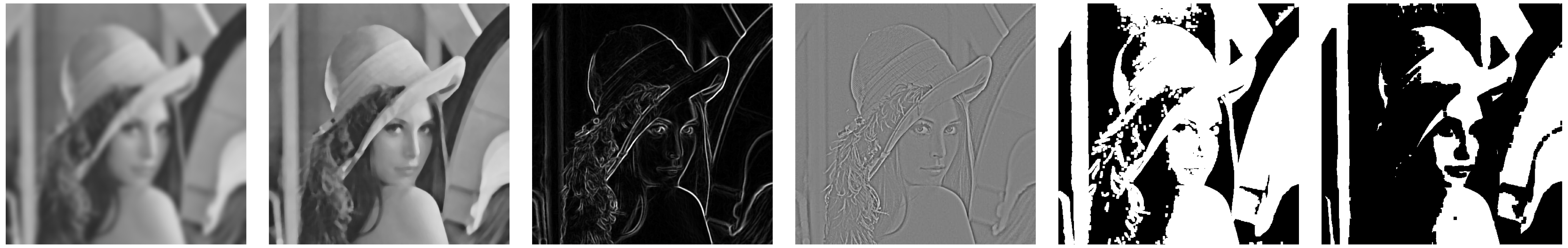
THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 5: Image Filtering (continued)

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today (**September 19, 2024**)

Topics:

- — **Linear Filtering** recap + wrap up
- — Efficient convolution, Fourier aside

— **Non-linear** Filters:
Median, ReLU, Bilateral Filter

Readings:

- — **Today's** Lecture: Szeliski 3.3-3.4, Forsyth & Ponce (2nd ed.) 4.4

Reminders:

- — **Assignment 1:** Image Filtering and Hybrid Images due **September 26**
- — Lectures 2-4 have been posted (on **Canvas** under **Modules**)
- — **Lecture Notes** for Image Filtering by Friday

Today’s “**fun**” Example: **Visual Question Answering**

https://huggingface.co/spaces/nielsr/vilt-vqa

Today's "**fun**" Example: **Clever** Hans

Today’s “**fun**” Example: **Clever** Hans

Hans could get 89% of the math questions right

Today's "**fun**" Example: **Clever** Hans

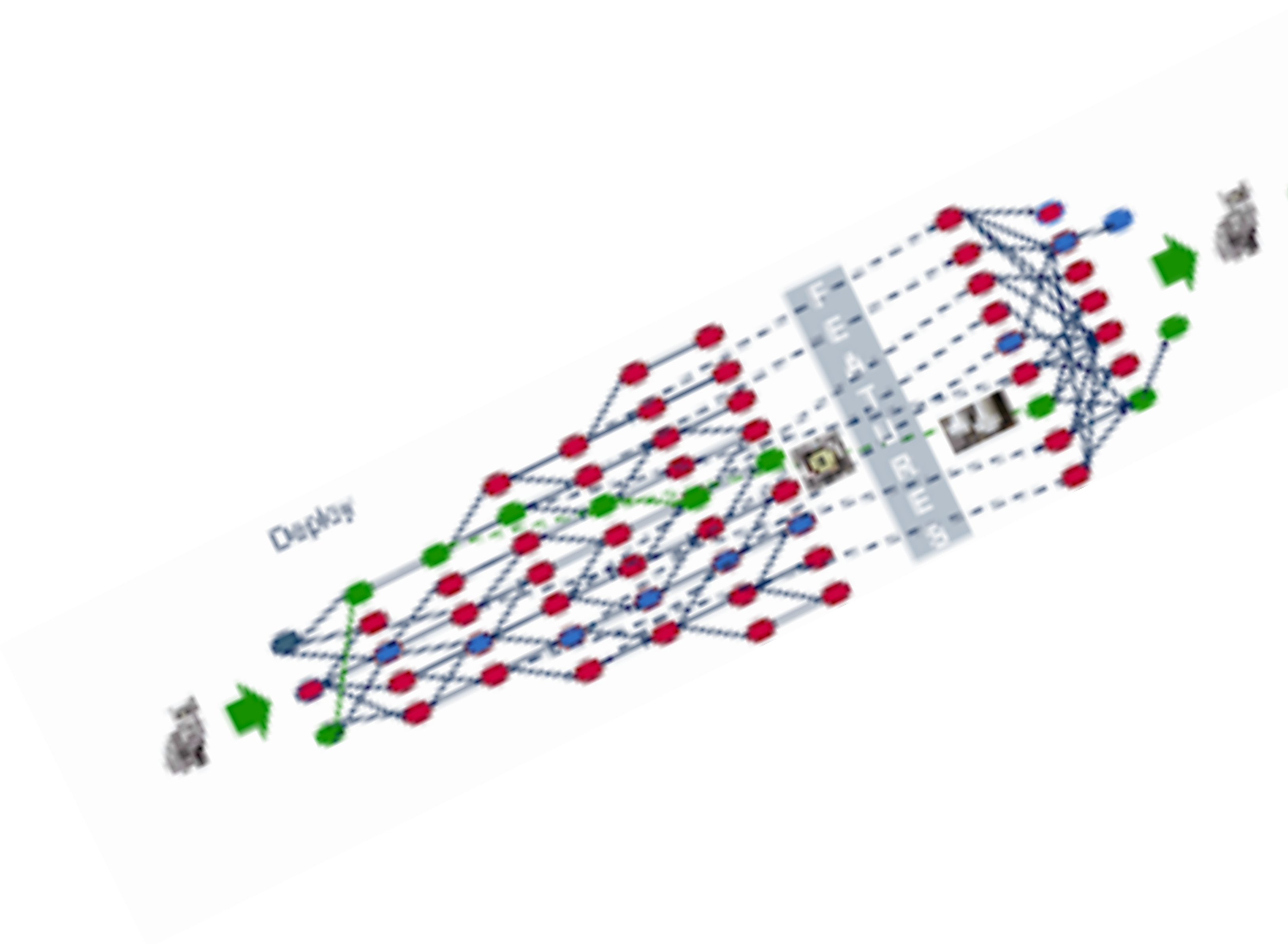
Clever Hans
(Orlov Trotter horse)

Wilhelm
von Osten

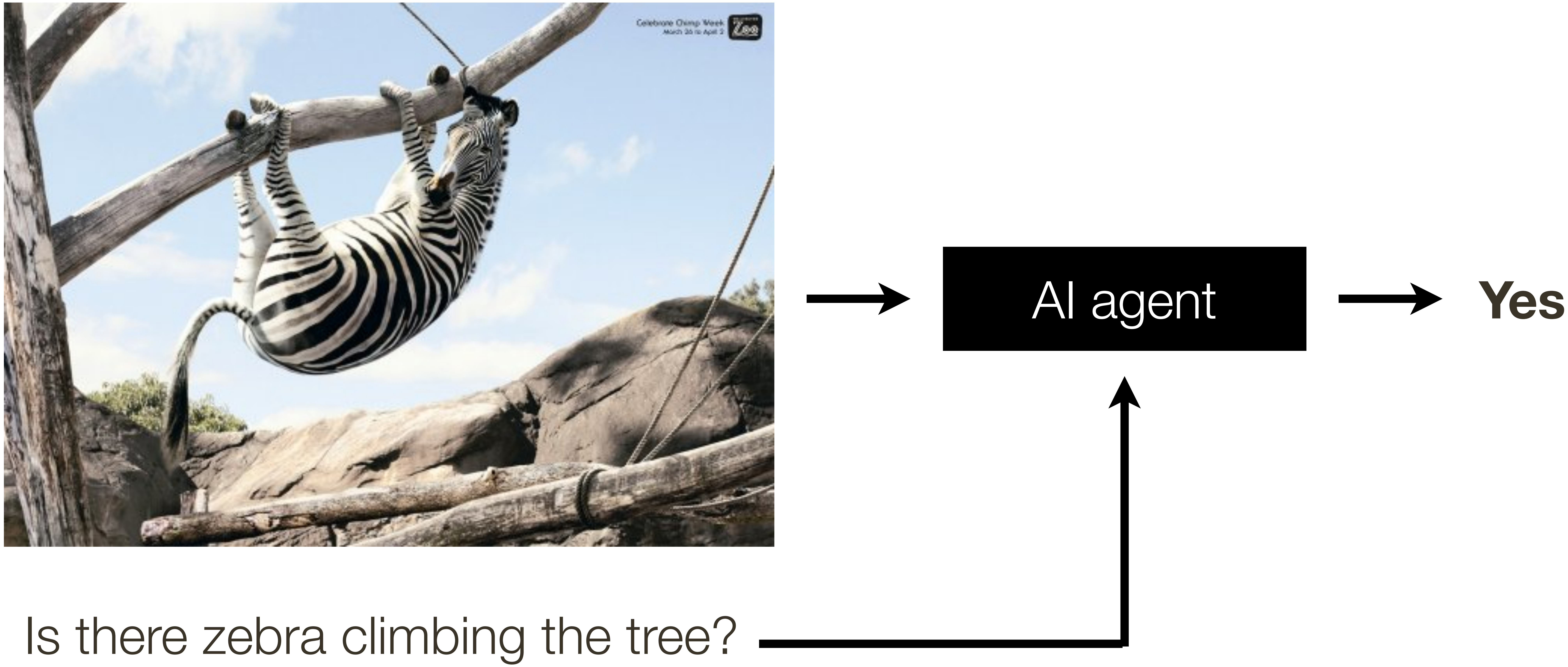
The course was **smart**, just not in the way van Osten thought!

Hans could get 89% of the math questions right

Clever DNN



Visual **Question Answering**

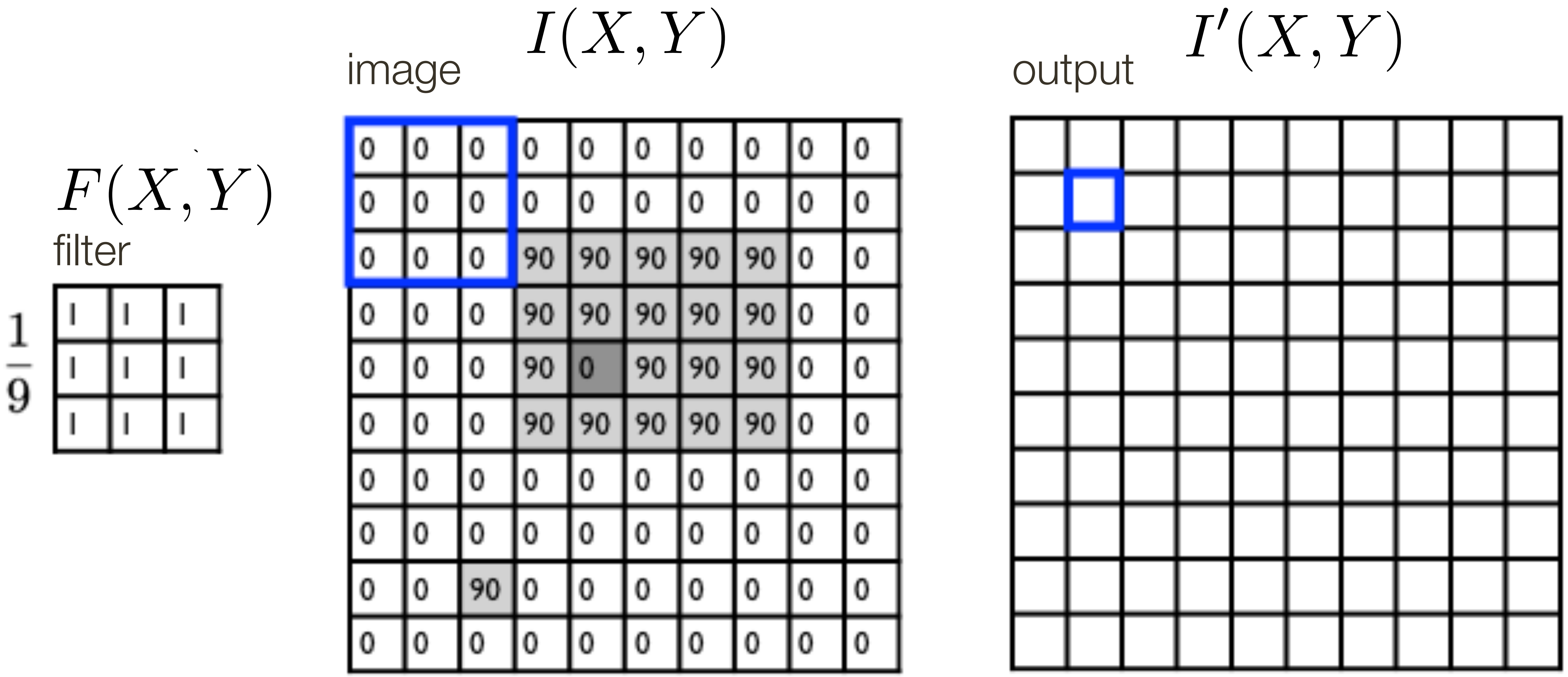


AI agent

Yes

Is there zebra climbing the tree?

Lecture 4: Re-cap Linear Filter



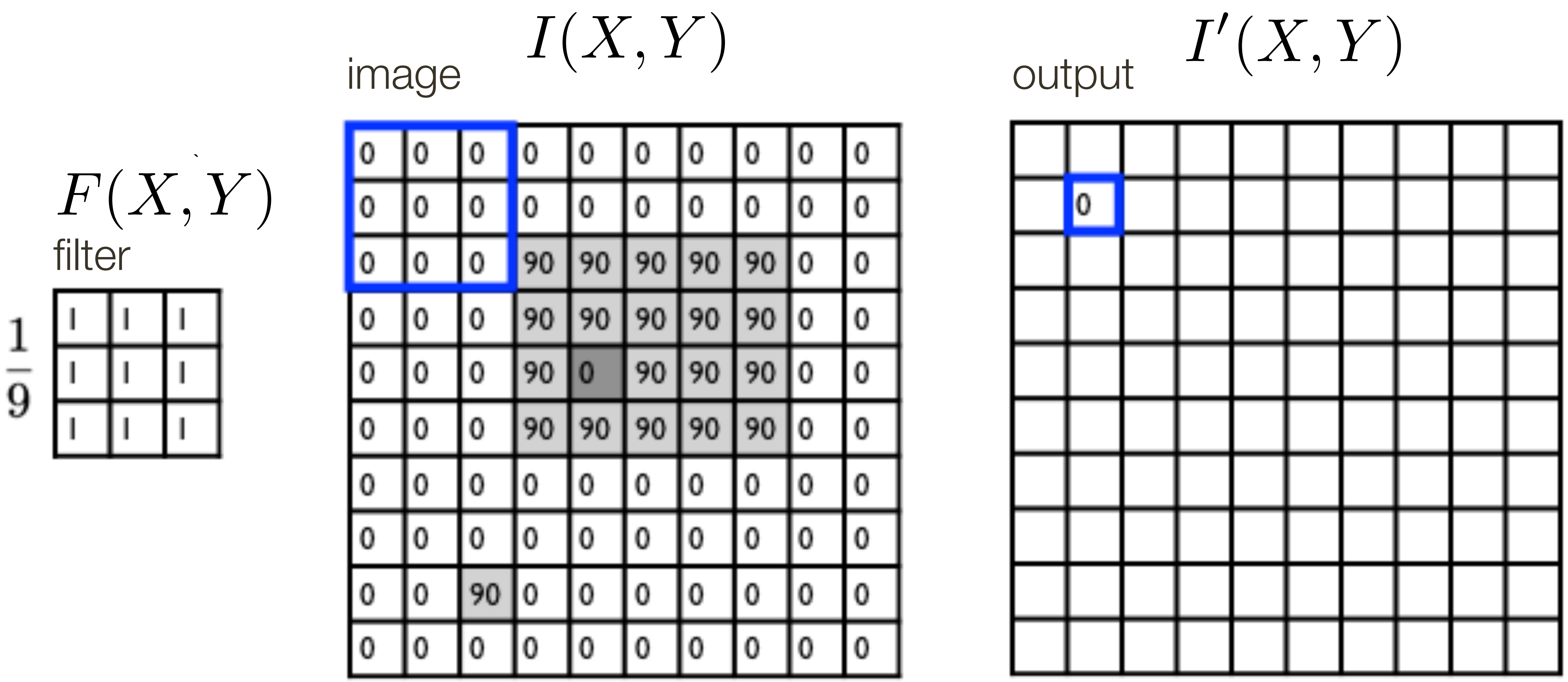
1	1	1
1	1	1
1	1	1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}}\,\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 4: Re-cap Linear Filter



$F(X,Y)$

filter

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

image $I(X,Y)$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

output $I'(X,Y)$

	0								

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k} \sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}} \underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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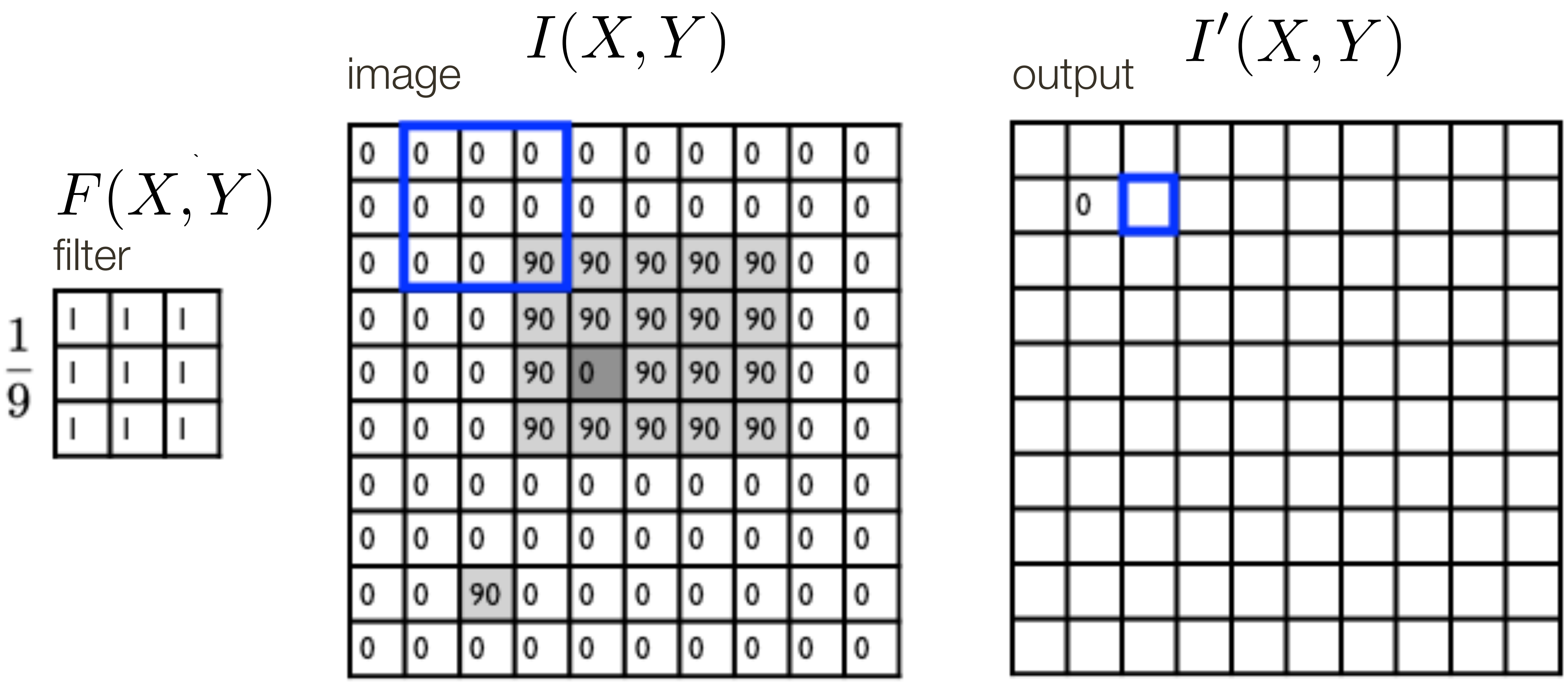
Lecture 4: Re-cap Linear Filter



$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

	0								

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}}\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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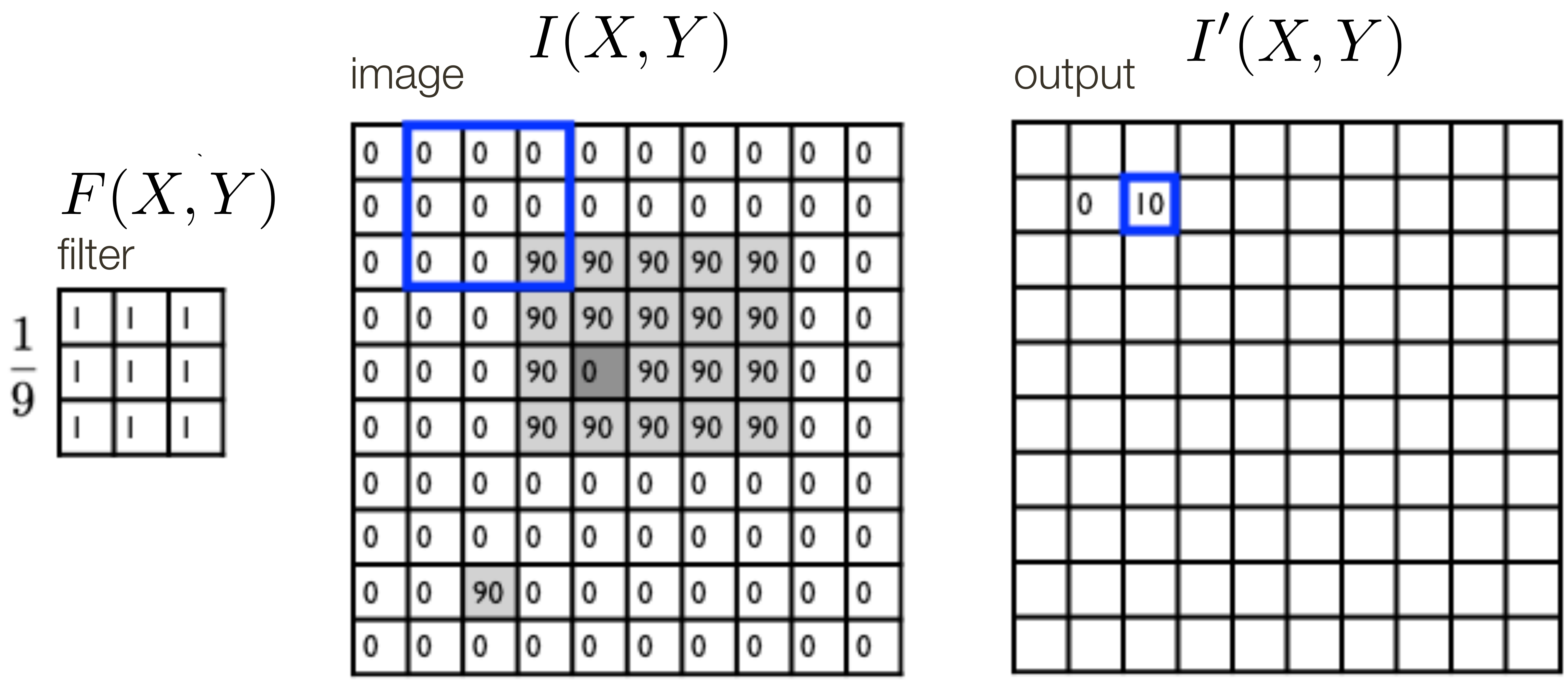
Lecture 4: Re-cap Linear Filter



$F(X,Y)$

filter

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

image $I(X,Y)$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

output $I'(X,Y)$

	0	10							

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k} \sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}} \underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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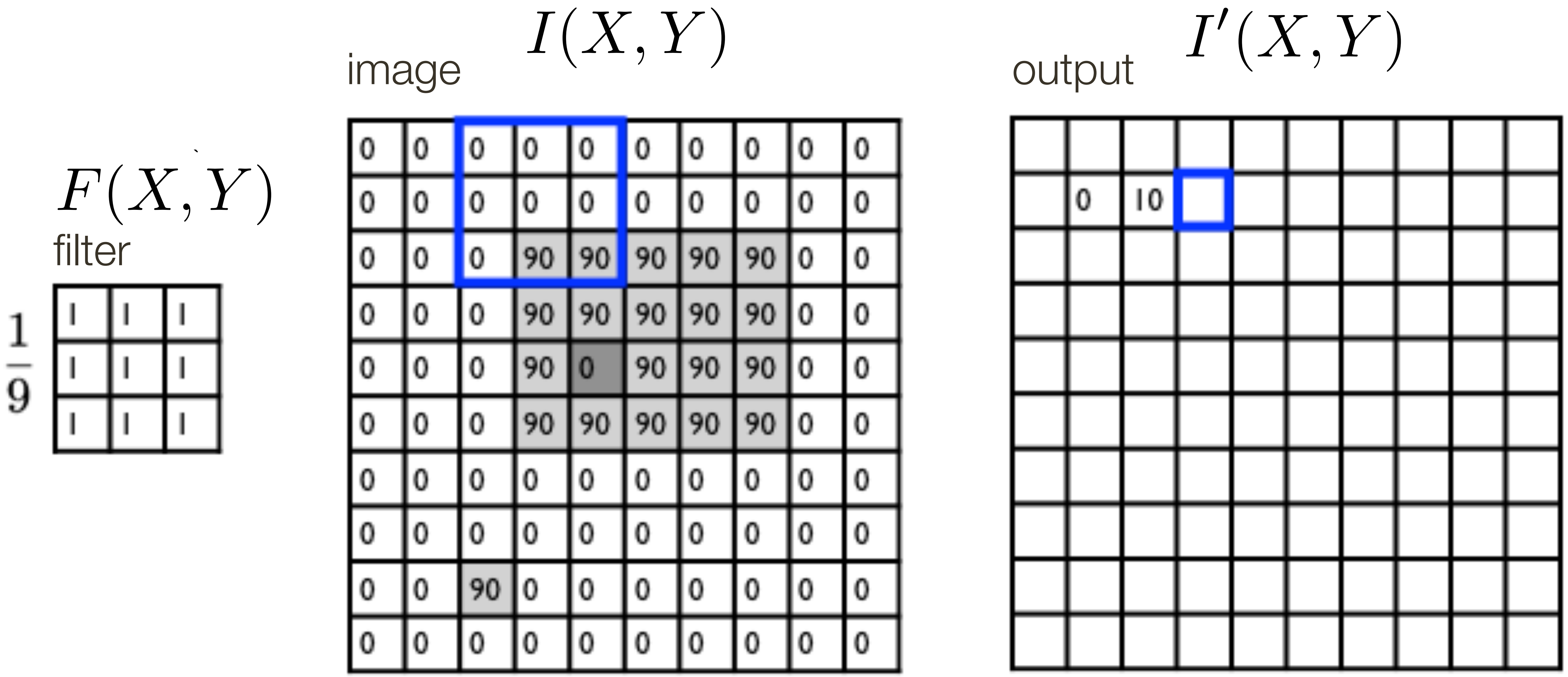
Lecture 4: Re-cap Linear Filter



1	1	1
1	1	1
1	1	1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

	0	10							

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}}\,\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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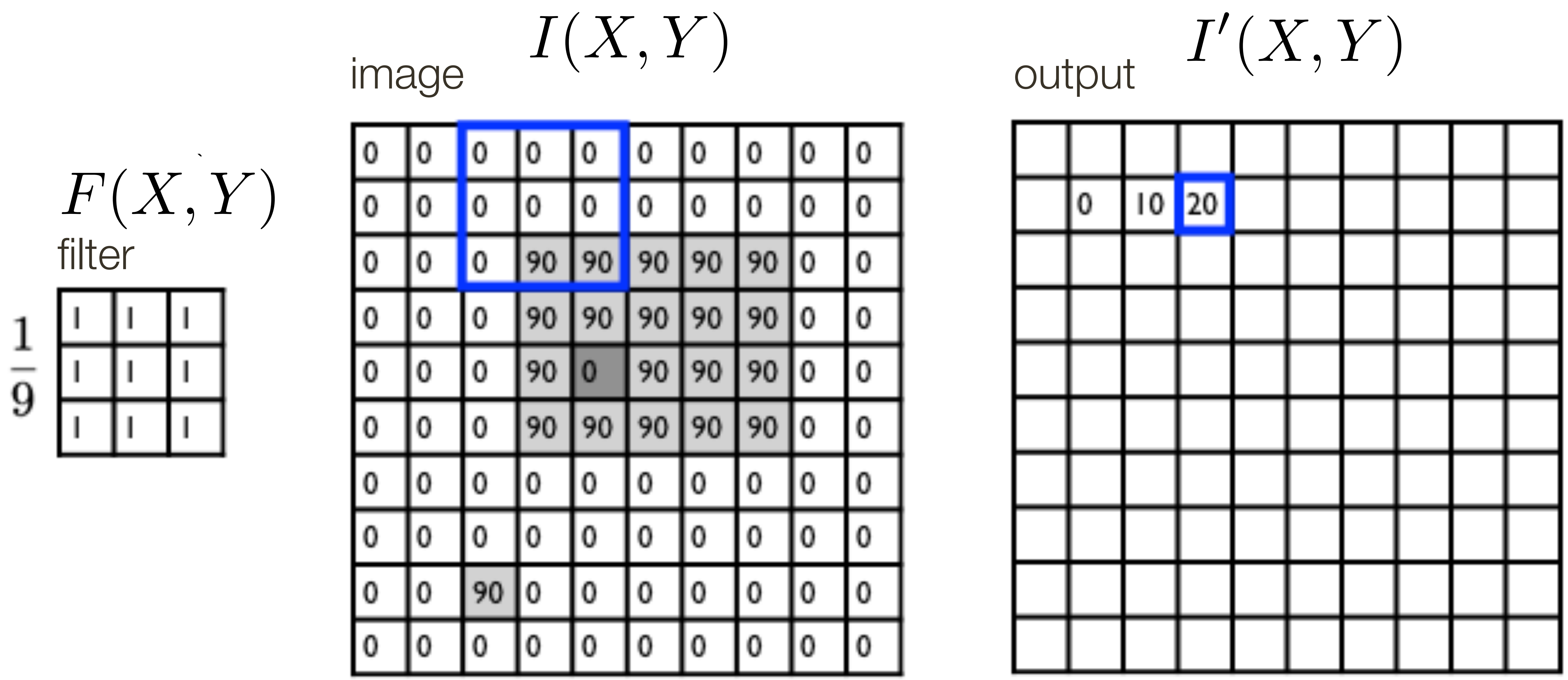
Lecture 4: Re-cap Linear Filter



$F(X,Y)$

filter

$$\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

image $I(X,Y)$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

output $I'(X,Y)$

	0	10	20						

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}}\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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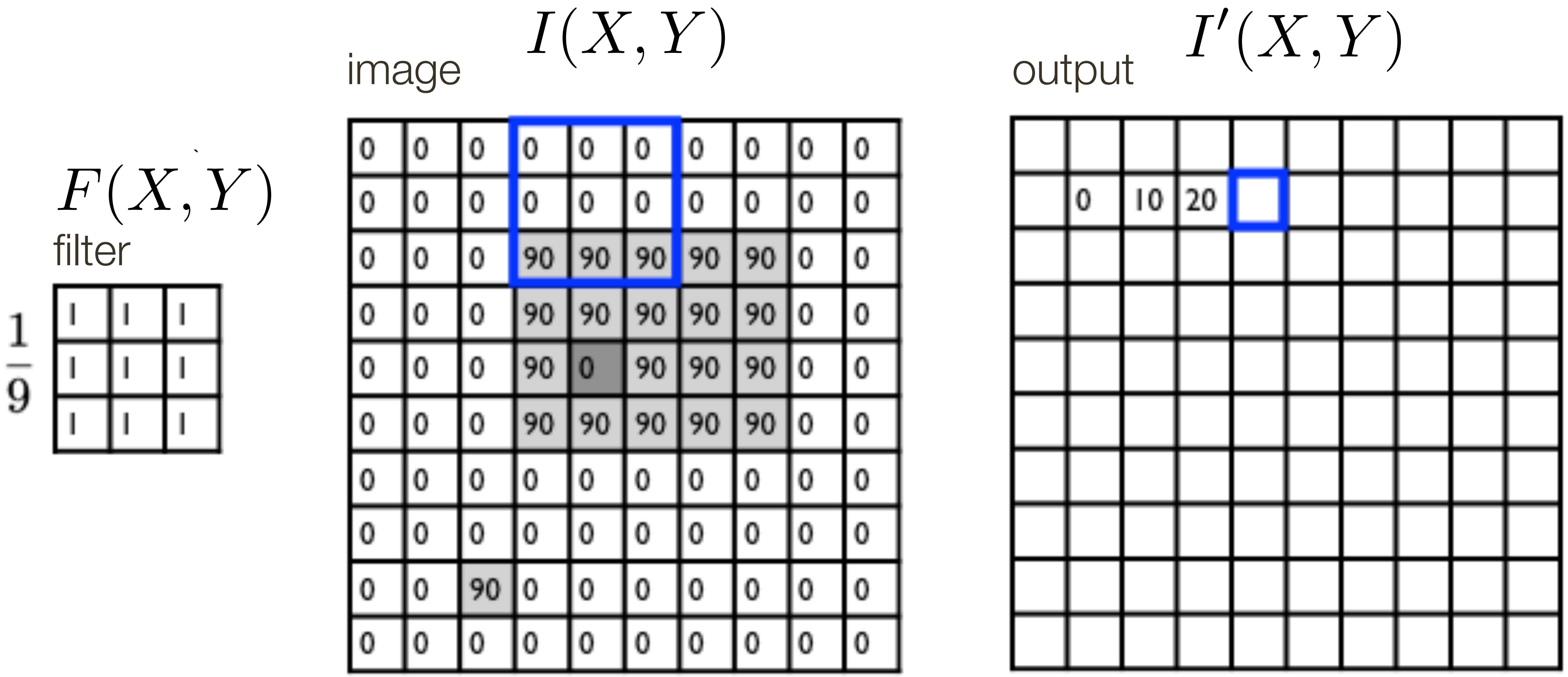
Lecture 4: Re-cap Linear Filter



$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

	0	10	20						

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}}\,\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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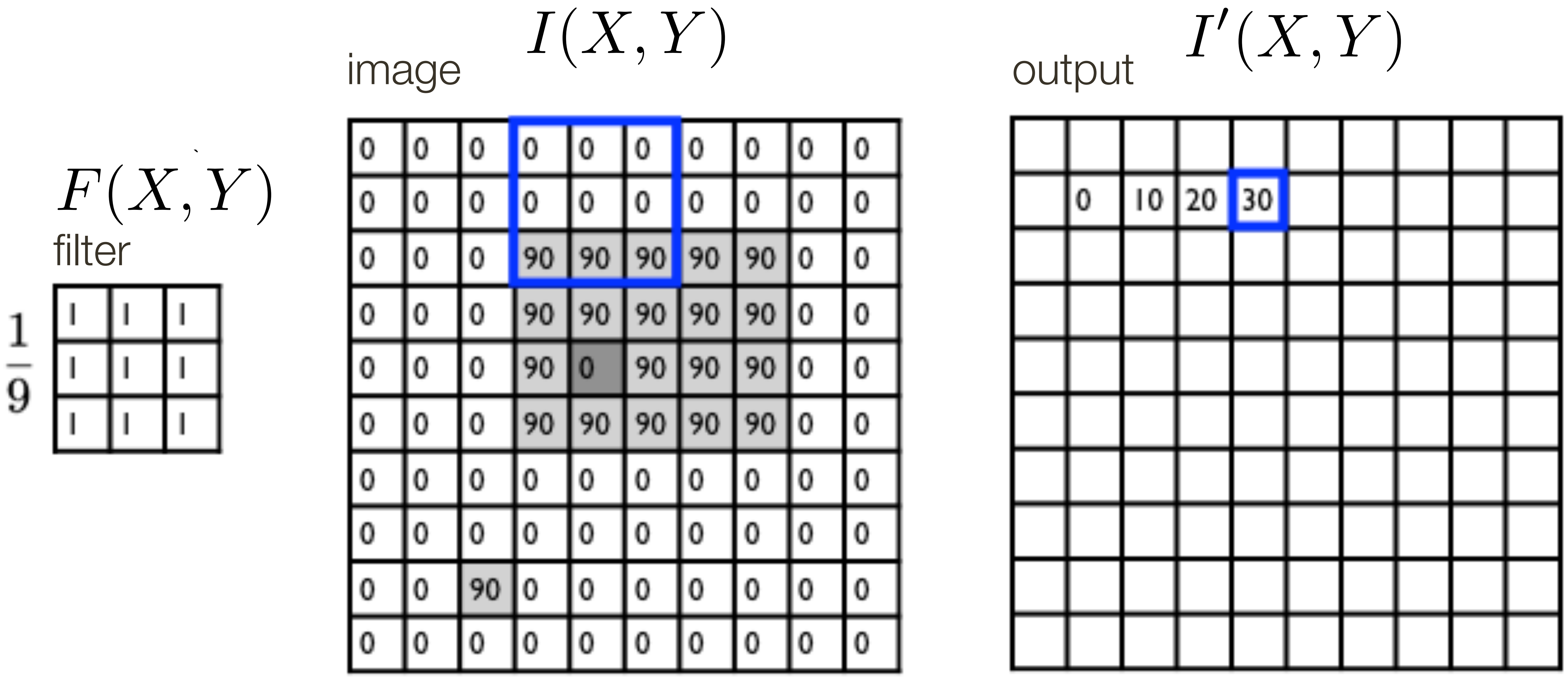
Lecture 4: Re-cap Linear Filter



1	1	1
1	1	1
1	1	1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

	0	10	20	30					

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k} \sum_{i=-k}^{k} \underbrace{F(i,j)}_{\text{filter}} \underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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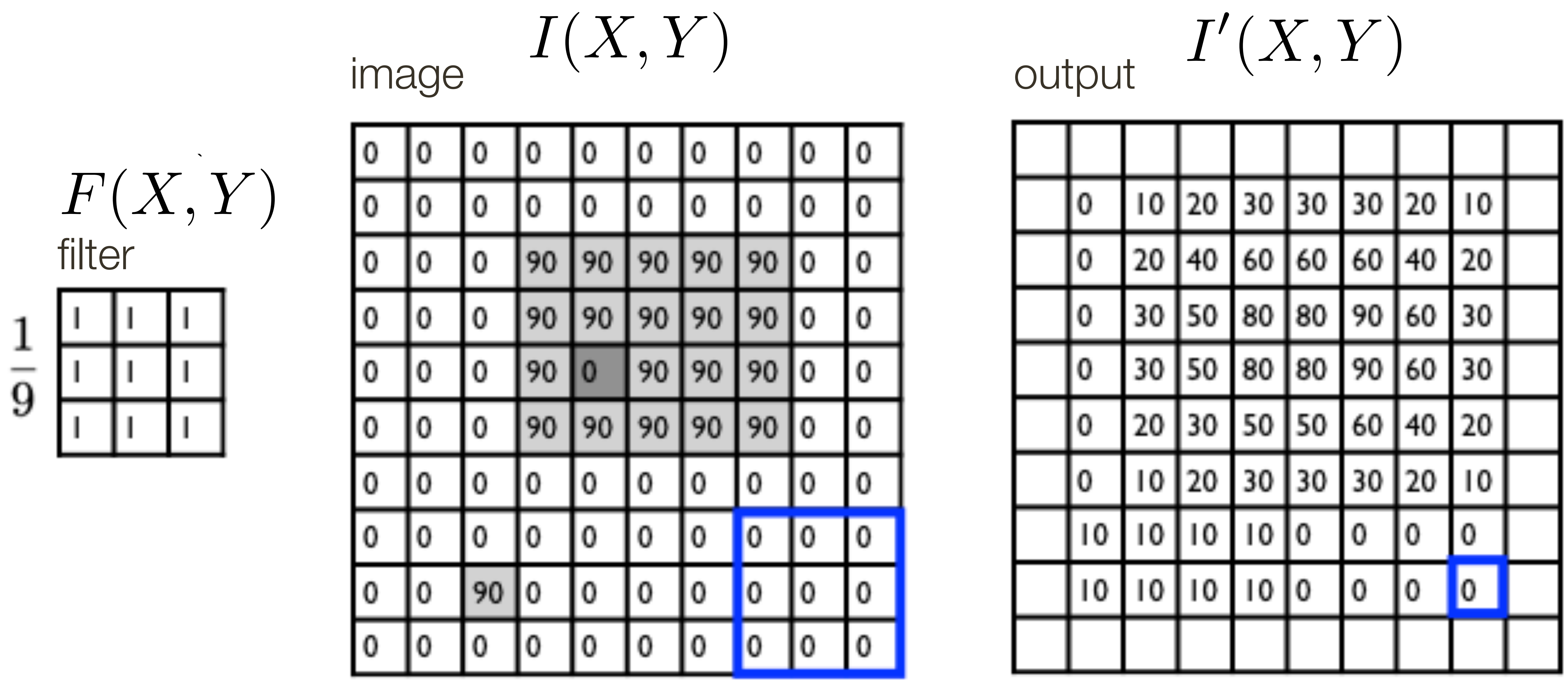
Lecture 4: Re-cap Linear Filter



$F(X,Y)$

filter

$$\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

image $I(X,Y)$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

output $I'(X,Y)$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	0	10	20	30	30	30	20	10	
	10	10	10	10	0	0	0	0	
	10	10	10	10	0	0	0	0	

$$\underbrace{I'(X,Y)}_{\text{output}} = \sum_{j=-k}^{k}\sum_{i=-k}^{k}\underbrace{F(i,j)}_{\text{filter}}\underbrace{I(X+i,Y+j)}_{\text{image (signal)}}$$

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Lecture 4: Re-cap Linear Filters Properties

Let $\otimes$ denote convolution. Let $I(X,Y)$ be a digital image

Superposition: Let F_1 and F_2 be digital filters

$$(F_1 + F_2) \otimes I(X,Y) = F_1 \otimes I(X,Y) + F_2 \otimes I(X,Y)$$

Scaling: Let F be digital filter and let k be a scalar

$$(kF) \otimes I(X,Y) = F \otimes (kI(X,Y)) = k(F \otimes I(X,Y))$$

Shift Invariance: Output is local (i.e., no dependence on absolute position)

Lecture 4: Re-cap Smoothing Filters

Smoothing with a box **doesn’t model lens defocus** well

— Smoothing with a box filter depends on direction

— Image in which the center point is 1 and every other point is 0

Smoothing with a (circular) **pillbox** is a better model for defocus (in geometric optics)

The **Gaussian** is a good general smoothing model

— for phenomena (that are the sum of other small effects)

— whenever the Central Limit Theorem applies

Lets talk about **efficiency**

Efficient Implementation: **Separability**

A 2D function of x and y is **separable** if it can be written as the product of two functions, one a function only of x and the other a function only of y

Both the **2D box filter** and the **2D Gaussian filter** are **separable**

Both can be implemented as two 1D convolutions:

— First, convolve each row with a 1D filter

— Then, convolve each column with a 1D filter

— Aside: or vice versa

The **2D Gaussian** is the only (non trivial) 2D function that is both separable and rotationally invariant.

Separability: How do you know if filter is separable?

If a 2D filter can be expressed as an outer product of two 1D filters

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \end{bmatrix} \odot \frac{1}{3}\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

Separability: How do you know if filter is separable?

Mathematically: Rank of filter matrix is 1 (recall rank is number of linearly independent row vectors)

$$\frac{1}{9}\begin{array}{|c|c|c|}\hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} = \frac{1}{3}\begin{array}{|c|c|c|}\hline 1 & 1 & 1 \\ \hline \end{array} \odot \frac{1}{3}\begin{array}{|c|}\hline 1 \\ \hline 1 \\ \hline 1 \\ \hline \end{array}$$

Efficient Implementation: **Separability**

Naive implementation of 2D **Filtering**:

At each pixel, (X, Y), there are $m \times m$ multiplications

There are $n \times n$ pixels in (X, Y)

Total: $m^2 \times n^2$ multiplications

Efficient Implementation: **Separability**

Naive implementation of 2D **Filtering**:

At each pixel, (X, Y), there are $m \times m$ multiplications

There are $n \times n$ pixels in (X, Y)

Total: $m^2 \times n^2$ multiplications

Separable 2D **Filter**:

At each pixel, (X, Y), there are $2m$ multiplications

There are $n \times n$ pixels in (X, Y)

Total: $2m \times n^2$ multiplications

Speeding Up **Convolution** (The Convolution Theorem)

Let z be the product of two numbers, x and y, that is,

$$z = xy$$

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Taking logarithms of both sides, one obtains

$$\ln z = \ln x + \ln y$$

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Therefore

$$z = \exp^{\ln z} = \exp^{(\ln x + \ln y)}$$

Speeding Up **Convolution** (The Convolution Theorem)

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Taking logarithms of both sides, one obtains

$$\ln z = \ln x + \ln y$$

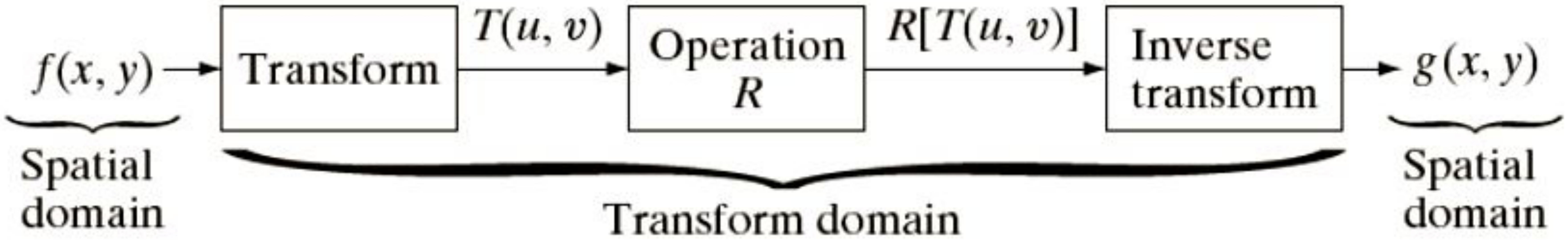
Therefore.

$$z = \exp^{\ln z} = \exp^{(\ln x + \ln y)}$$

Interpretation: At the expense of two $\ln()$ and one $\exp()$ computations, multiplication is reduced to addition … silly I know

Speeding Up **Convolution** (The Convolution Theorem)

Similarly, some image processing operations become cheaper in a transform domain



Gonzales & Woods (3rd ed.) Figure 2.39

Speeding Up **Convolution** (The Convolution Theorem)

Convolution **Theorem**:

Let $i'(x,y) = f(x,y) \otimes i(x,y)$

then $\mathcal{I}'(w_x, w_y) = \mathcal{F}(w_x, w_y)\, \mathcal{I}(w_x, w_y)$

where $\mathcal{I}'(w_x, w_y)$, $\mathcal{F}(w_x, w_y)$, and $\mathcal{I}(w_x, w_y)$ are Fourier transforms of $i'(x,y)$, $f(x,y)$ and $i(x,y)$

At the expense of two **Fourier** transforms and one inverse Fourier transform, convolution can be reduced to (complex) multiplication

Speeding Up **Convolution** (The Convolution Theorem)

General implementation of **convolution**:

At each pixel, (X, Y), there are $m \times m$ multiplications

There are $n \times n$ pixels in (X, Y)

Total: $m^2 \times n^2$ multiplications

Convolution if FFT space:

Cost of FFT/IFFT for image: $\mathcal{O}(n^2 \log n)$

Cost of FFT/IFFT for filter: $\mathcal{O}(m^2 \log m)$

Cost of convolution: $\mathcal{O}(n^2)$

Note: not a function of filter size !!!

Lets take a **detour** …

What follows is for fun

(you will **NOT** be tested on this)

Fourier Transform (you will **NOT** be tested on this)

Basic building block:

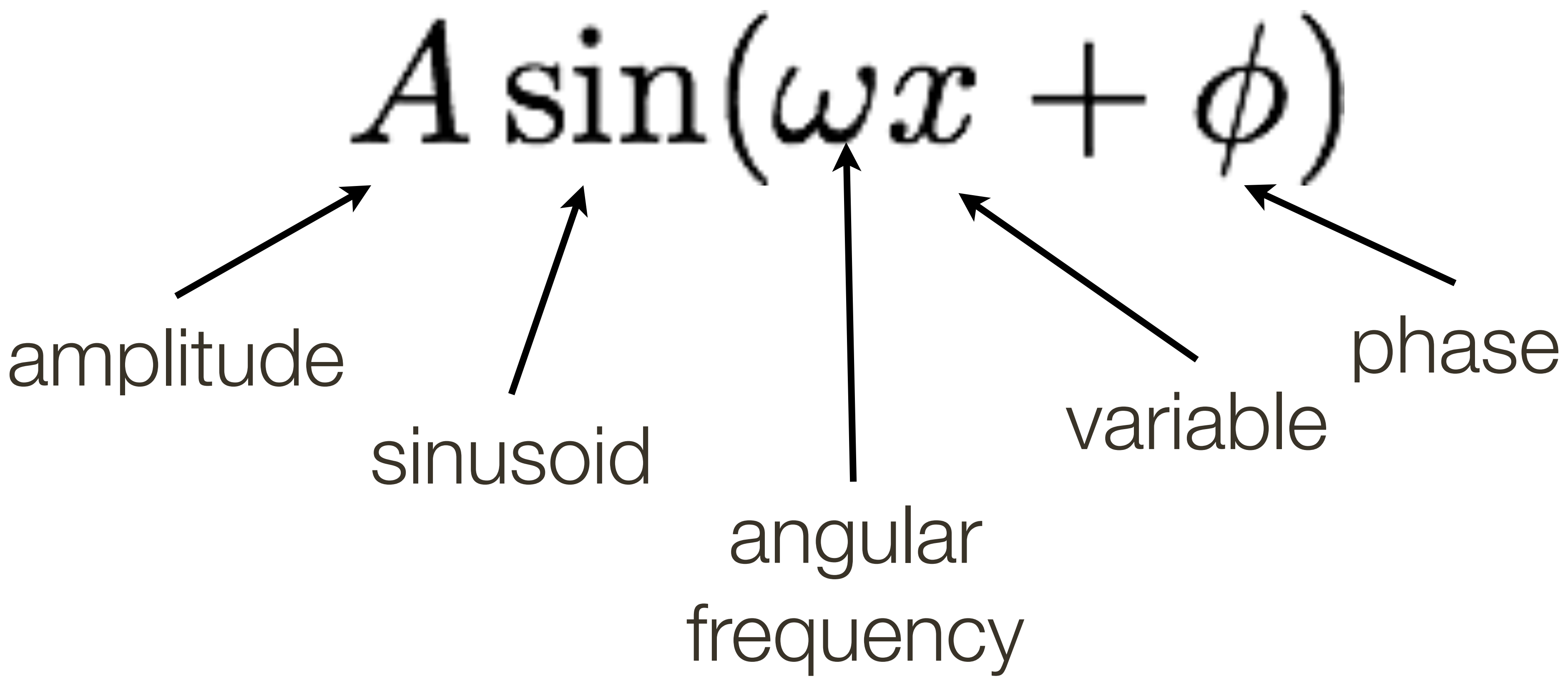
$$A \sin(\omega x + \phi)$$

Fourier's claim: Add enough of these to get any periodic signal you want!

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

Basic building block:



$$A\sin(\omega x+\phi)$$

amplitude

sinusoid

angular frequency

variable

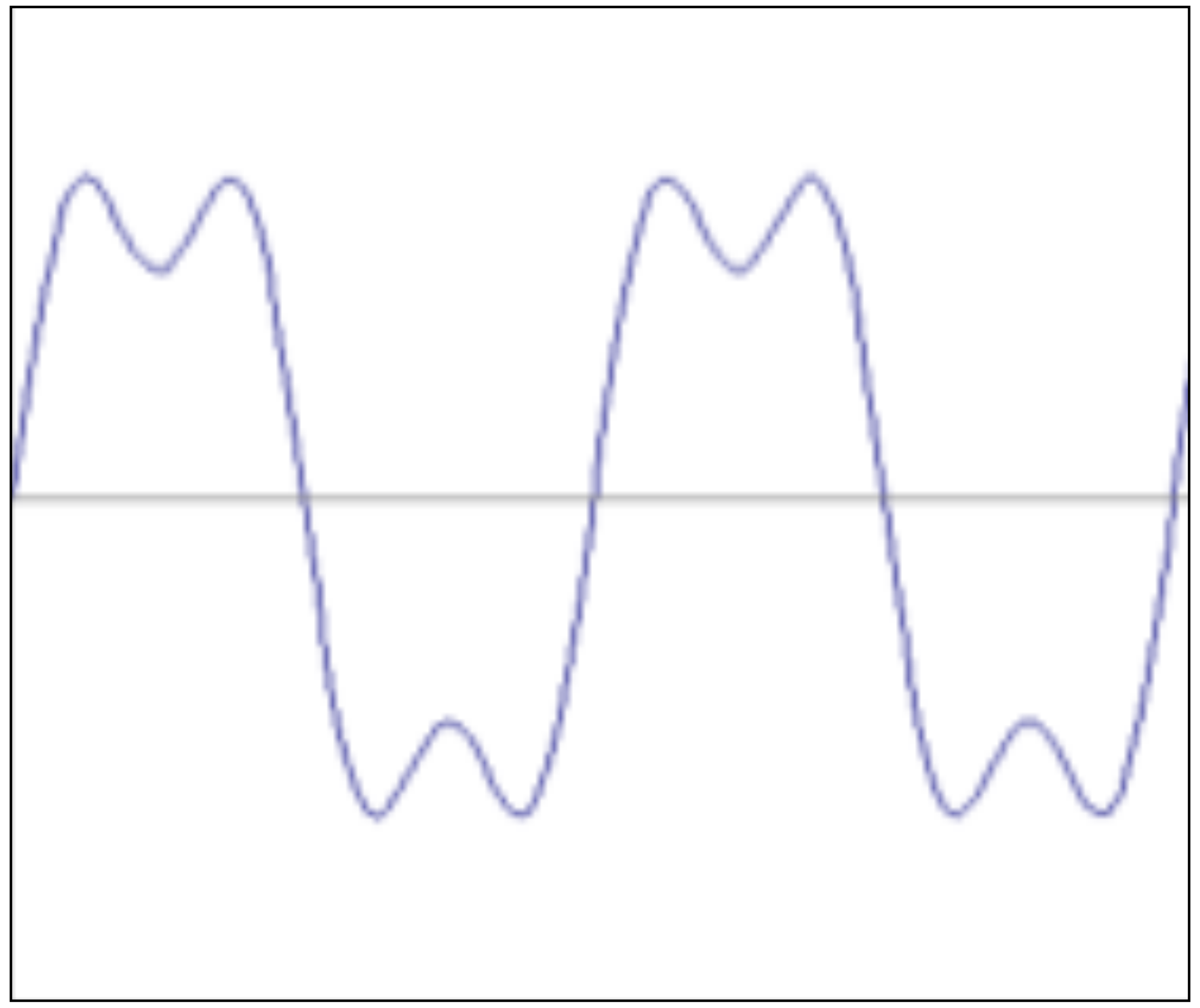
phase

Fourier's claim: Add enough of these to get <u>any</u> periodic signal you want!

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



= ? + ?

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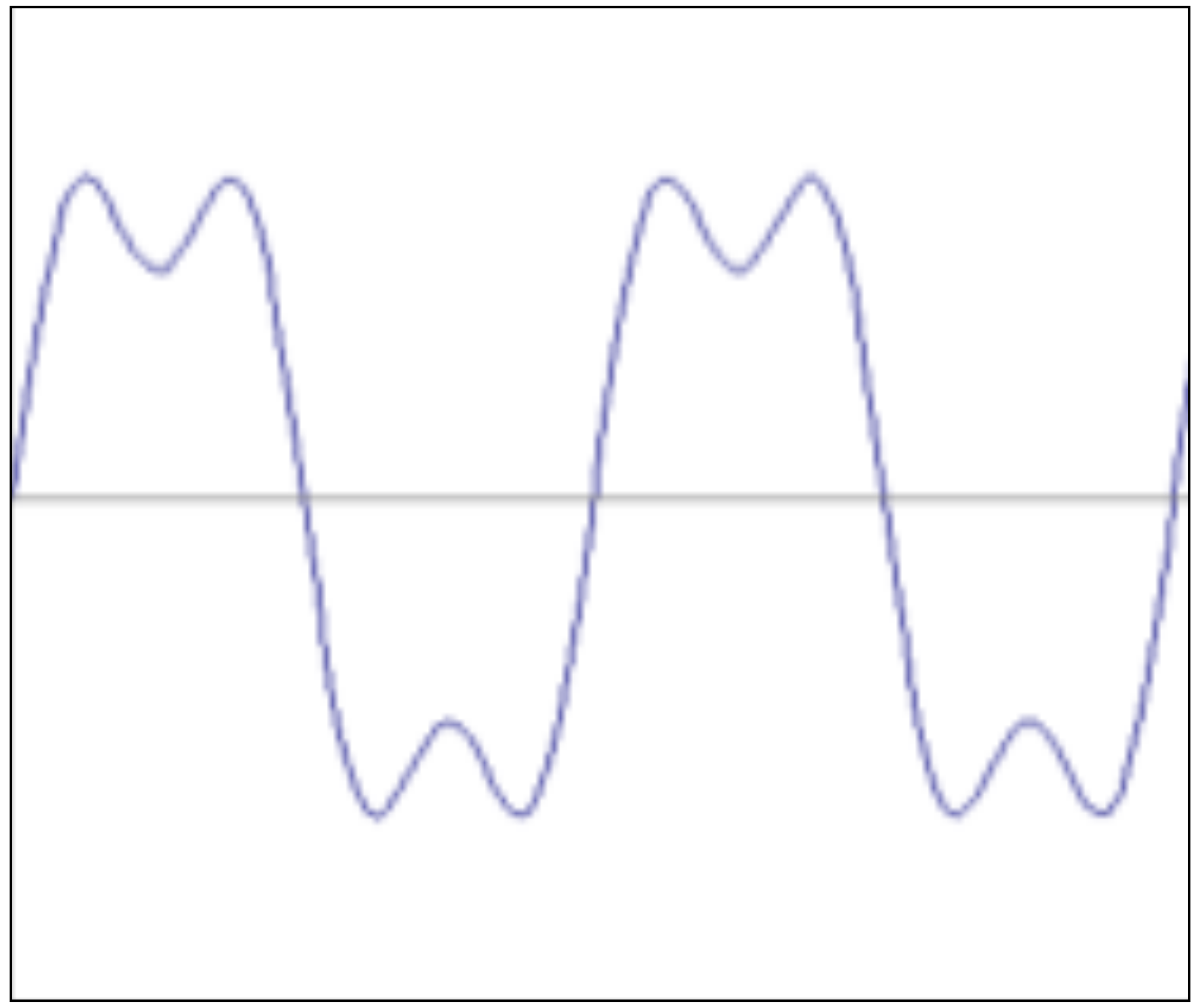
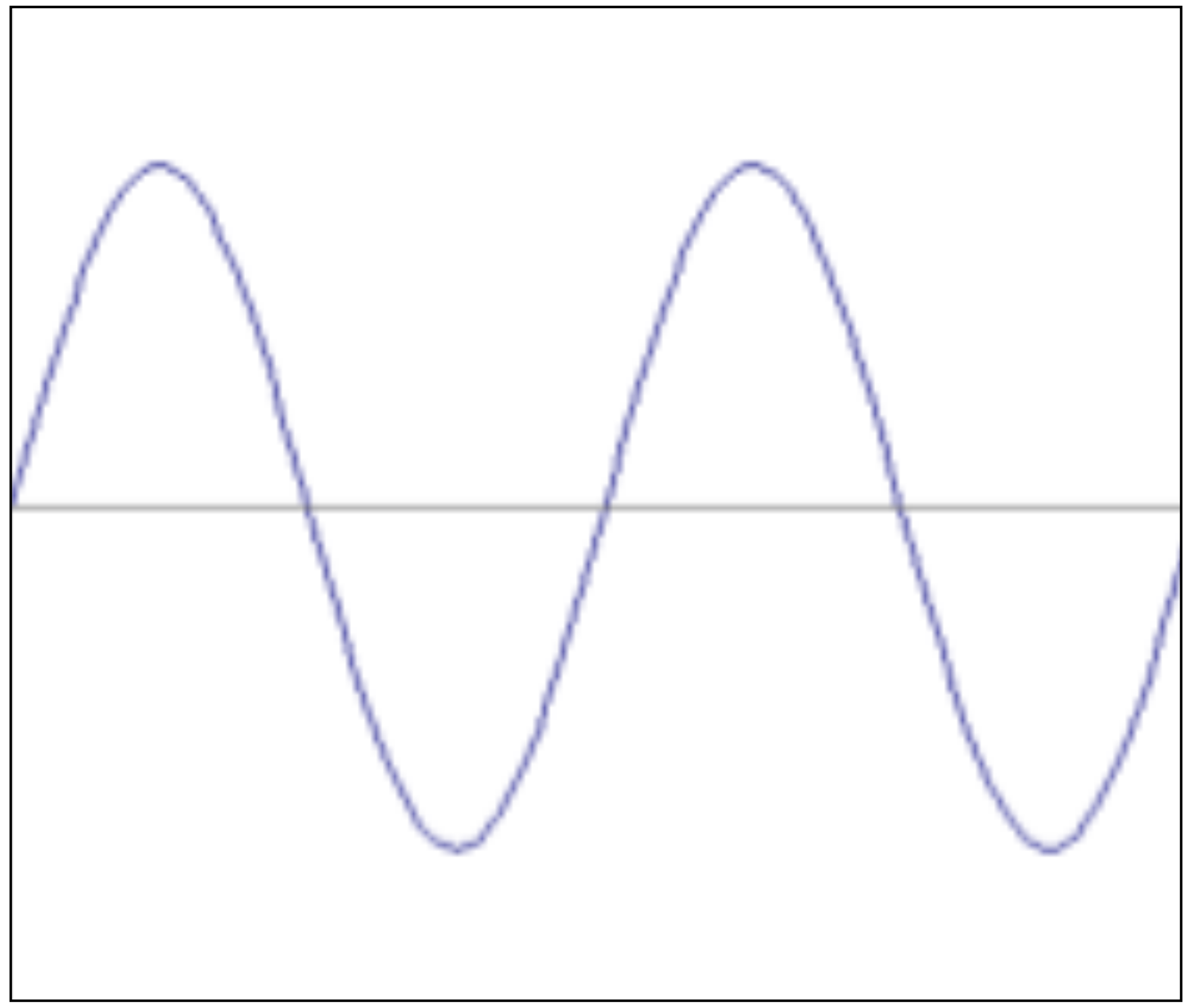
Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



=



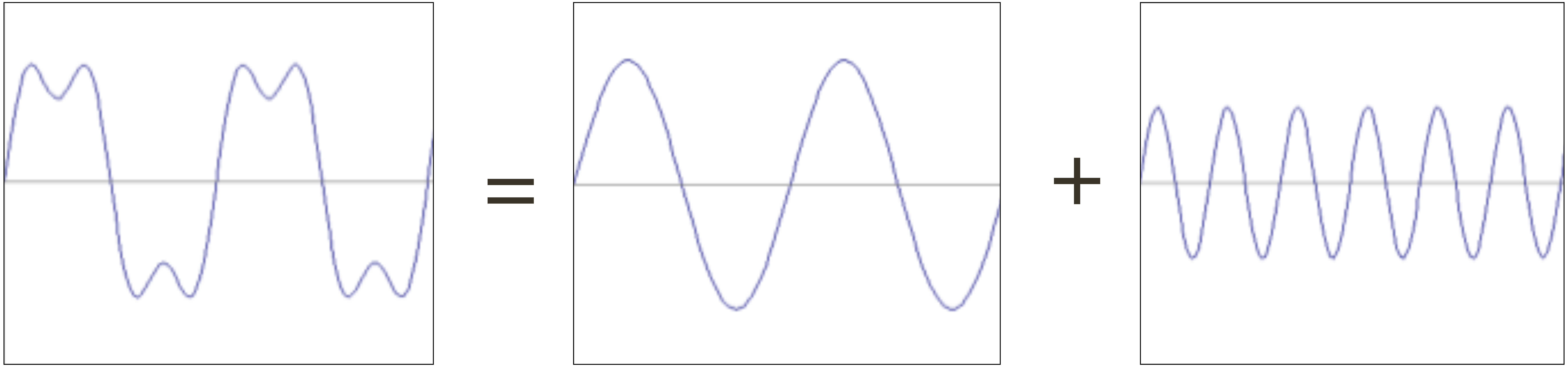
$\sin(2\pi x)$

+ ?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



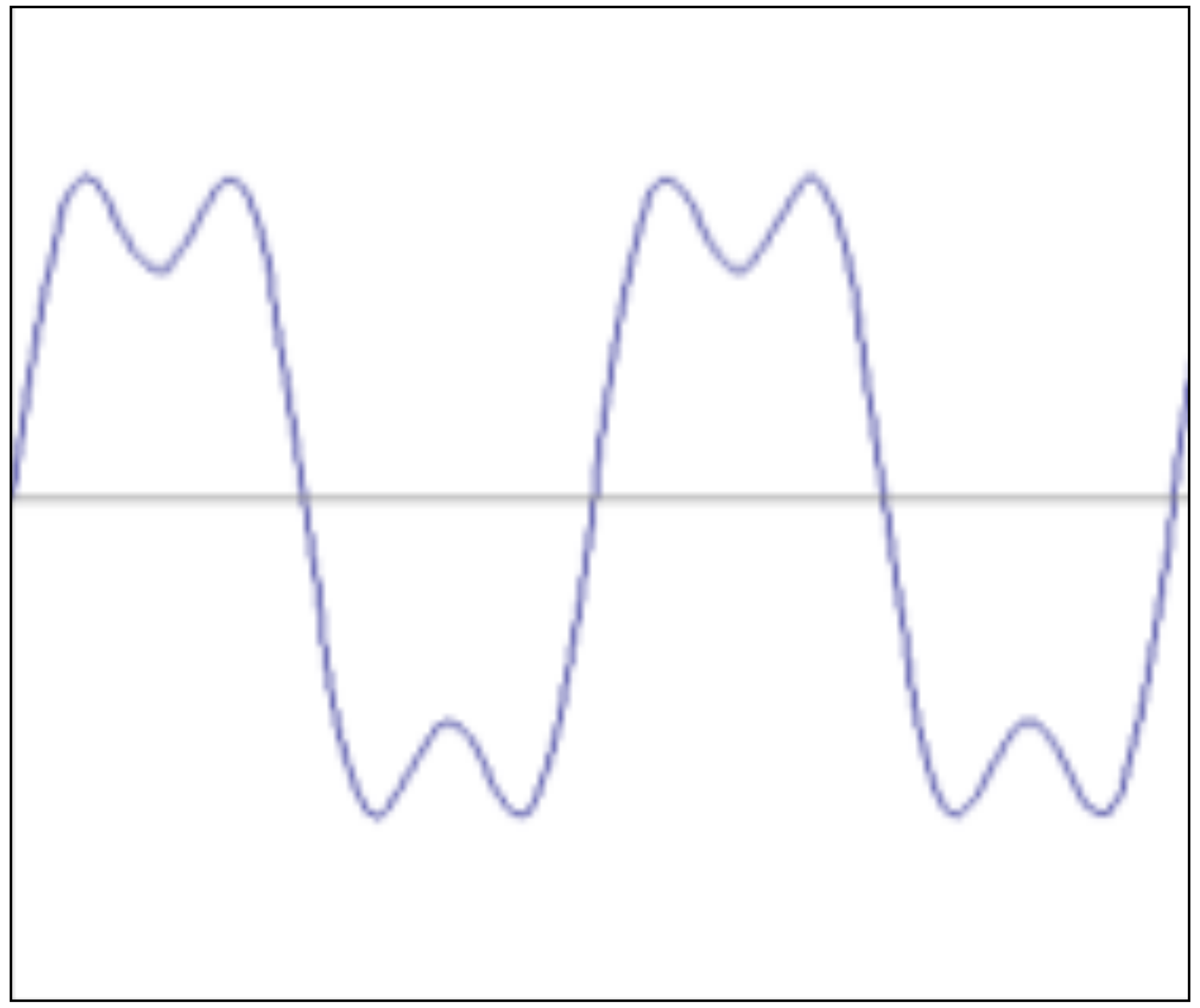
$\sin(2\pi x)$

$\frac{1}{3}\sin(2\pi 3x)$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

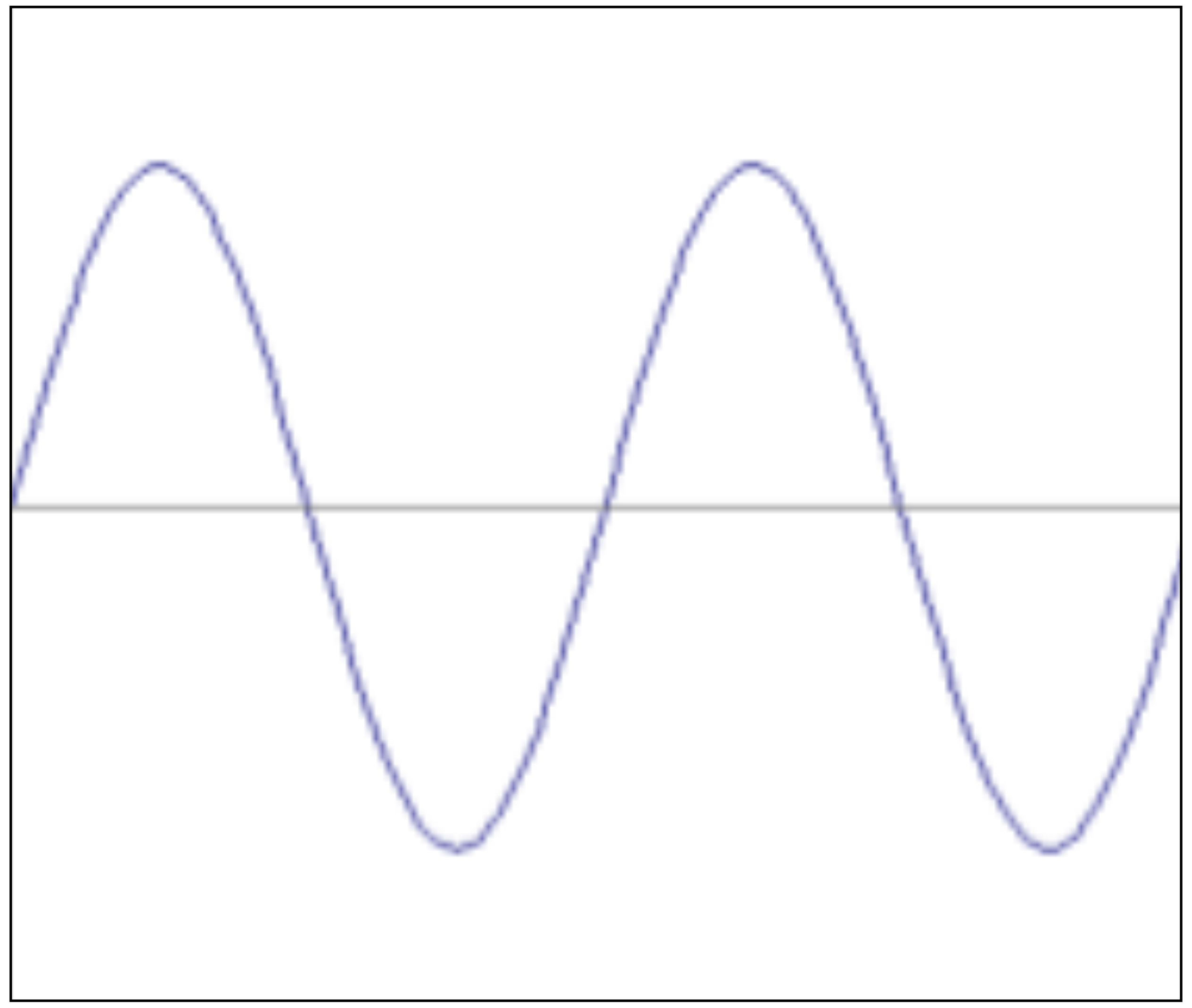
Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



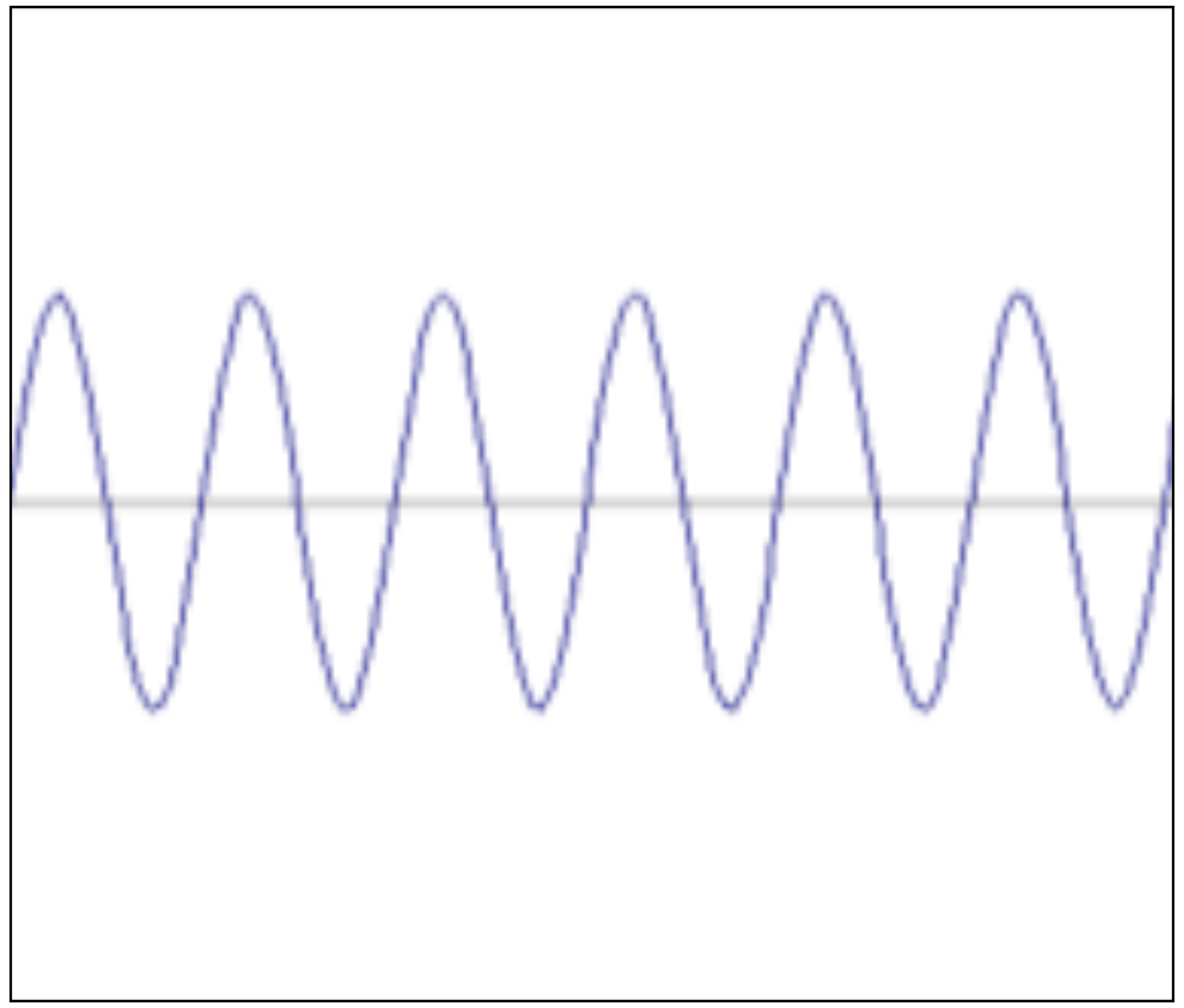
$$f(x) = \sin(2\pi x) + \frac{1}{3}\sin(2\pi 3x)$$

=



$$\sin(2\pi x)$$

+



$$\frac{1}{3}\sin(2\pi 3x)$$

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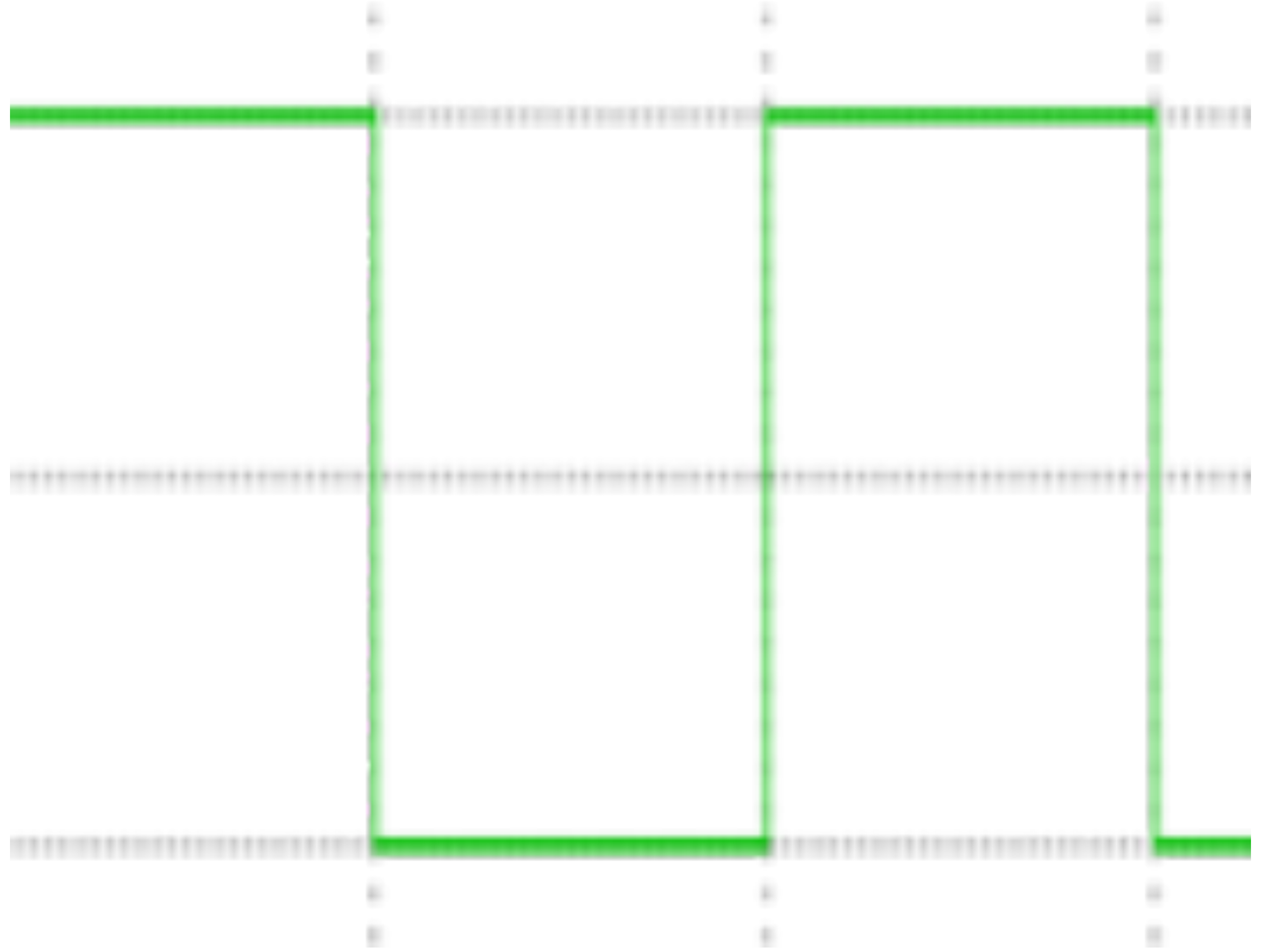
Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



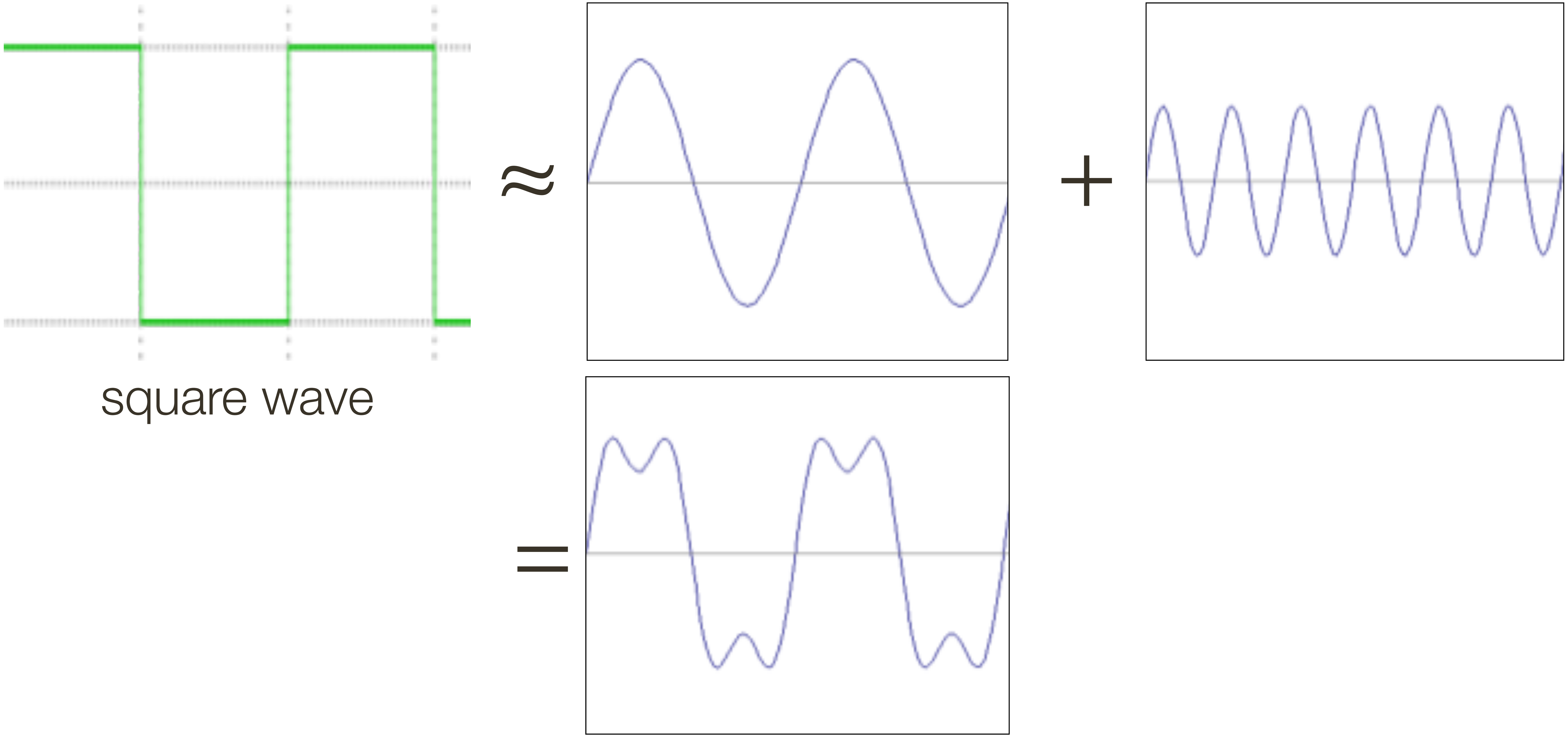
square wave

≈ ? + ?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?

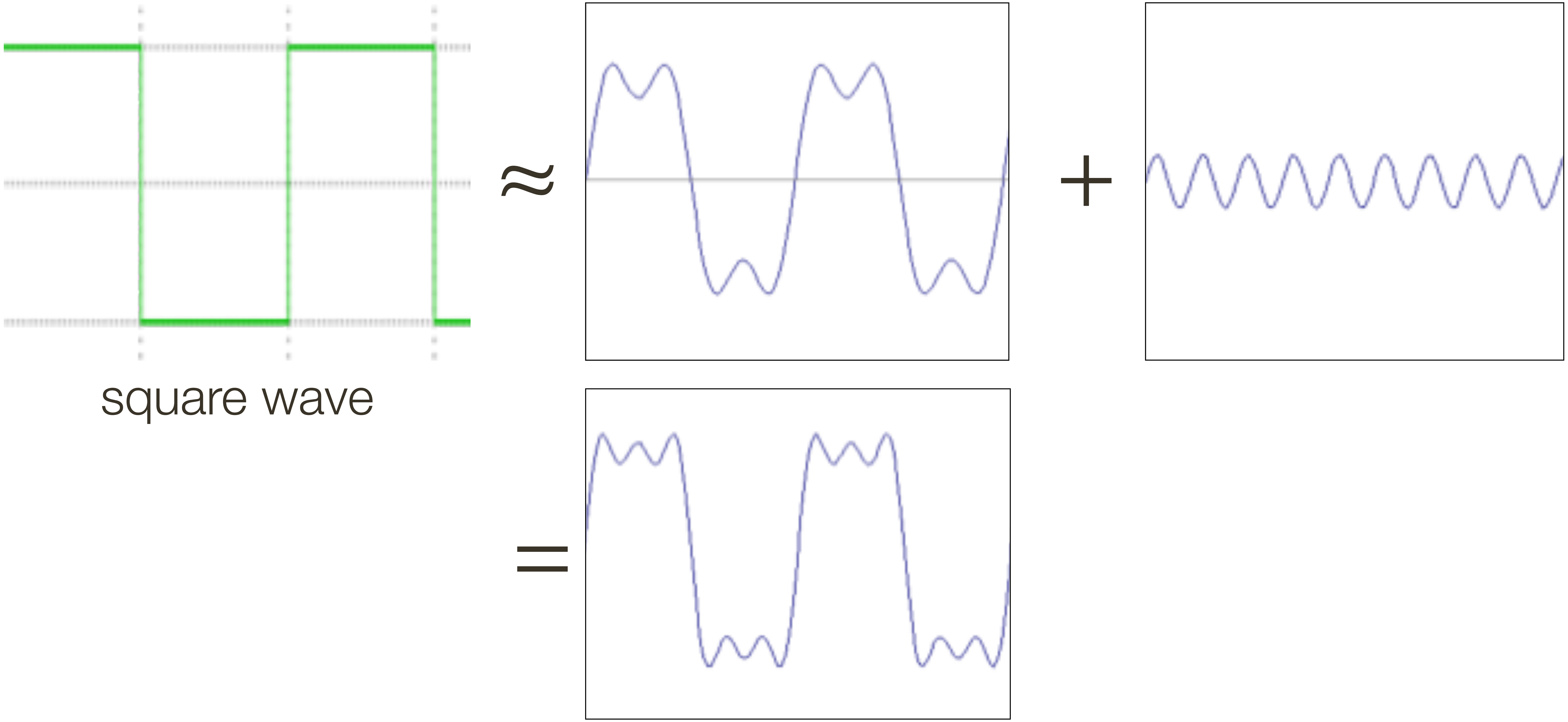


square wave

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

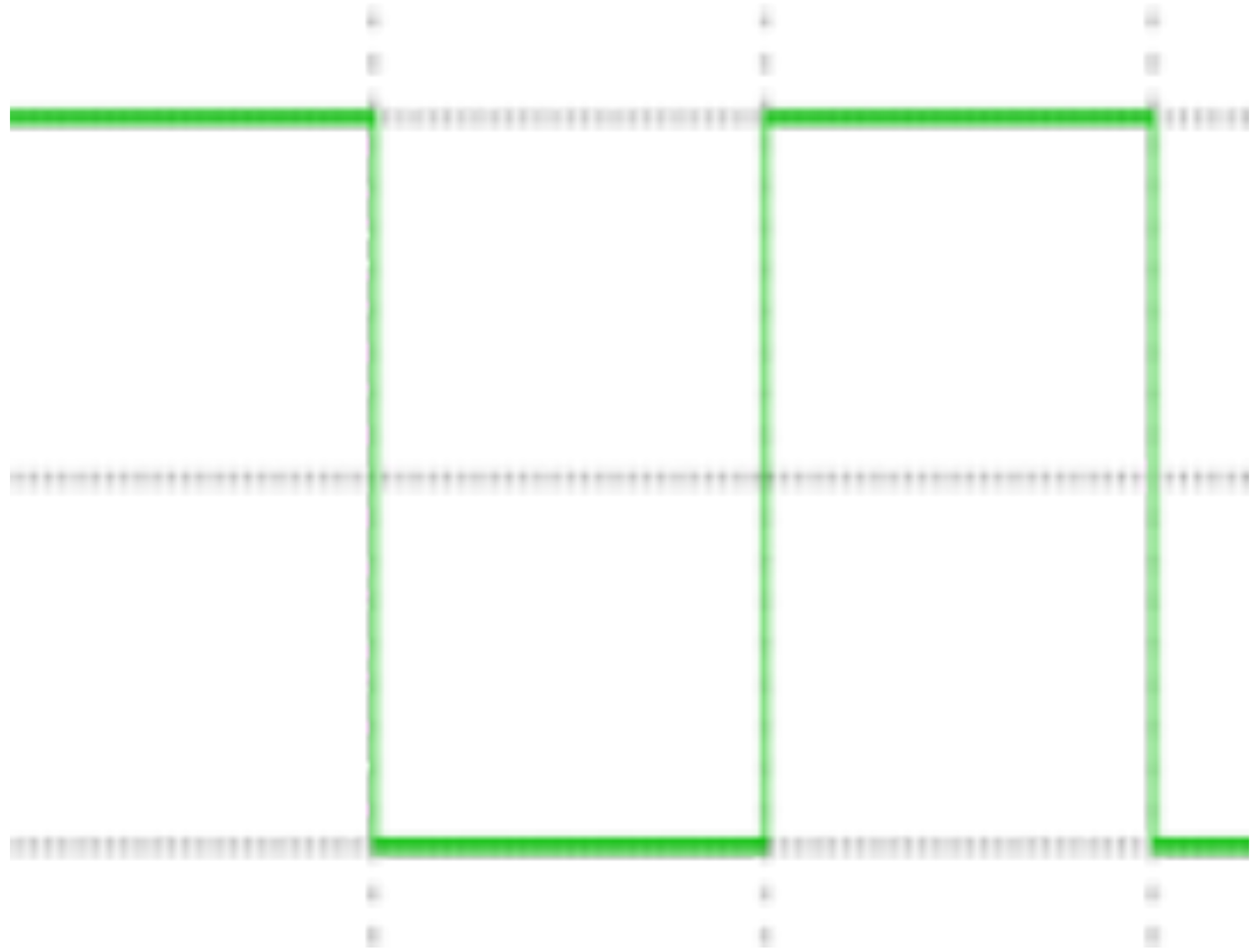
How would you generate this function?



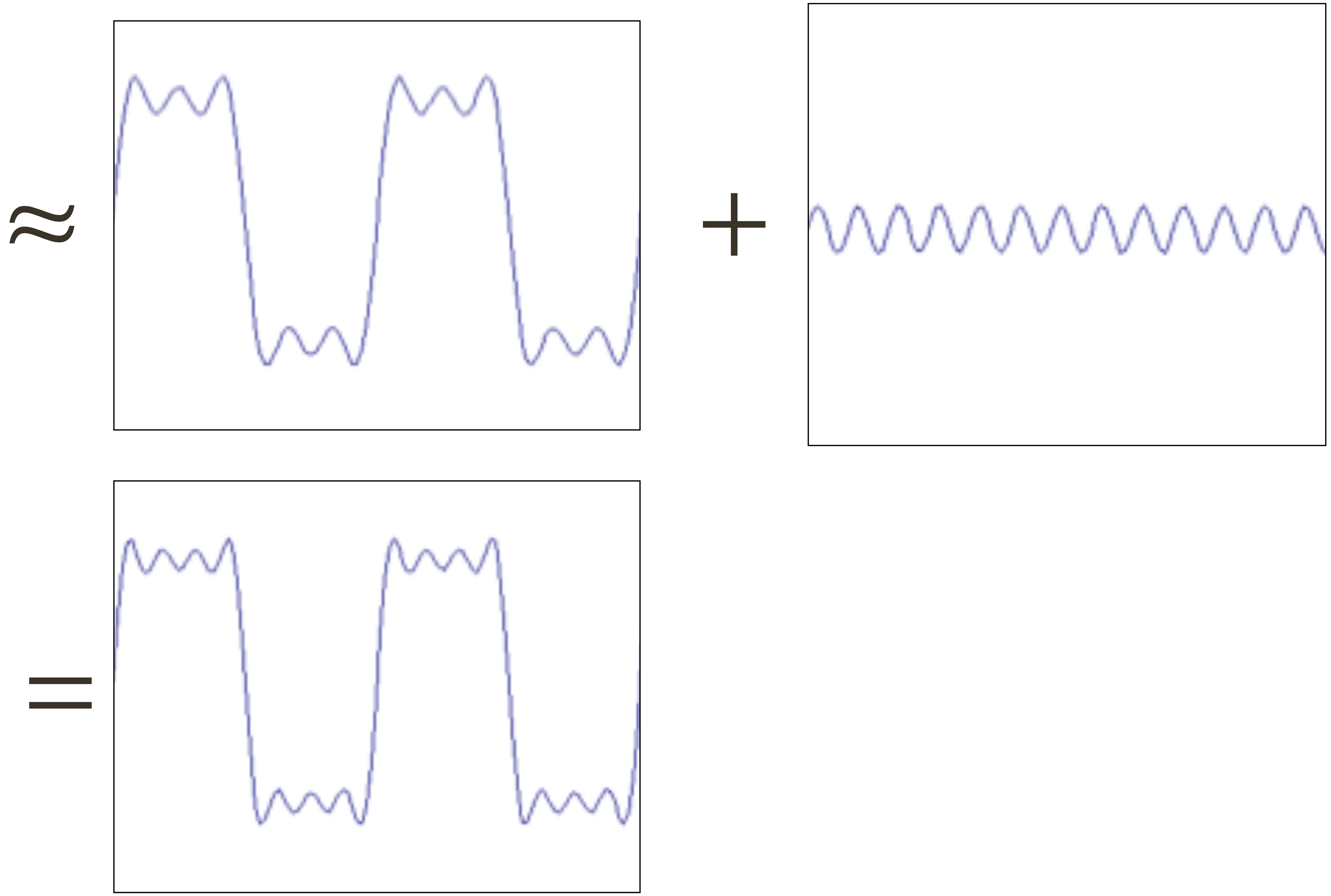
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



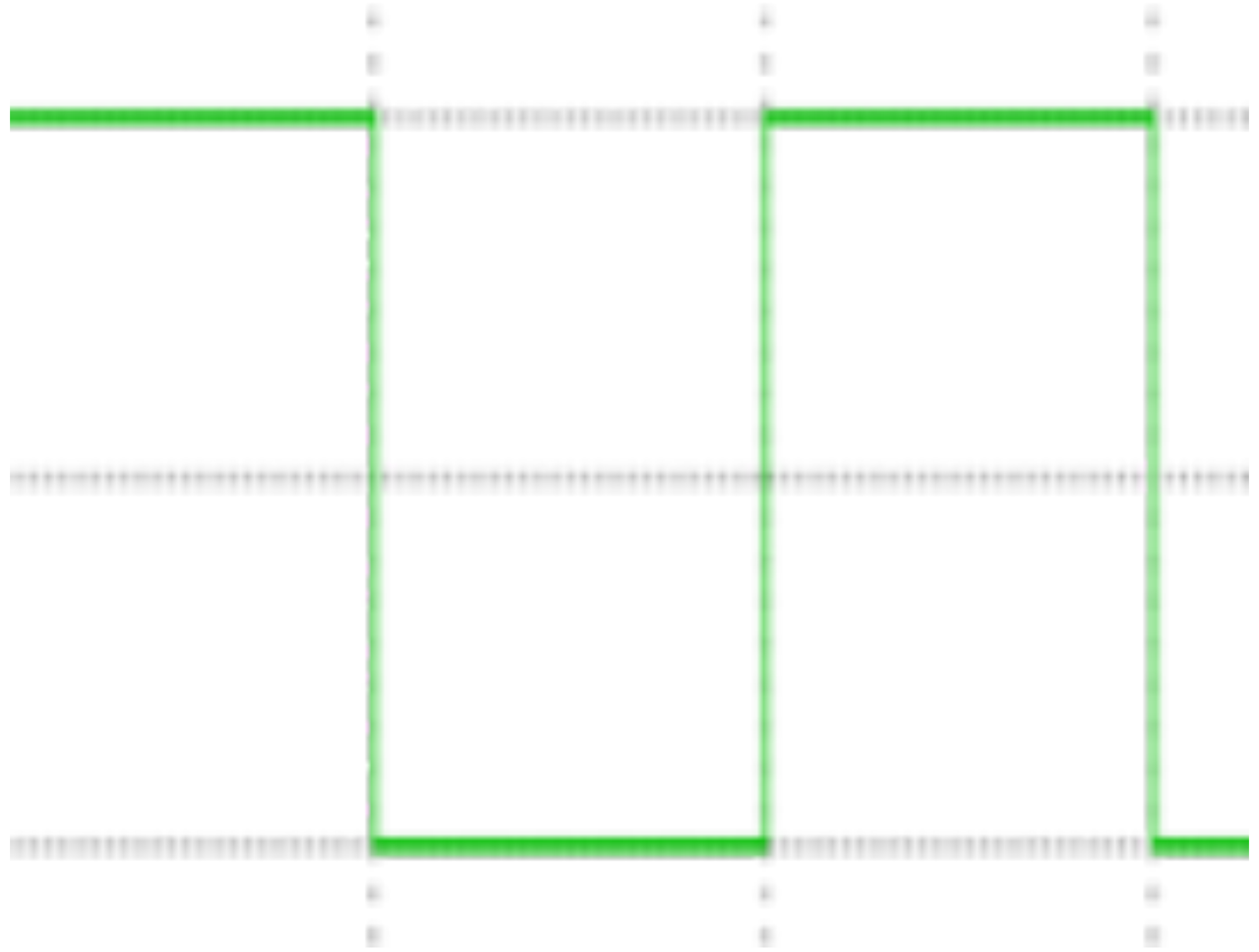
square wave



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

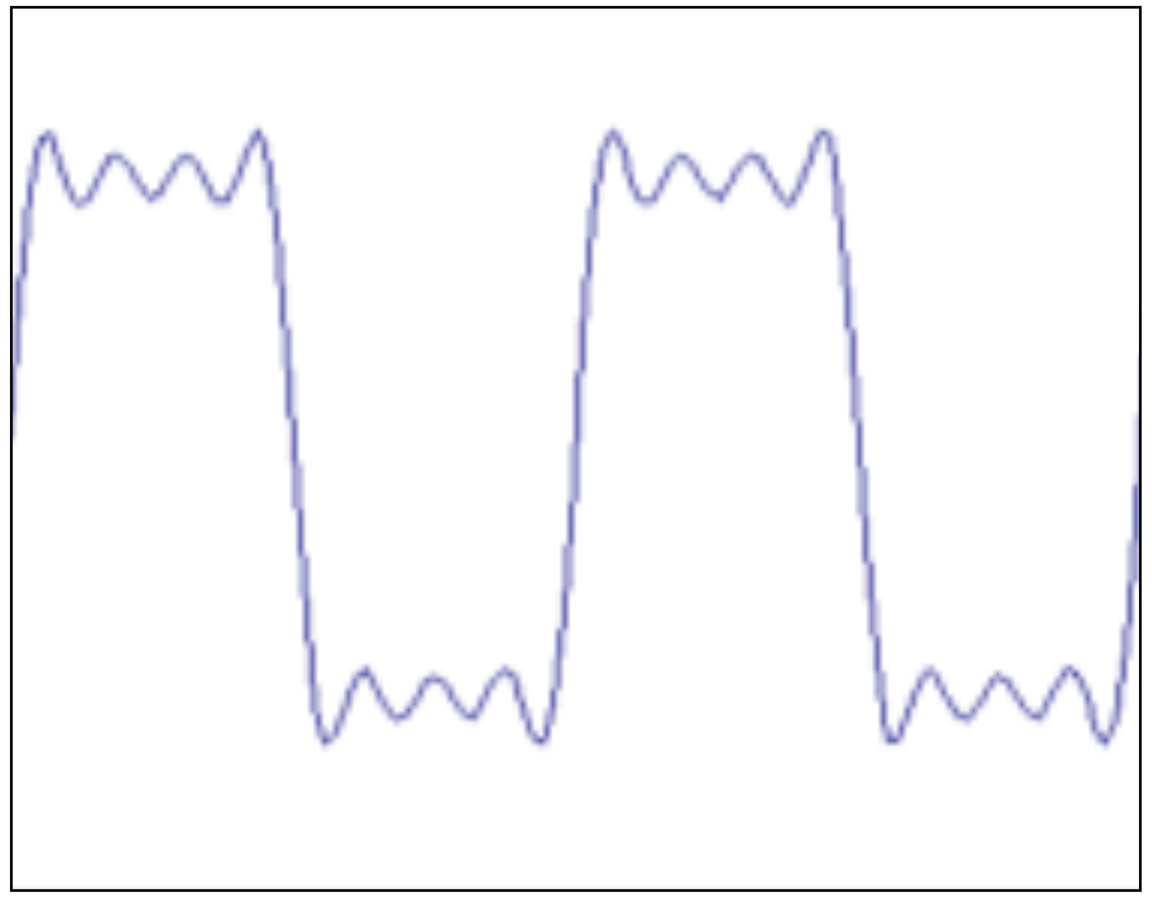
Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?

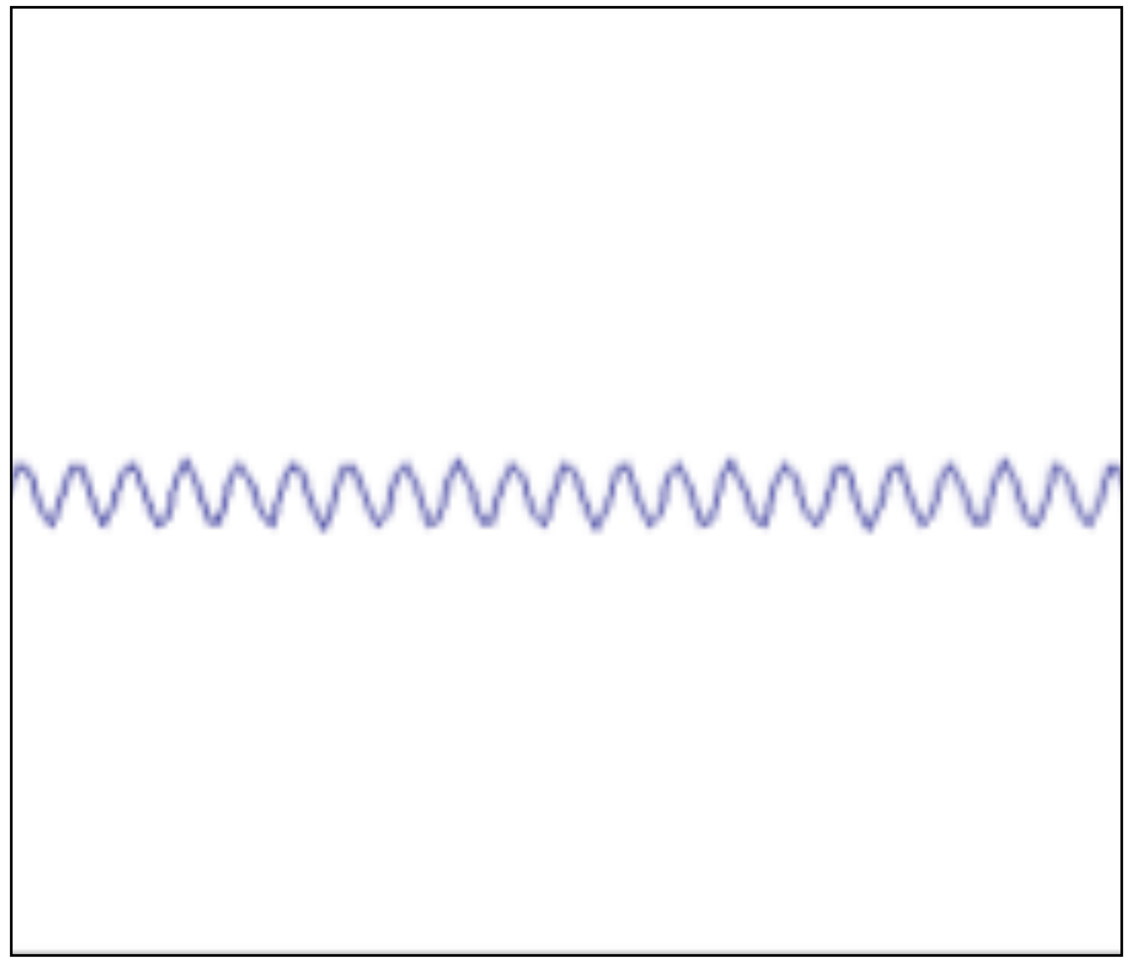


square wave

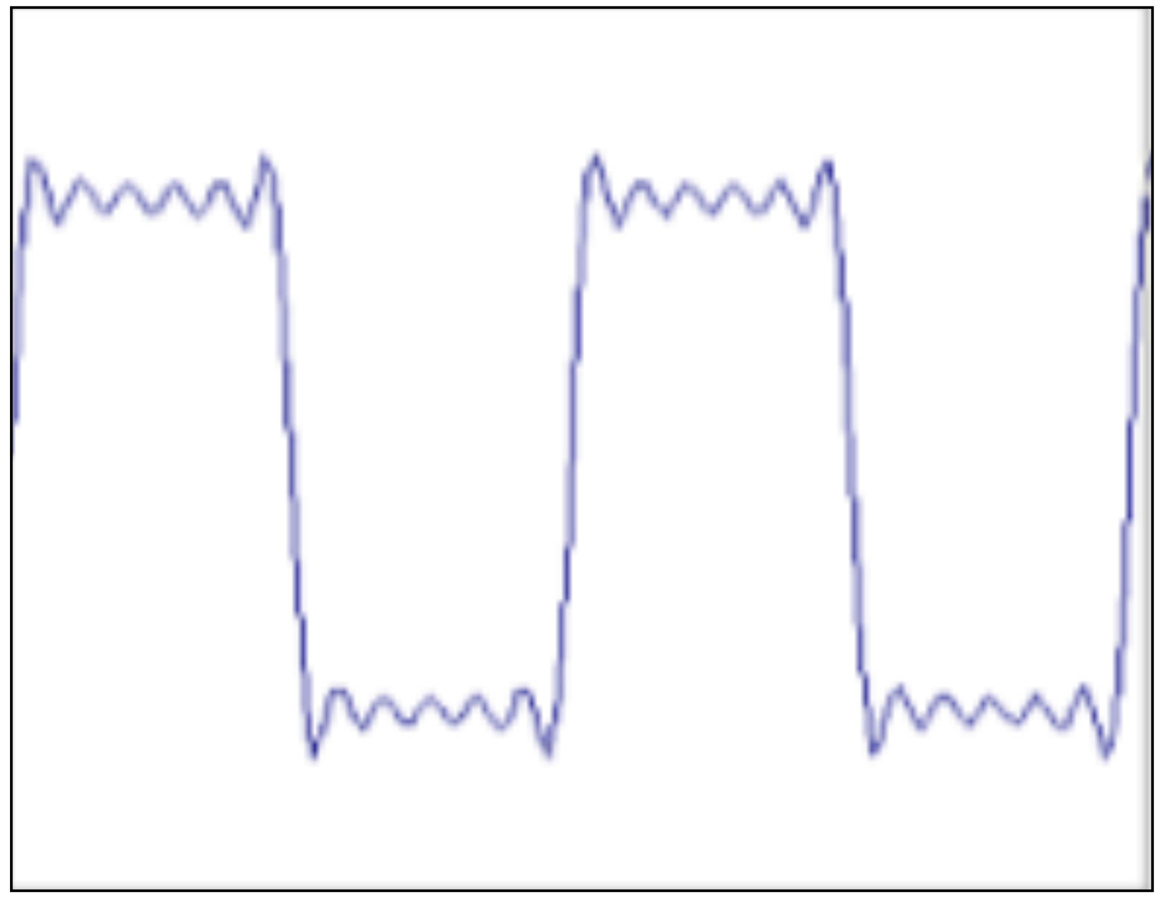
≈



+



=

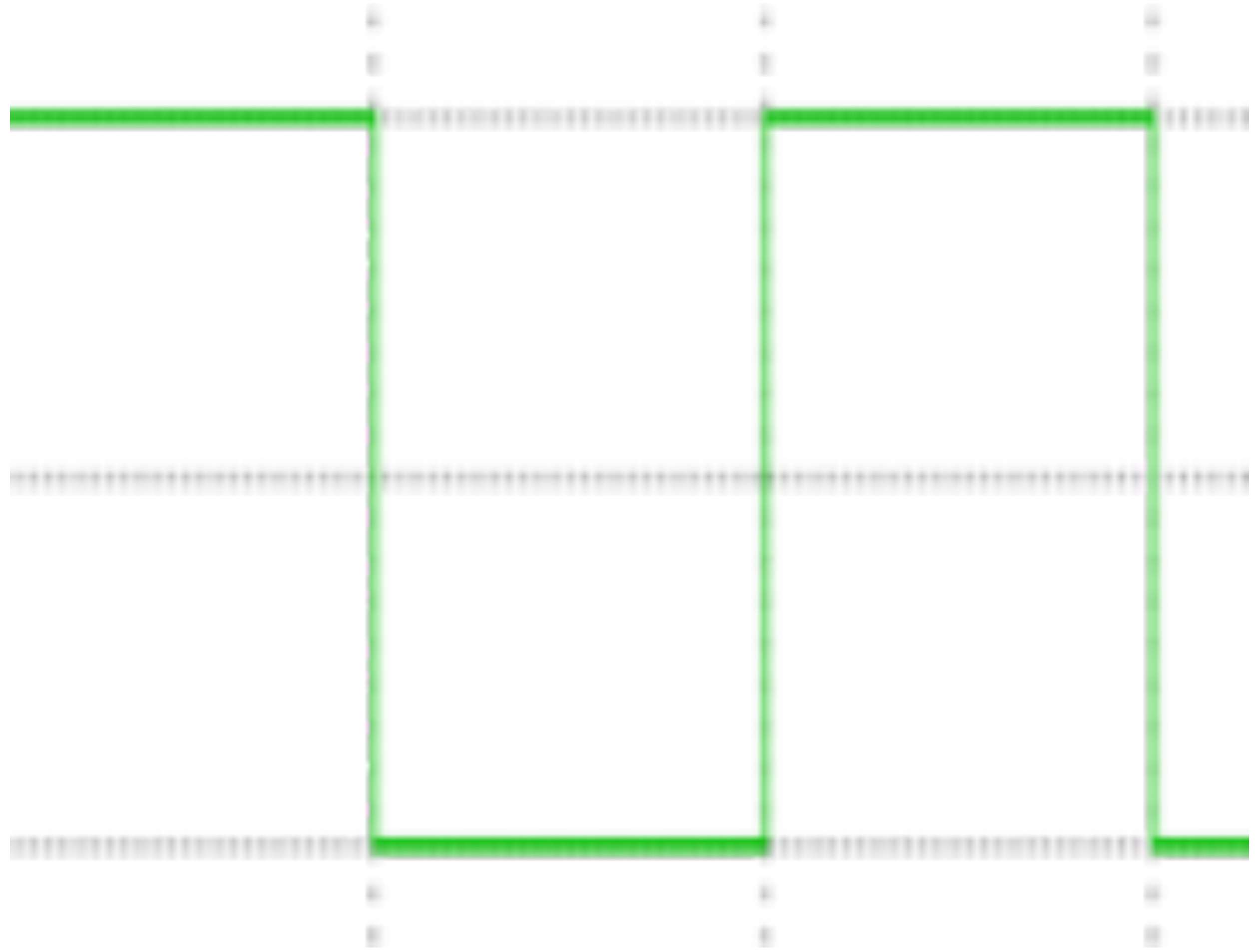


How would you express this mathematically?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

How would you generate this function?



square wave

$$= A\sum_{k=1}^{\infty}\frac{1}{k}\sin(2\pi kx)$$

infinite sum of sine waves

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

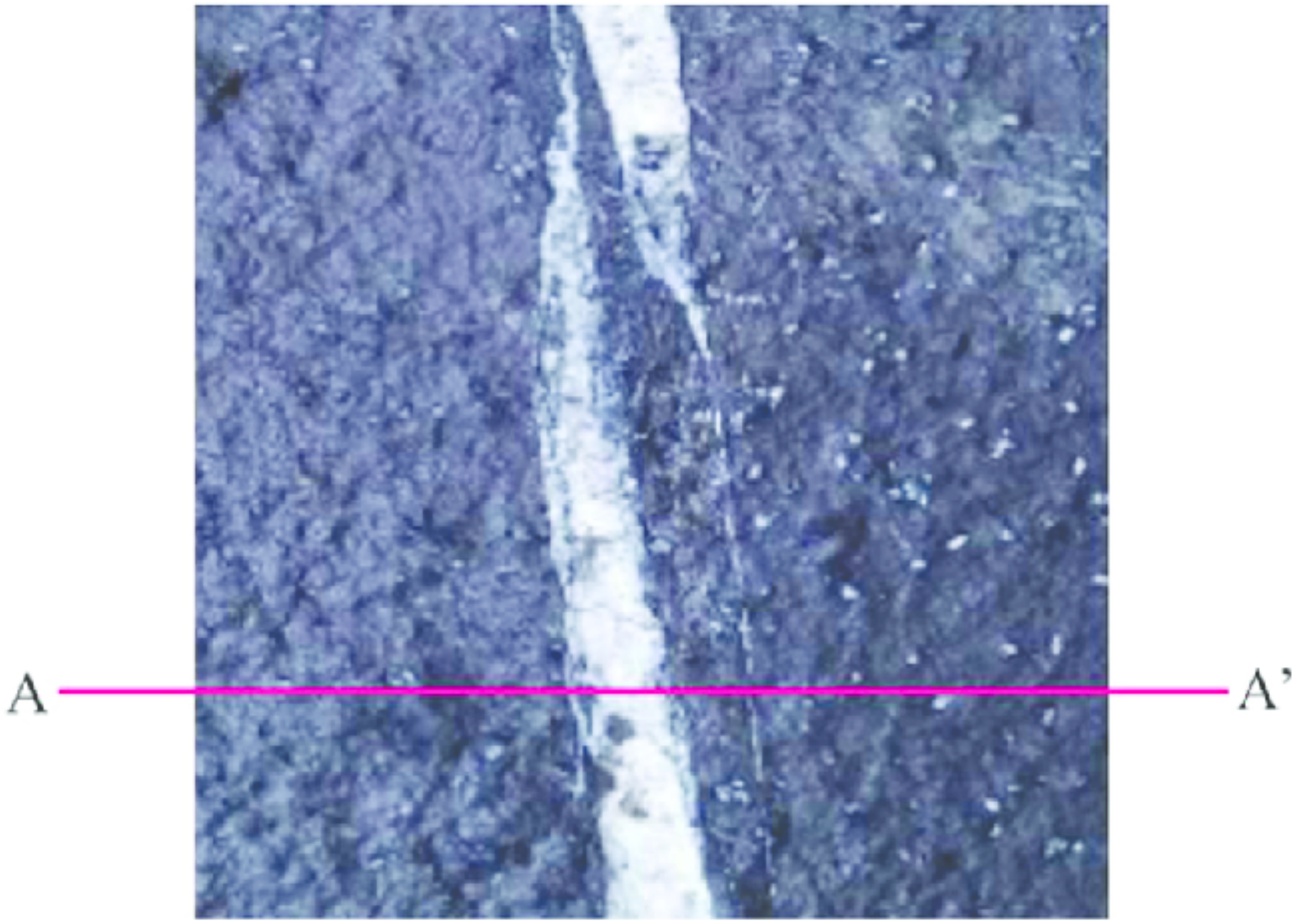
Basic building block:

$$A \sin(\omega x + \phi)$$

Fourier’s claim: Add enough of these to get any periodic signal you want!

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)



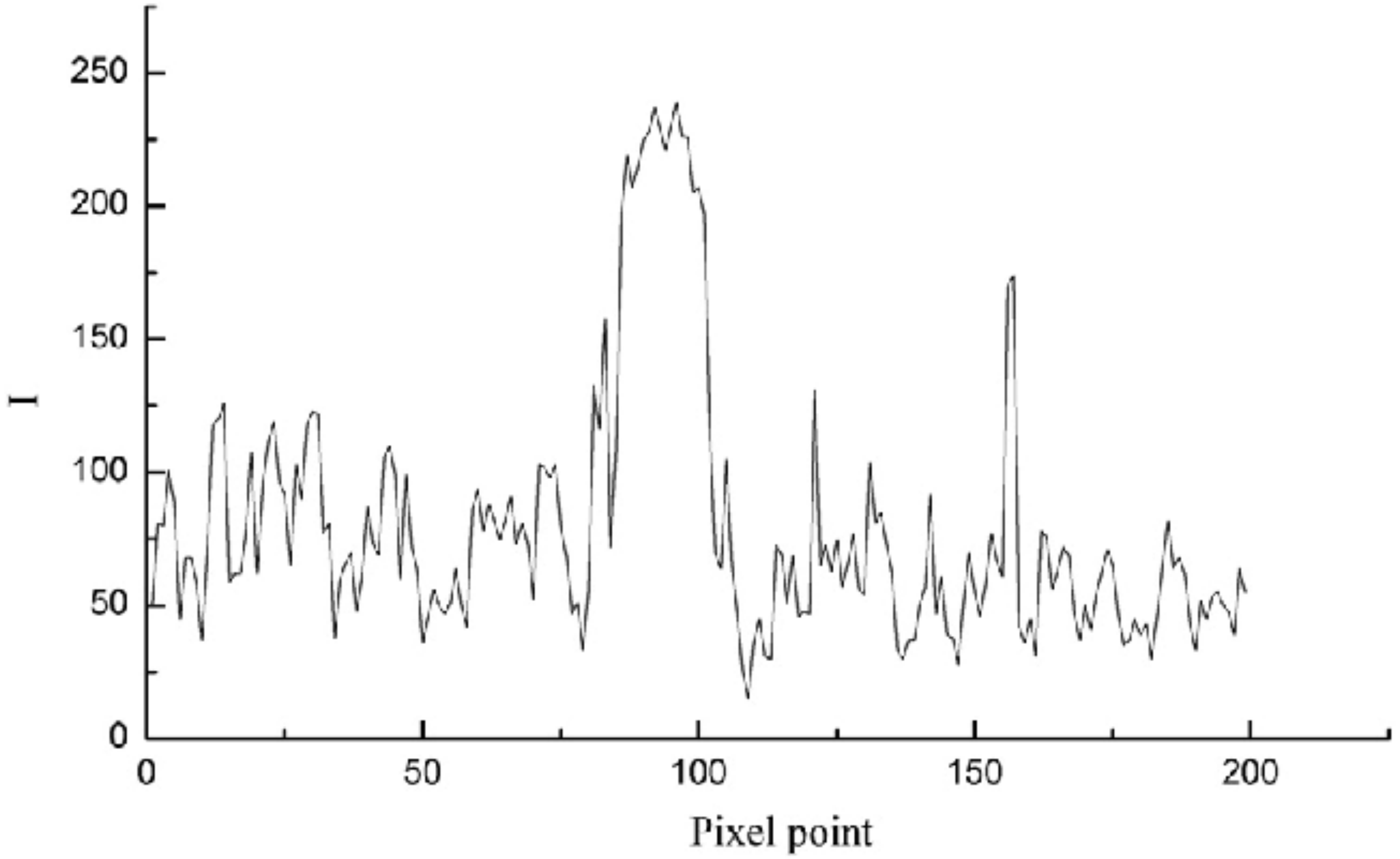


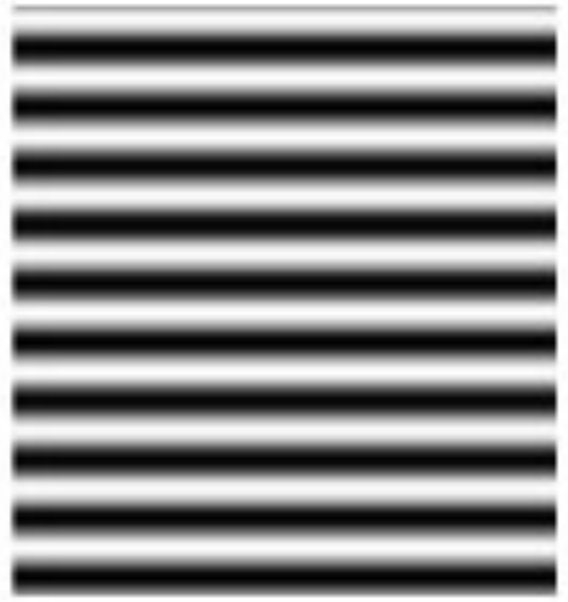
Image from: Numerical Simulation and Fractal Analysis of Mesoscopic Scale Failure in Shale Using Digital Images

Fourier Transform (you will **NOT** be tested on this)

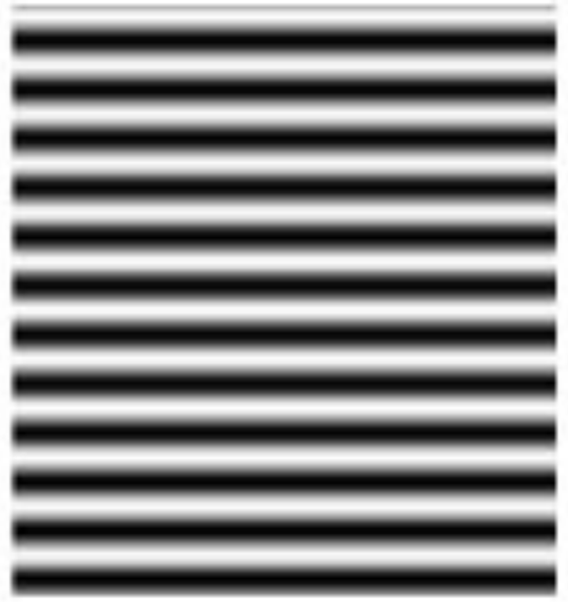
What are “frequencies” in an image?

Spatial frequency

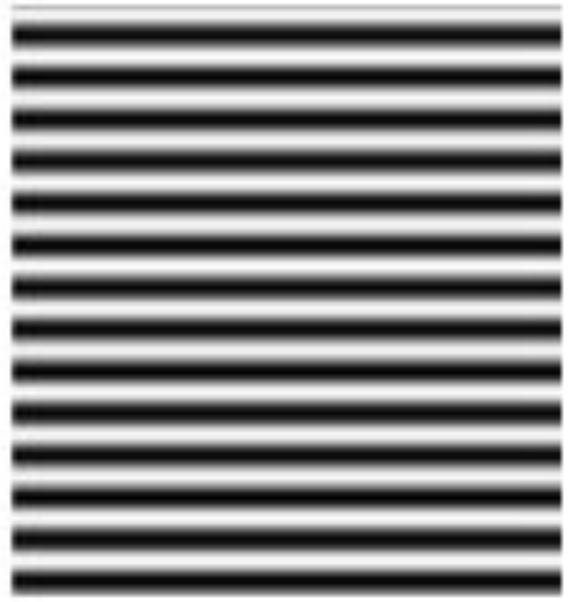
$f = 4$



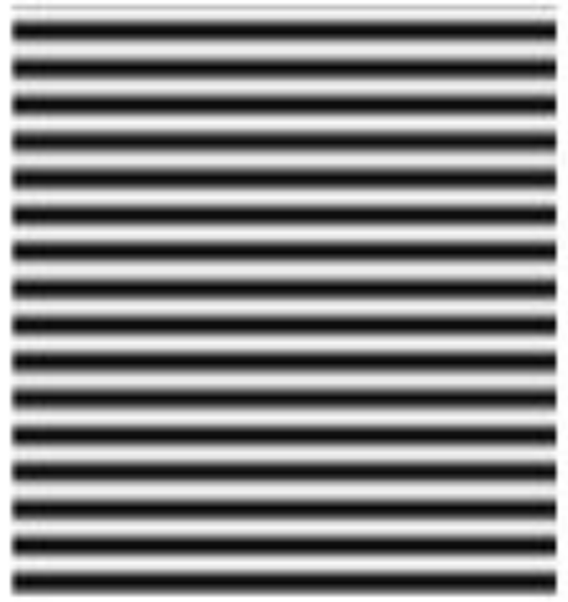
$f = 5$



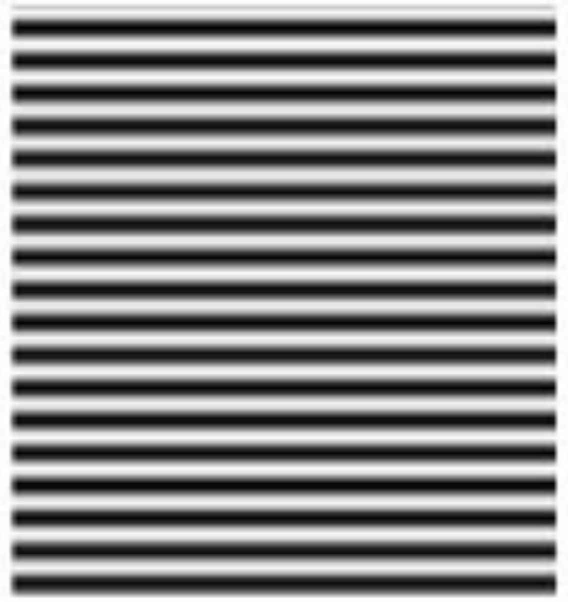
$f = 6$



$f = 7$



$f = 8$



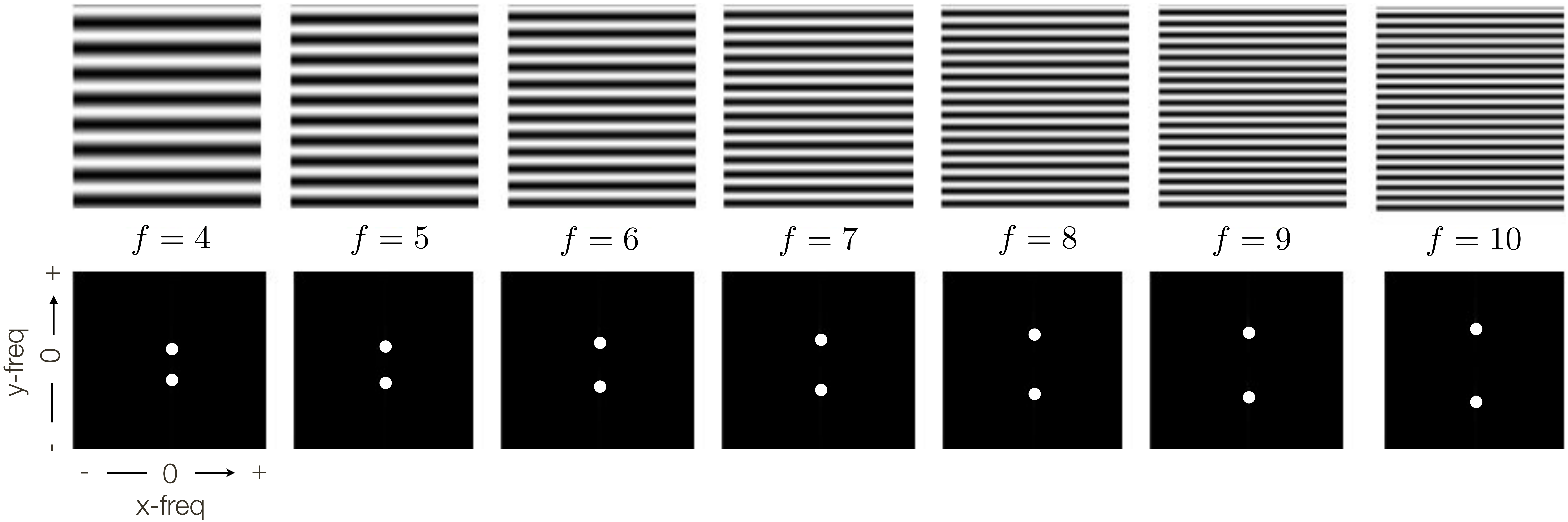
$f = 9$

$f = 10$

Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

Spatial frequency

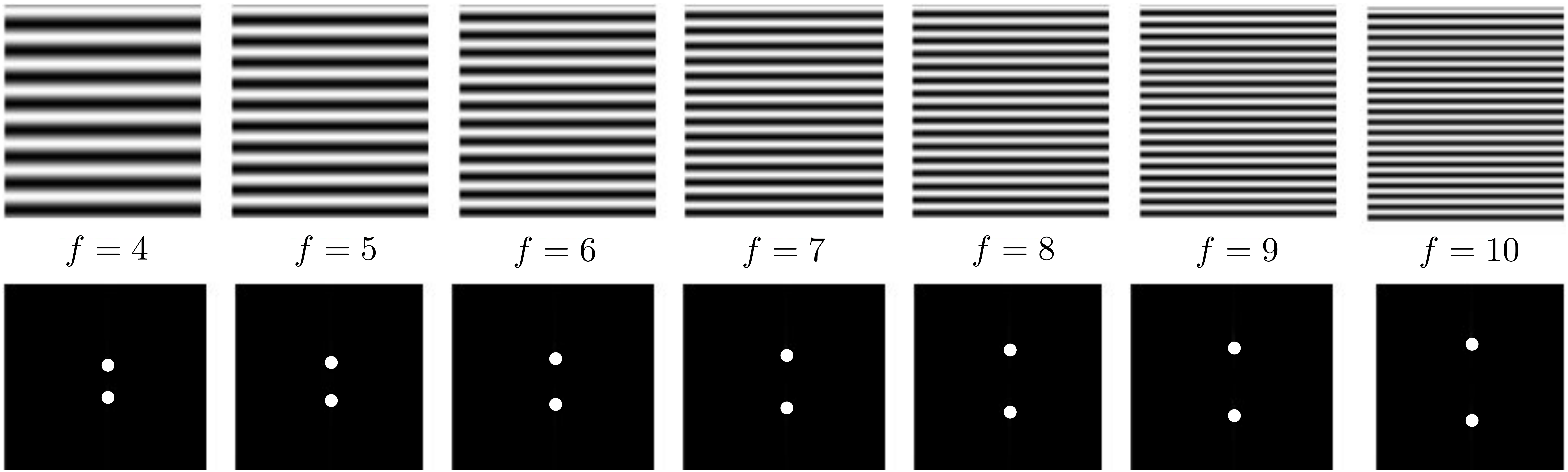


Amplitude (magnitude) of Fourier transform (phase does not show desirable correlations with image structure)

Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

Spatial frequency



$f = 4$ $f = 5$ $f = 6$ $f = 7$ $f = 8$ $f = 9$ $f = 10$

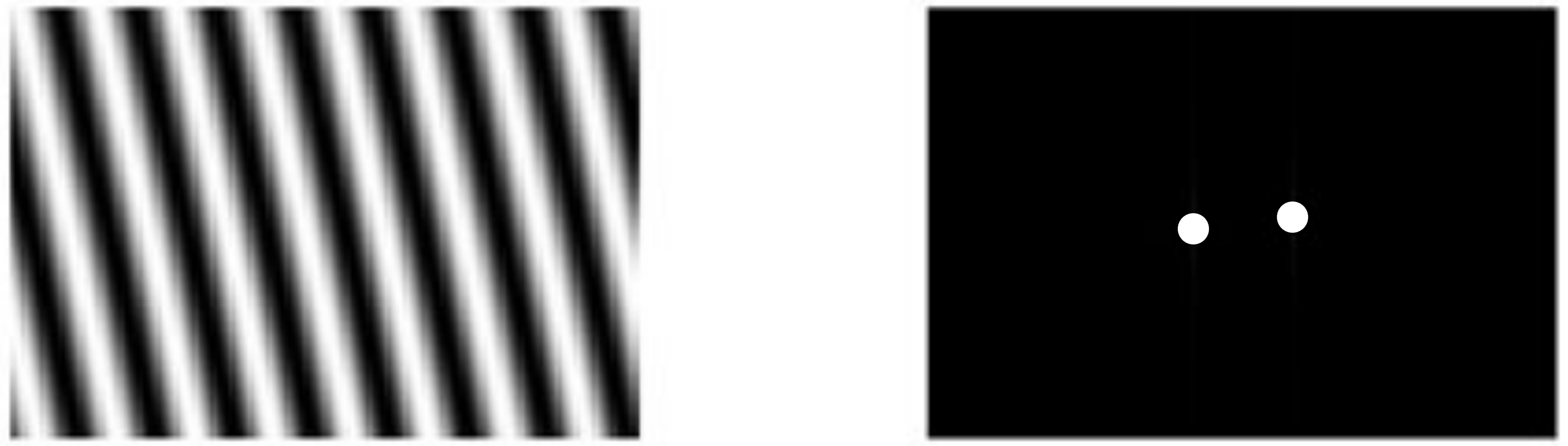
Amplitude (magnitude) of Fourier transform (phase does not show desirable correlations with image structure)

Observation: low frequencies close to the center

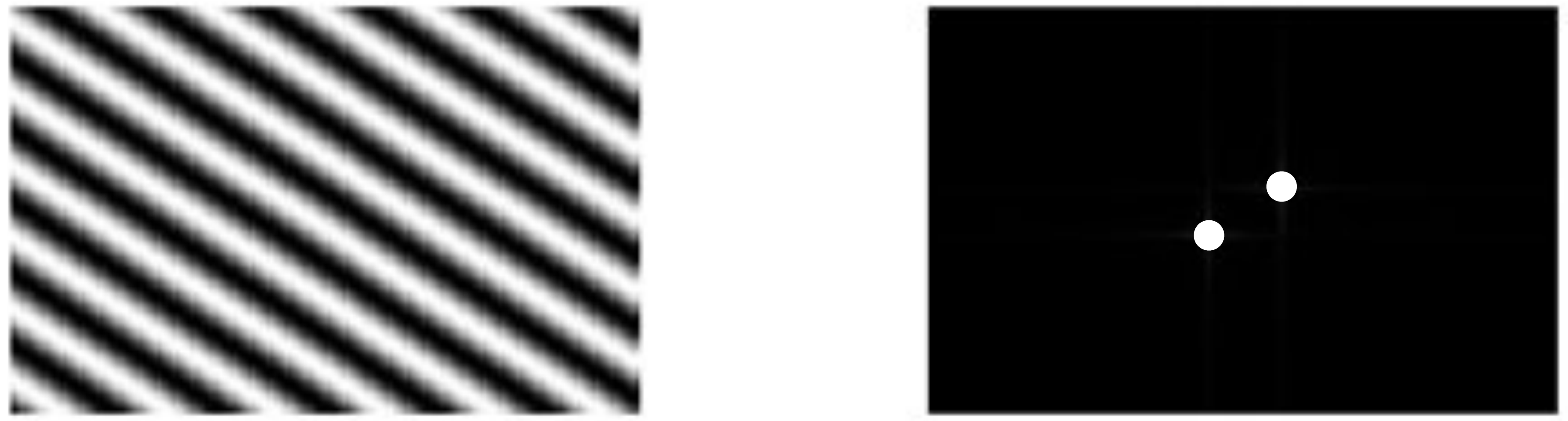
Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

Spatial frequency



Θ=30°

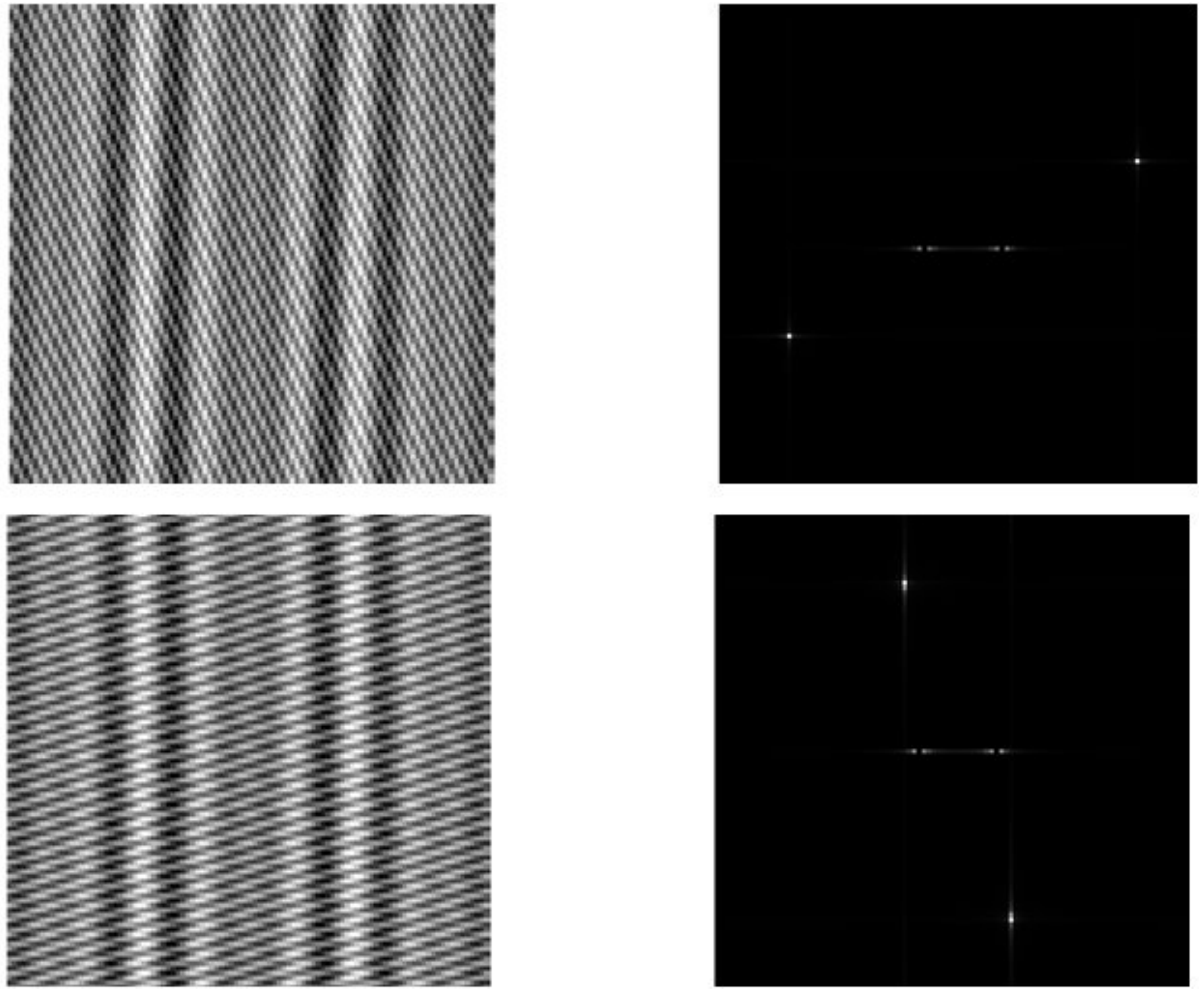


Θ=150°

Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

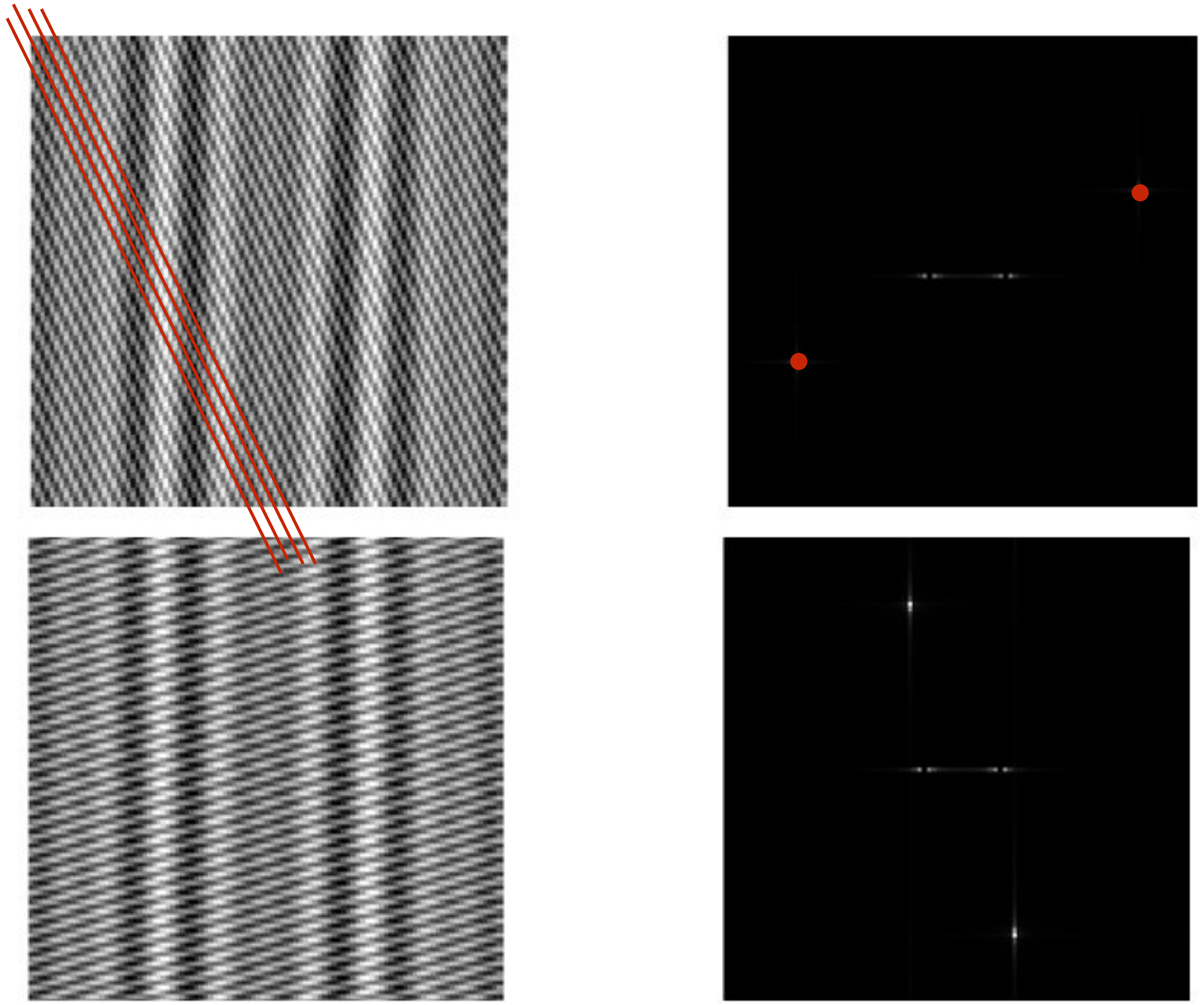
Spatial frequency



Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

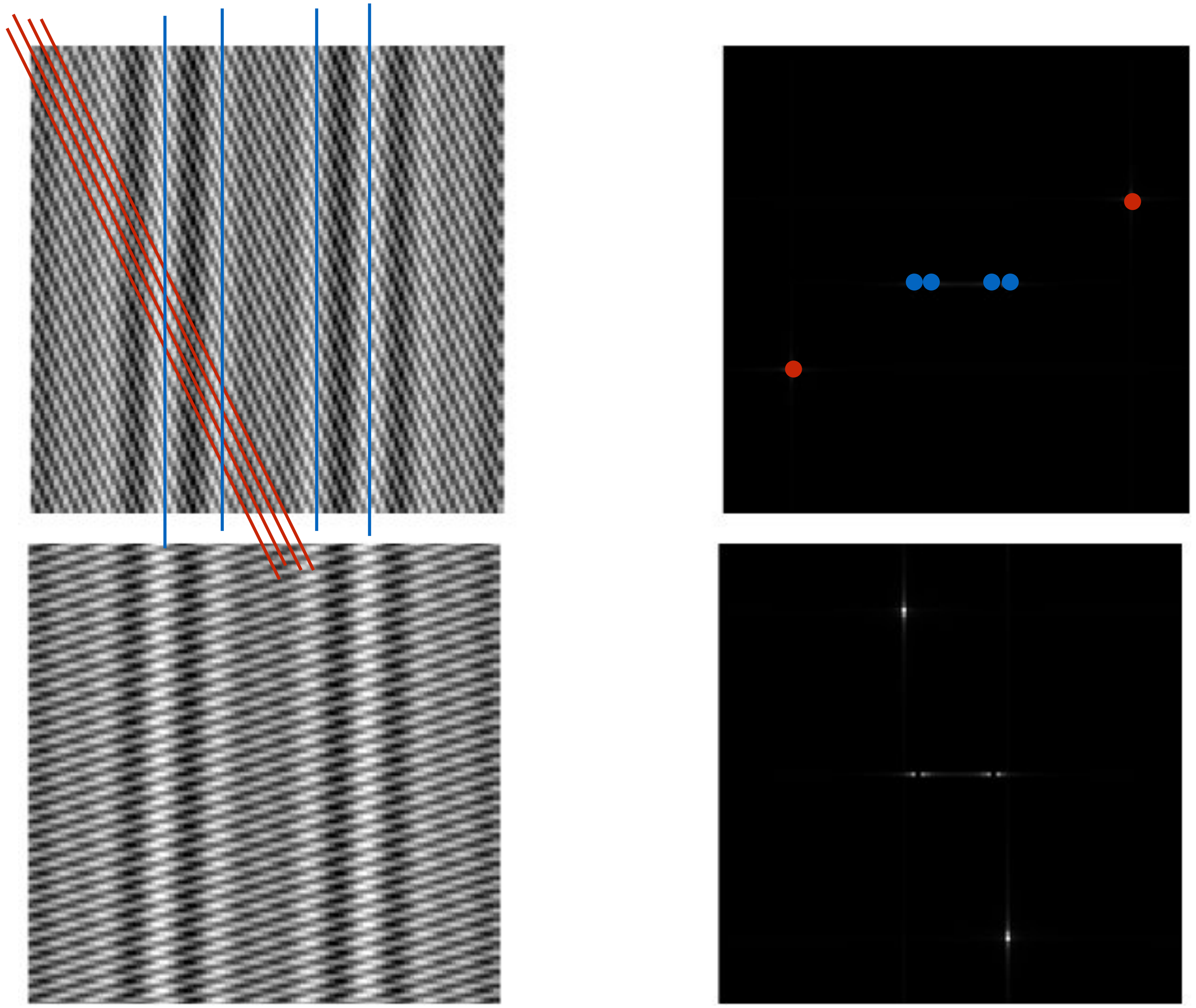
Spatial frequency



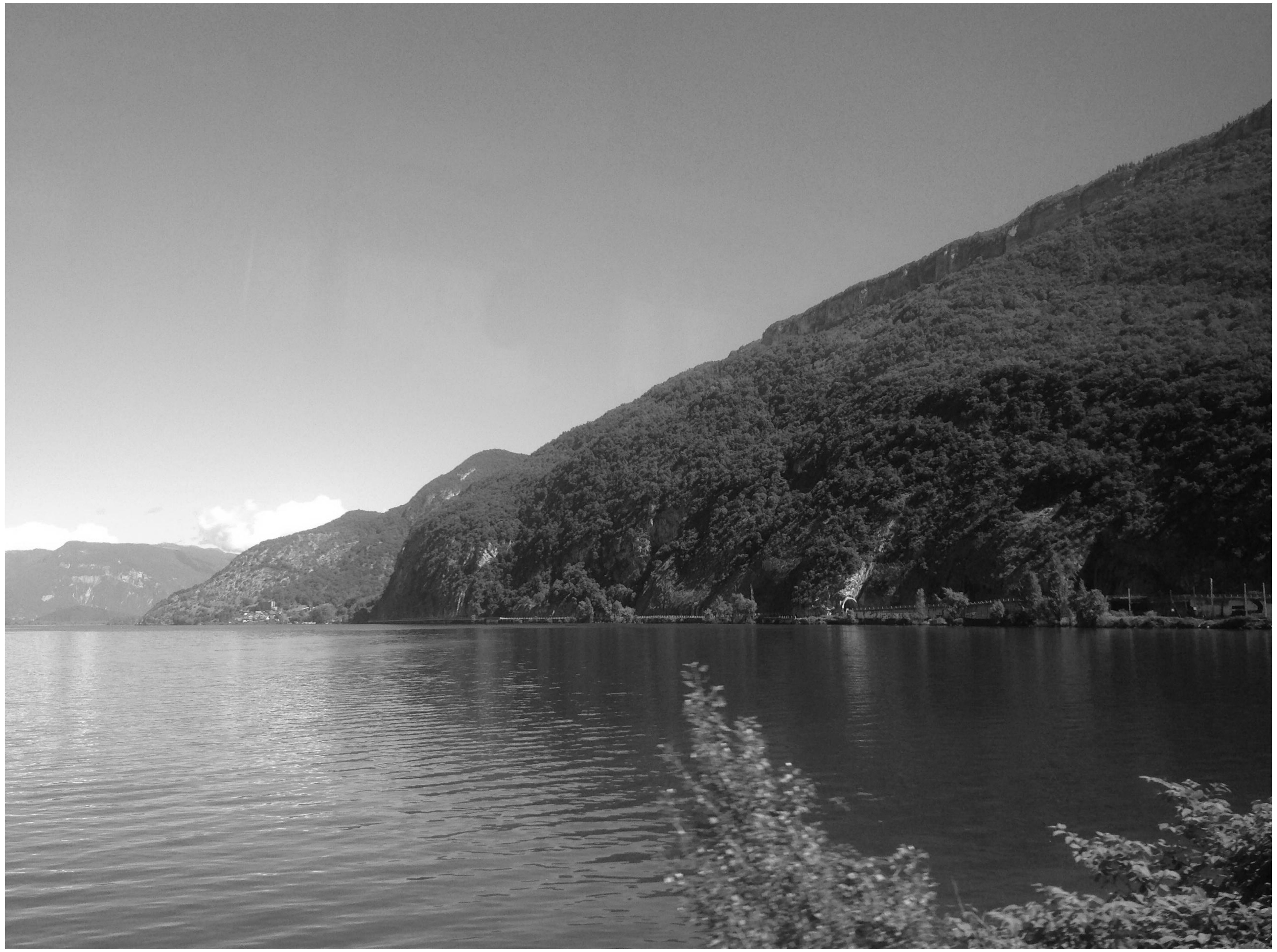
Fourier Transform (you will **NOT** be tested on this)

What are “frequencies” in an image?

Spatial frequency



Fourier Transform (you will **NOT** be tested on this)



Image

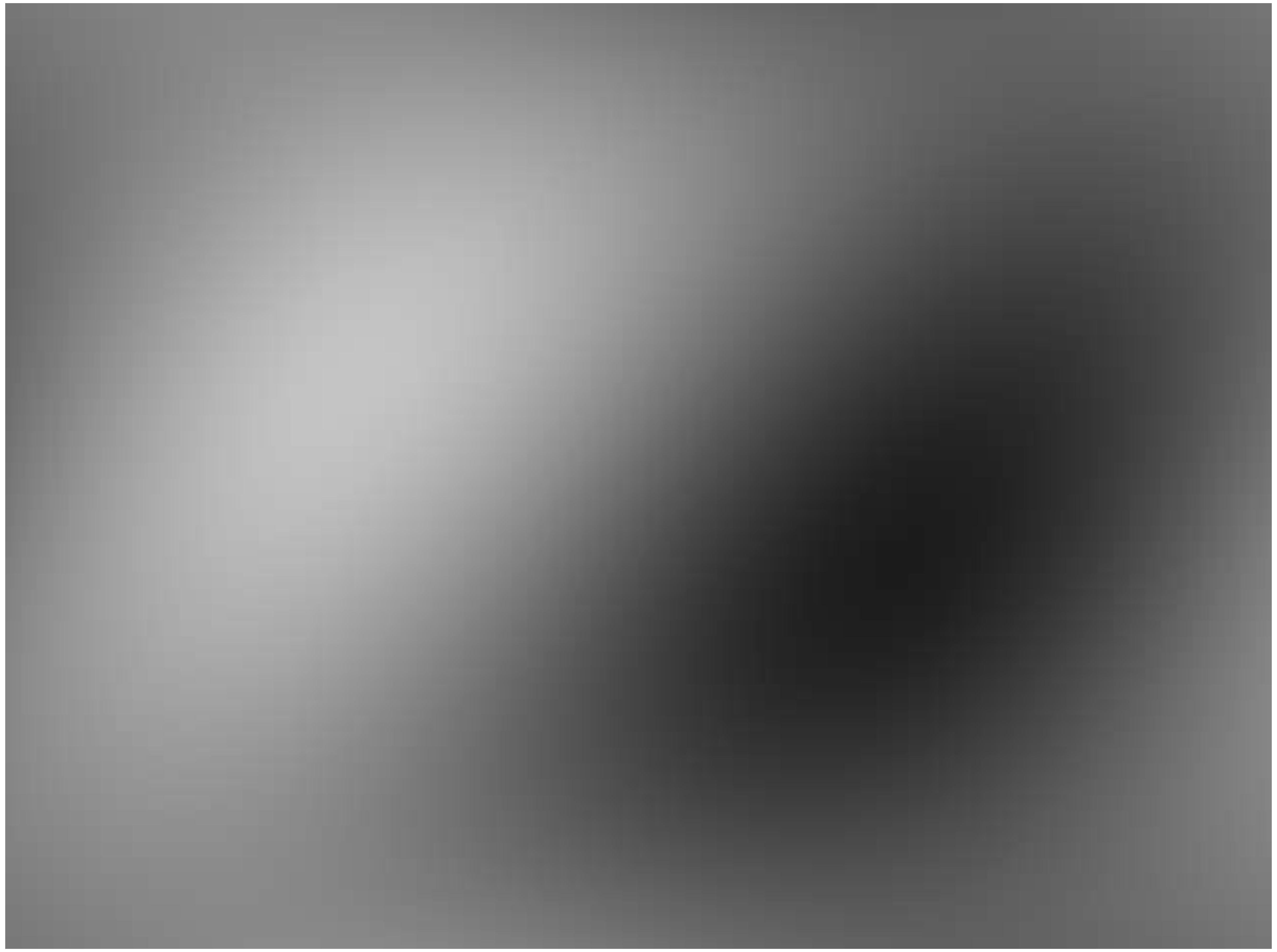
https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

Fourier Transform (you will **NOT** be tested on this)

First (lowest) frequency, a.k.a. average

https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

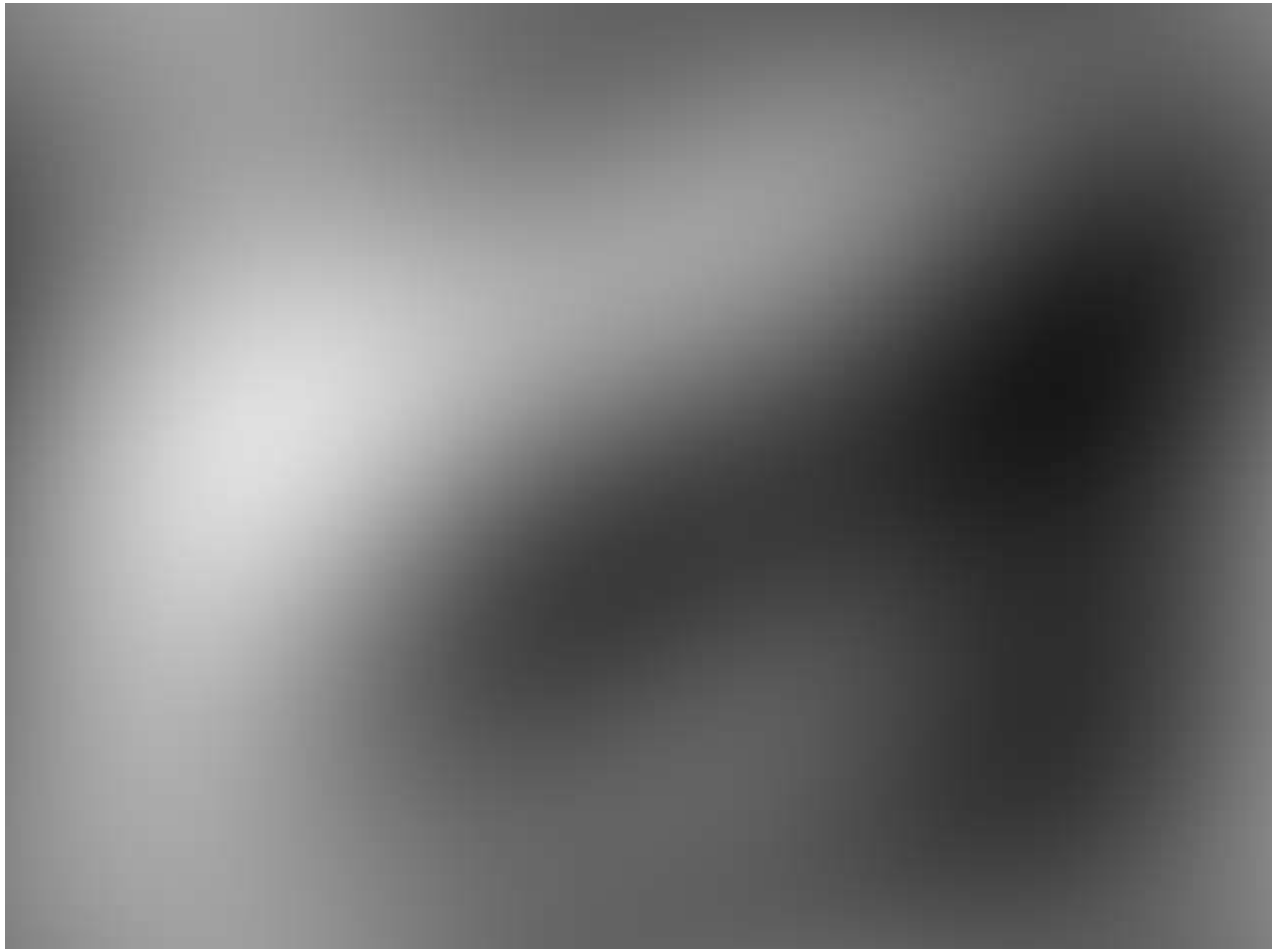
Fourier Transform (you will **NOT** be tested on this)



+ **Second** frequency

https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

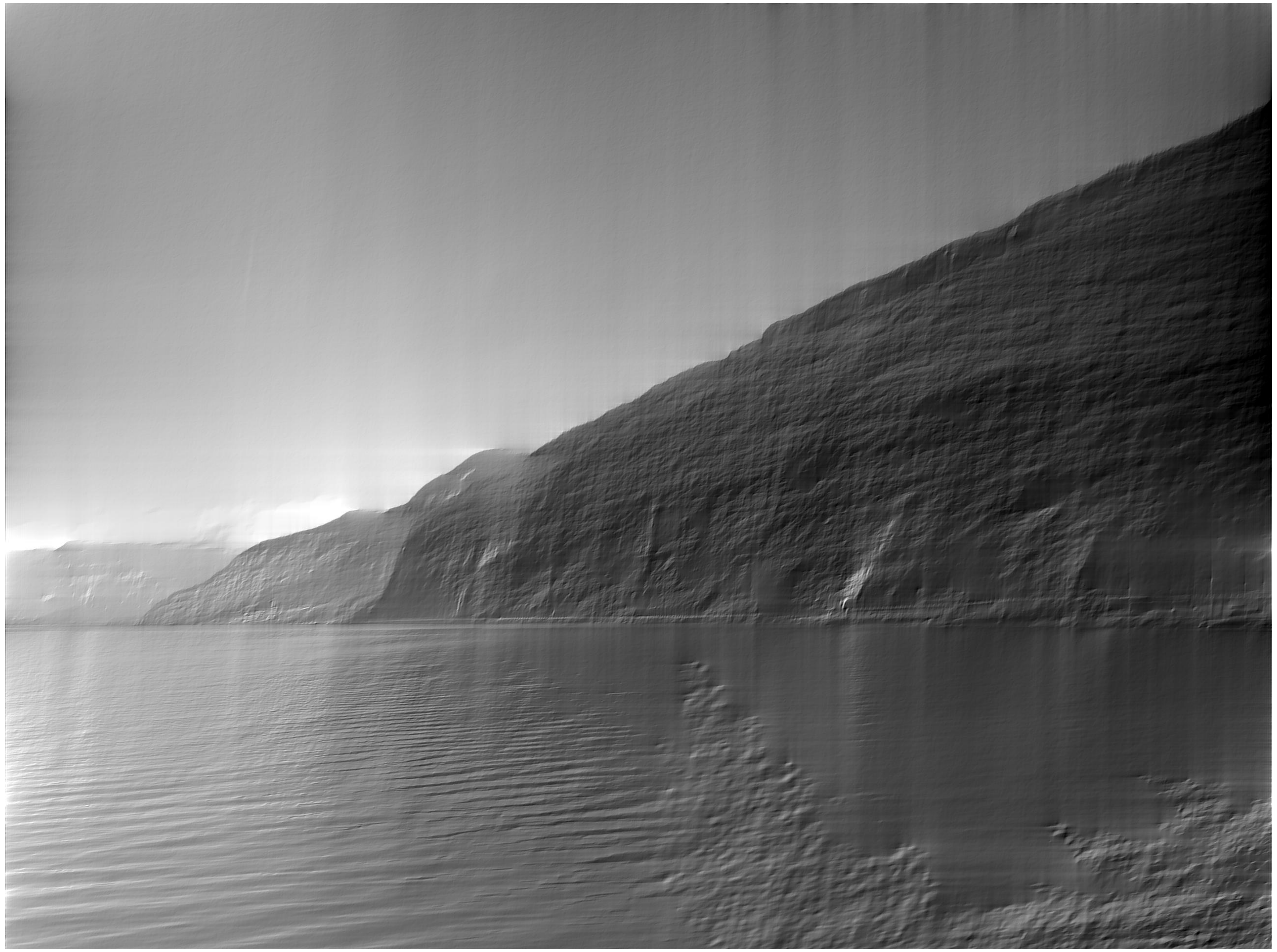
Fourier Transform (you will **NOT** be tested on this)



+ **Third** frequency

https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

Fourier Transform (you will **NOT** be tested on this)



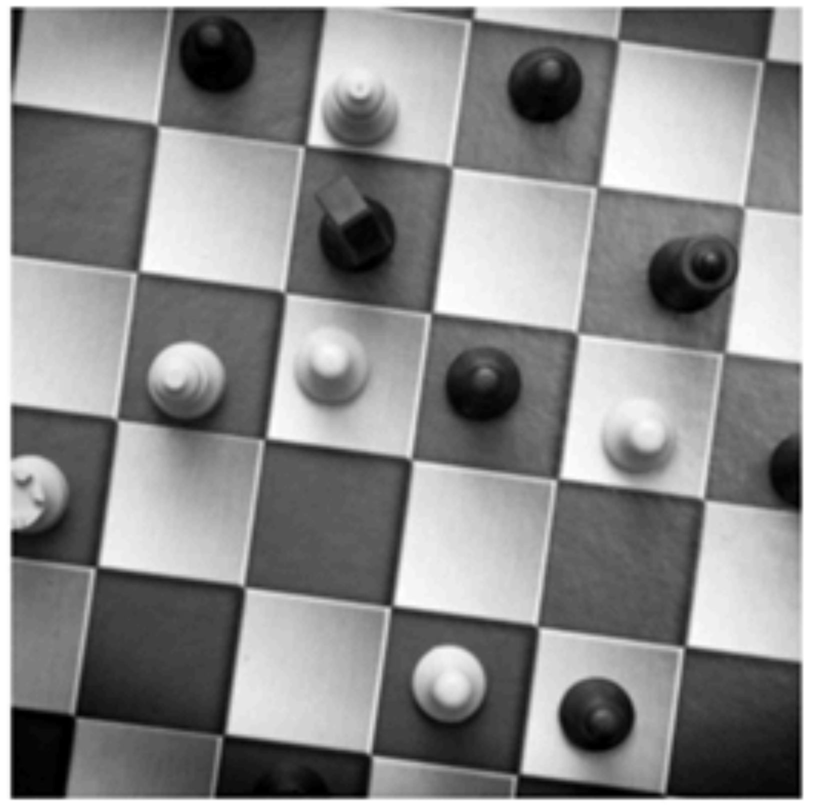
+ **50%** of frequencies

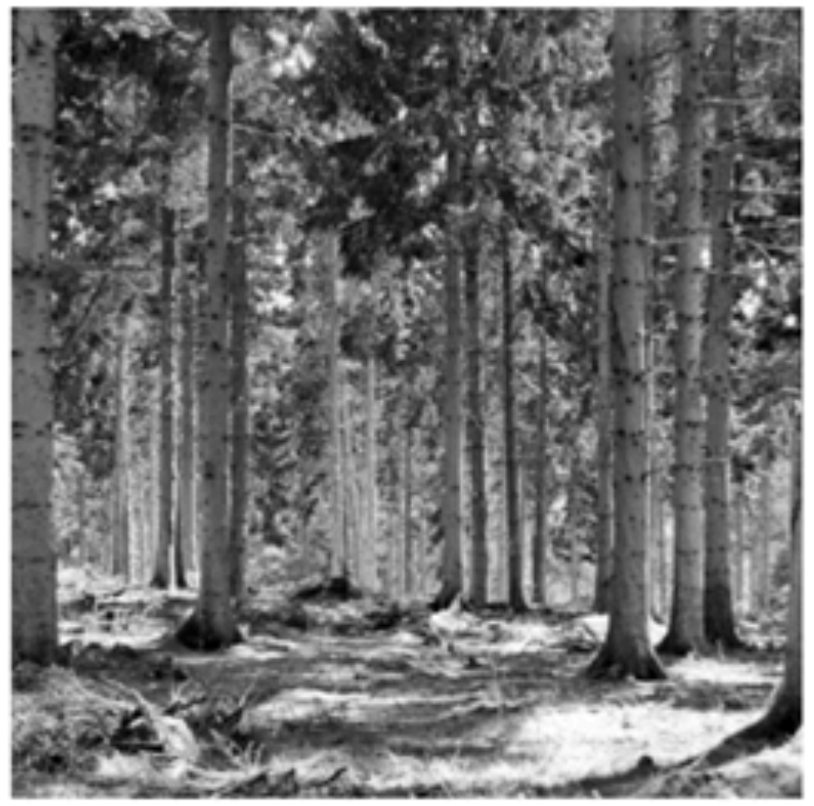
https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

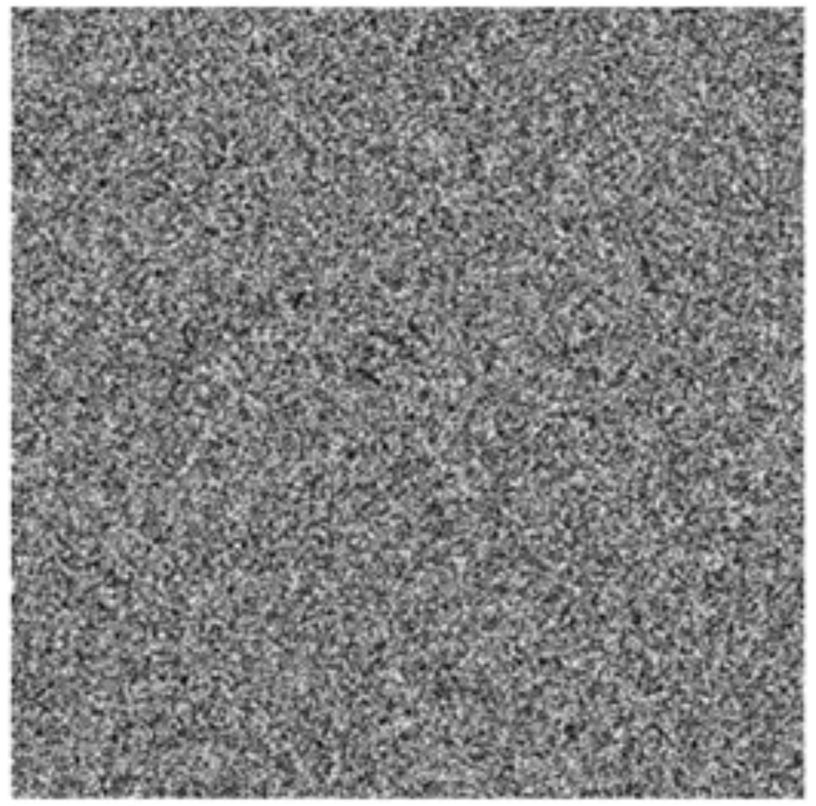
Fourier Transform (you will **NOT** be tested on this)

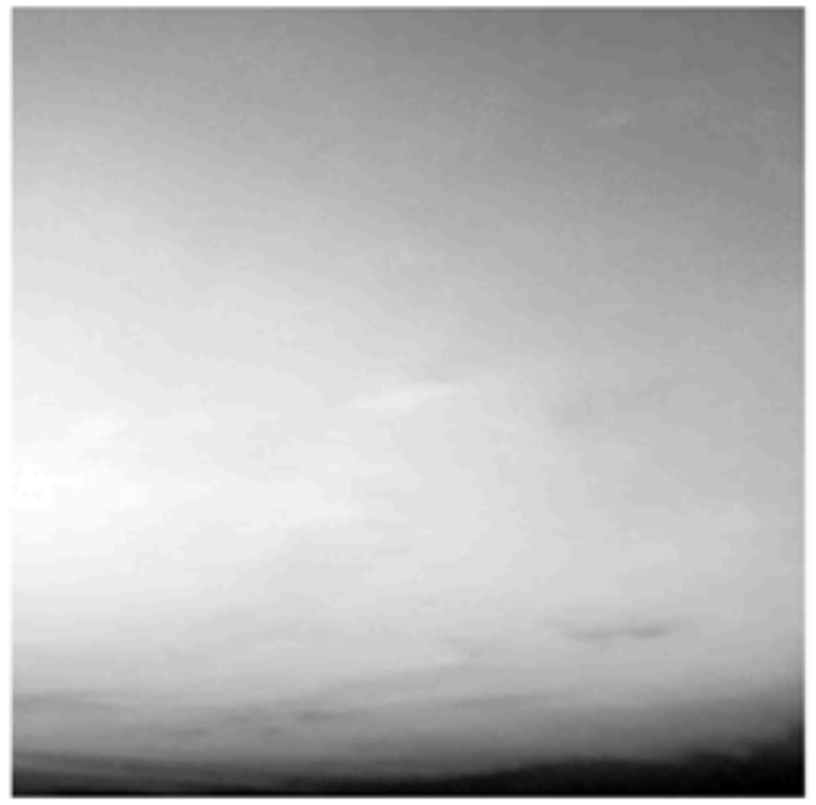
https://photo.stackexchange.com/questions/40401/what-does-frequency-mean-in-an-image/40410#40410

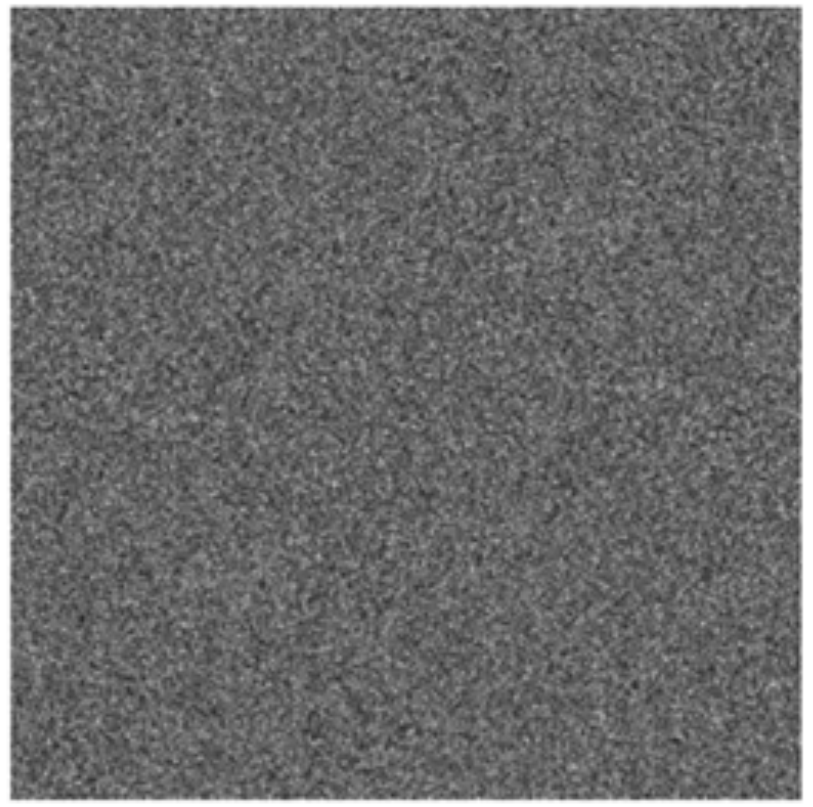
Fourier Transform (you will **NOT** be tested on this)

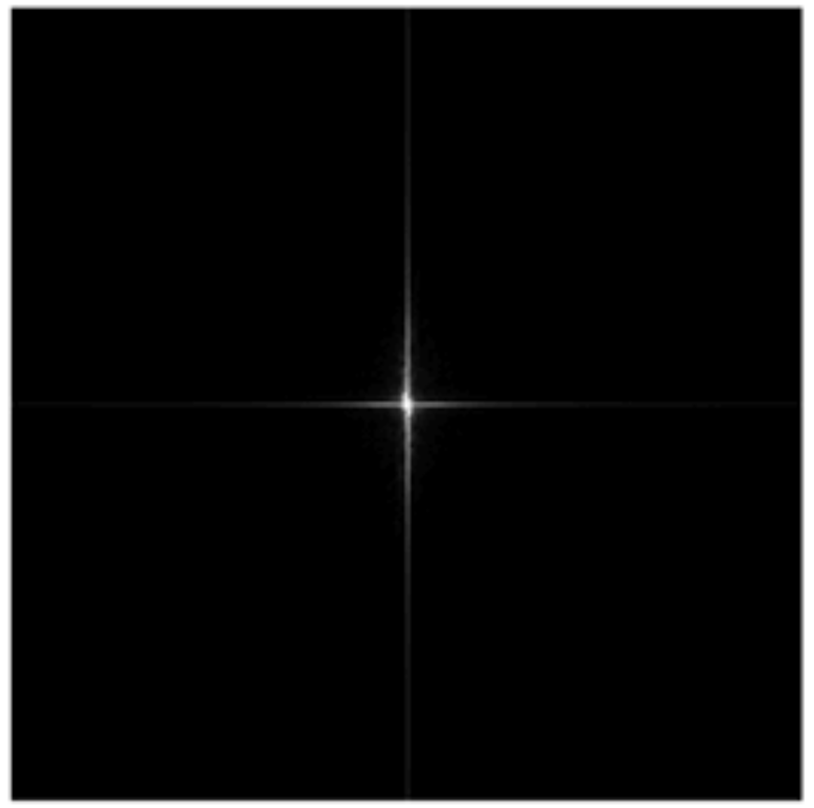

(I)

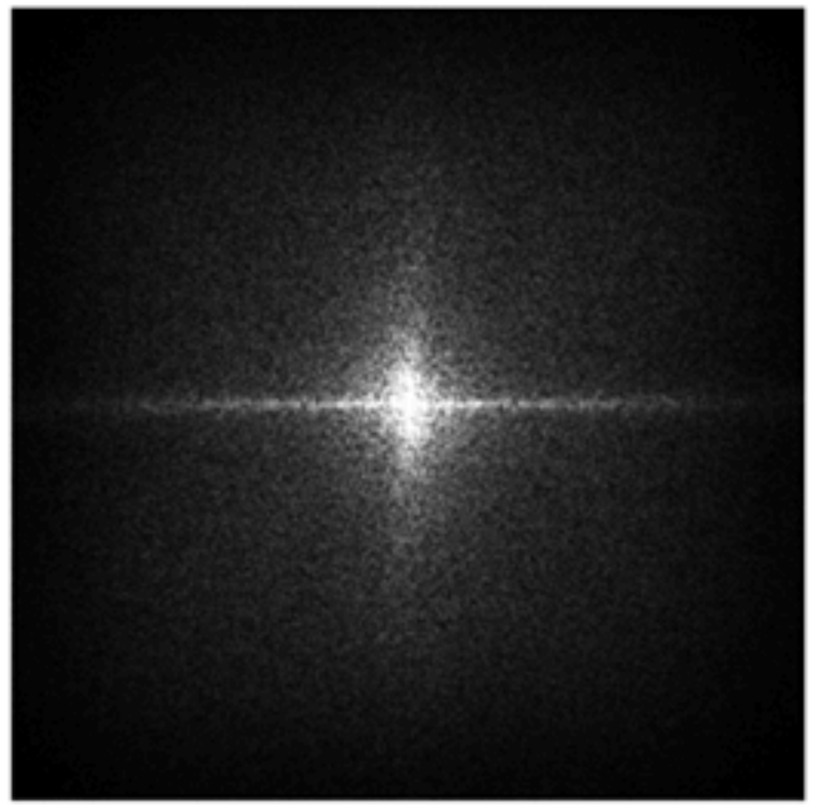

(II)

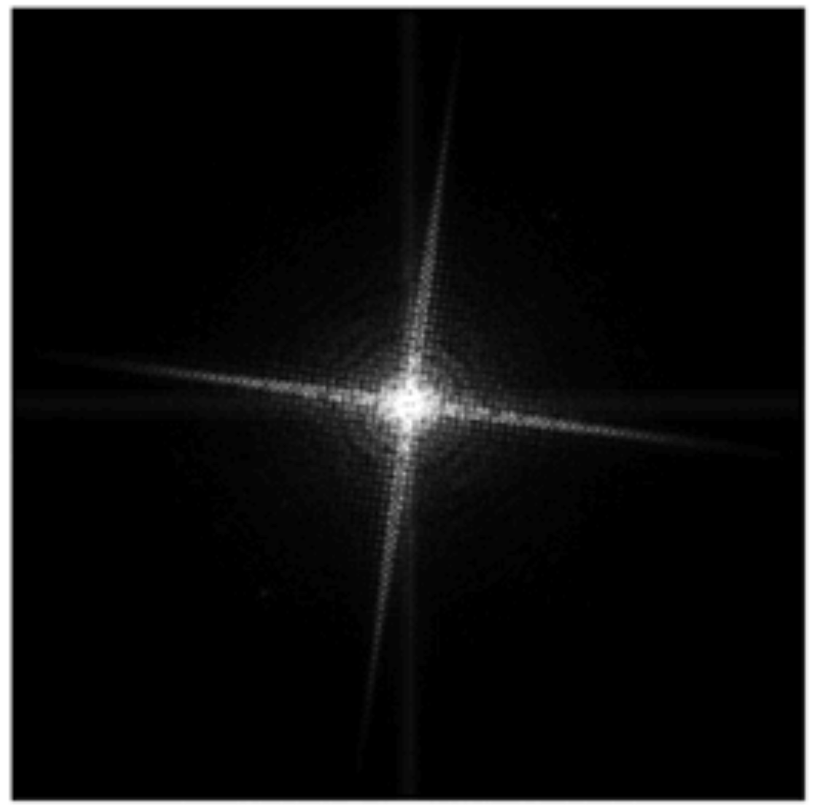

(III)


(IV)


(A)

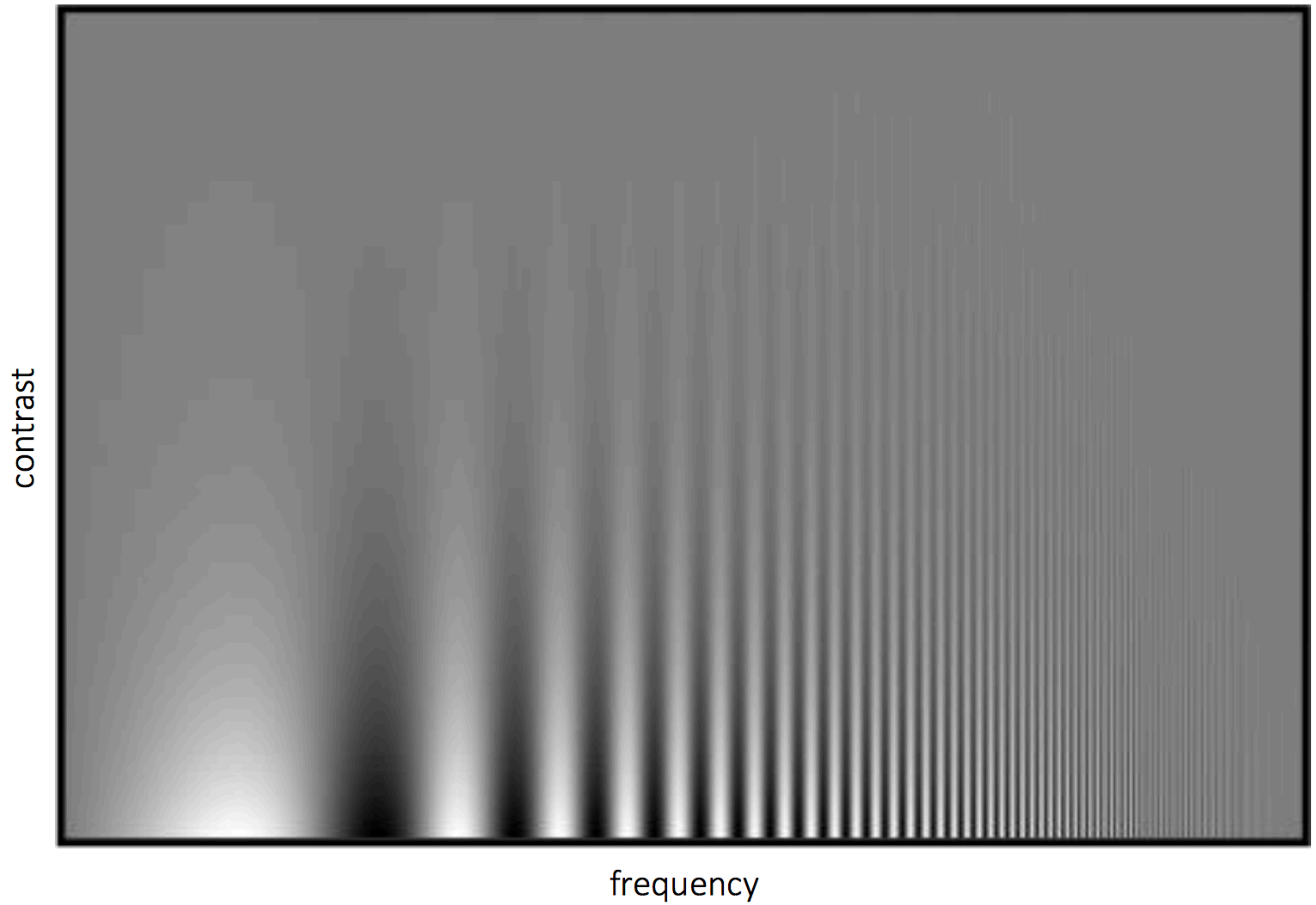

(B)


(C)


(D)

Fourier Transform (you will **NOT** be tested on this)

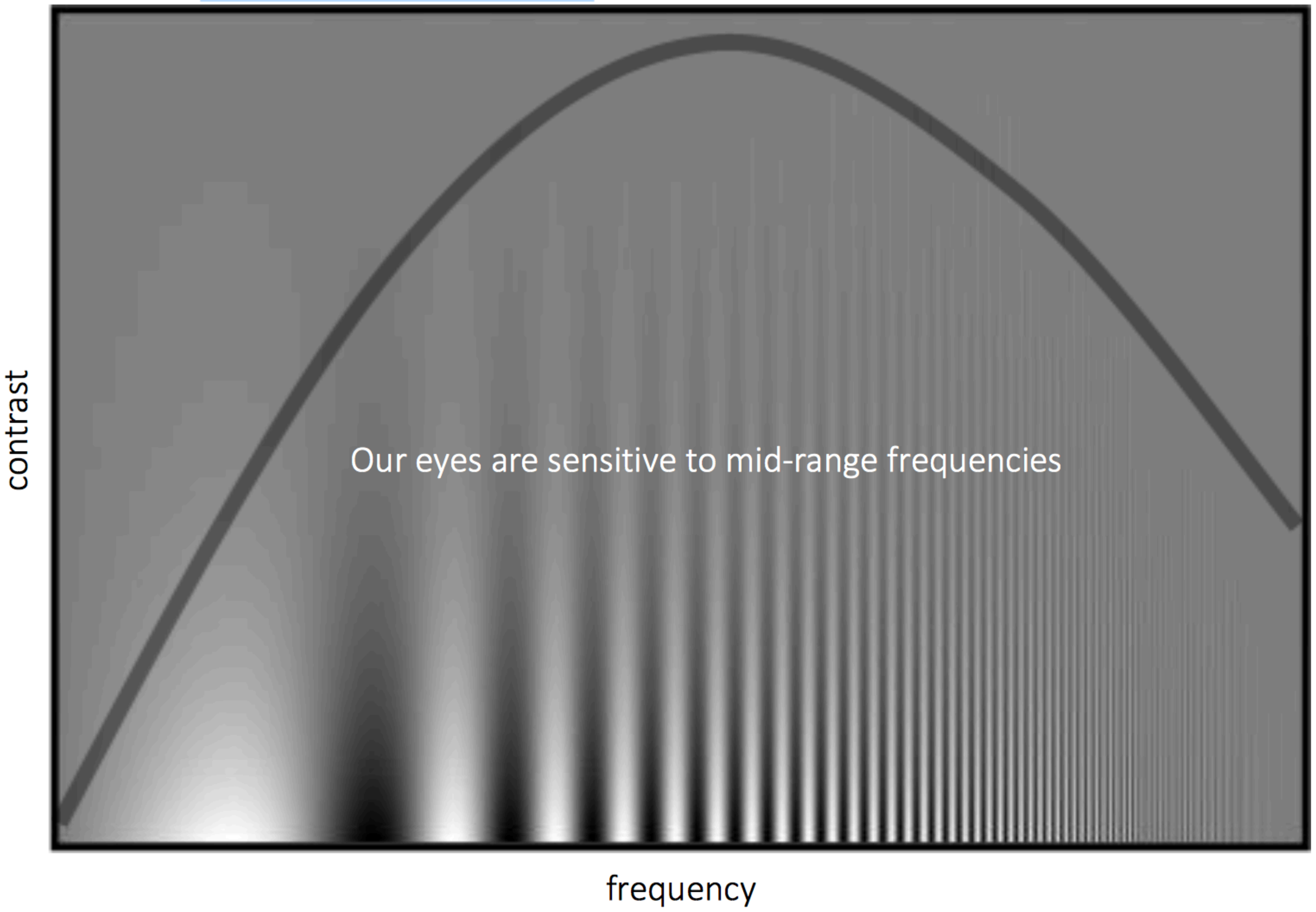
Experiment: Where of you see the stripes?



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Fourier Transform (you will **NOT** be tested on this)

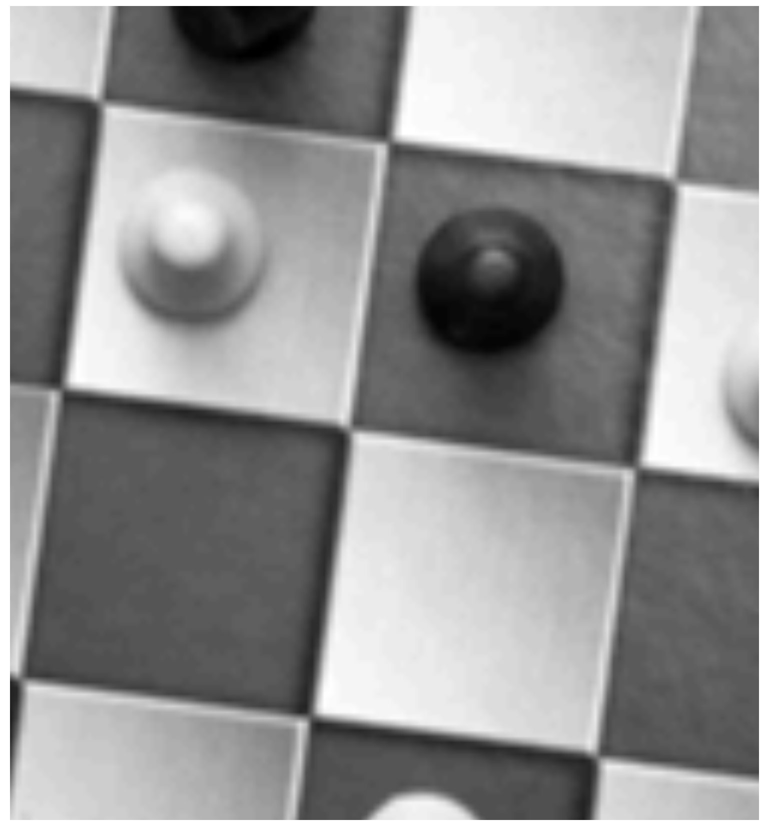
Campbell-Robson contrast sensitivity curve



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

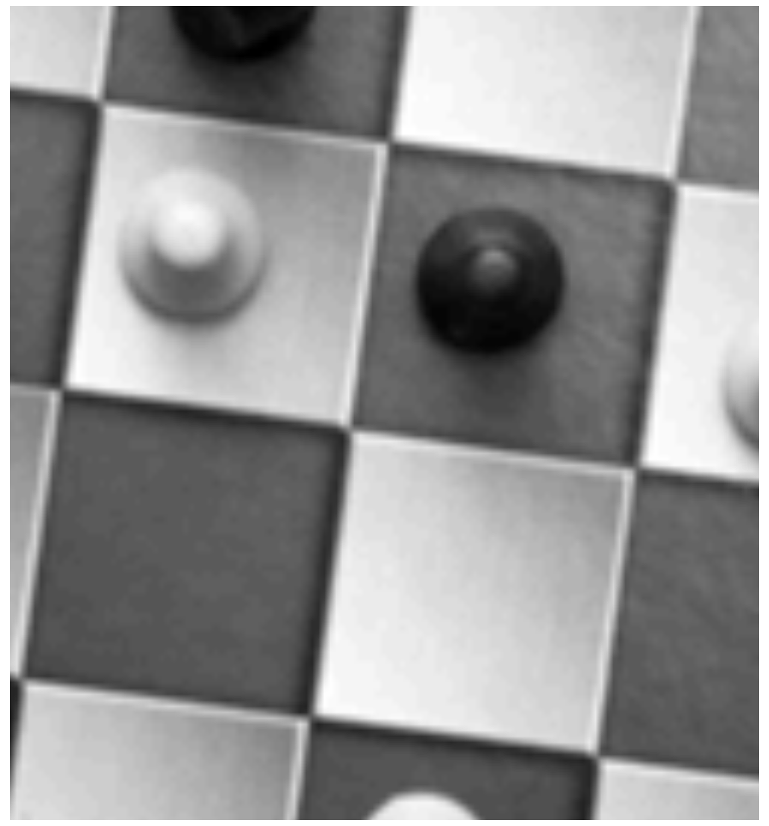
Fourier Transform (you will **NOT** be tested on this)

Distance to the screen will change the field of view of your eye and, as a result, frequency spectra of the image being formed on your retina



Fourier Transform (you will **NOT** be tested on this)

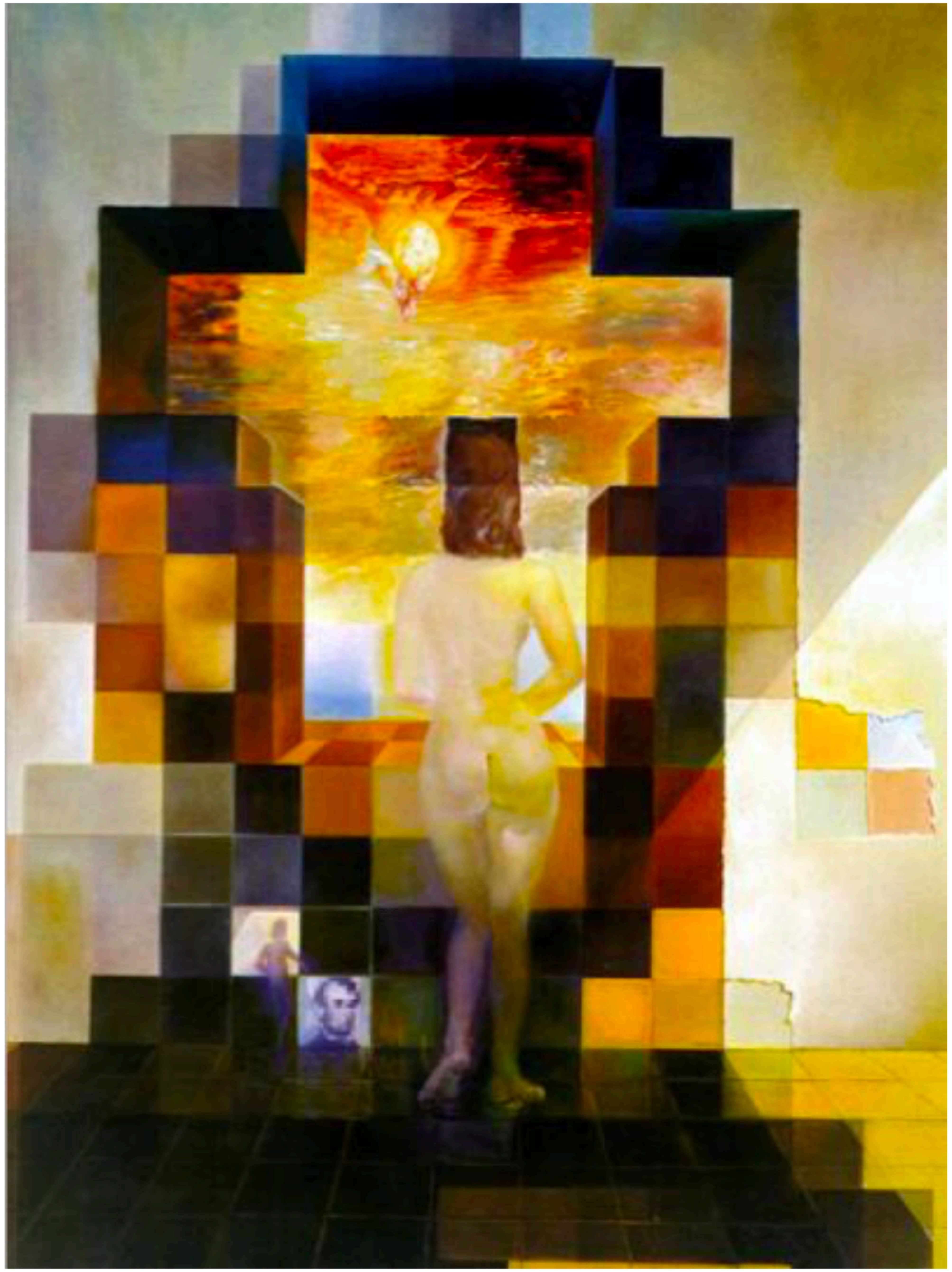
Distance to the screen will change the field of view of your eye and, as a result, frequency spectra of the image being formed on your retina



As you come **closer**, higher frequencies come into mid-range

As you move **away**, low frequencies come into mid-range

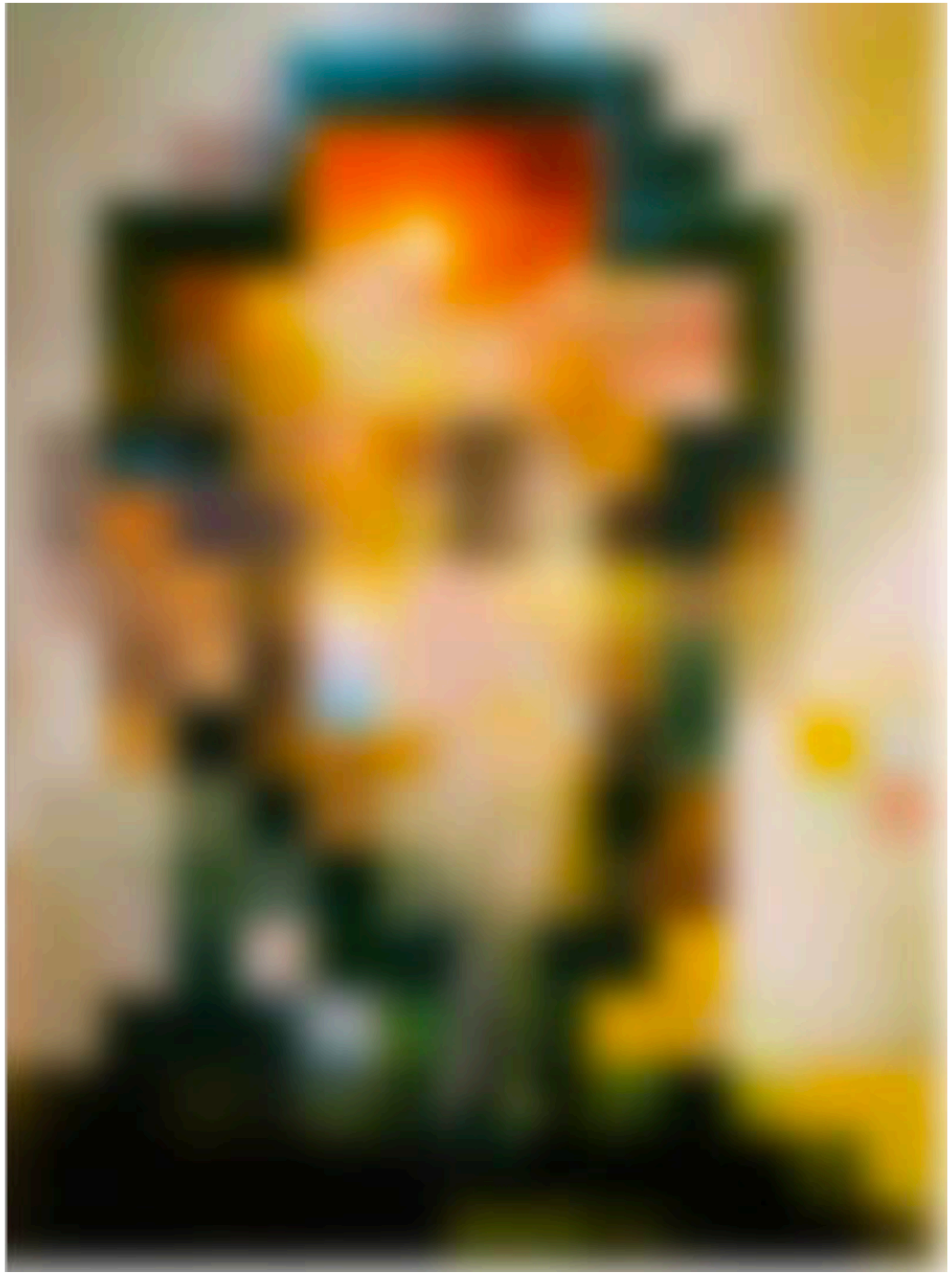
… back from **detour**



Gala Contemplating the Mediterranean Sea Which at Twenty Meters Becomes the Portrait of Abraham Lincoln (Homage to Rothko)

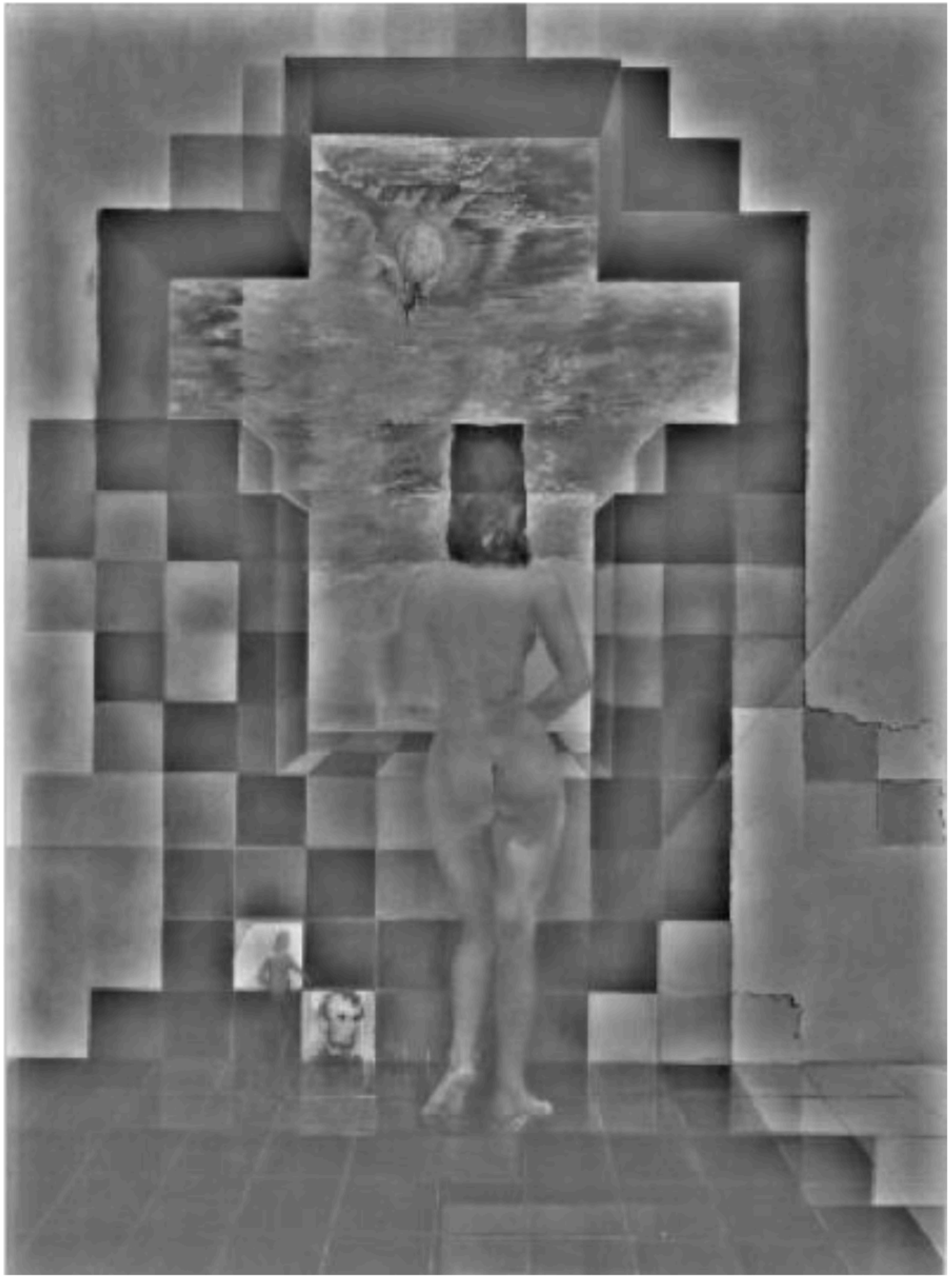
Salvador Dali, 1976

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)



Low-pass filtered version

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

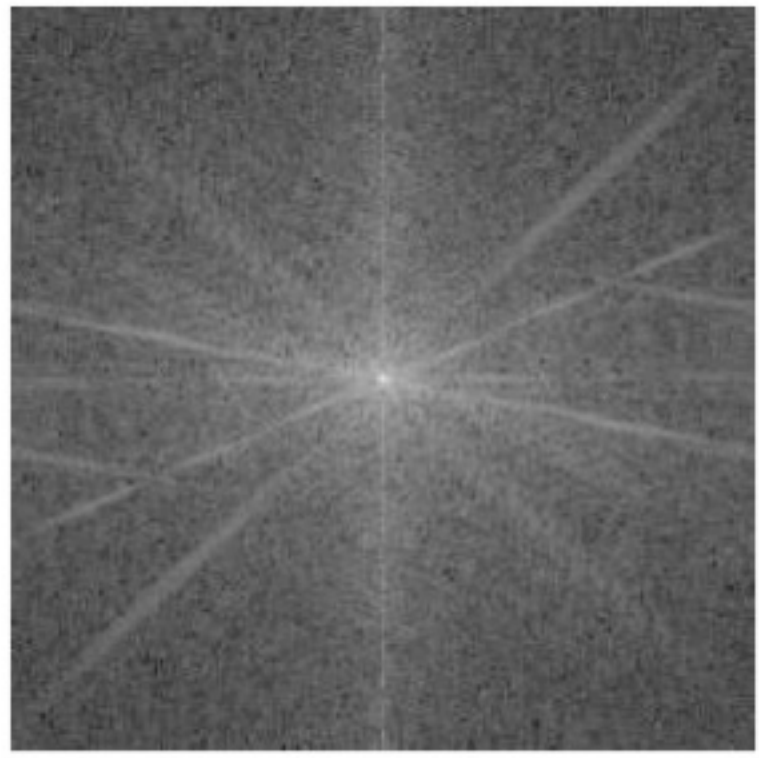


High-pass filtered version

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

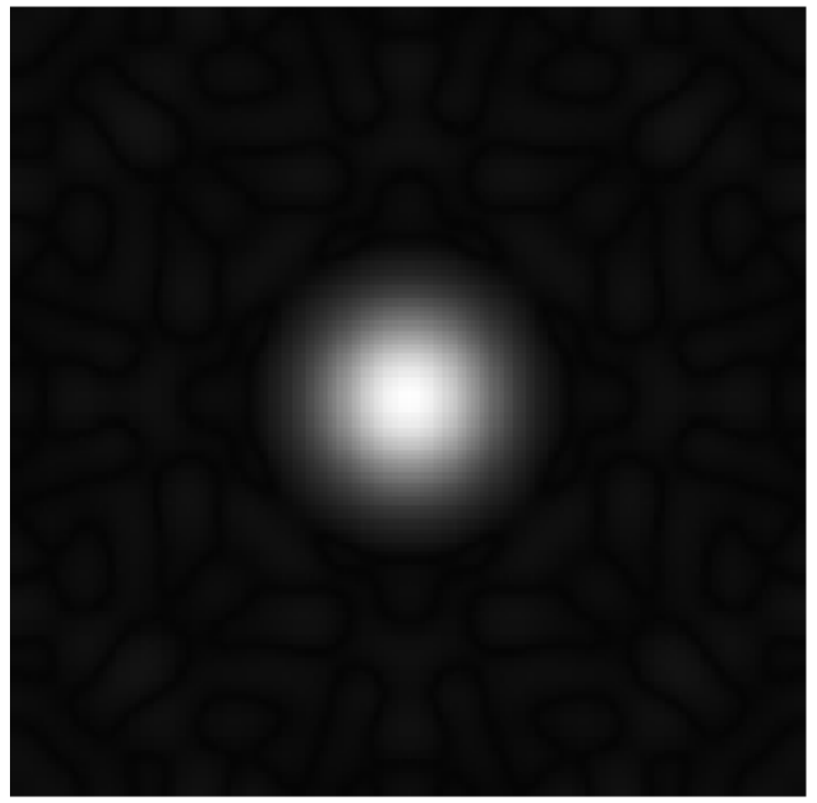
Low-pass / High-pass Filtering

image

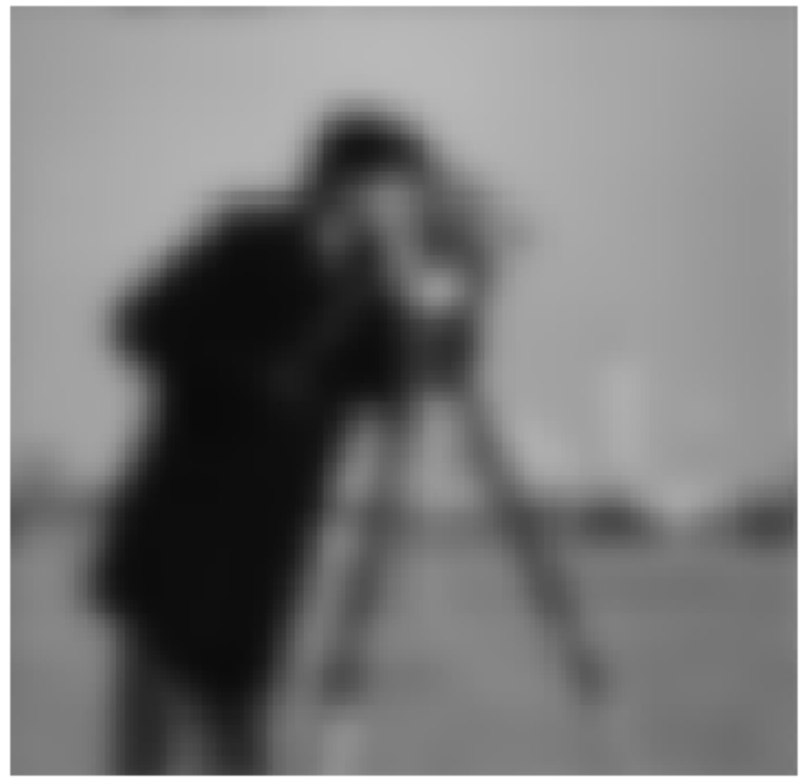


FFT (Mag)

complex
element-wise
multiplication

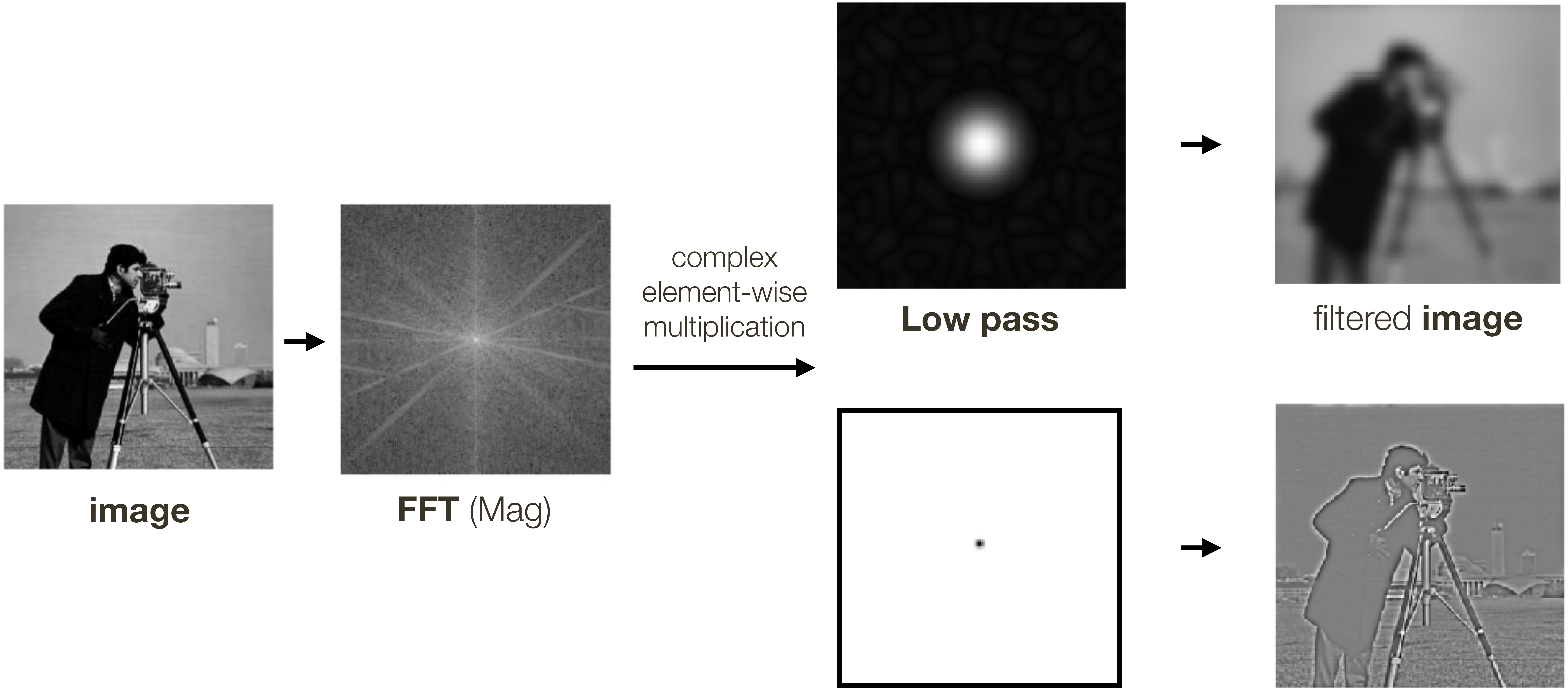


Low pass



filtered **image**

Low-pass / High-pass Filtering



complex
element-wise
multiplication

image

FFT (Mag)

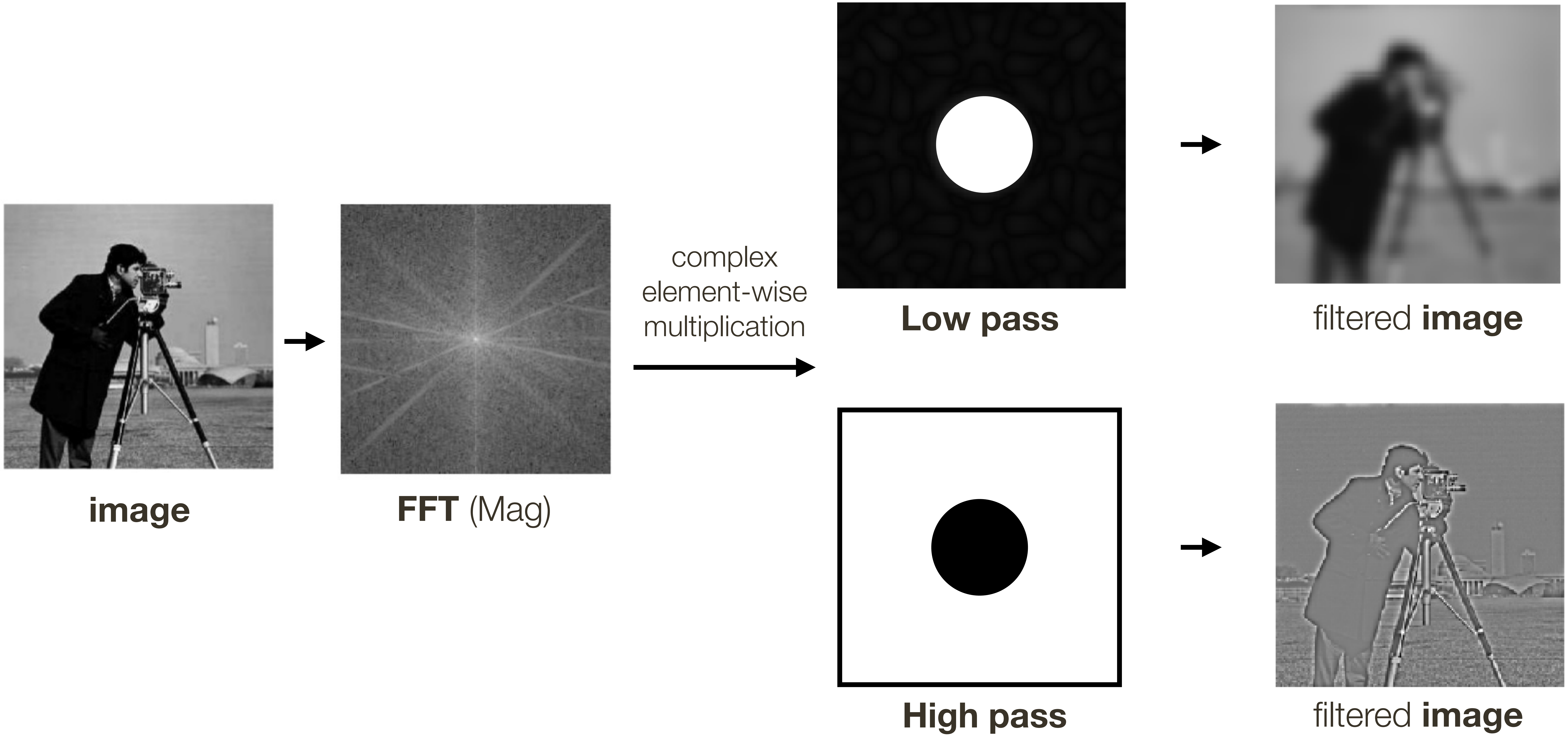
Low pass

High pass

filtered **image**

filtered **image**

Perfect **Low-pass / High-pass** Filtering



image

FFT (Mag)

complex element-wise multiplication

Low pass

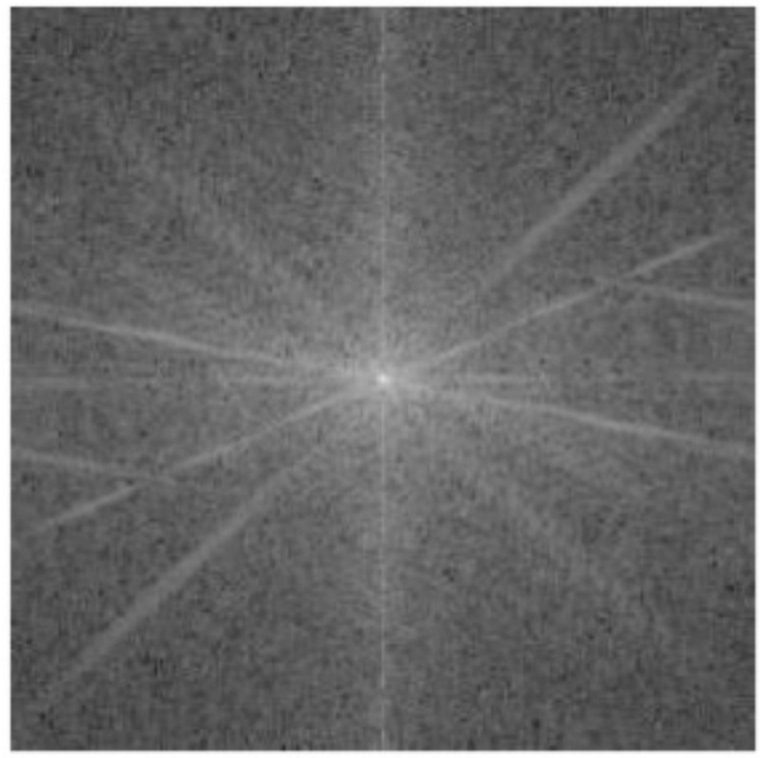
High pass

filtered **image**

filtered **image**

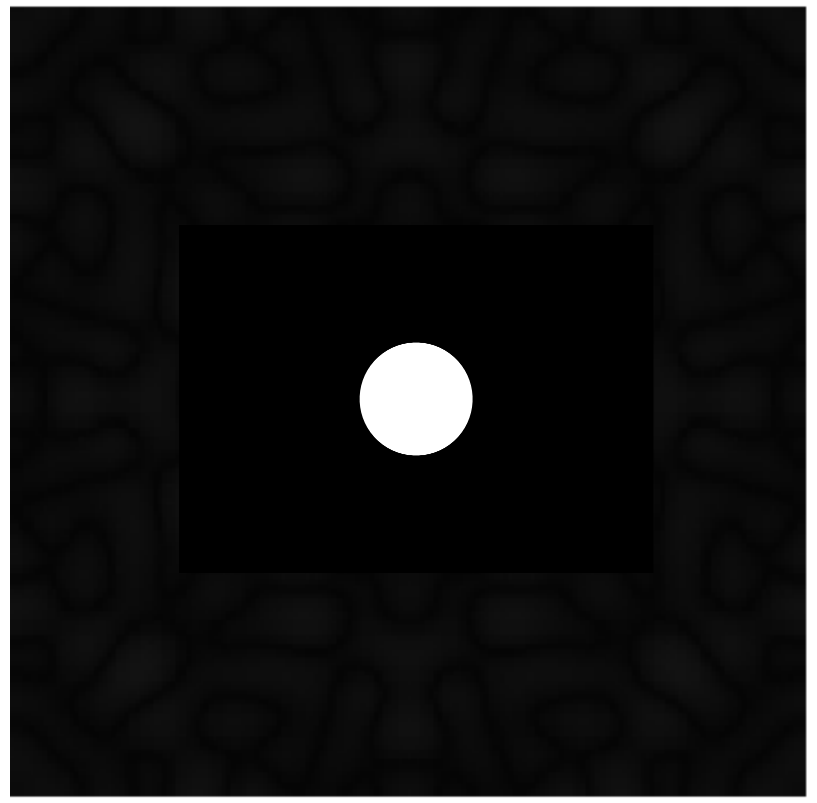
Perfect **Low-pass / High-pass** Filtering

image

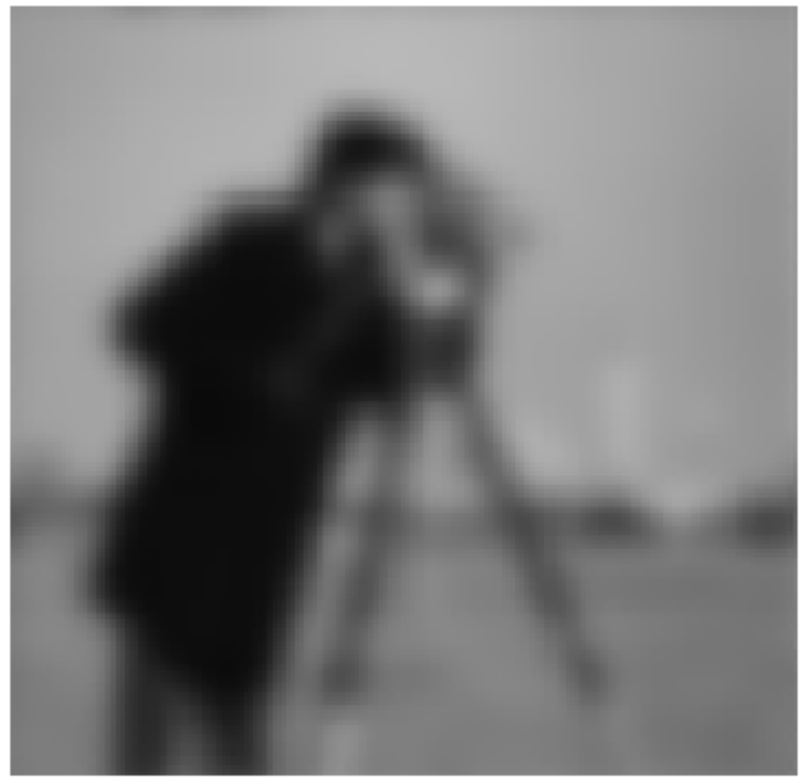


FFT (Mag)

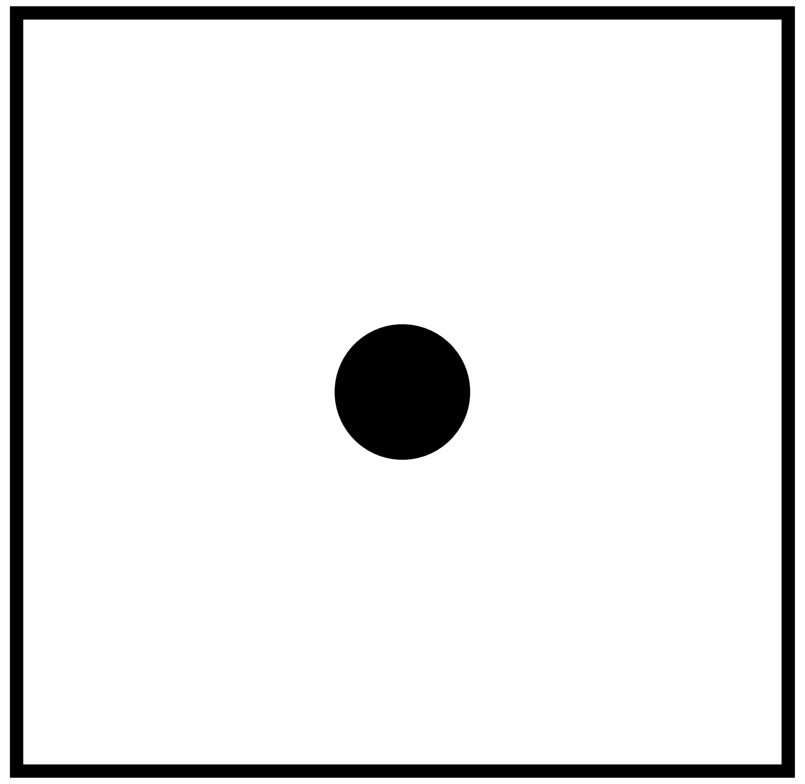
complex
element-wise
multiplication



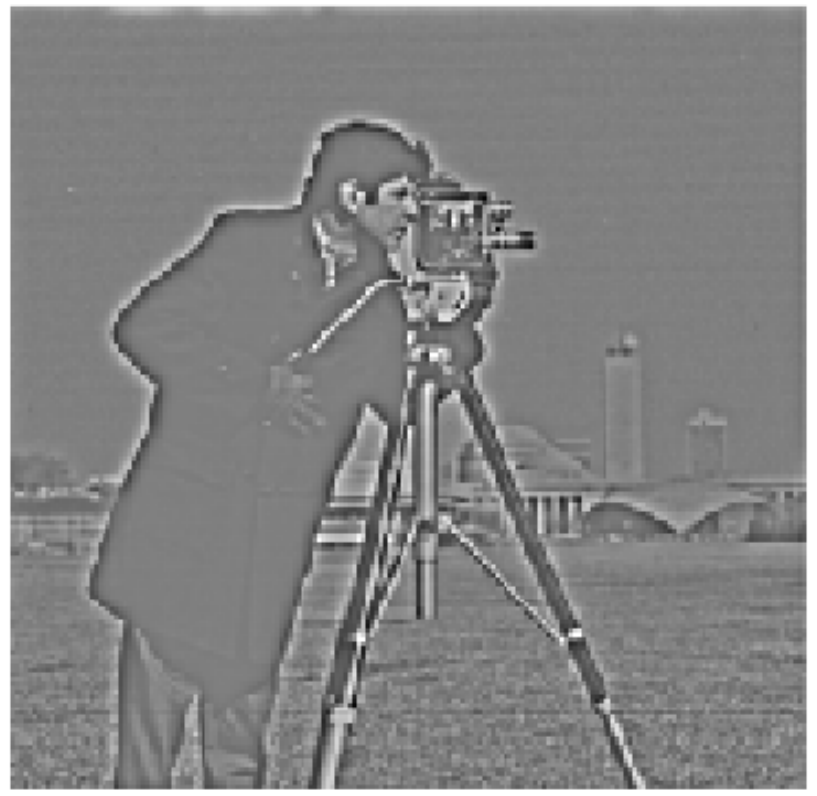
Low pass



filtered **image**



High pass



filtered **image**

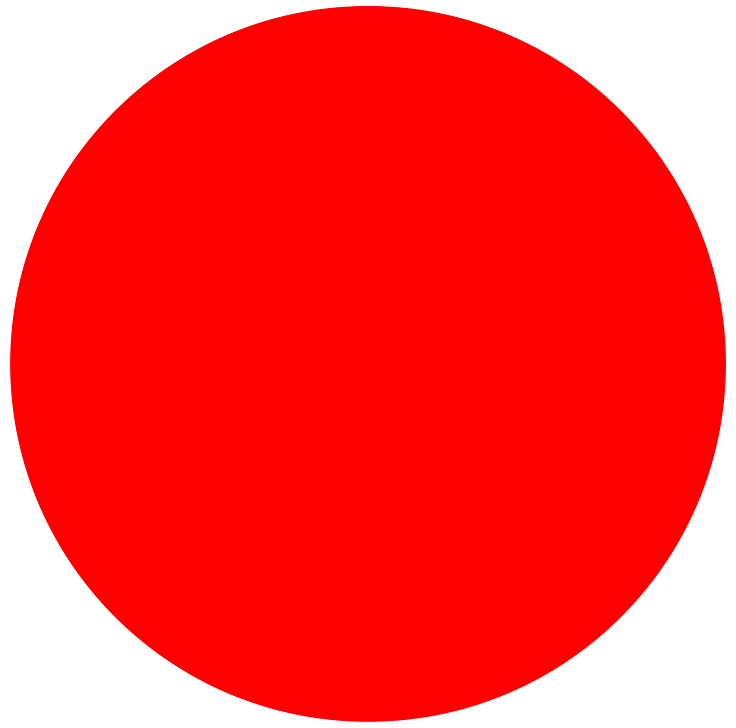
Low-pass Filtering = “Smoothing”?

Box Filter

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

Pillbox Filter



Gaussian Filter

$\frac{1}{256}$

1	4	6	4	1
4	16	24	16	4
6	24	36	24	6
4	16	24	16	4
1	4	6	4	1

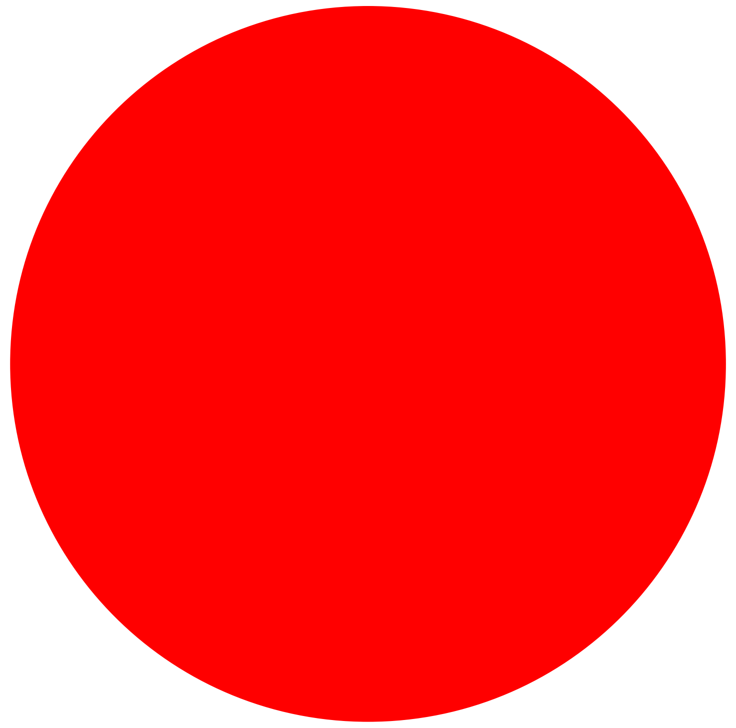
Are all of these **low-pass** filters?

Low-pass Filtering = “Smoothing”

Box Filter

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

Pillbox Filter



Gaussian Filter

$$\frac{1}{256}\begin{bmatrix}1 & 4 & 6 & 4 & 1\\ 4 & 16 & 24 & 16 & 4\\ 6 & 24 & 36 & 24 & 6\\ 4 & 16 & 24 & 16 & 4\\ 1 & 4 & 6 & 4 & 1\end{bmatrix}$$

Are all of these **low-pass** filters?

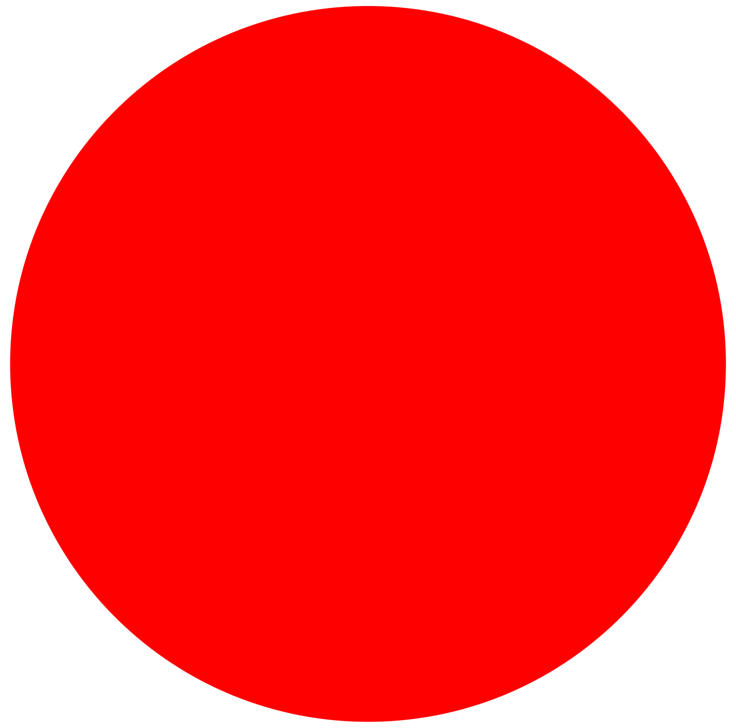
Low-pass filter: Low pass filter filters out all of the high frequency content of the image, only low frequencies remain

Low-pass Filtering = “Smoothing”

Box Filter

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

Pillbox Filter



Gaussian Filter

$$\frac{1}{256}\begin{bmatrix}1 & 4 & 6 & 4 & 1\\ 4 & 16 & 24 & 16 & 4\\ 6 & 24 & 36 & 24 & 6\\ 4 & 16 & 24 & 16 & 4\\ 1 & 4 & 6 & 4 & 1\end{bmatrix}$$

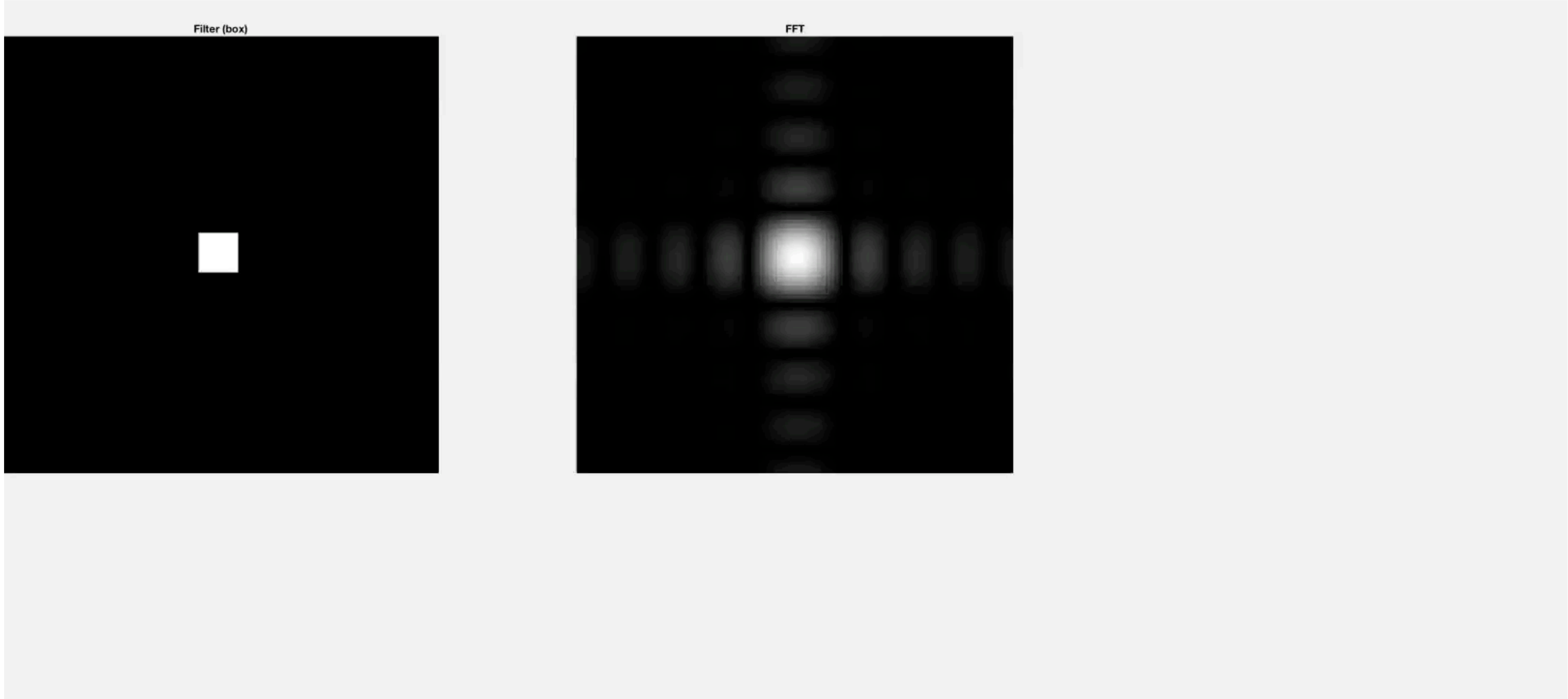
Are all of these **low-pass** filters?

Low-pass filter: Low pass filter filters out all of the high frequency content of the image, only low frequencies remain

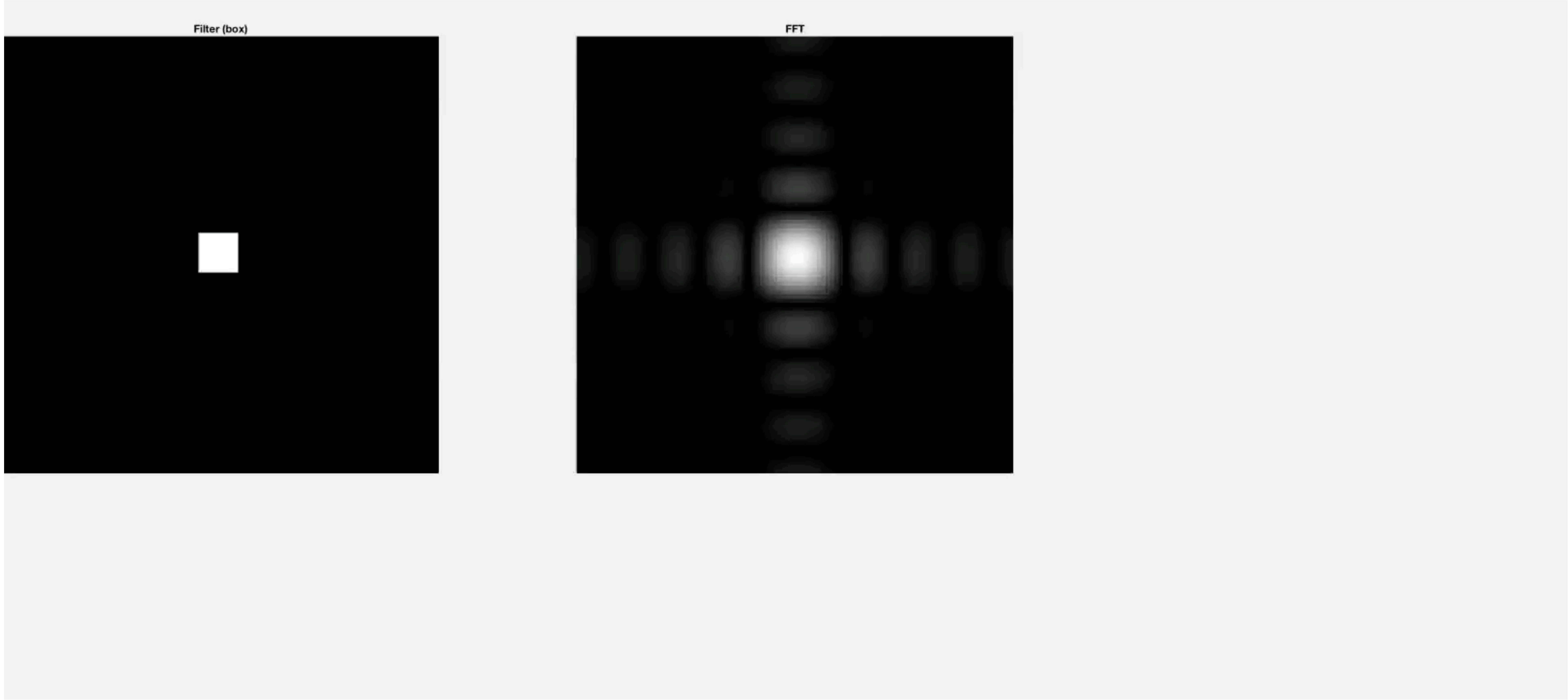
0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0

Image

Low-pass Filtering = “Smoothing”



Low-pass Filtering = “Smoothing”



Linear Filters: Properties

Let $\otimes$ denote convolution. Let $I(X, Y)$ be a digital image

Superposition: Let F_1 and F_2 be digital filters

$$(F_1 + F_2) \otimes I(X, Y) = F_1 \otimes I(X, Y) + F_2 \otimes I(X, Y)$$

Scaling: Let F be digital filter and let k be a scalar

$$(kF) \otimes I(X, Y) = F \otimes (kI(X, Y)) = k(F \otimes I(X, Y))$$

Shift Invariance: Output is local (i.e., no dependence on absolute position)

An operation is **linear** if it satisfies both **superposition** and **scaling**

Linear Filters: Additional Properties

Let $\otimes$ denote convolution. Let $I(X,Y)$ be a digital image. Let F and G be digital filters

— Convolution is **associative**. That is,

$$G \otimes (F \otimes I(X,Y)) = (G \otimes F) \otimes I(X,Y)$$

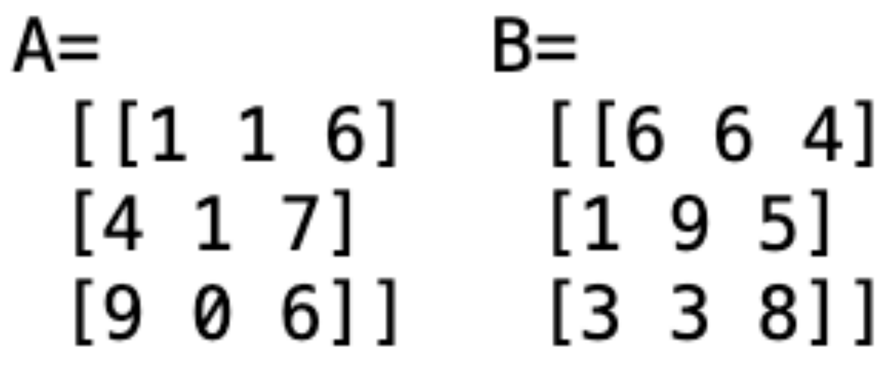
— Convolution is **symmetric**. That is,

$$(G \otimes F) \otimes I(X,Y) = (F \otimes G) \otimes I(X,Y)$$

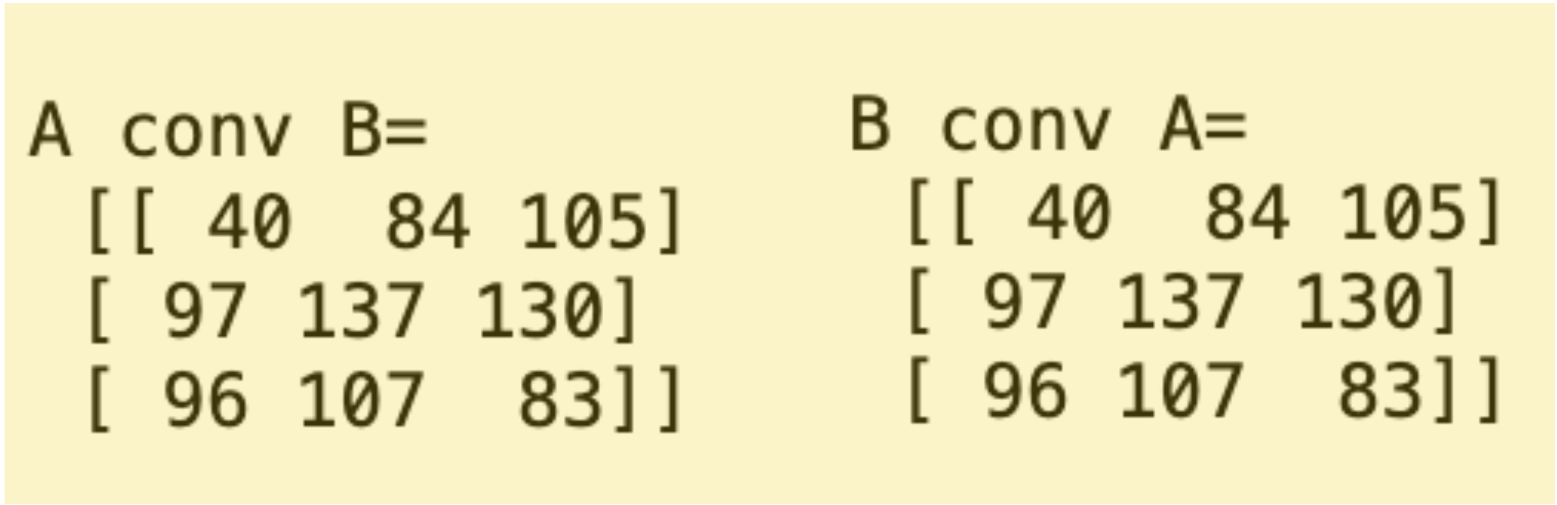
Convolving $I(X,Y)$ with filter F and then convolving the result with filter G can be achieved in single step, namely convolving $I(X,Y)$ with filter $G \otimes F = F \otimes G$

Note: Correlation, in general, is **not associative**.

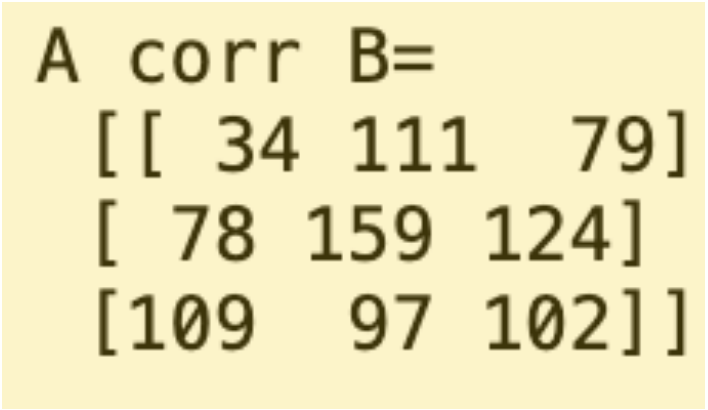
Associativity Example



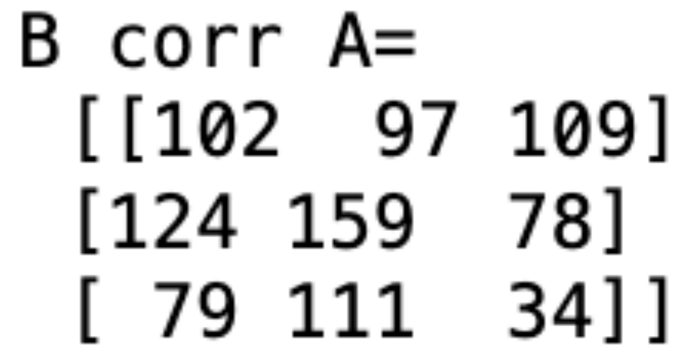
```
A=              B=
 [[1 1 6]        [[6 6 4]
 [4 1 7]         [1 9 5]
 [9 0 6]]        [3 3 8]]
```



```
A conv B=              B conv A=
 [[ 40  84 105]         [[ 40  84 105]
 [ 97 137 130]          [ 97 137 130]
 [ 96 107  83]]         [ 96 107  83]]
```



```
A corr B=
 [[ 34 111  79]
 [ 78 159 124]
 [109  97 102]]
```



```
B corr A=
 [[102  97 109]
 [124 159  78]
 [ 79 111  34]]
```

$$conv(A, B) = conv(B, A)$$

$$corr(A, B) \neq corr(B, A)$$

Linear Filters: Additional Properties

Let $\otimes$ denote convolution. Let $I(X,Y)$ be a digital image. Let F and G be digital filters

— Convolution is **associative**. That is,

$$G \otimes (F \otimes I(X,Y)) = (G \otimes F) \otimes I(X,Y)$$

— Convolution is **symmetric**. That is,

$$(G \otimes F) \otimes I(X,Y) = (F \otimes G) \otimes I(X,Y)$$

Convolving $I(X,Y)$ with filter F and then convolving the result with filter G can be achieved in single step, namely convolving $I(X,Y)$ with filter $G \otimes F = F \otimes G$

Note: Correlation, in general, is **not associative**.

Example: Two Box Filters

filter = boxfilter(3)
signal.correlate2d(filter, filter,′ full′)

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix} = \frac{1}{81}\begin{bmatrix}1 & 2 & 3 & 2 & 1\\2 & 4 & 6 & 4 & 2\\3 & 6 & 9 & 6 & 3\\2 & 4 & 6 & 4 & 2\\1 & 2 & 3 & 2 & 1\end{bmatrix}$$

3x3 **Box** 3x3 **Box**

Example: Two Box Filters

Note, in this case you have to pad maximally until two filters no longer overlap

Treat one filter as padded "image"

$$\frac{1}{9}\begin{array}{|c|c|c|c|c|c|c|}\hline 0&0&0&0&0&0&0\\ \hline 0&0&0&0&0&0&0\\ \hline 0&0&1&1&1&0&0\\ \hline 0&0&1&1&1&0&0\\ \hline 0&0&1&1&1&0&0\\ \hline 0&0&0&0&0&0&0\\ \hline 0&0&0&0&0&0&0\\ \hline\end{array} \otimes \frac{1}{9}\begin{array}{|c|c|c|}\hline 1&1&1\\ \hline 1&1&1\\ \hline 1&1&1\\ \hline\end{array} = \frac{1}{81}\begin{array}{|c|c|c|c|c|c|c|}\hline &&&&&&\\ \hline &1&&&&&\\ \hline &&&&&&\\ \hline &&&&&&\\ \hline &&&&&&\\ \hline &&&&&&\\ \hline &&&&&&\\ \hline\end{array}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

Treat one filter as padded "image"

$$\frac{1}{9}\begin{bmatrix}0&0&0&0&0&0&0\\0&0&0&0&0&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&0&0&0&0&0\\0&0&0&0&0&0&0\end{bmatrix}\otimes\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}=\frac{1}{81}\begin{bmatrix}\;&\;&\;&\;&\;&\;&\;\\ &1&\boxed{2}& & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \end{bmatrix}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

Treat one filter as padded “image”

$$\frac{1}{9}\begin{bmatrix}0&0&0&0&0&0&0\\0&0&0&0&0&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&0&0&0&0&0\\0&0&0&0&0&0&0\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} = \frac{1}{81}\begin{bmatrix}\;&\;&\;&\;&\;&\;&\;\\ &1&2&\boxed{3}&&&\\ &&&&&&\\ &&&&&&\\ &&&&&&\\ &&&&&&\\ &&&&&&\end{bmatrix}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

Treat one filter as padded "image"

$$\frac{1}{9}\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \frac{1}{81}\begin{bmatrix} & & & & & & \\ & 1 & 2 & 3 & 2 & 1 & \\ & 2 & 4 & \boxed{6} & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \end{bmatrix}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

Treat one filter as padded “image”

$$\frac{1}{9}\begin{bmatrix}0&0&0&0&0&0&0\\0&0&0&0&0&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&0&0&0&0&0\\0&0&0&0&0&0&0\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} = \frac{1}{81}\begin{bmatrix} & & & & & & \\ &1&2&3&2&1& \\ &2&4&6&4&2& \\ &3&6&9&6&3& \\ &2&4&6&4&2& \\ &1&2&3&2&\boxed{1}& \\ & & & & & & \end{bmatrix}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

Treat one filter as padded “image”

$$\frac{1}{9}\begin{bmatrix}0&0&0&0&0&0&0\\0&0&0&0&0&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&1&1&1&0&0\\0&0&0&0&0&0&0\\0&0&0&0&0&0&0\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} = \frac{1}{81}\begin{bmatrix}1&2&3&2&1\\2&4&6&4&2\\3&6&9&6&3\\2&4&6&4&2\\1&2&3&2&1\end{bmatrix}$$

3x3 **Box**

3x3 **Box**

Output

Example: Two Box Filters

filter = boxfilter(3)
temp = signal.correlate2d(filter, filter,′ full′)
signal.correlate2d(filter, temp,′ full′)

$$\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} \otimes \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix} = \frac{1}{729}\begin{bmatrix}1&3&6&7&6&3&1\\3&9&18&21&18&9&3\\6&18&36&42&36&18&6\\7&21&42&49&42&21&7\\6&18&36&42&36&18&6\\3&9&18&21&18&9&3\\1&3&6&7&6&3&1\end{bmatrix}$$

3x3 **Box** 3x3 **Box** 3x3 **Box**

Example: Separable Gaussian Filter

$$\frac{1}{16}\begin{array}{|c|c|c|c|c|}\hline 1 & 4 & 6 & 4 & 1 \\ \hline\end{array} \otimes \frac{1}{16}\begin{array}{|c|}\hline 1 \\ \hline 4 \\ \hline 6 \\ \hline 4 \\ \hline 1 \\ \hline\end{array} = \frac{1}{256}\begin{array}{|c|c|c|c|c|}\hline 1 & 4 & 6 & 4 & 1 \\ \hline 4 & 16 & 24 & 16 & 4 \\ \hline 6 & 24 & 36 & 24 & 6 \\ \hline 4 & 16 & 24 & 16 & 4 \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline\end{array}$$

Example: Separable Gaussian Filter

$$\frac{1}{16}\begin{array}{|c|c|c|c|c|}\hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline \end{array} \otimes \frac{1}{16}\begin{array}{|c|}\hline 1 \\ \hline 4 \\ \hline 6 \\ \hline 4 \\ \hline 1 \\ \hline \end{array} = \frac{1}{256}\begin{array}{|c|c|c|c|c|}\hline & & & & \\ \hline & & & & \\ \hline 1 & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline \end{array}$$

Example: Separable Gaussian Filter

$$\frac{1}{16}\begin{array}{|c|c|c|c|c|}\hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline \end{array} \otimes \frac{1}{16}\begin{array}{|c|}\hline 1 \\ \hline 4 \\ \hline 6 \\ \hline 4 \\ \hline 1 \\ \hline \end{array} = \frac{1}{256}\begin{array}{|c|c|c|c|c|}\hline & & & & \\ \hline & & & & \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline 4 & \boxed{16} & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline & & & & \\ \hline \end{array}$$

Example: Separable Gaussian Filter

$$\frac{1}{16}\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \otimes \frac{1}{16}\begin{bmatrix} 1 \\ 4 \\ 6 \\ 4 \\ 1 \end{bmatrix} = \frac{1}{256}\begin{bmatrix} & & & & \\ & & & & \\ 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & \boxed{1} \\ & & & & \\ & & & & \end{bmatrix}$$

Example: Separable Gaussian Filter

$$\frac{1}{16}\begin{array}{|c|c|c|c|c|}\hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 \\ \hline \end{array} \otimes \frac{1}{16}\begin{array}{|c|}\hline 1 \\ \hline 4 \\ \hline 6 \\ \hline 4 \\ \hline 1 \\ \hline \end{array} = \frac{1}{256}\begin{array}{|c|c|c|c|c|}\hline 1 & 4 & 6 & 4 & 1 \\ \hline 4 & 16 & 24 & 16 & 4 \\ \hline 6 & 24 & 36 & 24 & 6 \\ \hline 4 & 16 & 24 & 16 & 4 \\ \hline 1 & 4 & 6 & 4 & 1 \\ \hline \end{array}$$

Pre-Convolving Filters

Convolving two filters of size $m \times m$ and $n \times n$ results in filter of size:

$$(n + m - 1) \times (n + m - 1)$$

More broadly for a set of K filters of sizes $m_k \times m_k$ the resulting filter will have size:

$$\left(m_1 + \sum_{k=2}^{K}(m_k - 1)\right) \times \left(m_1 + \sum_{k=2}^{K}(m_k - 1)\right)$$

Gaussian: An Additional Property

Let $\otimes$ denote convolution. Let $G_{\sigma_1}(x)$ and $G_{\sigma_2}(x)$ be be two 1D Gaussians

$$G_{\sigma_1}(x) \otimes G_{\sigma_2}(x) = G_{\sqrt{\sigma_1^2+\sigma_2^2}}(x)$$

Convolution of two Gaussians is another Gaussian

Special case: Convolving with $G_\sigma(x)$ twice is equivalent to $G_{\sqrt{2}\sigma}(x)$

Non-linear Filters

We’ve seen that **linear filters** can perform a variety of image transformations

— shifting

— smoothing

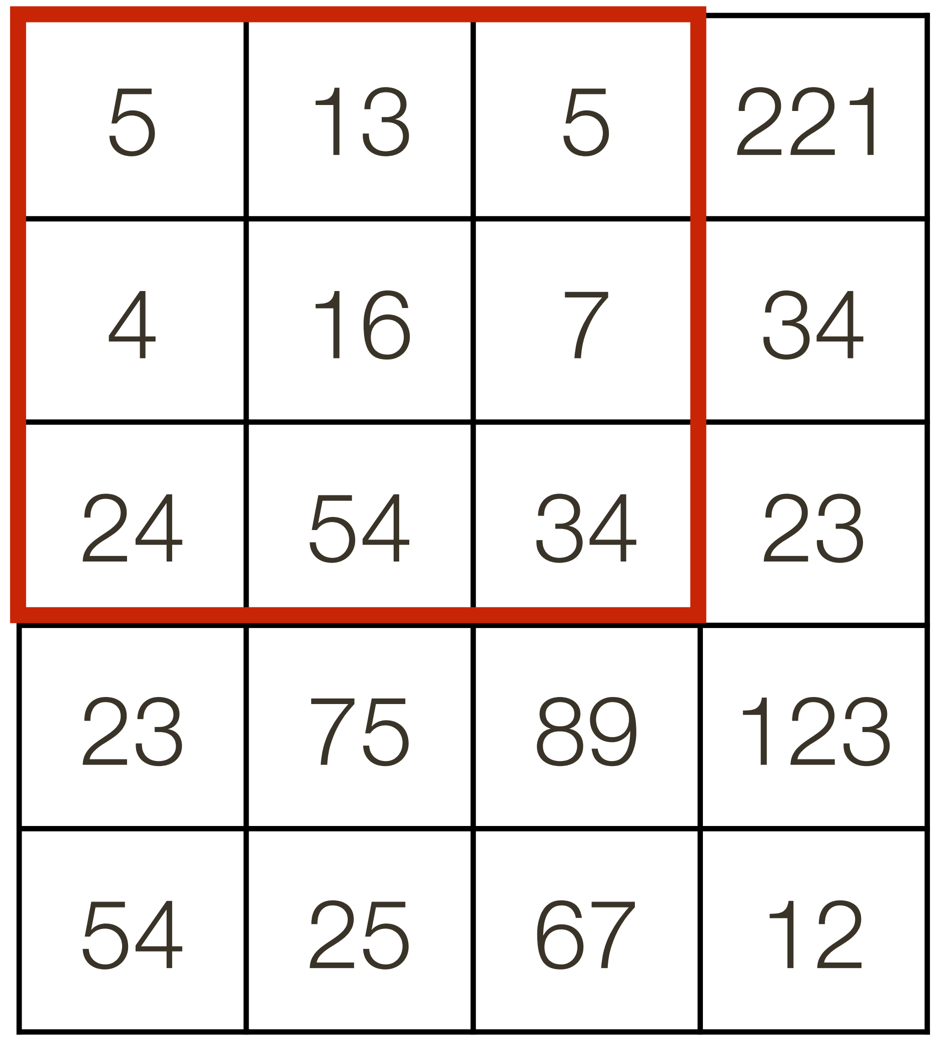
— sharpening

In some applications, better performance can be obtained by using **non-linear filters**.

For example, the median filter (which is a very effective de-noising / smoothing filter) selects the **median** value from each pixel’s neighborhood.

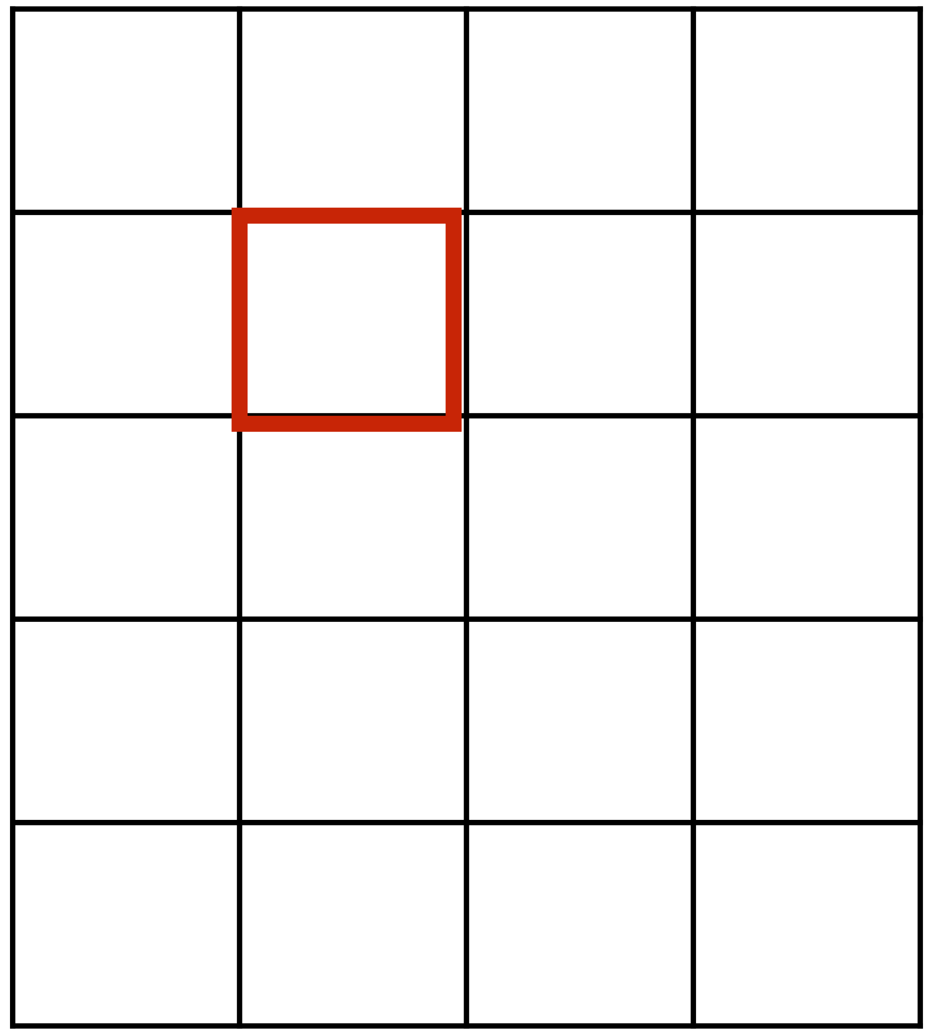
Median Filter

Take the **median value** of the pixels under the filter:



5	13	5	221
4	16	7	34
24	54	34	23
23	75	89	123
54	25	67	12

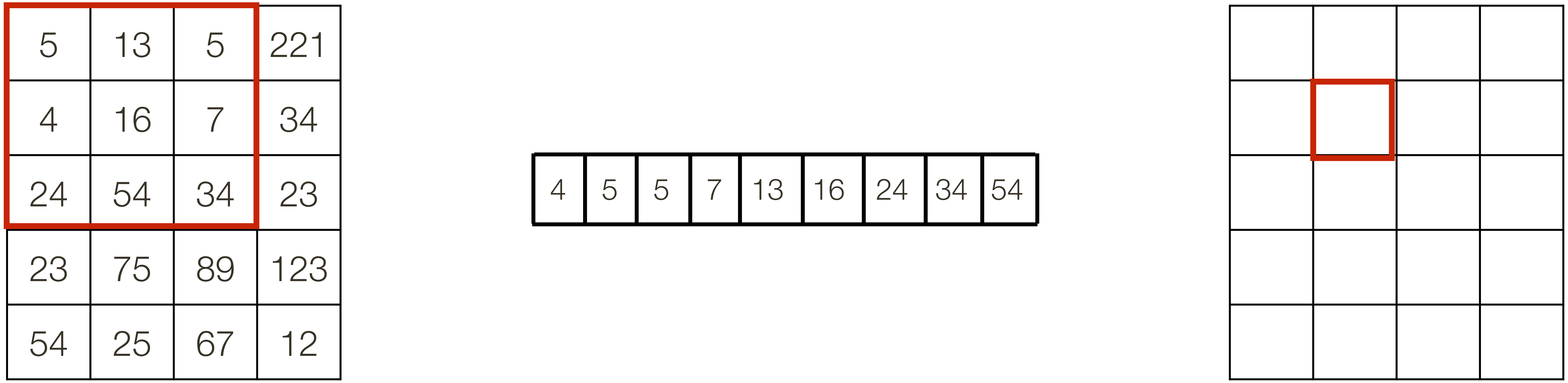
Image



Output

Median Filter

Take the **median value** of the pixels under the filter:



5	13	5	221
4	16	7	34
24	54	34	23
23	75	89	123
54	25	67	12

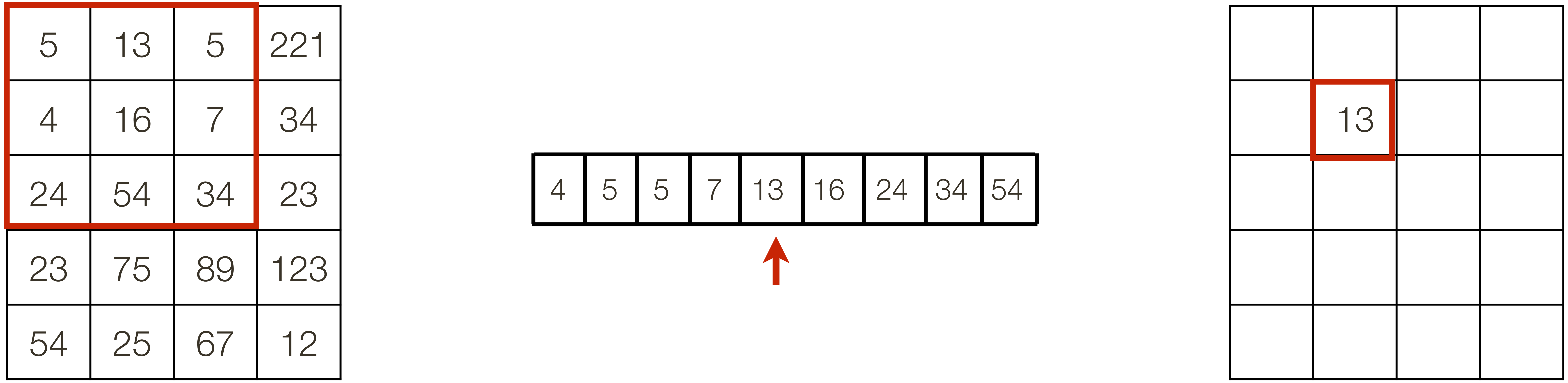
4	5	5	7	13	16	24	34	54

Image

Output

Median Filter

Take the **median value** of the pixels under the filter:



5	13	5	221
4	16	7	34
24	54	34	23
23	75	89	123
54	25	67	12

Image

4	5	5	7	13	16	24	34	54

	13		

Output

Median Filter

Effective at reducing certain kinds of noise, such as impulse noise (a.k.a ‘salt and pepper’ noise or ’shot’ noise)

The median filter forces points with distinct values to be more like their neighbors

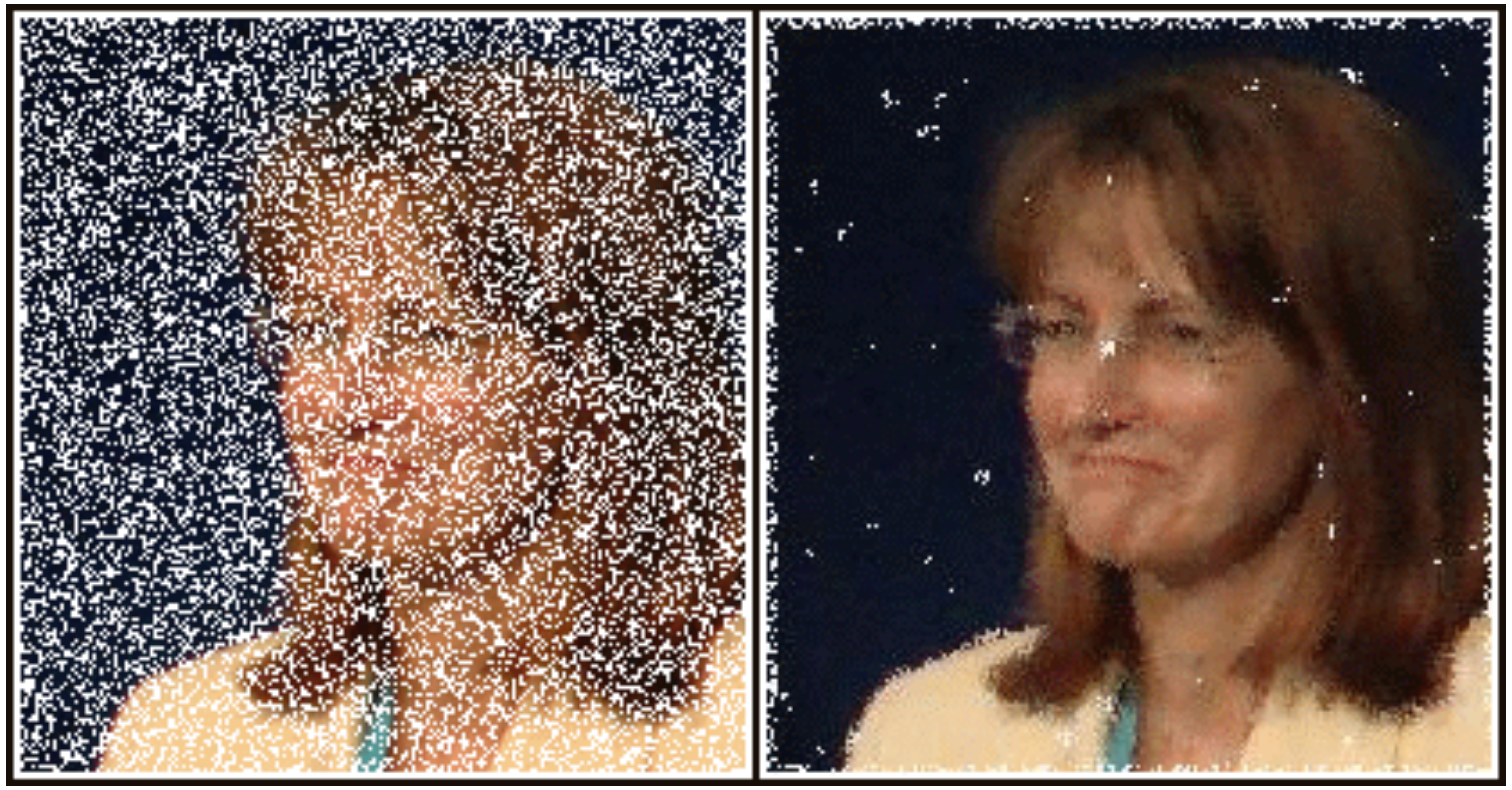


Image credit: https://en.wikipedia.org/wiki/Median_filter#/media/File:Medianfilterp.png

Bilateral Filter

An edge-preserving non-linear filter

Like a Gaussian filter:

— The filter weights depend on spatial distance from the center pixel
— Pixels nearby (in space) should have greater influence than pixels far away

Unlike a Gaussian filter:

— The filter weights also depend on range distance from the center pixel
— Pixels with similar brightness value should have greater influence than pixels with dissimilar brightness value

Bilateral Filter

Gaussian filter: weights of neighbor at a spatial offset (x, y) away from the center pixel $I(X, Y)$ given by:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

(with appropriate normalization)

Bilateral Filter

Gaussian filter: weights of neighbor at a spatial offset (x, y) away from the center pixel $I(X, Y)$ given by:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

(with appropriate normalization)

Bilateral filter: weights of neighbor at a spatial offset (x, y) away from the center pixel $I(X, Y)$ given by a product:

$$\exp^{-\frac{x^2+y^2}{2\sigma_d^2}} \exp^{-\frac{(I(X+x, Y+y)-I(X,Y))^2}{2\sigma_r^2}}$$

(with appropriate normalization)

Bilateral Filter

Gaussian filter: weights of neighbor at a spatial offset (x, y) away from the center pixel $I(X, Y)$ given by:

$$G_\sigma(x, y) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

(with appropriate normalization)

Bilateral filter: weights of neighbor at a spatial offset (x, y) away from the center pixel $I(X, Y)$ given by a product:

domain kernel

$$\exp^{-\frac{x^2+y^2}{2\sigma_d^2}} \quad \exp^{-\frac{(I(X+x,Y+y)-I(X,Y))^2}{2\sigma_r^2}}$$

range kernel

(with appropriate normalization)

Bilateral Filter

image $I(X, Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

Bilateral Filter

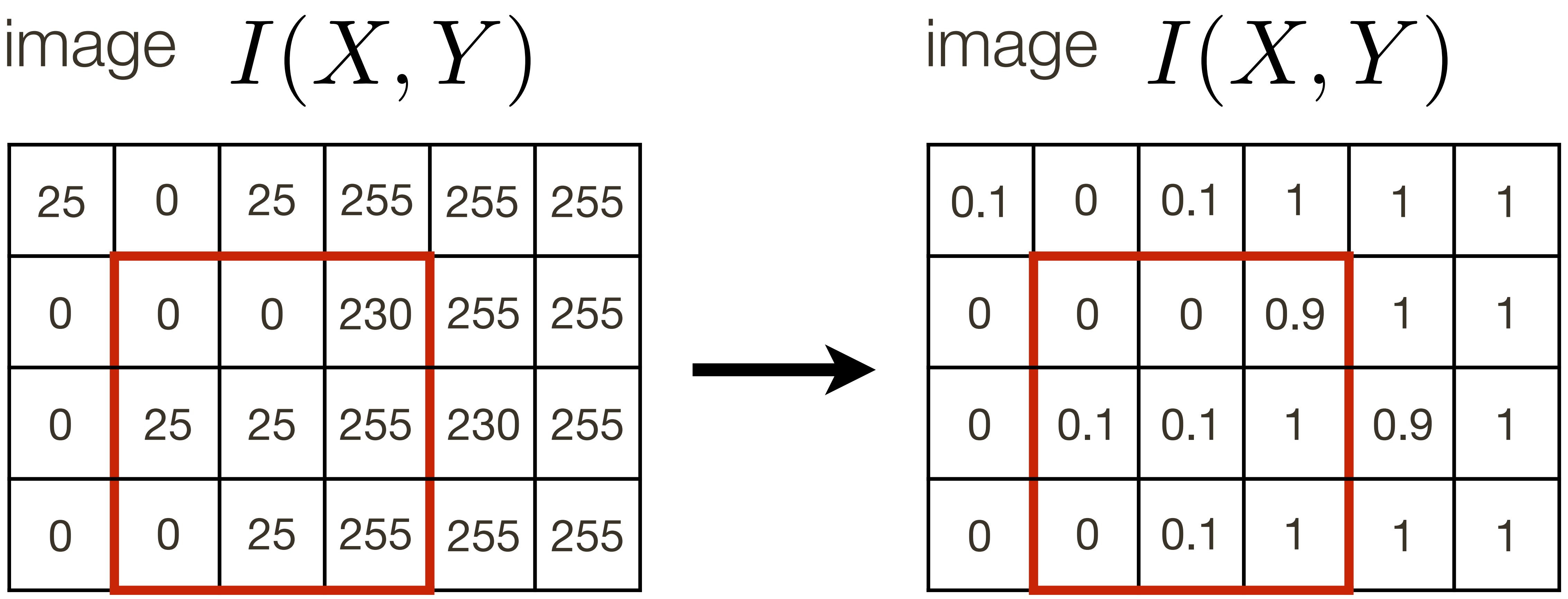


image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

$\rightarrow$

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Bilateral Filter

image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

→

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$\sigma_d = 0.45$

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Bilateral Filter

image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

→

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$\sigma_d = 0.45$

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Range Kernel

$\sigma_r = 0.45$

0.98	0.98	0.2
1	1	0.1
0.98	1	0.1

(this is different for each locations in the image)

Bilateral Filter

image $I(X, Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

image $I(X, Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$\sigma_d = 0.45$

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Range Kernel

$\sigma_r = 0.45$

0.98	0.98	0.2
1	1	0.1
0.98	1	0.1

(this is different for each locations in the image)

multiply

Range * **Domain** Kernel

0.08	0.12	0.02
0.12	0.20	0.01
0.08	0.12	0.01

Bilateral Filter

image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

→

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$\sigma_d = 0.45$

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Range Kernel

$\sigma_r = 0.45$

0.98	0.98	0.2
1	1	0.1
0.98	1	0.1

(this is different for each locations in the image)

multiply →

Range * **Domain** Kernel

0.08	0.12	0.02
0.12	0.20	0.01
0.08	0.12	0.01

sum to 1 →

0.11	0.16	0.03
0.16	0.26	0.01
0.11	0.16	0.01

Bilateral Filter

image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

→

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$$\sigma_d = 0.45$$

0.08	0.12	0.08
0.12	0.20	0.12
0.08	0.12	0.08

Range Kernel

$$\sigma_r = 0.45$$

0.98	0.98	0.2
1	1	0.1
0.98	1	0.1

(this is different for each locations in the image)

multiply →

Range * **Domain** Kernel

0.08	0.12	0.02
0.12	0.20	0.01
0.08	0.12	0.01

$$\sum \begin{bmatrix} 0.11 & 0.16 & 0.03 \\ 0.16 & 0.26 & 0.01 \\ 0.11 & 0.16 & 0.01 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & 0.9 \\ 0.1 & 0.1 & 1 \\ 0 & 0.1 & 1 \end{bmatrix} = 0.1$$

Bilateral Filter

Bilateral Filter

image $I(X,Y)$

25	0	25	255	255	255
0	0	0	230	255	255
0	25	25	255	230	255
0	0	25	255	255	255

→

image $I(X,Y)$

0.1	0	0.1	1	1	1
0	0	0	0.9	1	1
0	0.1	0.1	1	0.9	1
0	0	0.1	1	1	1

Domain Kernel

$\sigma_d = 0.45$

$$\sum \begin{bmatrix} 0.08 & 0.12 & 0.08 \\ 0.12 & 0.20 & 0.12 \\ 0.08 & 0.12 & 0.08 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & 0.9 \\ 0.1 & 0.1 & 1 \\ 0 & 0.1 & 1 \end{bmatrix} = 0.3$$

Gaussian Filter (only)

Range Kernel

$\sigma_r = 0.45$

0.98	0.98	0.2
1	1	0.1
0.98	1	0.1

(this is different for each locations in the image)

multiply →

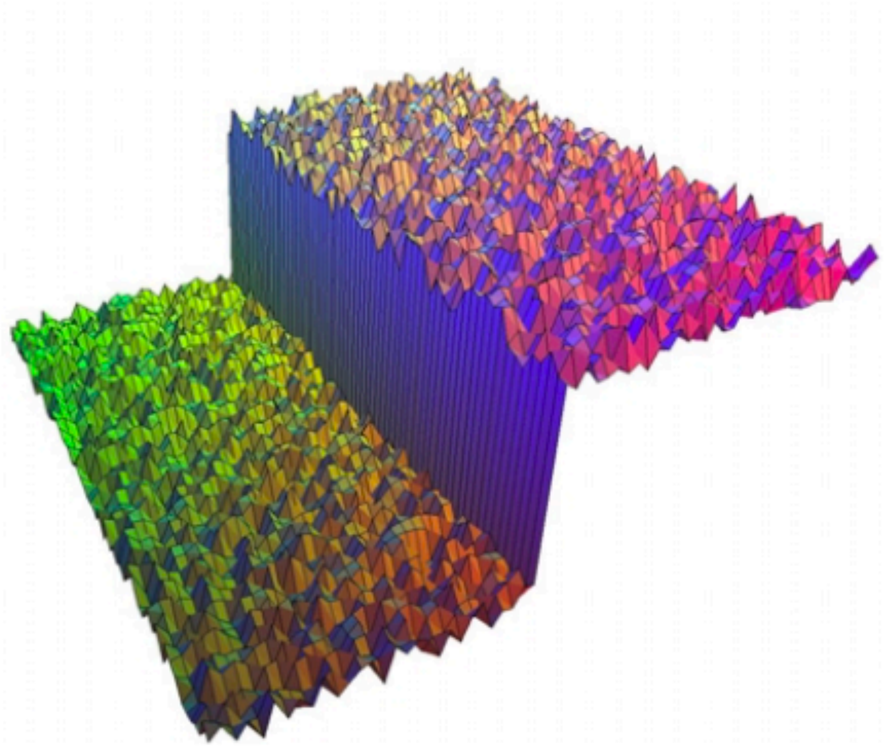
Range * **Domain** Kernel

0.08	0.12	0.02
0.12	0.20	0.01
0.08	0.12	0.01

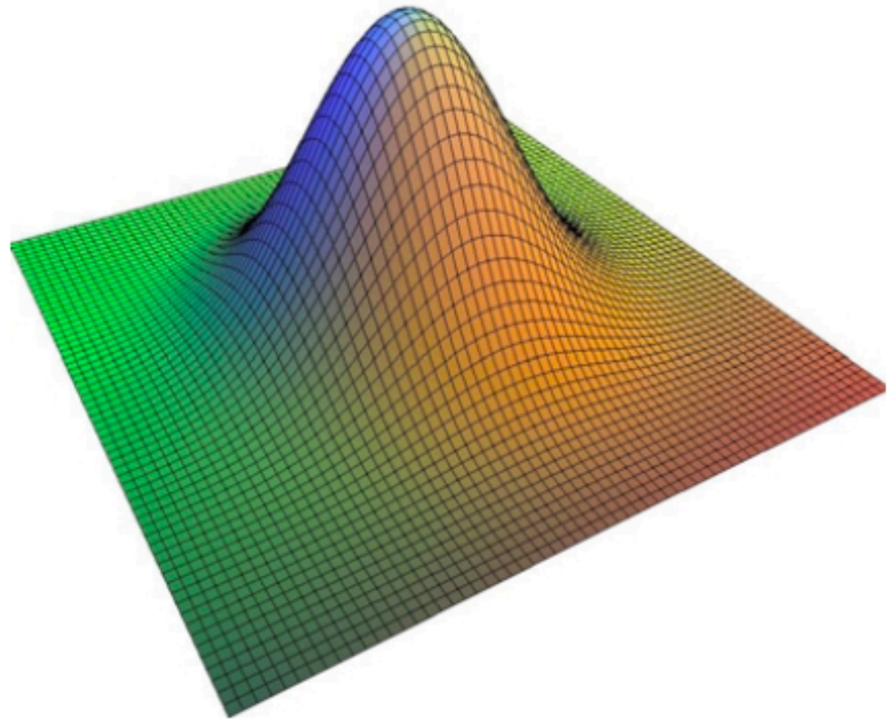
$$\sum \begin{bmatrix} 0.11 & 0.16 & 0.03 \\ 0.16 & 0.26 & 0.01 \\ 0.11 & 0.16 & 0.01 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & 0.9 \\ 0.1 & 0.1 & 1 \\ 0 & 0.1 & 1 \end{bmatrix} = 0.1$$

Bilateral Filter

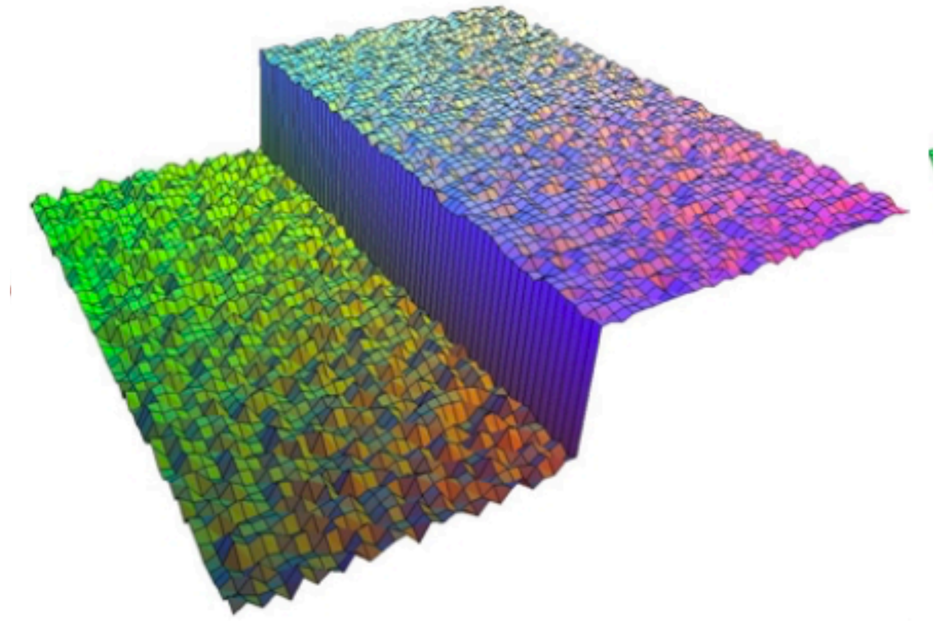
Bilateral Filter



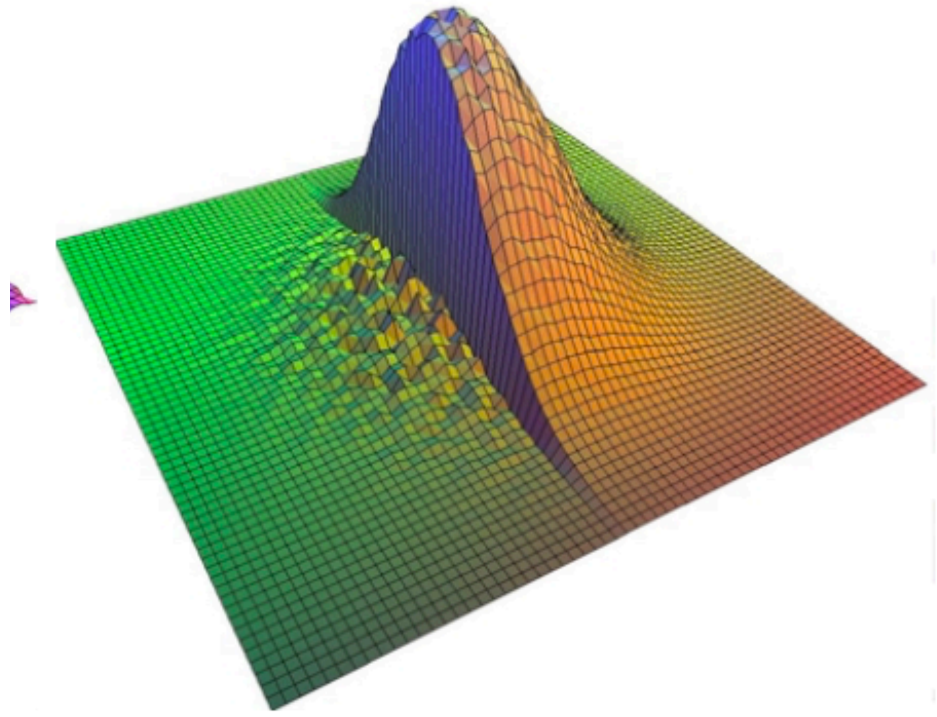
Input



Domain Kernel

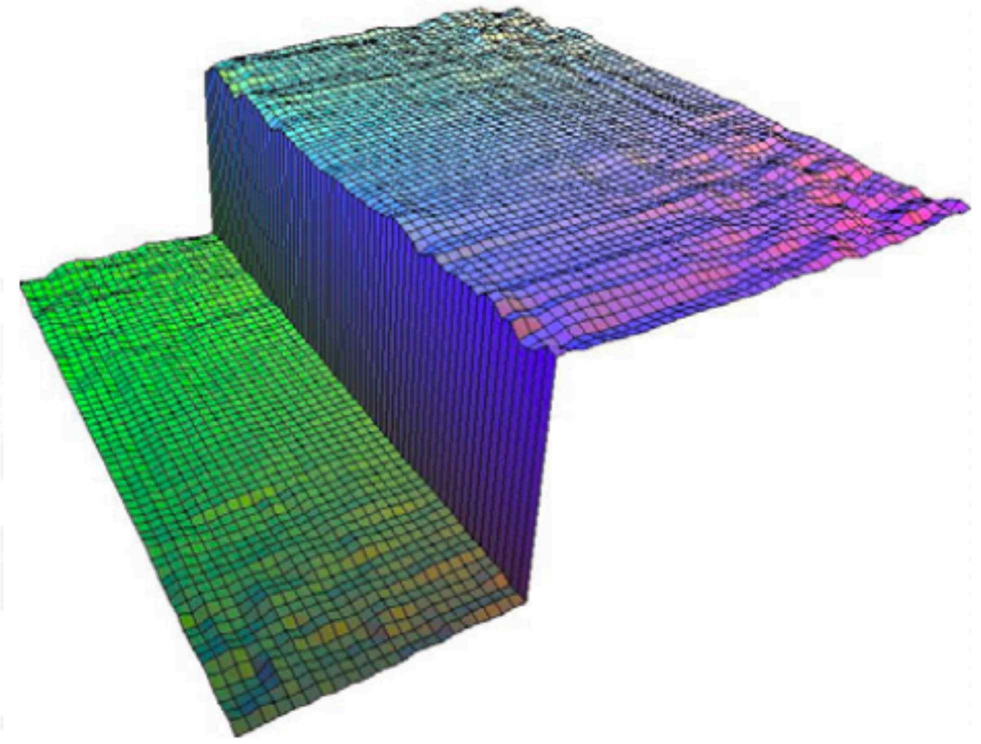


Range Kernel Influence



Bilateral Filter

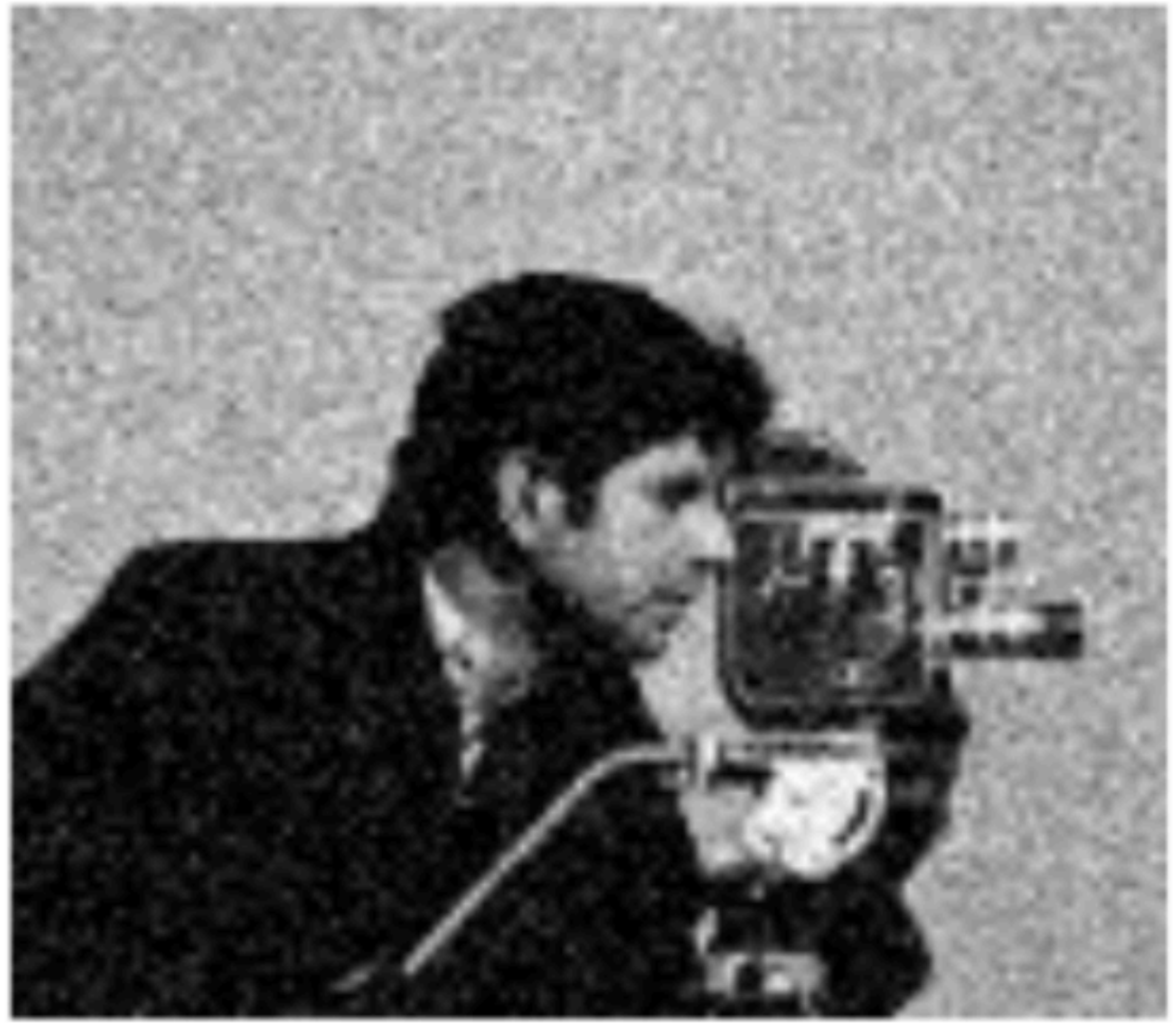
(domain * range)



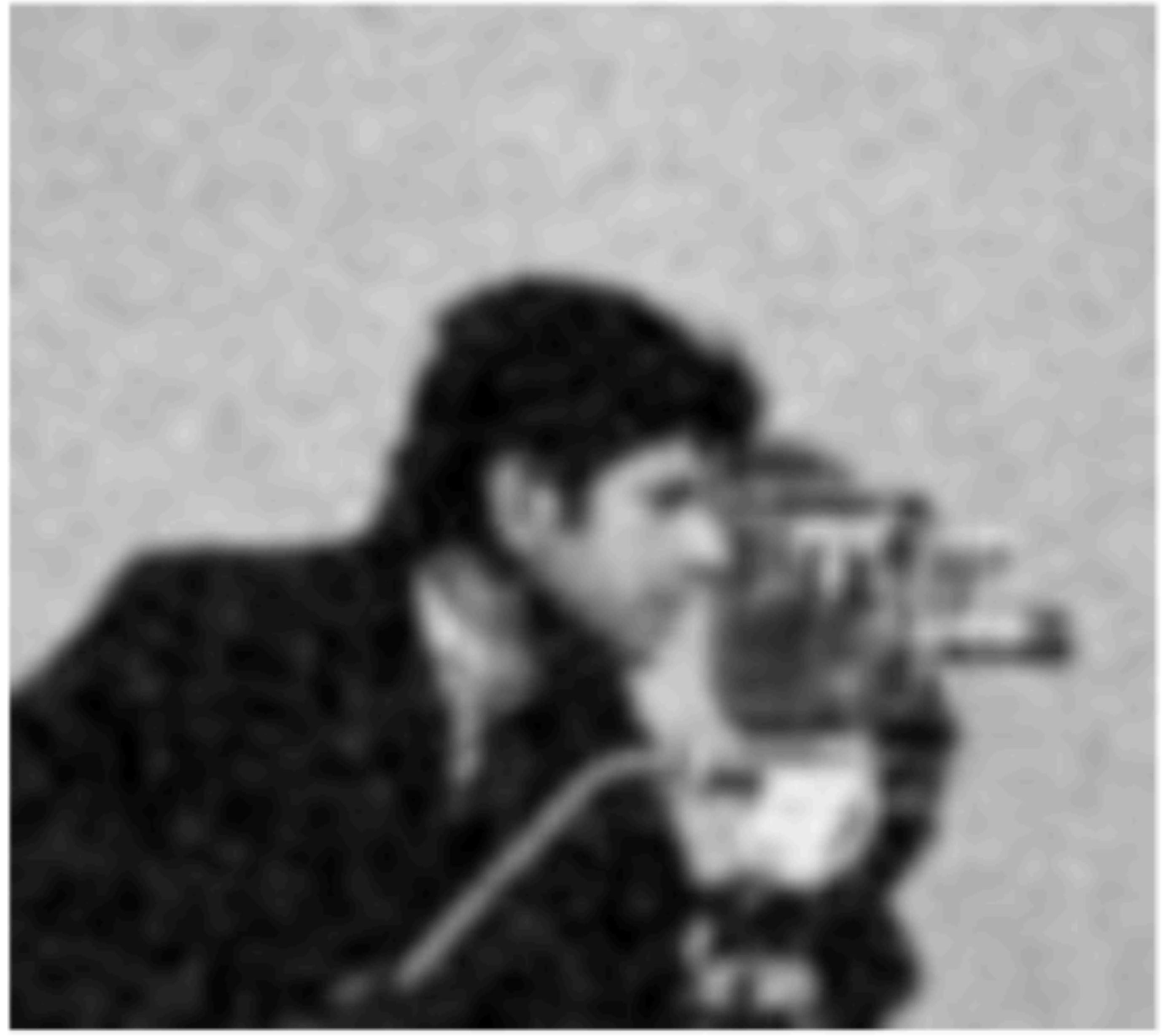
Output

Images from: Durand and Dorsey, 2002

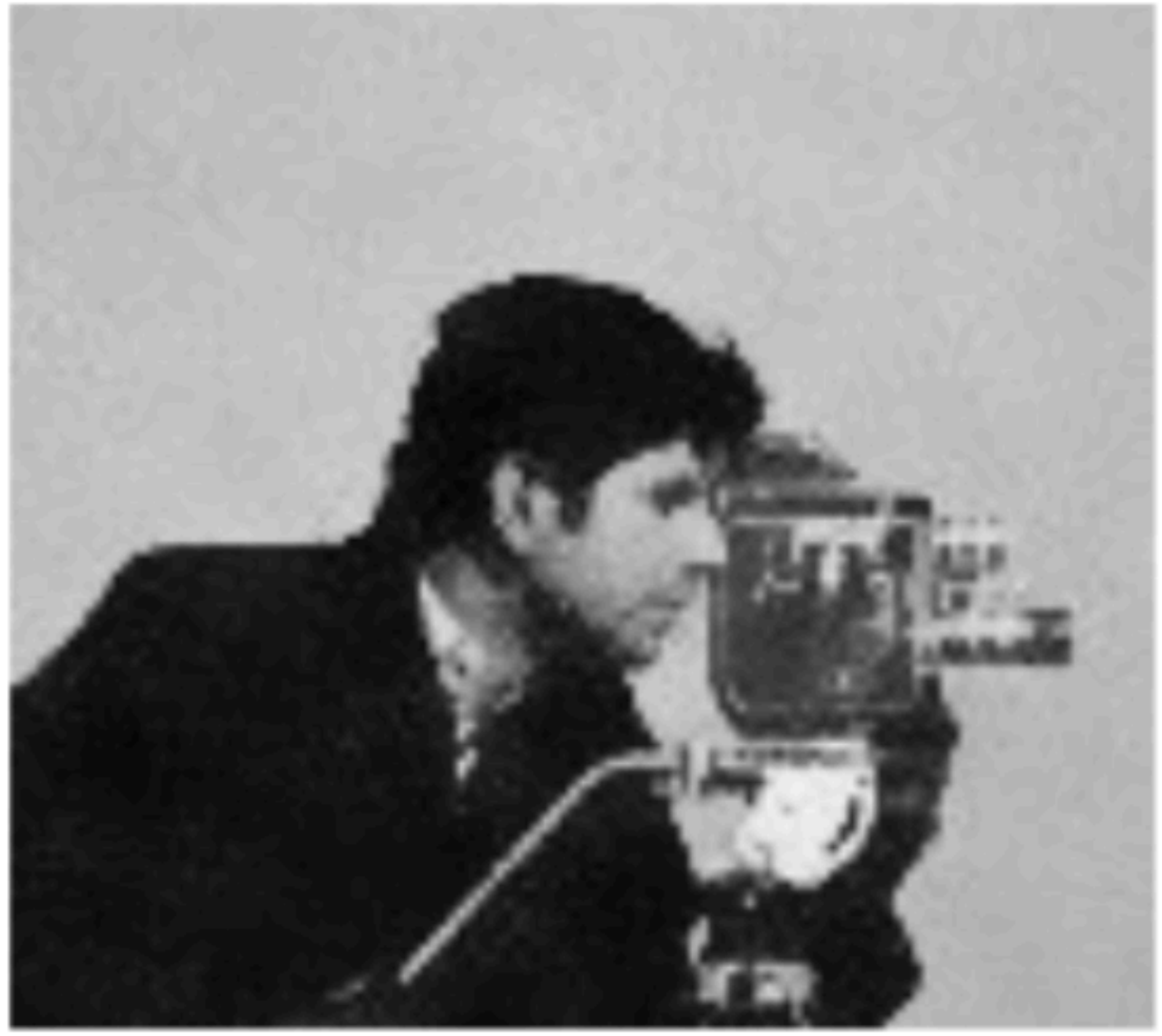
Bilateral Filter Application: Denoising



Noisy Image



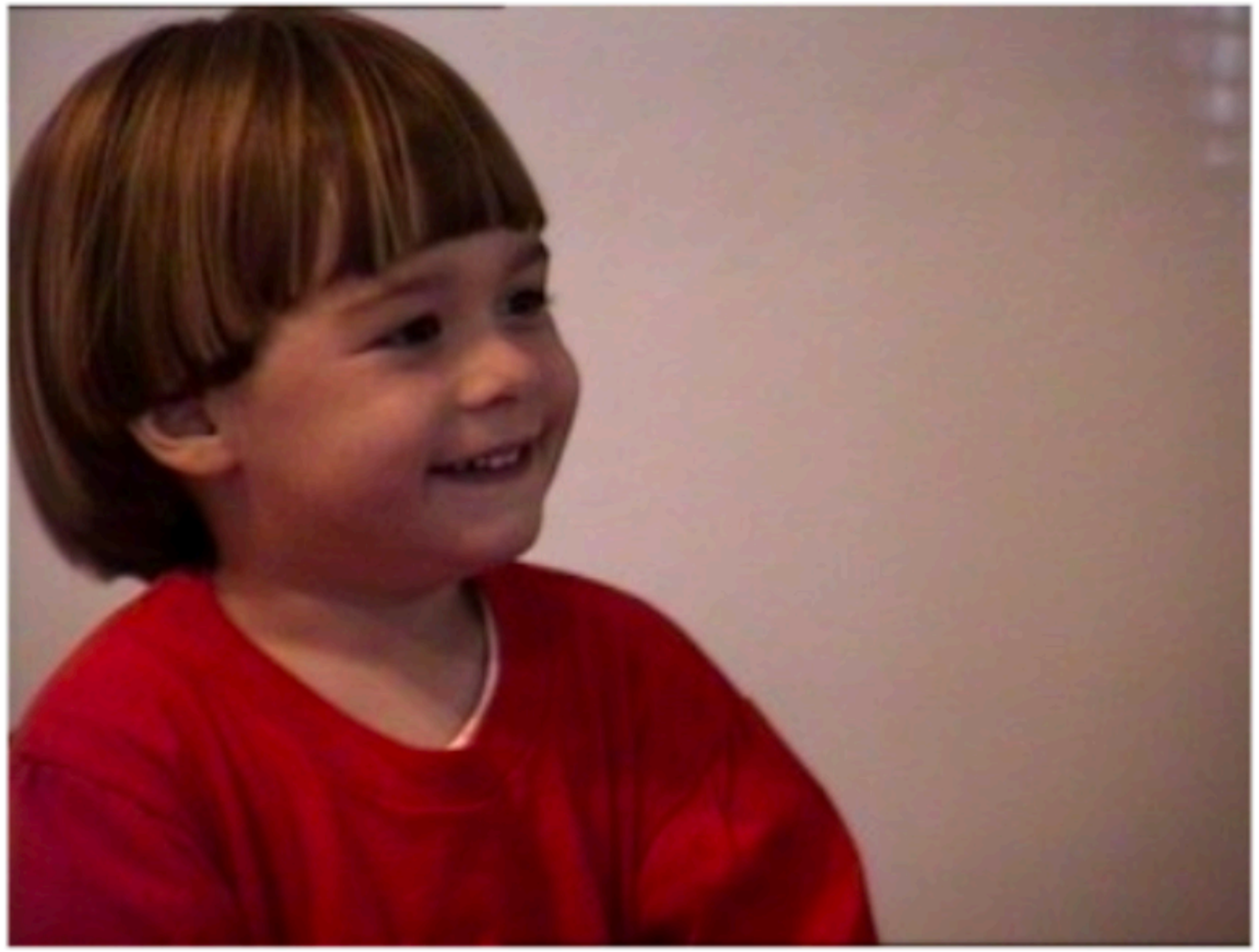
Gaussian Filter



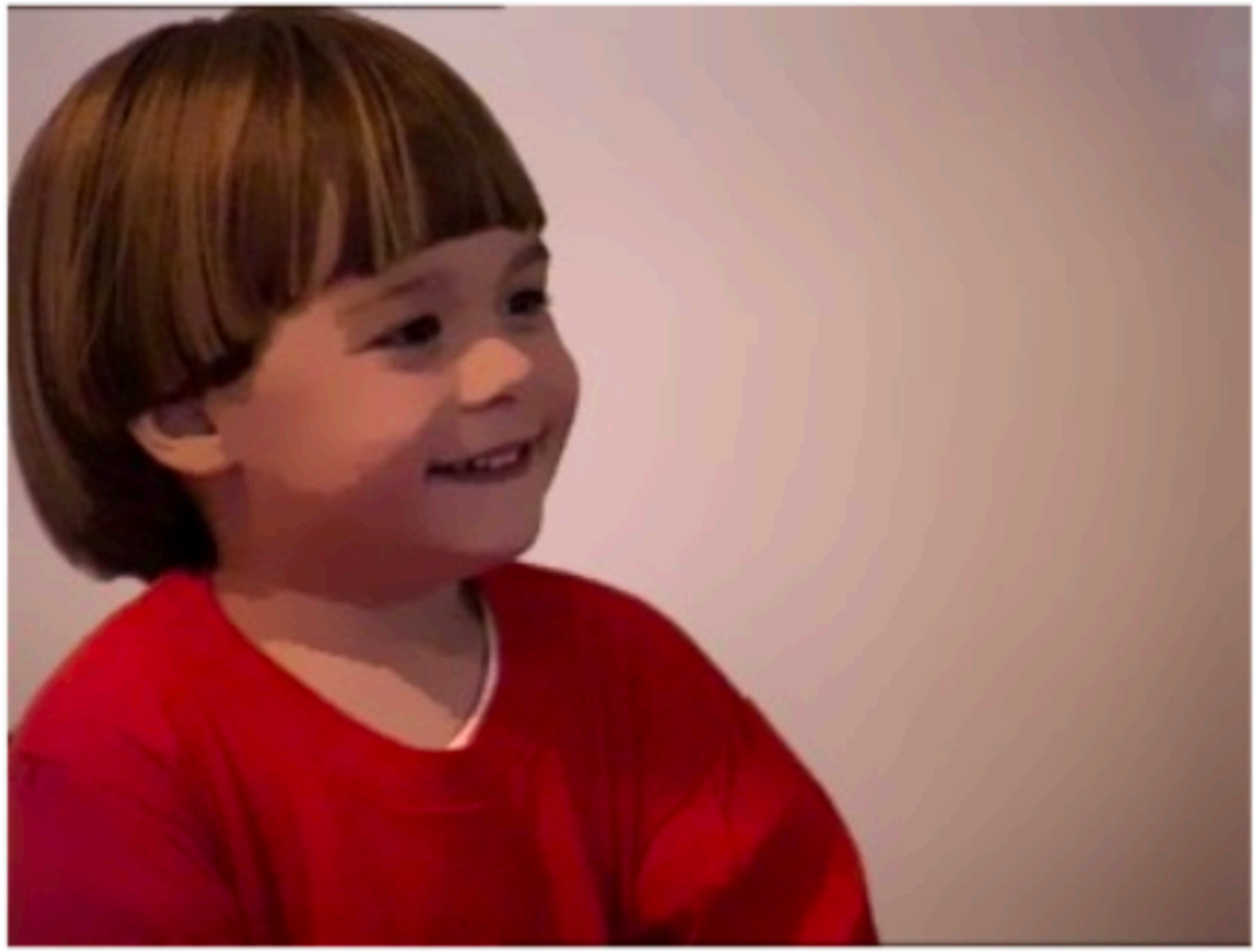
Bilateral Filter

Slide Credit: Alexander Wong

Bilateral Filter Application: Cartooning



Original Image



After 5 iterations of **Bilateral** Filter

Slide Credit: Alexander Wong

Bilateral Filter Application: Flash Photography

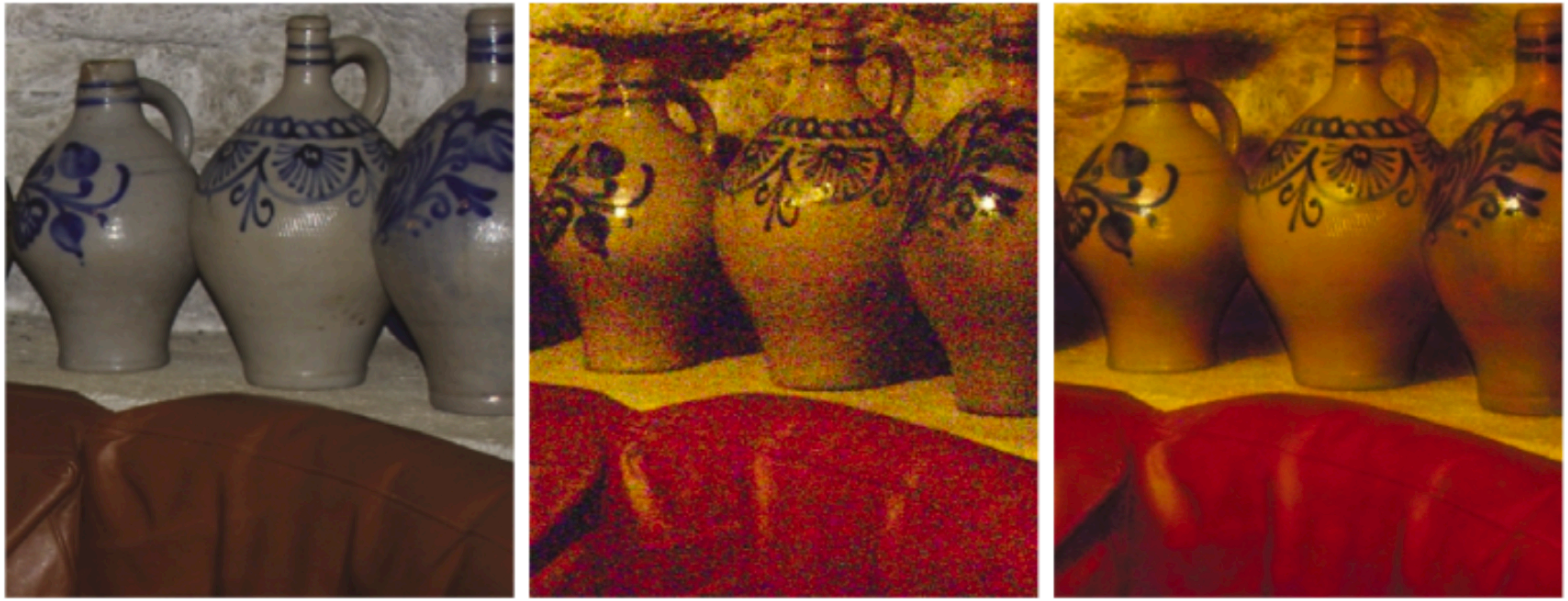
Non-flash images taken under low light conditions often suffer from excessive **noise** and **blur**

But there are problems with **flash images**:
— colour is often unnatural
— there may be strong shadows or specularities

Idea: Combine flash and non-flash images to achieve better exposure and colour balance, and to reduce noise

Bilateral Filter Application: Flash Photography

System using ‘joint’ or ‘cross’ bilateral filtering:



Flash

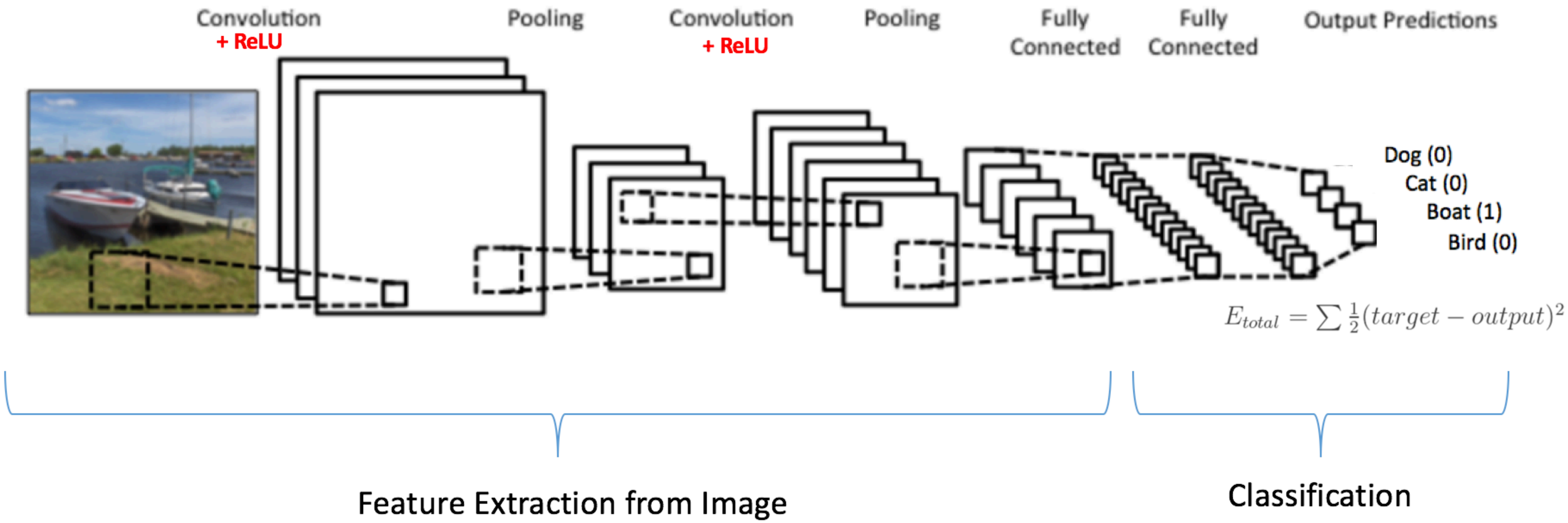
No-Flash

Detail Transfer with Denoising

’Joint’ or ’Cross’ bilateral: Range kernel is computed using a separate guidance image instead of the input image

Figure Credit: Petschnigg et al., 2004

Aside: Linear Filter with ReLU



$E_{total} = \sum \frac{1}{2}(target - output)^2$

9	3	5	-8
-6	2	-3	1
1	3	4	1
3	-4	5	1

→

9	3	5	0
0	2	0	1
1	3	4	1
3	0	5	1

Result of: Linear Image Filtering After Non-linear ReLU

Summary

We covered two three **non-linear filters**: Median, Bilateral, ReLU

Separability (of a 2D filter) allows for more efficient implementation (as two 1D filters)

Convolution is **associative** and **symmetric**

Convolution of a Gaussian with a Gaussian is another Gaussian

The **median filter** is a non-linear filter that selects the median in the neighbourhood

The **bilateral filter** is a non-linear filter that considers both spatial distance and range (intensity) distance, and has edge-preserving properties