

# CSE 152 Section 3

## **Review of Filters and Frequencies**

October 19, 2018

Owen Jow

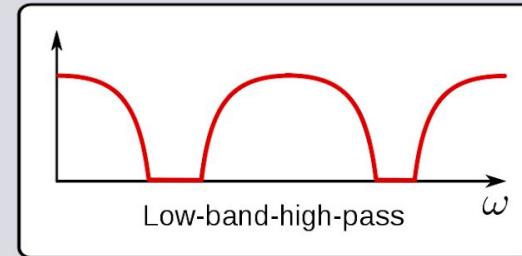
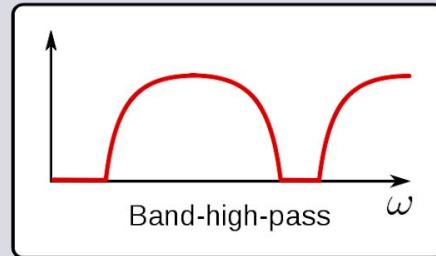
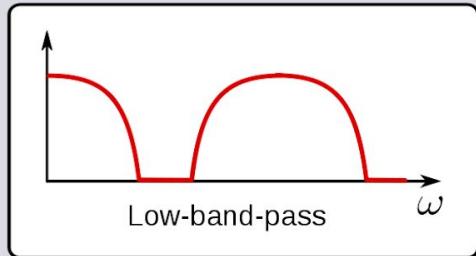
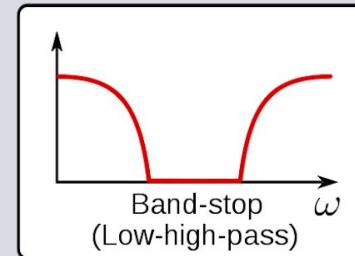
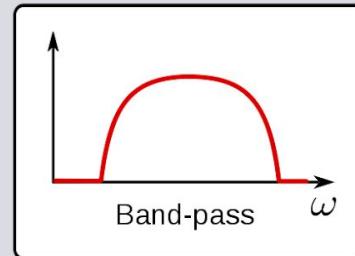
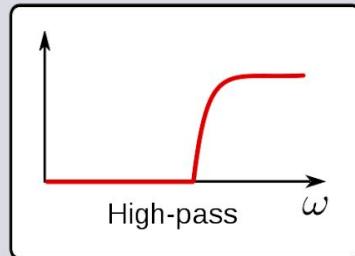
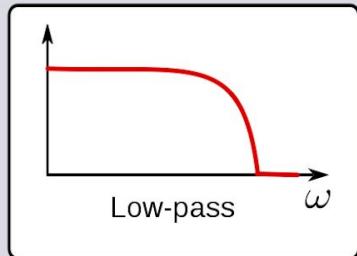
# What is a filter?

What comes to mind?

**A device that lets only some of its inputs through**



## A process that lets only some of its inputs through



## A process that lets some scalings of its inputs through

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

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

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

source: Steven Seitz

**and so transforms content**



# What does a linear filter do to an image?

Hint: why is it called a *linear* filter?

## Linear Filter (An Image Processing View)

Replace each pixel with a **linear combination** of values in its neighborhood.

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Correlation

$$\underbrace{h(x, y)}_{\text{output}} = \sum_{k, l} \underbrace{f(k, l)}_{\text{filter}} \underbrace{I(x + k, y + l)}_{\text{image}}$$

- not commutative or associative
- (preferably) use for measuring similarity

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- “**flip filter horizontally and vertically**”

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- commutative and associative
- (preferably) use for filtering
- “flip filter horizontally and vertically”
- denoted  $h = f * I$
- btw,  $k, l$  defined w.r.t. center of kernel

Why do we care about associativity?

# Why do we care about associativity?

Associativity means that  $f * (g * I) = (f * g) * I$ .

If we want to apply multiple filters, we can pre-convolve them and use (then reuse) them as a single filter!

## Properties of Linear Filters

- They obey the superposition principle.

$$f * (\alpha I + J) = \alpha(f * I) + f * J$$

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- They are shift-invariant.

$$f * \text{shifted}(I) = \text{shifted}(f * I)$$

“we can shift the image to the left by one pixel, then filter –  
or we can filter, then shift the result to the left by one pixel”

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“we perform the same operation no matter where we are”

## Filtering Results



sharpening via  
**unsharp filtering**

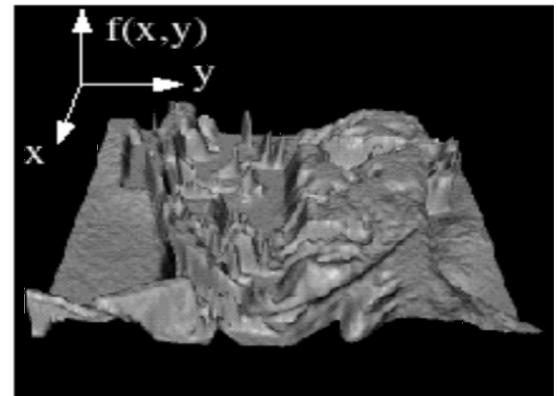
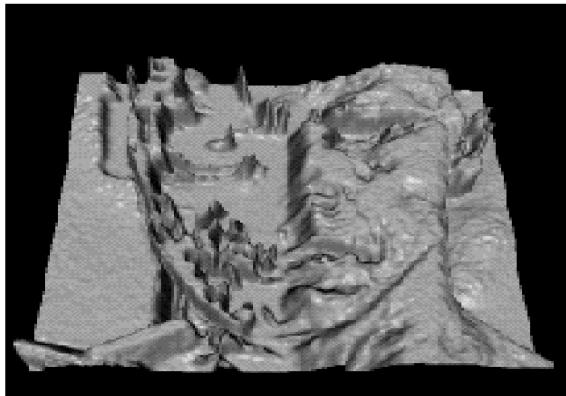
## Filtering Results



denoising via  
**median filtering**  
(nonlinear)

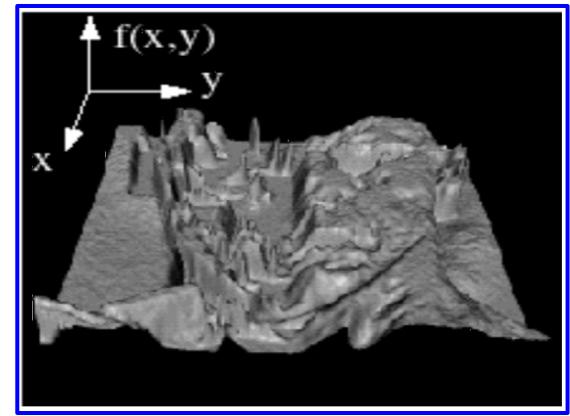
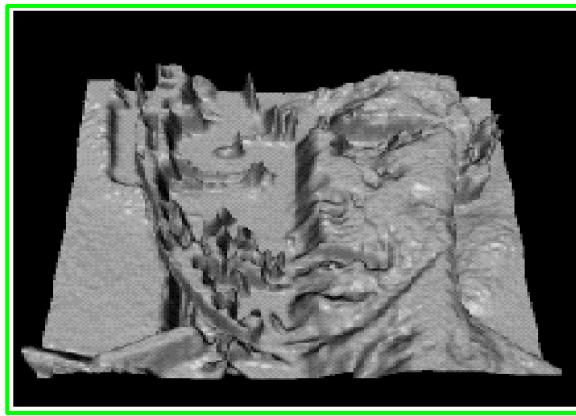
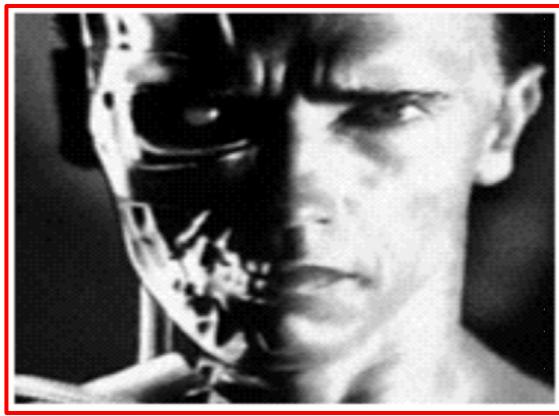
## An image is a function $f(x, y)$

It is a mapping from pixel locations  $\in \mathbb{R}^2$  to intensities  $\in \mathbb{R}$ .



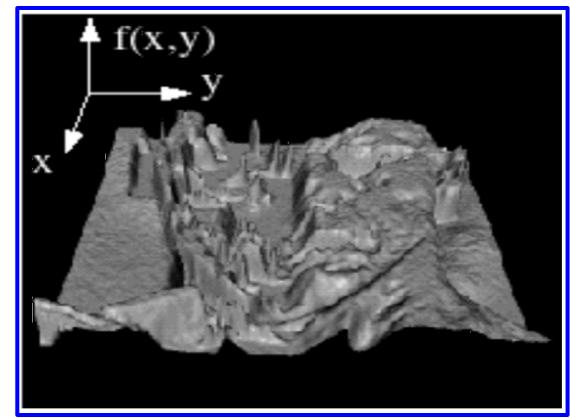
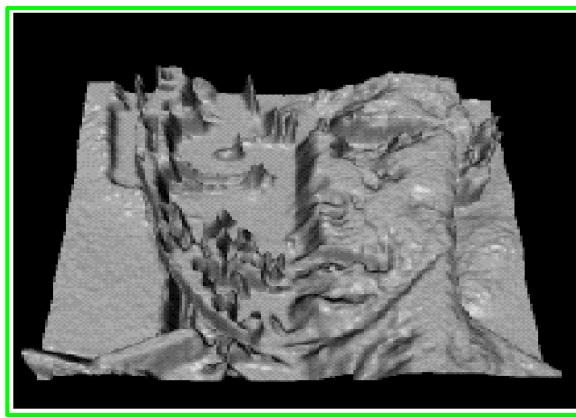
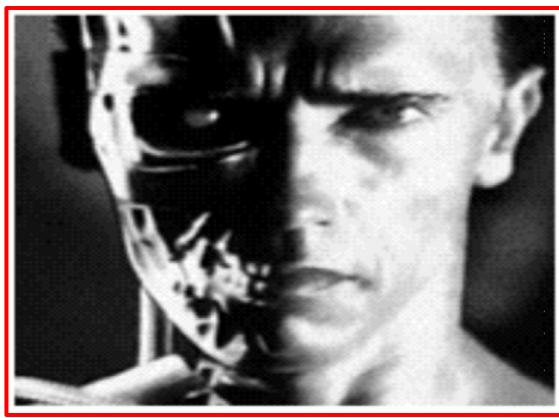
## An image is a function $f(x, y)$

A color image is a mapping from pixel locations  $\in \mathbb{R}^2$  to RGB intensities  $\in \mathbb{R}^3$ .



# An image is a signal $f(x, y)$

In the case of digital images, we discretely sample an underlying continuous function.



The background of the slide features a dark, textured surface with glowing particles. These particles are organized into several distinct, wavy, ribbon-like structures that curve across the frame. The colors of these structures vary, with some appearing in shades of blue and green, while others are a bright red-orange. The overall effect is reminiscent of light trails or data visualization.

So what we're really doing...

...is signal processing

image source: [Daniel Sierra](#)

**A digital image is a discrete 2D signal (function) (vector).**

Traditionally, we think of them as  
they exist in the spatial domain.

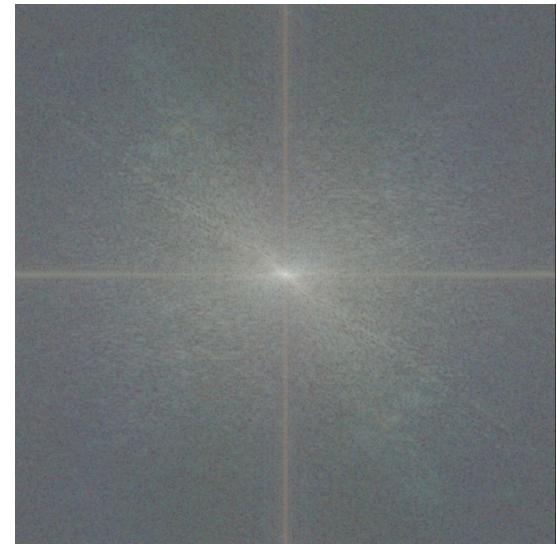


## A digital image is a discrete 2D signal (function) (vector).

Traditionally, we think of them as they exist in the spatial domain.



But signal processing gives us a new way to think about things...

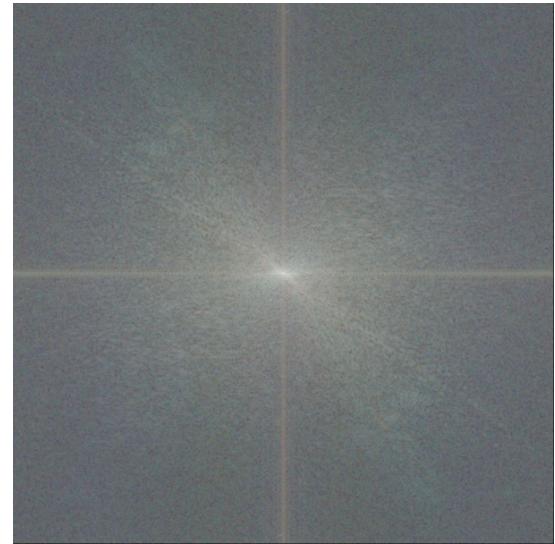


**A digital image is a discrete 2D signal (function) (vector).**

Spatial Domain



Frequency Domain

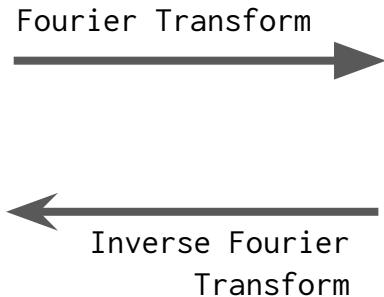
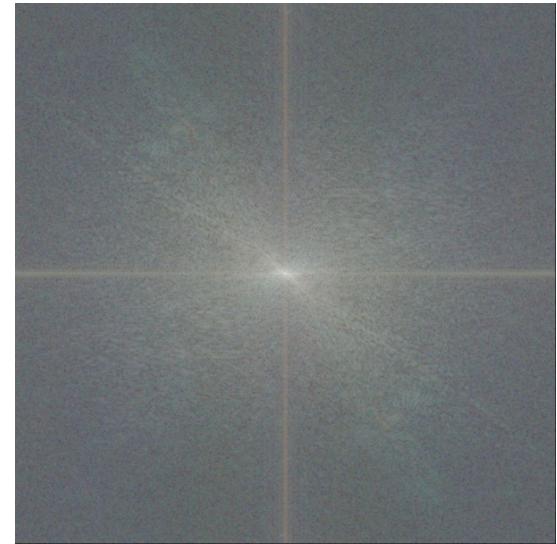


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Frequency Domain



A digital image is a discrete 2D signal (function) (vector).

Spatial Domain

$$f(x, y)$$

x: distance (px) in horizontal direction  
y: distance (px) in vertical direction

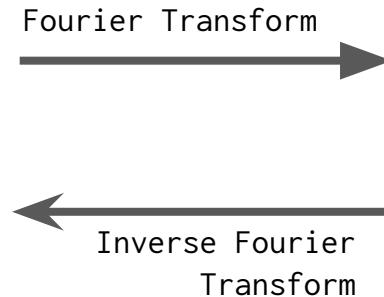
$f(x, y)$ : intensity at  $(x, y)$

Frequency Domain

$$F(u, v)$$

u: frequency (cycles/px) in horizontal direction  
v: frequency (cycles/px) in vertical direction

$F(u, v)$ : magnitude of frequency  $(u, v)$



## 1D case (scan line)

Spatial Domain

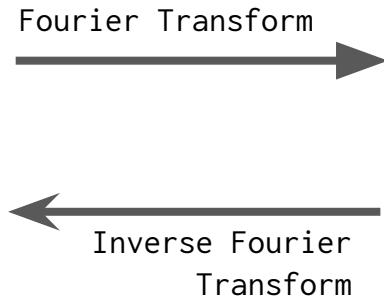
$$f(x)$$

$x$ : distance (px) in horizontal direction  
 $f(x)$ : intensity at pixel  $x$  on scan line

Frequency Domain

$$F(u)$$

$u$ : frequency (cycles/px)  
 $F(u)$ : magnitude of frequency  $u$



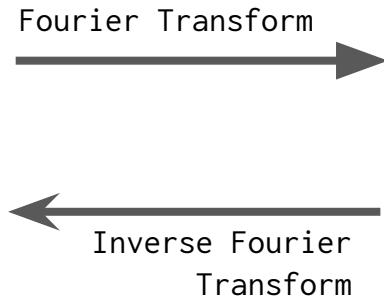
## 1D case (time-varying signal)

Spatial Domain

$$f(t)$$

Frequency Domain

$$F(\omega)$$



# (1D Discrete) Fourier Transform

A discrete Fourier transform (DFT) turns a function into a weighted sum of sines and cosines.

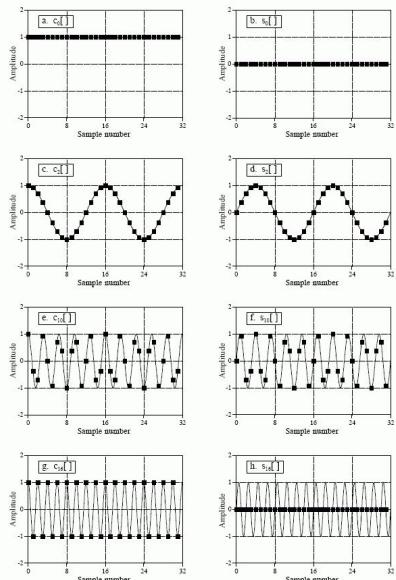


FIGURE 8-5  
DFT basis functions. A 12 point DFT has 17 discrete cosine waves and 17 discrete sine waves for its basis functions. Eight of these are shown in this figure. These are discrete signals; the continuous lines are shown in these graphs only to help the reader's eye follow the waveforms.

## (1D Discrete) Fourier Transform

A Fourier transform is a **change of basis** into a basis of sine and cosine functions.

If the signal contains **N** samples, the basis will contain **N** sine/cosine functions with different frequencies.

$$\begin{aligned} F(k) &= \sum_{t=0}^{N-1} f(t) e^{(-2\pi kt/N)i} \\ &= \sum_{t=0}^{N-1} f(t) [\cos(2\pi kt/N) - i \sin(2\pi kt/N)] \\ &= \sum_{t=0}^{N-1} f(t) \cos(2\pi kt/N) - i \sum_{t=0}^{N-1} f(t) \sin(2\pi kt/N) \end{aligned}$$

$$\cos(2\pi kt/N)$$

$$\sin(2\pi kt/N)$$

$$0 \leq k \leq N - 1$$

## (1D Discrete) Fourier Transform

$F(k)$  is a complex number from which we can obtain the magnitude (amplitude) of frequency  $k$  in the Fourier decomposition.

We can think of the output of our Fourier transform as a **magnitude** for each **frequency**.

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$$\cos(2\pi kt/N)$$

$$\sin(2\pi kt/N)$$

$$0 \leq k \leq N - 1$$

**Incidentally**

$$A \sin(2\pi kt + \varphi)$$

A: amplitude, magnitude, strength, “how much”

k,  $2\pi k$ : frequency, cycles per pixel or second

$\varphi$ : phase, shift, “where” the sinusoid is

**Incidentally**

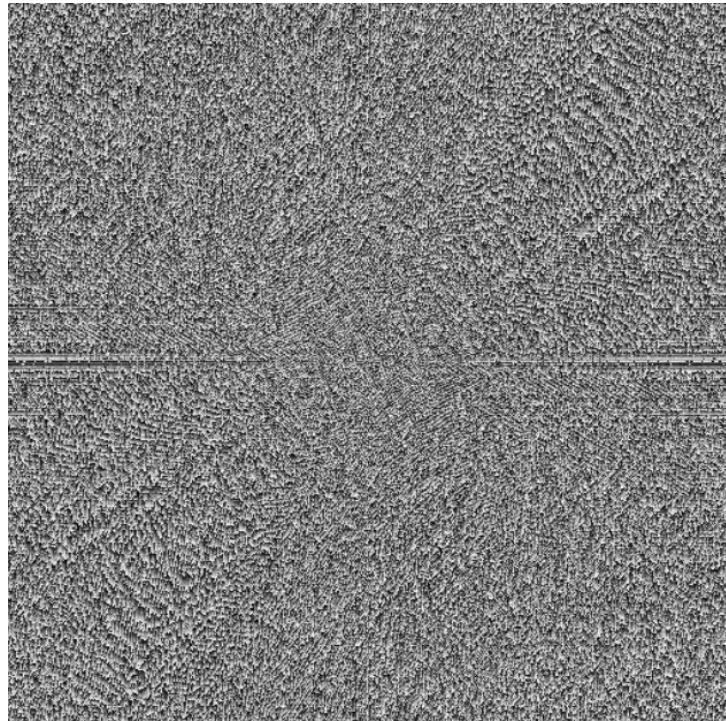
$$A \sin(\omega t) + B \cos(\omega t) = C \sin(\omega t + \varphi)$$

adding a sine and cosine of the same frequency  
gives a phase-shifted sine of that frequency

**total amplitude** is  $\sqrt{A^2 + B^2}$   
**phase shift** is  $\arctan(A / B)$

## (1D Discrete) Fourier Transform

We can also get phase information out of a Fourier transform. But we won't talk about phase much because it isn't very helpful for interpretability.



## In Summary: The 1D Fourier Transform

converts a signal  $f(t)$  into the frequencies that compose it.

$$F(\omega)$$

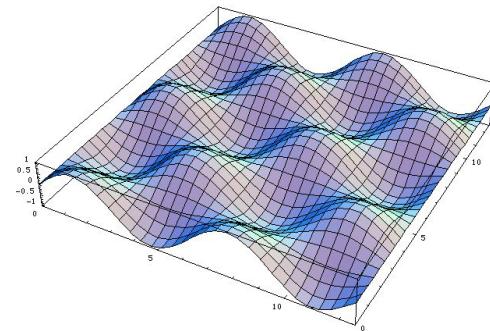
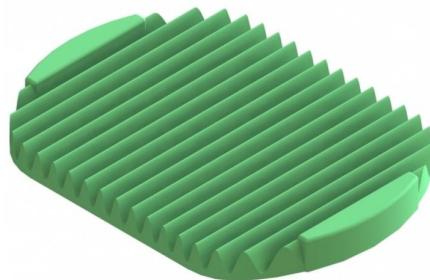
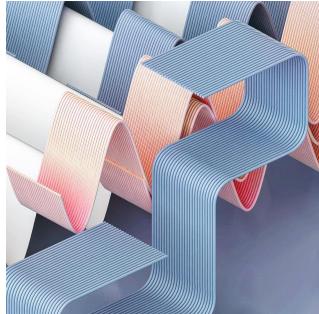
“what is the strength of the frequency- $\omega$  sinusoid in the decomposition of  $f(t)$ ? ”

## 2D DFT

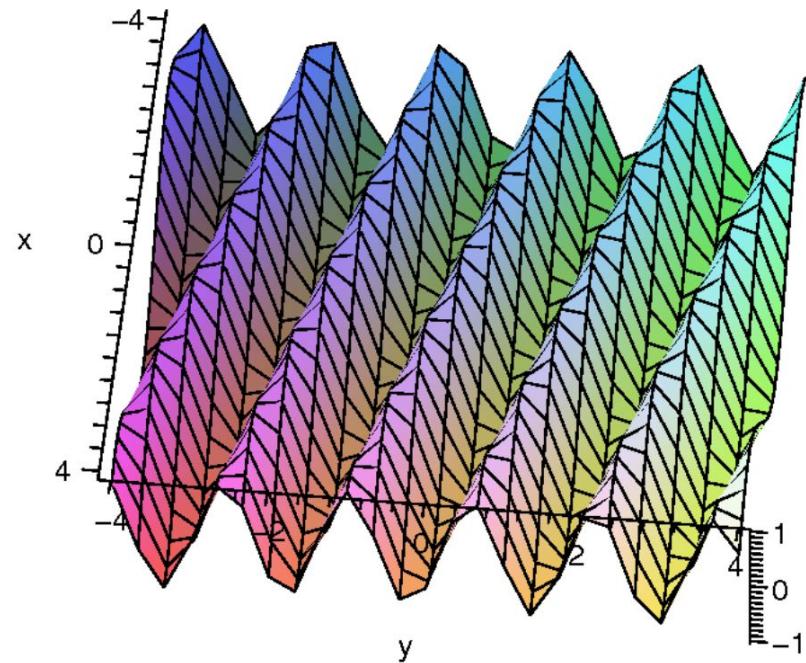
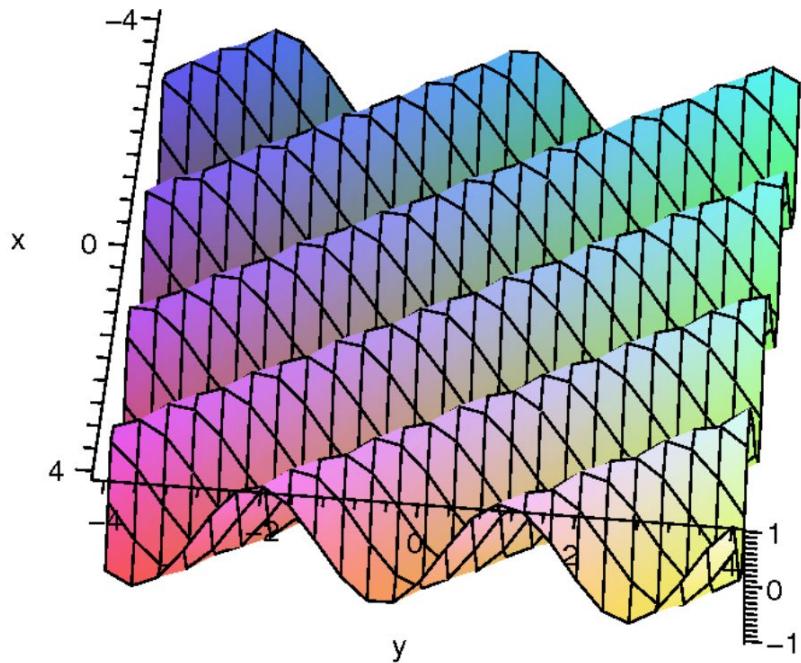
- The 2D DFT is analogous to the 1D DFT; just add another dimension to the input.

$$F(u, v)$$

- The main difference is that the sines/cosines can now be **oriented** in 2D.

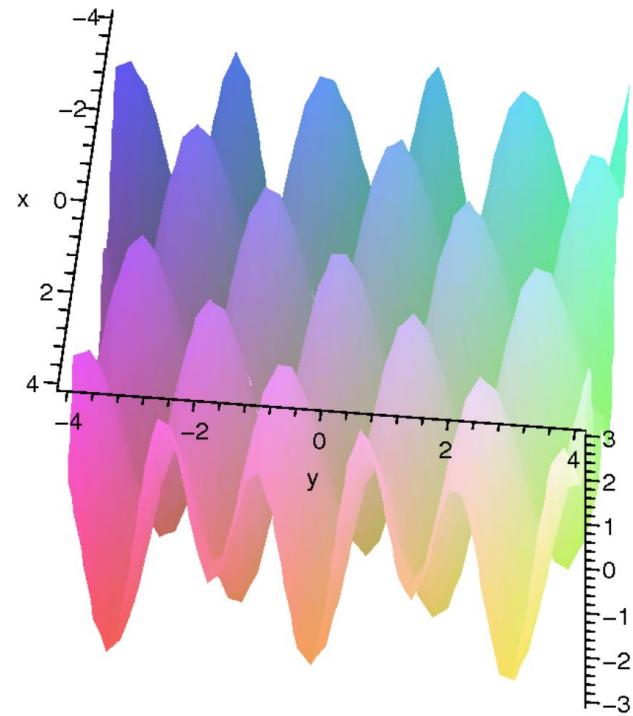
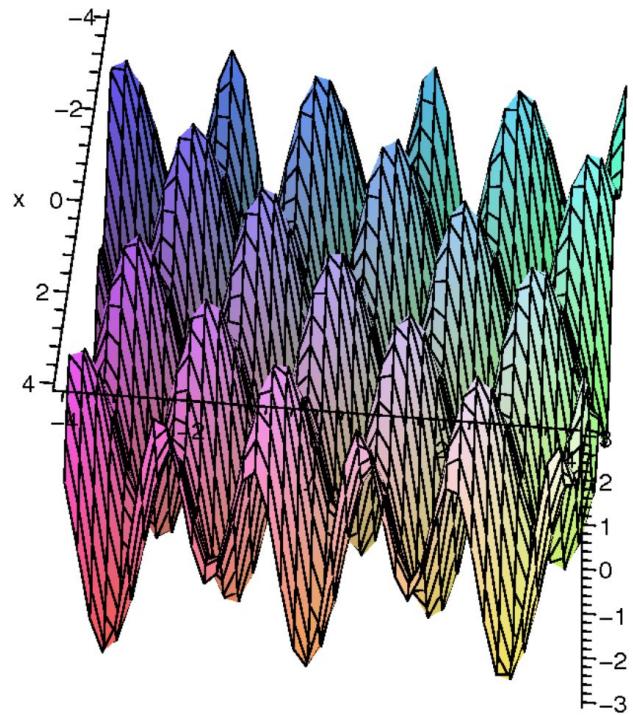


## 2D Basis Functions



source: Václav Hlaváč

## Sum of 2D Basis Functions



source: Václav Hlaváč

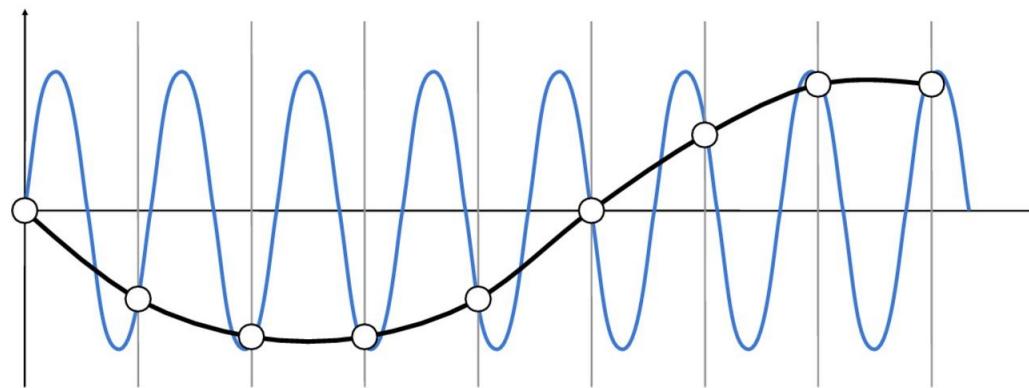
Cycles per pixel?

# Cycles per pixel?

We are thinking about **spatial frequency**. The basis sinusoids appear as oriented, repeating stripes. The number of pixels it takes to move along a sinusoid from some intensity back to the same intensity is  $1 / (\text{the frequency})$ .

# Nyquist frequency

To avoid aliasing, the maximum frequency we can have in a signal is  $\frac{1}{2}$  of the sampling frequency.



**Aliasing**

## Nyquist frequency

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In other words, the maximum frequency we can have in an image is 0.5 cycles per pixel. What does this mean?

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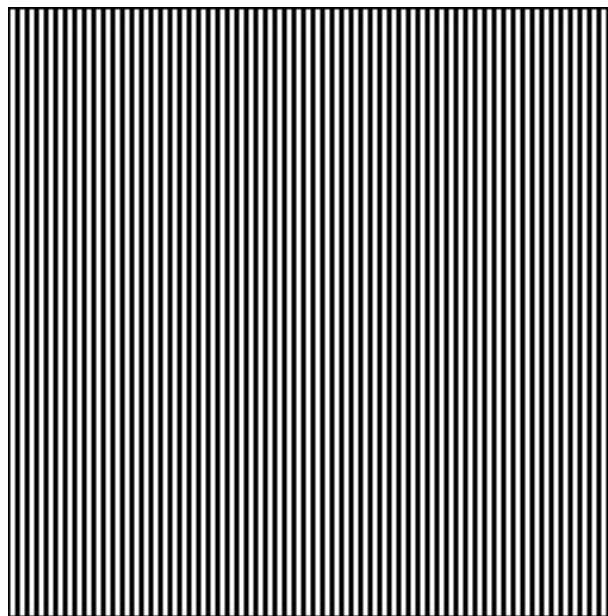
Presumably, the sampling frequency for an image is 1 sample per pixel.

In other words, the maximum frequency we can have in an image is 0.5 cycles per pixel. What does this mean?

**at max 1 stripe per pixel extent**

**0.5 cycles per pixel → intensity alternates between low and high every pixel**

## Half of the Nyquist frequency



- stripe width 2px
- period 4px
- frequency 0.25 cycles/px

## High vs. low frequencies

High frequency means a signal is changing quickly over its domain.

- In the previous visualization, the pixel values were changing very quickly from left to right, and the frequency was almost at its maximum (the Nyquist frequency).

In images,

- **high frequencies correspond to...**



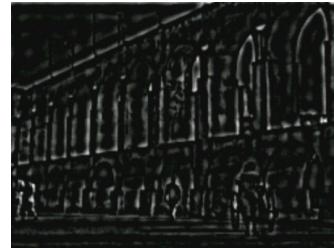
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- **low frequencies correspond to...**



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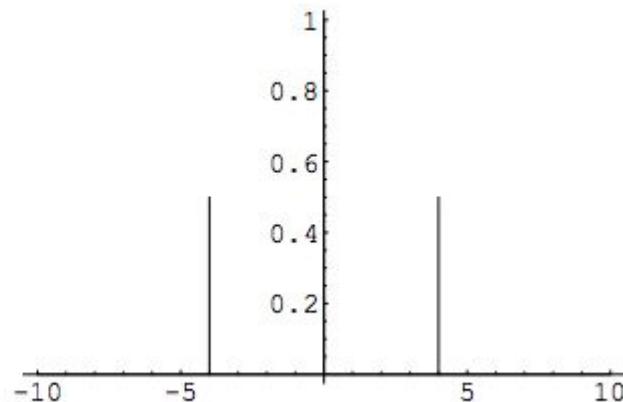
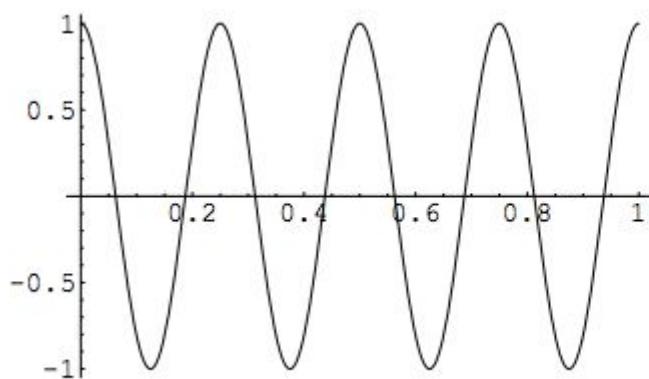
- high frequencies correspond to rapid/sharp changes in intensity (edges)
- low frequencies correspond to **smooth/slow changes in intensity (blurred/smoothed regions)**



# Frequency Domain Images (1D)

understanding the frequency domain

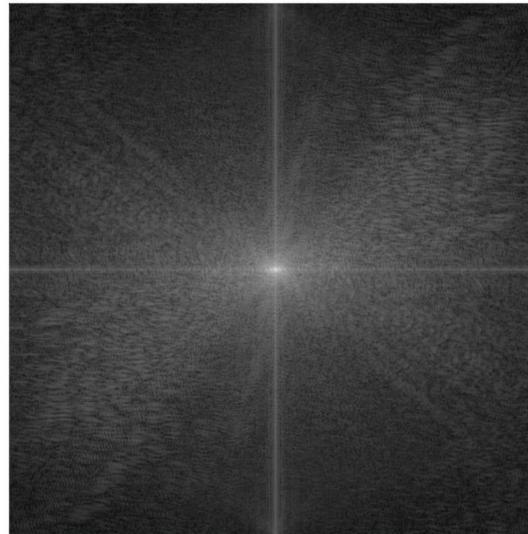
For a 1D signal, we visualize the frequency domain as a 2D plot  
of **frequency** on the horizontal axis and **magnitude** on the vertical axis.



# Frequency Domain Images (2D)

understanding the frequency domain

For a 2D signal, we can think of the frequency domain as a 3D plot with **oriented frequency** on the xy-plane and **magnitude** on the z-axis.

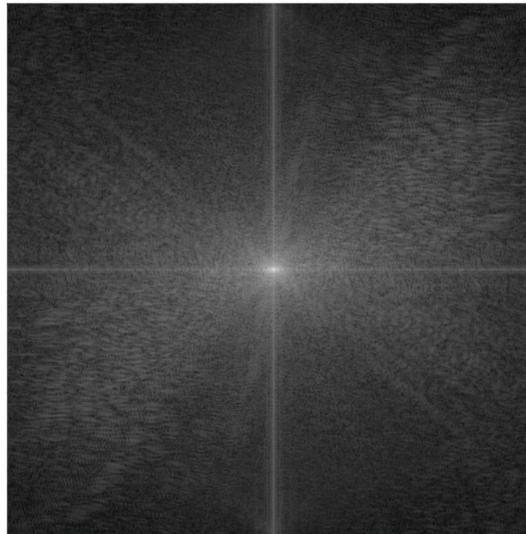


unlike a standard image,  
the origin of the plot is in the center

# Frequency Domain Images (2D)

understanding the frequency domain

However, we pretty much always view magnitude as brightness  
(i.e. as part of an image), instead of plotting it on a z-axis in 3D.

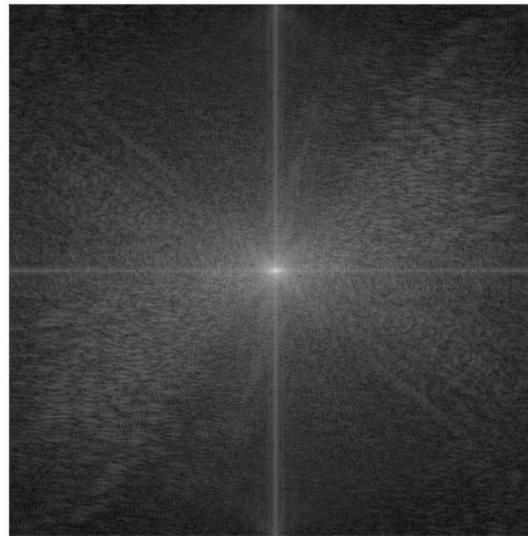


**higher magnitude**  
**means higher brightness**  
**means closer to white**

# Frequency Domain Images (2D)

understanding the frequency domain

The spatial domain and frequency domain images are the same size, i.e. the number of frequencies is equivalent to the number of pixels.



note that frequencies always range from -0.5 to 0.5, so what changes is the step between successive frequencies

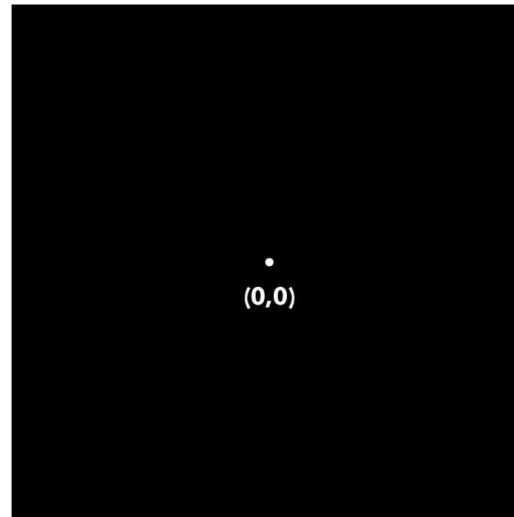
# Frequency Domain Images (2D)

understanding the frequency domain

zero frequency (constant; average value in image)



Spatial Domain

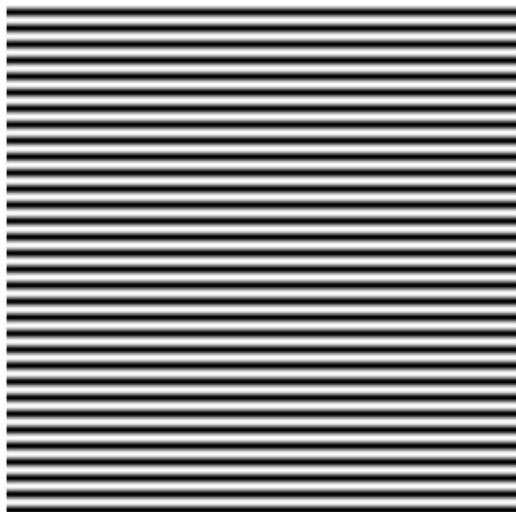


Frequency Domain

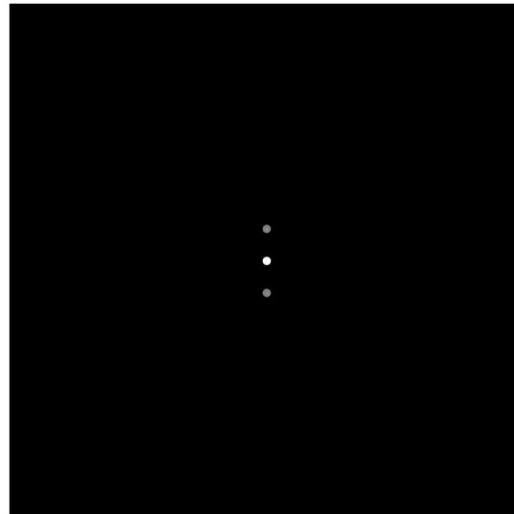
# Frequency Domain Images (2D)

understanding the frequency domain

$$\sin(2\pi/16)y$$



Spatial Domain



Frequency Domain

# Interpreting Frequency Visualizations

Let's say we're interested in the point  $(u, v)$ .

- Draw an arrow from the origin to  $(u, v)$ . This is a vector.

There are three pieces of information we can obtain.

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# Interpreting Frequency Visualizations

Let's say we're interested in the point  $(u, v)$ .

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Let's say we're interested in the point  $(u, v)$ .

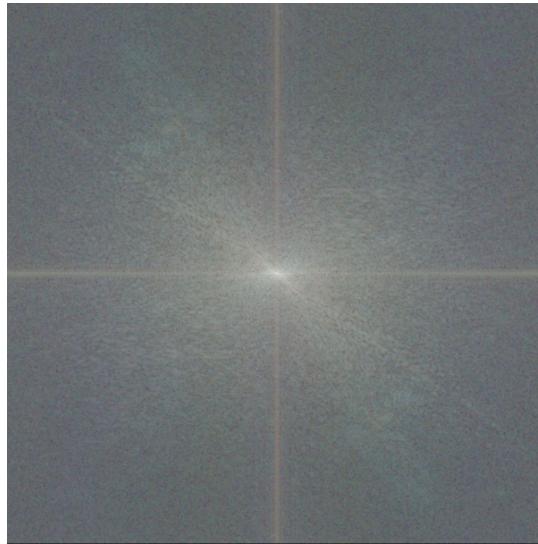
- Draw an arrow from the origin to  $(u, v)$ . This is a vector.

There are three pieces of information we can obtain.

1. The direction of vector  $(u, v)$  gives the **direction of the sinusoid**.
2. The length of vector  $(u, v)$  gives the **frequency of the oriented sinusoid**.
3. The brightness at point  $(u, v)$  gives the **magnitude of the sinusoid** (contrast from low to high).

## The + Artifact

The DFT does its computation for an image that is tiled infinitely, meaning we (usually) end up with high-frequency edges where the top/bottom and left/right of the tiled images meet.



## Convolution Theorem

Convolution in the spatial domain is equivalent to point-by-point multiplication in the frequency domain.

and what do we use convolution for?

## **Convolution Theorem**

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**Filtering!**

## Convolution Theorem

Convolution in the spatial domain is equivalent to  
point-by-point multiplication in the frequency domain.

and what do we use convolution for?

## Filtering!

So we have a choice.

- we can filter by sliding window in the spatial domain (`convolve`)
  - or -
- we can filter by multiplication in the frequency domain (`fftconvolve`)  
(multiply frequency version of the image by the frequency version of the convolution filter)

## Why would we want to filter in the frequency domain?

Efficiency.

Note: we don't get the element-wise multiplication completely for free.

We also have to perform Fourier transforms **to** and **from** the frequency domain.

For large arrays, it's faster to go to the frequency domain and filter there.

For smaller arrays, it's faster to stay in the spatial domain and do a gridded convolution.

## **Why would we want to filter in the frequency domain?**

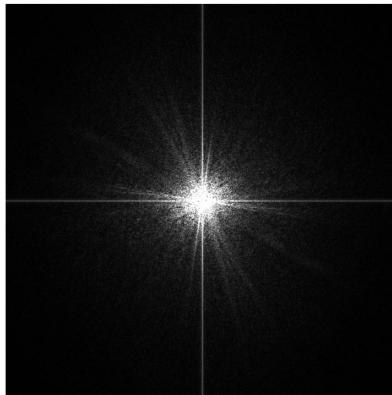
**Interpretability.**

We can look at convolution as an operation over a grid of numbers, or as modifying the frequencies of an image. It is often intuitive to think in terms of frequencies.

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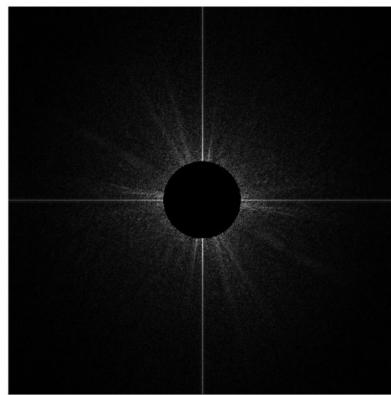
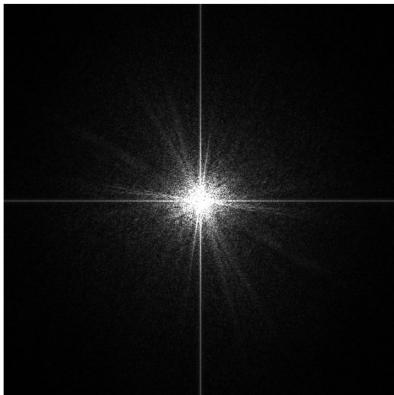


source: Ren Ng

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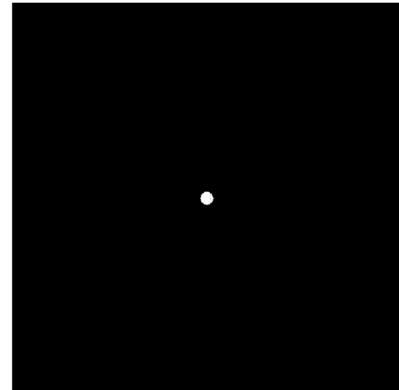
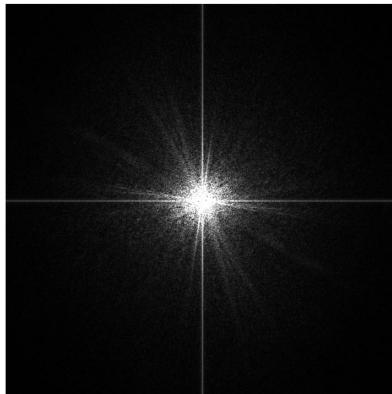
high-pass filtering:  
pass only the high frequencies

source: Ren Ng

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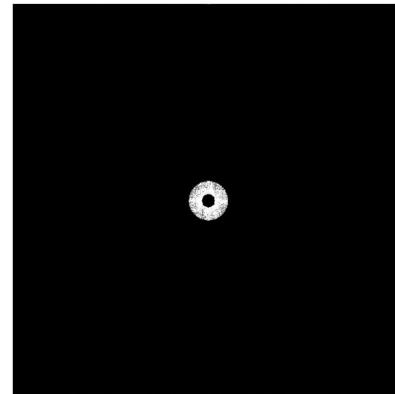
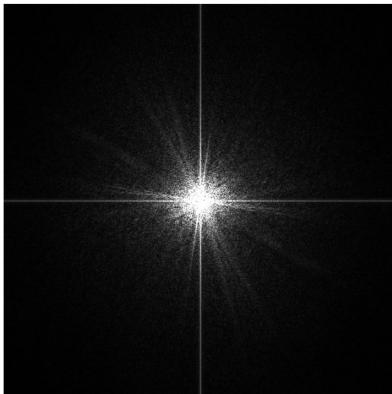
easy to see smoothness in frequency domain!

source: Ren Ng

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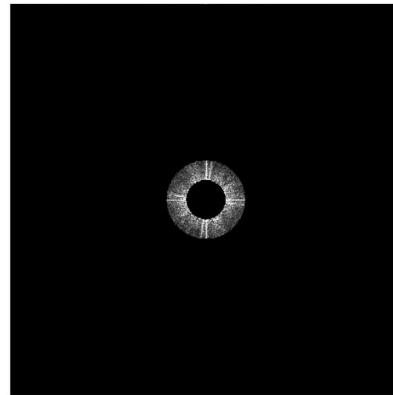
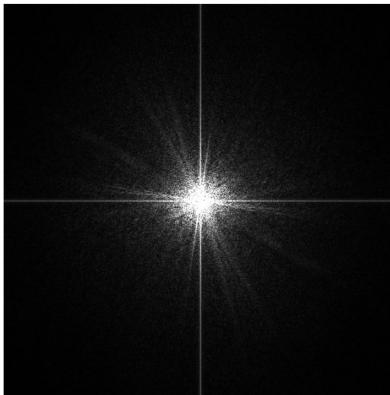
band-pass filter: filters out both high and low frequencies, looks like a band

source: Ren Ng

# Why would we want to filter in the frequency domain?

Interpretability.

We can look at convolution as an operation over a grid of numbers, or as modifying the frequencies of an image. It is often intuitive to think in terms of frequencies.



source: Ren Ng

## **(Extra) Basic Convolution Practice**

Convolve the signal **[1, 2, 3, 4, 5]** with the filter **[1, 2, 3]**.

(No need to pad.)

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[10

1x3 + 2x2 + 3x1

## (Extra) Basic Convolution Practice

Convolve the signal **[1, 2, 3, 4, 5]** with the filter **[1, 2, 3]**.

(No need to pad.)

[10, 16

2x3 + 3x2 + 4x1

## (Extra) Basic Convolution Practice

Convolve the signal **[1, 2, 3, 4, 5]** with the filter **[1, 2, 3]**.

(No need to pad.)

**[10, 16, 22]**

3x3 + 4x2 + 5x1

# The Edge Case

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

source: Steven Seitz

## Padding Options

```
cv2.filter2D(src, ddepth, kernel[, dst[, anchor[, delta[, borderType]]]])
```

How to extrapolate pixels over the border?

```
/*
Various border types, image boundaries are denoted with '/'

* BORDER_REPLICATE:      aaaaaa|abcdefg|hhhhhhh
* BORDER_REFLECT:        fedcba|abcdefg|hgfedcb
* BORDER_REFLECT_101:     gfedcb|abcdefg|gfedcba
* BORDER_WRAP:           cdefgh|abcdefg|abcdefg
* BORDER_CONSTANT:        iiieee|abcdefg|iiieee with some specified 'i'
*/
```

# Padding Options

```
scipy.signal.fftconvolve(in1, in2, mode='full')
```

Do we even want to extrapolate?

**mode** : str {'full', 'valid', 'same'}, optional

A string indicating the size of the output:

**full**

The output is the full discrete linear convolution of the inputs. (Default)

**valid**

The output consists only of those elements that do not rely on the zero-padding.

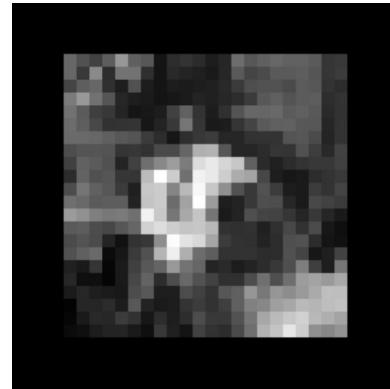
**same**

The output is the same size as *in1*, centered with respect to the 'full' output.

# Padding Options

- **Constant**

Pretend that everything outside the image is some specified constant (commonly zero).



source: Richard Szeliski

# Padding Options

- Constant
- Replicate

Pretend that everything outside the image is whatever's already on the edge.

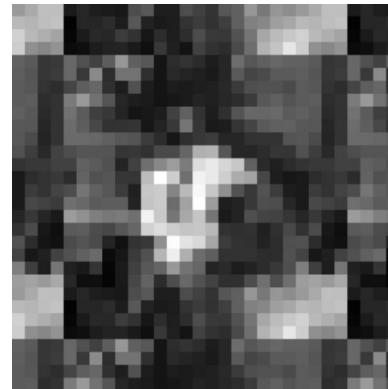


source: Richard Szeliski

# Padding Options

- Constant
- Replicate
- Wrap

Pretend that the image is tiled indefinitely, i.e. “loop over the image.”

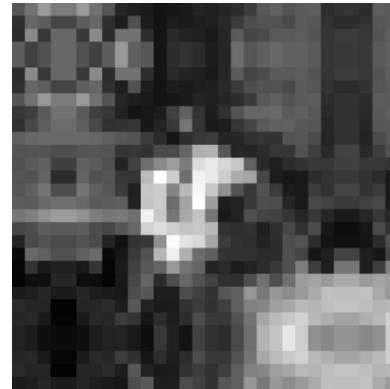


source: Richard Szeliski

# Padding Options

- Constant
- Replicate
- Wrap
- Mirror

Reflect the image across its edges.



source: Richard Szeliski

## Padding Options

- Constant
- Replicate
- Wrap
- Mirror
- ...

# Additional Readings

## Sobel filter

- <https://stackoverflow.com/questions/17078131/why-sobel-operator-looks-that-way>

## Fourier domain images

- <http://cns-alumni.bu.edu/~slehar/fourier/fourier.html>
- <https://www.cs.toronto.edu/~guerzhoy/320/lec/FreqDomain.pdf>

## Circular paths

- <https://betterexplained.com/articles/an-interactive-guide-to-the-fourier-transform/>