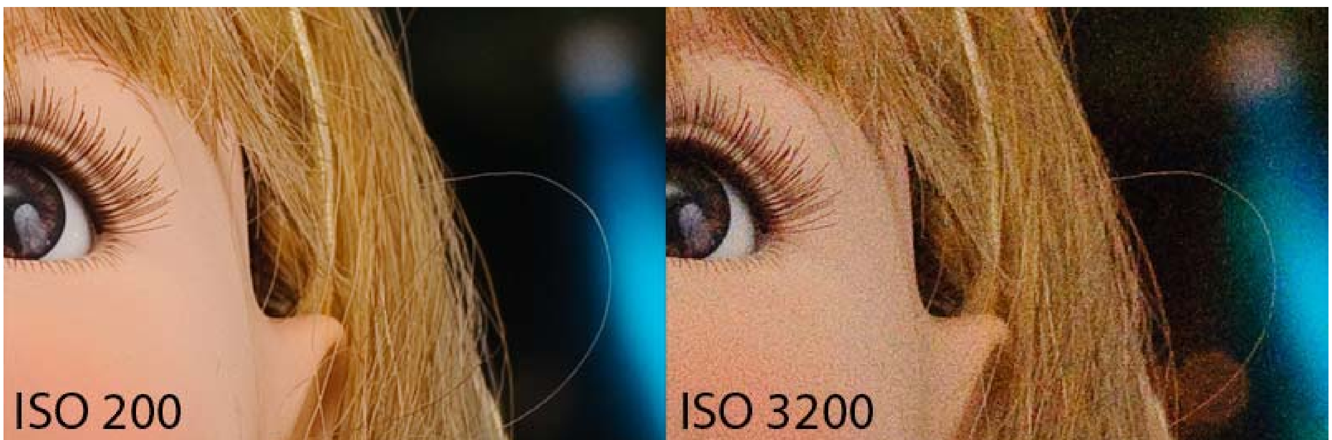
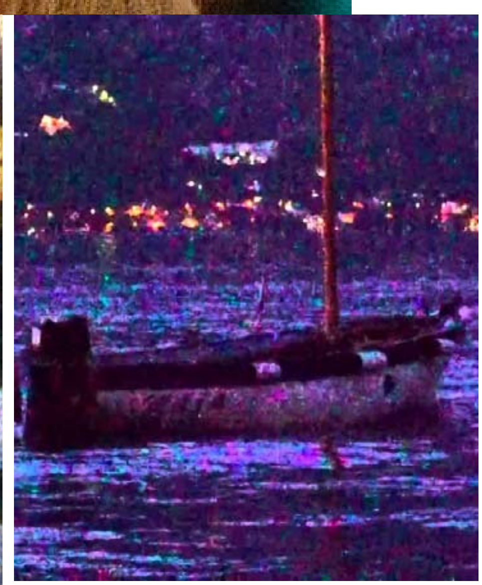
Images Noise Reduction

- One of the keys to making digital sensors work is noise reduction
- Imaging Sensors, especially APS, have way more noise than film
- Film has grain noise
- But does not get noise with long exposures except for shot noise
- Imaging sensors have a base noise
- + noise that grows with exposure time
- There has been substantial effort in noise reduction software
- 2005 top ISO with reasonable noise ~800ISO
- Now 3200ISO is nearly noise free



12,800 ISO

12,800 ISO



409,600 ISO

Image Noise Model

- First recall the sources of noise from lesson 9
- Shot noise, thermal noise, flicker noise
- Assume that the pixel has a 0 to 255 response
- Assume for an image noise is added to the true image
- For each pixel location i,j the pixel value is

$$Y_{ij} = X_{ij} + N_{ij}$$

- Where Y_{ij} is the measured pixel value
- X_{ij} = the true value for the pixel (ie the illumination response)
- N_{ij} = is the added noise from some source
- This is called additive noise

$$g(x, y) = f(x, y) + n(x, y)$$

- Where g(x,y) is the gray scale output response
- f(x,y) is the true response
- n(x,y) is the pixel noise
- This is often a “white noise” or Gaussian noise

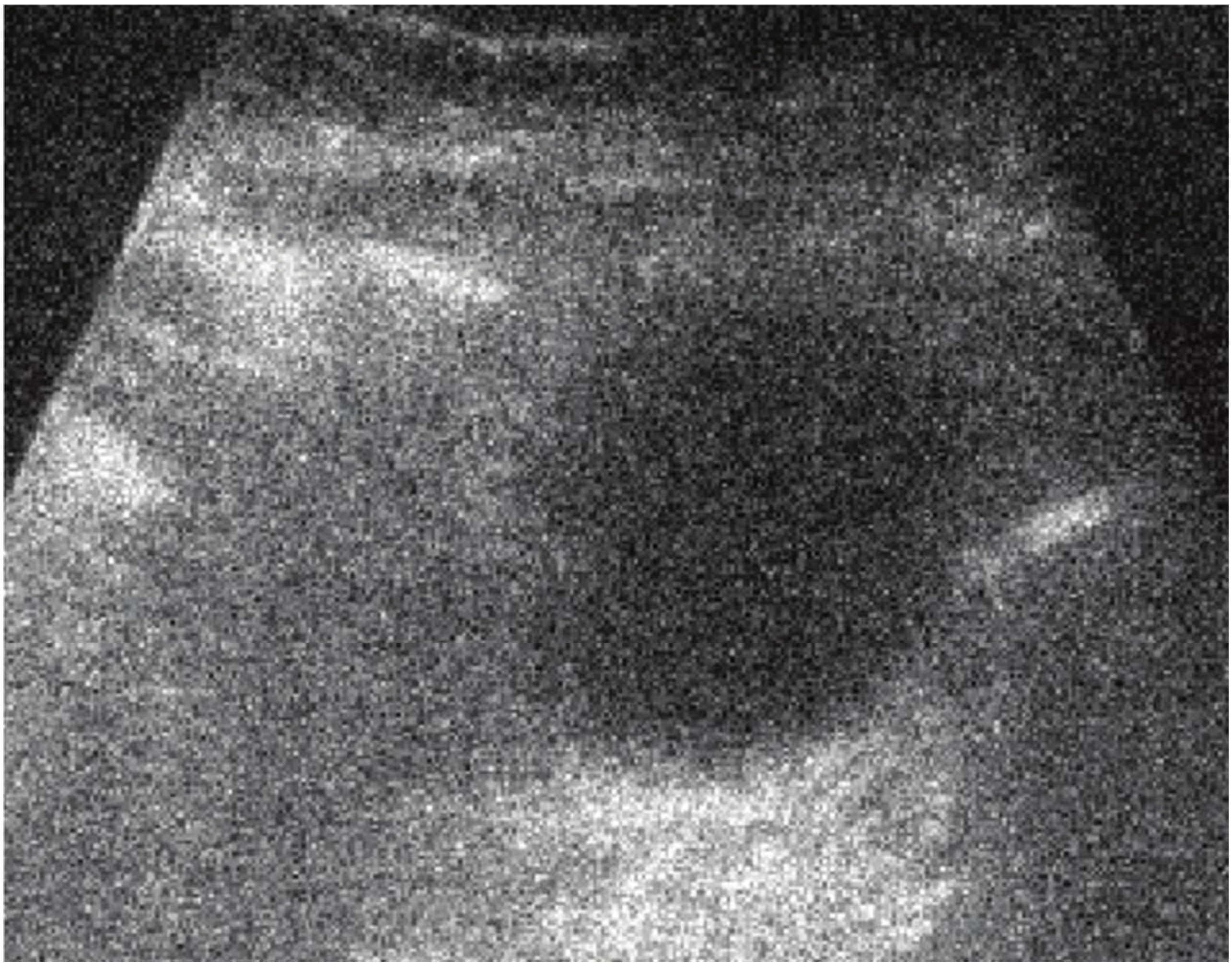
$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

- Note almost all noise simulation is done on B&W images

Speckle noise

- Speckle noise occurs with laser and medical images
- actually a multiplicative noise

$$g(x, y) = f(x, y) * n(x, y)$$



Impulse or Salt and Pepper noise

- where the noise is either full black or white
- Salt and Pepper Noise
- Bipolar fixed value impulse noise

$$g(x, y) = (1 - p)f(x, y) + p_i(x, y)$$

- Where p is the probability of the noise
- Very often used in noise simulations
- Not often seen in real images
- Black would be dead pixels
- White stuck high pixels

Signal to Noise Ratio

- Noise may be there but is not seen
- The important factor is the signal to noise ratio (SNR)

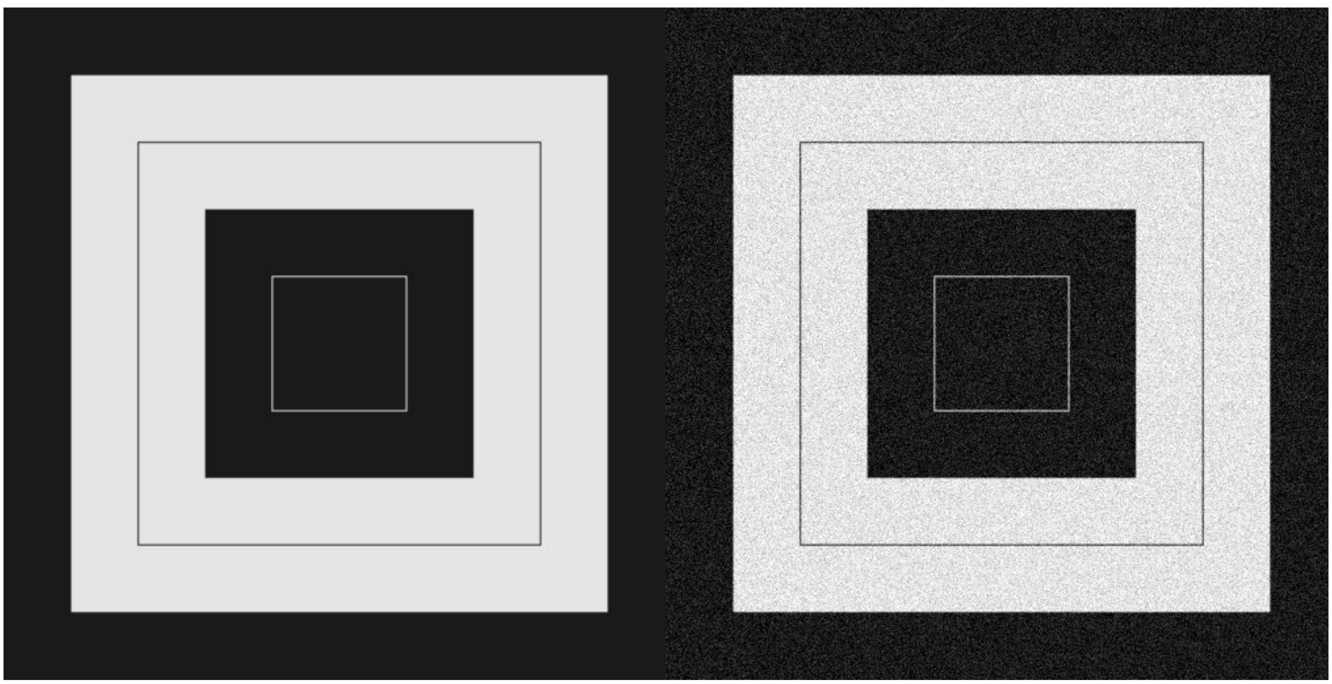
$$SNR = \frac{\sigma(u)}{\sigma(n)},$$

- Where σ(u) is the empirical standard deviation of the image

$$\sigma(u) = \left(\frac{1}{|I|} \sum_i (u(i) - \overline{u})^2 \right)^{\frac{1}{2}}$$

$$\overline{u} = \frac{1}{|I|} \sum_{i \in I} u(i)$$

- Ie the average gray value in the image
- Good pictures have σ(u) ~60
- Noise is added to this



When Does Noise become Visible

- When σ ~3 noise is almost invisible
- SNR then is

$$SNR = \frac{60}{3} = 20$$

- Really SNR needs to be near 2 or 1 for notice in this case
- To remove noise you need to know the noise model
- General method: create a smoothness model
- Either local or global
- Note this is true with B&W image
- Not true with color images – where chrominance error is visible
- Almost all test add either white Gaussian or Salt & Pepper noise
- Then test if they can remove most of image errors
- Compared to the original image

Figure 1: A digital image with standard deviation 55, the same with noise added (standard deviation 3), the signal noise ratio being therefore equal to 18, and the same with signal noise ratio slightly larger than 2. In this second image, no alteration is visible. In the third, a conspicuous noise with standard deviation 25 has been added but, surprisingly enough with a two to 1 signal ratio, all details of the original image still are visible.

Lina Test Image

- Linna (Lina) is a standard test image for this
- Lina was a Swedish model doing secretary work at Standford
- Image comes from the Nov. 1972 playboy center fold
- In 1973 Lawrence G. Robert digitized the image for his thesis
- Became the standard test image for imaging community
- In 1997 she was given an award by the
- Society for Imaging Science and Technology

Denoising Algorithms

- Many types of Denoising Algorithms
- A Review and Comprehensive Comparison of Image Denoising Techniques, Gupta and Meenakshi, 2014