

Introduction to Image Processing

Digital Image Acquisition and Representation

Lens and Image Plane

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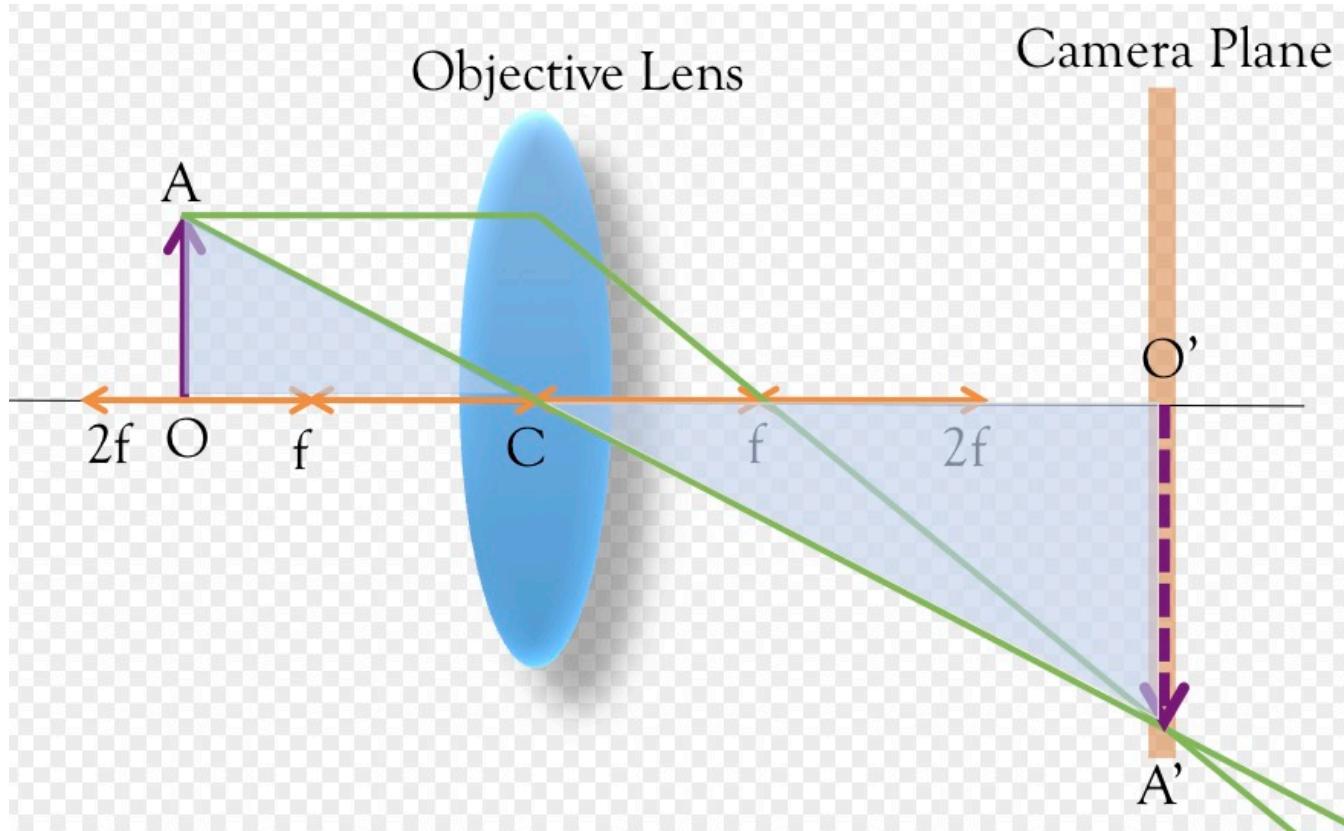


Image Sensor

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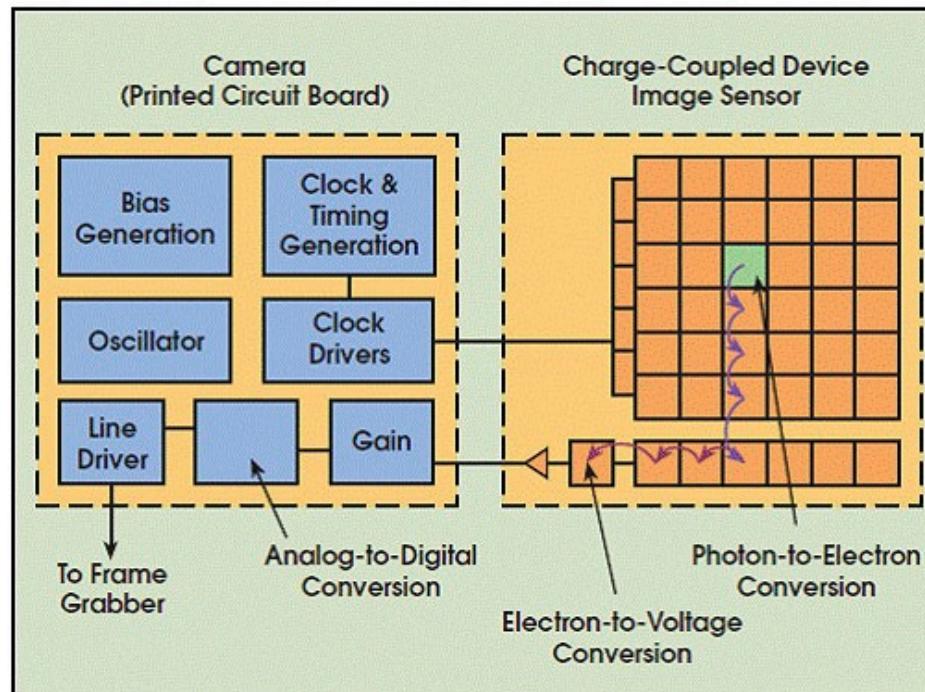


Figure 1: Diagram of a CCD.

RGB Images (e.g. BMP)

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- ▶ Digital images are generated by sampling light intensity in a 2-D plane
- ▶ Conceptually, three values are measured at each location: (R, G, B)
 - The sample density determines the resolution

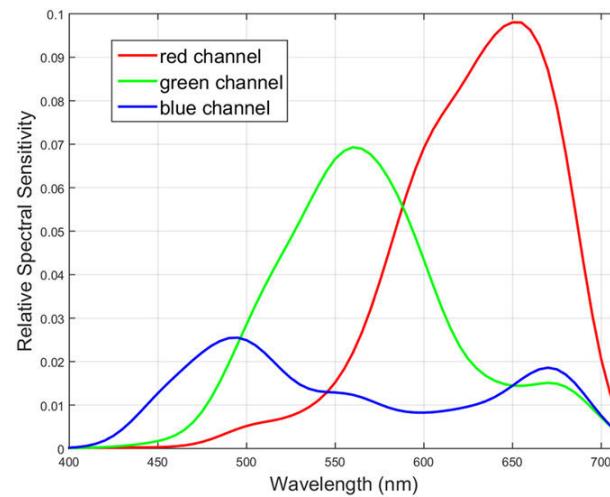
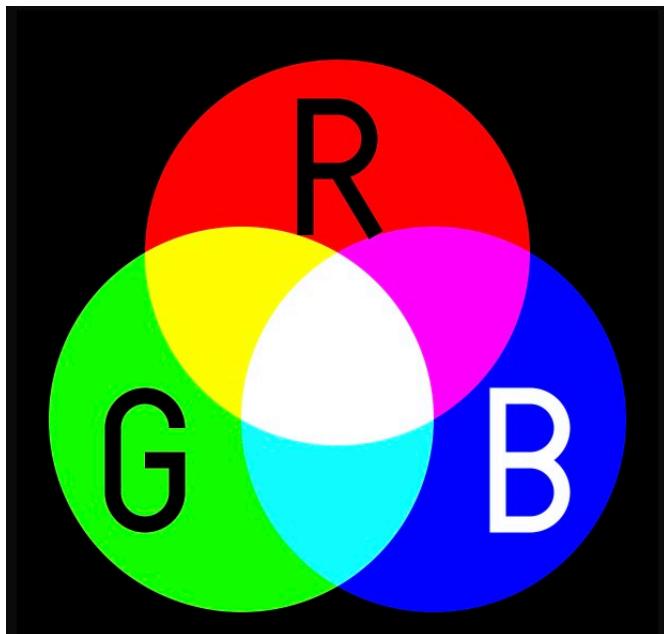
(R,G,B)	(R,G,B)	(R,G,B)	(R,G,B)
(R,G,B)	(R,G,B)	(R,G,B)	(R,G,B)
(R,G,B)	(R,G,B)	(R,G,B)	(R,G,B)
(R,G,B)	(R,G,B)	(R,G,B)	(R,G,B)

Each value R, G, B is
a number from [0, 255]

Primary Colors

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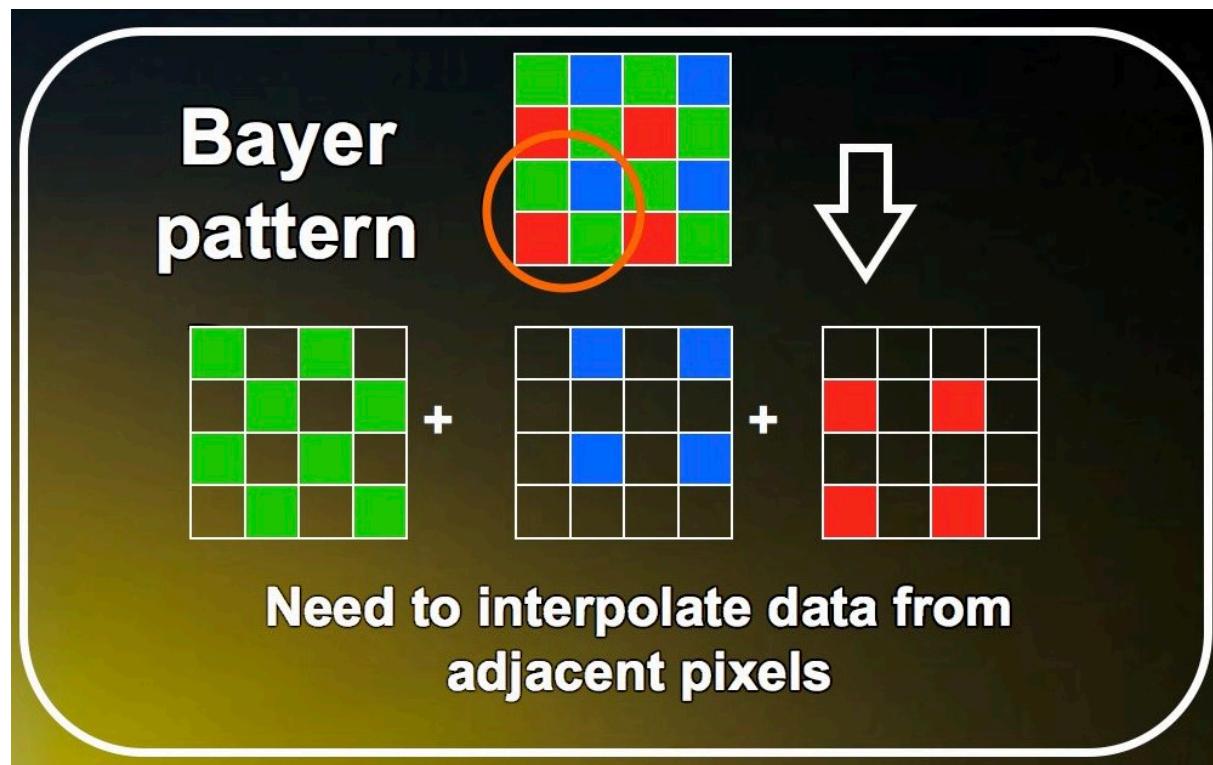
- ▶ **Different mixtures of (R, G, B) determine which color you perceive**
 - R, G, and B aren't "pure" colors, they have a spectrum



Bayer Sampling Pattern

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- ▶ The RGB Pixels on an image sensor are close to each other, but not exactly co-located



RGB to Grayscale Conversion

RGB to Grayscale conversion

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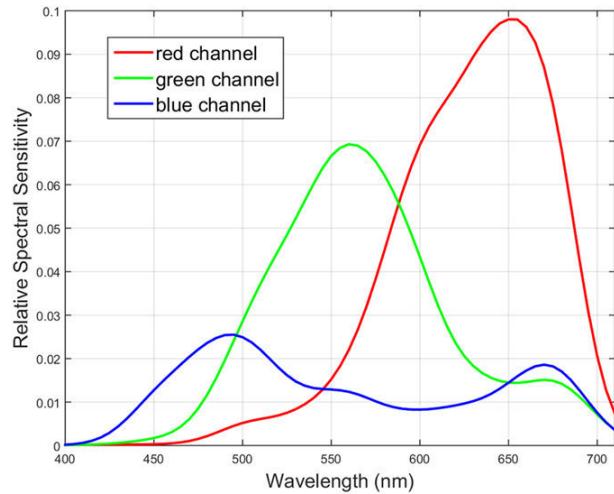
- ▶ Often it is sufficient to process only a grayscale image
 - Less computation



RGB to Grayscale conversion cont.

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- ▶ In general, converting between color spaces is a matrix multiply
 - Different colorspaces assume different spectral characteristics for their primaries
 - ✓ Different primary spectral characteristics require different weights to generate the same perceived color



Color space conversion can be implemented as a matrix multiply

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} .299 & .587 & .114 \\ -.14713 & -.28886 & .436 \\ .615 & -.51499 & -.10001 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

RGB to Grayscale conversion cont.

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- ▶ **(Y, U, V) is the color space used for TV**
- ▶ **When converting (R, G, B) to grayscale, it is only necessary to compute Y**
 - Computing Y is just a dot product (first row of matrix “dot” (R, G, B))

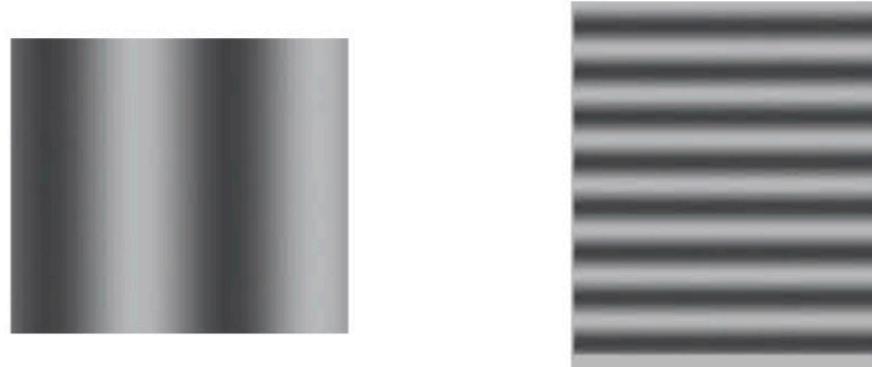
$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} .299 & .587 & .114 \\ -.14713 & -.28886 & .436 \\ .615 & -.51499 & -.10001 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Contrast Enhancement

Contrast

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- ▶ **Contrast, intuitively, deals with how distinct two things are**



One example of image contrast. Other definitions are also used in other contexts

Low frequency horizontal High frequency vertical

Figure 8: Spatial frequency patterns for measuring contrast sensitivity

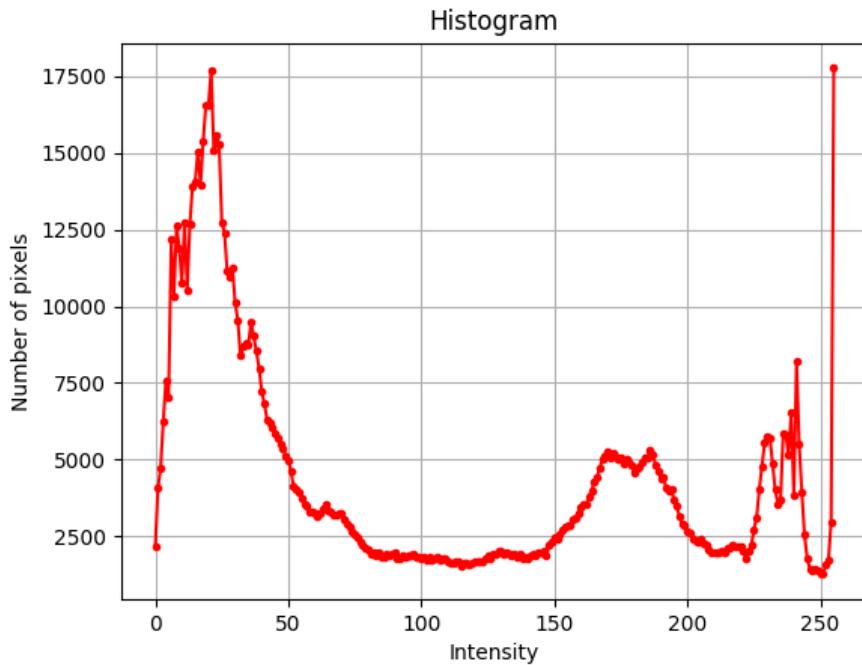
The sine wave's frequency, orientation, and intensity (i.e. peak-to-peak magnitude variation) can all varied, and a viewer's ability to detect the sine wave can be measured. The contrast used for this measurement is known as the *Michelson contrast* and is defined as

$$C(I_{max}, I_{min}) = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \quad (13)$$

Image Histogram

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- ▶ **Count the number of pixels at each intensity level and graph them**
 - Often normalize to yield relative frequencies

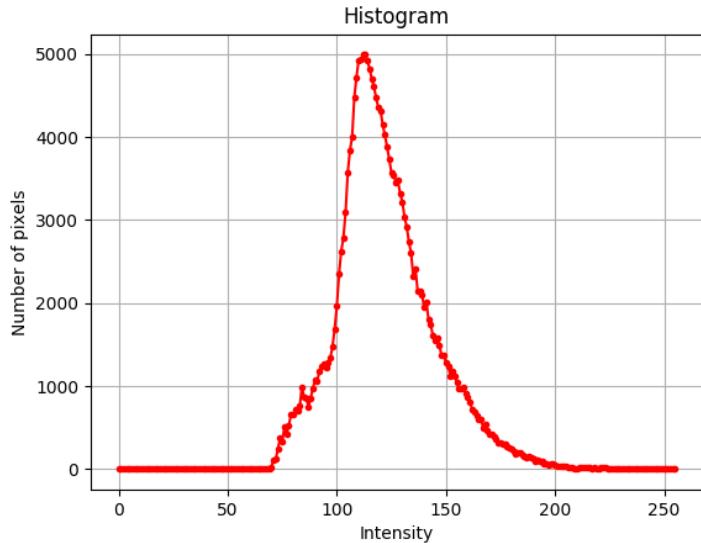


Histogram of previous picture: note the saturation at 255

Low-Contrast Image

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- ▶ **Low-contrast Images have narrow histograms**



Histogram of a low-contrast image

Contrast Enhancement

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- ▶ **To enhance the contrast, we need to “spread-out” the histogram**
 - One possibility: apply a linear-stretch to the image, mapping all values less than t_{min} to 0, and all values greater than t_{max} to 255
- ▶ **Another approach is to apply a non-linear function to the pixel intensities**
 - A common choice is “equalize” the histogram. Ideally, every intensity would then occur with the same frequency
 - ✓ This is called *histogram equalization* in the literature

Algorithm for Lab

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- ▶ **Build a table of 256 entries that maps input intensities to output intensities**
 - A numpy array of size 256, indexed by input intensity
- ▶ **Do not remap pixels in the original image that have intensities of 0 or 255**
 - Only remap pixels that have intensities between [1, 254]
- ▶ **Find the sum, S , of how many pixels have an intensity in the range [1, 254] (you will need the histogram)**
- ▶ **Compute the ideal number of pixels, P , for each intensity level**
 - $P = S / 254$

Algorithm for Lab cont.

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- ▶ Define a current target T . Initially, $T = P$
- ▶ Starting at input intensity 1 (i.e. histogram index 1) and output intensity (out_val) 1:
 - Step through the histogram, incrementing a temporary sum ($curr_sum$), until a number of pixels greater than T have been processed
 - ✓ Map all these input levels to 1 by making appropriate entries in your remapping array
 - Determine the next output intensity (we skip forward depending on by how much we exceeded our target)
 - ✓ $out_val = round(curr_sum / P)$
 - Update T to $T = out_val * P$
 - Repeat until the remapping array is complete

Edge Detection

Edge Detection

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- ▶ In many computer vision applications, it is useful to detect the edges of objects
- ▶ What characterizes edges?
 - Edges occur where transitions occur
 - ✓ Intensity
 - ✓ Color
 - ✓ Texture
- ▶ We'll focus on intensity since we're processing grayscale images
 - Rapid intensity transitions occur where the derivative is large

Gradient Review

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- ▶ **The gradient of a real-valued function with an N-D domain is an N-D vector which points in the direction of maximum change**
 - Its magnitude is the rate of change in that direction. In 2-D we have

$$\nabla f(x, y) = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right)$$

$$\|\nabla f(x, y)\|^2 = \left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2$$

Edge Detection with the Gradient

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- ▶ **Image intensity is a 2-D function of (x, y)**
- ▶ **Compute the magnitude of the gradient**
 - Apply a threshold. Declare values *greater* than the threshold to be edges
- ▶ **We can locally approximate the gradient at each pixel**
- ▶ **The Sobel edge detection operator combines two operations**
 - Lowpass image filtering
 - Estimating the gradient of the filtered image

Convolution

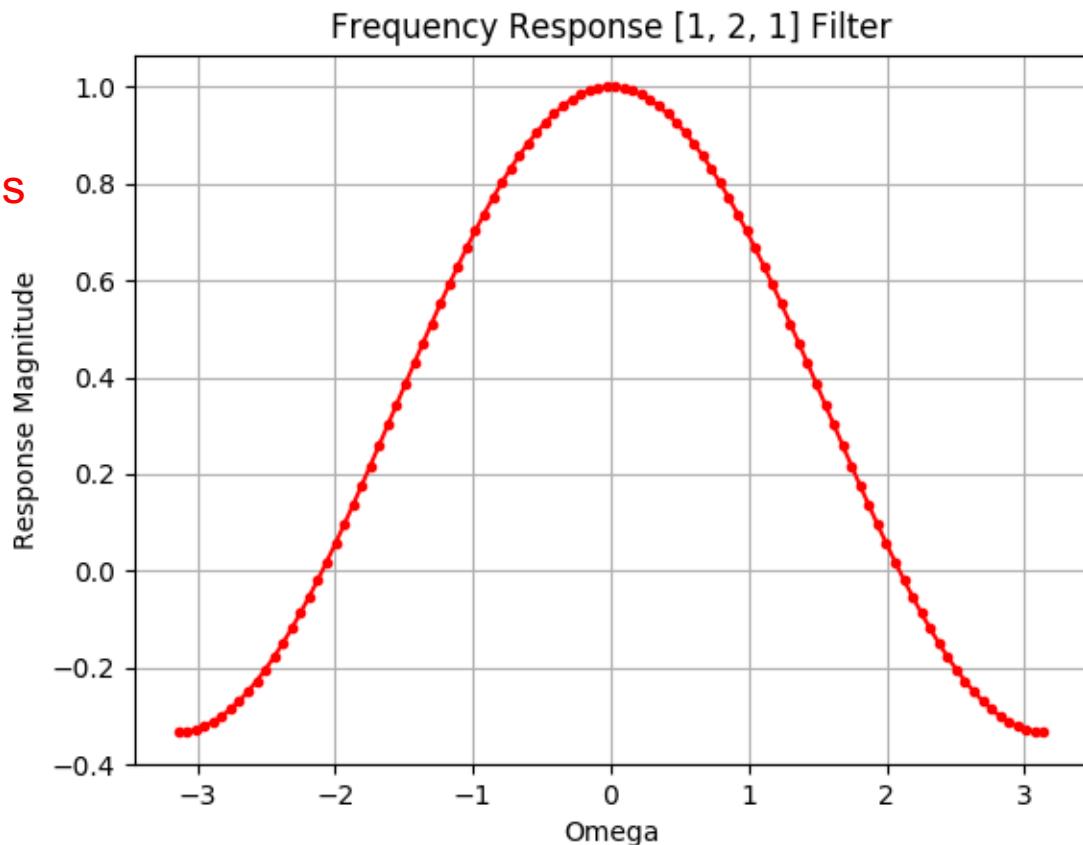
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- ▶ **Convolution in the time domain is multiplication in the frequency domain**
- ▶ **Exercise: Convolve {1, 2, 1} with {1, 2, 3, 4, 5, 4, 3, 2, 1}**
 - Convolution by strips of paper!

A Simple lowpass filter: (1, 2, 1)

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- ▶ Frequency response of (1, 2, 1) is a gentle rolloff
 - Convolving with (1, 2, 1) is lowpass filtering



Estimating the Horizontal Derivative

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▶ Estimating $\partial f / \partial x$

- First, lowpass filter the image vertically
- Second, take the difference in the horizontal direction
 - ✓ The 2-D convolution kernel to apply to the image looks like this

$$\Delta h = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$$

This estimates the horizontal derivative for the center pixel

Estimating the Vertical Derivative

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▶ Estimating $\partial f / \partial y$

- First, lowpass filter the image horizontally
- Second, take the difference in the vertical direction
 - ✓ The 2-D convolution kernel to apply to the image looks like this

$$\Delta v = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

This estimates the horizontal derivative for the center pixel

Estimating the Gradient

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- ▶ Use the horizontal and vertical derivate estimates to estimate the magnitude of the gradient for a pixel

$$\|\nabla f\| = \sqrt{(\Delta h)^2 + (\Delta v)^2}$$

Edge Detection for Previous Picture

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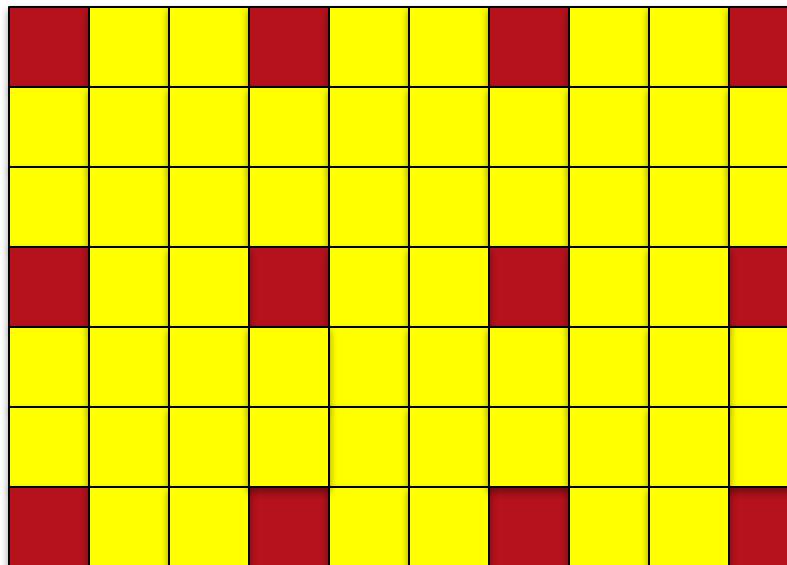
Image Resizing

Image Sampling

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► **Downsampling**

- This illustrates sub-sampling by 3 in each dimension: keep only the red pixels, and discard the yellow



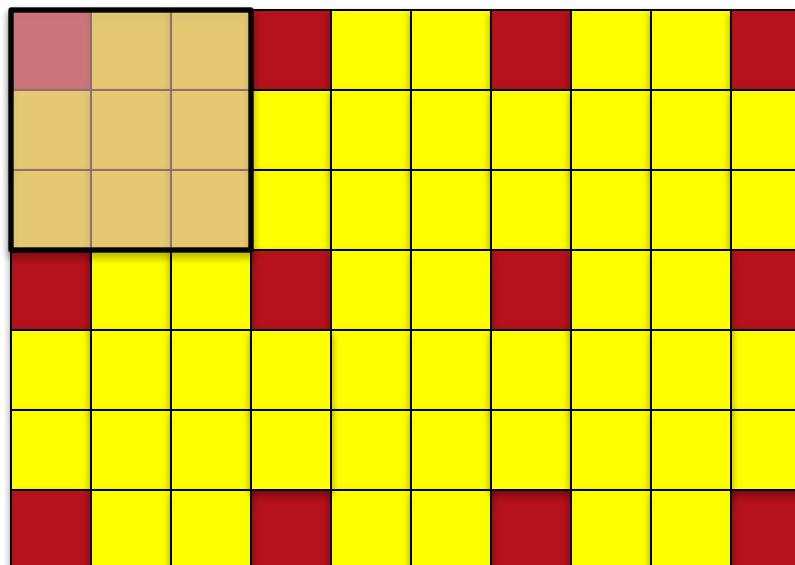
Filter Before Subsampling

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► Correct process

- Lowpass filter before subsampling
 - ✓ This minimizes aliasing
 - ✓ A simple lowpass filter: average 3-by-3 blocks

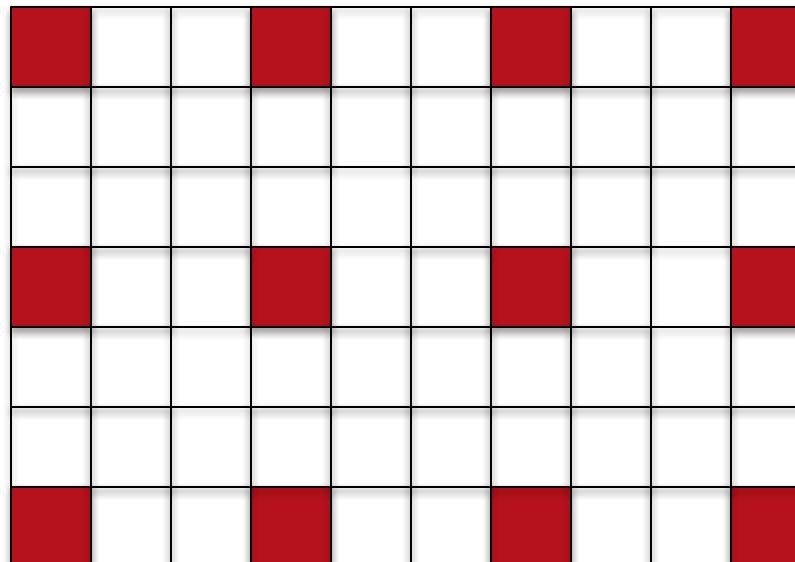
After filtering, each red pixel is the average of a 3-by-3 block



Upsampling

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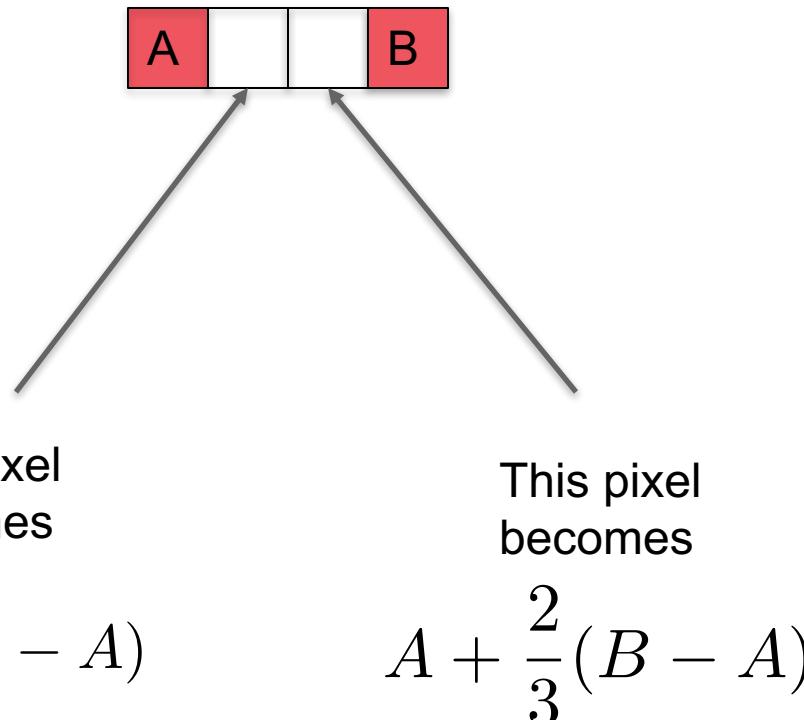
- ▶ **We upsample to make a larger image**
 - Spread out the pixels to occupy the red squares
 - ✓ The white squares need to be filled in by filtering or interpolation



1-D Linear interpolation

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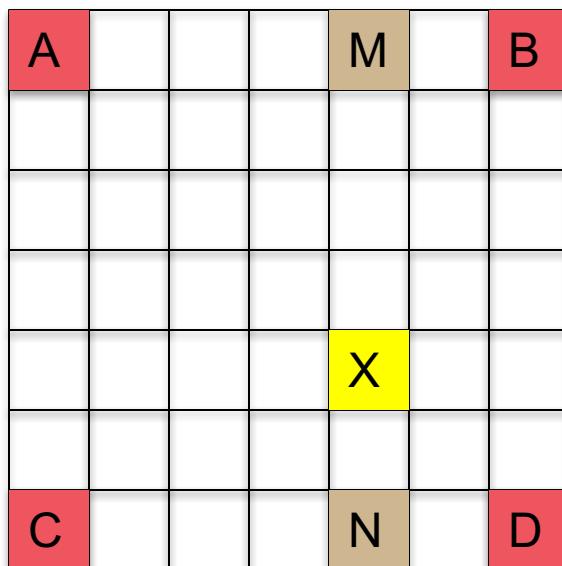
- ▶ Assume the intensities of the red pixels are as indicated



Bi-linear Interpolation

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- ▶ Assume the intensities of the red pixels are as indicated



To bi-linearly interpolate X:
--Interpolate M using A and B
--Interpolate N using C and D
--Interpolate X using M and N

Example

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- ▶ **Downsampling then up-sampling by 4**

