



University of
Nottingham

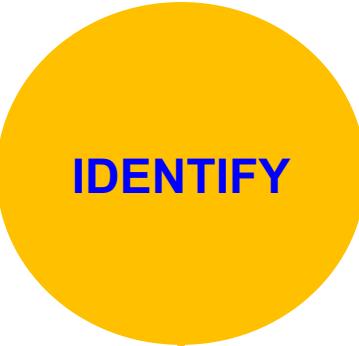
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COMP-2032
**Introduction to
Image Processing**

Lecture 9
Hough Transform & Frequency Domain



Learning Outcomes



1. How to find lines?
2. The Hough Transform
3. Other parameter spaces
4. What is frequency domain?
5. The frequency domain processing





Finding Lines: Template Matching



Why Lines?

Geometric primitives make important vision tasks easier

E.g., matching or classifying images

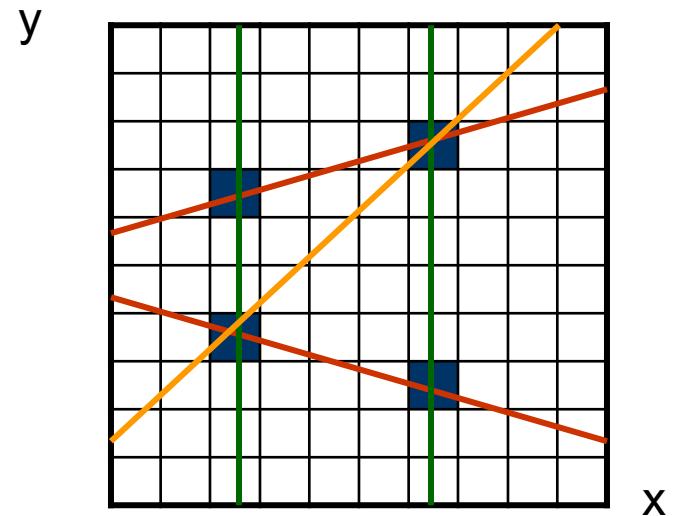
- Some geometric objects are invariant under projection from the (3D) world to (2D) image
 - Straight lines in the world create straight lines on the image
- A straight line in the image is evidence for a straight line in the world





The Problem

- Suppose straight lines are important
- Edge detection provides a set of points (x_i, y_i) which are likely to lie on those lines
- But how many lines are there and what are their parameters?



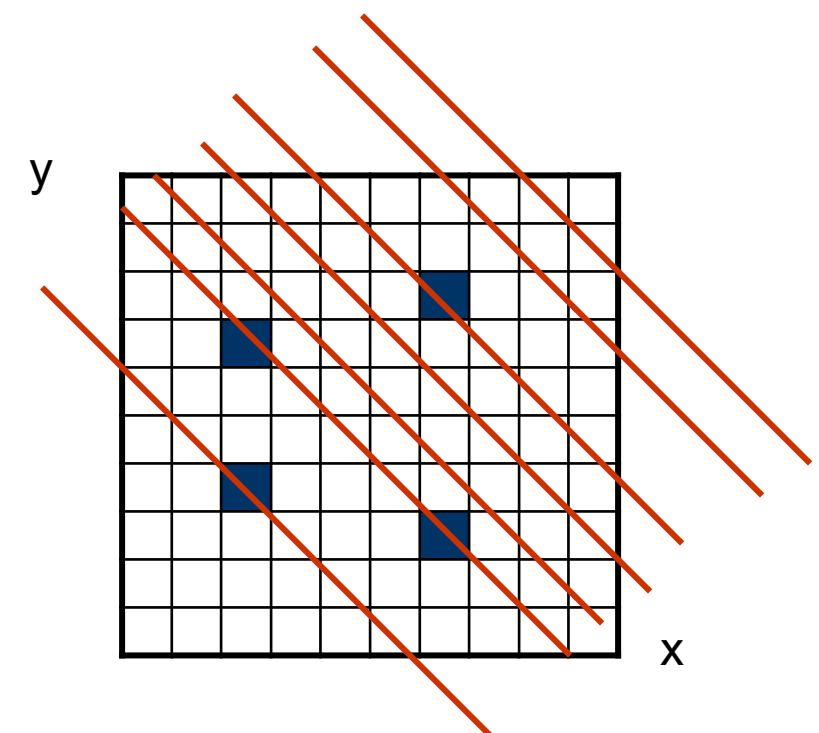


Template Matching

- One solution is to take a straight line and match it to all possible image positions and orientations
- Compute a measure of fit to the edge data

E.g., count how many edges are under each possible line

Incredibly expensive!





Template Matching vs. Hough

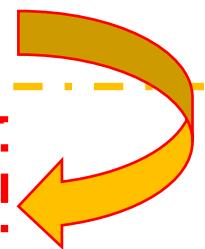
Classic template matching takes a line, lies it on the image data and asks:

- Does it fit here?
- Here?
- Here?
- How about here?
- Here then?
-



The Hough takes each data item (edge) and asks:

What lines could pass through this?





The Hough Transform

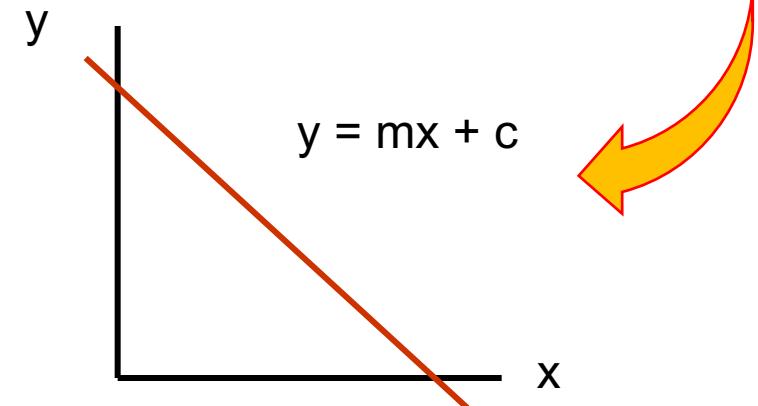


Line Parameters

The standard equation of a line is

$$y = mx + c$$

- If we know the line parameters m, c - we can vary x , compute y and draw the line
- This line represents the set of (x,y) pairs that satisfy the above equation



But we don't know the line parameters – we just have some data points (x_i, y_i)



Parameter Space

But if a data point (x_i, y_i) lies on a line then that line's parameters m, c must satisfy

$$y_i = mx_i + c$$

So we can represent all possible lines through (x_i, y_i) by the set of (m, c) pairs that satisfy this equation

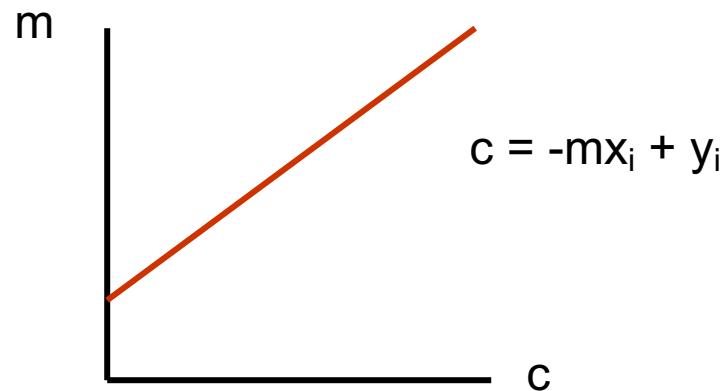
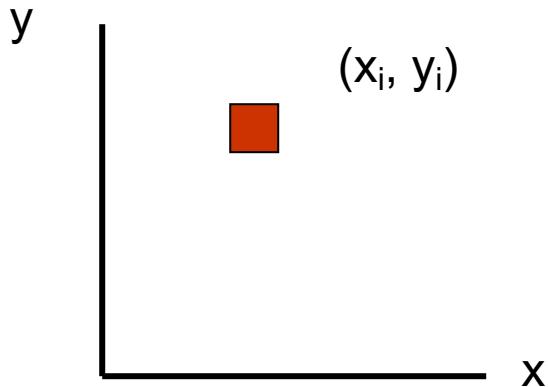
Rearranging the equation gives

$$c = -mx_i + y_i$$

This also describes a straight line, but as x_i and y_i are known and m and c are unknown, that line is in m, c space – a parameter space



Parameter Space

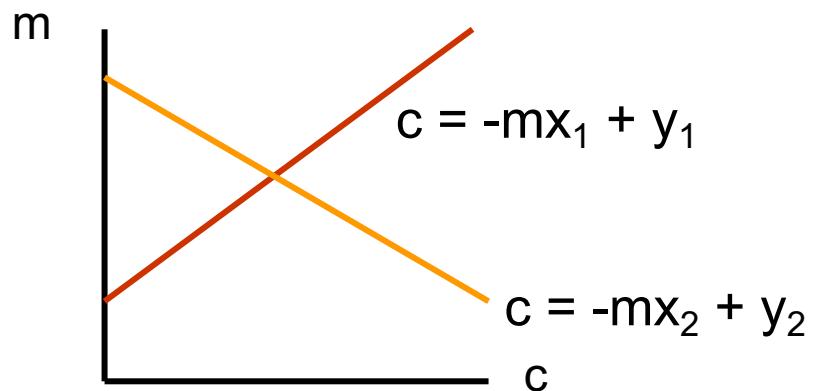
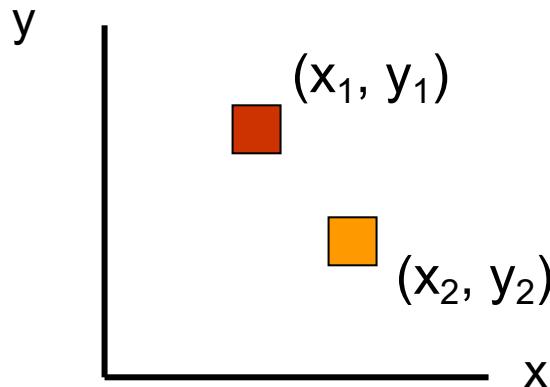


This straight line in m, c space represents all the values of (m, c) that satisfy $y_i = mx_i + c$, and so the parameters of all the lines that could pass through (x_i, y_i)



Parameter Space

Suppose there are 2 edges in our image (x_1, y_1) and (x_2, y_2)

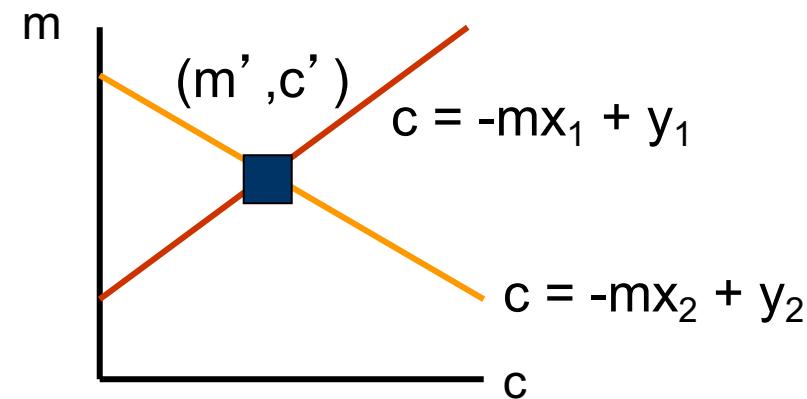
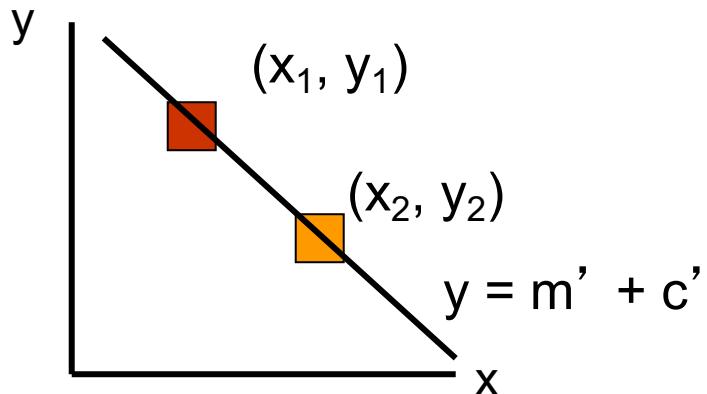


They will each generate a line in (m, c) space representing the set of lines that could pass through them



Parameter Space

The intersection of our 2 lines is the intersection of 2 sets of line parameters



The point of intersection therefore gives the parameters of a line through both (x_1, y_1) and (x_2, y_2)



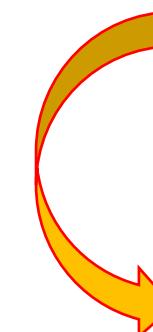
Parameter Space

Taking this one step further

- All pixels which lie on a line in (x,y) space are represented by lines which all pass through a single point in (m,c) space
- The point through which they all pass gives the values of m' and c' in the equation of the line: $y = m'x + c'$



To detect lines all we need to do is transform each edge point into m,c space and look for places where lots of lines intersect



This is what Hough Transform do



The Hough Transform

1

Quantise (m, c) space into a two-dimensional array A for appropriate steps of m and c

2

Initialise all elements of $A(m, c)$ to zero

3

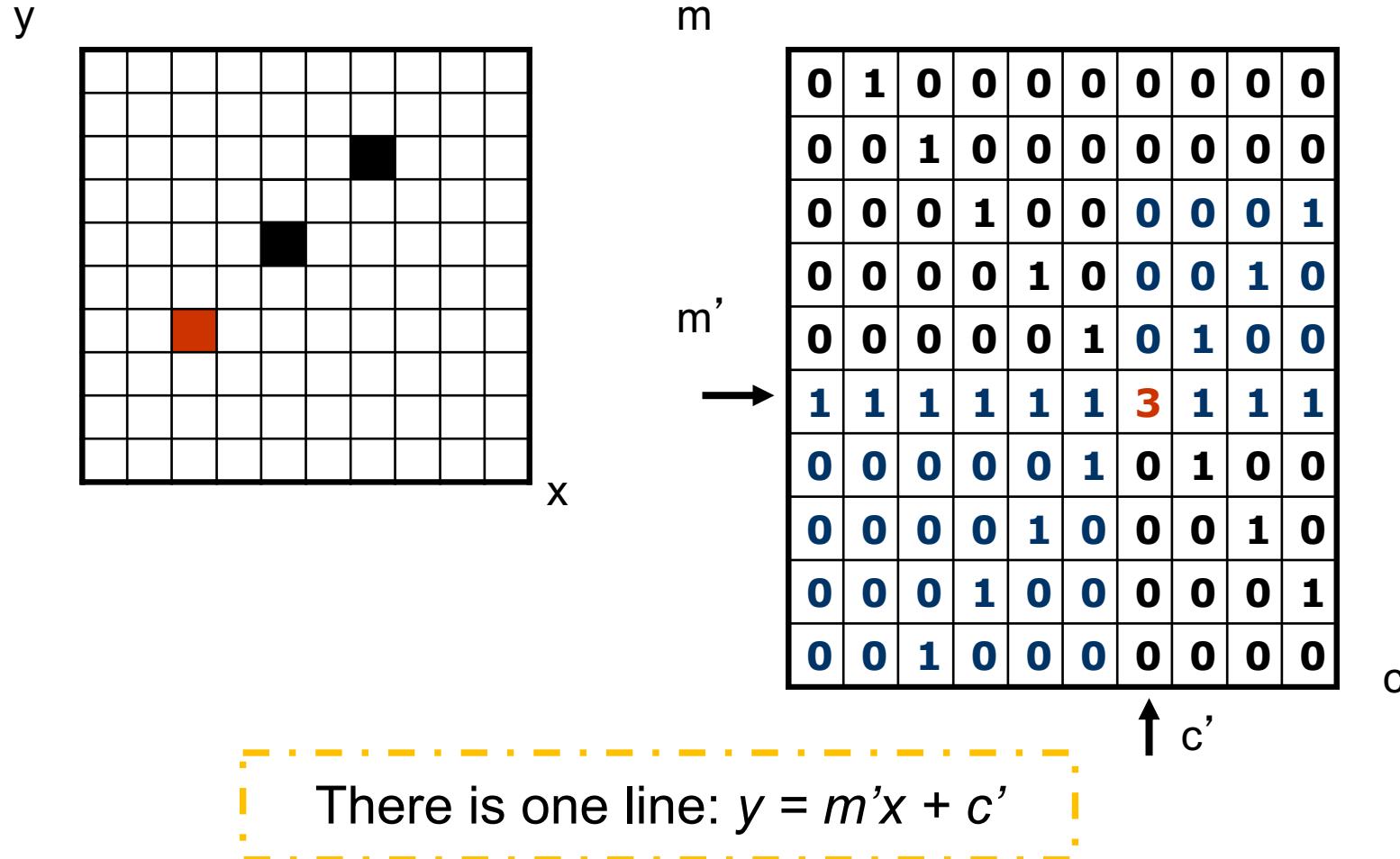
For each pixel (x_i, y_i) which lies on some edge in the image, we add 1 to all elements of $A(m, c)$ whose indices m and c satisfy $y_i = mx_i + c$

4

Search for elements of $A(m, c)$ which have large values – each one found corresponds to a line in the original image

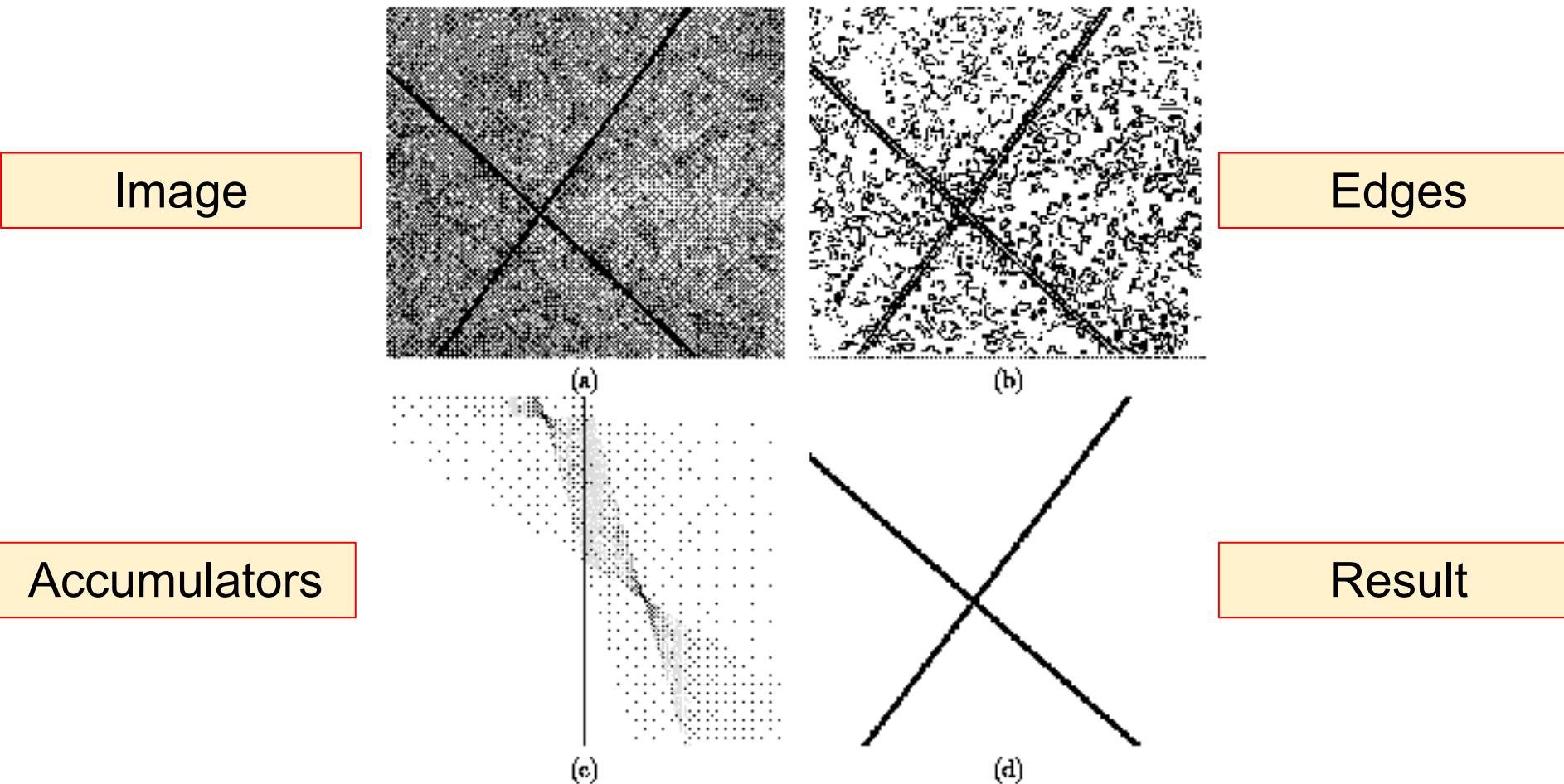


The Hough Transform





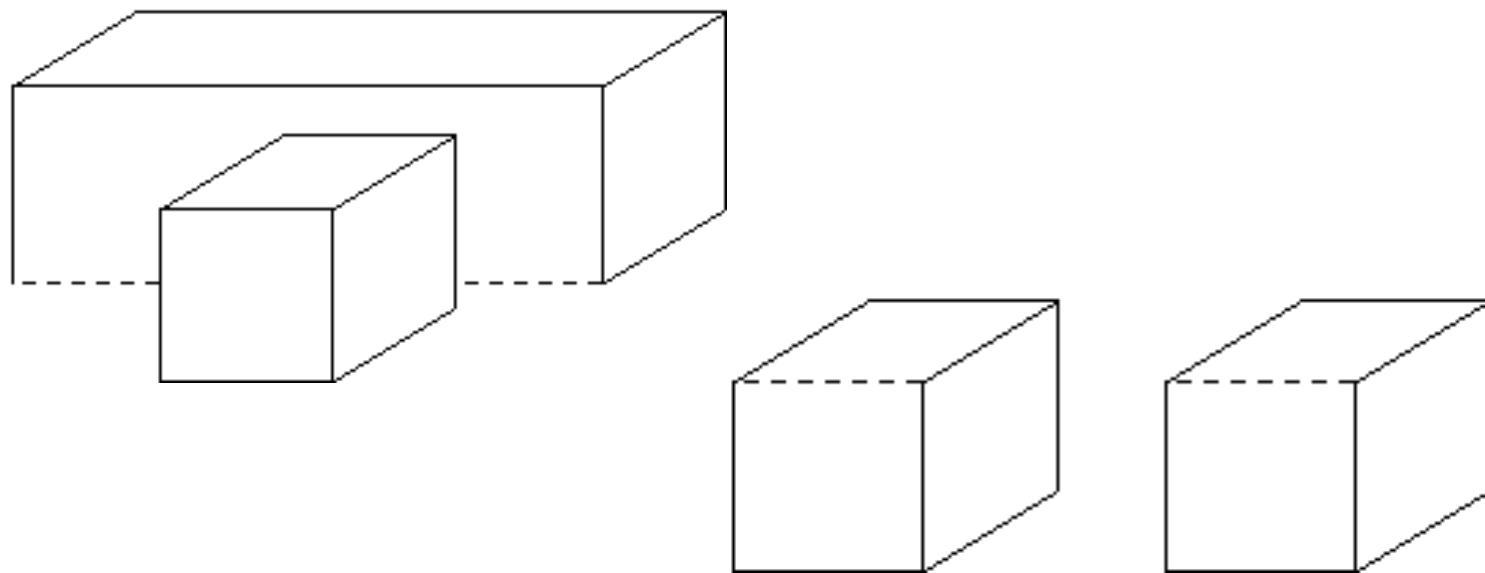
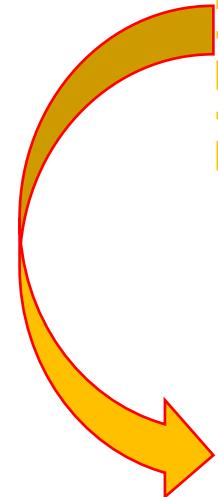
A (More) Real Example





Line Parameters

The Hough Transform only supplies the parameters of the lines it detects; this can be an advantage or a disadvantage





Other Parameter Spaces



Straight Lines AGAIN

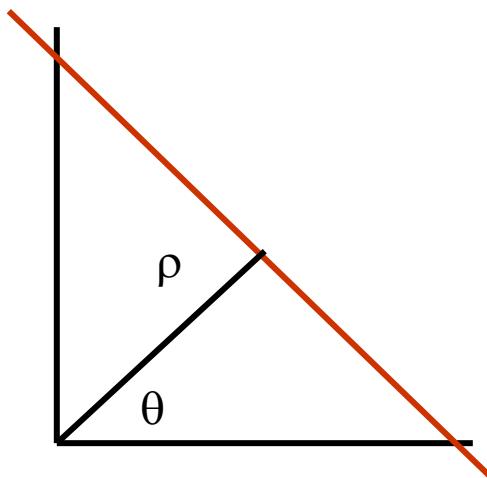
Another equation for a straight line

$$\rho = x \cdot \cos(\theta) + y \cdot \sin(\theta)$$



For an $n \times n$ image

- ρ is in range $[0, 2n]$
- θ is in range $[0, 2\pi]$



Each x_i, y_i generates a sinusoid in ρ, θ space

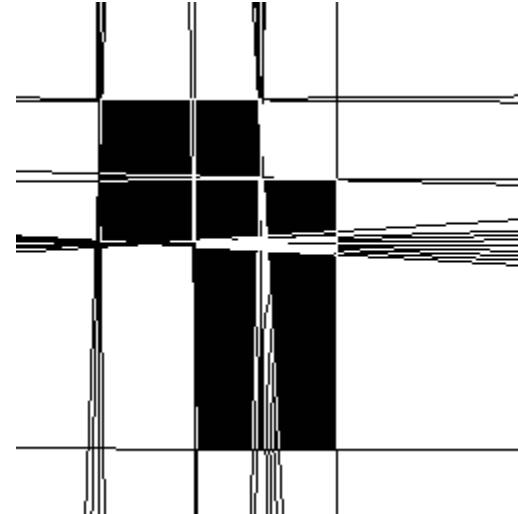
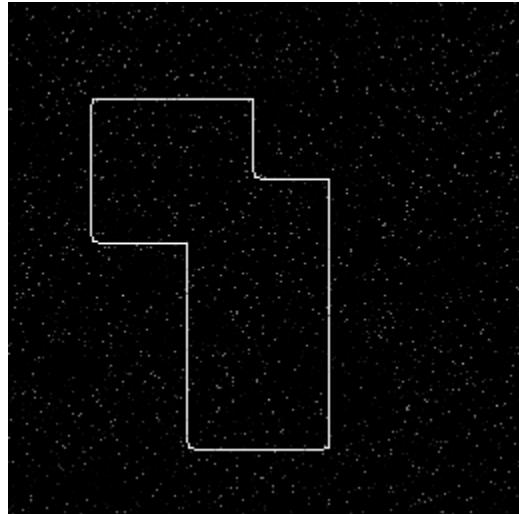


A ρ , θ Example





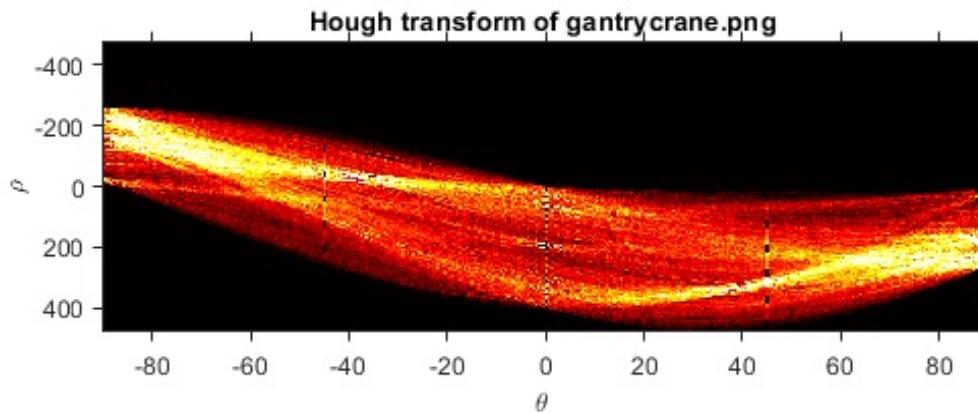
A ρ , θ Example



A key question is what happens to peaks in parameter space when noise or occlusion arise?



The Hough Transform in Matlab



Like many implementations, Matlab's Hough allows you to specify which part of the parameter space you're interested in...

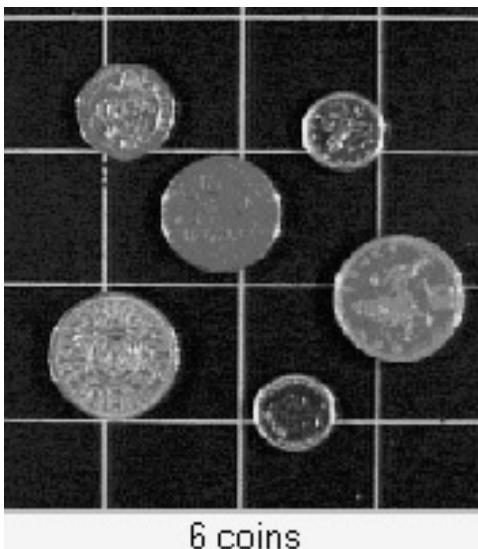
<https://uk.mathworks.com/help/images/ref/hough.html>



Circles

Parametric equation is $r^2 = (x-a)^2 + (y-b)^2$

- Full problem → cones in (a, b, r) space
- Known $r \rightarrow$ circles in (a, b) space



How about ellipses?



The Hough can in principle be applied to any parameterizable curve, though it's not always practical



Break



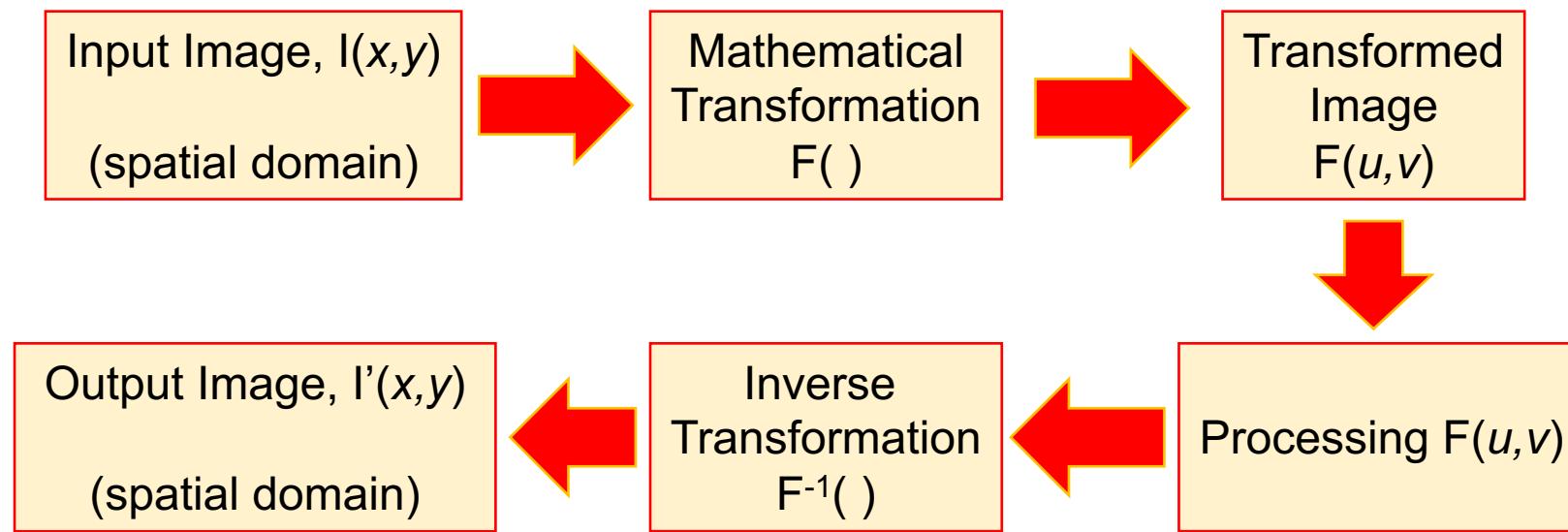


Frequency Domain

An Alternative Representation



Image Transform: The Idea





The Fourier Transform

- There are many different transformations, the **Fourier Transform** (FT) or its fast implementation (FFT) is the best known
- COMP 2032 will treat FFT as a black box and will **NOT** consider the underlying mathematics in detail
- Focus will be on the key idea, the frequency space representation, and how it can be used

Any given function (*an image is a 2D function*) can be approximated by a weighted sum of **basis functions**, e.g., sines and cosines



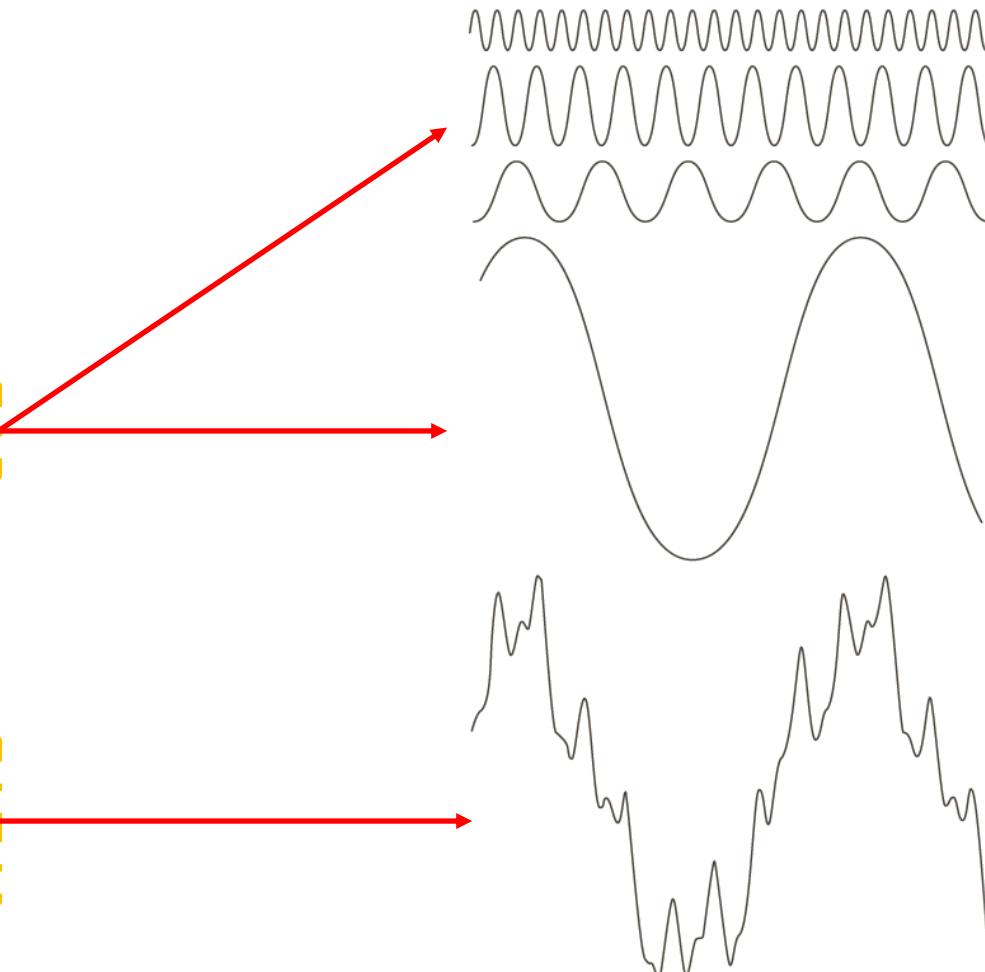
The Fourier Transform

The basic idea (Fourier 1807)

These 4 functions



... can be combined to form
this one



ACK: Prof. Tony Pridmore, UNUK



Image Transforms

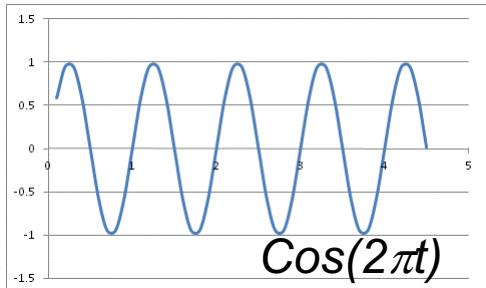
Suppose we just use cosines:

$$f(t) = \sum_i F_i \cos(u_i t)$$

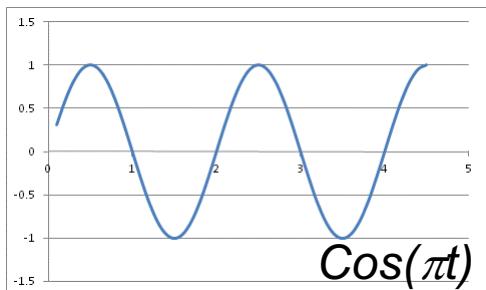
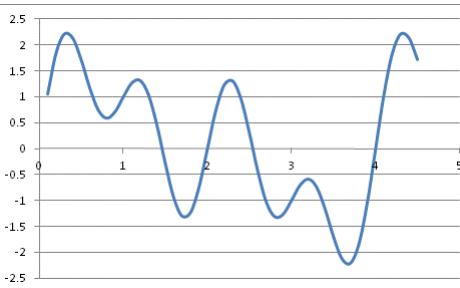
- The weight, F_i , indicates the importance of $\cos(u_i t)$
- u_i represents the frequency of the cosine signal
- A larger u_i means $\cos(u_i t)$ changes faster → higher frequency component of $f(t)$
- A smaller u_i means $\cos(u_i t)$ changes slower → lower frequency component of $f(t)$



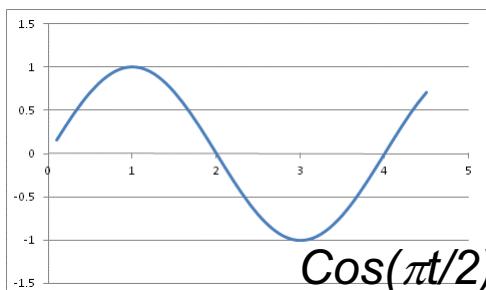
Image Transforms



$$\text{Cos}(2\pi t)$$



$$\text{Cos}(\pi t)$$



$$\text{Cos}(\pi t/2)$$

$$f(t) = \text{Cos}(\pi t/2) + \text{Cos}(\pi t) + \text{Cos}(2\pi t)$$

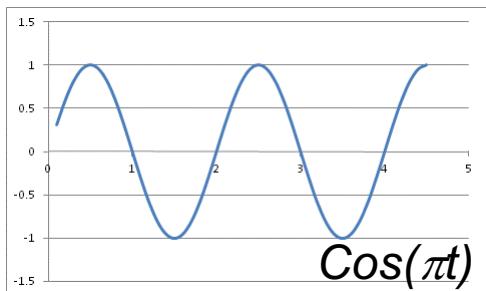
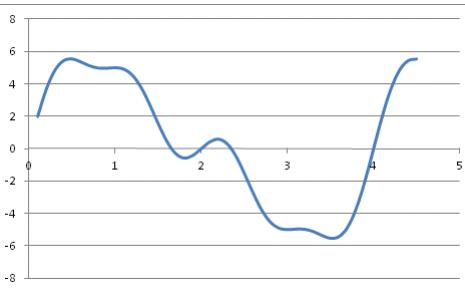
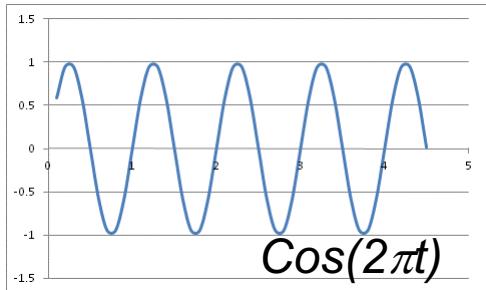
$$F_1 = 1 \quad u_1 = \pi/2$$

$$F_2 = 1 \quad u_2 = \pi$$

$$F_3 = 1 \quad u_3 = 2\pi$$



Image Transforms



$$f(t) = 5 * \text{Cos}(\pi t/2) + 2 * \text{Cos}(\pi t) + \text{Cos}(2\pi t)$$

$$F_1 = 5 \quad u_1 = \pi/2$$

$$F_2 = 2 \quad u_2 = \pi$$

$$F_3 = 1 \quad u_3 = 2\pi$$

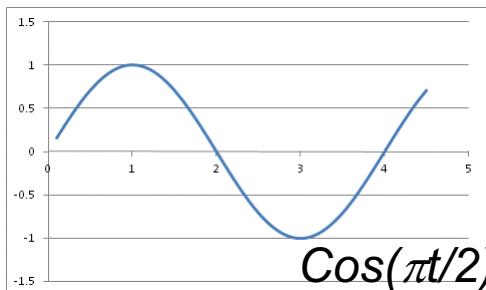
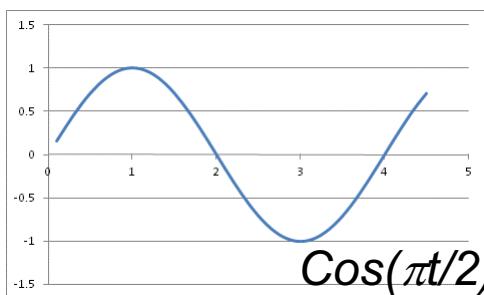
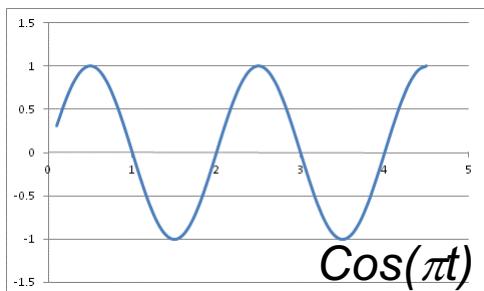
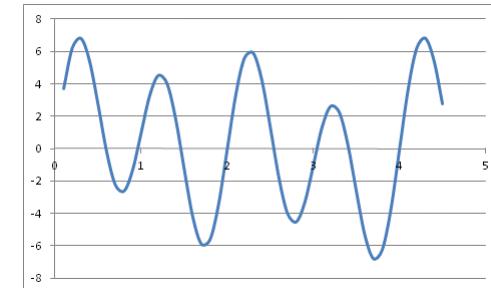
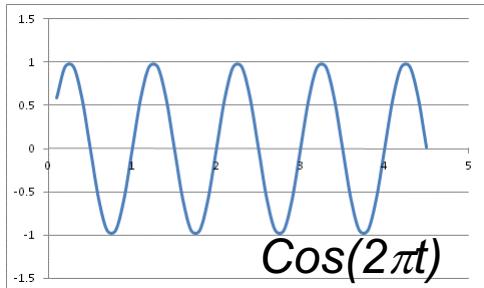




Image Transforms



$$f(t) = \text{Cos}(\pi t/2) + 2 * \text{Cos}(\pi t) + 5 * \text{Cos}(2\pi t)$$

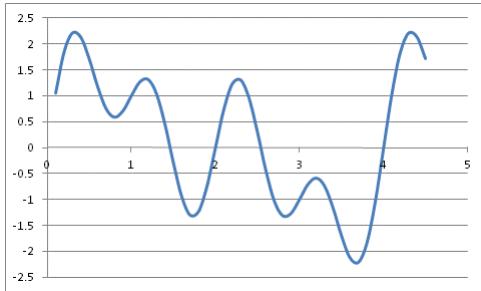
$$F_1 = 1 \quad u_1 = \pi/2$$

$$F_2 = 2 \quad u_2 = \pi$$

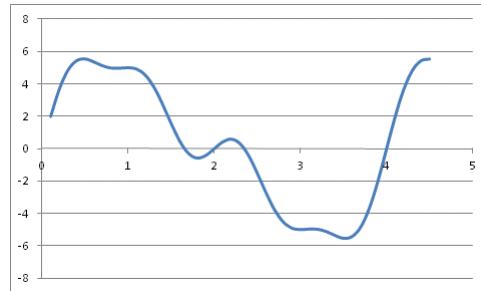
$$F_3 = 5 \quad u_3 = 2\pi$$



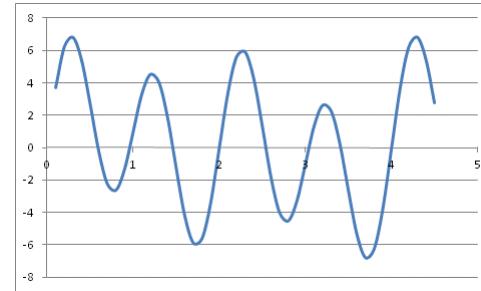
Image Transforms



$$\begin{aligned}F_1 &= 1 & u_1 &= \pi/2 \\F_2 &= 1 & u_2 &= \pi \\F_3 &= 1 & u_3 &= 2\pi\end{aligned}$$

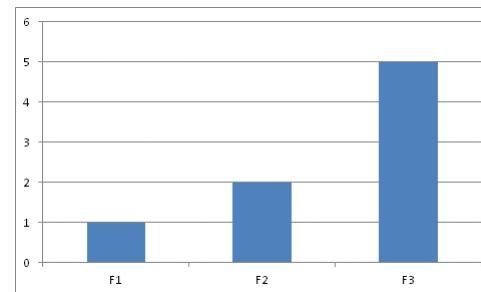
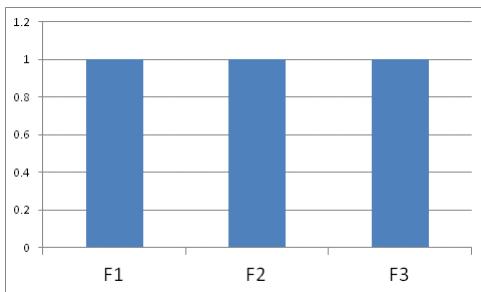


$$\begin{aligned}F_1 &= 5 & u_1 &= \pi/2 \\F_2 &= 2 & u_2 &= \pi \\F_3 &= 1 & u_3 &= 2\pi\end{aligned}$$



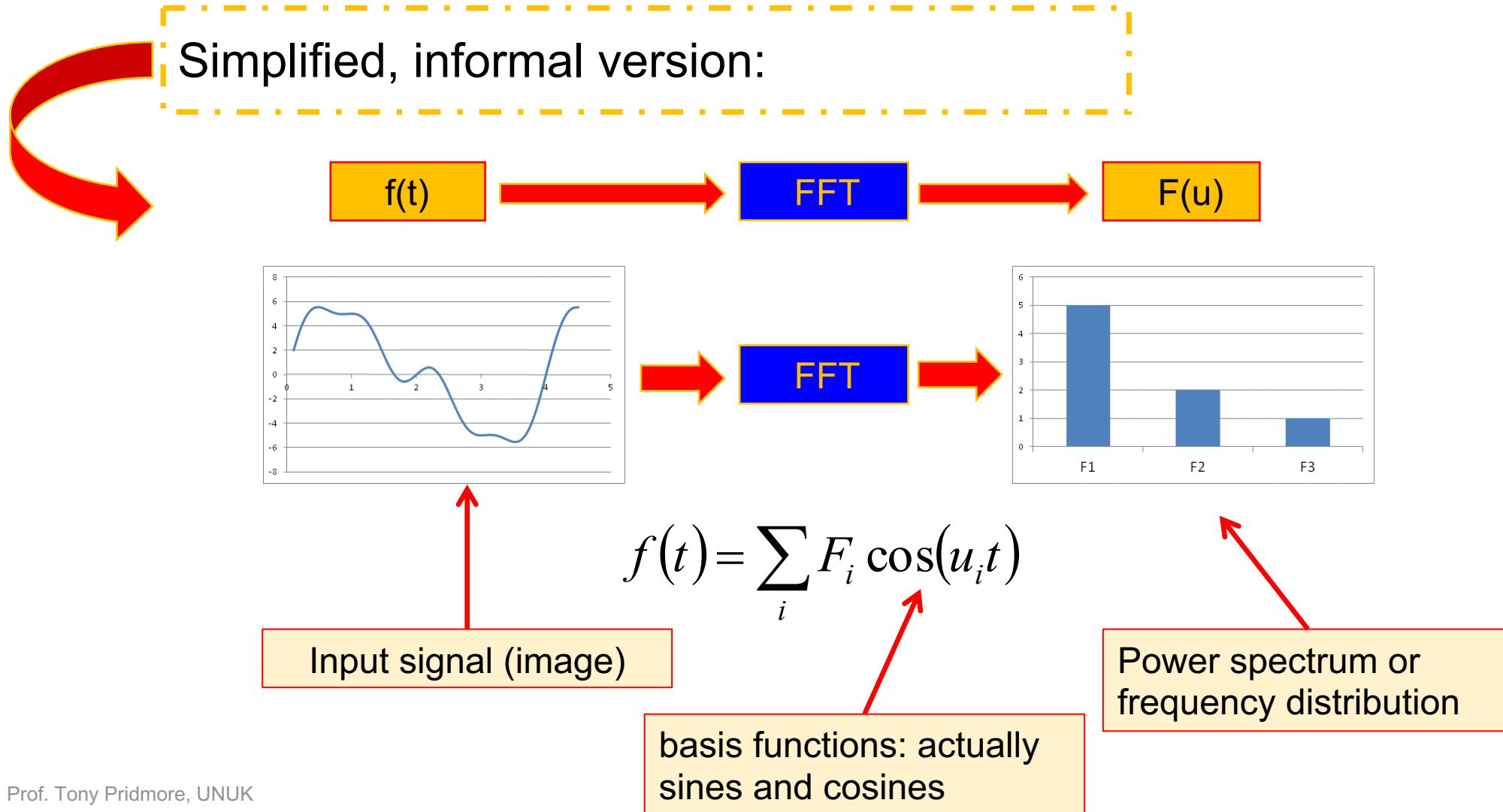
$$\begin{aligned}F_1 &= 1 & u_1 &= \pi/2 \\F_2 &= 2 & u_2 &= \pi \\F_3 &= 5 & u_3 &= 2\pi\end{aligned}$$

$$f(t) = F_1 * \text{Cos}(\pi t/2) + F_2 * \text{Cos}(\pi t) + F_3 * \text{Cos}(2\pi t)$$





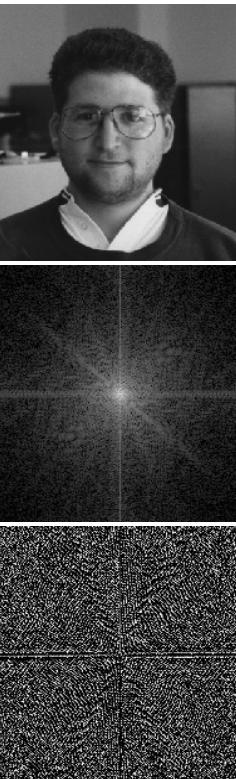
The Fourier Transform



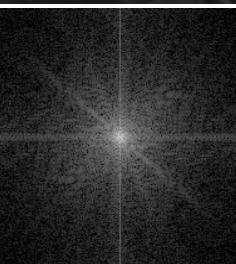


Amplitude vs Phase

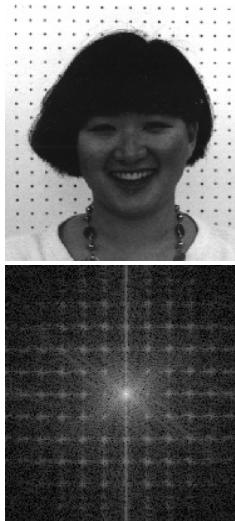
A = "Aron"



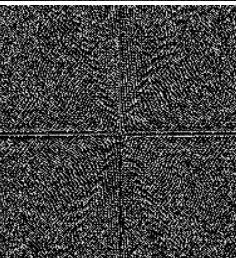
FA = fft2(A)



P = "Phyllis"



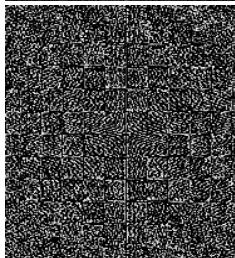
FP = fft2(P)



log(abs(FA))

log(abs(FP))

angle(FA)



angle(FP)

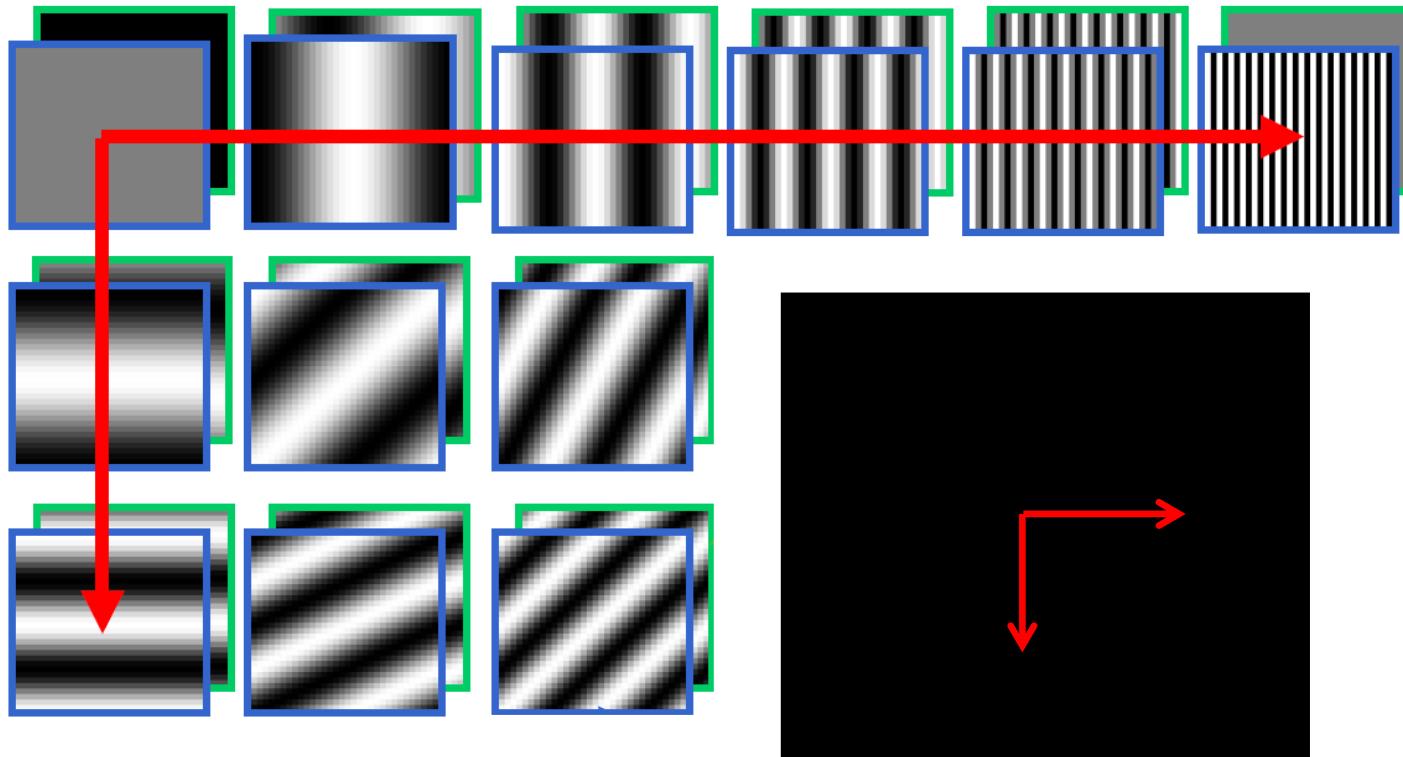
Image processing focuses on the power spectrum, the amplitude

To accurately represent a signal (image), basis functions need to be shifted (and rotated)

- **Amplitude:** relative prominence of basis function
- **Phase:** relative displacement of basis function



The Power Spectrum in 2D

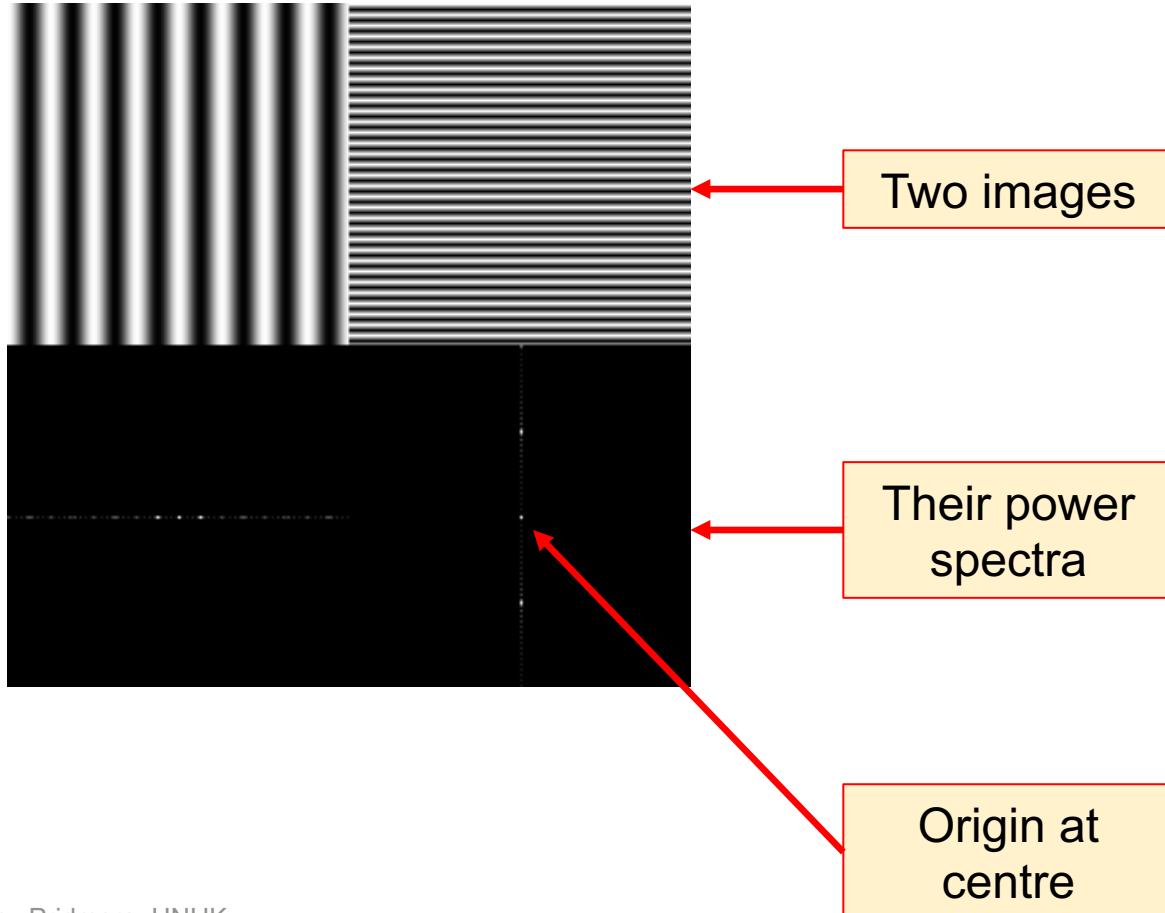


The principle is the same,
but the *basis functions*
are oriented

- Distance from centre reflects frequency of corresponding basis function
- Direction from centre reflects orientation of corresponding basis function
- Origin records lowest possible frequency – flat, proportional to mean intensity



The Power Spectrum in 2D

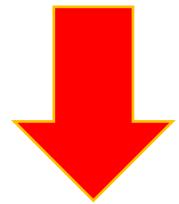


Two responses because basis functions are even: $f(-x) = f(x)$

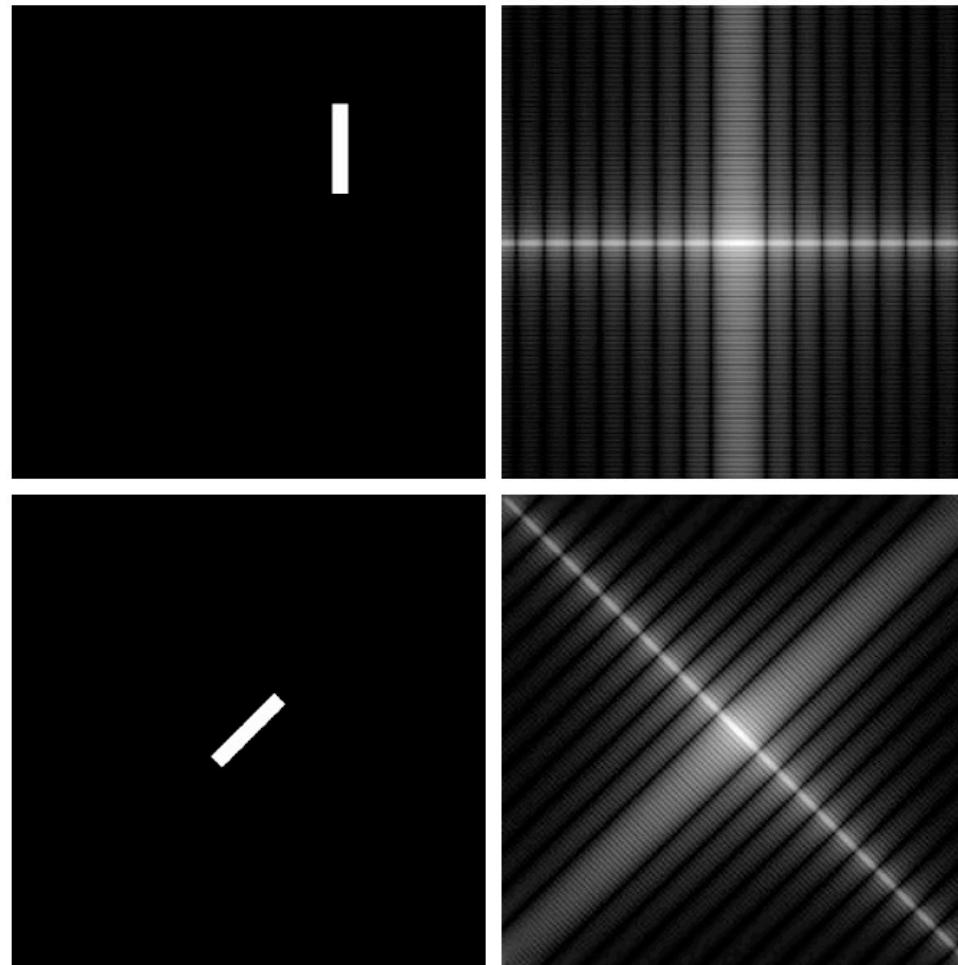


Frequency Domain

Translation does not
change the spectrum



Rotation does



Image

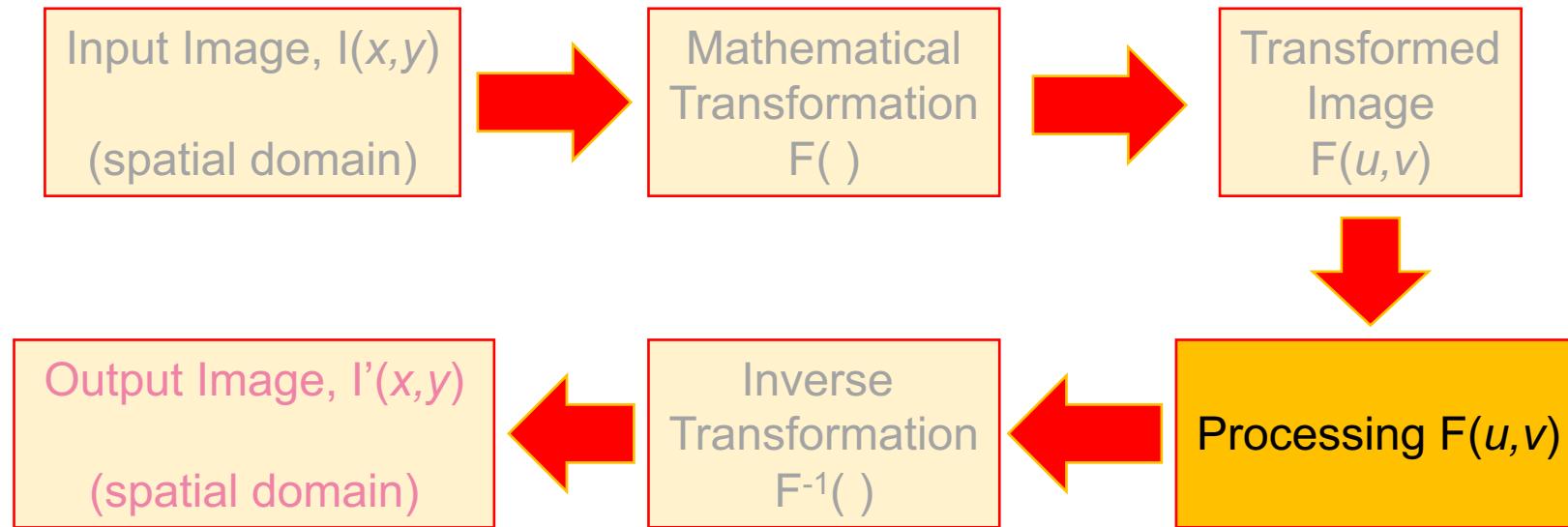
Spectrum



Frequency Domain Processing



Frequency Domain Processing



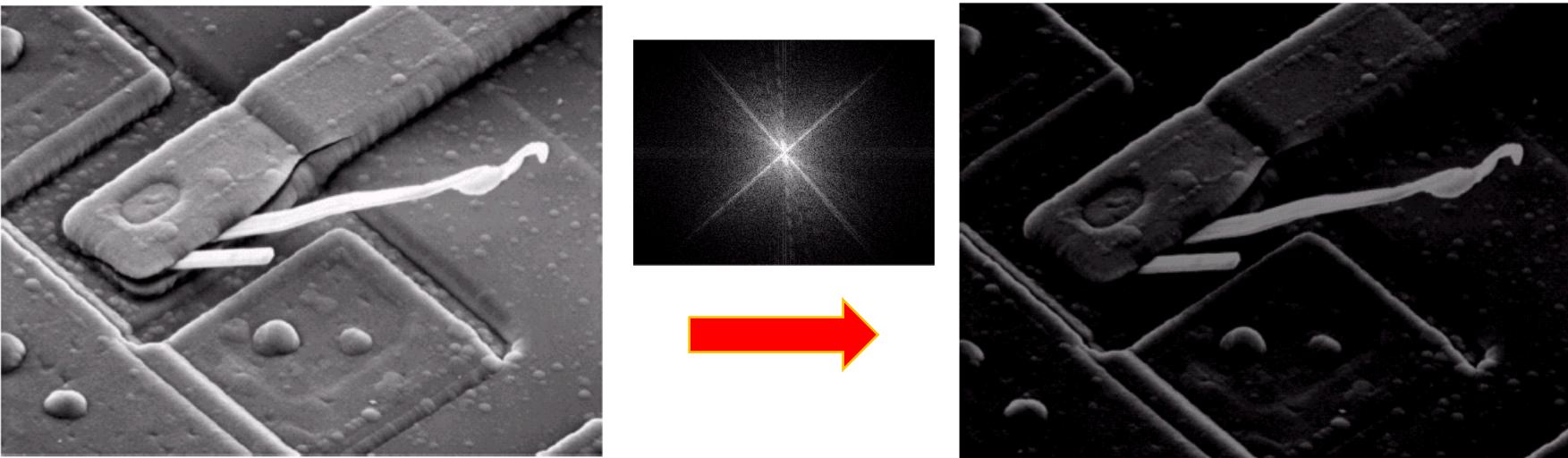
- Smoothing = low pass filtering = attenuate **high** frequency components
- Sharpening = high pass filtering = attenuate **low** frequency components
- Band limiting = set all components to 0 outside a given frequency range



The Simplest Example

Set the origin of the power spectrum to zero, leave the rest unchanged

- Reduces average intensity of image to 0
- Negative intensities have been set to 0 in the display



ACK: Prof. Tony Pridmore, UNUK

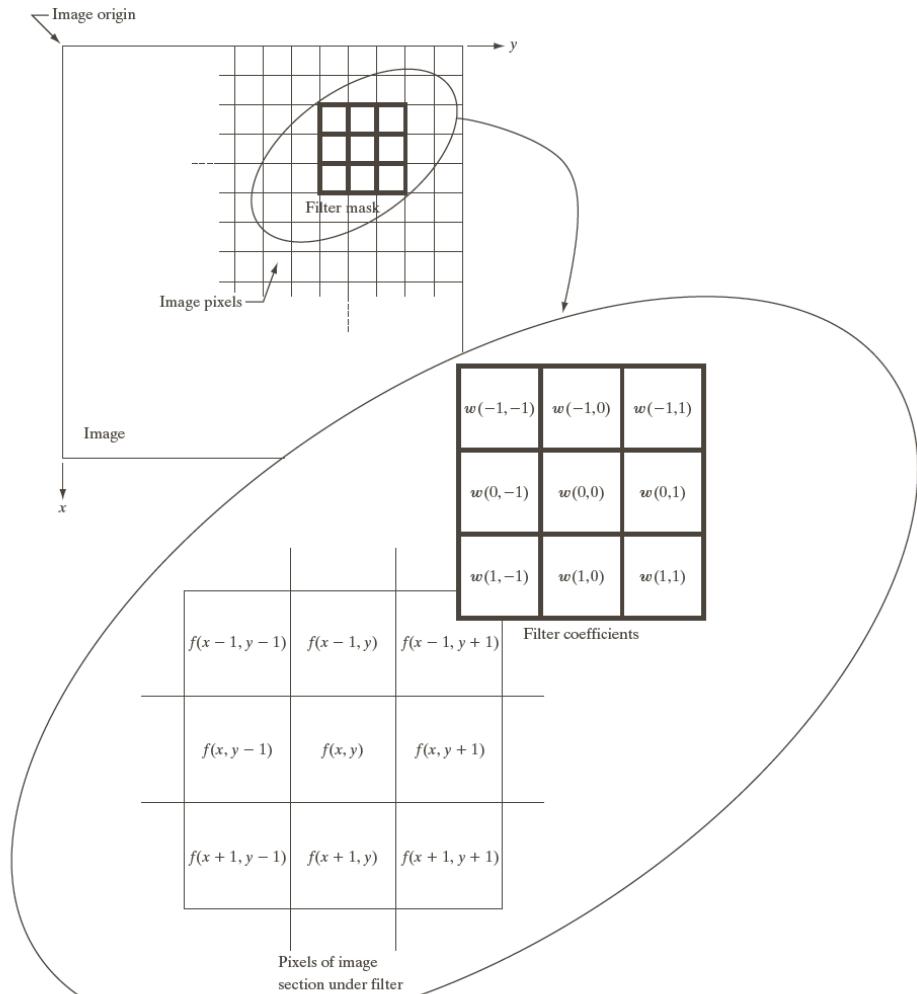


Convolution

- In spatial domain, processing is achieved via convolution (*)
- The *convolution theorem* underpins frequency domain processing

$$f(x, y) * g(x, y) \Leftrightarrow F(u, v)G(u, v)$$

Convolution in spatial domain becomes multiplication in frequency domain





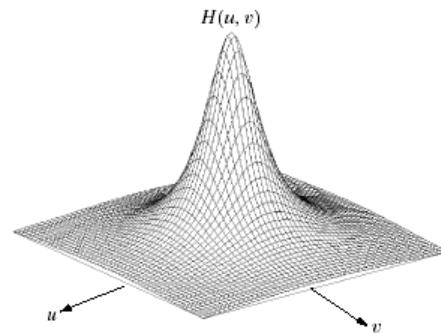
Filtering in Frequency Domain

Filtering

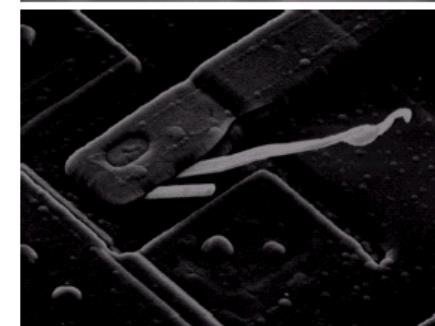
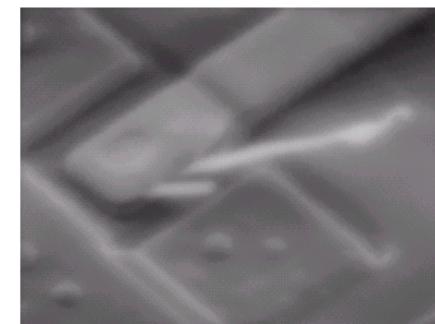
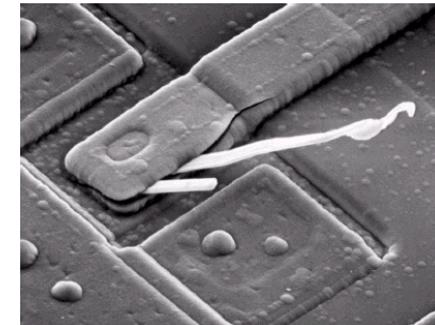
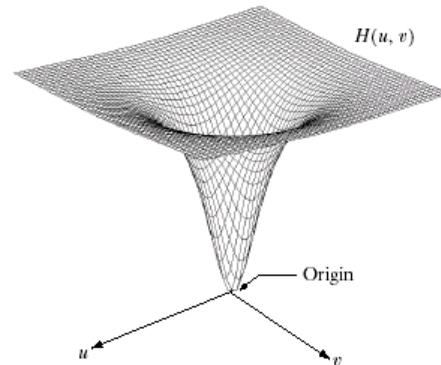
=

Multiply power spectrum by a mask
designed to change the weights of
selected basis functions

Low-pass filtering

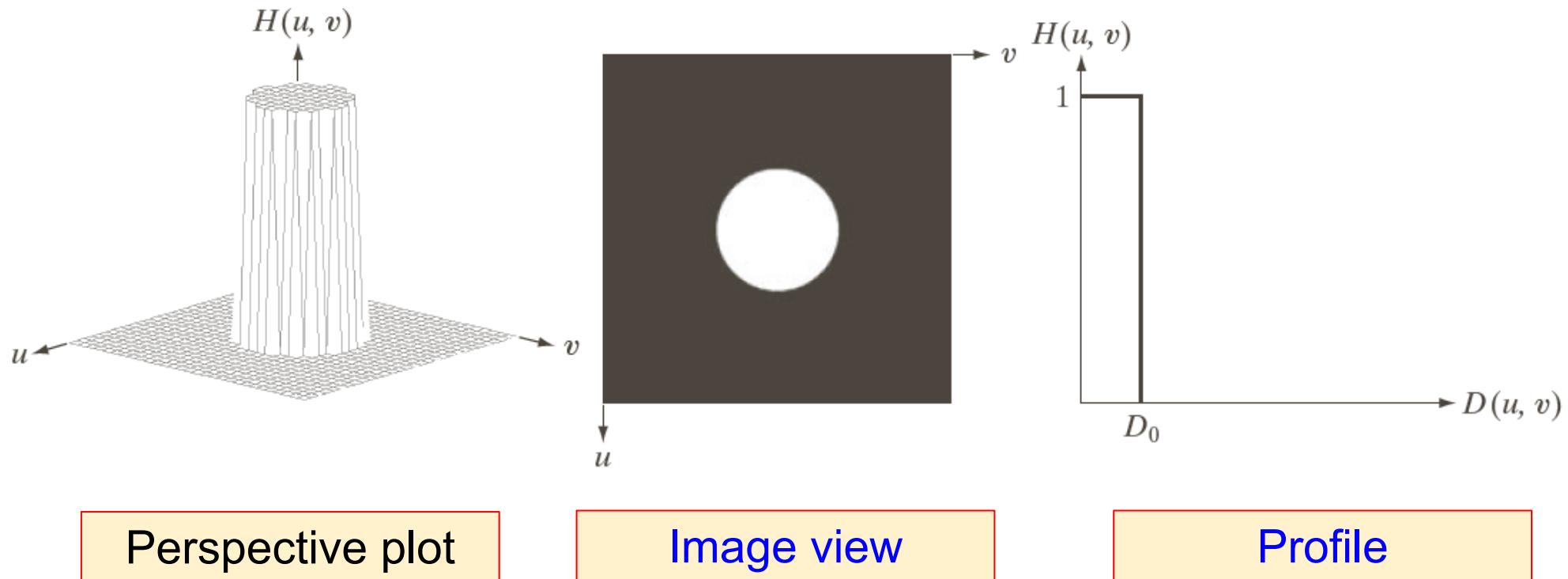


High-pass filtering





Ideal Low-pass Filtering

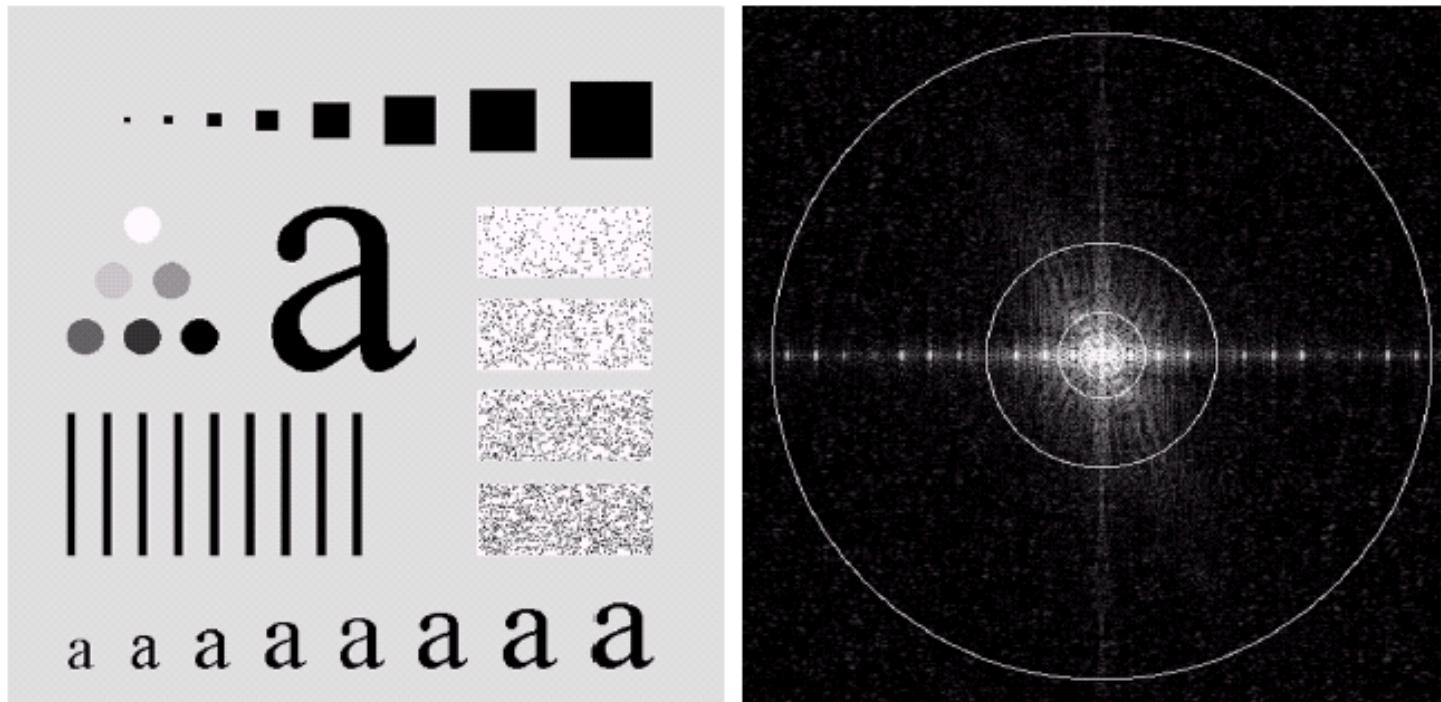


- Allows user to specify precisely which frequencies are to be kept and which removed – good if you know which are which



Ideal Low-pass Filtering

- Sample image and its Fourier spectrum
- Circles mark ideal cut-offs at $D_0 = 5, 15, 30, 80, 230$



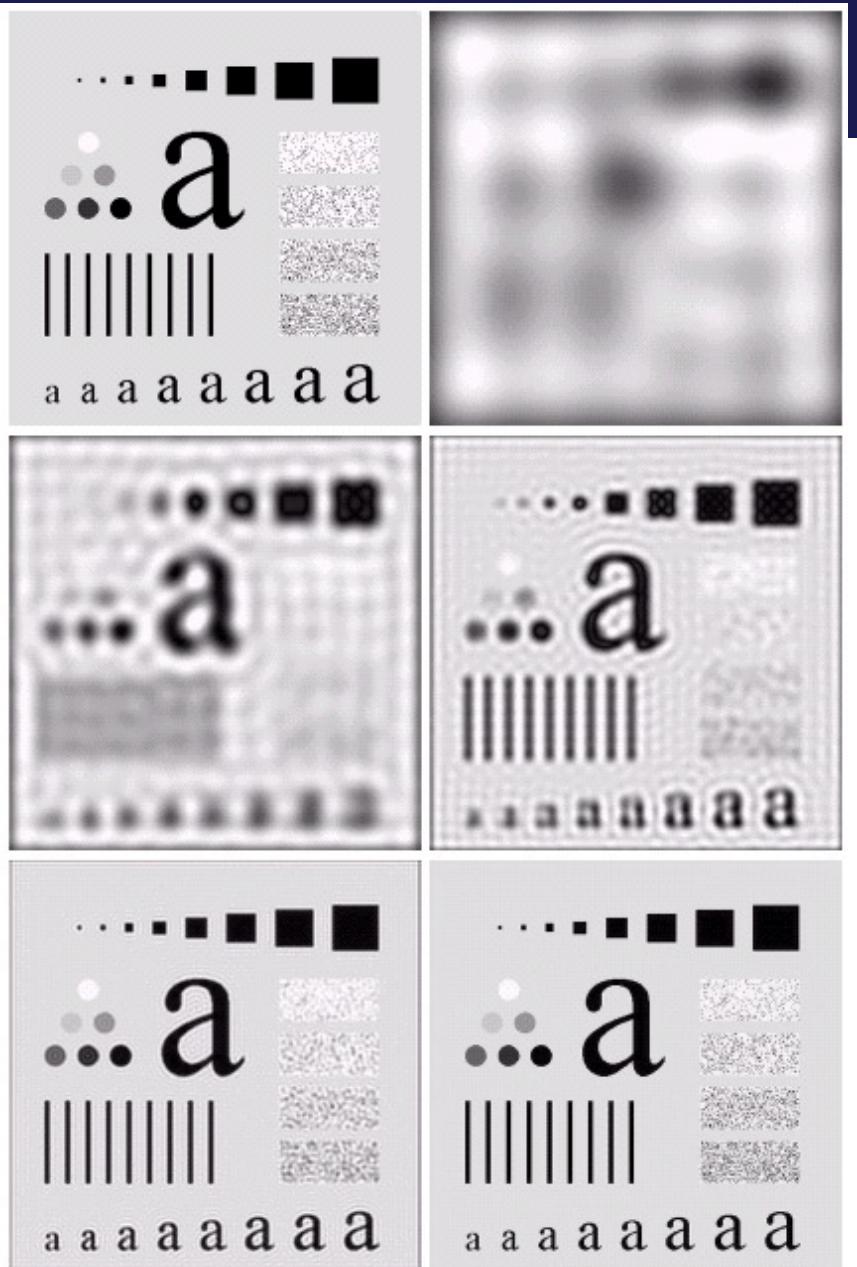
ACK: Prof. Tony Pridmore, UNUK



Unintended Consequences

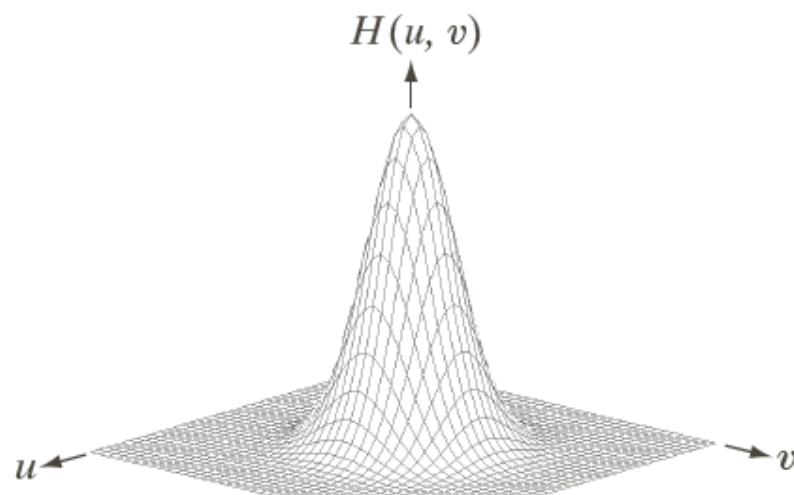
- Ideal low-pass filtering with (*top-left to bottom-right*) $D_0 = 5, 15, 30, 80, 230$
- Note the *ringing* artefact caused by hard boundary between frequencies kept and removed
- Frequency of ringing effect increases with D_0

- The “missing” components needed to make the uniform regions uniform become higher frequency as D_0 increases





Low-pass Gaussian Filters



Perspective plot

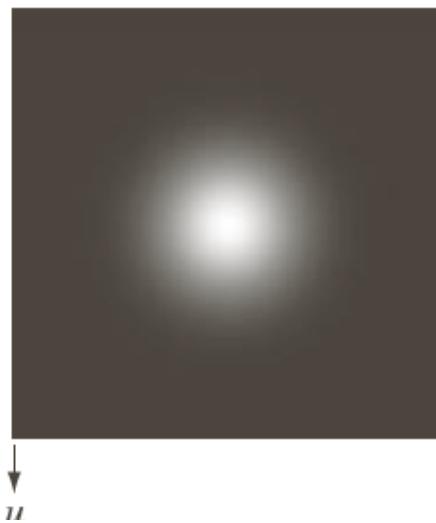
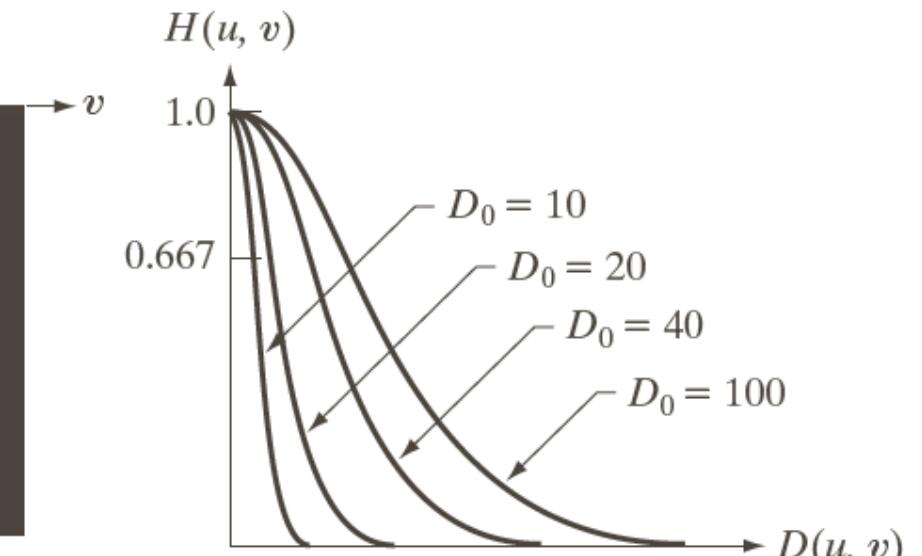


Image view

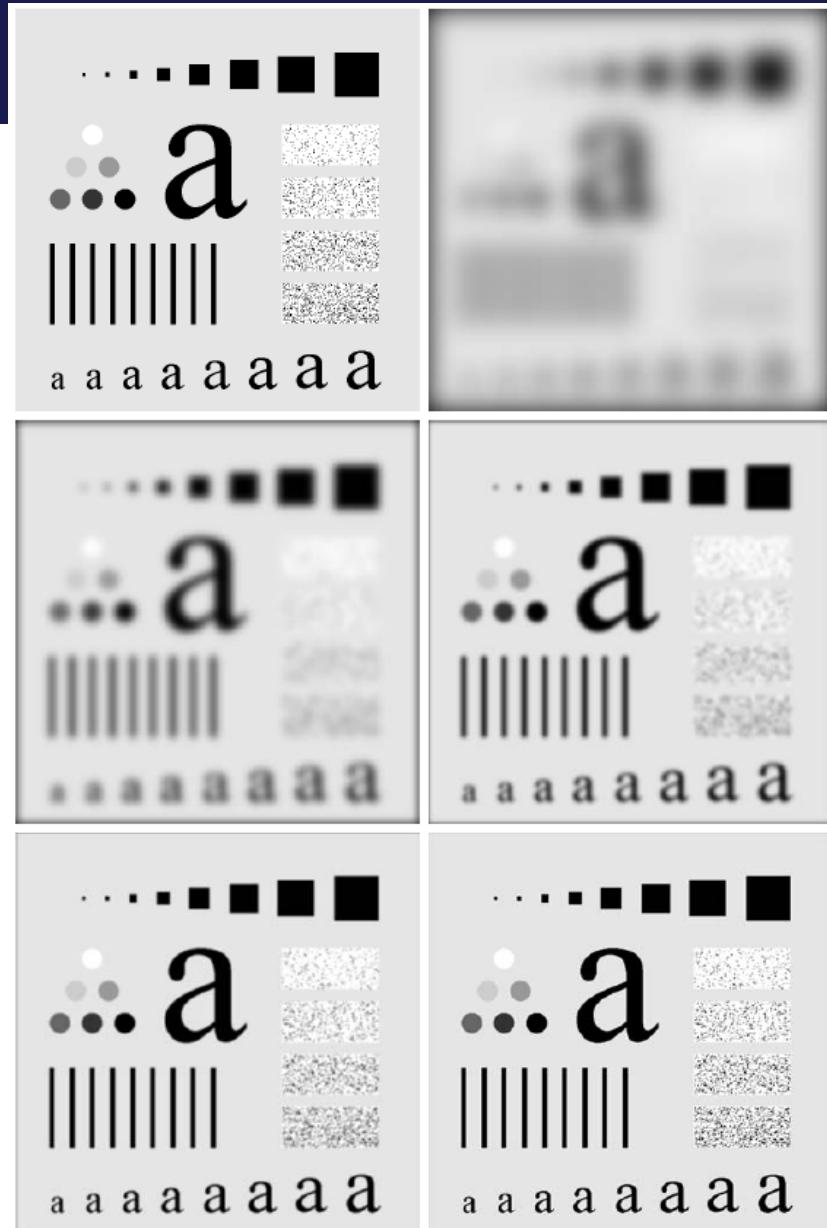


Profile



Low-pass Gaussian Filters

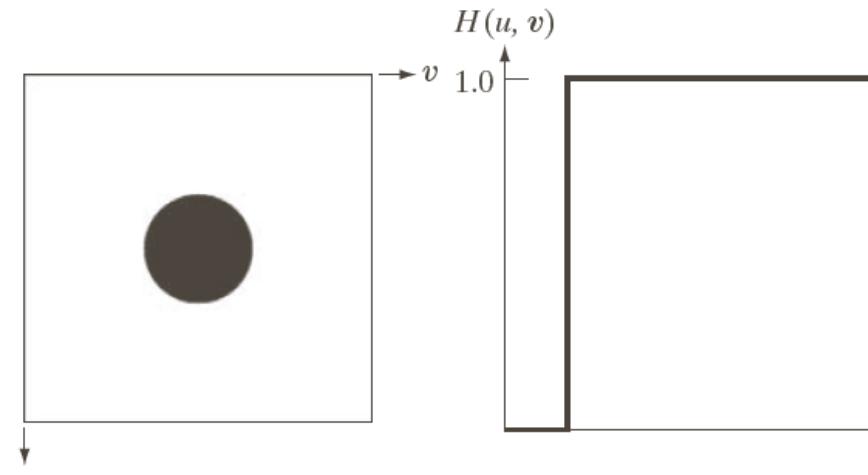
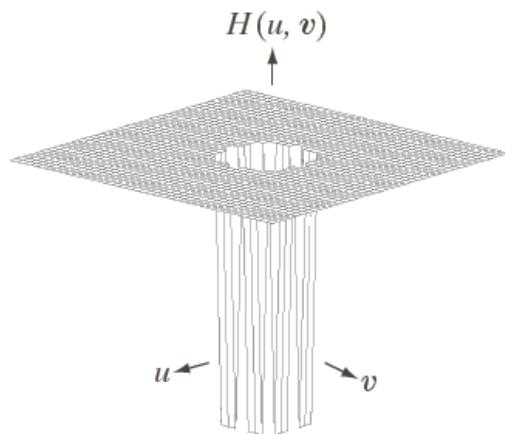
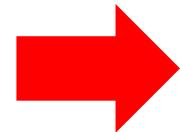
Low-pass Gaussian Filtering with cut-off frequencies at (top-left to bottom-right)
 $D_0 = 5, 15, 30, 80, 230$





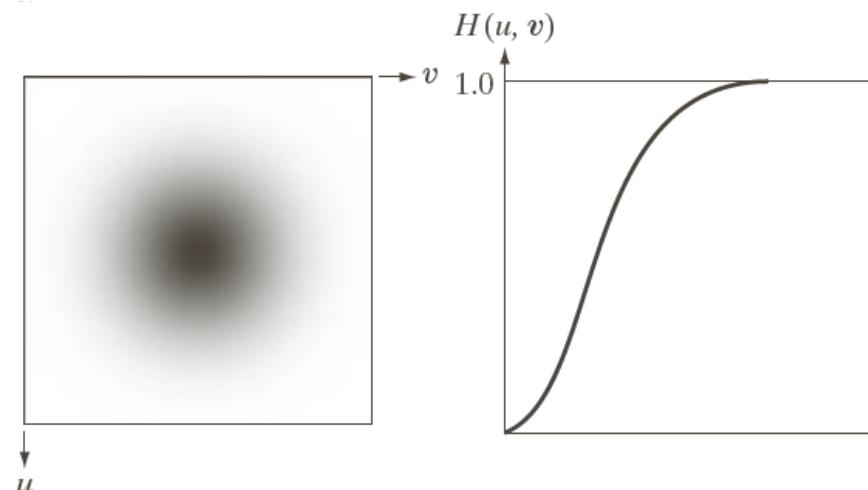
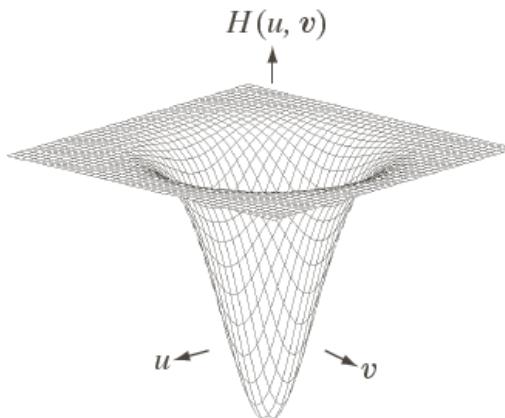
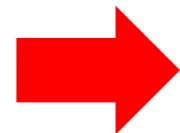
High-pass Filters

Ideal



$D(u, v)$

Gaussian



$D(u, v)$

ACK: Prof. Tony Pridmore, UNUK



High-pass Gaussian Filters



Gaussian High-pass filtering with $D_0 = 30, 60$ and 160

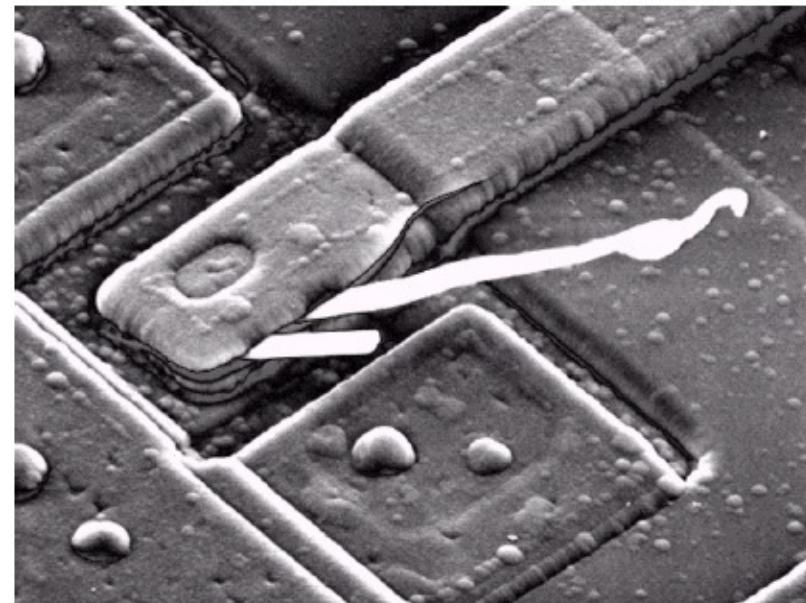


High-pass Filtering

Raw high-pass filters set origin, and so mean intensity to 0, making images dark. Add a small constant to the filter so the mean remains positive



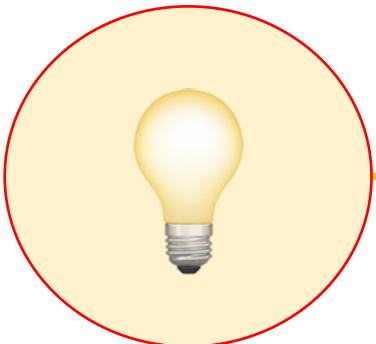
Gaussian high pass filtered
SEM image



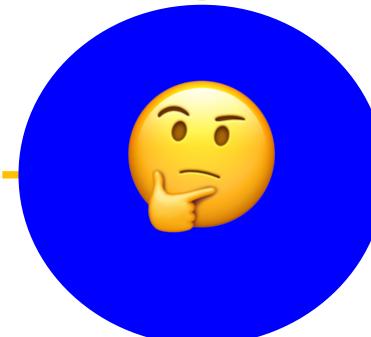
Gaussian high pass filter
plus a constant



Summary



1. How to find lines?
2. The Hough Transform
3. Other parameter spaces
4. What is frequency domain?
5. The frequency domain processing





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Questions



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A large rectangular frame is centered over the upper portion of the Earth's horizon, containing the text "NEXT:" and "Image Compression". The background of the slide is a photograph of Earth at night, showing the curvature of the planet and the glowing lights of cities in Europe and Africa.

NEXT:

Image Compression