

Computational Imaging

Computational Photography

CSE 273

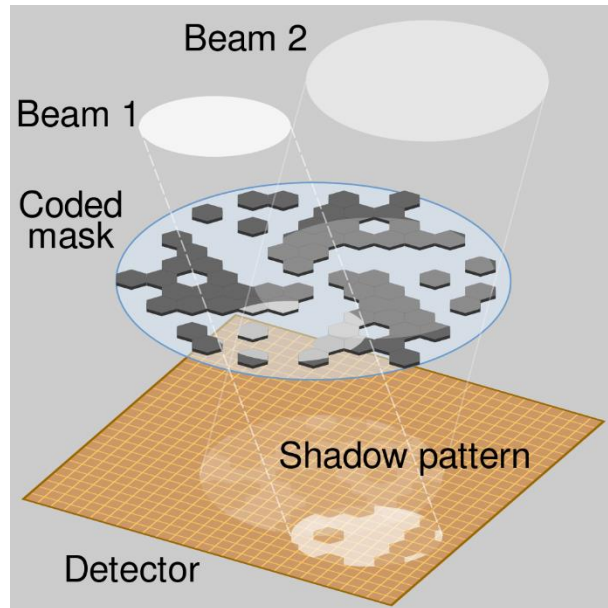
Lecture 6

Announcements

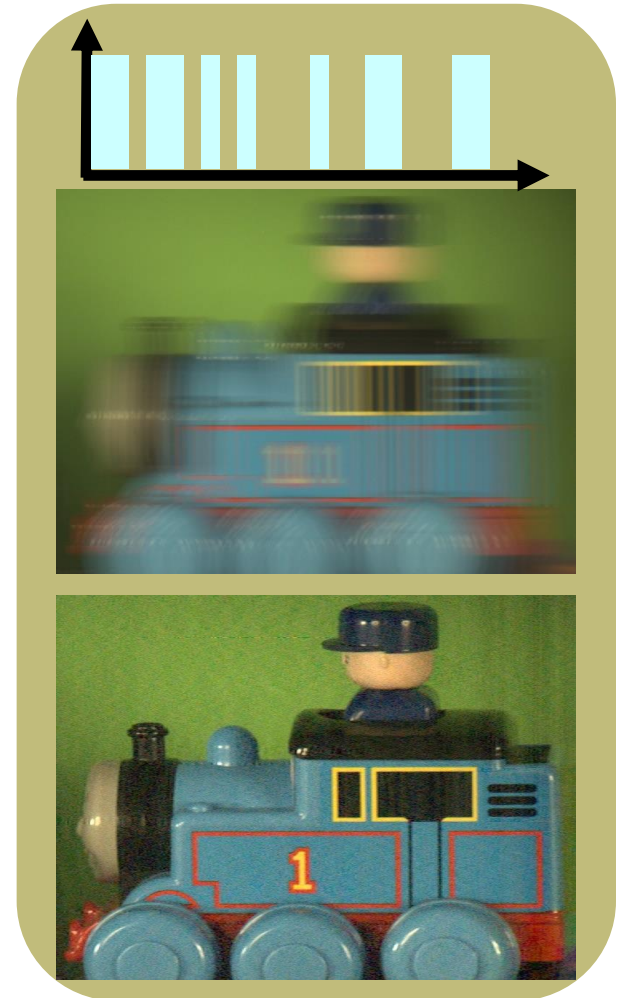
- Assignment 3 is due Jan 31, 11:59 PM
- Assignment 4 will be released Jan 31
 - Due Feb 7, 11:59 PM

Computational imaging

- Coded photography
- Compressive imaging



Coded aperture



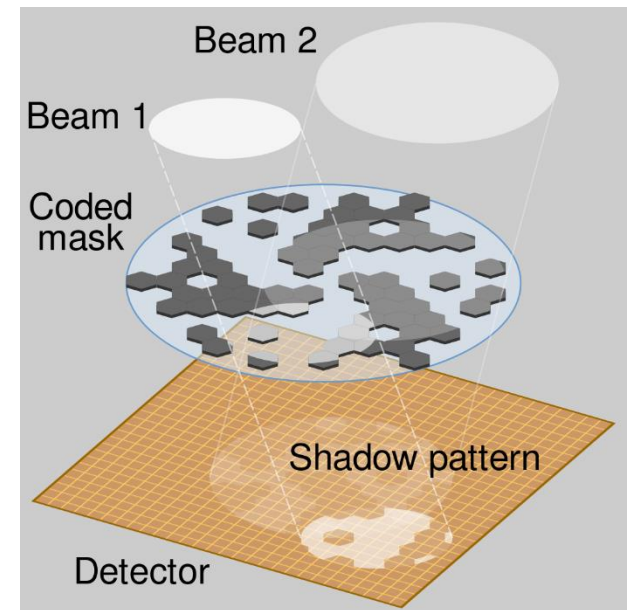
Coded exposure

Coded photography

- Acquisition of images with known encoding
- Techniques
 - Coded aperture
 - Coded exposure

Coded photography

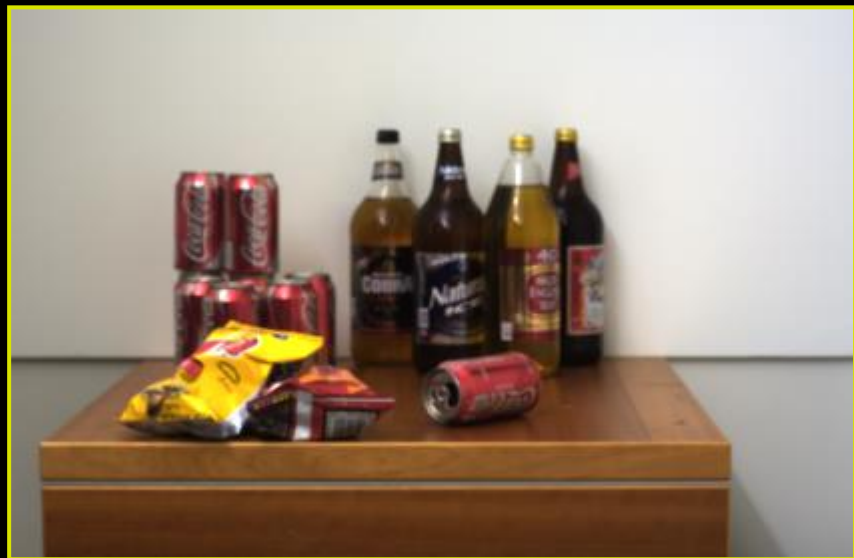
- Coded aperture
 - Mask of opaque material, blocking radiation in a known pattern to cast a coded shadow on the image plane
 - Properties of the original radiation sources are reconstructed from the shadow



Coded photography

- Image and depth from a conventional camera with a coded aperture
 - Anat Levin, Rob Fergus, Fredo Durand, and William Freeman

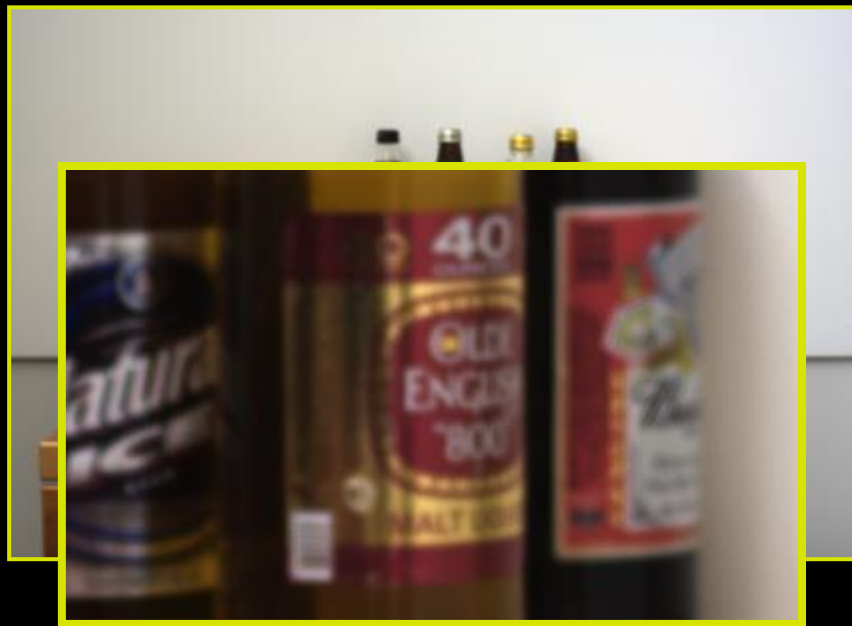
Single input image:



Output #1: Depth map



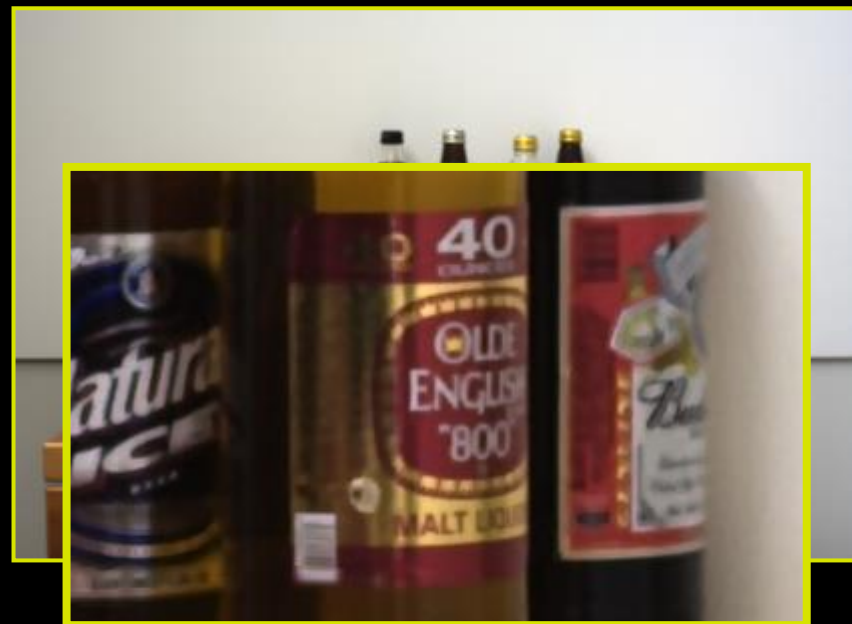
Single input image:



Output #1: Depth map



Output #2: All-focused image



Lens and defocus

Lens' aperture

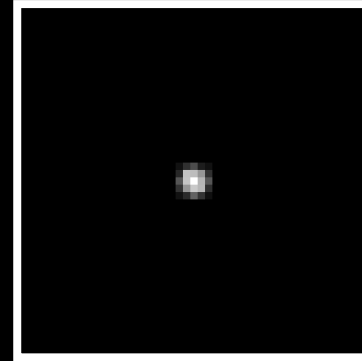
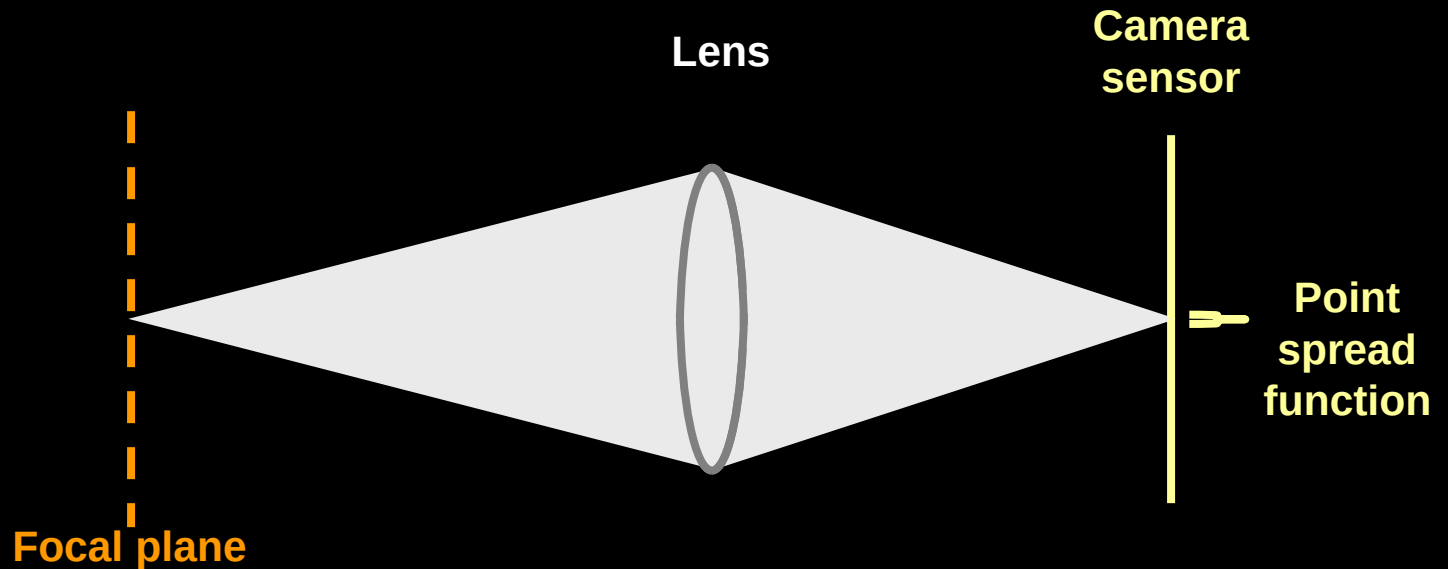


Image of a point light source



Lens and defocus

Lens' aperture

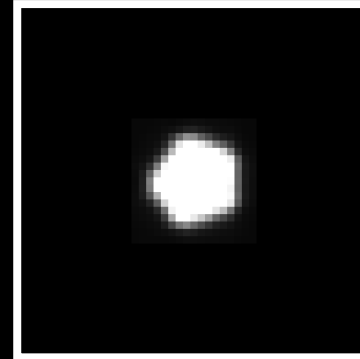
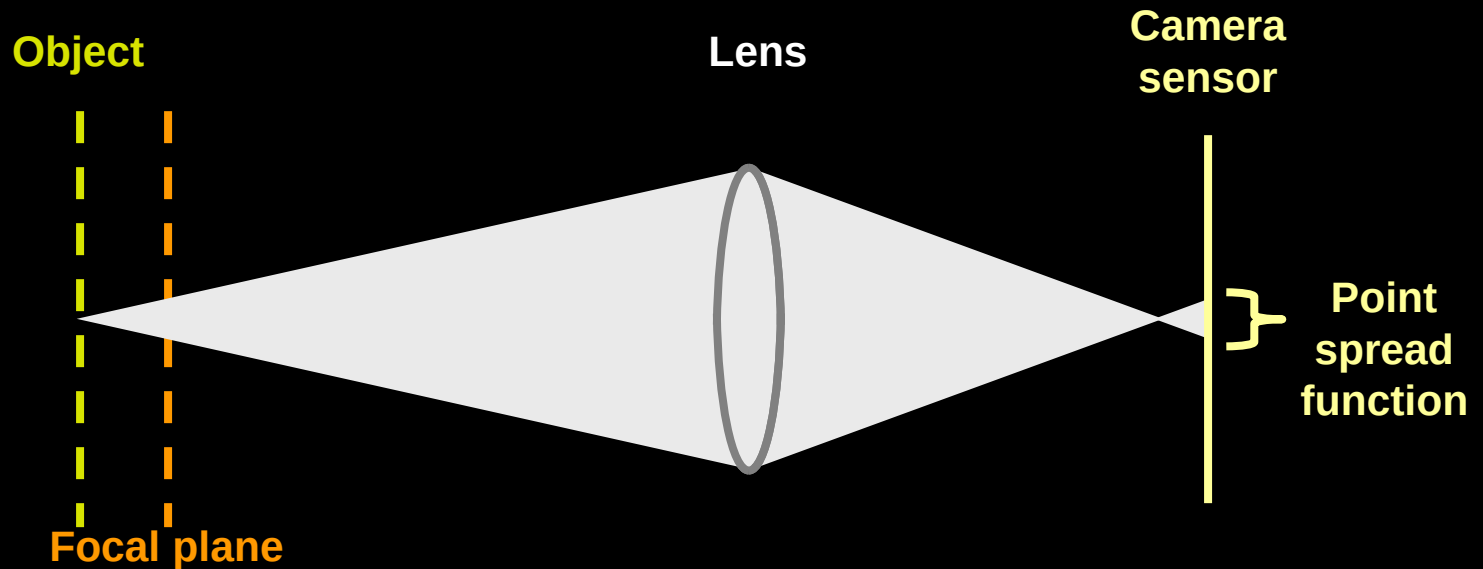


Image of a
defocused point
light source



Lens and defocus

Lens' aperture

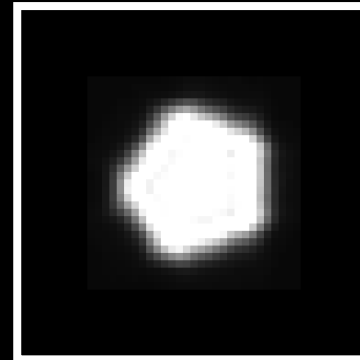
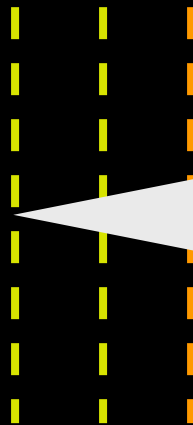


Image of a
defocused point
light source

Object

Lens

Camera
sensor



Focal plane



Point
spread
function

Lens and defocus

Lens' aperture

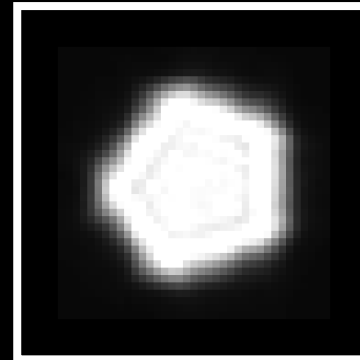
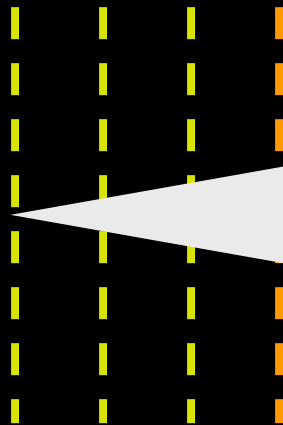


Image of a
defocused point
light source

Object

Lens

Camera
sensor



Focal plane

Point
spread
function



Lens and defocus

Lens' aperture

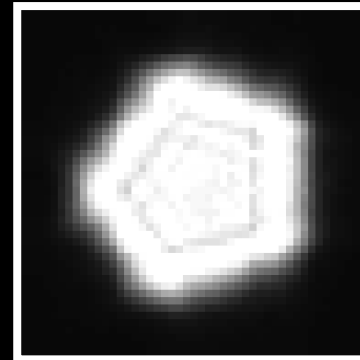
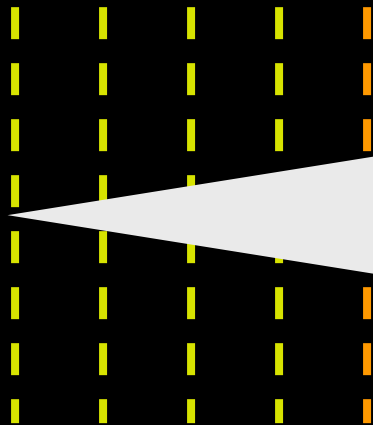


Image of a
defocused point
light source

Object

Lens

Camera
sensor

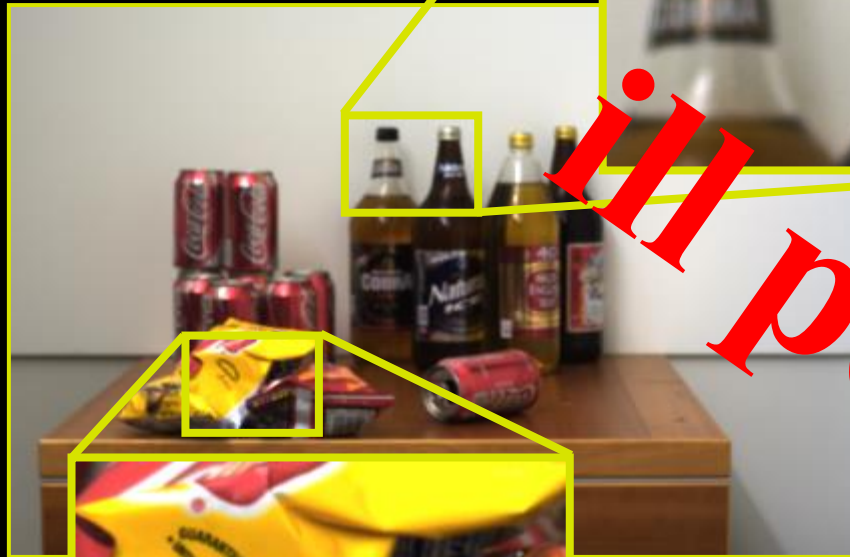


Focal plane

Point
spread
function

Depth and defocus

Out of focus



In focus



Depth from defocus:

Infer depth by analyzing
local scale of defocus blur

ill posed

Challenges

- Hard to discriminate a smooth scene from defocus blur

?

Out of focus



- Hard to undo defocus blur



Input



Ringings with conventional
deblurring algorithm

Key ideas

- Exploit prior on natural images

- Improve deconvolution
- Improve depth discrimination



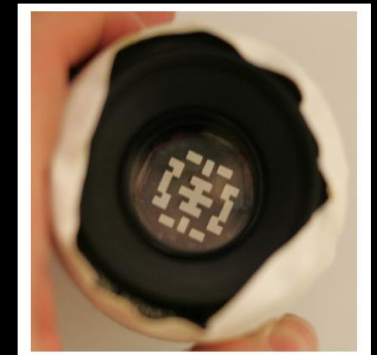
Natural



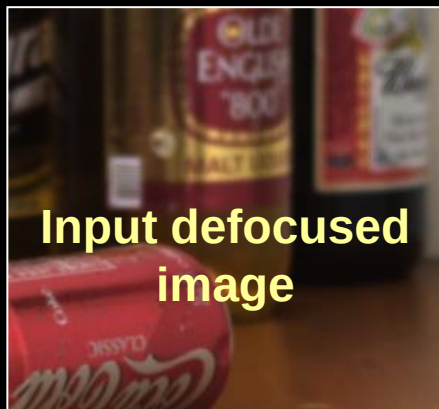
Unnatural

- Coded aperture (mask inside lens)

- make defocus patterns different from natural images and easier to discriminate



Defocus as local convolution



$$y = f_k \otimes x$$

Local sub-window Calibrated blur kernels at depth k Sharp sub-window

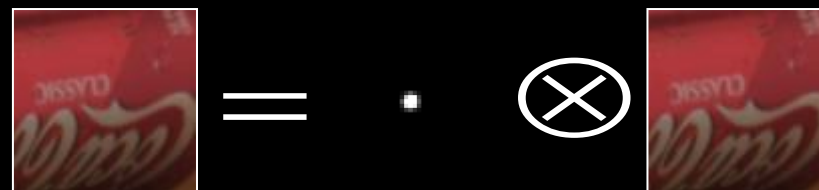
Depth $k=1$:



Depth $k=2$:

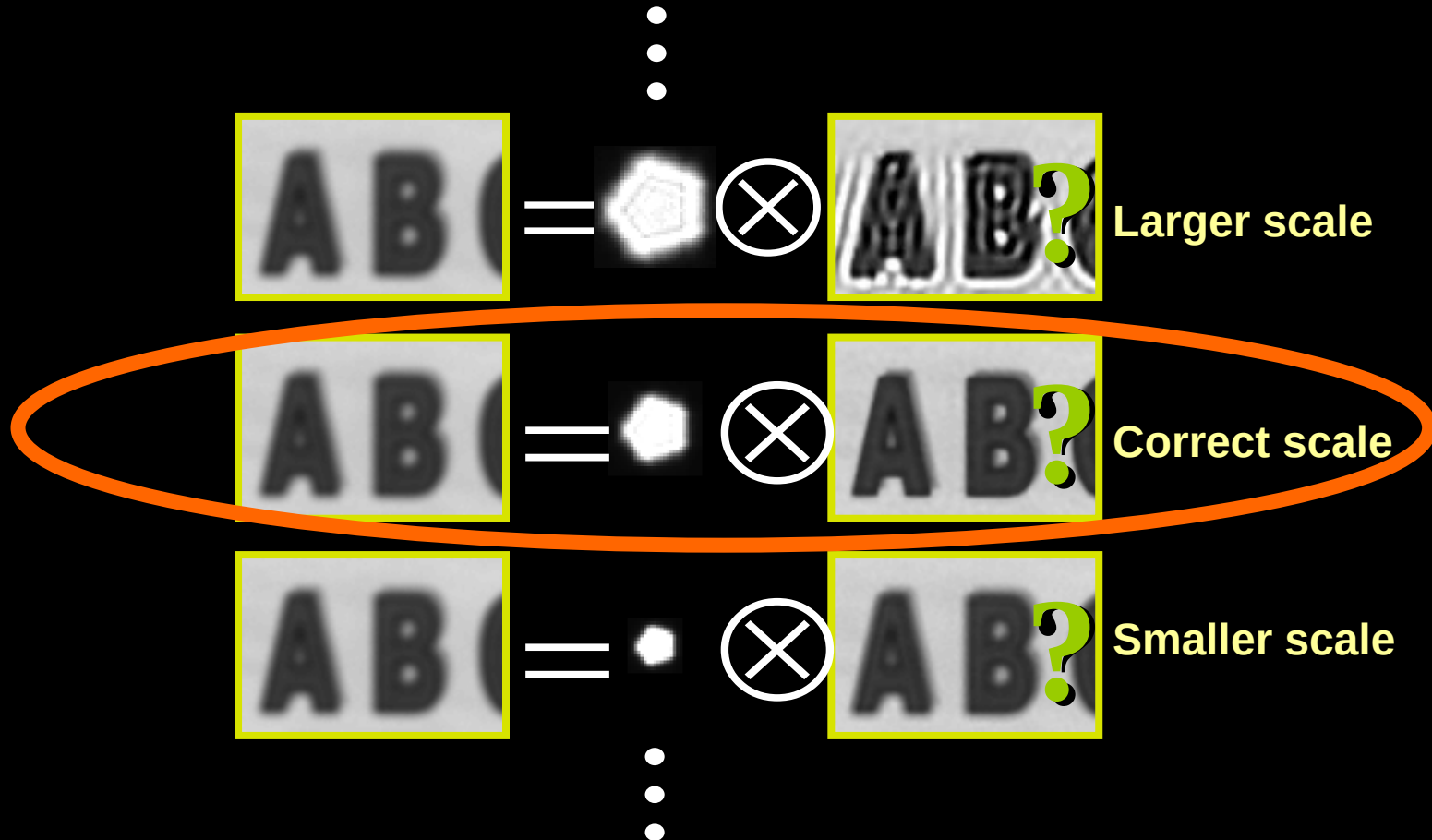


Depth $k=3$:



Overview

Try deconvolving local input windows with different scaled filters:



Somehow: select best scale.

Challenges

- Hard to deconvolve even when kernel is known



Input



Ringings with the traditional Richardson-Lucy deconvolution algorithm

- Hard to identify correct scale:

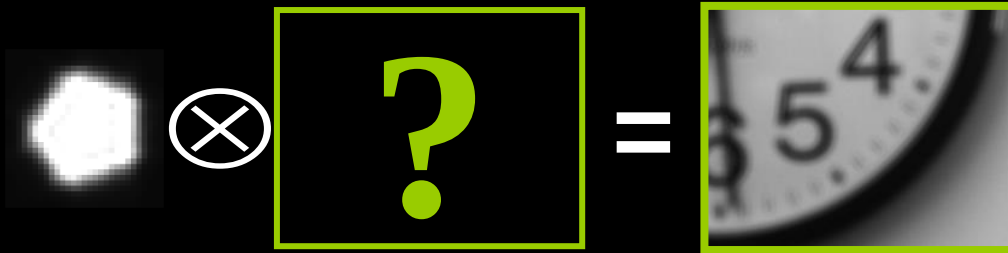
Diagram illustrating the challenge of identifying the correct deconvolution scale. Three rows show the input image (ABC) being deconvolved with different kernel scales, resulting in different output images:

- Larger scale:** The input image is deconvolved with a large, blurry kernel (represented by a large white hexagon). The resulting output image is highly distorted and noisy, marked with a red 'X'.
- Correct scale:** The input image is deconvolved with a medium-sized kernel (represented by a medium white hexagon). The resulting output image is sharp and clear, marked with a blue checkmark.
- Smaller scale:** The input image is deconvolved with a small, sharp kernel (represented by a small white hexagon). The resulting output image is also sharp and clear, marked with a blue checkmark.

The "Correct scale" and "Smaller scale" results are circled in orange, indicating that both can appear visually correct, making it difficult to identify the true correct scale.

Deconvolution is ill posed

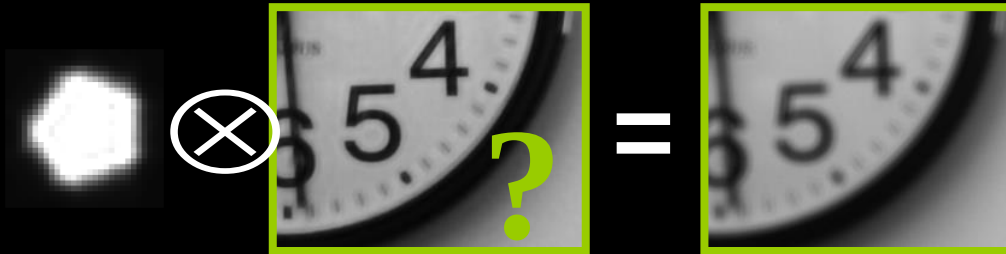
$$f \otimes x = y$$



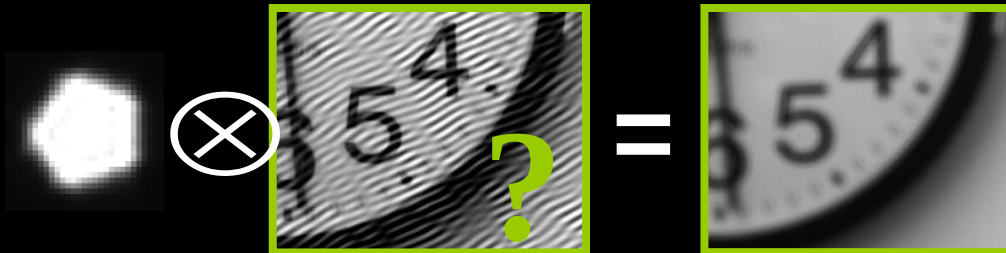
Deconvolution is ill posed

$$f \otimes x = y$$

Solution 1:

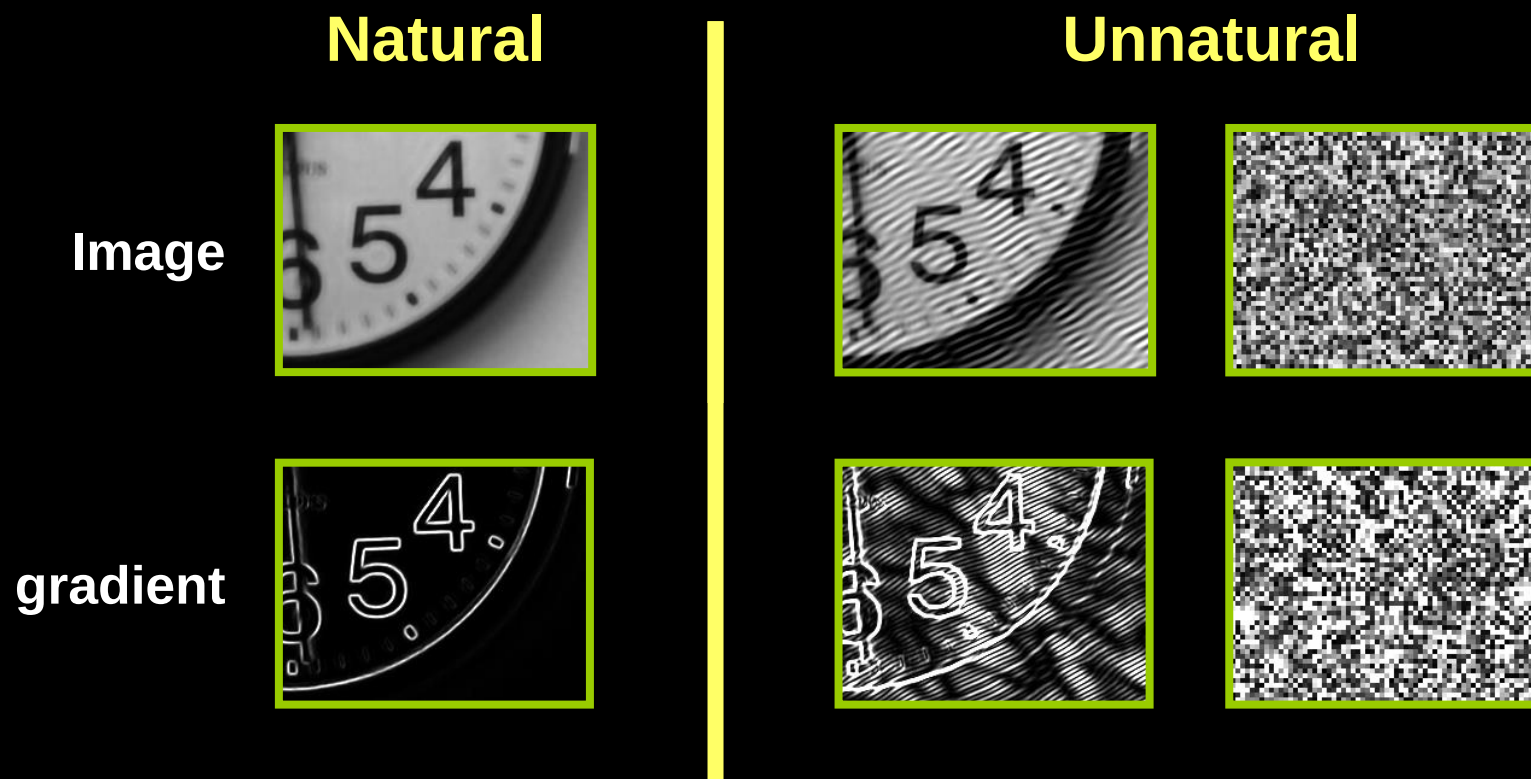


Solution 2:



Idea 1: Natural images prior

What makes images special?

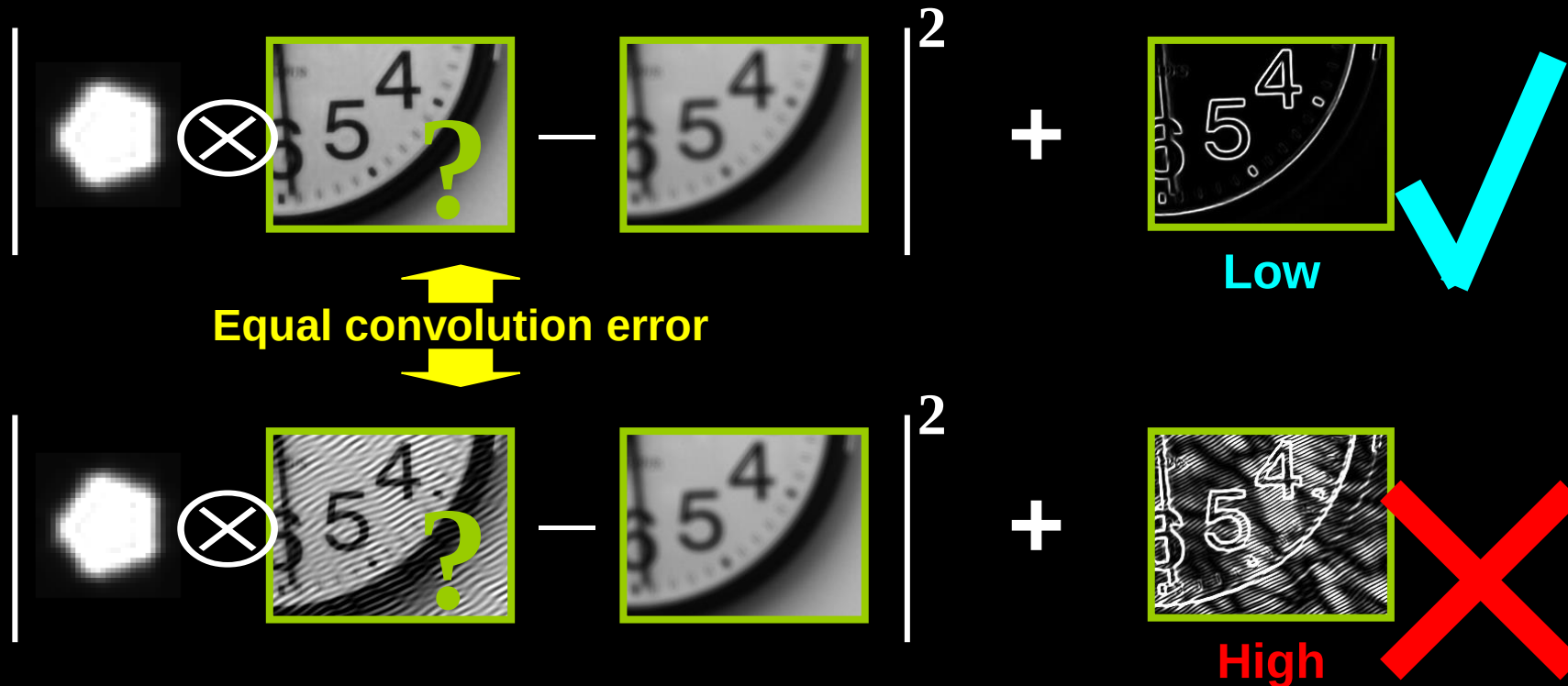


Natural images have sparse gradients

➡ put a penalty on gradients

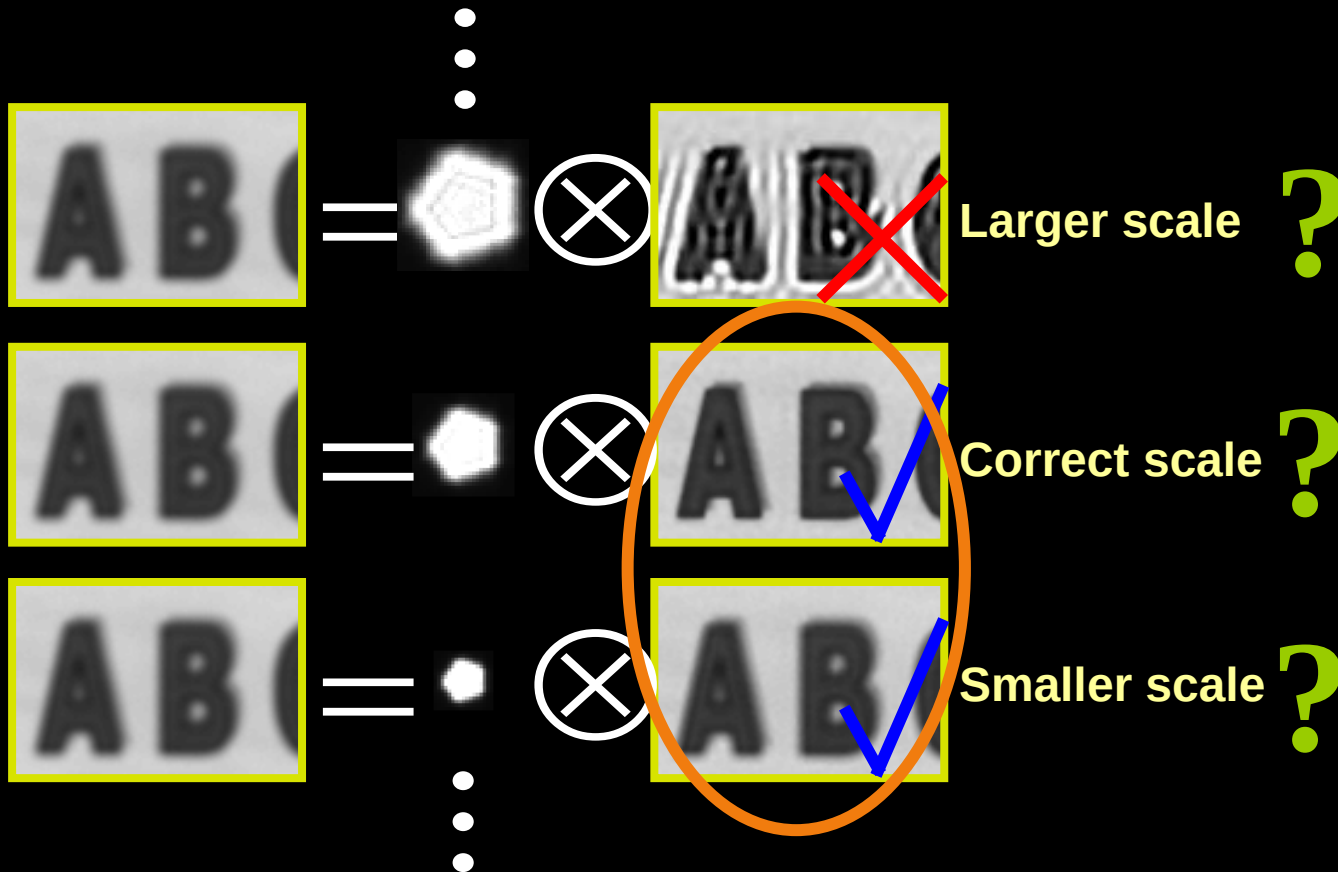
Deconvolution with prior

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



Recall: Overview

Try deconvolving local input windows with different scaled filters:



Somehow: select best scale.

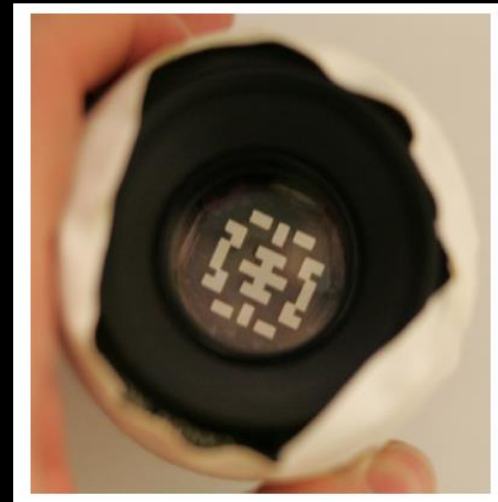
Challenge: smaller scale not so different than correct

Idea 2: Coded Aperture

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



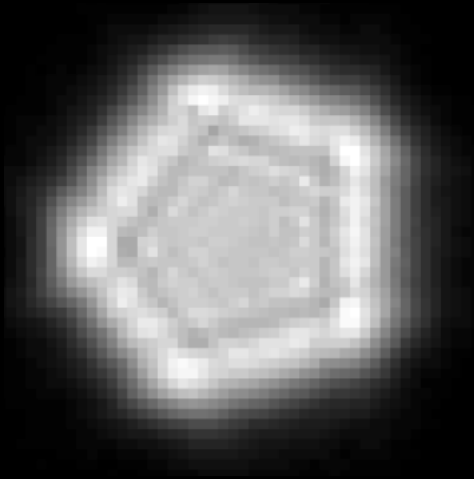
**Conventional
aperture**



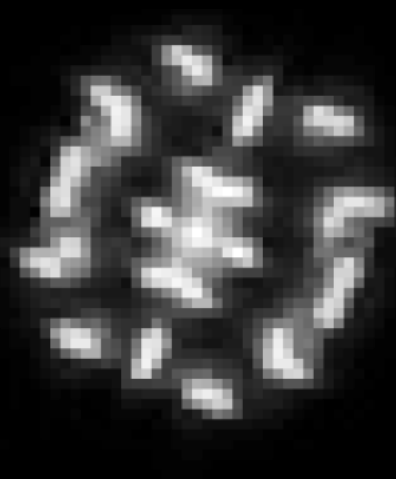
**Our coded
aperture**

Idea 2: Coded Aperture

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



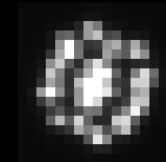
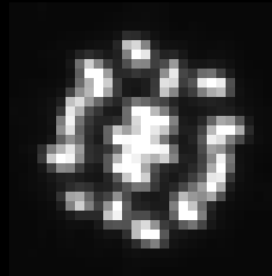
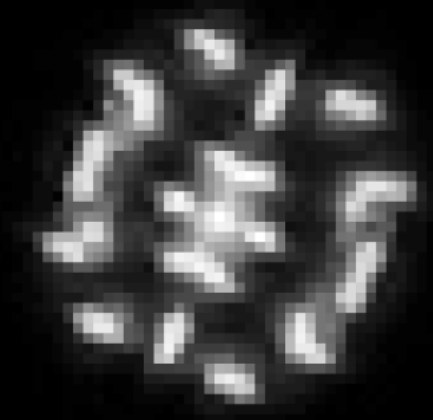
**Conventional
aperture**



**Coded
aperture**

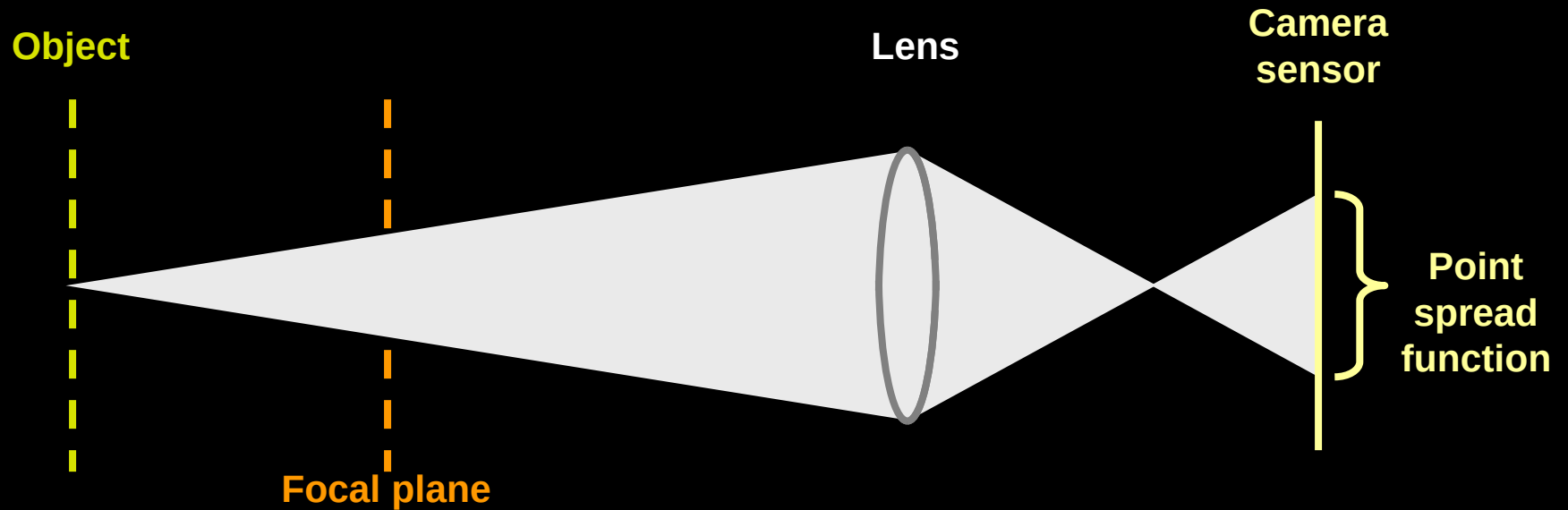
Idea 2: Coded Aperture

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



**Coded
aperture**

Solution: lens with occluder



Solution: lens with occluder

Aperture pattern

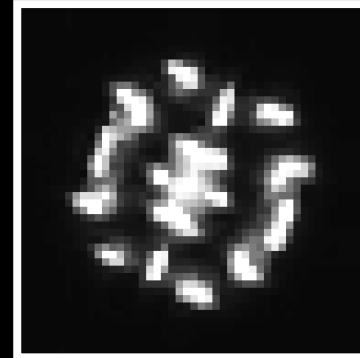
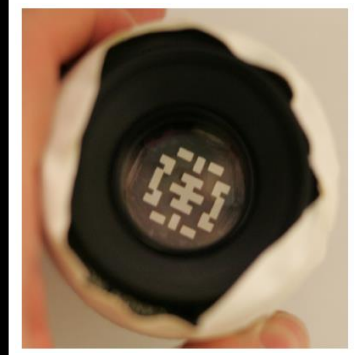


Image of a
defocused point
light source

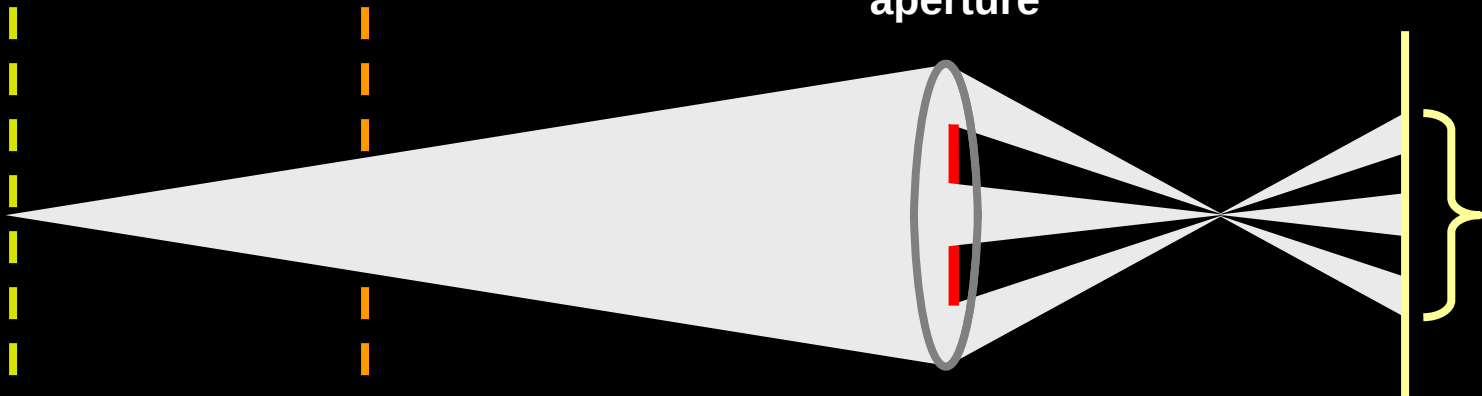
Object

Lens with coded
aperture

Camera
sensor

Focal plane

Point
spread
function



Solution: lens with occluder

Aperture pattern

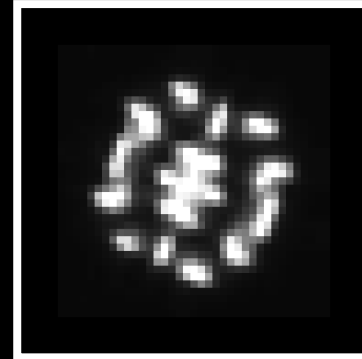
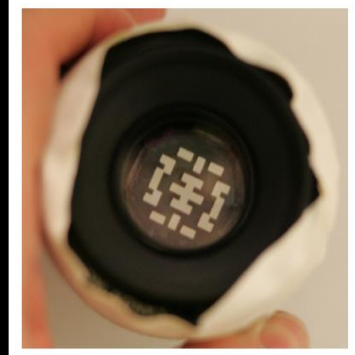
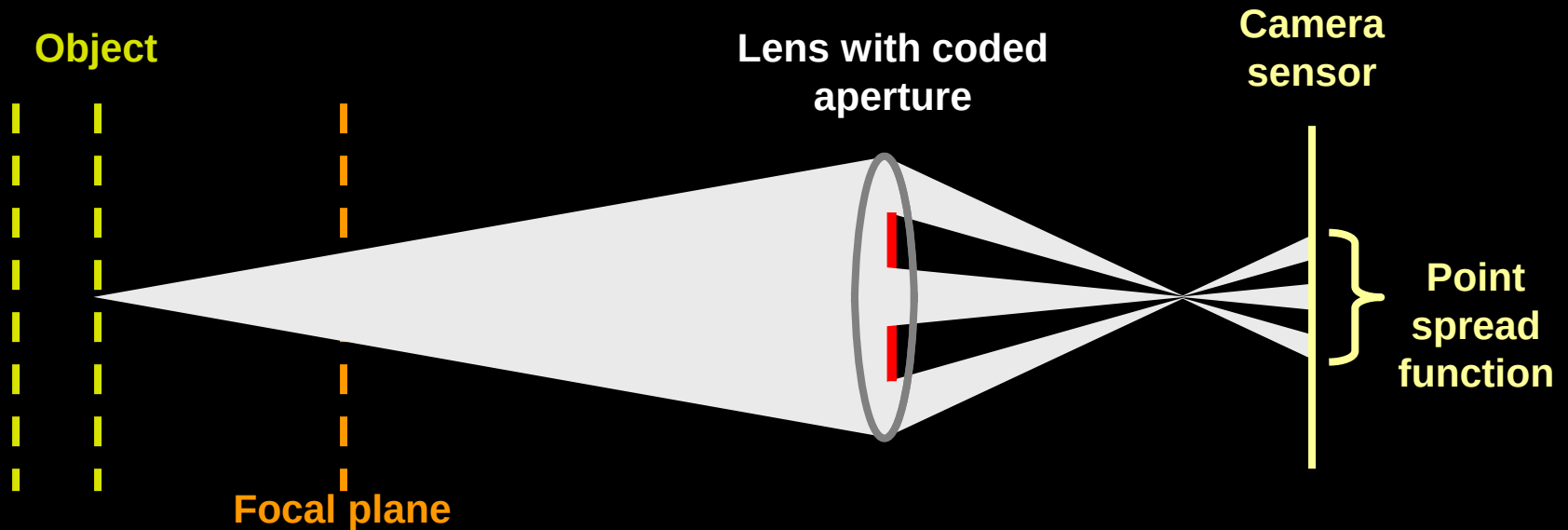


Image of a
defocused point
light source



Solution: lens with occluder

Aperture pattern

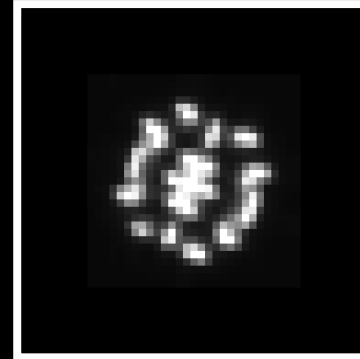
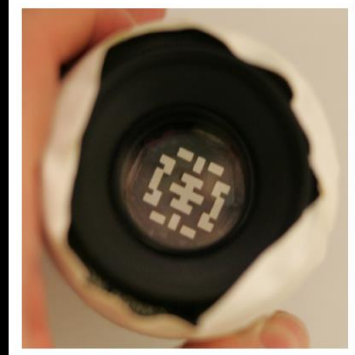
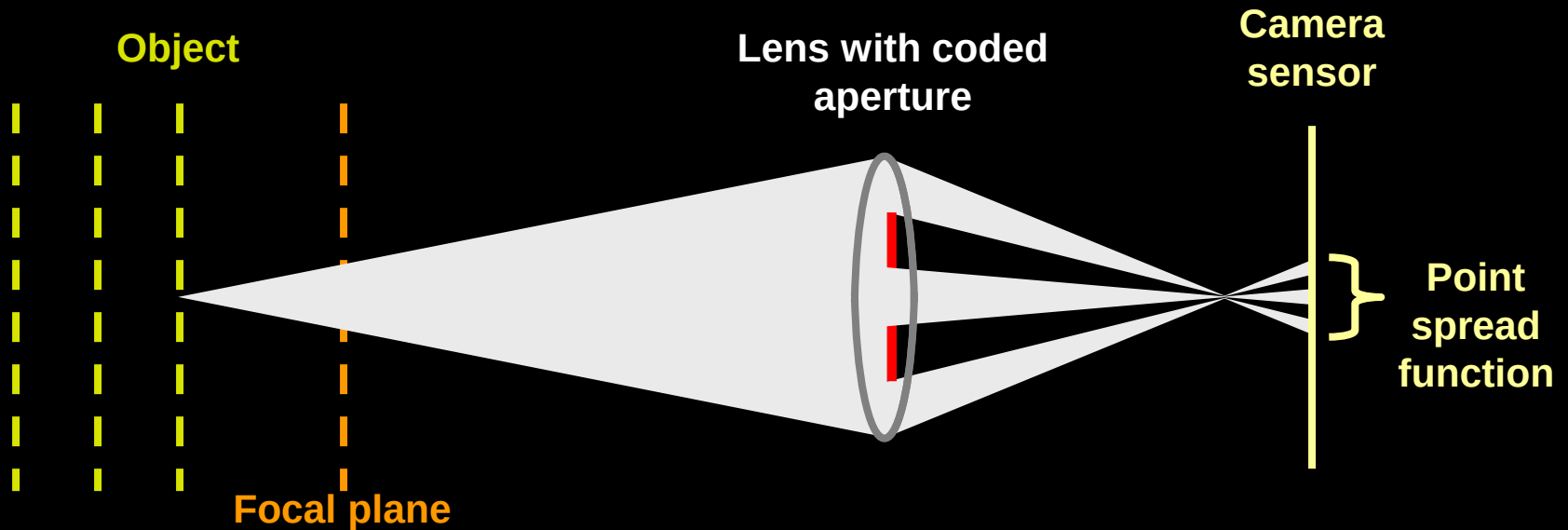


Image of a
defocused point
light source



Solution: lens with occluder

Aperture pattern

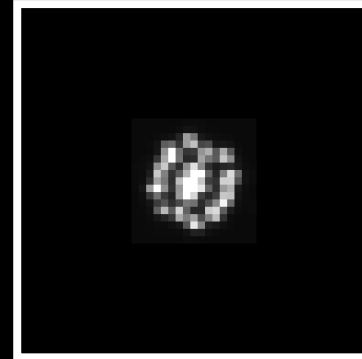
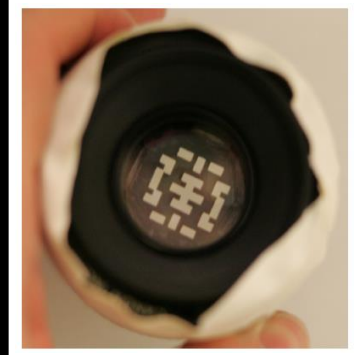
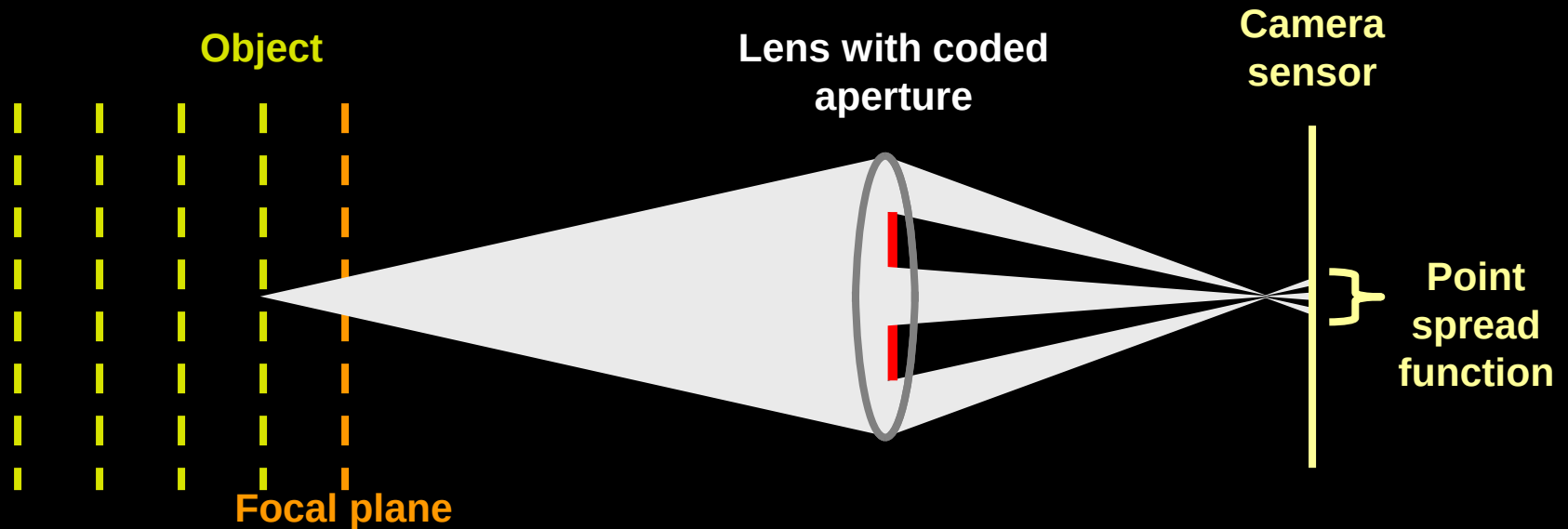


Image of a
defocused point
light source



Solution: lens with occluder

Aperture pattern

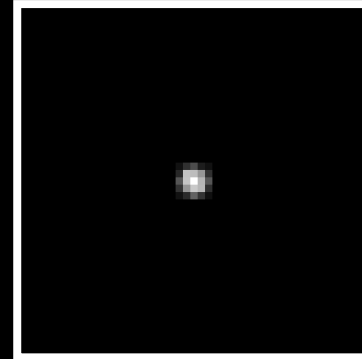
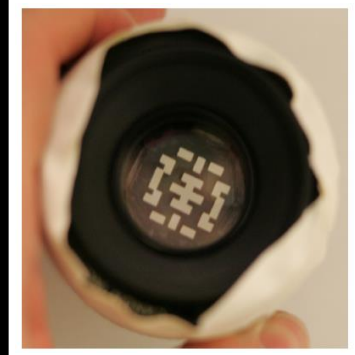
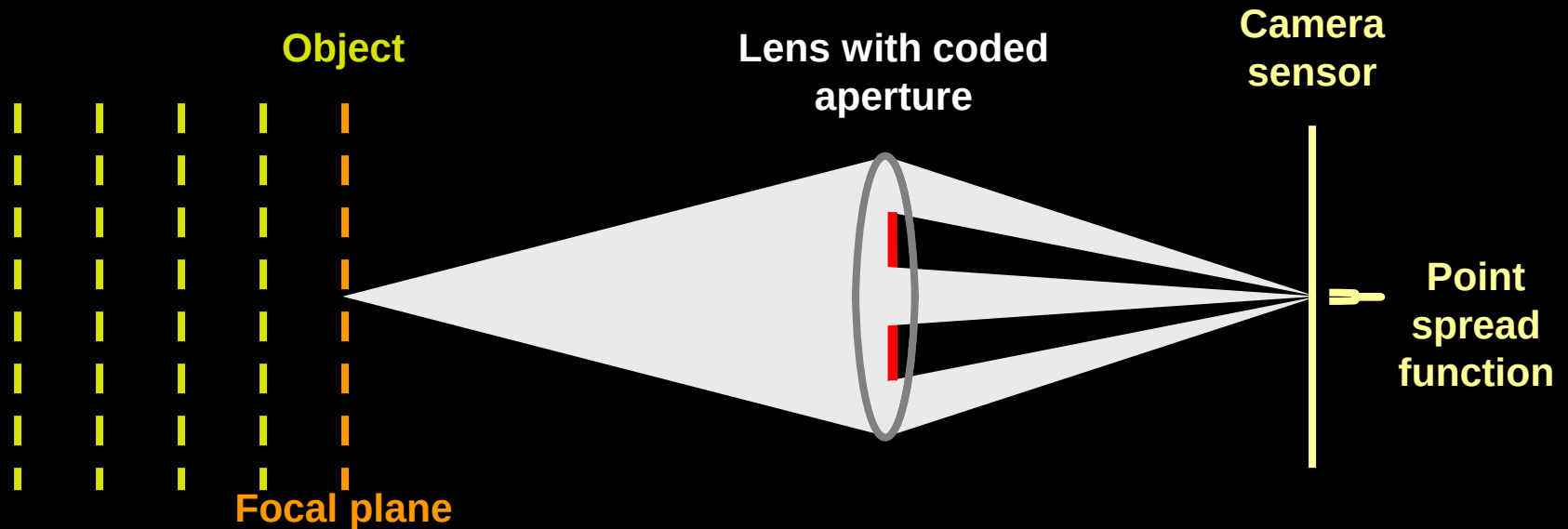


Image of a
defocused point
light source

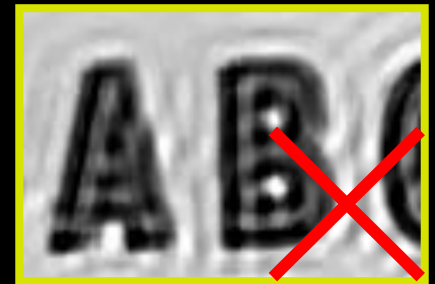
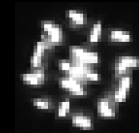
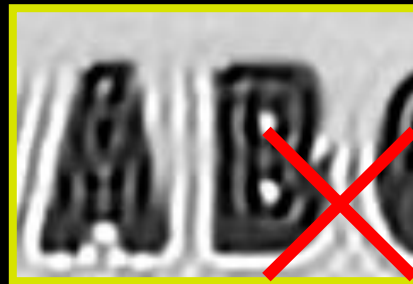


Coded aperture reduces uncertainty in scale identification

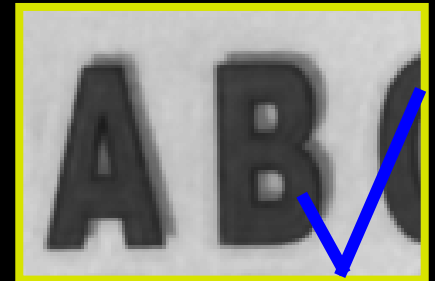
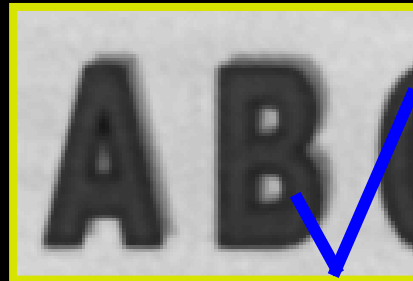
Conventional

Coded

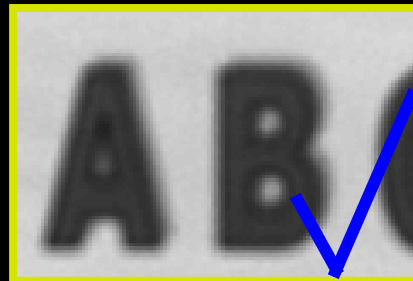
Larger scale



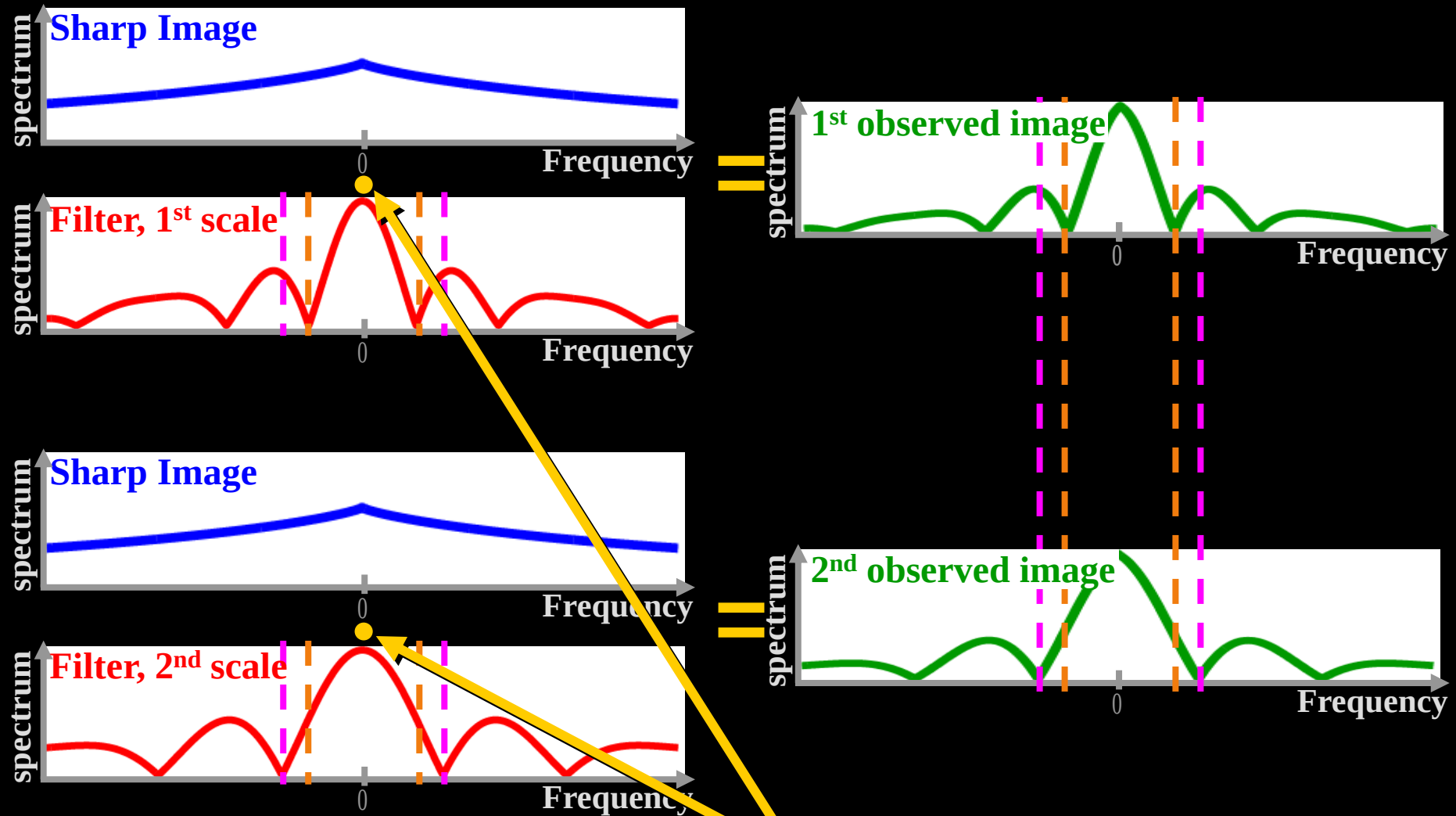
Correct scale



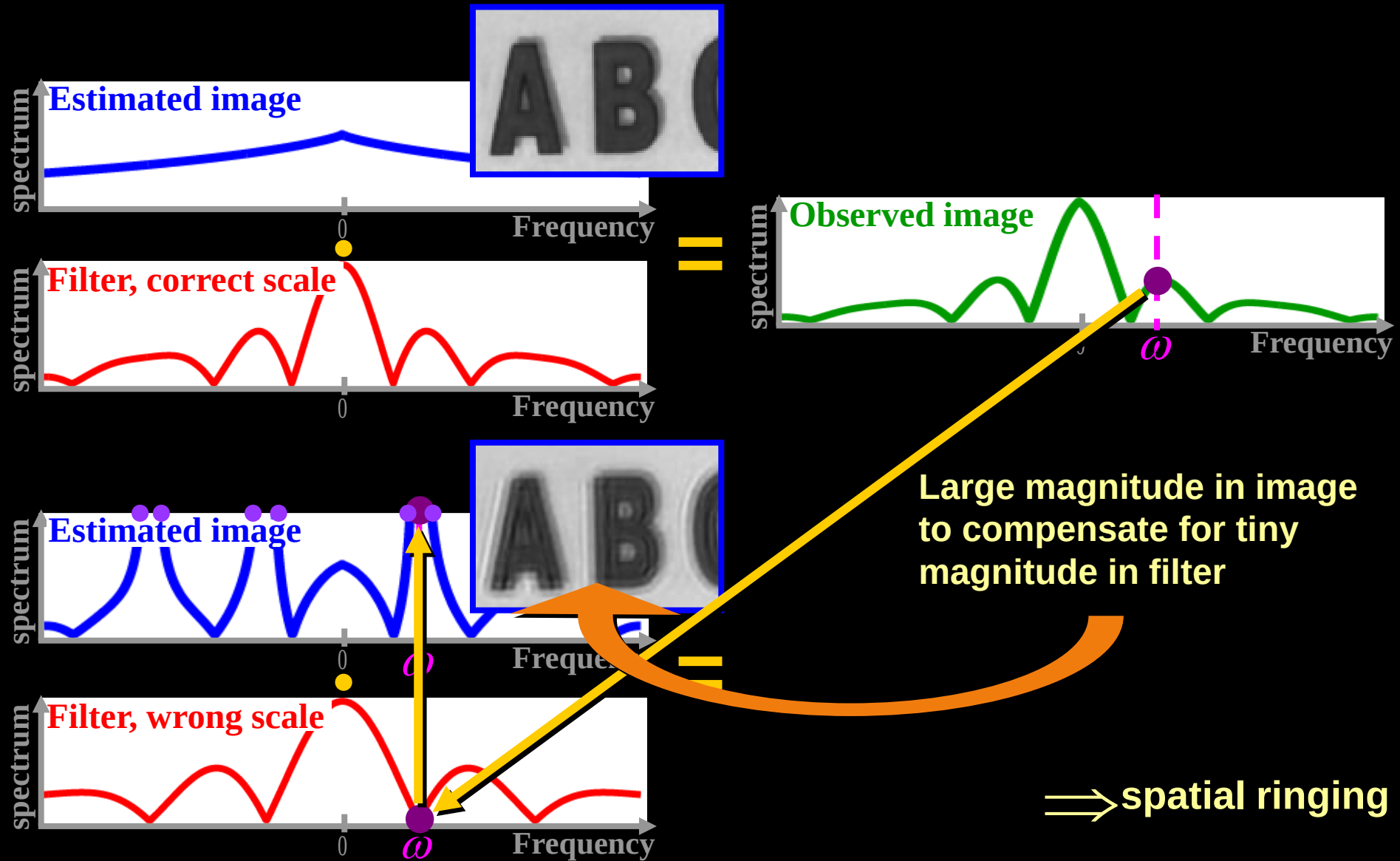
Smaller scale



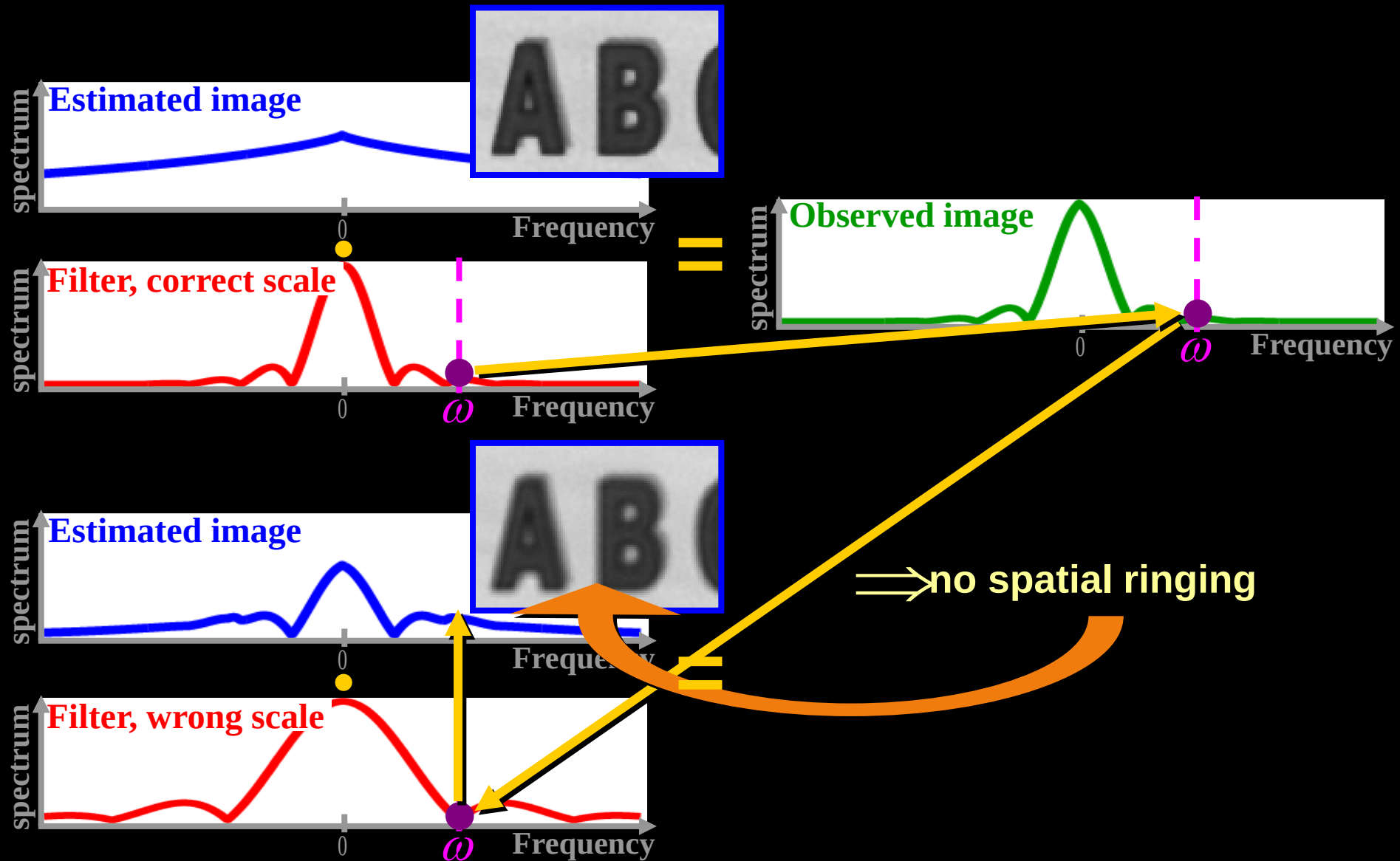
Convolution- frequency domain representation



Spatial convolution $\Leftrightarrow$ frequency multiplication
Output spectrum has zeros where filter spectrum has zeros



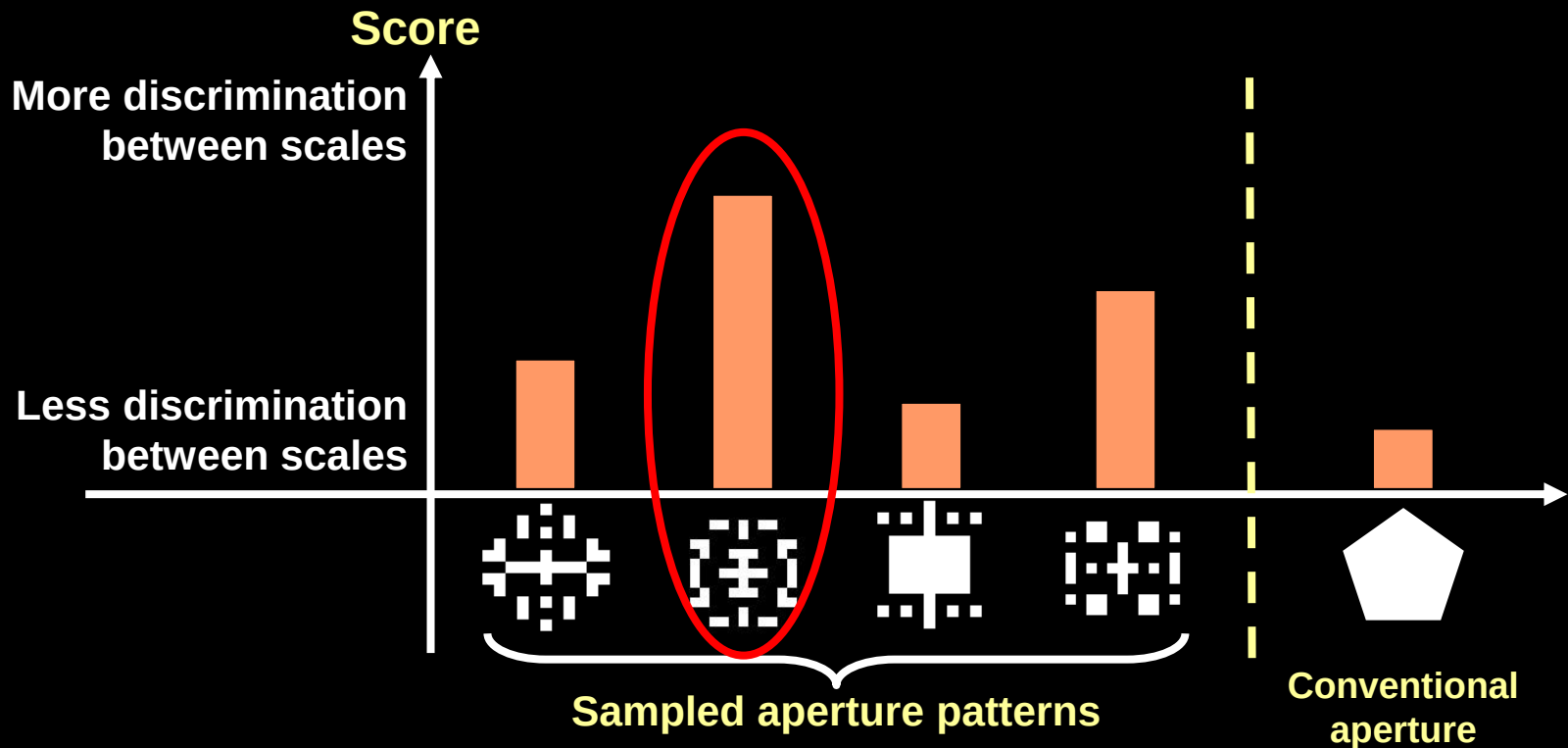
Division by zero with a conventional aperture?



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

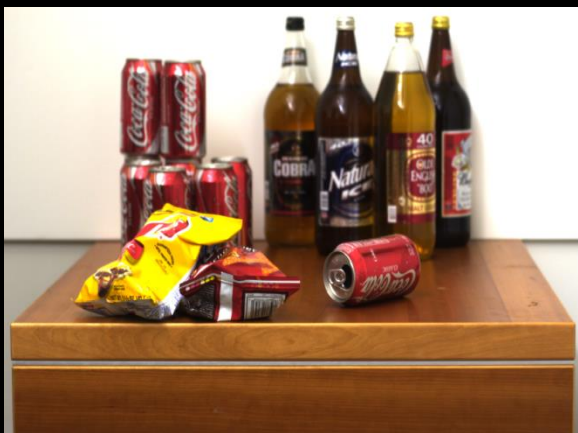
Regularizing depth estimation

Try deblurring with 10 different aperture scales

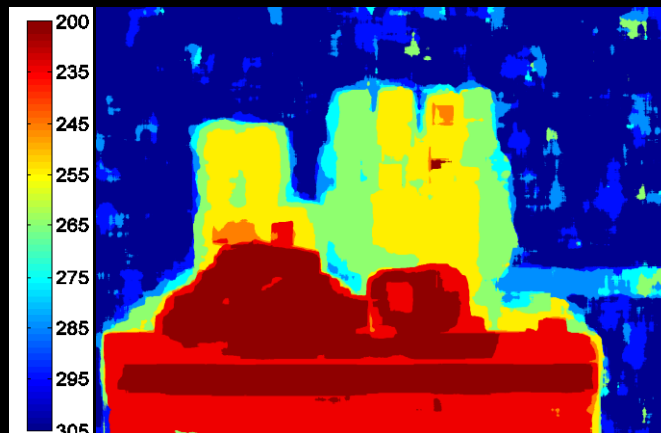
$$x = \arg \min \underbrace{|f \otimes x - y|^2}_{\text{Convolution error}} + \underbrace{\lambda \sum_i \rho(\nabla x_i)}_{\text{Derivatives prior}}$$



Keep minimal error scale in each local window + regularization



Input



Local depth estimation

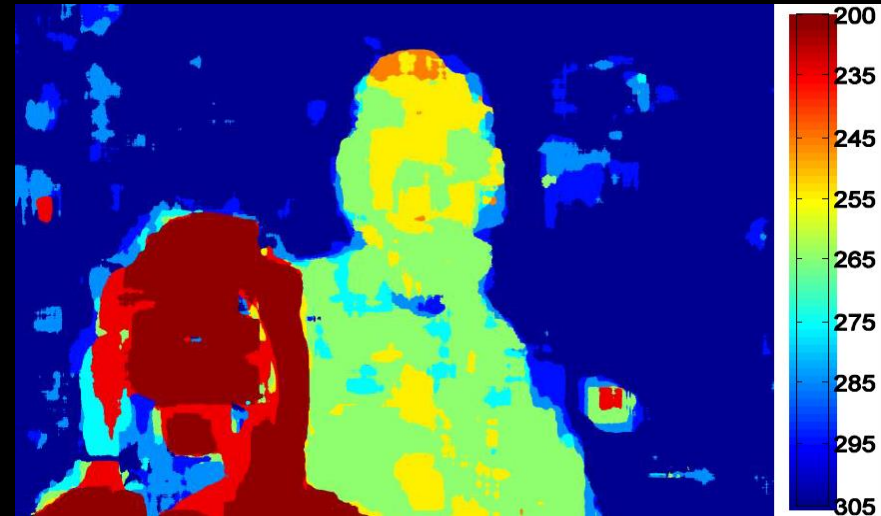


Regularized depth

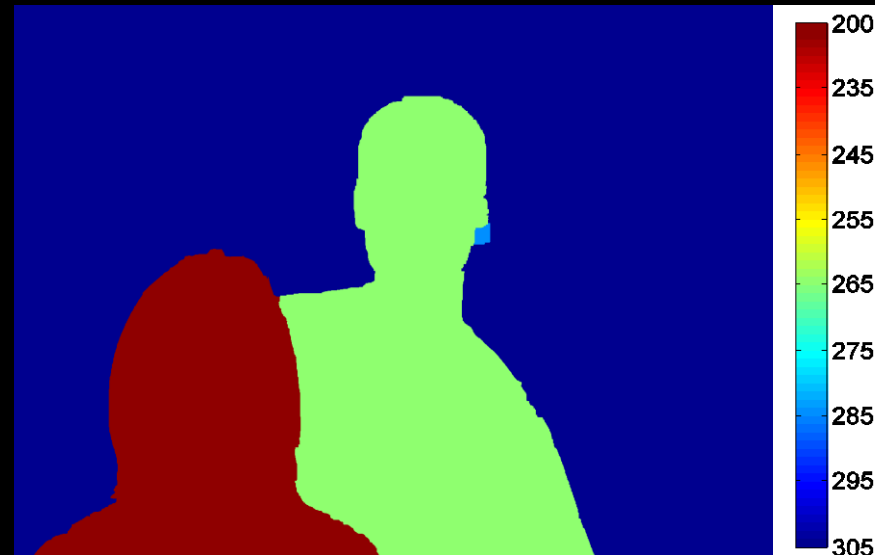
Regularizing depth estimation



Input



Local depth estimation



Regularized depth

All focused results

Input

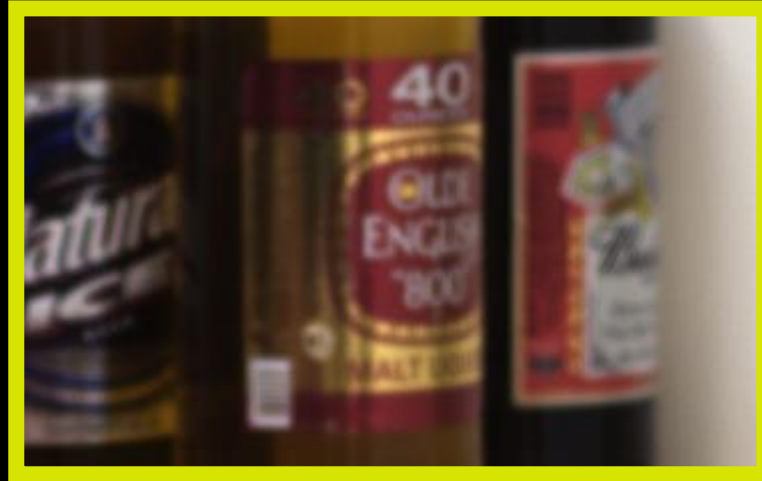


All-focused (deconvolved)



Close-up

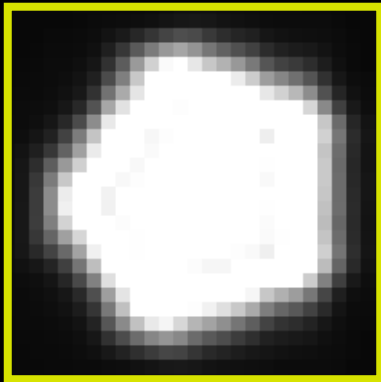
Original image



All-focus image



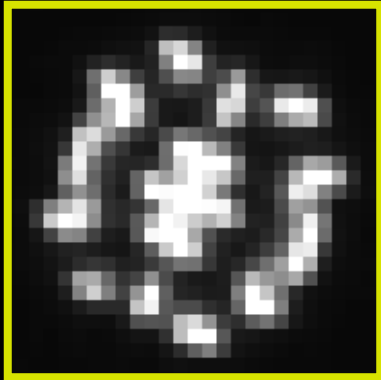
Comparison- conventional aperture result



Ringing due to wrong scale estimation



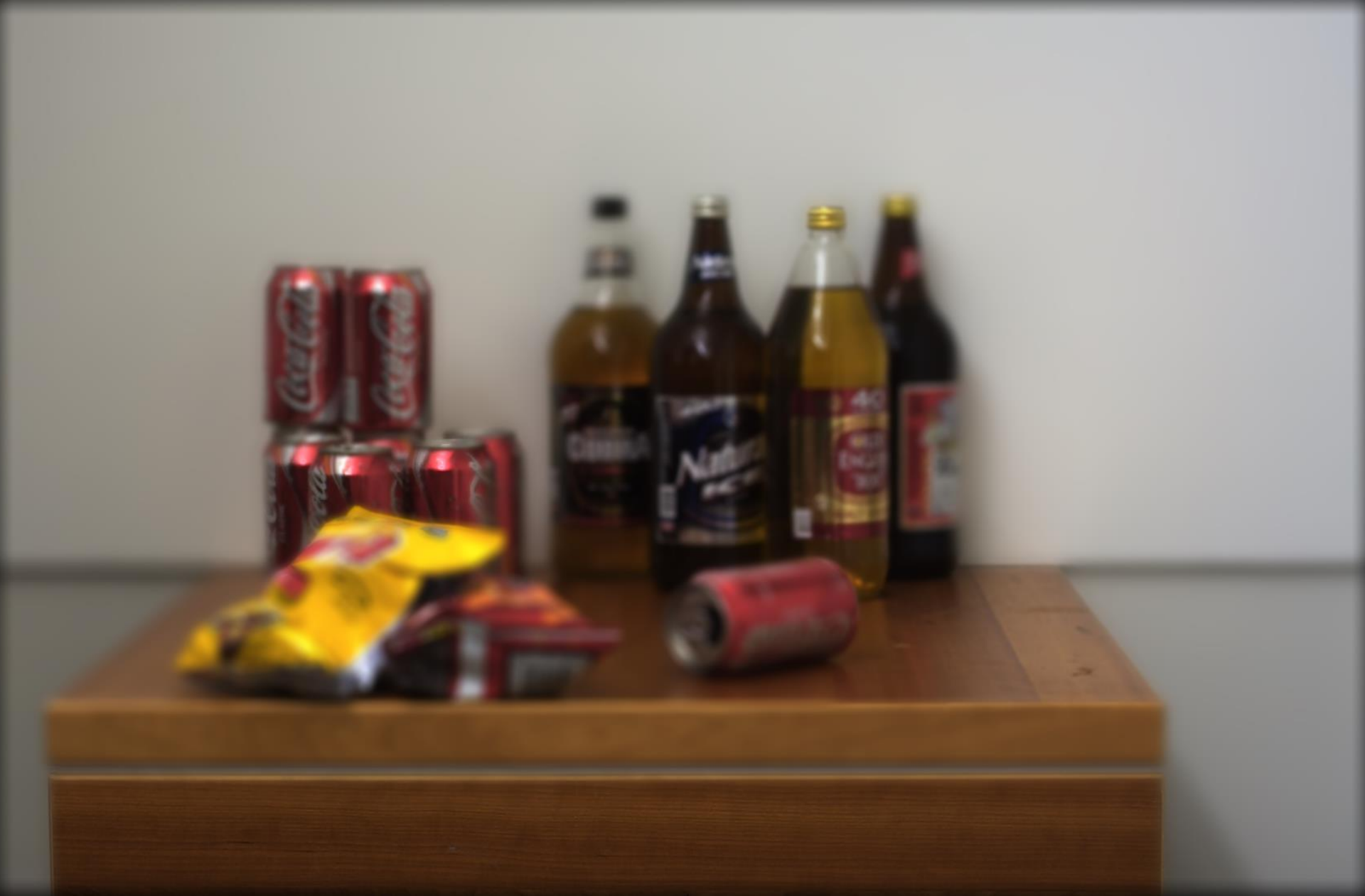
Comparison- coded aperture result



Application: Digital refocusing from a single image



Application: Digital refocusing from a single image

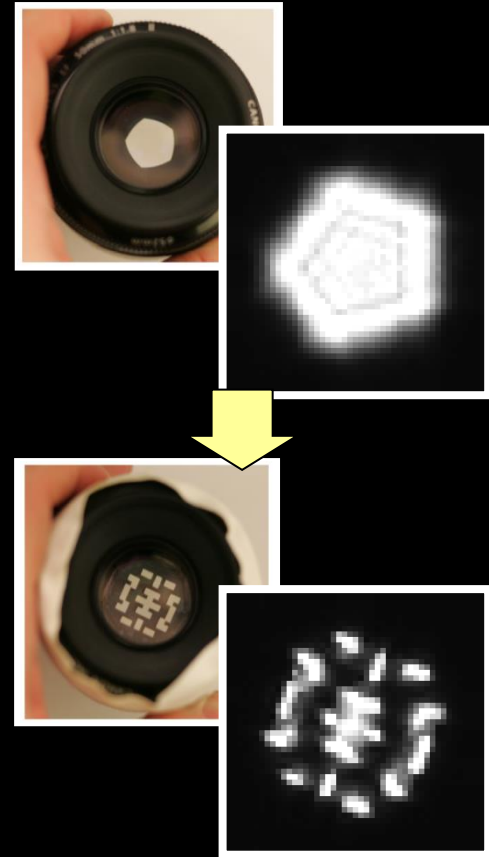


Application: Digital refocusing from a single image



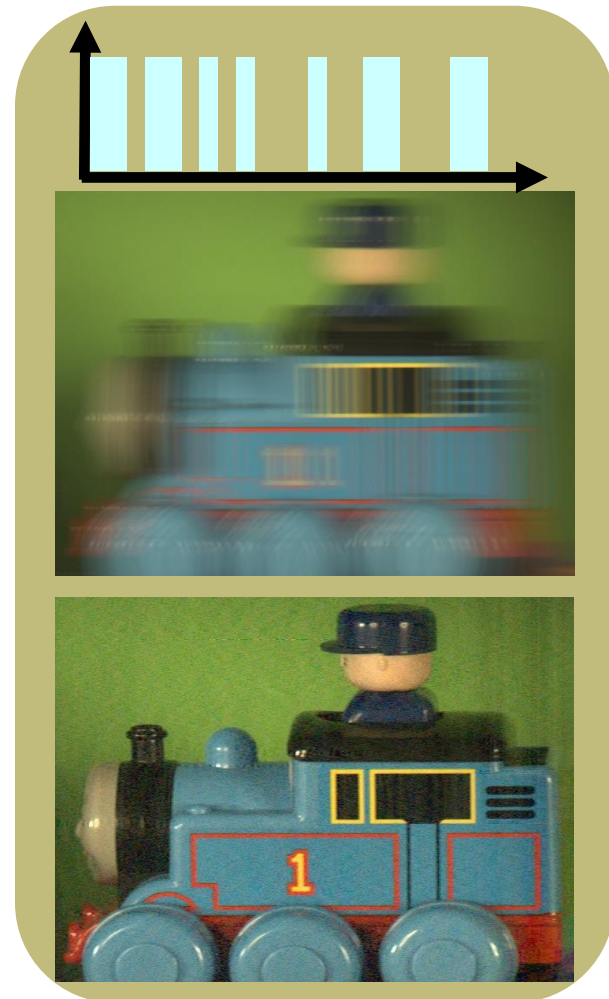
Coded aperture: pros and cons

- + 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



Coded photography

- Coded exposure
 - Reduces the effects of motion blur using the relationship between the photon exposure of the light sensor and the shutter code



Coded photography

- Coded exposure photography: motion deblurring using fluttered shutter
 - Ramesh Raskar, Amit Agrawal, and Jack Tumblin







Input Image



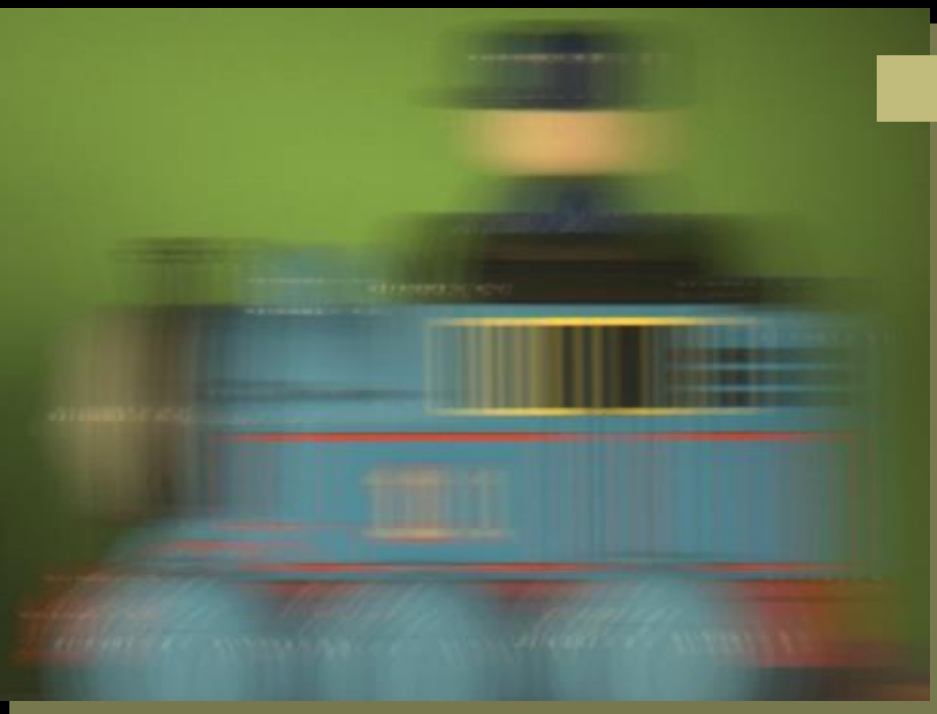
Rectified Crop



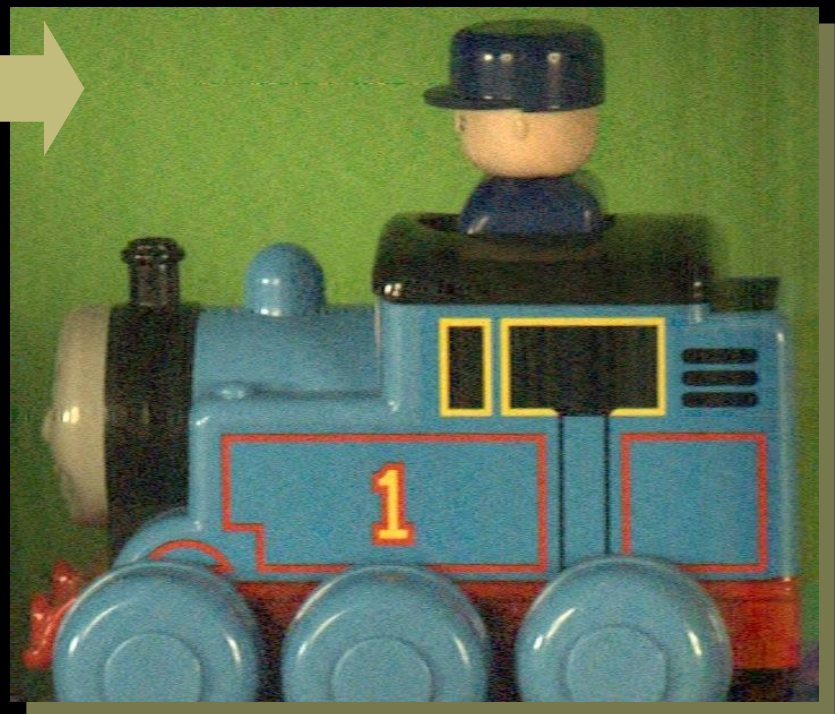
Deblurred Result







Input Photo

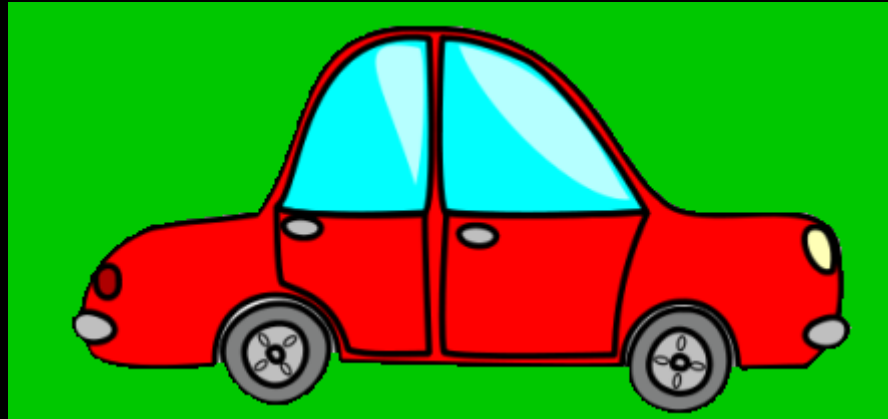


Deblurred Result



Traditional Camera

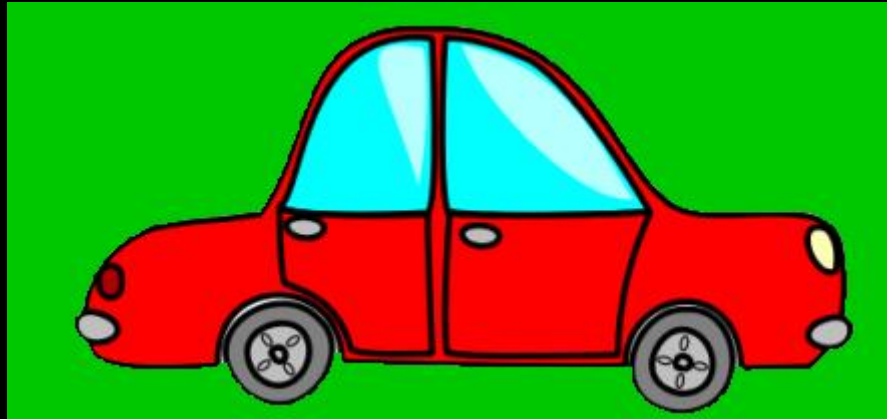
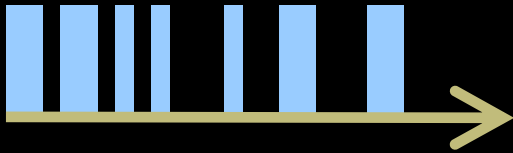
Shutter is OPEN

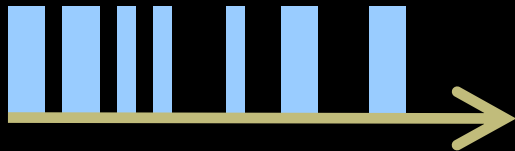




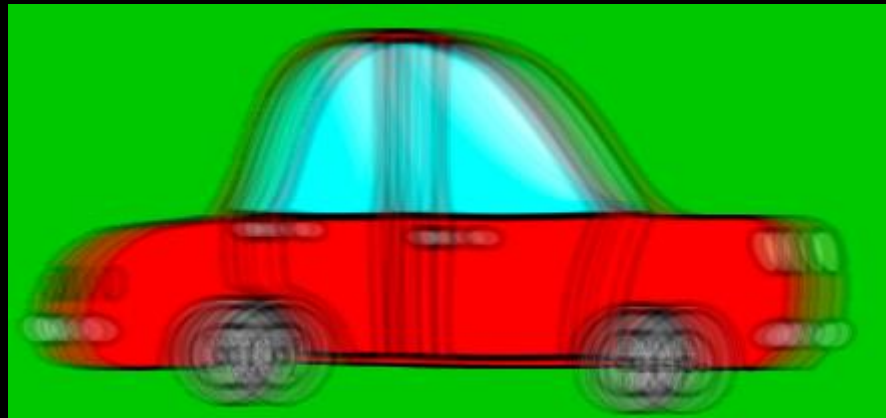
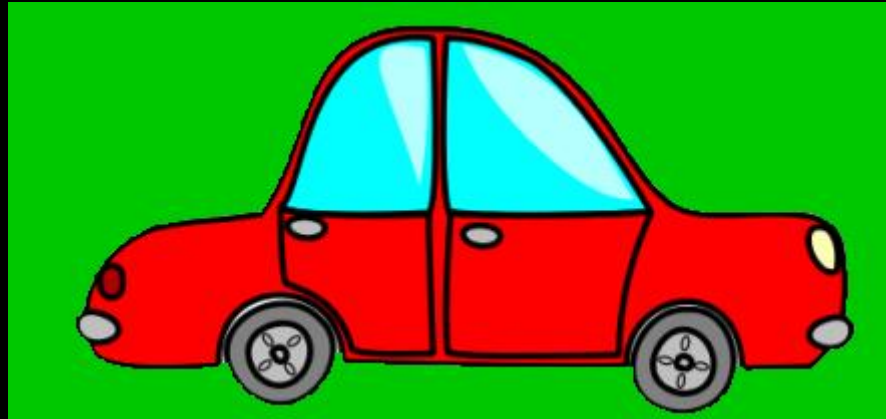
Our Camera

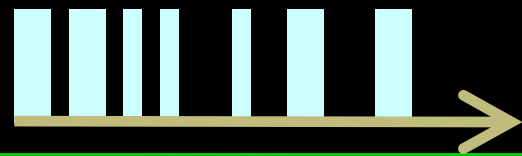
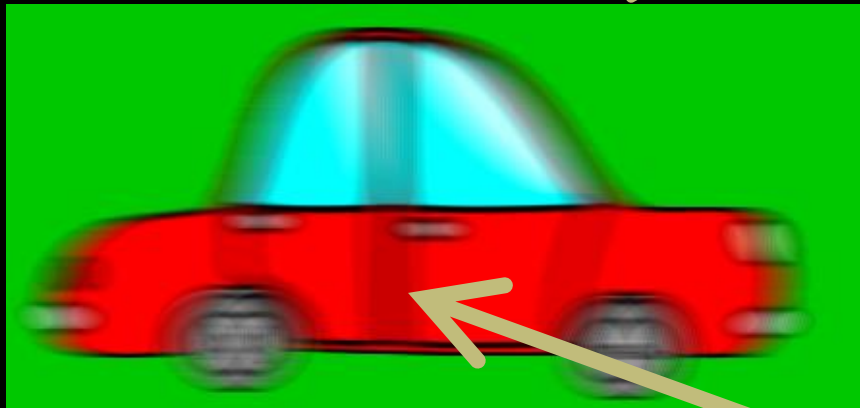
Flutter Shutter





Shutter is OPEN
and CLOSED



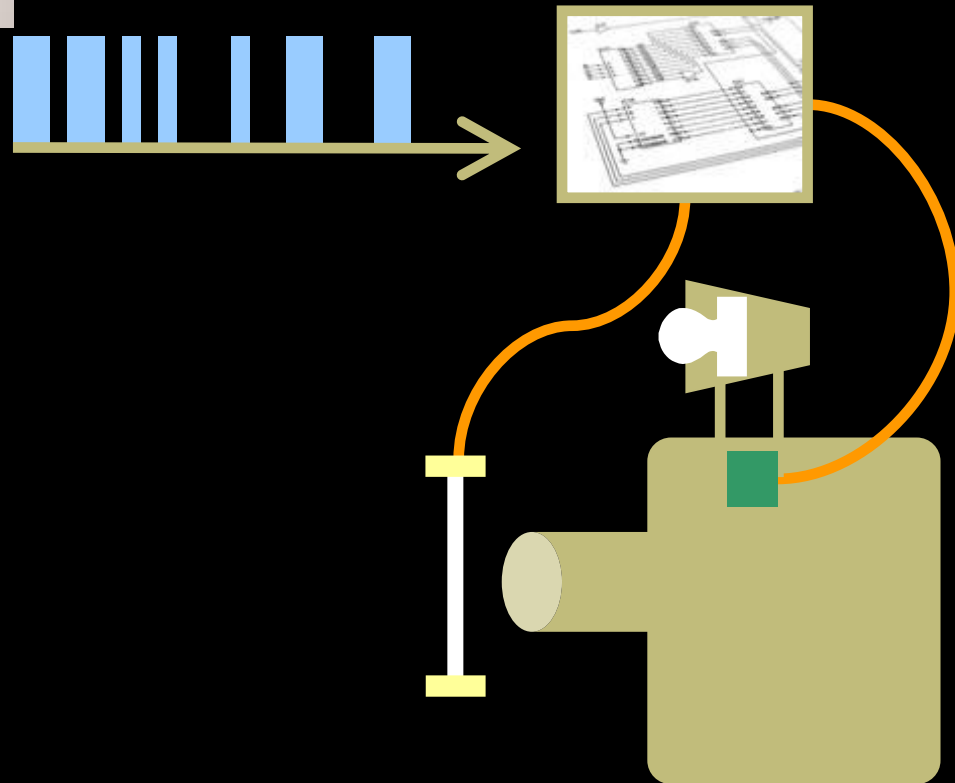


Comparison of Blurred Images

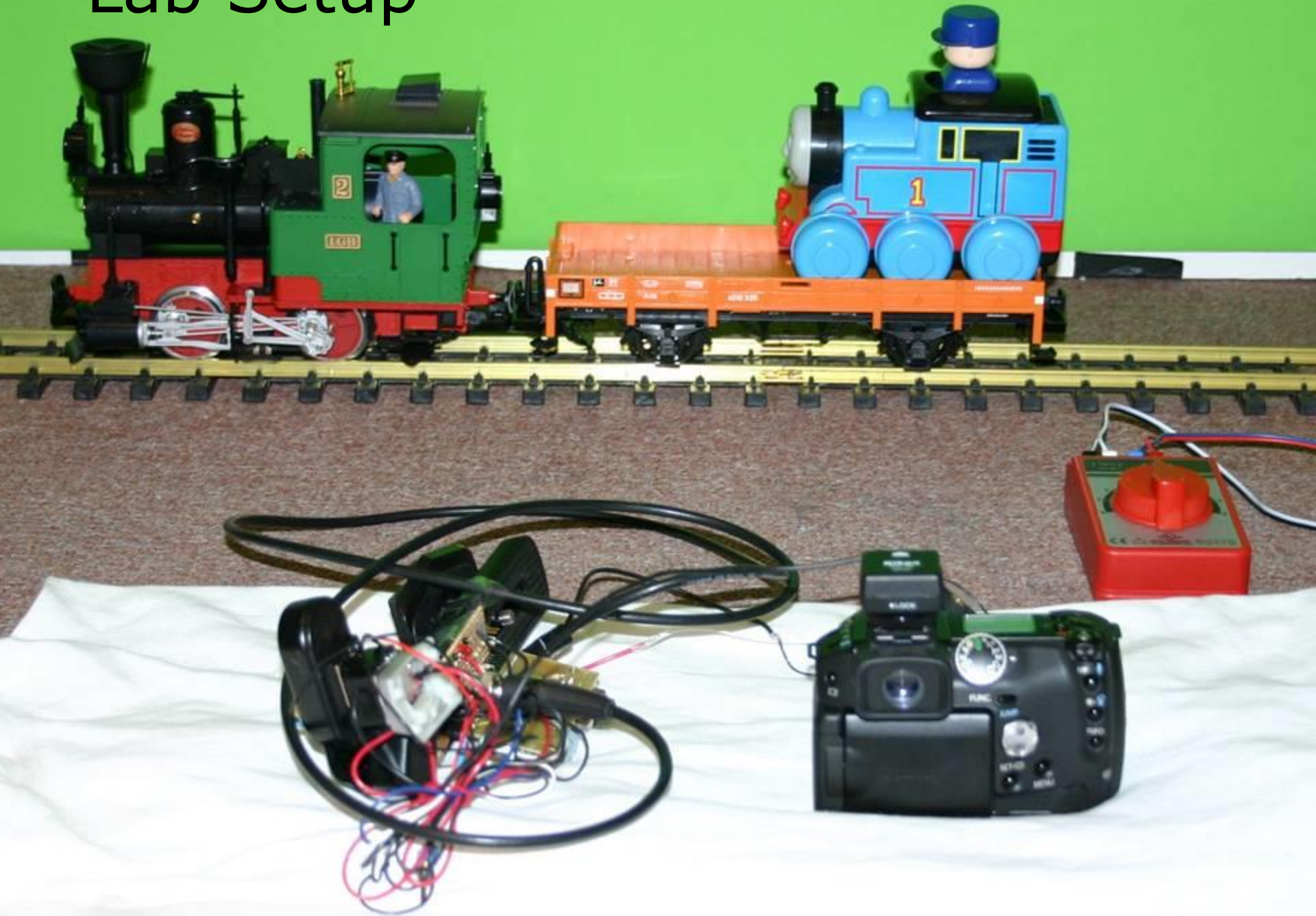


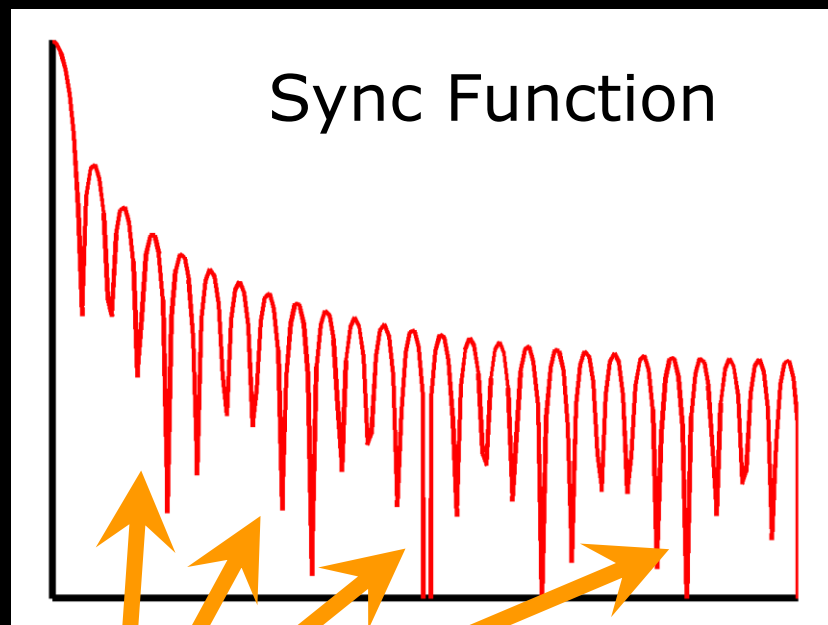
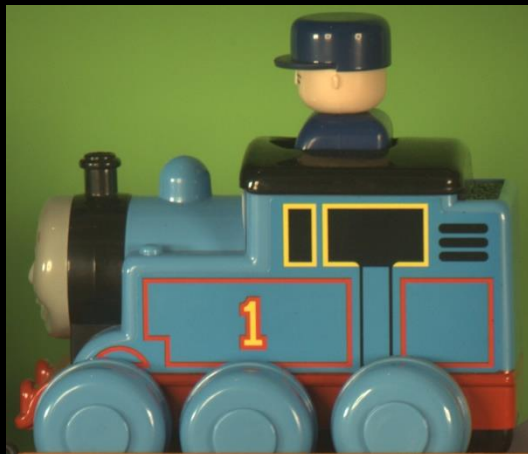
Implementation

Completely Portable



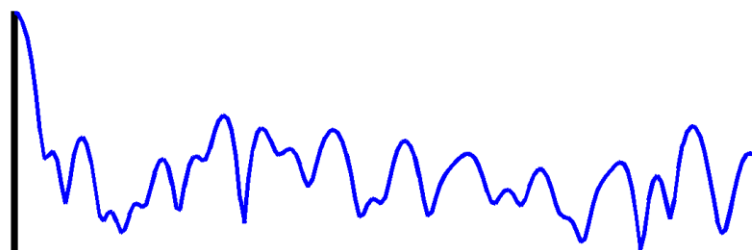
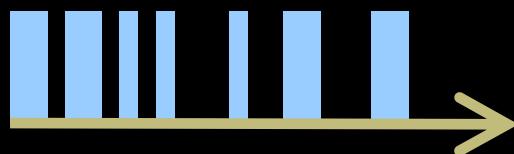
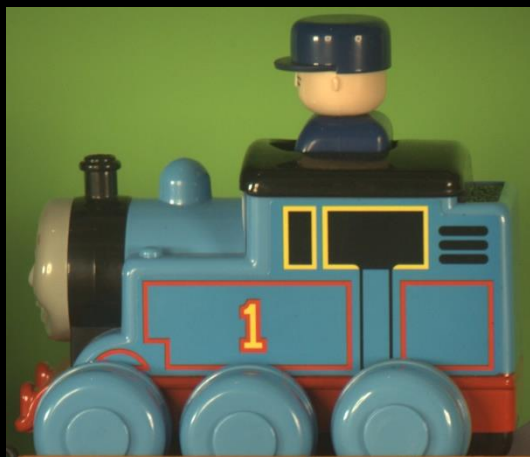
Lab Setup





Blurring
==
Convolution

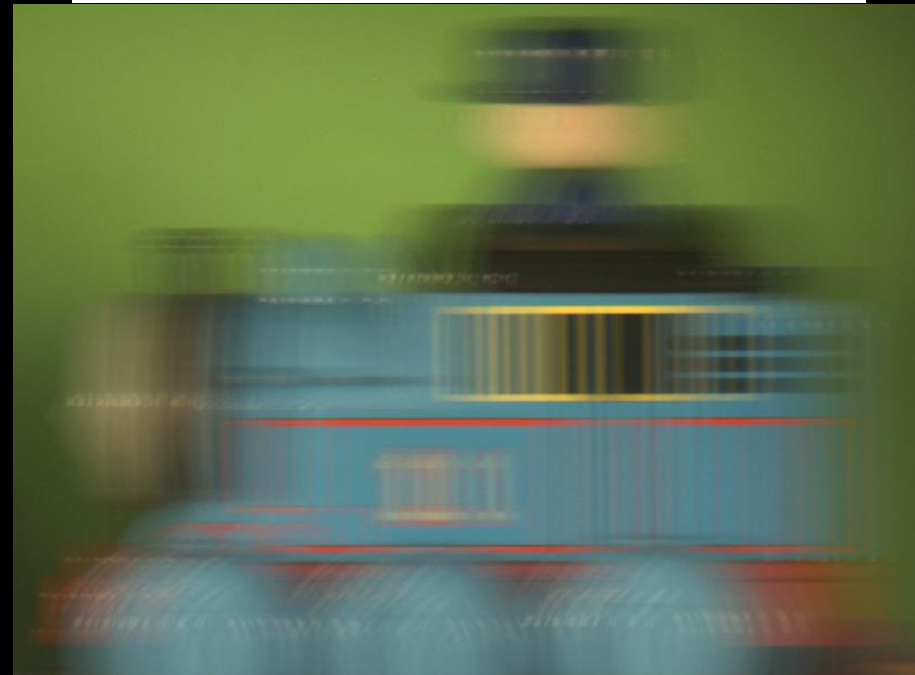
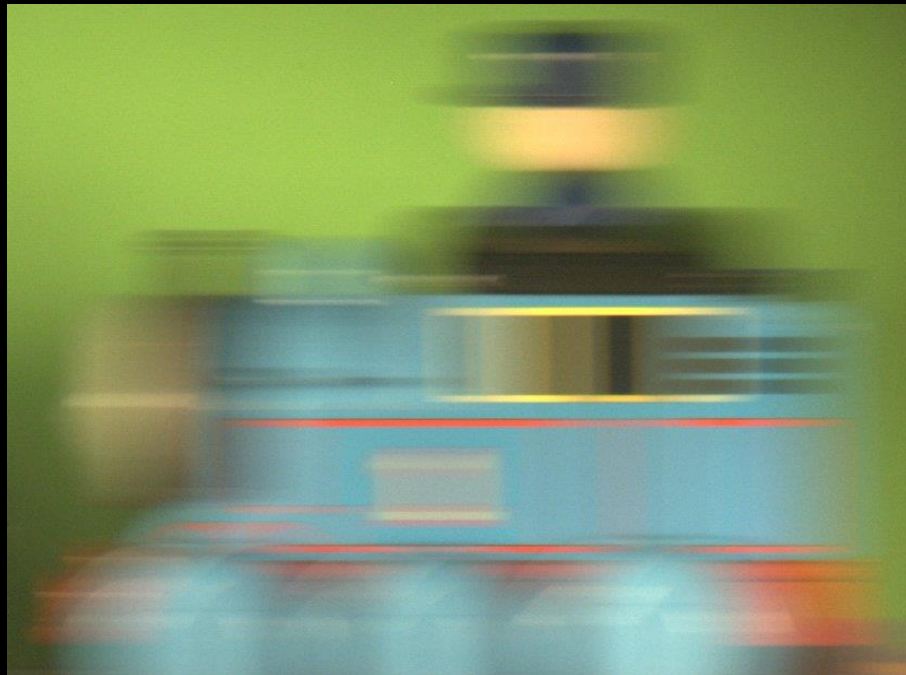
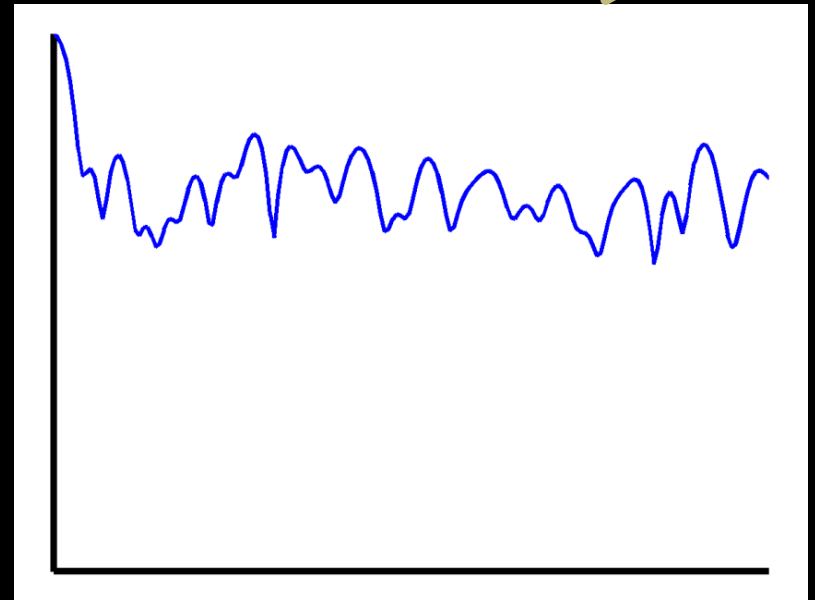
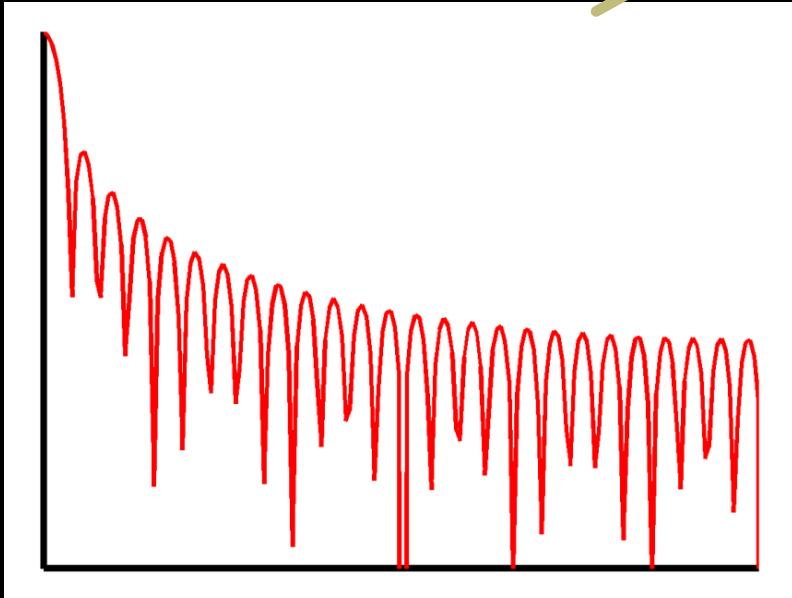
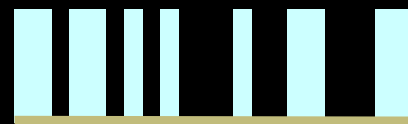
Traditional Camera: Box Filter

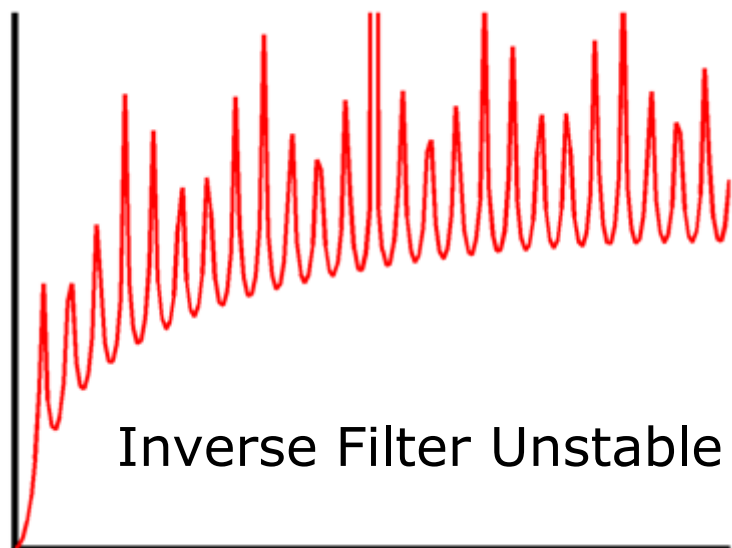
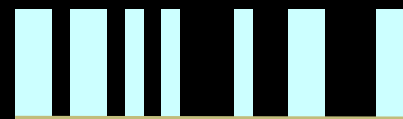


Preserves High
Frequencies!!!

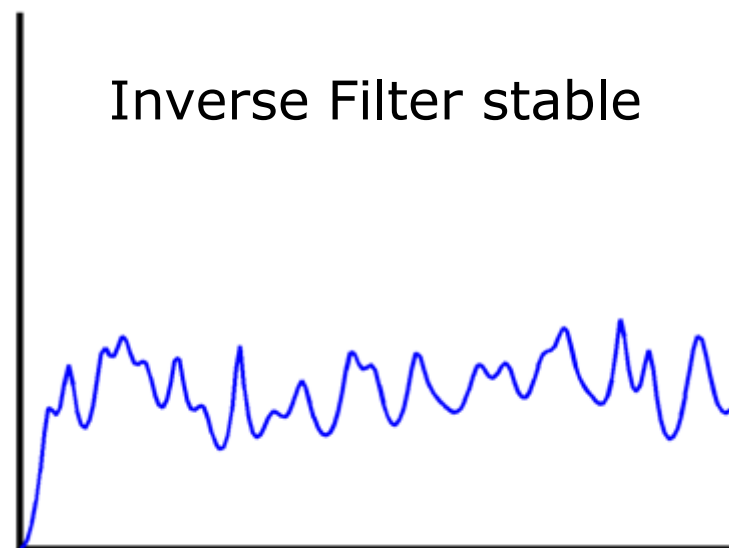
Flutter Shutter: Coded Filter

Comparison

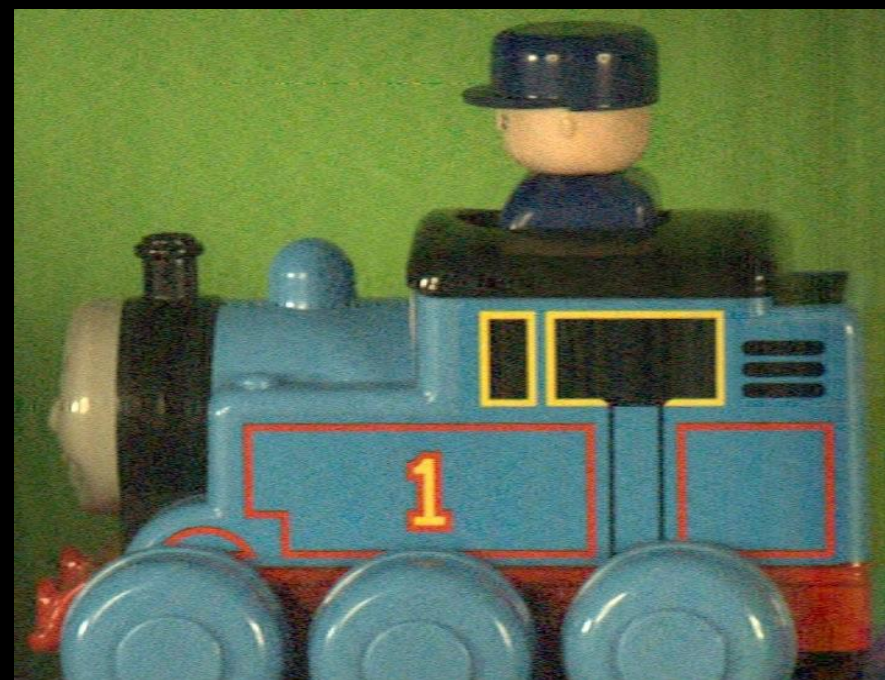
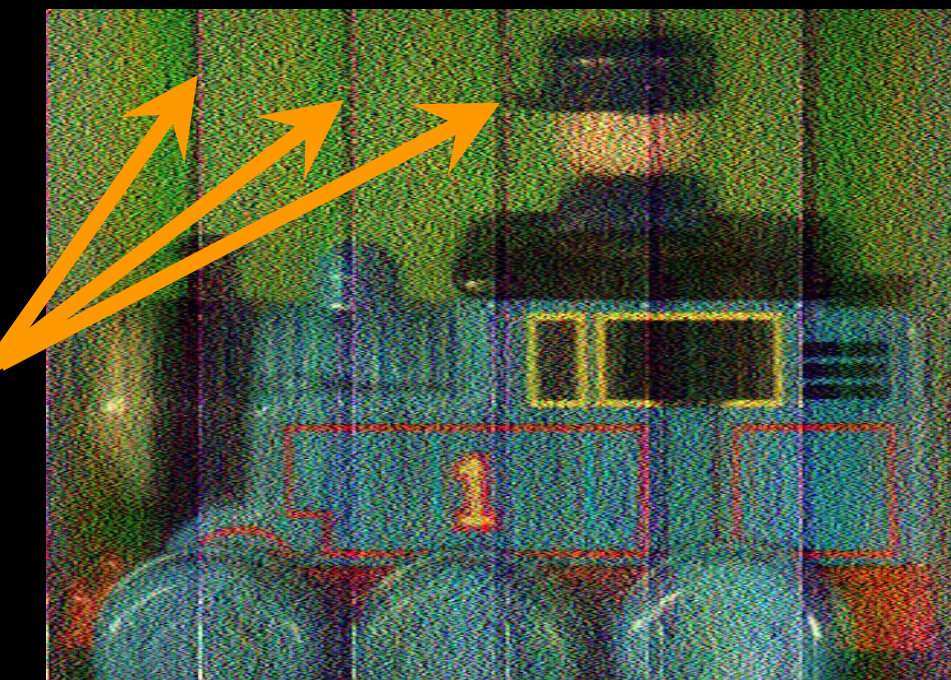




Inverse Filter Unstable



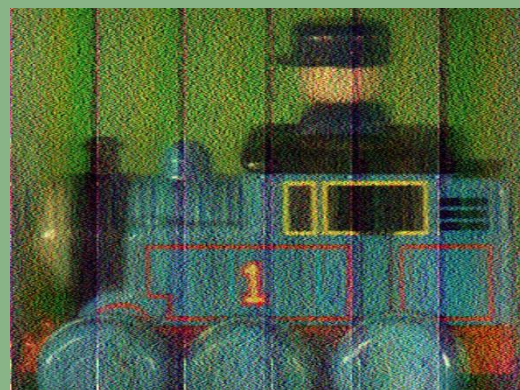
Inverse Filter stable



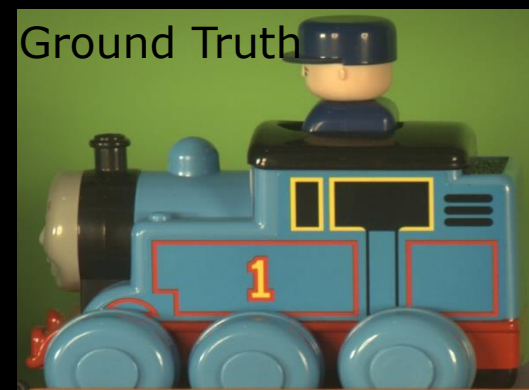
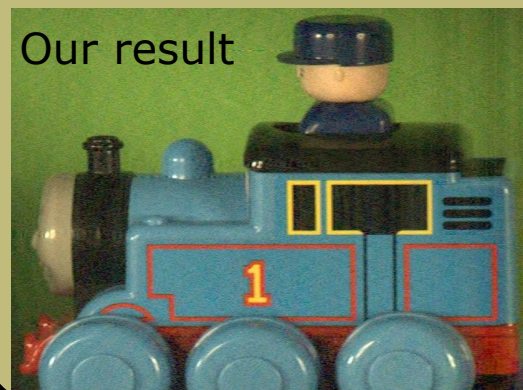
Short Exposure



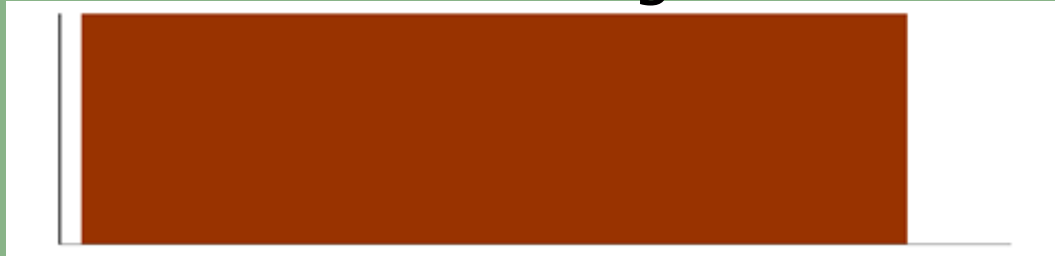
Long Exposure



Coded Exposure



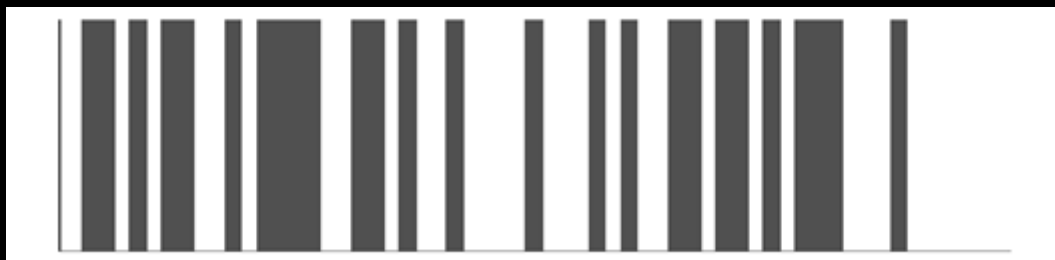
Are all codes "good"?



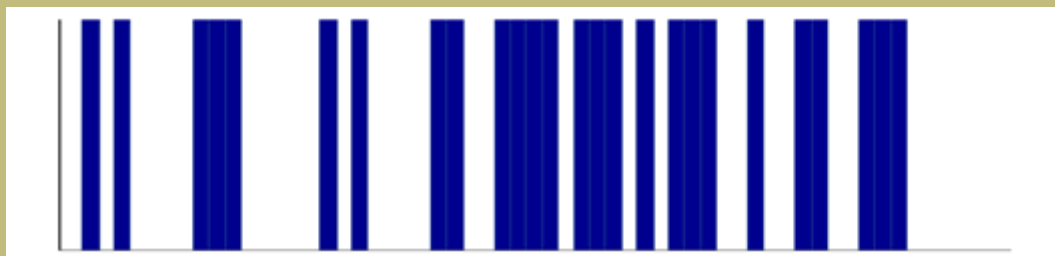
All ones



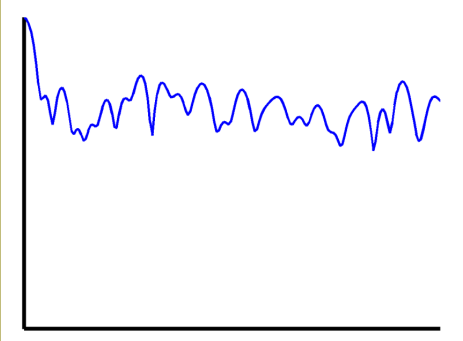
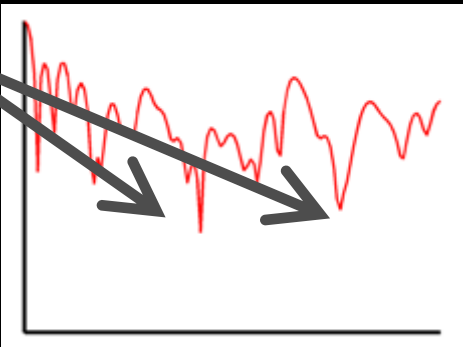
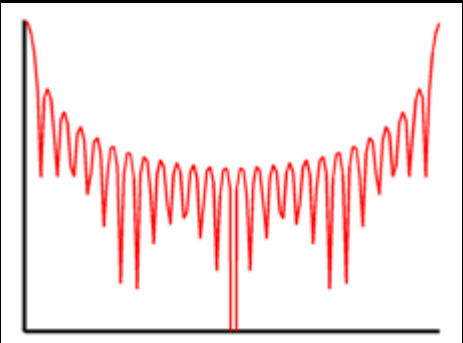
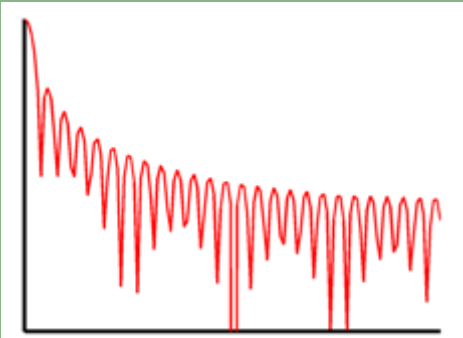
Alternate



Random



Our Code





License Plate Retrieval



License Plate Retrieval

Compressive imaging

- Compressive sensing of images
- Compressive sensing is also called compressed sensing, compressive sampling, or sparse sampling

Compressive imaging

- Nyquist-Shannon sampling theorem
 - Sample at twice the highest observed frequency
 - You cannot compress an image until you have the image
- Compressive imaging
 - Compress the image before it is digitized

Compressive imaging

Example

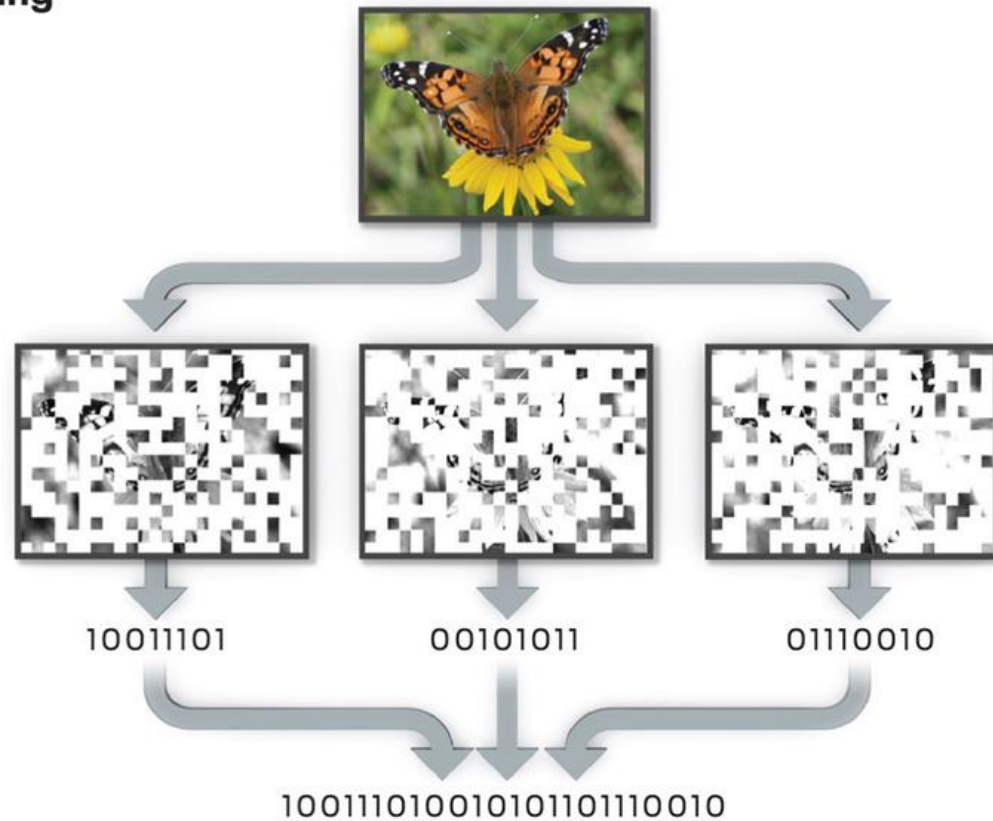
Compressed Sensing

1. An image can be sensed and compressed at the same time.

2. The trick is to sum the analog voltages of randomly chosen sets of pixels. You need many such sets, but far fewer than the number of pixels.

3. Only the sums are digitized.

4. These digitized values constitute the compressed image. Significant computation is needed to decompress it.



Compressive imaging

- Single pixel camera

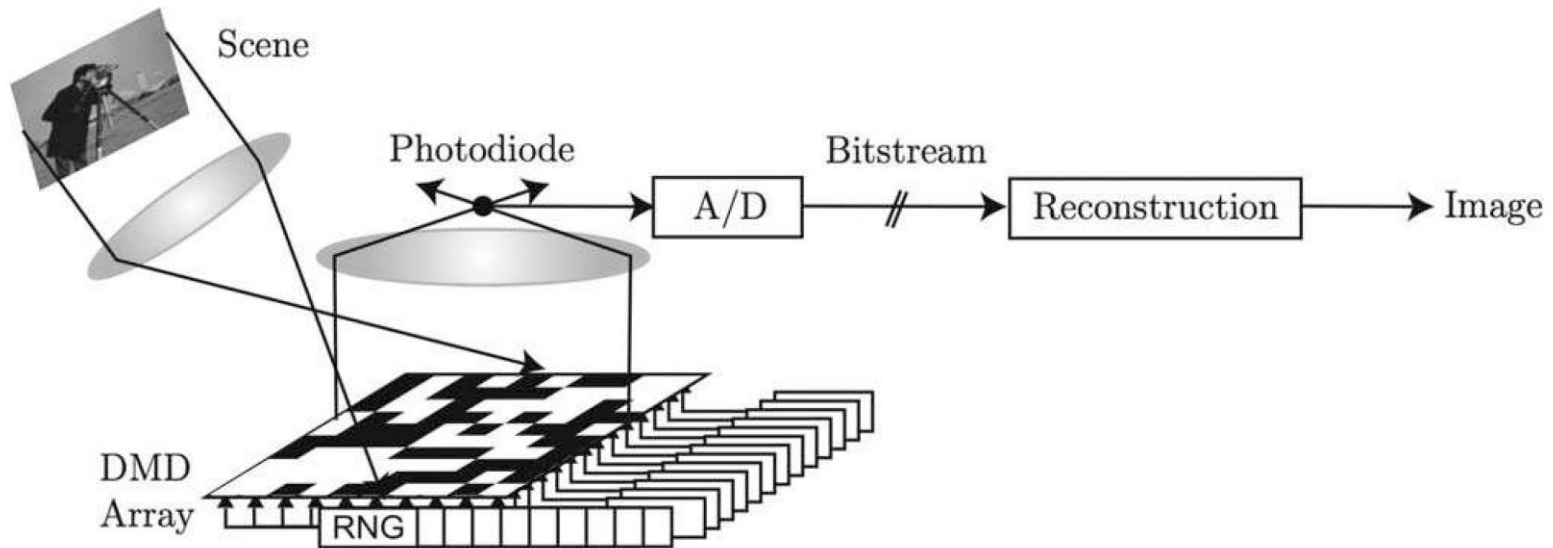


Figure 6. A schematic diagram of the “one-pixel camera.” The “DMD” is the grid of micro-mirrors that reflect some parts of the incoming light beam toward the sensor, which is a single photodiode. Other parts of the image (the black squares) are diverted away. Each measurement made by the photodiode is a random combination of many pixels. In *“One is Enough”* (p.114), 1600 random measurements suffice to create an image comparable to a 4096-pixel camera. (Figure courtesy of Richard Baraniuk.)

Compressive imaging

- Conditions for reconstructing the image
 - Image is sparse in some domain
 - Incoherence
 - Easily satisfied by sparse images
 - Applied using the (restricted) isometry property (RIP)
- Find solution to underdetermined linear system
 - More unknowns than equations
 - Multiple solutions

Compressive imaging

- Single pixel camera



One is Enough. A photograph taken by the “single-pixel camera” built by Richard Baraniuk and Kevin Kelly of Rice University. (a) A photograph of a soccer ball, taken by a conventional digital camera at 64×64 resolution. (b) The same soccer ball, photographed by a single-pixel camera. The image is derived mathematically from 1600 separate, randomly selected measurements, using a method called compressed sensing. (Photos courtesy of R. G. Baraniuk, *Compressive Sensing* [Lecture Notes], Signal Processing Magazine, July 2007. ©2007 IEEE.)

Next lecture

- Camera and image motion