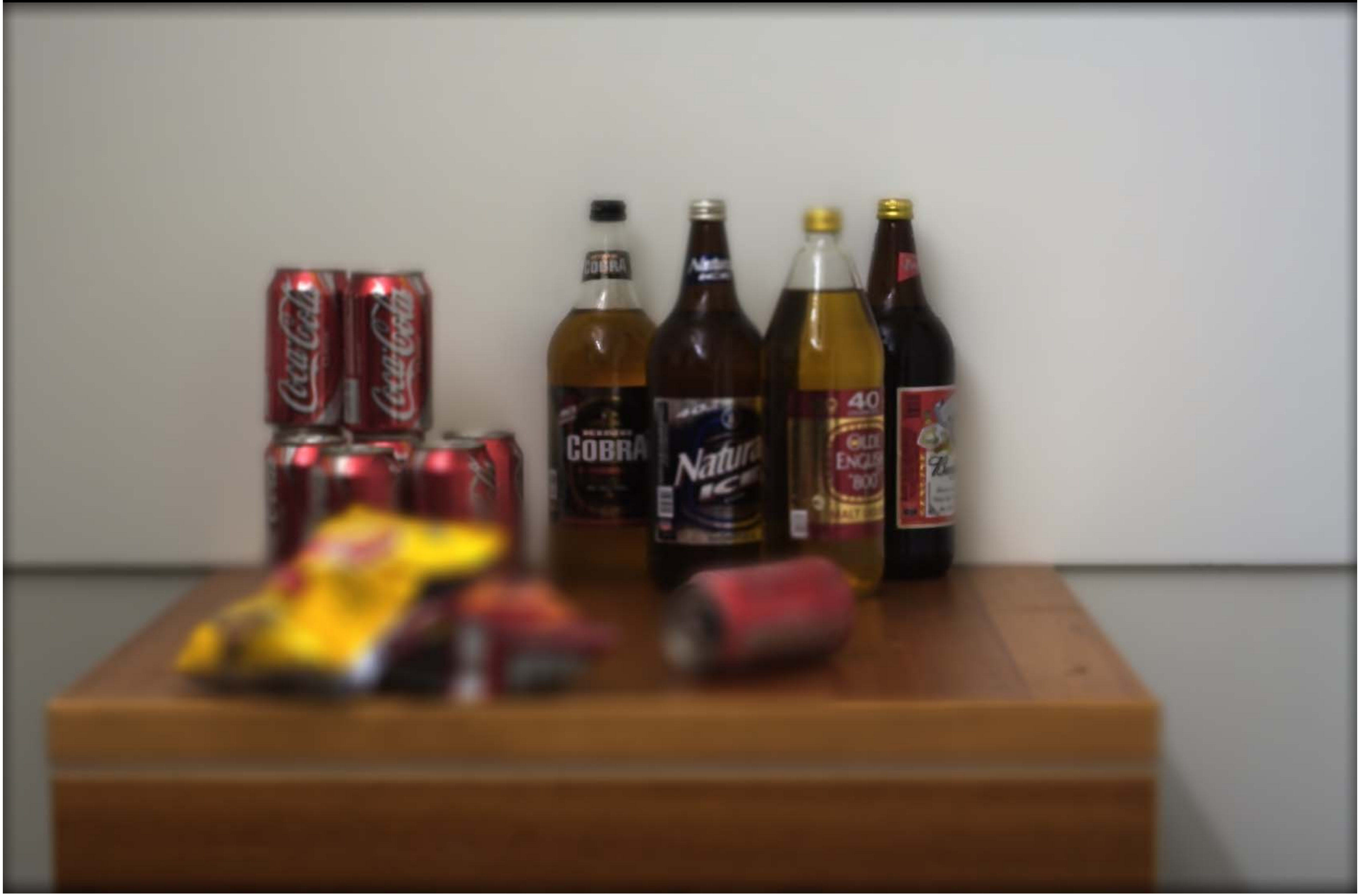
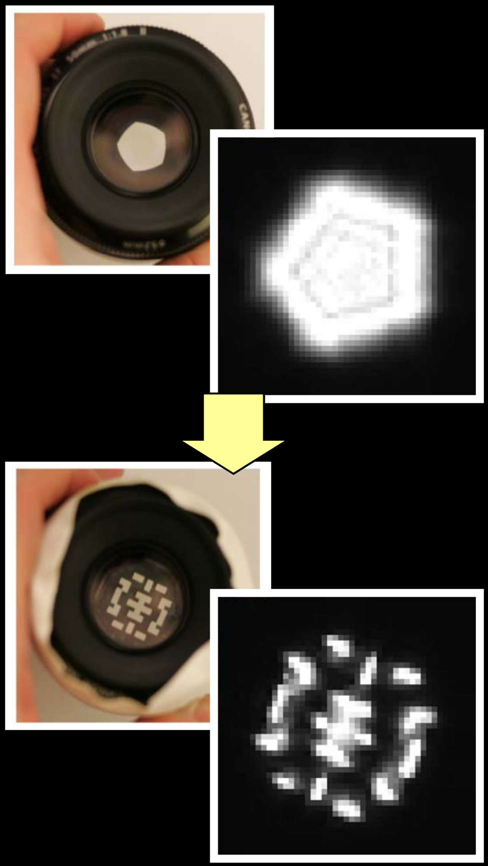


# Application: Digital refocusing from a single image



# Coded aperture: pros and cons

+ Image AND depth at a single shot
+ No loss of image resolution
+ Simple modification to lens
− Depth is coarse
  - unable to get depth at untextured areas, might need manual corrections.
+ But depth is a pure bonus
− Lose some light
+ But deconvolution increases depth of field




| | |
|---|---|
| **50mm f/1.8:** | **$79.95** |
| **Cardboard:** | **$1** |
| **Tape:** | **$1** |
| **Depth acquisition:** | **priceless** |

**CodedAperture**

# Some more quick examples

Motion-Invariant Photography

Anat Levin Peter Sand Taeg Sang Cho Frédo Durand William T. Freeman

Massachusetts Institute of Technology, Computer Science and Artificial Intelligence Laboratory

- Quickly move camera in a parabola when taking a picture
- A motion at any speed in the direction of the parabola will give the same blur kernel

# Results

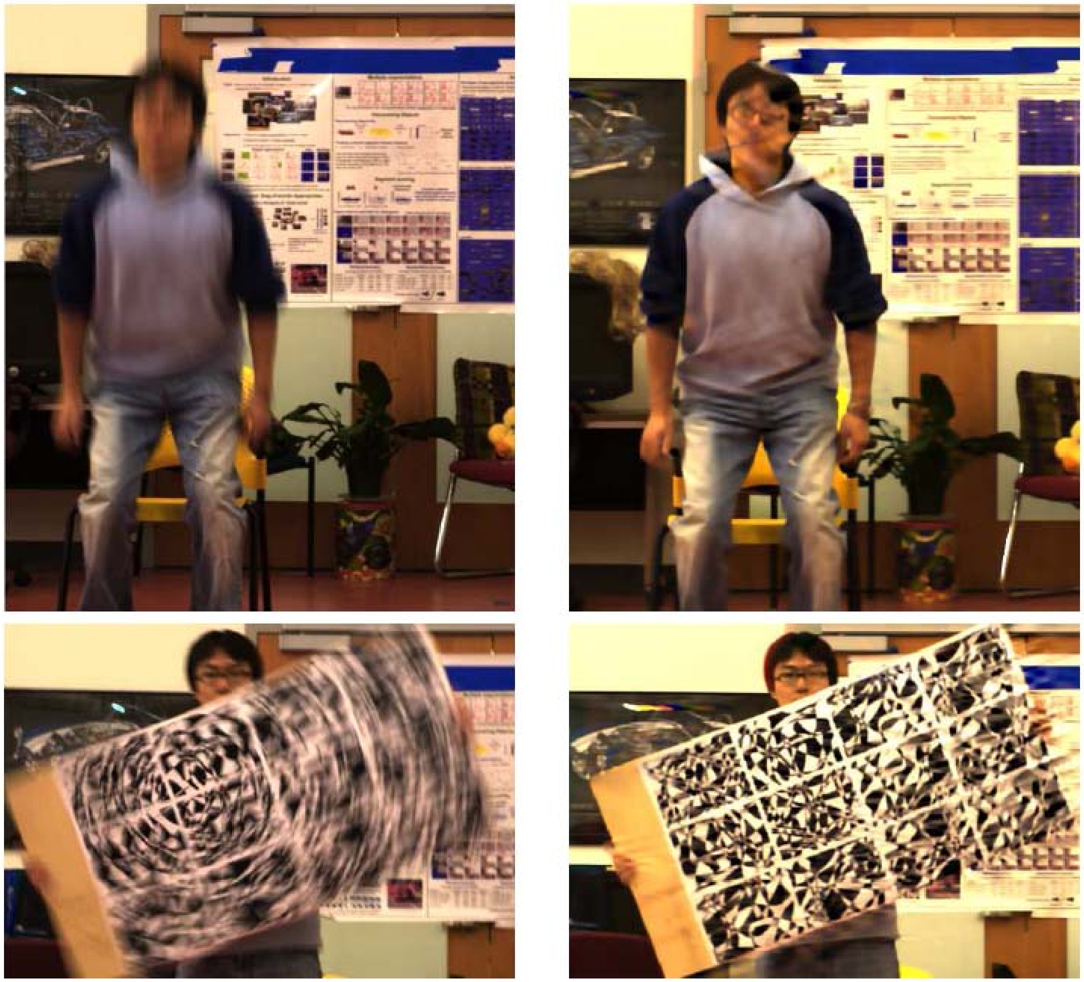
Static Camera

Parabolic Camera

# Results

Static Camera

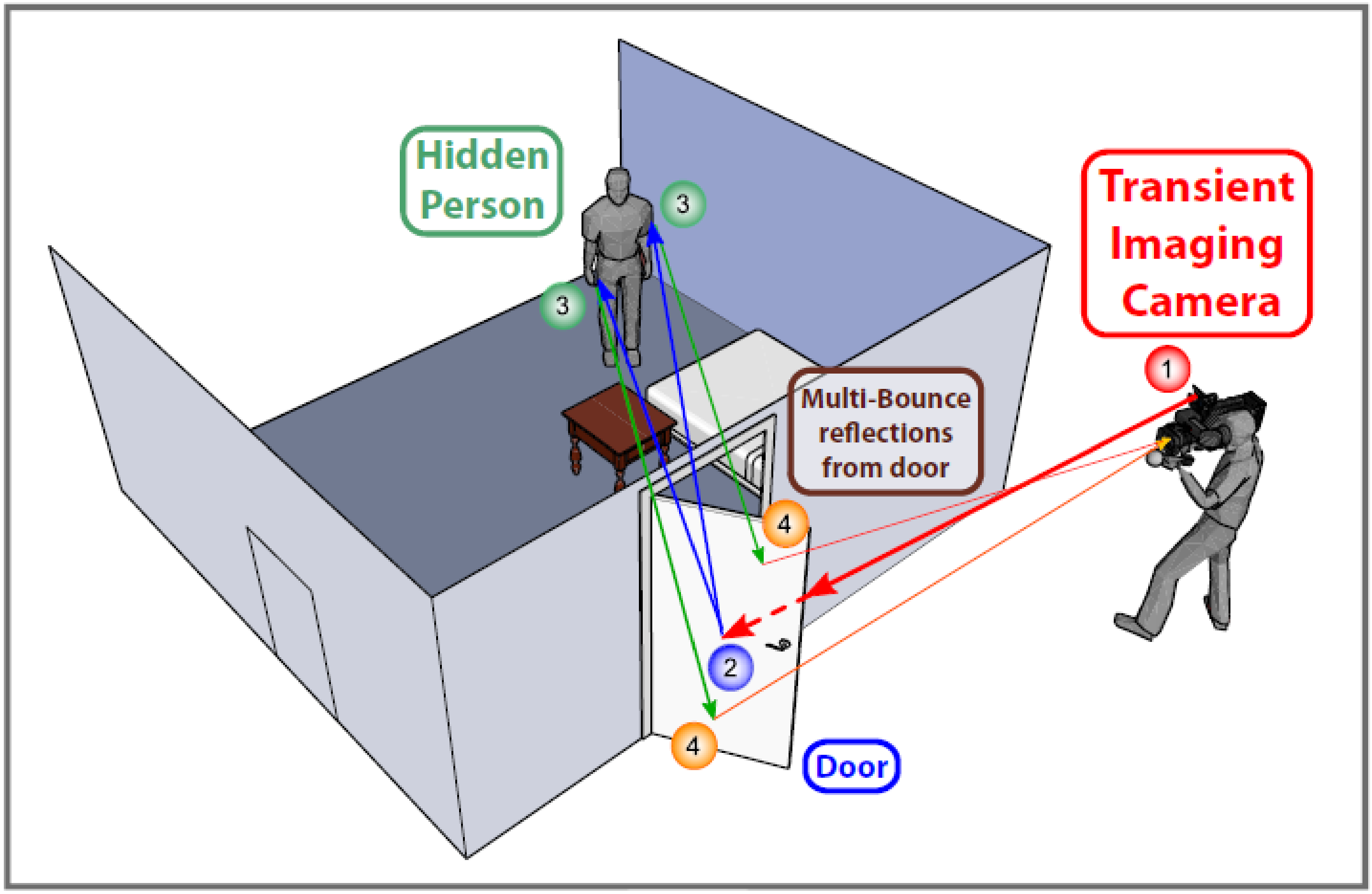
Parabolic Camera



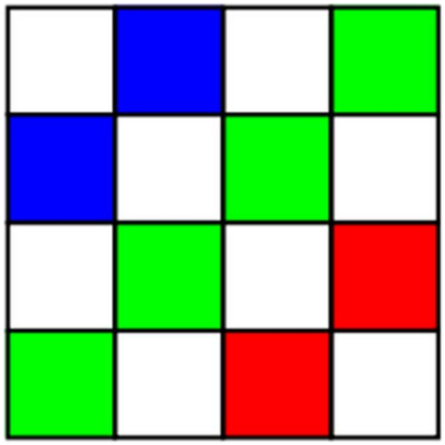
Motion in
wrong
direction

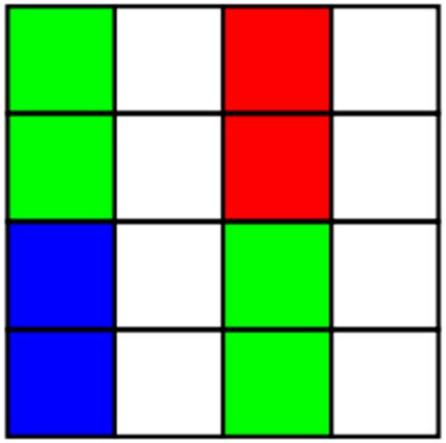
# Looking Around the Corner using Transient Imaging

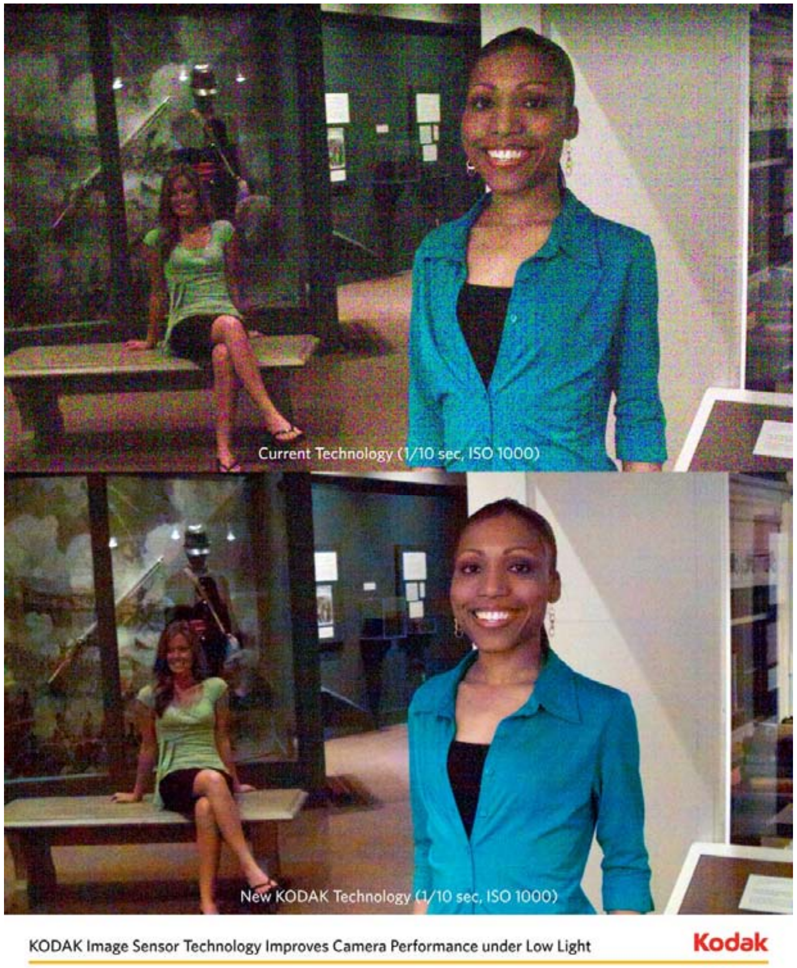
Ahmed Kirmani *[1], Tyler Hutchison[1], James Davis †[2], and Ramesh Raskar‡[1]
[1]MIT Media Laboratory [2] UC Santa Cruz



# RGBW Sensors








- 2007: Kodak 'Panchromatic' Pixels
- Outperforms Bayer Grid
  - 2X-4X sensitivity (W: no filter loss)
  - May improve dynamic range (W >> RGB sensitivity)

http://www.dpreview.com/news/2007/6/14/kodakhighsens

# Computational Approaches to Display

- 3D TV without glasses
  - 20”, $2900, available in Japan (2010)
  - You see different images from different angles


Toshiba

http://news.cnet.com/8301-13506_3-20018421-17.html
Newer version: http://www.pcmag.com/article2/0,2817,2392380,00.asp
http://reviews.cnet.com/3dtv-buying-guide/

# Recap of questions

- How can we represent all of the information contained in light?
- What are the fundamental limitations of cameras?
- What sacrifices have we made in conventional cameras? For what benefits?
- How else can we design cameras for better focus, deblurring, multiple views, depth, etc.?

# Next class

- Exam review