SMOOTHING, RESTORATION

AND

ENHANCEMENT

Spatial filters for de-noising additive noise

- Skills similar to image enhancement
- Mean filters
- Order-statistics filters
- Adaptive filters

Courtesy: Jen-Chang Liu

Order-statistics filters

- Based on the ordering(ranking) of pixels
  - Suitable for unipolar or bipolar noise (salt and pepper noise)
- Median filters
- Max/min filters
- Midpoint filters
- Alpha-trimmed mean filters

Smoothing - Spatial Domain

The simplest approach is *neighborhood averaging*, where each pixel is replaced by the average value of the pixels contained in some neighborhood about it.

The simplest case is probably to consider the group of pixels centered on the given pixel, and to replace the central pixel value by the un-weighted (for weighted - Gaussian function is commonly used) average of these (nine, in case of 3*3 neighborhood) pixels.

For example, the central pixel in Figure below is replaced by the value:

13 (the nearest integer to the average).

10	12	11
11	23	12
10	14	15

If any one of the pixels in the neighborhood has a faulty value due to noise, this fault will now be smeared over nine pixels as the image is smoothed. This tends to blur the image.

A better approach is to use a ***median filter***.

A similar neighborhood around the pixel under consideration is used, but this time the pixel value is replaced by the *median* pixel value in the neighborhood.

Thus, if we have a 3*3 neighborhood, we write the 9 pixel values in sorted order, and replace the central pixel by the fifth highest value. For example, again taking the data shown in Figure above, the central pixel is replaced by the value:

12

This approach has two advantages.

- Occasional spurious high or low values are not averaged in -- they are ignored

- The sharpness of edges is preserved. To see this, consider the pixel data shown in the next slide.

10	10	20	20
10	10	20	20
10	10	20	20

When the neighborhood covers the left-hand nine pixels, the median value is 10; when it covers the right hand ones, the median value is 20; thus the edge is preserved.

- If there are large amounts of noise in an image, more than one pass of median filtering may be useful to further reduce the noise.

- A rather different real space technique for smoothing is to average multiple copies of the image.

- The idea is that over several images, the noise will tend to cancel itself out if it is independent from one image to the next.

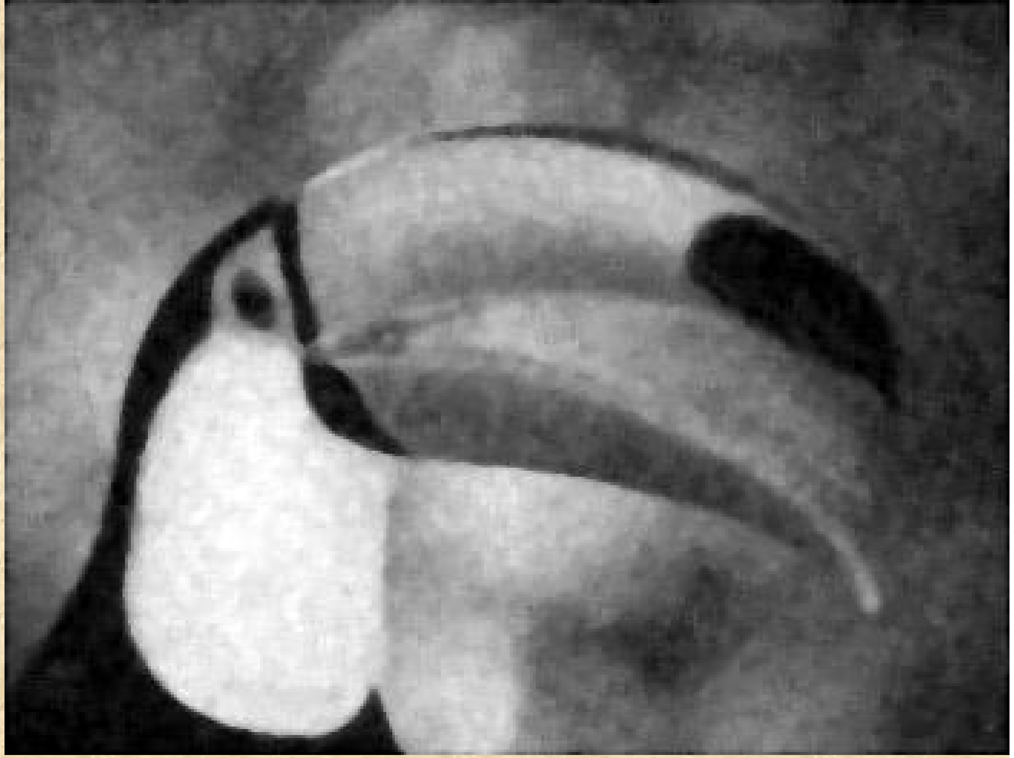
- Statistically, we expect the effects of noise to be reduced by a factor $n^{-1/2}$, if we use *n* images. One particular situation where this technique is of use, is in low lighting conditions.

Original Image

Median Filtered Image

Noisy Image

Original Image



Median Filtered Image

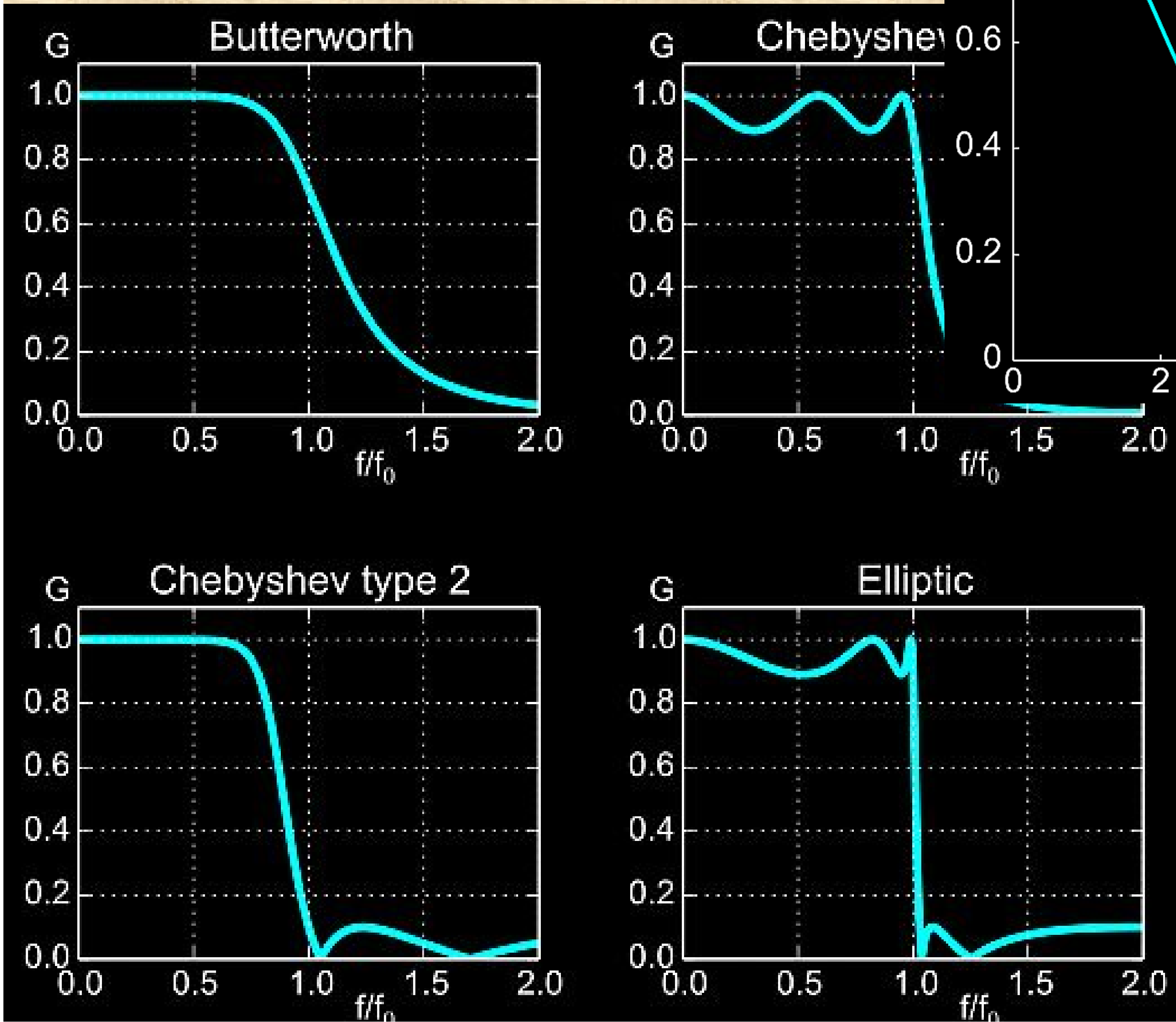
Noisy Image

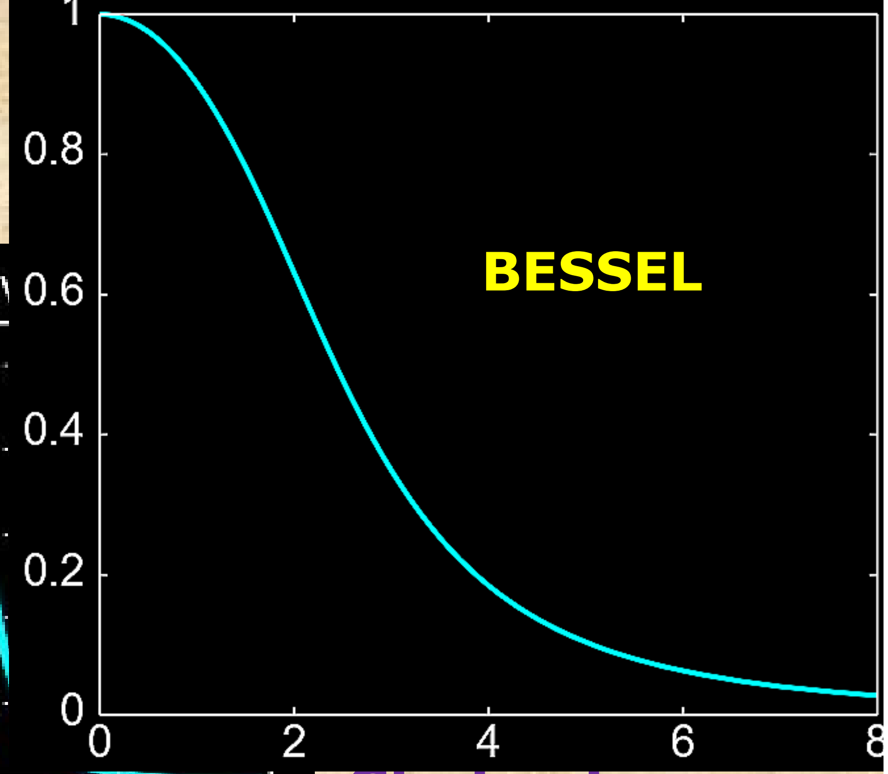
Original Image

Median Filtered Image

Noisy Image

Periodic noise





- Chebyshev
- Weiner
- Bessel
- Gaussian
- Bilateral, Box;
- Ring filters
- Gabor
- DWT, DCT

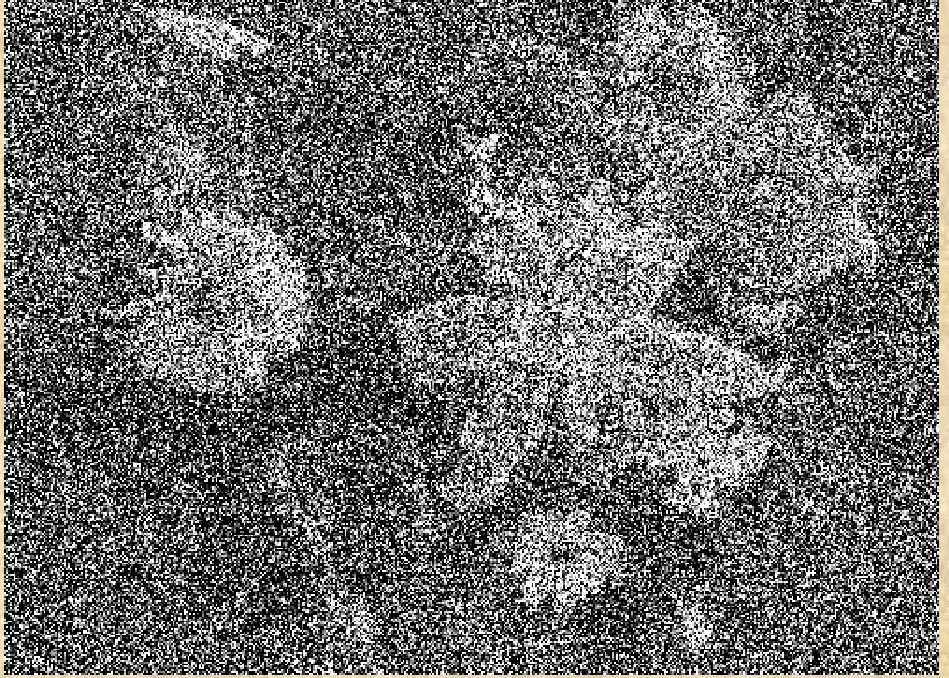
Original Image

Noisy Image

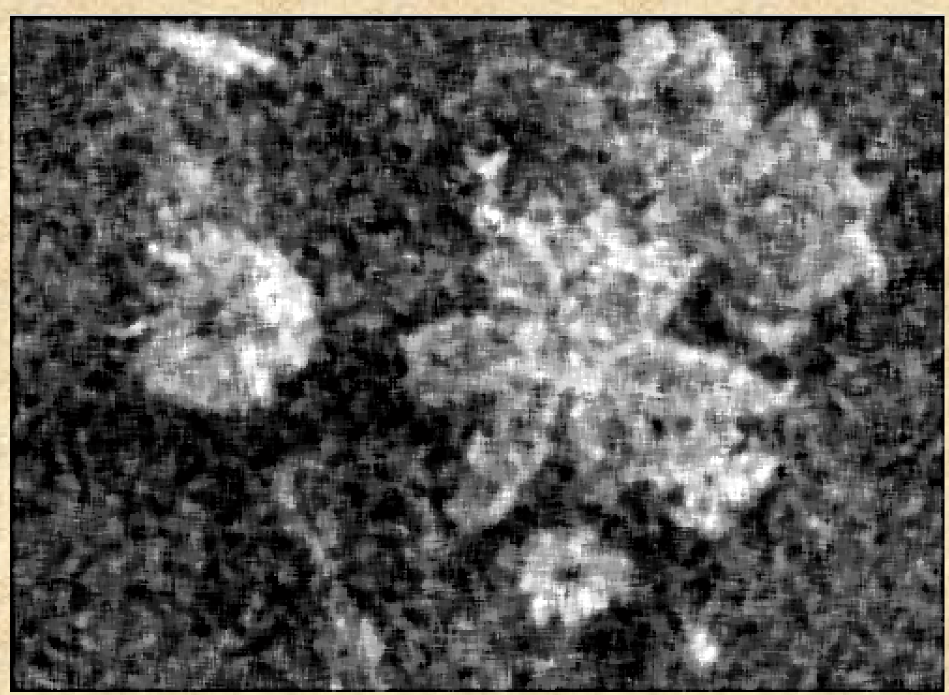
Median Filtered Image

Filtered using Wiener Filter

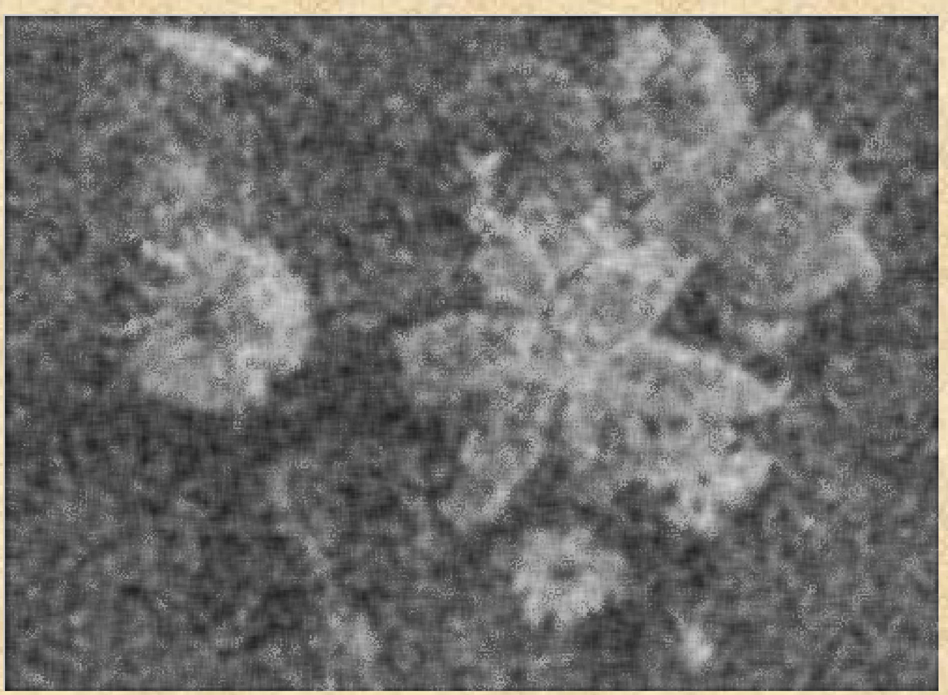
Original Image



Noisy Image



Median Filtered Image



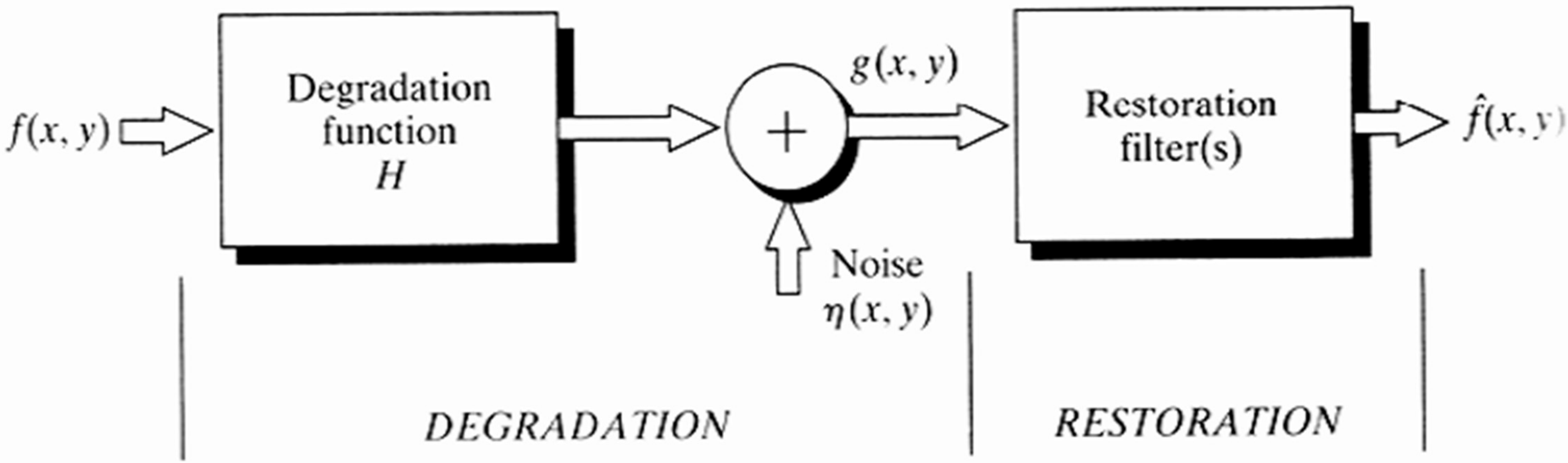
Filtered using Wiener Filter

MATHEMATICAL MODEL OF IMAGE DEGRADATION

$$g(x,y) = H\{f(x,y)\} + n(x,y)$$

$$H(u,v).F(u,v) = G(u,v)$$

$$H_s(u,v) = G_s(u,v) / F_s(u,v) \qquad \hat{F}(u,v) = G(u,v) / H_s(u,v)$$



$$H(u,v) = e^{-k(u^2+v^2)^{\frac{5}{6}}}$$

Obtain restoration as: $$F(u,v) = H^{-1}(u,v)G(u,v)$$

Minimize
(by Optimization): $$\sum [g(x,y) - h(x,y) * f(x,y)]^2$$

(Constrained Least Squares, Splines, TV-Reg)

Refs:
https://www.clear.rice.edu/elec431/projects95/lords/wolf.html;

https://user.eng.umd.edu/~fywang/assets/lab3/html/lab3.html;

https://www.cs.uoi.gr/~cnikou/Courses/Digital_Image_Processing/Chapter_05b_Image_Restoration_(Linear_Restoration).pdf

Inverse filtering

- With the estimated degradation function H(u,v)

G(u,v)=F(u,v)H(u,v)+N(u,v)

Unknown noise

=> $$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

Estimate of original image

Problem: 0 or small values

Sol: limit the frequency around the origin

Psuedo- Inverse Filter

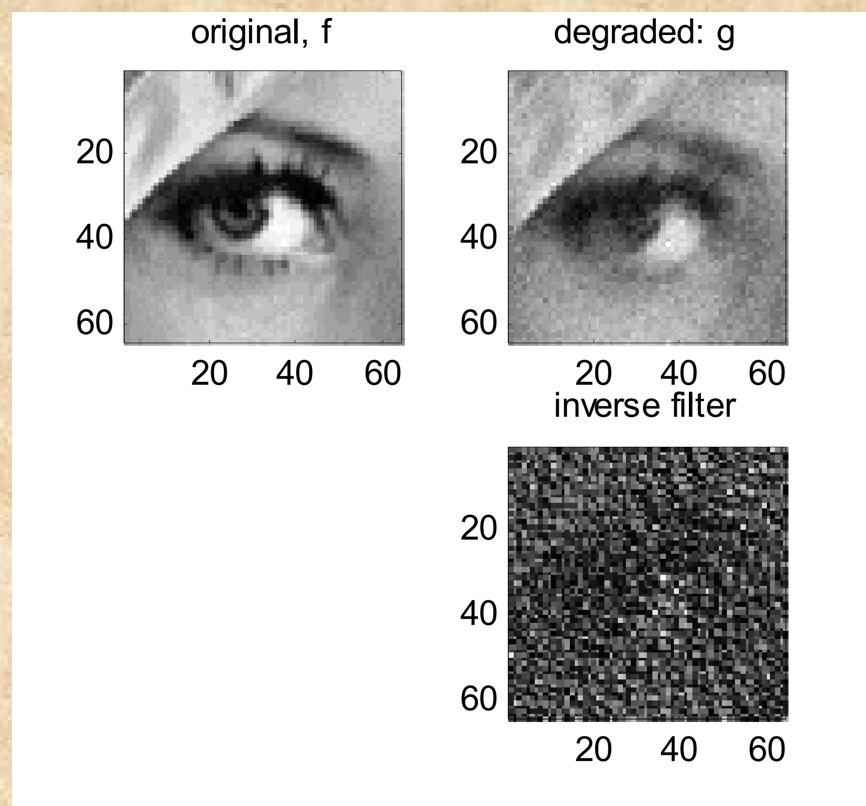
Given H(u,v), one may directly estimate the original image by

$$G(u,v) = H(u,v)F(u,v) + N(u,v)$$

At (u,v) where H(u,v) ≈ 0, the noise N(u,v) term will be amplified!

$$\hat{F}(u,v) = G(u,v) / H(u,v)$$

$$= F(u,v) + \frac{N(u,v)}{H(u,v)}$$



WEINER FILTER

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)S_f(u,v)}{S_f(u,v)|H(u,v)|^2 + S_\eta(u,v)}\right]G(u,v)$$

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2 + K}\right]G(u,v)$$

Where K is a specified constant

$$= \left[\frac{1}{H(u,v)}\frac{|H(u,v)|^2}{|H(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right]G(u,v)$$

Where H(u,v)= Degradation function

H*(u,v)=complex conjugate of H(u,v)

$| H(u,v)|^2=H^* (u,v) H(u,v)$

H (u, v) is the transform of the degradation function and
G (u, v) is the transform of the degraded image.

$S_f(u,v)=|F(u,v)|^2$= power spectrum of the underrated image

$S_n(u,v)=|N(u,v)|^2$= power spectrum of the noise

$$P(u,v) = H(u,v)\ Q(u,v),$$

where

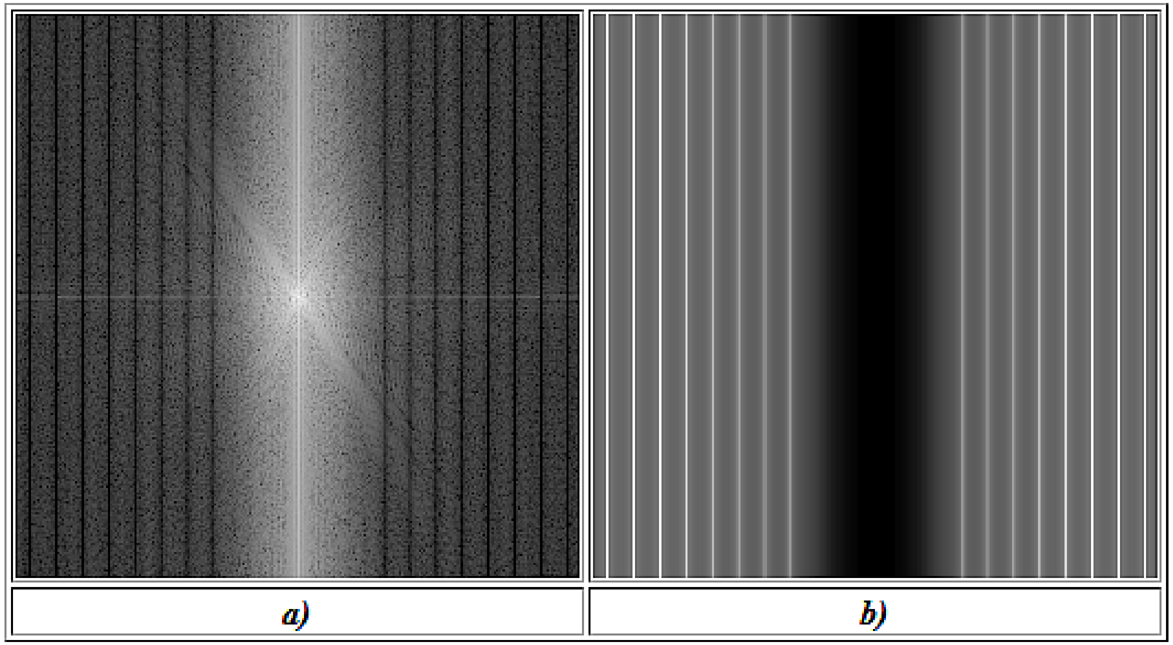
$P(u,v)$ is the degraded image,

$H(u,v)$ is the degradation transfer function, and

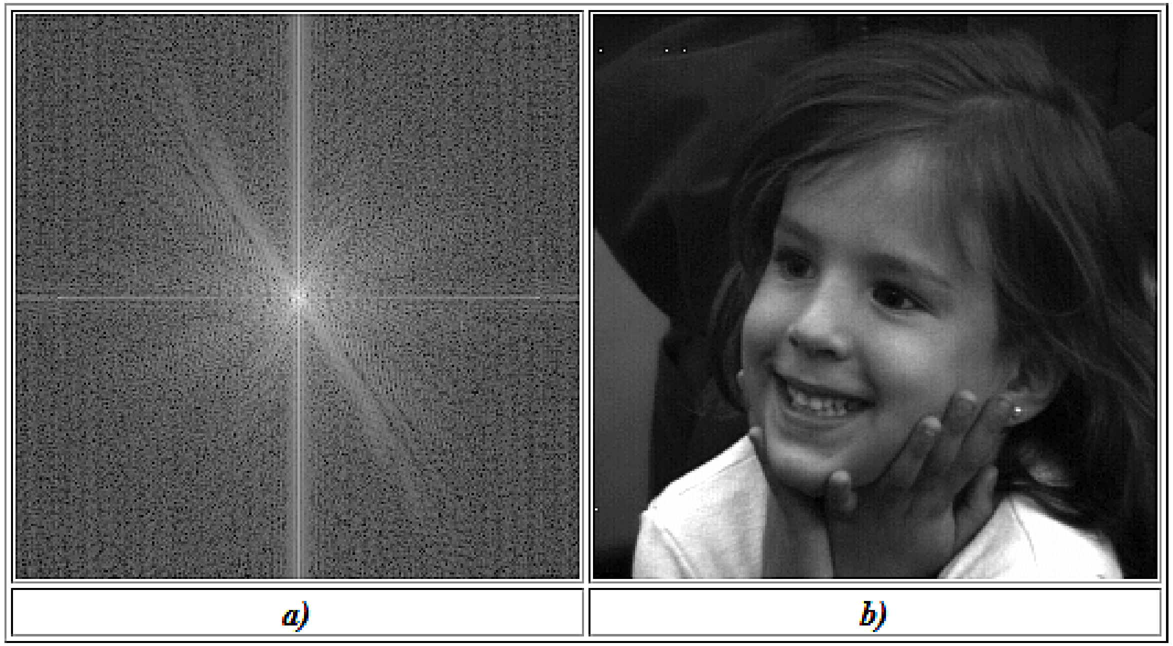
$Q(u,v)$ is the original image.

The inverse filtering process is then

$$Q(u,v) = P(u,v)\ /\ H(u,v).$$



a)spectrum of the blurred image; b)spectrum of R(u) = 1/H(u)



a)restored DFT; b)inverse DFT of restored DFT

Al- Khwarizmi Engineering Journal, Vol.3, No.1, pp 48-62 (2007)

inverse filtering

Wiener filtering

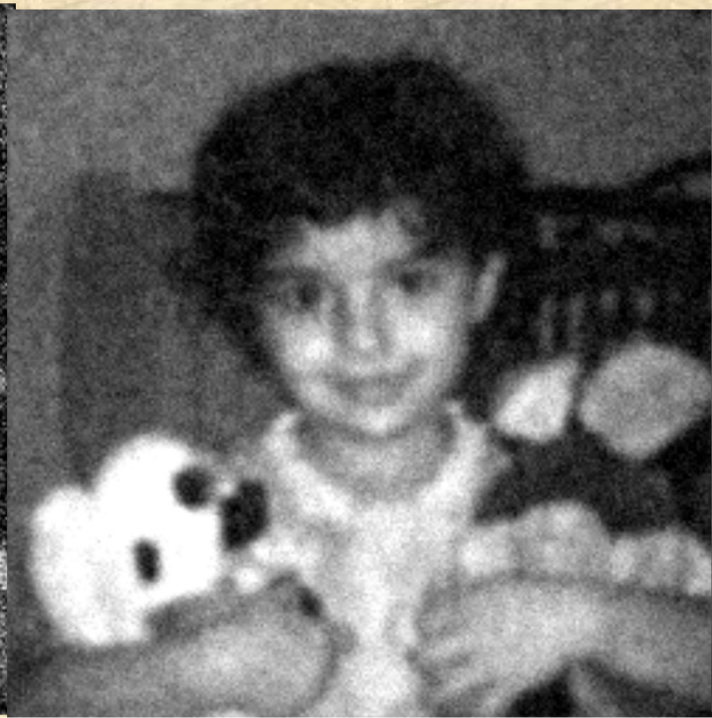


Fig. 1. (a)-(c) Blur Image Model showing Original image, Wiener filter, Regularization Filter and Lucy-Richardson Filter.

Other types of **degradations**, typically present in images/videos:

- **Low contrast**
- **Low illumination**
- **Optical distortions (more on this later)**
- **Blur : defocus, motion**
- **Scratches**
- **Low resolution**
- **Ghosts**
- **Fog/mist; atmospheric conditions**
- **Glare**
- **Degraded ink or Material (due to aging, lack of proper preservation etc.) being imaged**
- **Ice/water/dirt on lens**
- **Color Saturation, fading, diffusion,** ….
- …..

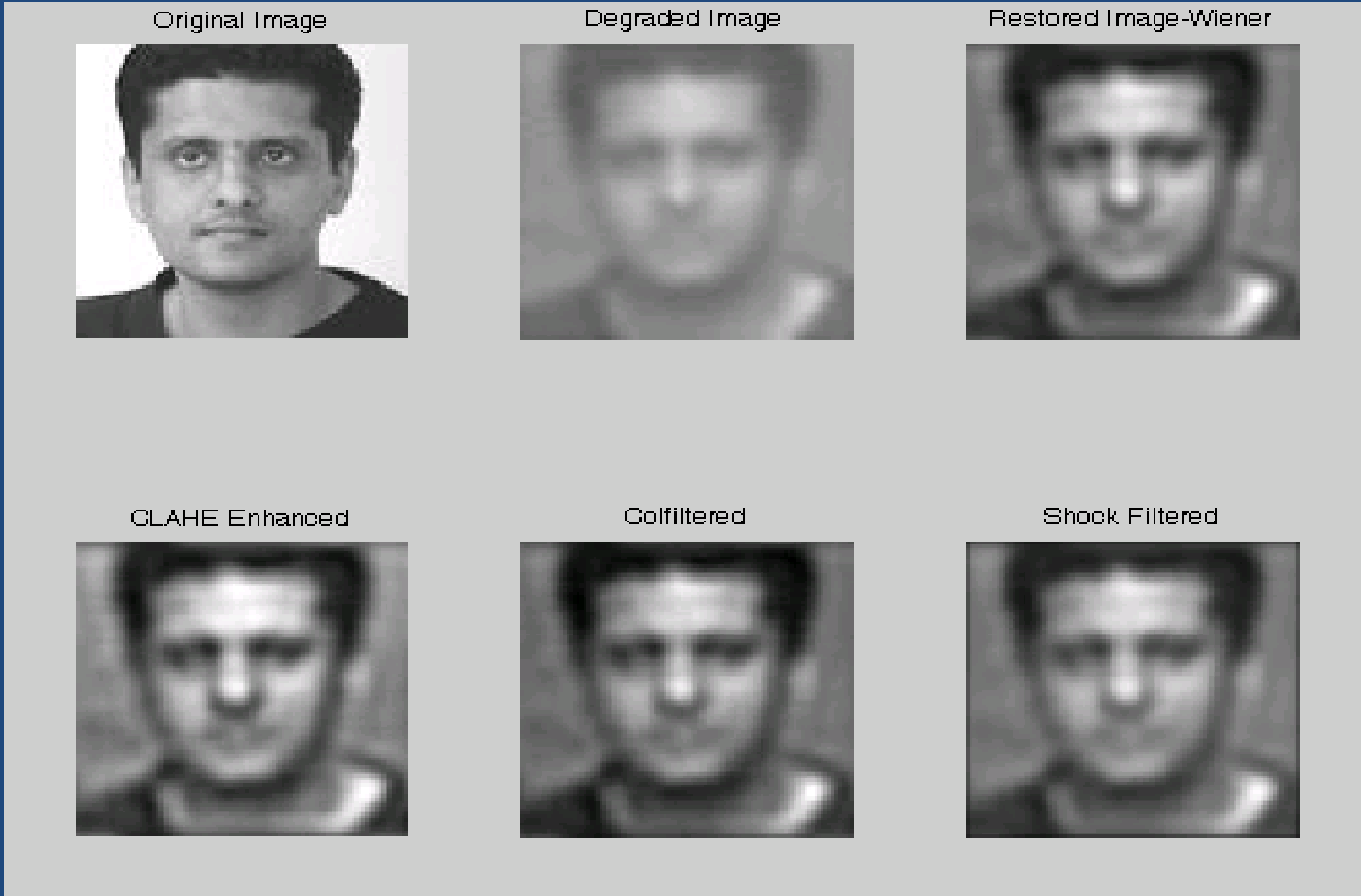
These could be spatially varying, or even exist as combinations.

Modern methods of Noise Removal use:

- Iterative and Adaptive Kalman Filtering
- Discrete Wavelet (multi-channel) transform
- SVD (PCA), ICA
- Fuzzy-based methods
- Optimization frameworks
- Non-linear ANNs
- Anisotropic diffusion (filtering)
- Bilateral & Homomorphic filtering
- Non-local means
- Particle Filtering

- Level Set Methods
- Basis Pursuit
- Graph-based approaches
- Stanford – DUDE
- Minimax Risk
- Manifold-based learning
- **CLAHE**
- Shock Filter
- DL based methods ??

IMAGE RESTORATION (WIENER) AND ENHANCEMENT



LENA-IMAGE RESTORATION (REGULARIZATION) AND ENHANCEMENT

LENA-IMAGE RESTORATION (WIENER) AND ENHANCEMENT

ve histogram equalization

IMAGE RESTORATION-WIENER DECONVOLUTION

ORIGINAL IMAGE

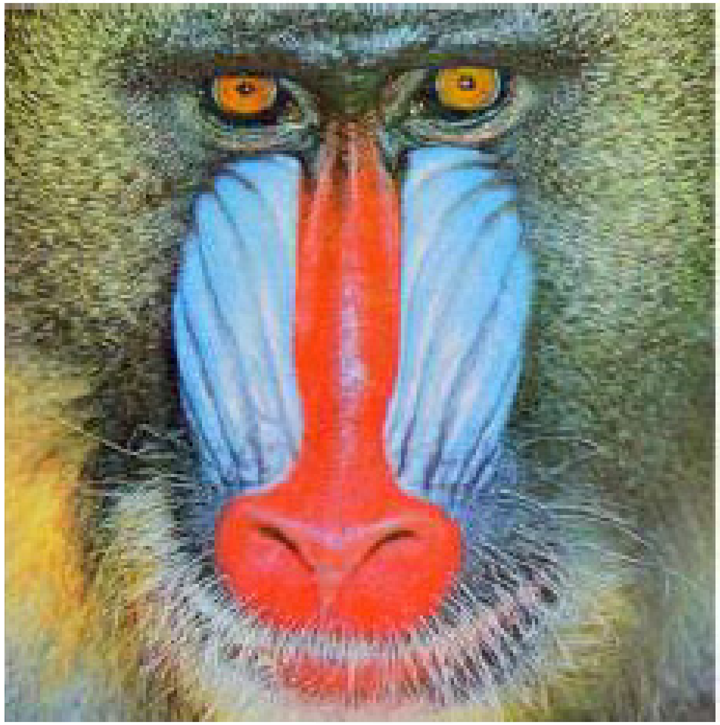
BLURRED&NOISY IMAGE

RESTORED IMAGE,NSR=0.25

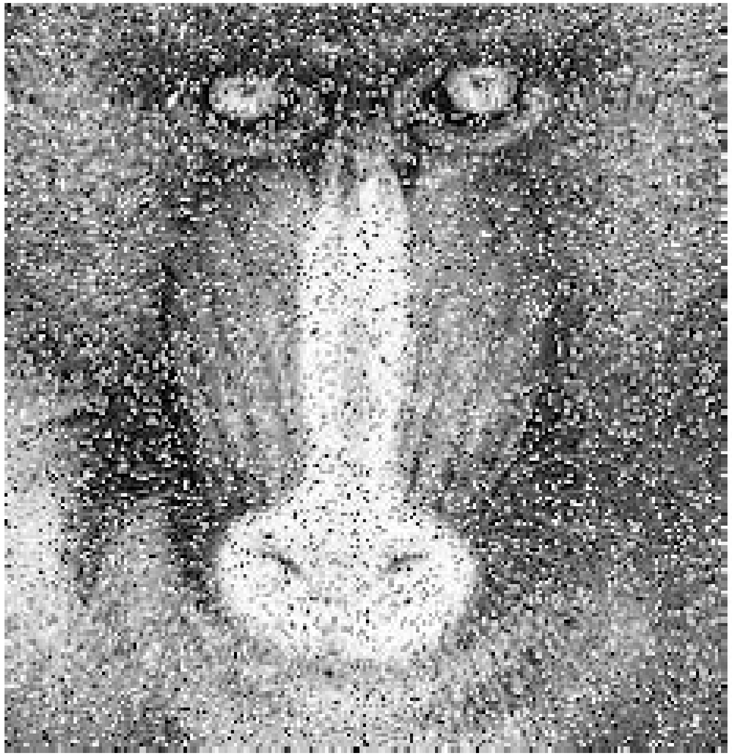
Standard Lena Image
PSNR = Infinity, MSE = Zero

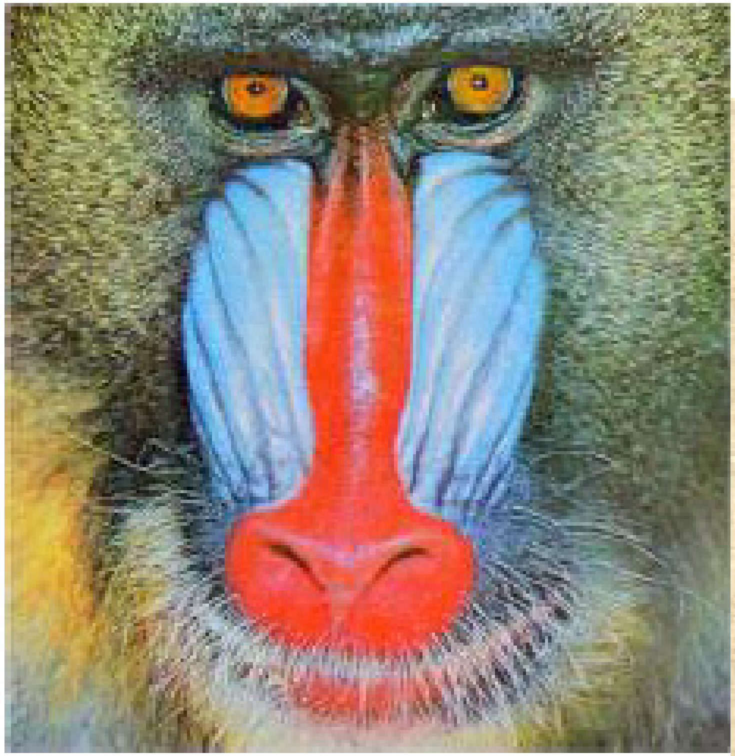
Blurred Lena Image
PSNR = 23.2993, MSE = 304.1938

Restored Lena Image
PSNR = 19.1447, MSE = 791.7906



PSNR=22.97
SSIM=0.6550





Weiner

And

Inverse filter outputs





Original
Restored


Original
Restored

Image Enhancement

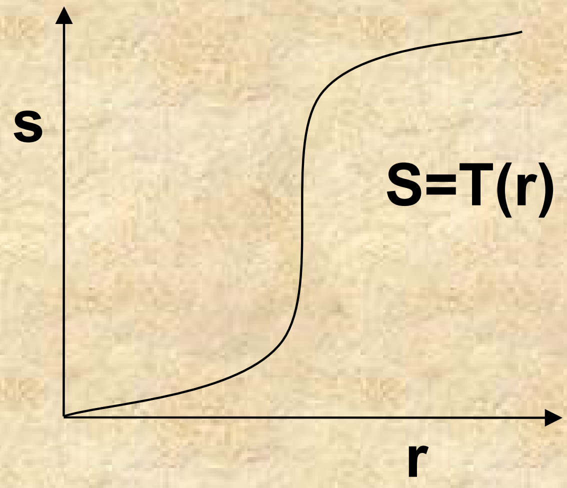
CONTRAST STRETCHING

This is a pixel-based operation, where a given gray level $r \in [0, L]$ mapped into a gray level $s \in [0, L]$ according to a transformation function:

$$s = T(r)$$

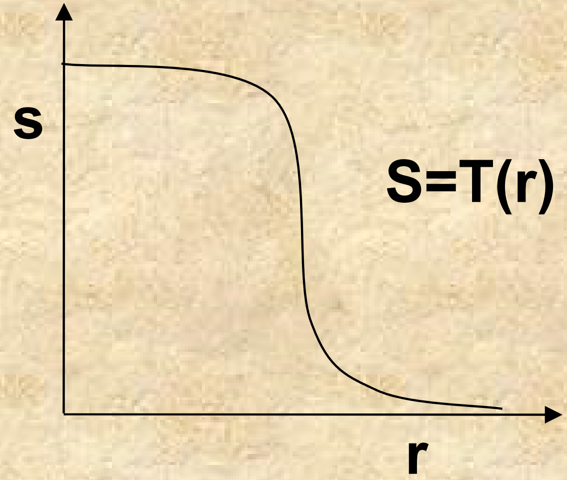
This process is mainly used to enhance done to handle low-contrast images occurring due to poor or non-uniform lighting conditions or due to non-linearity or small dynamic range of the imaging sensor.

Following examples shows some typical contrast stretching transformations.



Original image

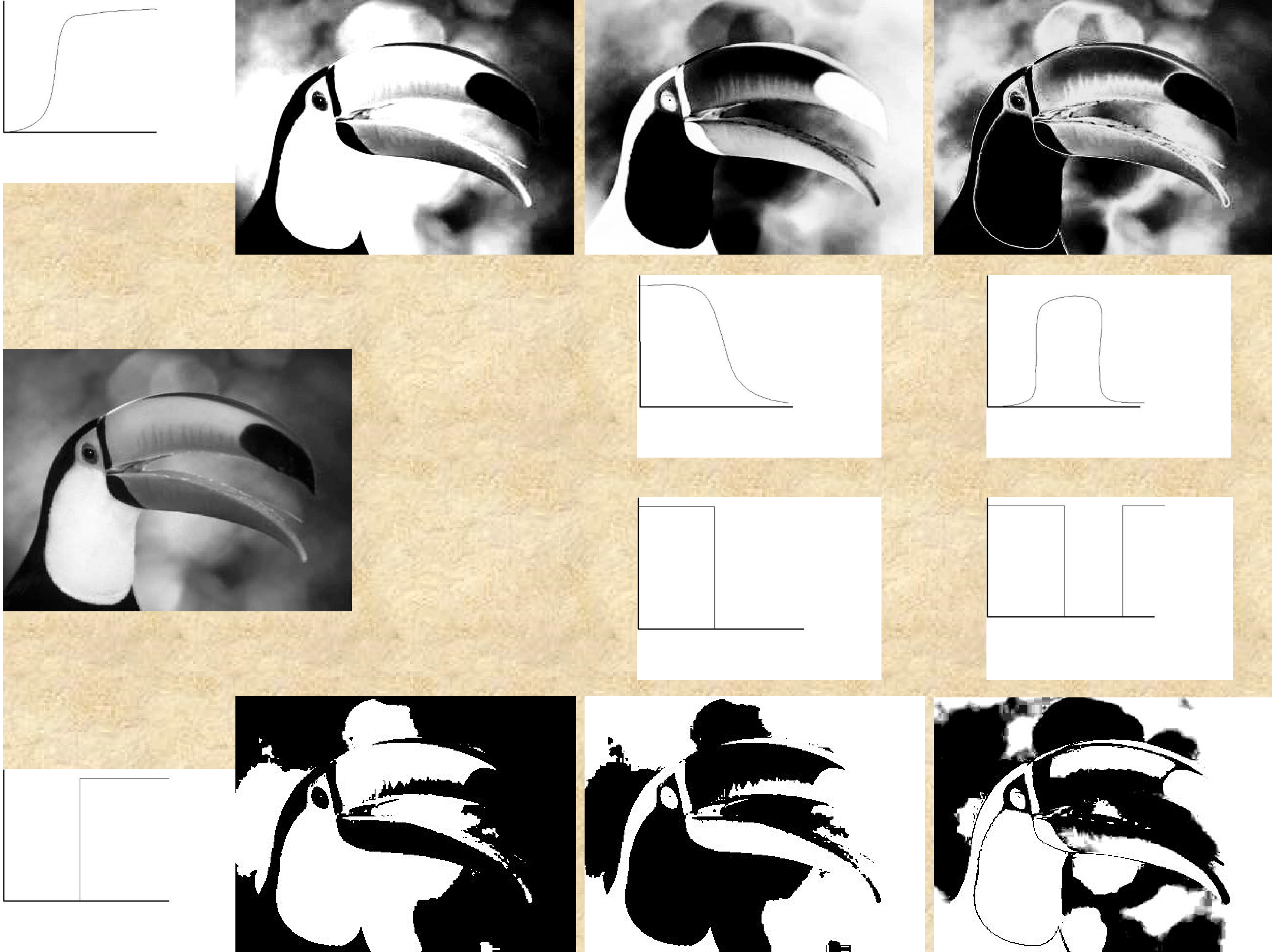
After contrast stretching



Original image

After contrast stretching


original image
original image
original image
original image
original image



How to find a **s = T(r),** **which depends on the image data and hence produces a global transform/enhancement of the image, and not simply a local transformation of the pixel ??**

Let us look at **Histogram Equalization** next**.**