

COMP 471

# Fourier Transform

Wednesday 25 Sep 2006

- Sinusoidal Image
- Discrete Fourier Transform
- Meaning of Image Frequencies of DFT

# Sinusoidal Images

- We shall make frequent discussion in this module of image frequency content.
- The image having the simplest frequency content is the sinusoidal image.

# Sinusoidal Images

- A discrete sine image  $I$  has elements
- $$I(i, j) = \sin [2\pi ( i M/u + j N/v)]$$
- for  $0 \leq i \leq N-1, 0 \leq j \leq M-1$
- and a discrete cosine image has elements
- $$I(i, j) = \cos [2\pi( i M/u + j N /v)]$$
- where  $u, v$  are integer frequencies in the  $i$ - and  $j$ -directions (cycles/image).



- Spatial Frequencies (this is...)

# Radial Frequency

- The radial frequency (how fast the image oscillates in its direction of propagation) is

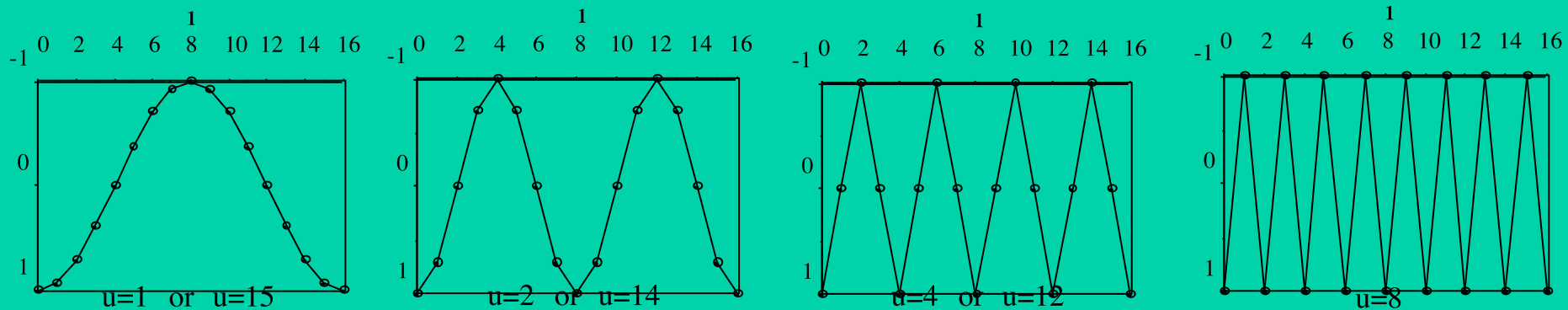
$$\Omega = \sqrt{u^2 + v^2}$$

- The angle of the wave (relative to i-axis) is

$$\theta = \arctan\left(\frac{v}{u}\right)$$

# Digital Sinusoidal Example

- Let  $N = 16$ ,  $v = 0$ :  $l(i) = \cos(2\pi ui/16)$ : a cosine wave oriented in  $i$ -direction with frequency  $u$ . One row:



- Note that  $l(i) = \cos(2\pi ui/16) = \cos[2\pi(16-u)i/16]$ .
- Thus the highest frequency wave occurs at  $u = N/2$  ( $N$  is even here). This will be important later.



# Values of Complex Exponential

- The complex exponential

$$W_K^{um} = e^{-2\pi i \frac{u}{M} m}$$

- is a frequency representation indexed by exponent  $ui$ .
- Minimum physical frequencies: If  $u = kM$ , then as a function of  $m$

$$W_M^{kMm} = 1 \quad \forall k \in \mathbb{Z}$$

- Maximum physical frequencies: If  $u = (k+1/2)M$ , then

$$W_M^{um} = W_M^{(k+\frac{1}{2})Mm} = (-1)^m$$

period 2 function of  $m$  (Q. What could this look like as  
bitmap?)

# Complex Exponential Image

- We'll use complex exponential functions to define the Discrete Fourier Transform.
- Define the 2-D complex exponential functions of  $(u,v)$ :

$$e^{2\pi\sqrt{-1}(Um+Vn)}$$

- $0 \leq m \leq M-1, 0 \leq n \leq N-1$
- The complex exponential allows convenient representation and manipulation of frequencies.



# Properties of Complex Exponential

- We will use the abbreviation

$$W_K = \exp\left[-\frac{2\pi\iota}{K}\right]$$

$$\iota = \sqrt{-1}$$

(K = image dimension, M or N).

- Powers of  $W_K$  index the frequencies of the component sinusoids.
- This gives functions of (u,v):

$$W_K^{um} W_K^{vn} = \cos\left[2\pi\left(\frac{u}{M}m + \frac{v}{N}n\right)\right] - \iota \sin\left[2\pi\left(\frac{u}{M}m + \frac{v}{N}n\right)\right]$$

using Euler's identity  $e^{\iota\theta} = \cos(\theta) - \iota \sin(\theta)$

- Will be our *basis* functions for the finite images

# Basis Functions

$$W_{mn}[u, v] = W_M^{um} W_N^{vn}$$

These basis functions  $W_{mn}[u, v] = W_M^{um} W_N^{vn}$  are orthogonal w/r to this inner product:

$$\begin{aligned} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} W_{mn}[u, v] W_{pq}[-u, -v] &= \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} W_M^{um} W_M^{-up} W_N^{vn} W_N^{-vq} \\ &= M N \quad \text{if } m=n \text{ and } p=q, \\ &\quad 0 \quad \text{otherwise} \end{aligned}$$

# Comments

- It's possible to develop frequency domain concepts w/o complex numbers - but the math is much lengthier.
- Using  $W_{mn}[u, v] = W_M^{um} W_N^{vn}$  to represent a frequency component oscillating at  $u$  (cycles/image) and  $v$  (cy/im) in the  $M$ - and  $N$ -directions simplifies things considerably.
- It is useful to think of  $W_{mn}$  as a representation of a direction and frequency of oscillation.

# DISCRETE FOURIER TRANSFORM

$$\tilde{F}[u, v] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f[m, n] W_M^{um} W_N^{vn}$$

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# Inverse Discrete Fourier Transform

$$\mathbf{f}[m, n] = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \tilde{F}[u, v] W_M^{-um} W_N^{-vn}$$

- Any  $M \times N$  image  $\mathbf{f}[m, n]$ ,  $0 \leq m \leq M-1$ ,  $0 \leq n \leq N-1$  is uniquely expressed as the weighted sum of a finite number of complex exponential images.

The weights  $\tilde{F}[u, v]$  are unique. (Why?)

# properties of DFT

- If  $\tilde{F}$  is the DFT of  $f$
- Linear:  $\text{DFT}[af + bg] = a \text{DFT}[f] + b \text{DFT}[g]$
- Invertible
- Symmetric:
- Periodic  $\Rightarrow$  image periodicity

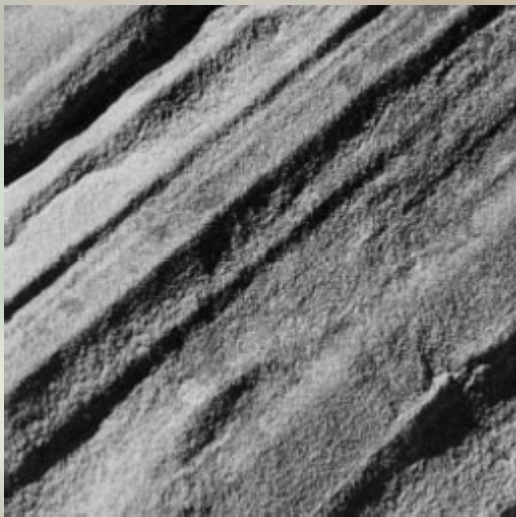


# Convolution

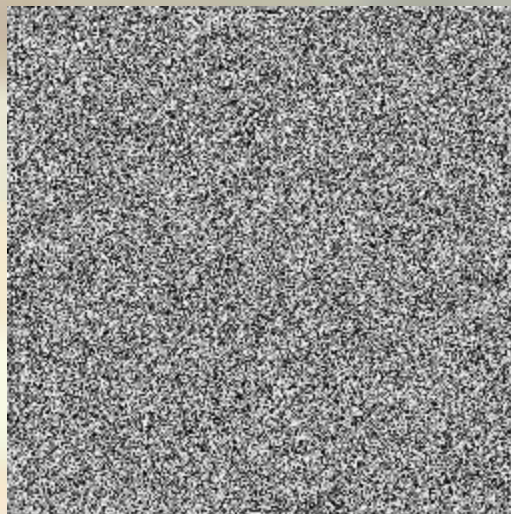
- $f * g \leftrightarrow F G ?$
- true for infinite images...

# Interpreting the DFT

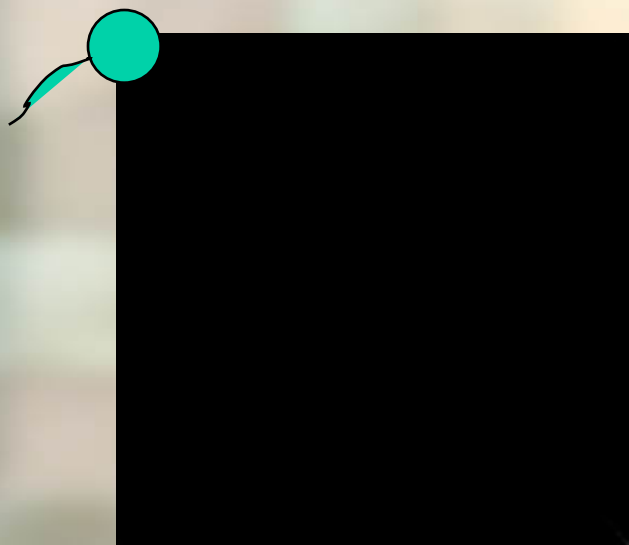
- The DFT of an image is usually displayed as images of magnitude and of phase.
- The magnitude and phase values are given gray-scale values / intensities.
- The phase is usually visually meaningless.
- The magnitude matrix is usually logarithmically transformed (followed by a FSCS) prior to display:



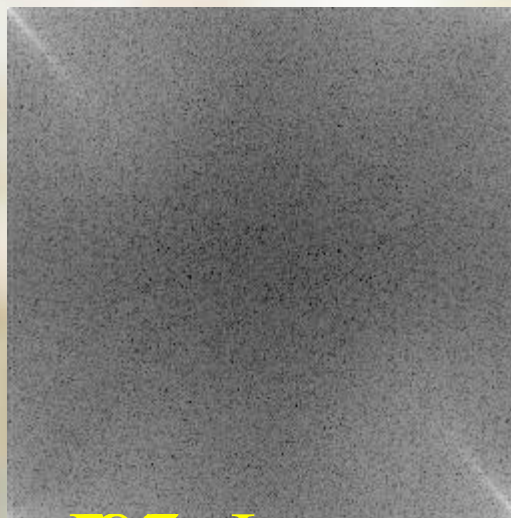
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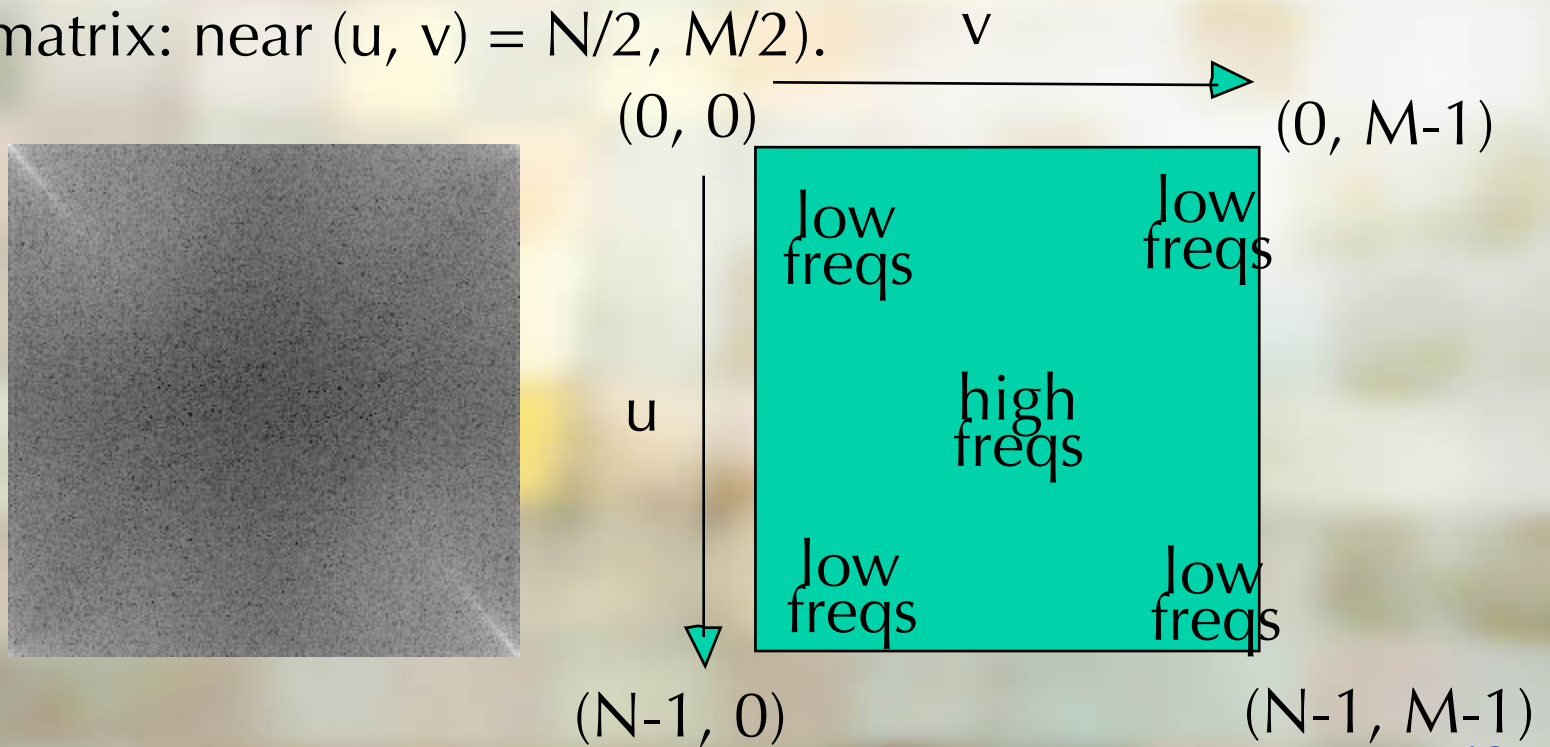


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- Note that the coefficients of the highest physical frequencies are located near the center of the DFT matrix: near  $(u, v) = N/2, M/2$ .





# Periodicity of the DFT

- The DFT matrix is finite ( $M \times N$ ):

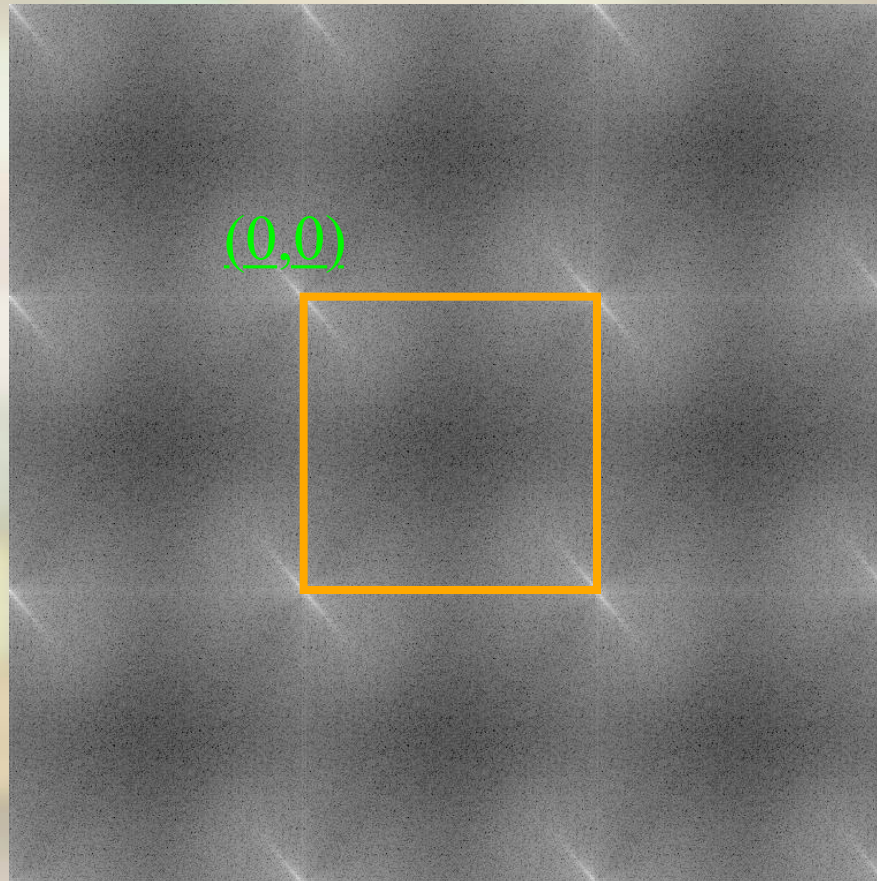
$$\tilde{F}[u, v] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f[m, n] W_M^{um} W_N^{vn}$$

$$0 \leq u \leq M-1, 0 \leq v \leq N-1$$

- Yet if the indices are allowed to range outside  $[0, M-1] \times [0, N-1]$ , we see the DFT is periodic with periods  $M$  and  $N$ :

$$\tilde{F}[u + aM, v + bN] = \tilde{F}[u, v]$$

for any integers  $a$  and  $b$ .



- Periodic extension of DFT



# Periodic Extension of Image

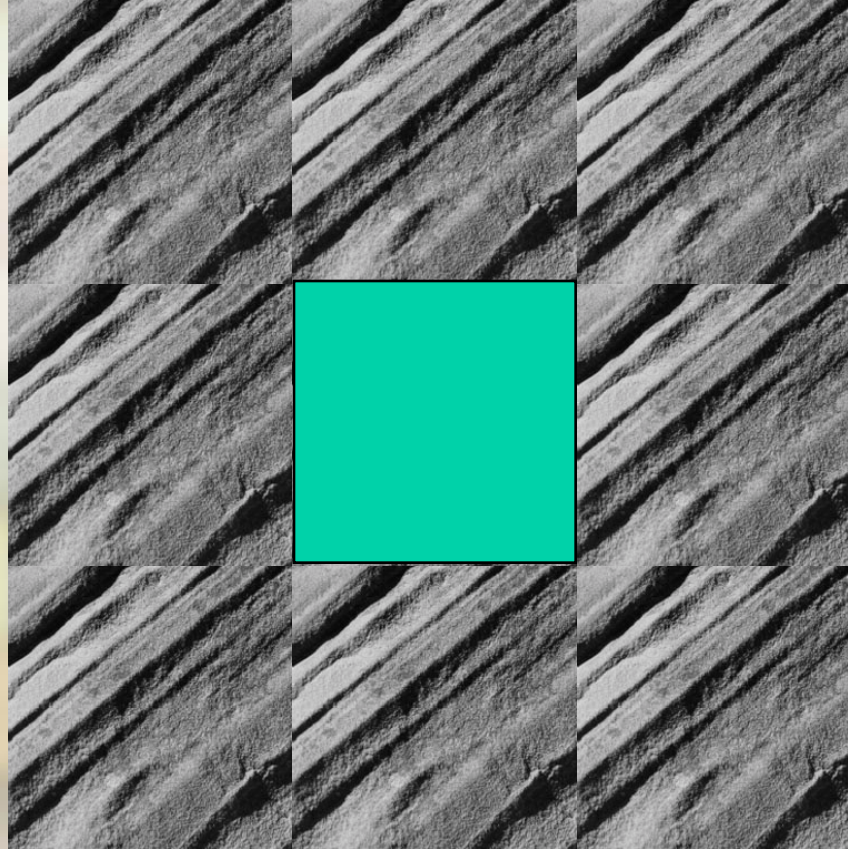
- The IDFT equation

$$f[m, n] = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} \tilde{F}[u, v] W_M^{-um} W_N^{-vn}$$

- Implies the periodic extension of the image as well:

$$f(m + a M, n + b N) = f(m, n)$$

# Periodic extension of image



# Centering the DFT

- Usually, the DFT is displayed with DC coordinate  $(u, v) = (0, 0)$  at the center.
- Then low frequency info (which dominates most images) will cluster at the center of the display.
- Centering is accomplished by taking the DFT of the alternating image:
  - $$[(-1)^{i+j}I(i,j) ; 0 \leq i, j \leq N-1]$$
- This is for display only!

# Centering the DFT

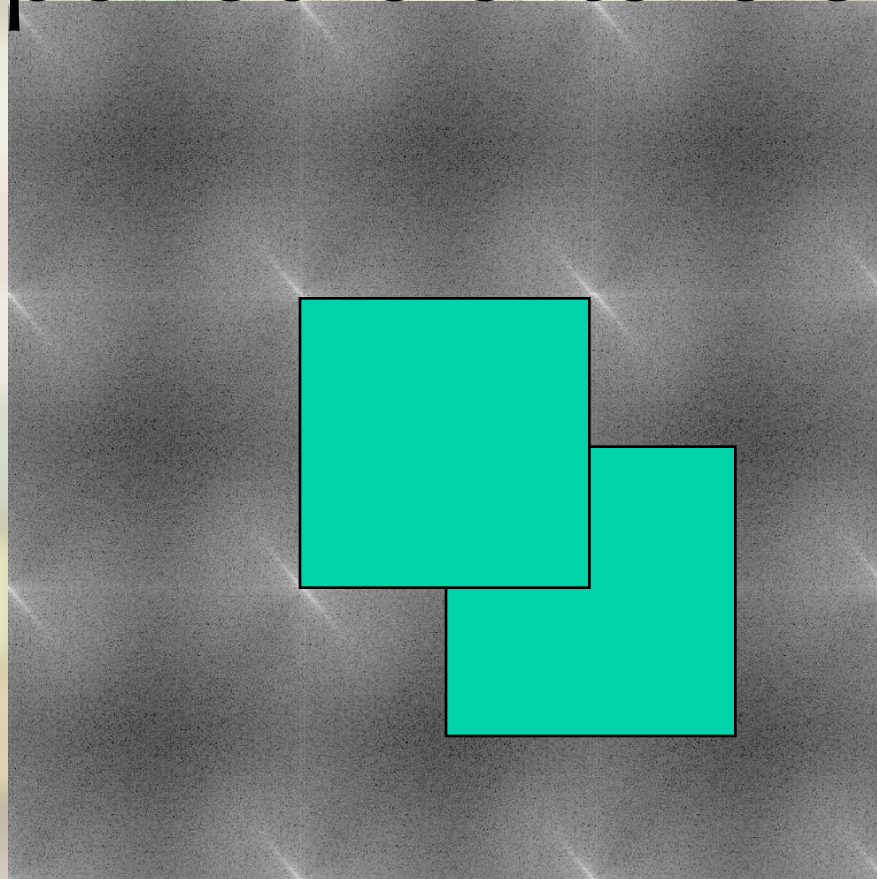
- Note that

$$(-1)^{i+j} = e^{\pi(i+j)} = e^{N(i+j)/2} =$$

so

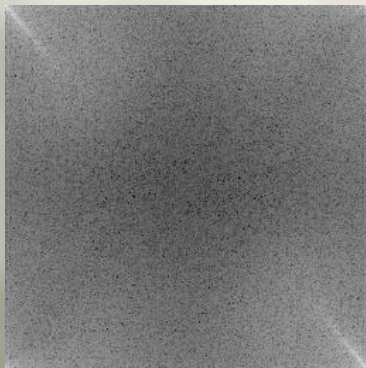
$$\begin{aligned} \bullet \text{DFT}[(-1)^{m+n} F[m, n]] &= \sum_{m,n=0}^{N-1} F[m, n] (-1)^{m+n} W_N^{um+vn} \\ &= \sum_{m,n=0}^{N-1} F[m, n] W_N^{-N(m+n)/2} W_N^{um+vn} \\ &= \sum_{m,n=0}^{N-1} F[m, n] W_N^{(u-N/2)m+(v-N/2)n} \\ &= \tilde{F}[u - N/2, v - N/2] \end{aligned}$$

# Shifted (centered) DFT from periodic extension

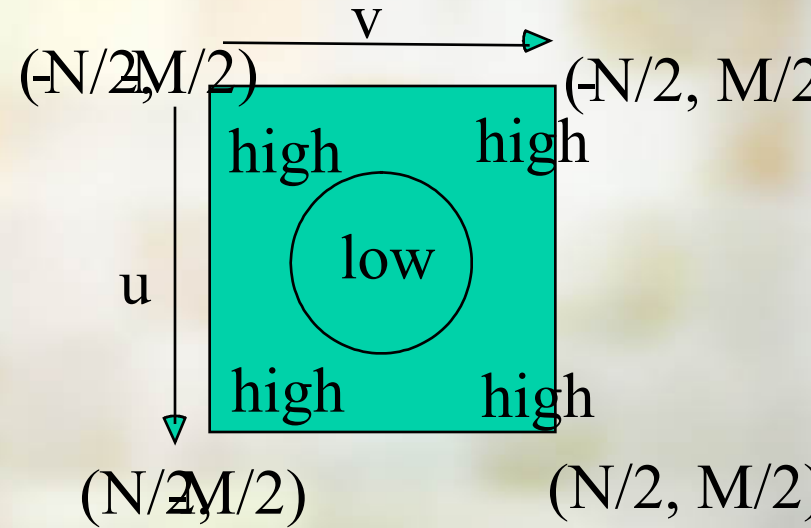
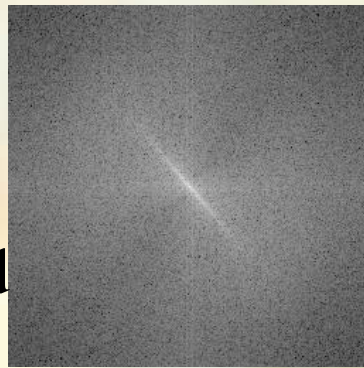




# Centered DFT



centered



- DFT Example DEMO



# Computation of the DFT

- Fast DFT algorithms collectively referred to as the Fast Fourier Transform (FFT).
- We won't study these – take a DSP class.
- Available in any math software library, Jitter!
- Forward and inverse DFTs essentially identical.  
Q. How are they different?

# THE MEANING OF IMAGE FREQUENCIES

- It's easy to lose track of the meaning of the DFT and the notion of frequency content in all the math.
- By examining the DFT or spectrum of an image (especially its magnitude), we can often deduce much about the image.

# QUALITATIVE PROPERTIES OF THE DFT

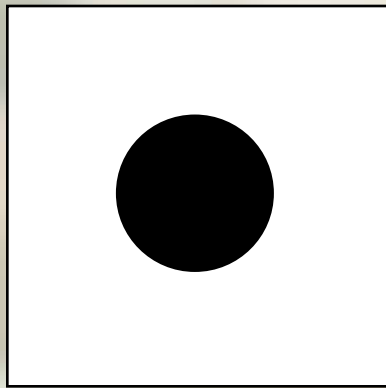
- We may regard the DFT magnitude as an image of frequency content.
- Bright regions in the DFT magnitude "image" correspond to frequencies having large magnitudes in the actual image.
- It is intuitive to think of image frequency content in terms of granularity (distribution of radial frequencies) and orientation.

# IMAGE GRANULARITY

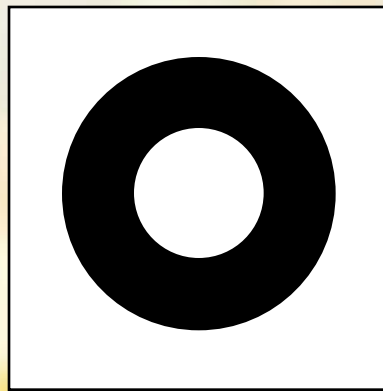
- Large DFT coefficients near the origin correspond to smooth image regions or a strong background. Since images are positive, image DFTs usually have a large peak at  $(u, v) = (0, 0)$ .
- The distribution of DFT coefficients relative to the origin is related to the granularity of the image.

# MASKING DFT GRANULARITY

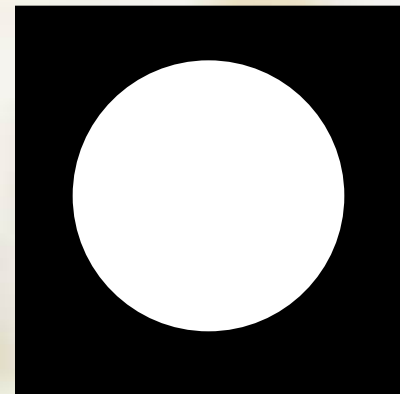
- Define toroidal zero-one masks (black = 1)



low-frequency mask



mid-frequency mask



high-frequency mask

- Masking (multiplying) a DFT with these will produce IDFT images with only low-, middle-, or high frequencies: EXERCISE. Do this at home!

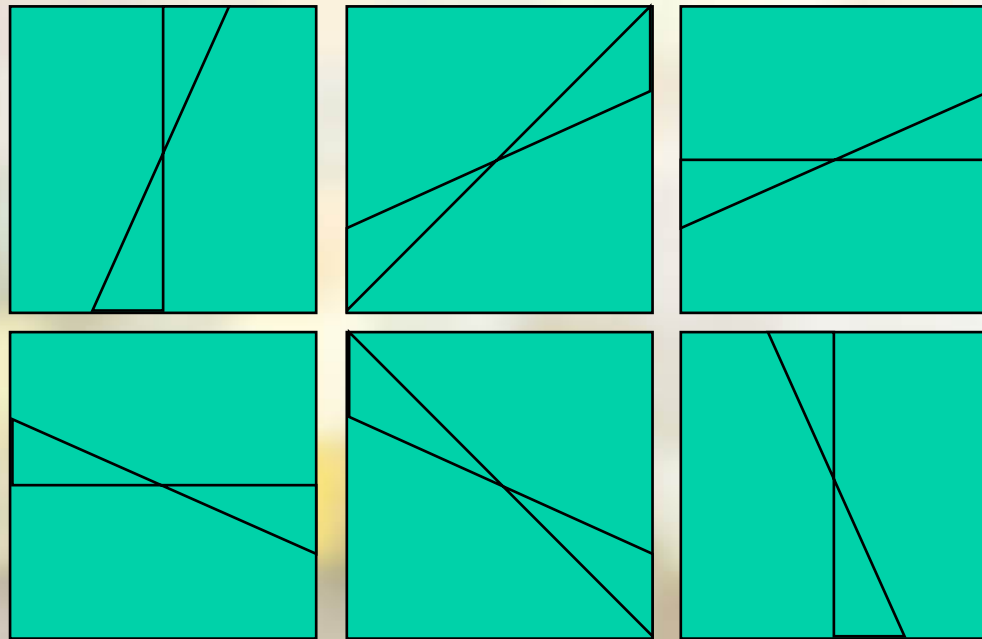
# Image Directionality

- Large DFT coefficients along certain orientations correspond to highly directional image patterns.
- The distribution of DFT coefficients as a function of angle relative to the axes is related to the directionality of the image.



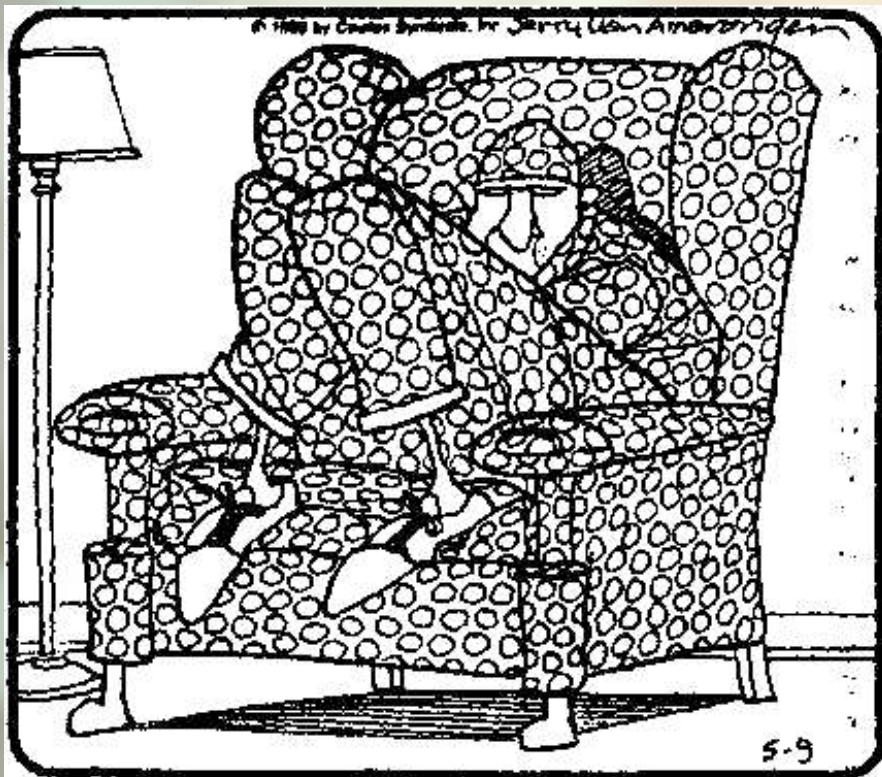
# MASKING DFT GRANULARITY

- Try oriented, angular zero-one masks like these:



- The frequency origin is at the center of each mask.

# Test Images



You get the feeling Bob's not going out and grabbing life by the throat anytime soon.



**When the monster came, Lola, like the peppered moth and the arctic hare, remained motionless and undetected. Harold, of course, was immediately devoured.**

- For Journal of Irreproducible Results

# Aliased Chirp Image

- A chirp image

$$I(x, y) = A [1 + \cos(\alpha x + \beta y)]$$

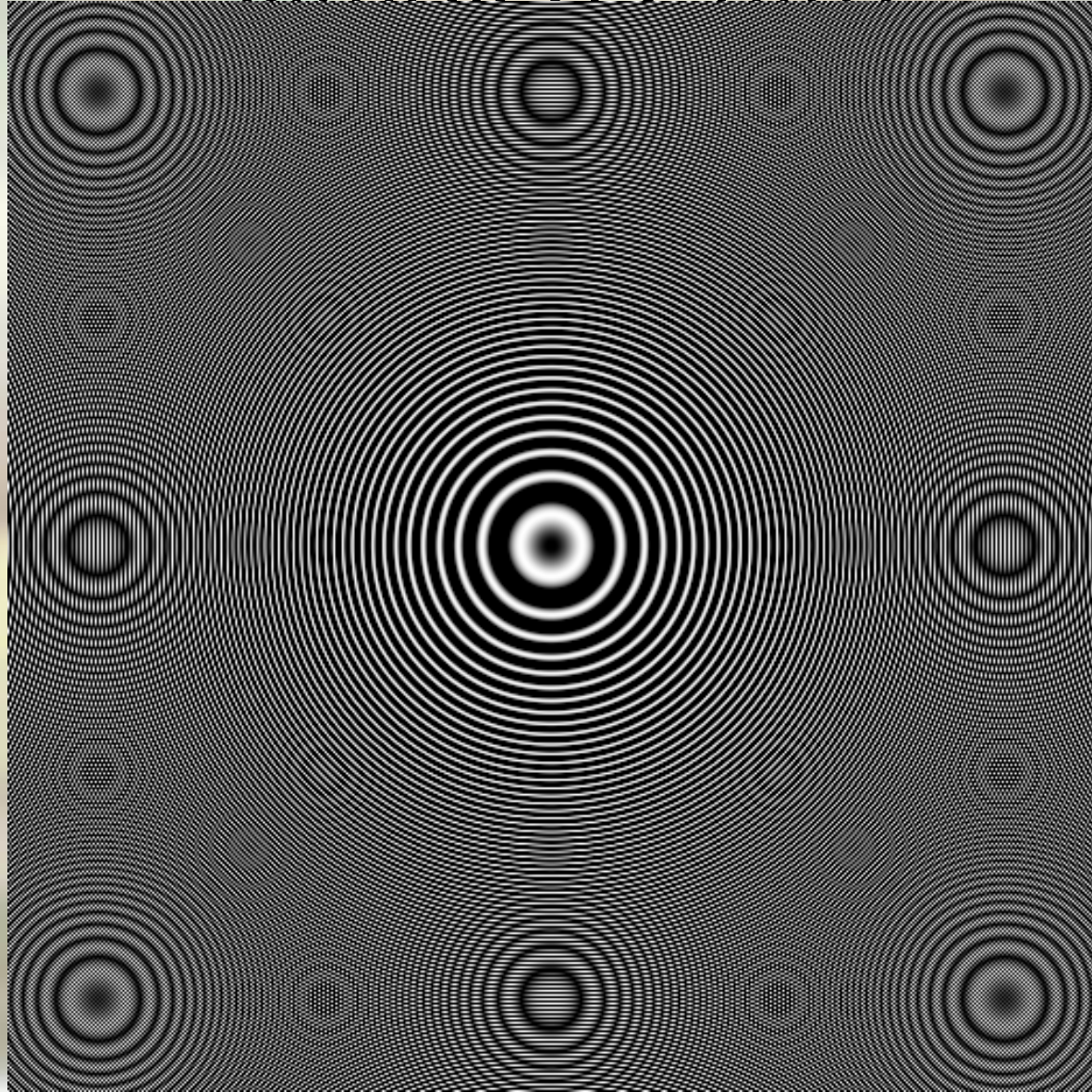
- has instantaneous spatial frequencies

$$f_x(x, y) = \alpha$$

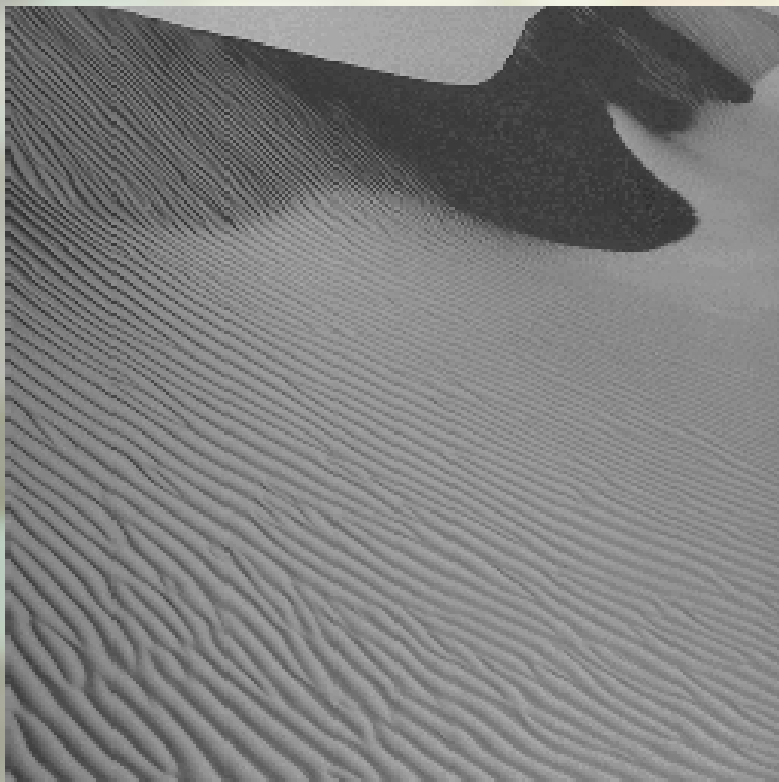
- which increase linearly away from the origin.



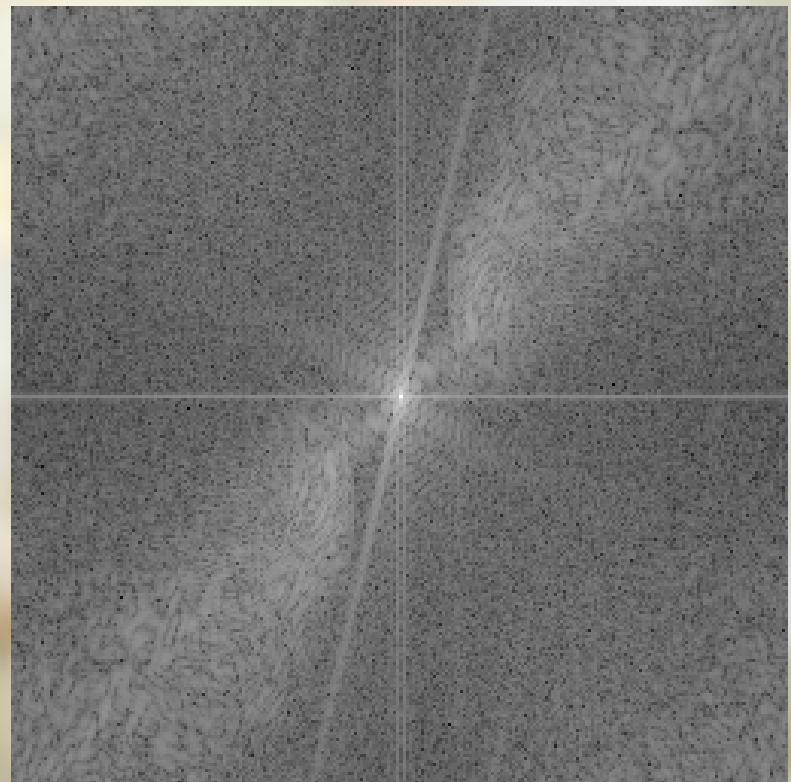
# Sampled Chirp



# Aliased Image



Sand Dune Image



Centered DFT Showing Aliasing

# IMPORTANT 2-D FUNCTIONS AND THEIR DFTS

- It is worthwhile to examine the DFTs of some specific images. This is usually hard to do explicitly for the DFT / DSFT (infinite discrete image).
- So we'll give some simple ones.
- Then state some others as CFT transform pairs.



# Constant Image

- If  $\mathbf{f}(i, j) = c$ , for  $0 \leq i \leq N-1, 0 \leq j \leq M-1$

Then

$$\text{DFT}[\mathbf{f}][u, v] = N^2 \cdot c \cdot \delta(u, v)$$

where

- $\delta(u, v) = \text{unit impulse function}$
- $= \{1 \text{ at } (u=0, v=0)$
- $0 \text{ elsewhere } \}$

# 2-D Unit Pulse Image

- Let  $\mathbf{F}[m, n] = c \cdot \delta[m, n]$
- Then

$$\begin{aligned}\tilde{F}[u, v] &= \sum_{m, n=0}^{N-1} c \cdot \delta[m, n] W_N^{um+vn} \\ &= c \cdot W_N^0 = c\end{aligned}$$

# Cosine Wave Image

- Let

$$F[m, n] = d \cdot \cos[\pi(bm + cn)] = \frac{d}{2} [W_N^{bm+cn} + W_N^{-(bm+cn)}]$$

- by the Euler formula. Then

$$\begin{aligned} \tilde{F}[u, v] &= \frac{d}{2} \sum_{m,n=0}^{N-1} [W_N^{bm+cn} + W_N^{-(bm+cn)}] W_N^{um+vn} \\ &= \frac{d}{2} \sum_{m,n=0}^{N-1} [W_N^{(u+b)m+(v+c)n} + W_N^{(u-b)m+(v-c)n}] \end{aligned}$$

using the lemma  $\text{DFT}[\text{impulse}] = \text{constant } W_N^0$

$$= \frac{d}{2} N^2 [\delta(u + b, v + c) + \delta(u - b, v - c)]$$

so DFT is non-zero *only* at the frequencies of cosine wave

# Sinusoidal Images

- Ditto for sine wave
- Sinusoids are concentrated single frequencies

# Gaussian Function

- If

$$F_{\sigma}[m, n] = e^{-(m^2+n^2)/\sigma^2}$$

then

$$\widetilde{F}_{\sigma}[u, v] = e^{-2\pi^2\sigma^2(u^2+v^2)}$$

- The Fourier transform of a Gaussian is also Gaussian.

# Comments

- We now have a basic understand of frequency-domain concepts
- We can put them to use in linear filtering applications.