SMOOTHING, RESTORATION AND

ENHANCEMENT

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.

and the second s			
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

Noisy Image





Median Filtered Image





Original Image



Median Filtered Image

Noisy Image



Original Image



Noisy Image



Median Filtered Image



Filtered using Wiener Filter



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)

 $H_{s}(u,v) = \frac{G_{s}(u,v)}{F_{s}(u,v)} + \frac{G(u,v)}{F_{s}(u,v)} + \frac{G(u,v)}{F$



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

Obtain restoration as:

 $F(u,v) = H^{-1}(u,v)G(u,v)$

Minimize:

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

Modern methods of Noise Removal use:

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

- Level Set Methods
- Basis Pursuit
- Graph-based approaches
- Stanford DUDE
- Minimax Risk
- Manifold-based learning
- CLAHE
- Shock Filter

IMAGE RESTORATION (WIENER) AND ENHANCEMENT

Original Image



Degraded Image



Restored Image-Wiener



GLAHE Enhanced



Colfiltered



Shock Filtered



LENA-IMAGE RESTORATION (REGULARIZATION) AND ENHANCEMENT







CLAHE Image





Shock Filtered Image



LENA-IMAGE RESTORATION (WIENER) AND ENHANCEMENT







CLAHE Image





Shock Filtered Image



ogram equalization

IMAGE RESTORATION-WIENER DECONVOLUTION

ORIGINAL IMAGE



BLURRED&NOISY IMAGE



RESTORED IMAGE,NSR=0.25





IMAGE RESTORATION- REGULARIZATION

Original Image



BLUPPED&NOISY IMAGE



PSNR=21.64 SSIM=0.4016 deconvineg(A,PSF,NP)



PSNR=22.97 SSIM=0.6550







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



After contrast stretching

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.