

Computational Imaging

Lecture 13: Computing Toolbox: Image Blurry



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Q: Why are Our Images Blurry?



Today's Topic

- Lens Imperfections and Physical Limit.
- Camera Shake.
- Scene Motion.
- Depth Defocus.



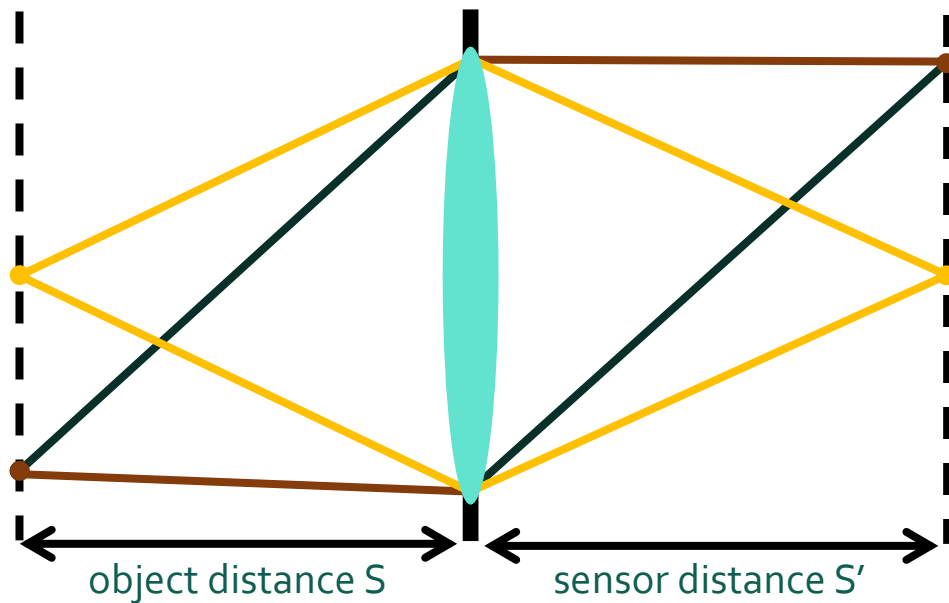
Lens Imperfections and Physical Limit



Lens Imperfections

- Ideal lens: A point maps to a point at a certain plane.

$$\frac{1}{S'} + \frac{1}{S} = \frac{1}{f}$$

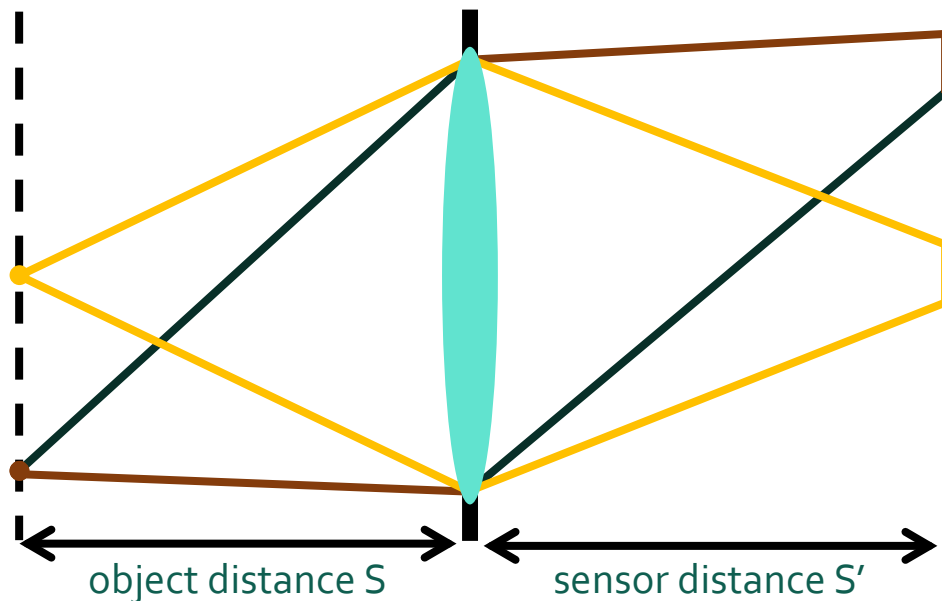




Lens Imperfections

- Ideal lens: A point maps to a point at a certain plane.
- Real lens: A point maps to a circle that has non-zero minimum radius among all planes.

$$\frac{1}{S'} + \frac{1}{S} = \frac{1}{f}$$



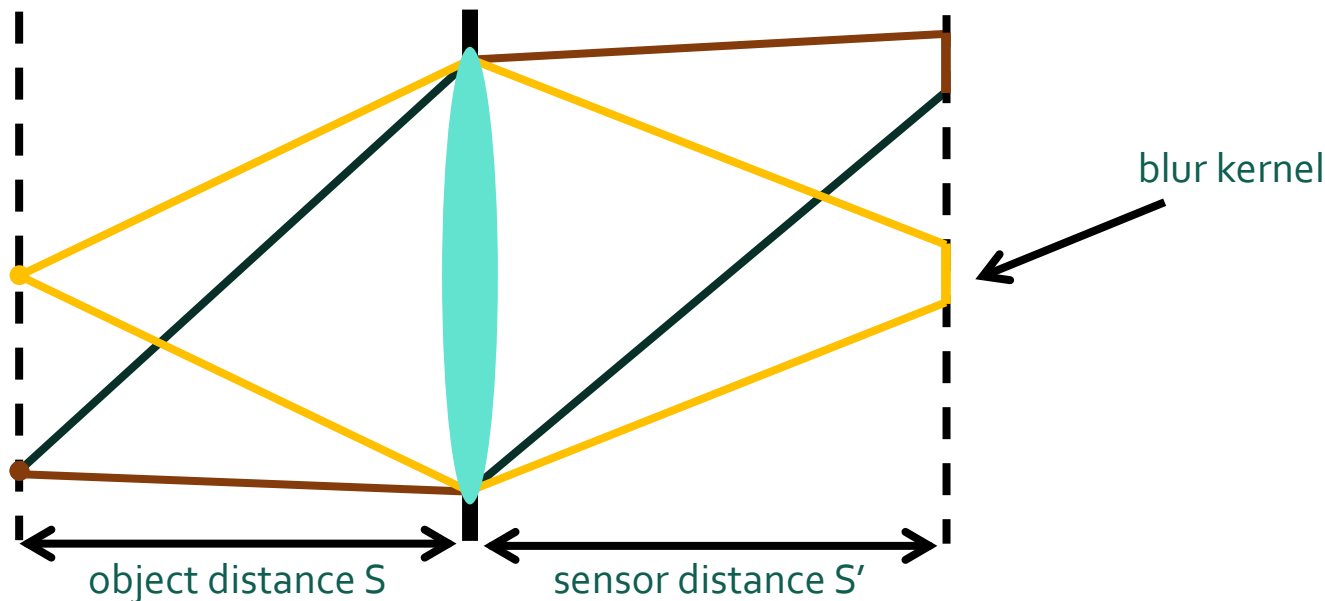
What is the effect of this on the images we capture?



Lens Imperfections

- Ideal lens: A point maps to a point at a certain plane.
- Real lens: A point maps to a circle that has non-zero minimum radius among all planes.

$$\frac{1}{S'} + \frac{1}{S} = \frac{1}{f}$$



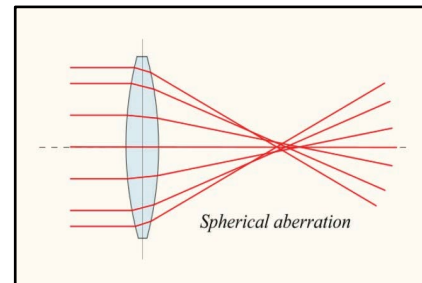
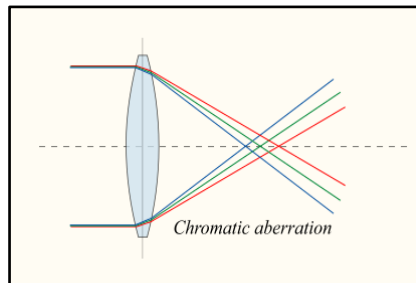
Shift-invariant blur.



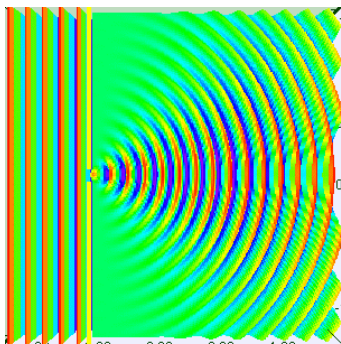
Lens Imperfections

- What causes lens imperfections?
 - Aberrations.

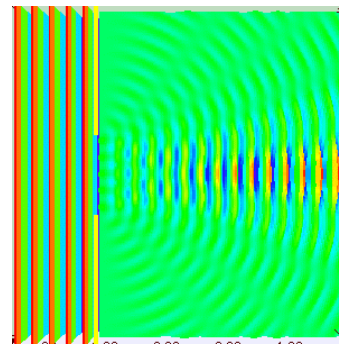
(Important note: Oblique aberrations like coma and distortion are not shift-invariant blur and we do not consider them here!)



- Diffraction



small
aperture



large
aperture

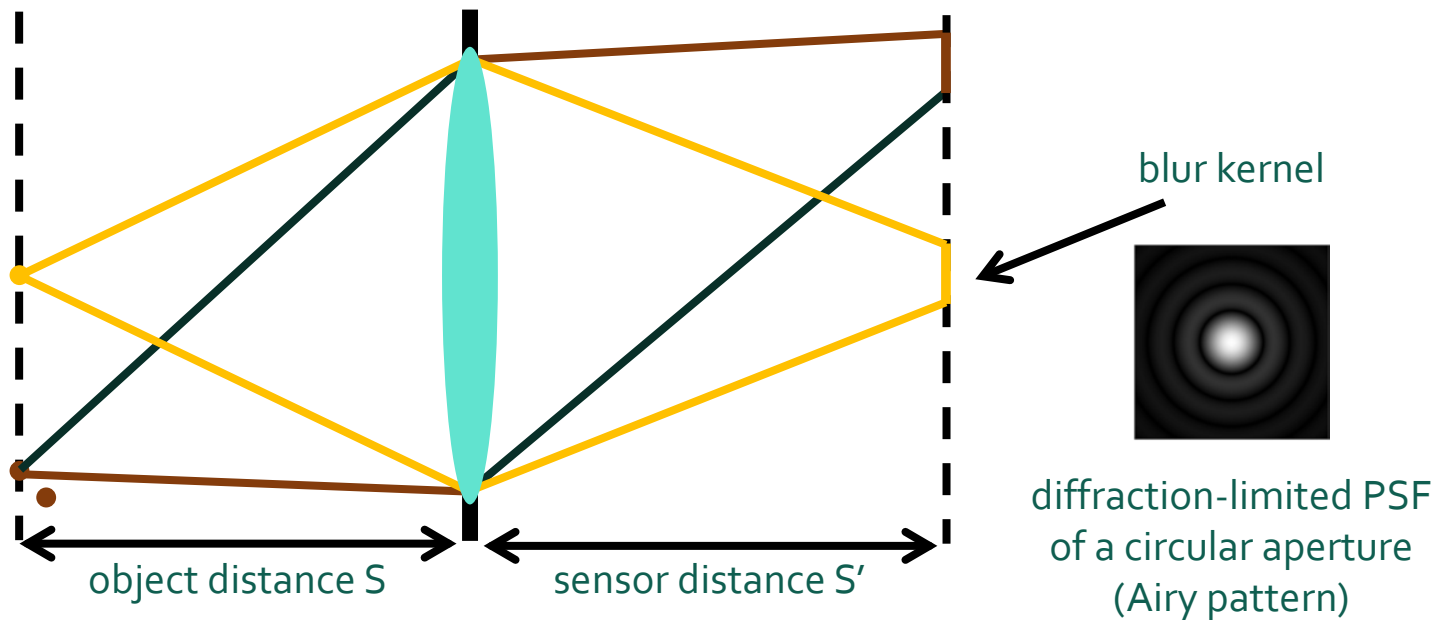
Lens: An Optical Low-pass Filter



Point spread function (PSF): The blur kernel of a lens.

- “Diffraction-limited” PSF: No aberrations, only diffraction. Determined by aperture shape.

$$\frac{1}{S'} + \frac{1}{S} = \frac{1}{f}$$





Assume that we can use:

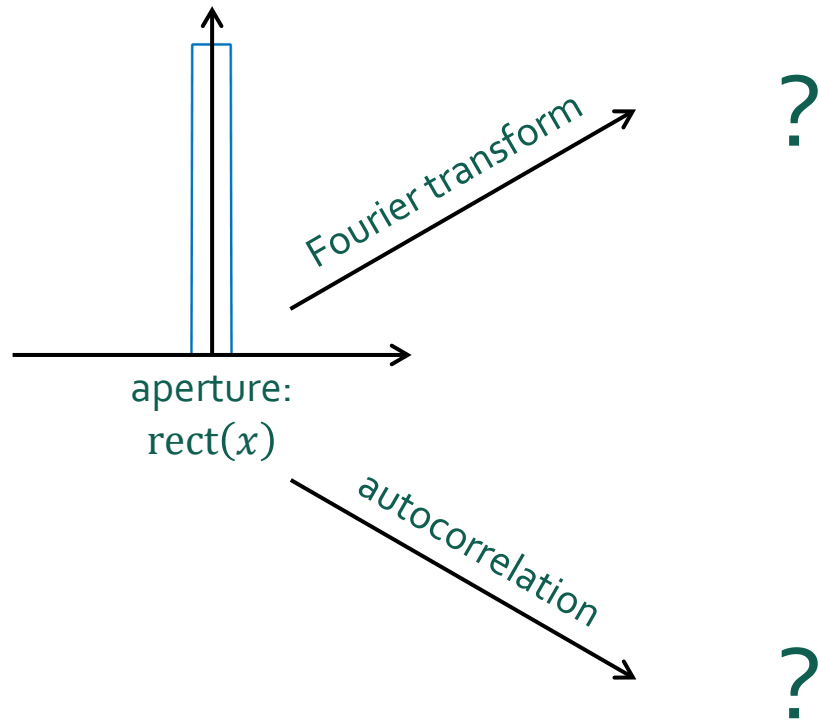
- ***Fraunhofer diffraction***
i.e., distance of sensor and aperture is large relative to wavelength.
- ***Incoherent illumination***
i.e., the light we are measuring is not laser light.

Ignore various scale factors. Different functions are not drawn to scale.

Basics of Diffraction Theory



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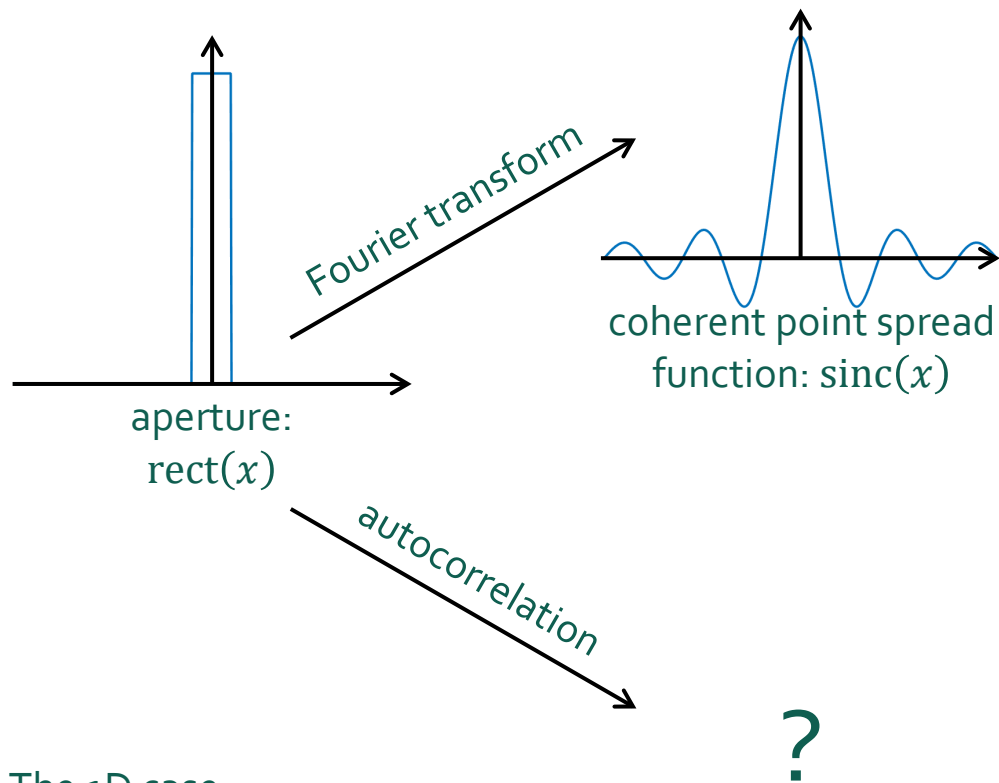


The 1D case

Basics of Diffraction Theory



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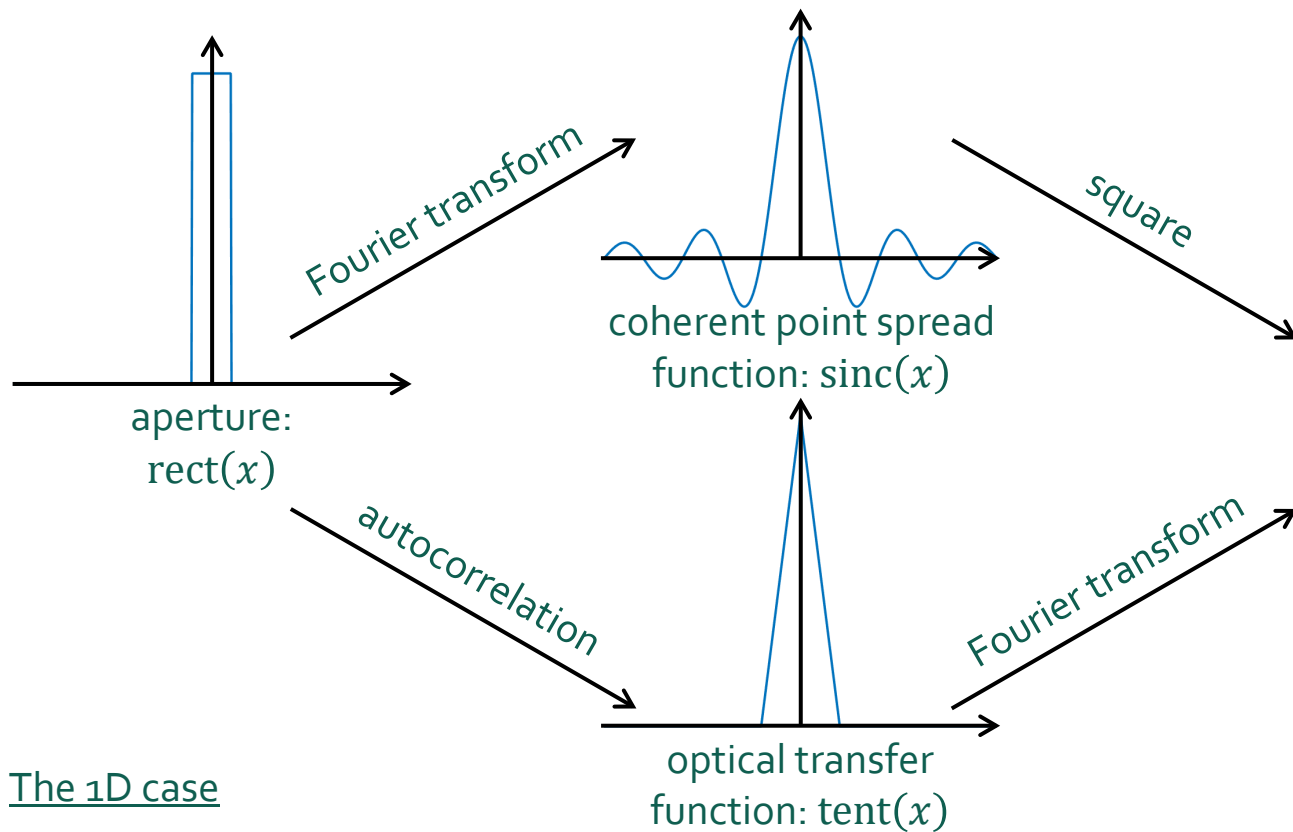


The 1D case

Basics of Diffraction Theory



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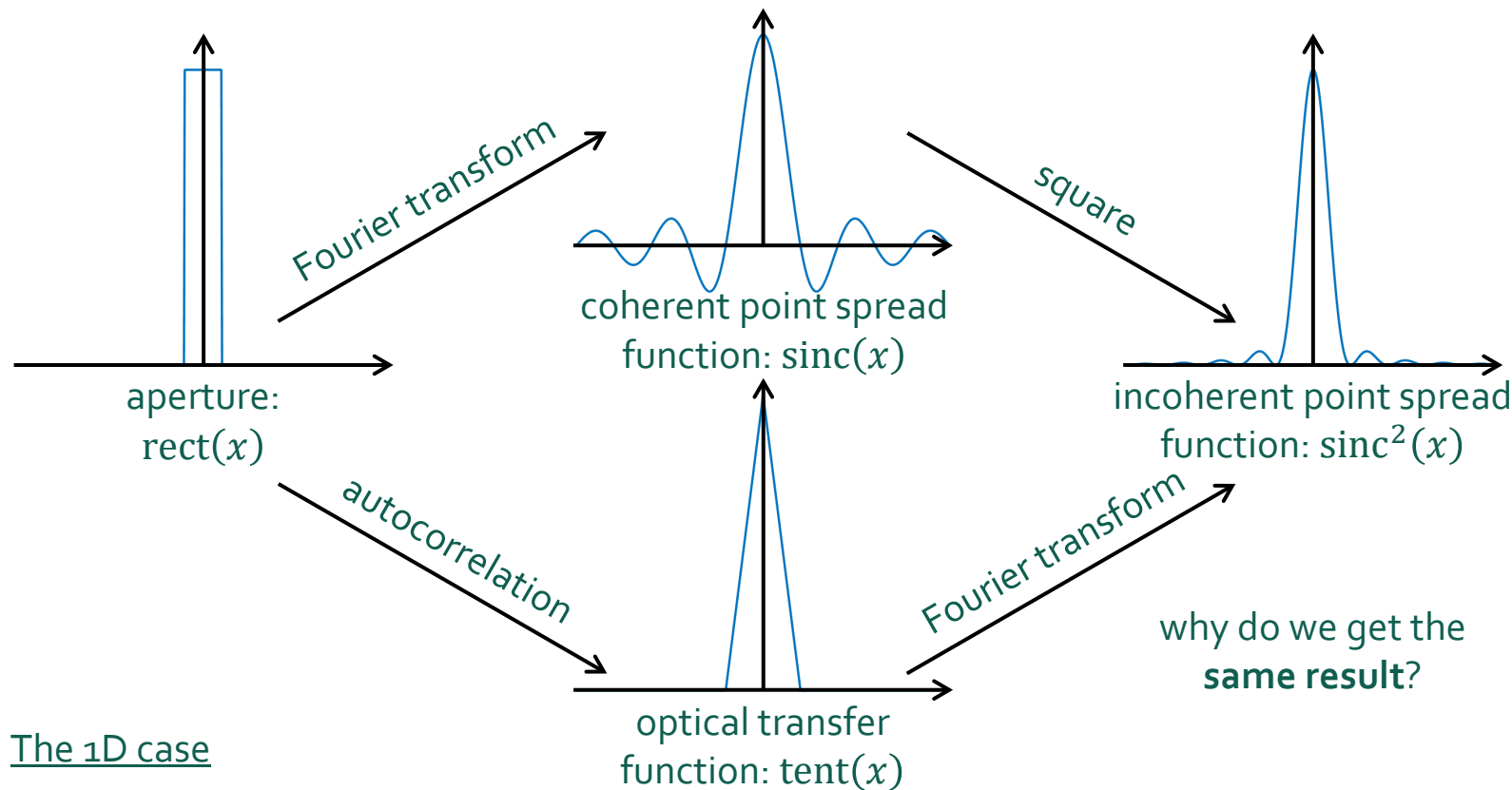


The 1D case

Basics of Diffraction Theory



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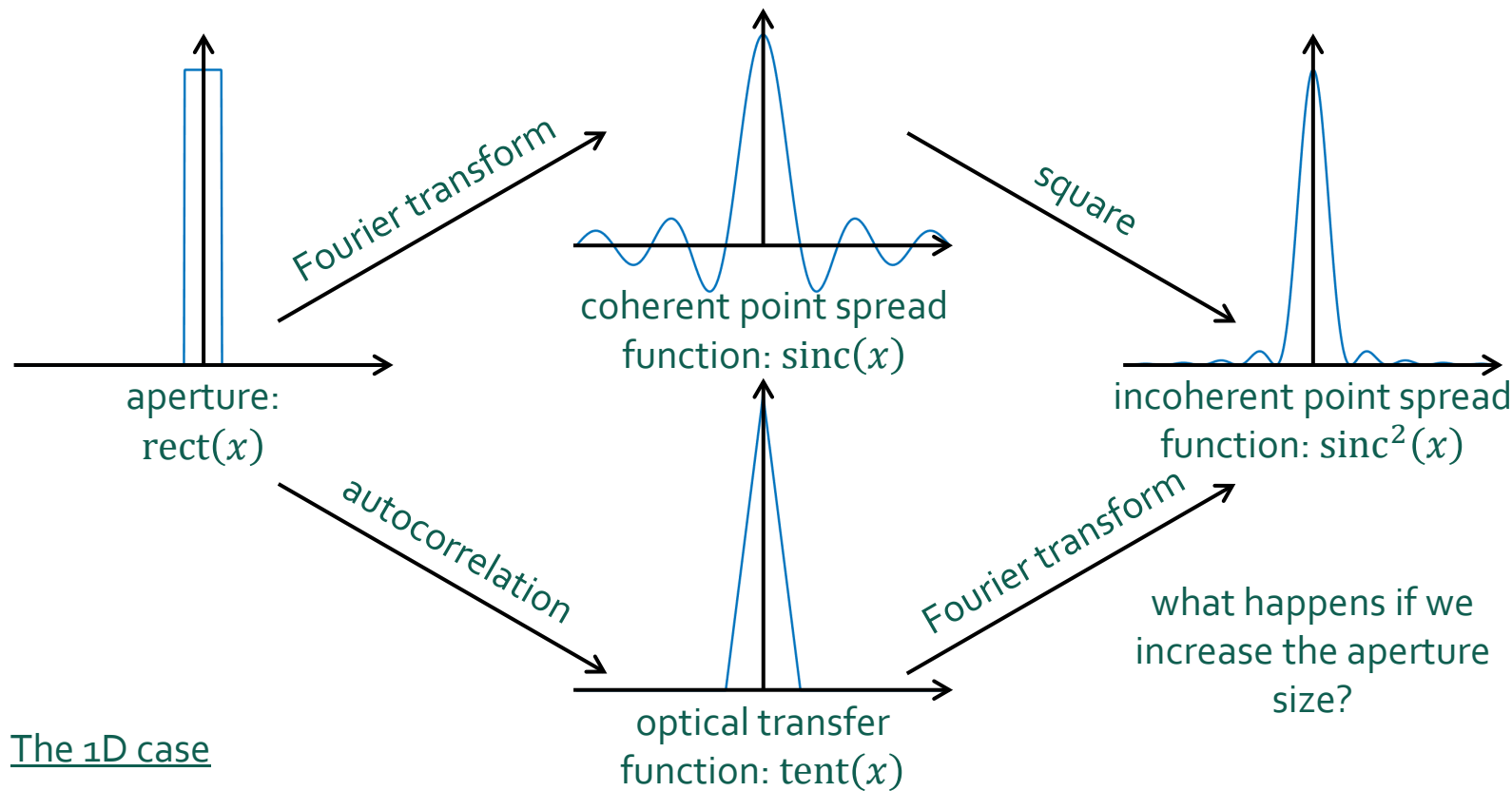


The 1D case

Basics of Diffraction Theory



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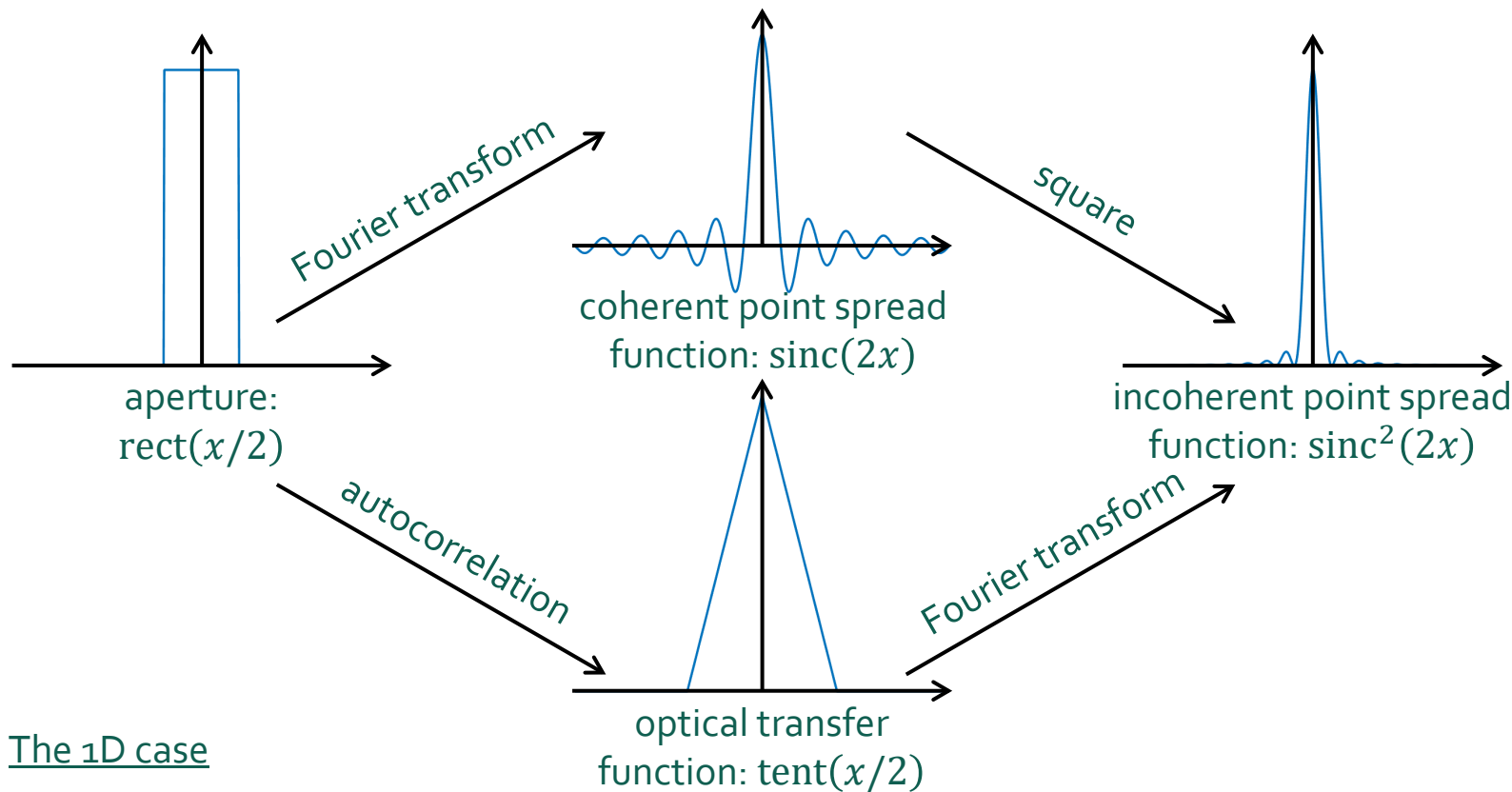


The 1D case

Basics of Diffraction Theory

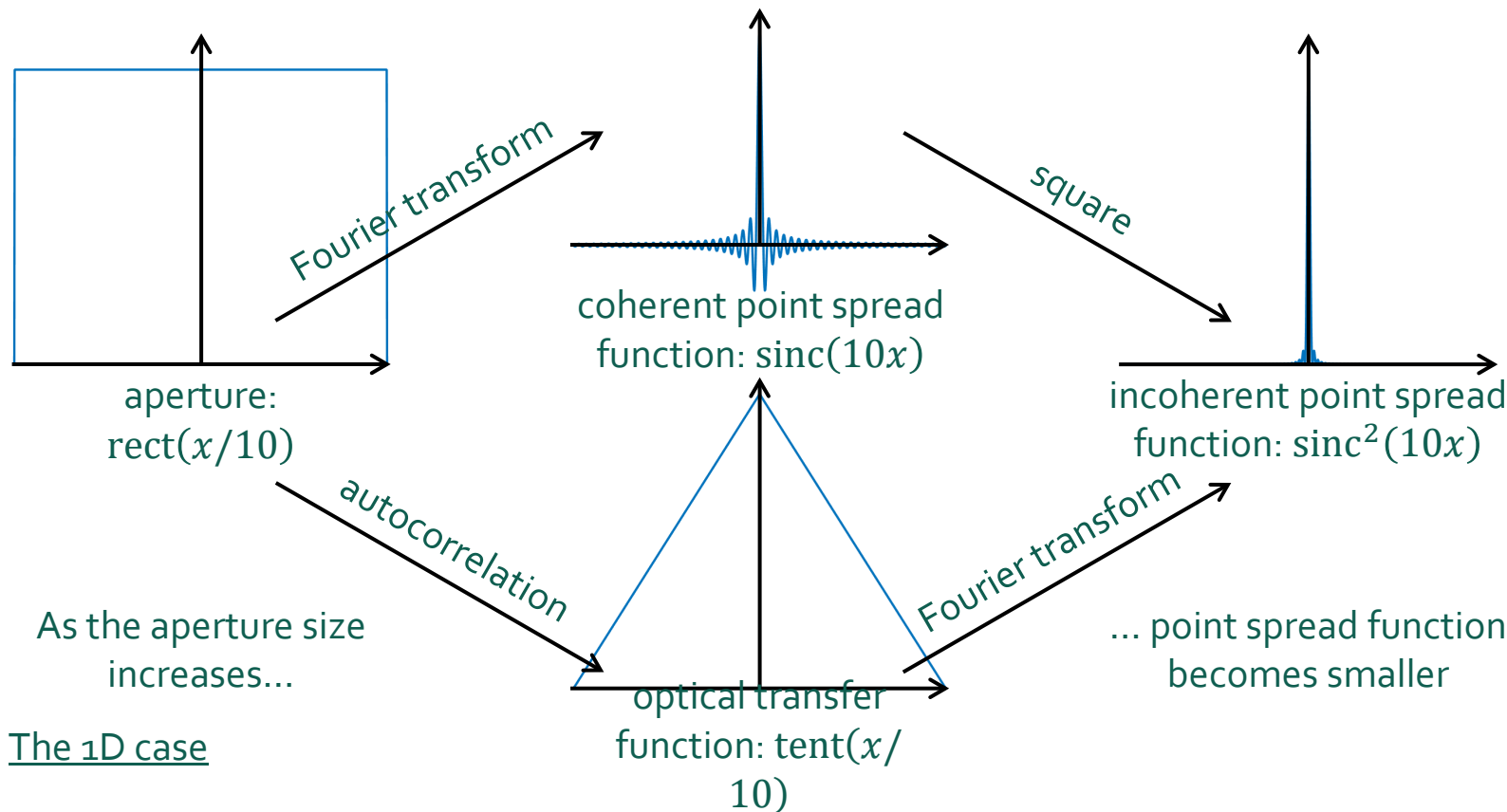


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The 1D case

Basics of Diffraction Theory

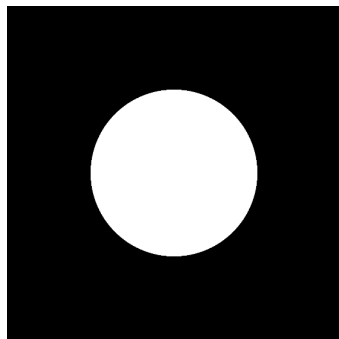


The 1D case

Basics of Diffraction Theory



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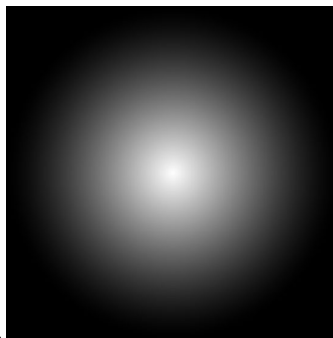


aperture

As the aperture size
increases...

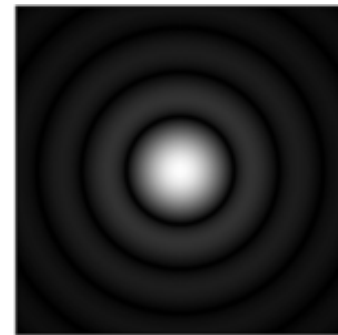
The 2D case

autocorrelation



optical transfer
function

Fourier transform



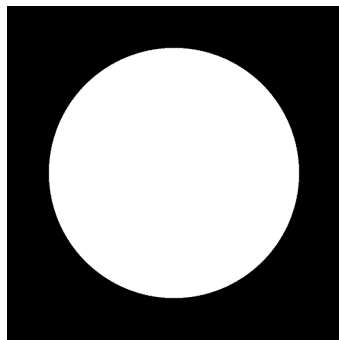
incoherent point spread
function

... point spread function
becomes smaller

Basics of Diffraction Theory



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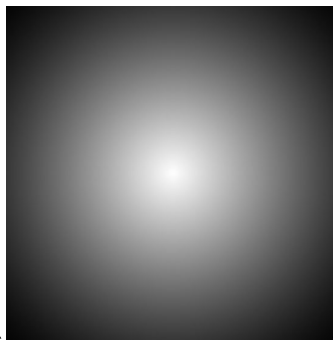


aperture

As the aperture size
increases...

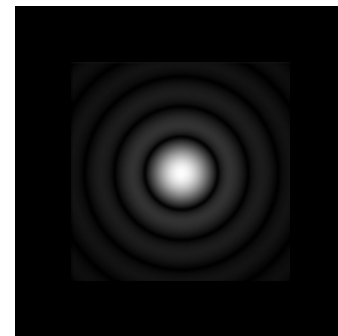
The 2D case

autocorrelation



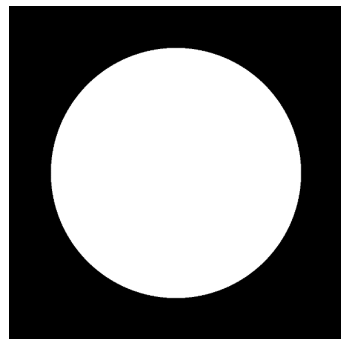
optical transfer
function

Fourier transform



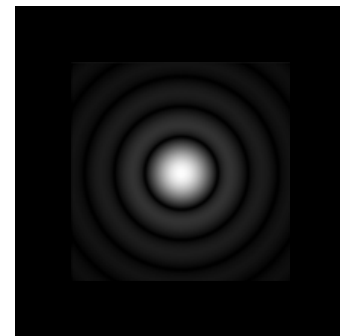
incoherent point spread
function

... point spread function
becomes smaller



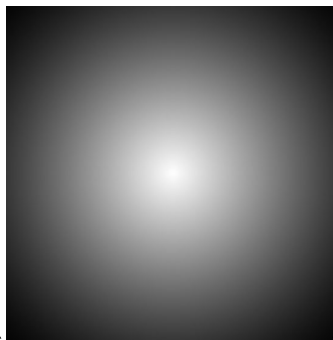
aperture

Why do we prefer circular apertures?



incoherent point spread
function

autocorrelation



optical transfer
function

Fourier transform

... point spread function
becomes smaller

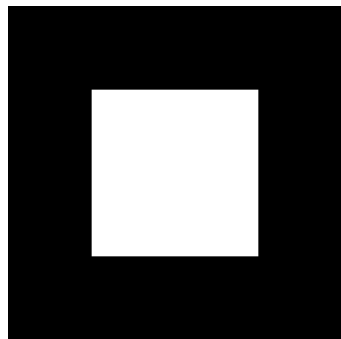
As the aperture size
increases...

The 2D case

Basics of Diffraction Theory

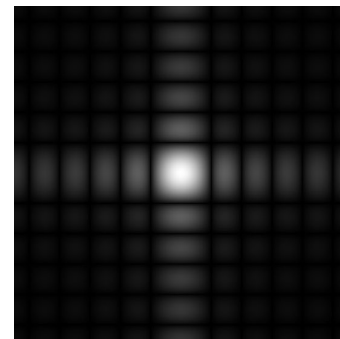


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aperture

Other shapes produce very
anisotropic blur.

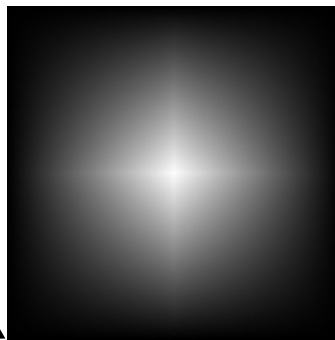


incoherent point spread
function

As the aperture size
increases...

The 2D case

autocorrelation



optical transfer
function

Fourier transform

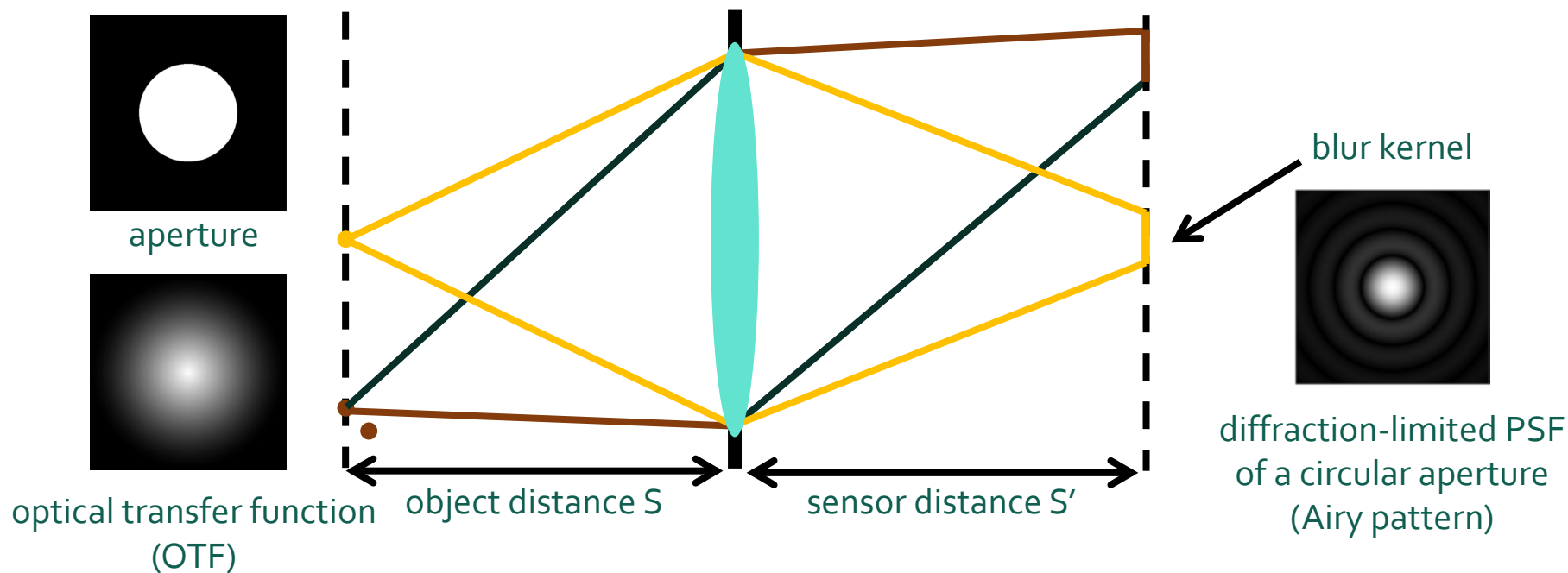
... point spread function
becomes smaller

Lens: An Optical Low-pass Filter



Point spread function (PSF): The blur kernel of a lens.

- “Diffraction-limited” PSF: No aberrations, only diffraction. Determined by aperture shape.



Lens: An Optical Low-pass Filter



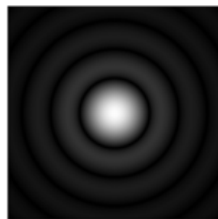
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image from a perfect lens

x

$*$



imperfect lens PSF

c

$=$

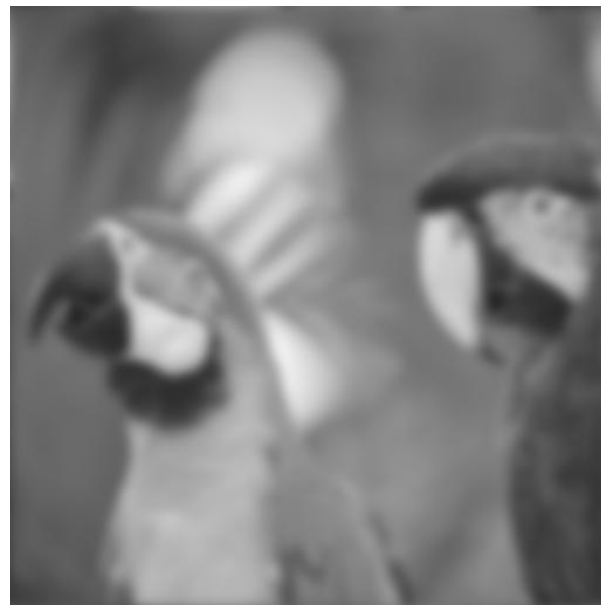


image from imperfect lens

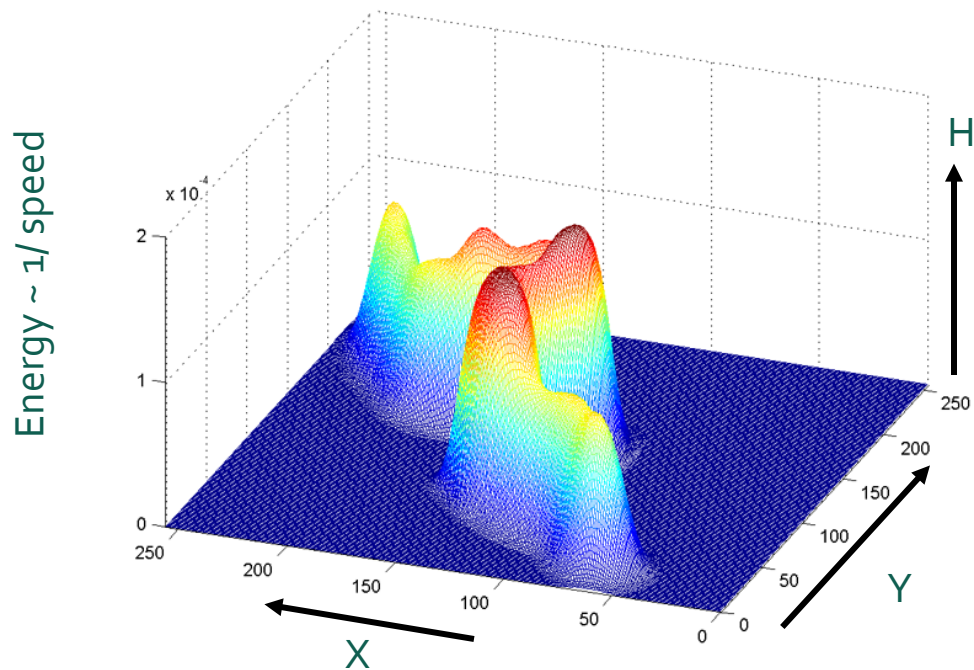
b

If we know b and c , can we recover x ?



Camera Shake

Camera Shake: Motion PSF



Spatial spread

Motion PSF is a
Function of:

- Motion path
- Motion speed



Camera Shake as A Filter



image from static camera

x

$*$



PSF

from camera motion

$*$

c

$=$



image from shaky camera

b

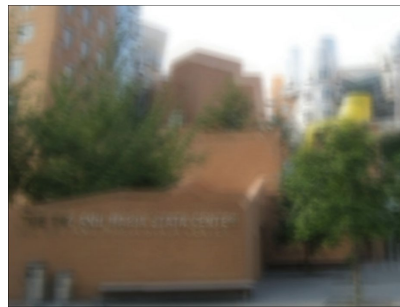
If we know b and c , can we recover x ?

Multiple Possible Solutions

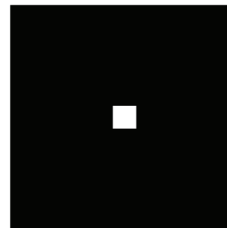


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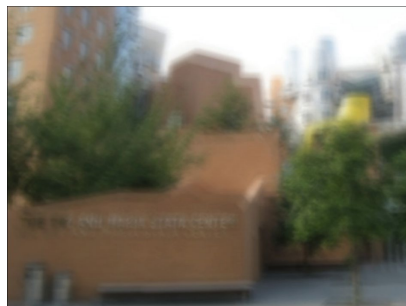
Sharp image



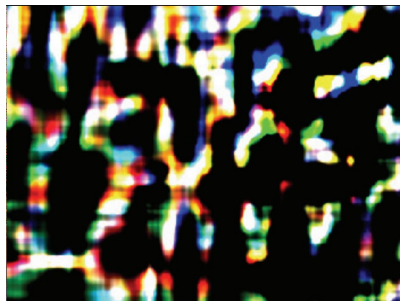
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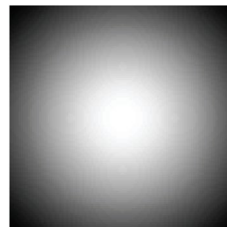
=



=



*



=



*



How do we
detect this
PSF?

Blurry image



Use Prior Information

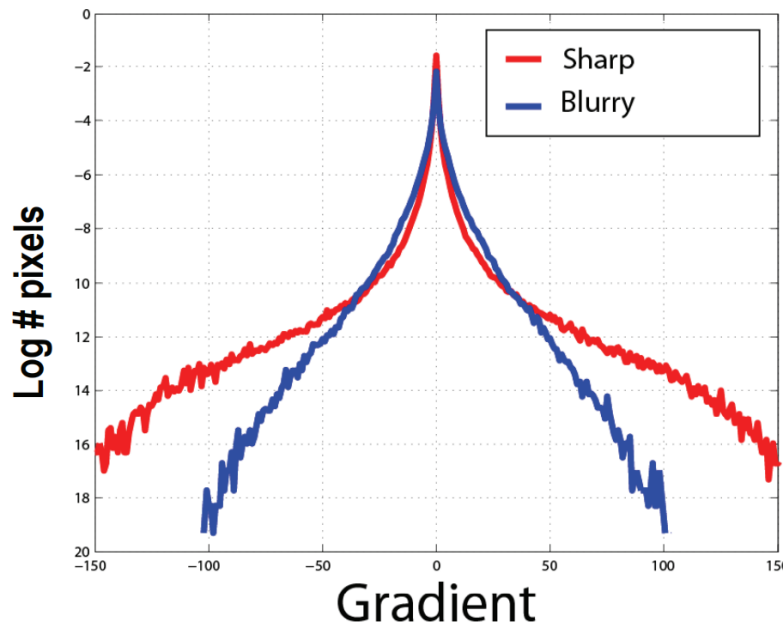
Among all the possible pairs of images and blur kernels, select the ones where:

- The image “looks like” a natural image.
- The kernel “looks like” a motion PSF.



Shake Kernel Statistics

Gradients in natural images follow a characteristic “heavy-tail” distribution.



Can be approximated by $\|\nabla x\|^{0.8}$



sharp
natural
image



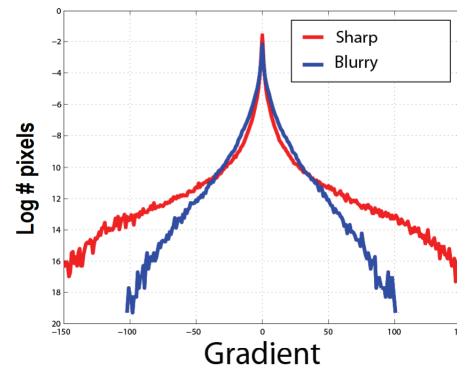
blurry
natural
image

Among all the possible pairs of images and blur kernels, select the ones where:

- The image “looks like” a natural image.

Gradients in natural images follow a characteristic “**heavy-tail**” distribution.

- The kernel “looks like” a motion PSF.



Shake **kernels** are very **sparse**, have continuous contours, and are always **positive**

How to use this information for blind deconvolution?





b = observed image

c = blur kernel

x = sharp image

$$p(c, x|b) = k p(b|c, x) p(x) p(b)$$

Posterior

1. Likelihood
(Reconstruction
constraint)

2. Image
prior

3. Blur
prior



Solve regularized least-squares optimization

$$\min_{x,c} \|b - c * x\|^2 + \|\nabla x\|^{0.8} + \|c\|_1$$

What does each term in this summation correspond to?

Regularized Blind Deconvolution



Solve regularized least-squares optimization

$$\min_{x,c} \|b - c * x\|^2 + \|\nabla x\|^{0.8} + \|c\|_1$$

data term

nature image prior

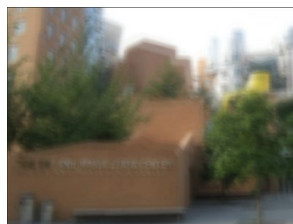
shake kernel prior



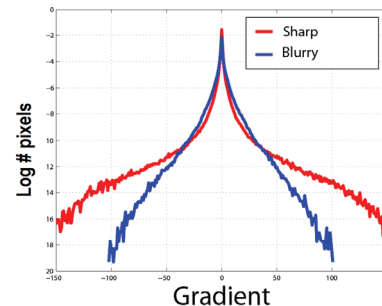
Sharp image



Estimated
Blur kernel



Blurry image



Note: Solving such optimization problems is complicated (no longer *linear* least squares).

A Demonstration



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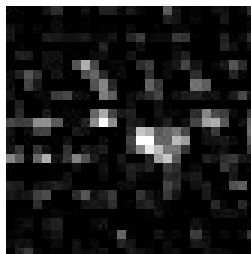
input



deconvolved image and kernel



This image looks worse
than the original...



This doesn't look like a
plausible shake kernel...

Regularized Blind Deconvolution



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Solve regularized least-squares optimization

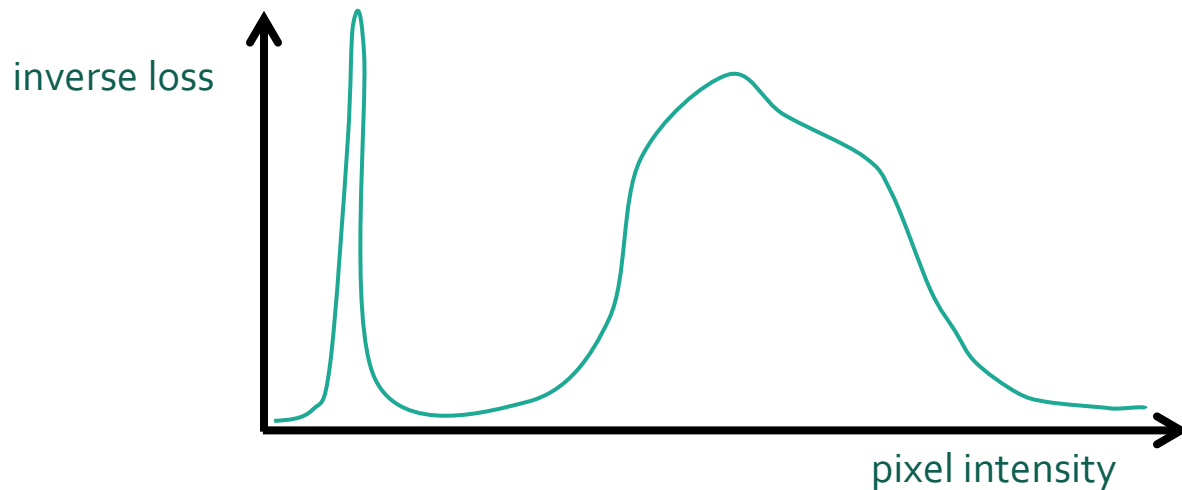
$$\min_{x,c} \underbrace{\|b - c * x\|^2 + \|\nabla x\|^{0.8} + \|c\|_1}_{\text{cost function}}$$

Regularized Blind Deconvolution



Solve regularized least-squares optimization

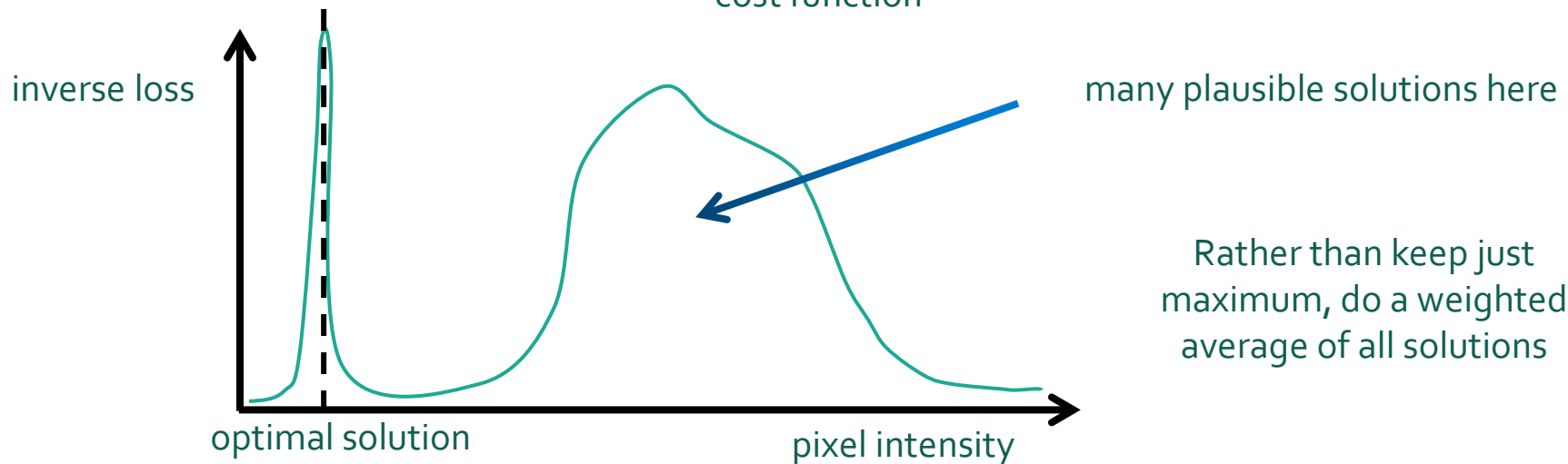
$$\min_{x,c} \underbrace{\|b - c * x\|^2 + \|\nabla x\|^{0.8} + \|c\|_1}_{\text{cost function}}$$



Where in this graph is the solution we find?

Solve regularized least-squares optimization

$$\min_{x,c} \underbrace{\|b - c * x\|^2 + \|\nabla x\|^{0.8} + \|c\|_1}_{\text{cost function}}$$



A Demonstration



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input

maximum-only

average

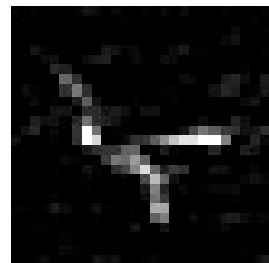
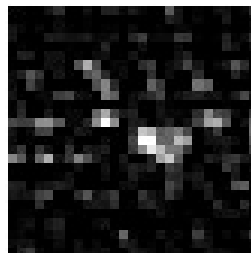


Image Artifacts & Estimated Kernels



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Blur kernels

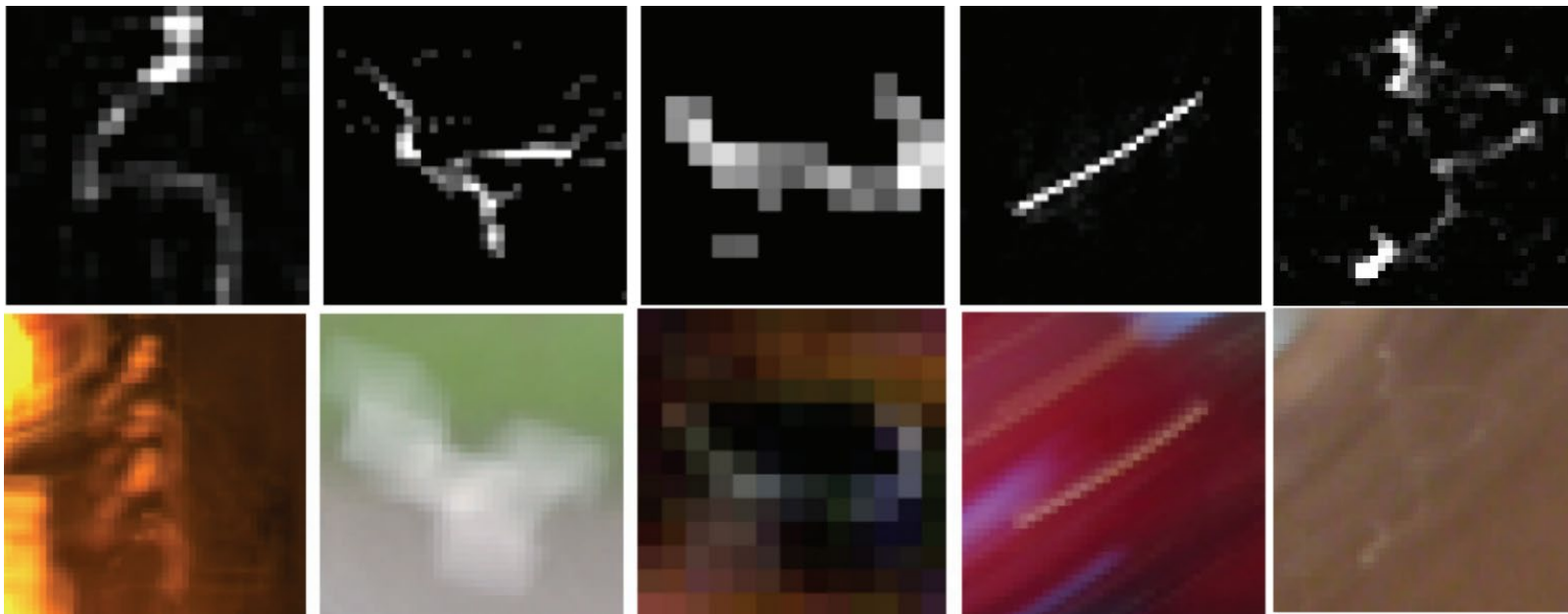


Image patterns

Note: blur kernels were inferred from large image patches, NOT the image patterns shown

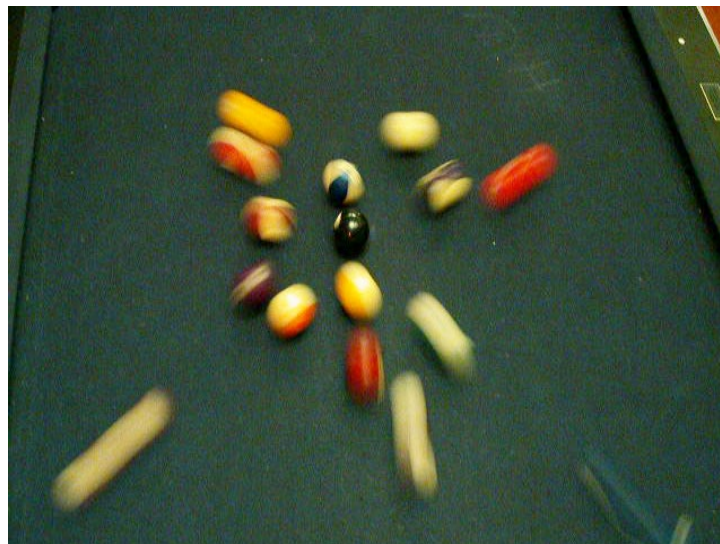


Scene Motion

Scene Motion Blur



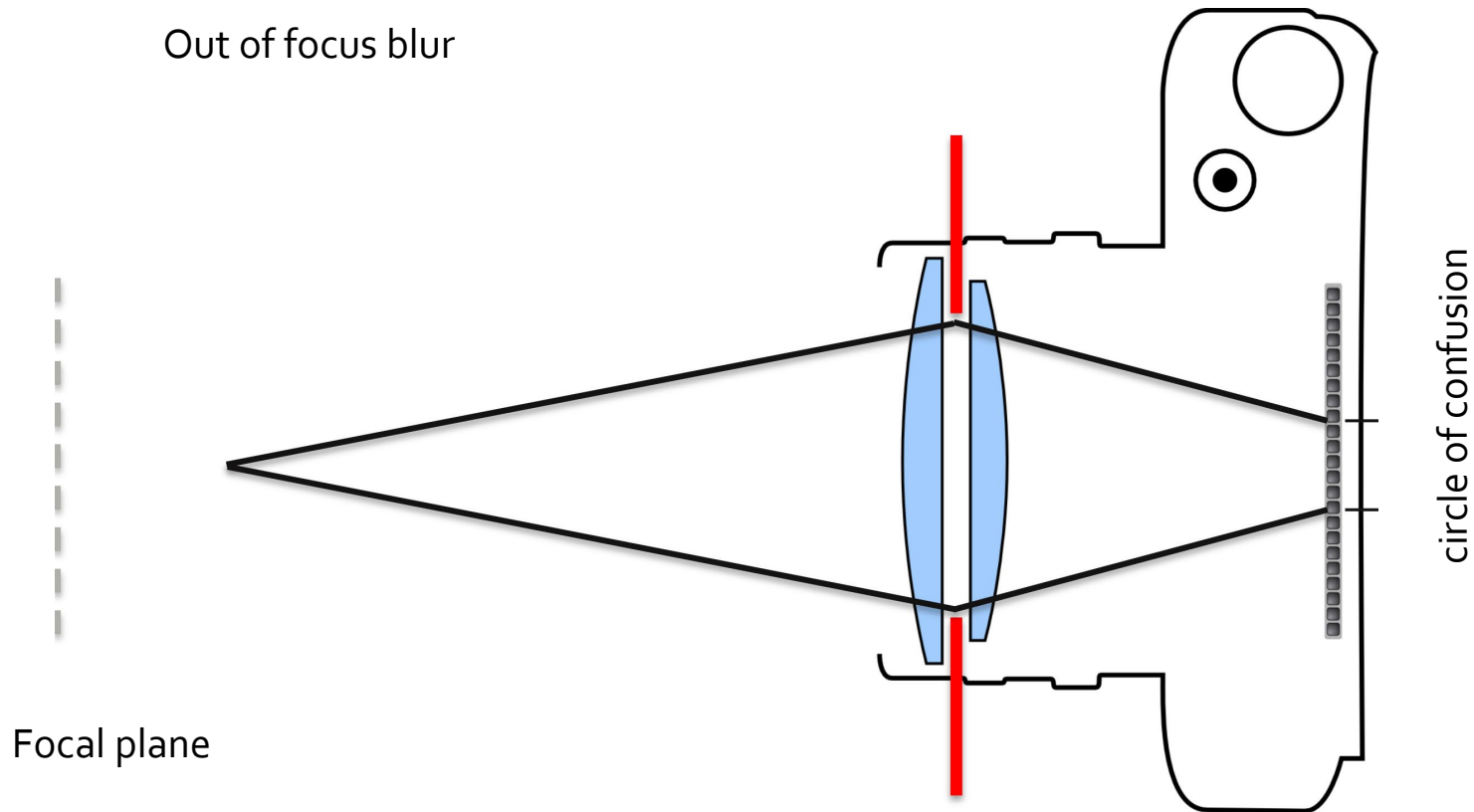
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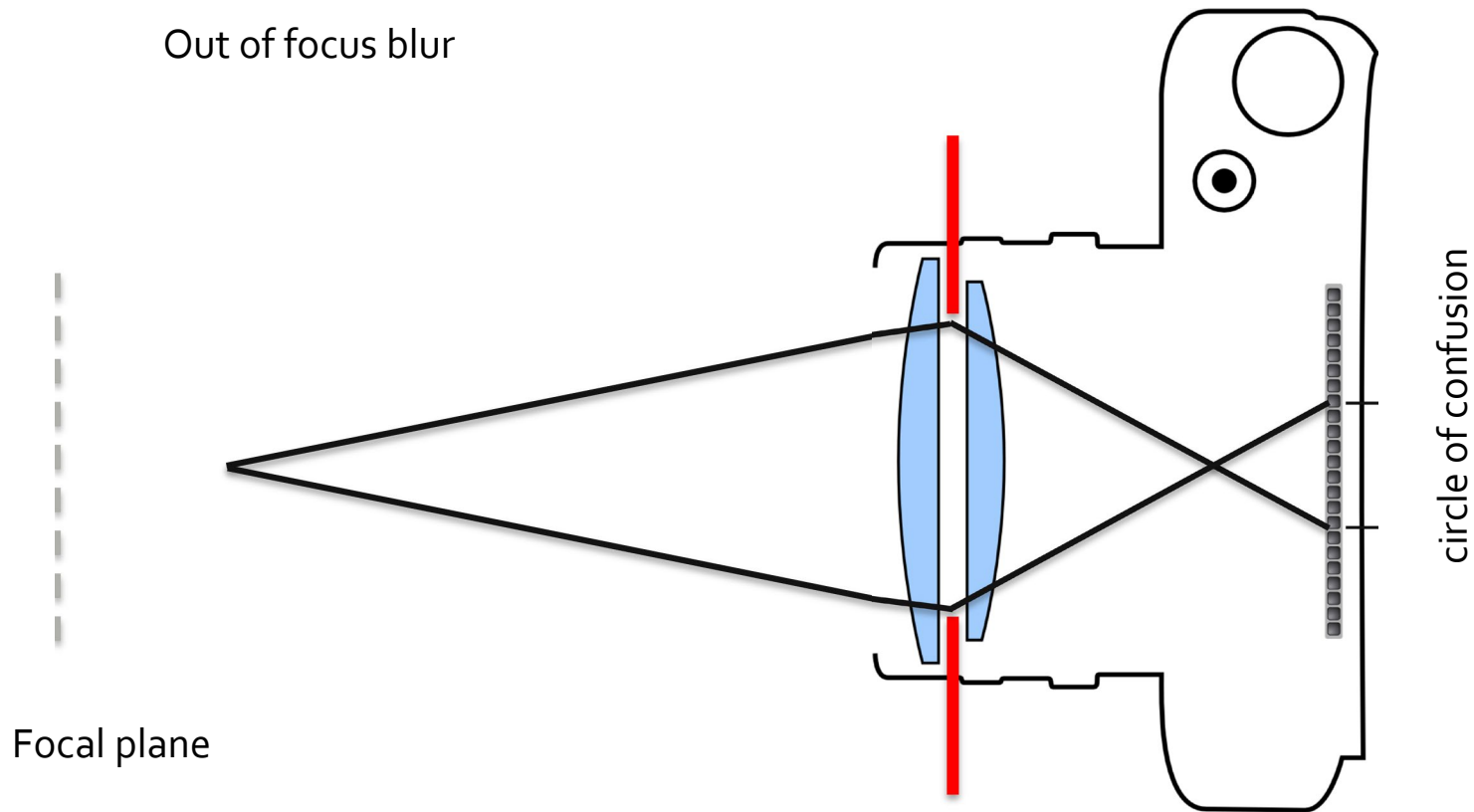


Depth Defocus

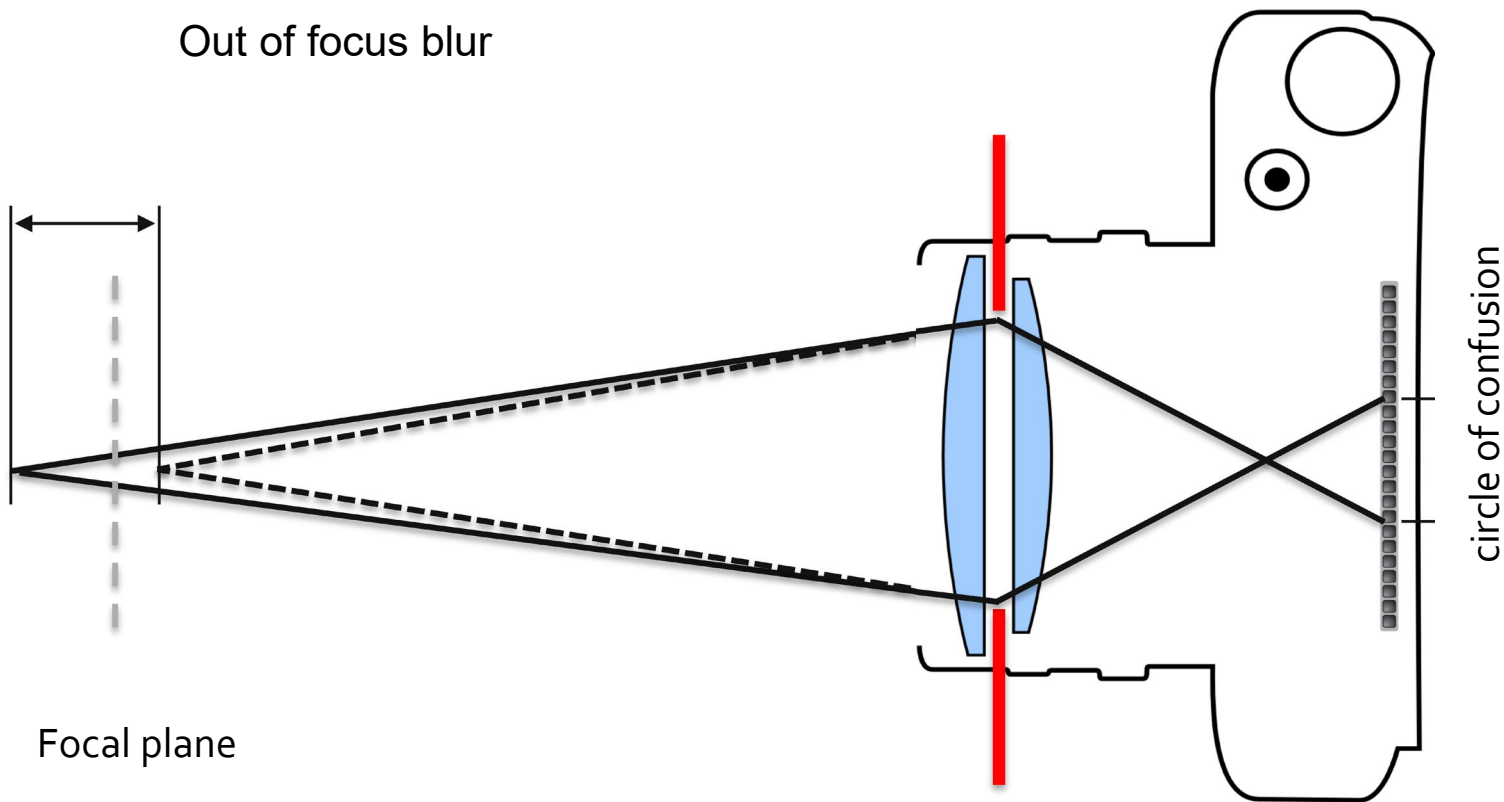
Recall: Out of Focus Blur



Recall: Out of Focus Blur



Recall: Out of Focus Blur



PSF Behavior of Different Depths



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AL2550



0.5m



0.7m



1.0m



1.5m



ACA254



0.5m



0.7m



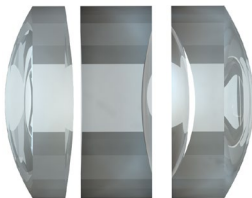
1.0m



1.5m



Ours



0.5m



0.7m



1.0m



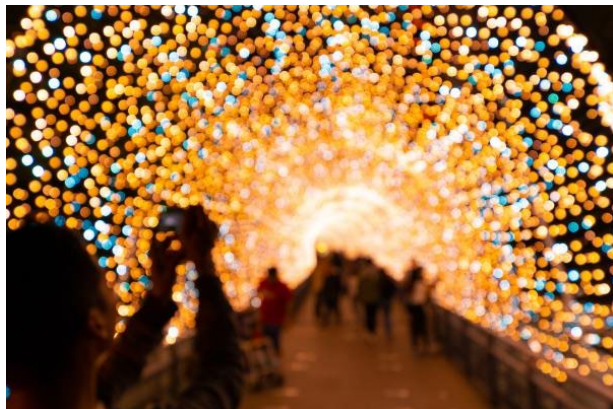
1.5m



Depth Defocus Examples



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<https://digital-photography-school.com/out-of-focus-photos/>



Today's Topic

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- Camera Shake.
- Scene Motion.
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Thank You!



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