

Image Restoration

Image Processing with Biomedical
Applications
ELEG-475/675
Prof. Barner

Image Restoration

- Image enhancement is subjective
 - Heuristic and ad hoc
- Image restoration is more theoretically motivated
 - A priori knowledge of image degradation utilized
 - Optimality criteria used to formulate restoration

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Preliminaries: Correlation and Power Spectrum

- Note self-convolution

$$f(t) * f(t) = \int_{-\infty}^{\infty} f(t) f(t - \tau) d\tau$$
- Correlation results if we do not reflect one term

$$R_f(\tau) = f(t) * f(-t) = \int_{-\infty}^{\infty} f(t) f(t + \tau) dt$$
 - Note maximum at $\tau=0$; also

$$\int_{-\infty}^{\infty} R_f(\tau) d\tau = \int_{-\infty}^{\infty} f(t) f(t) dt$$
- Power Spectral Density (PSD)

$$P_f(s) = \mathfrak{F}\{R_f(\tau)\} = \mathfrak{F}\{f(t) * f(-t)\} = F(s)F^*(s) = |F(s)|^2$$
- Cross correlation and PSD

$$R_{fg}(\tau) = f(t) * g(-t) = \int_{-\infty}^{\infty} f(t) g(t + \tau) dt$$

$$P_{fg}(s) = \mathfrak{F}\{R_{fg}(\tau)\}$$
- Assume ergodic signals (RVs) – interchange time/ensemble averages, e.g.,

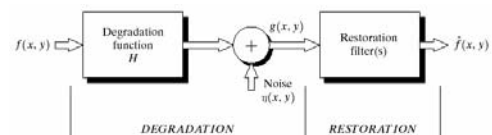
$$E\{x(t)\} = \int_{-\infty}^{\infty} x(t) dt$$

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Degradation and Restoration Model



- Degradation is taken to be a linear spatially invariant operator

$$g(x, y) = h(x, y) * f(x, y) + \eta(x, y)$$

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

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Noise Properties

- Arises in acquisition, digitization, and transmission/storage processes
- CCD cameras are affected by:
 - Light levels
 - Sensor temperature
 - Bad sensors
- Transmission noise can be due to interference
 - Wireless transmission interference
 - Lost networking packets
- Statistics depend on source
 - Common assumption: White Spectrum
 - Correlation: $R(T) = A\delta(T)$
 - Power spectrum: $P(s) = A$

Noise Probability Density Functions

■ Gaussian (normal) PDF

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

- Typically models electronics and sensor noise

■ Rayleigh PDF

$$p(z) = \begin{cases} \frac{2}{b}(z-a)e^{-(z-a)^2/b} & \text{for } z \geq a \\ 0 & \text{for } z < a \end{cases}$$

$$\mu = a + \sqrt{\pi b}/4, \quad \sigma^2 = \frac{b(4-\pi)}{4}$$

- Skewed distribution typically models range imaging noise

Noise Probability Density Functions II

■ Gamma PDF

$$p(z) = \begin{cases} \frac{a^b z^{b-1}}{(b-1)!} e^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

$$\mu = \frac{b}{a}, \quad \sigma^2 = \frac{b}{a^2}$$

■ Exponential PDF

$$p(z) = \begin{cases} ae^{-az} & \text{for } z \geq 0 \\ 0 & \text{for } z < 0 \end{cases}$$

$$\mu = \frac{1}{a}, \quad \sigma^2 = \frac{1}{a^2}$$

■ Both appropriate for laser imaging

- Heavy-tailed distributions
 - samples contain frequent outliers

Noise Probability Density Function III

■ Uniform PDF

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$\mu = \frac{a+b}{2}, \quad \sigma^2 = \frac{(b-a)^2}{12}$$

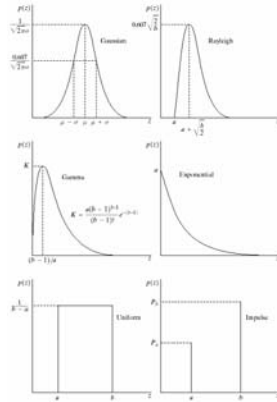
■ Impulsive (salt and pepper) PDF

$$p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

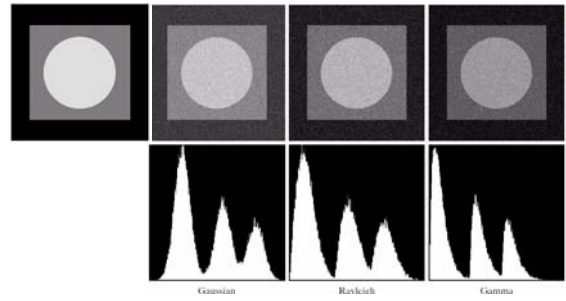
- Shot or spike noise appropriate faulty sensor or electronics, transmission error/drop

PDF Plots

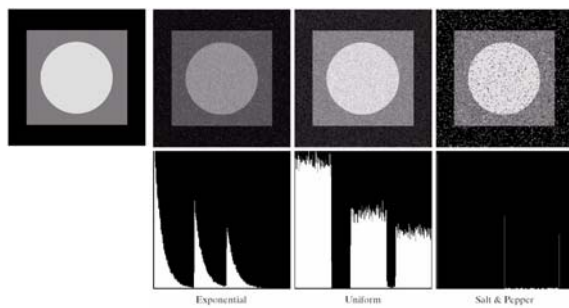
- Gaussian distribution is most widely used
 - Central Limit Theorem
 - Desirable properties
 - Independence and correlated
- Other distributions appropriate for specific cases
 - Simplicity of uniform enables derivation of results



Test Pattern Corruption Example



Test Pattern Corruption Example II



Noise Parameter Determination



- Generate statistics from uniform region
 - Histogram matching
 - Quantile-Quantile (Q-Q) plot
- Determined defining statistics, e.g.
 - $\mu = \sum_{i=0}^{255} z_i p(z_i)$, $\sigma^2 = \sum_{i=0}^{255} (z_i - \mu)^2 p(z_i)$

Q-Q Plot Example

- Are samples $x_1, x_2, \dots, x_N$, and $y_1, y_2, \dots, y_N$ governed by the same distribution?
 - Order the samples: $x_{(1)}, x_{(2)}, \dots, x_{(N)}$, and $y_{(1)}, y_{(2)}, \dots, y_{(N)}$
 - Plot $(x_{(1)}, y_{(1)}), (x_{(2)}, y_{(2)}), \dots, (x_{(N)}, y_{(N)})$
 - Samples governed by the same distribution will lie (approximately) along a line

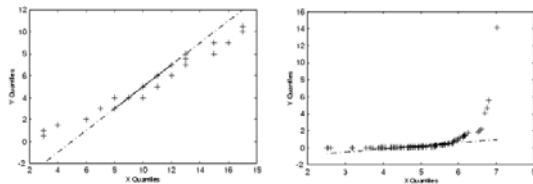


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Additive Noise Degradation Case

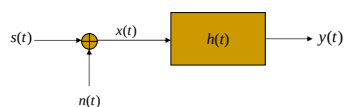
- Gaussian case: mean (averaging) filter is ML optimal (previously derived)
- Laplacian (double exponential) case: median filter is ML optimal (previously derived)
- Both assume iid noise, constant signal
 - See book for
 - Sample filtering results
 - Additional simple spatial filters
- We consider arbitrary noise PSD

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The Wiener Estimator



- Assume no channel distortion
- Derived in one dimension for simplicity
- Mean Square Error (MSE) optimality criteria:

$$\text{MSE} = \varepsilon\{e^2(t)\} = \int_{-\infty}^{\infty} e^2(t) dt$$

$$e(t) = s(t) - y(t)$$

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Rearrangement of MSE

- Calculus of variations approach:
 - Obtain a functional expression of MSE in terms of $h(t)$
 - Obtain an expression for the optimal impulse response, $h_o(t)$, in terms of known power spectra
 - Develop an expression for the MSE that results when $h_o(t)$ is used

Rewriting the MSE:

$$\text{MSE} = \varepsilon\{e^2(t)\} = \varepsilon\{[s(t) - y(t)]^2\} = \varepsilon\{s^2(t) - 2s(t)y(t) + y^2(t)\}$$

$$\text{MSE} = \varepsilon\{s^2(t)\} - 2\varepsilon\{s(t)y(t)\} + \varepsilon\{y^2(t)\} = T_1 + T_2 + T_3$$

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MSE Components

- Consider the first component:

$$T_1 = \mathcal{E}\{s^2(t)\} = \int_{-\infty}^{\infty} s^2(t) dt = R_s(0)$$

- Express the second component by writing the output as a convolution

$$T_2 = -2\mathcal{E}\left\{s(t) \int_{-\infty}^{\infty} h(\tau)x(t-\tau)d\tau\right\}$$

$$T_2 = -2 \int_{-\infty}^{\infty} h(\tau) \mathcal{E}\{s(t)x(t-\tau)\} d\tau$$

$$T_2 = -2 \int_{-\infty}^{\infty} h(\tau) R_{xs}(\tau) d\tau$$

MSE Components II

- Express the third component as the product of two convolutions:

$$T_3 = \mathcal{E}\left\{\int_{-\infty}^{\infty} h(\tau)x(t-\tau)d\tau \int_{-\infty}^{\infty} h(u)x(t-u)du\right\}$$

$$T_3 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau)h(u) \mathcal{E}\{x(t-\tau)x(t-u)\} d\tau du$$

utilizing change of variables: $v = t - u$

$$\mathcal{E}\{x(t-\tau)x(t-u)\} = \mathcal{E}\{x(v+u-\tau)x(v)\}$$

which is the autocorrelation evaluated at $u - \tau$

$$T_3 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau)h(u)R_x(u-\tau)d\tau du$$

- Final result:

$$\text{MSE} = R_s(0) - 2 \int_{-\infty}^{\infty} h(\tau)R_{xs}(\tau)d\tau + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau)h(u)R_x(u-\tau)d\tau du$$

- Function of: filter impulse response, known autocorrelation and crosscorrelation

MSE Minimization (I)

- Define arbitrary impulse response:

$$h(t) = h_0(t) + g(t)$$

- inserting into MSE expression

$$\text{MSE} = R_s(0) - 2 \int_{-\infty}^{\infty} [h_0(\tau) + g(\tau)]R_{xs}(\tau)d\tau + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [h_0(\tau) + g(\tau)][h_0(u) + g(u)]R_x(u-\tau)d\tau du$$

$$\begin{aligned} \text{MSE} = & R_s(0) - 2 \int_{-\infty}^{\infty} h_0(\tau)R_{xs}(\tau)d\tau + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_0(\tau)h_0(u)R_x(u-\tau)d\tau du \\ & + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_0(\tau)g(u)R_x(u-\tau)d\tau du + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h_0(u)g(\tau)R_x(u-\tau)d\tau du \\ & - 2 \int_{-\infty}^{\infty} g(\tau)R_{xs}(\tau)d\tau + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\tau)g(u)R_x(u-\tau)d\tau du \end{aligned}$$

- First three terms: optimal MSE (MSE_0)
- Autocorrelation $R_x(u-\tau)$ is an even function
 - Fourth and fifth terms are equal
 - Combine fourth, fifth, and sixth terms

MSE Minimization (II)

$$\begin{aligned} \text{MSE} = & \text{MSE}_0 + 2 \int_{-\infty}^{\infty} g(u) \left[\int_{-\infty}^{\infty} h_0(\tau)R_x(u-\tau)d\tau - R_{xs}(u) \right] du + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\tau)g(u)R_x(u-\tau)d\tau du \\ = & \text{MSE}_0 + T_4 + T_5 \end{aligned}$$

- Show T_5 is nonnegative

- Expanding autocorrelation

$$T_5 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\tau)g(u) \int_{-\infty}^{\infty} x(t-\tau)x(t-u)dt d\tau du$$

$$T_5 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(\tau)x(t-u)du \int_{-\infty}^{\infty} g(\tau)x(t-\tau)dt d\tau$$

- Define $z(t) = g(t)x(t)$

$$T_5 = \int_{-\infty}^{\infty} z^2(t)dt \geq 0$$

- Independent of h_0

MSE Minimization (III)

■ Expression to minimize

$$\text{MSE} = \text{MSE}_o + 2 \int_{-\infty}^{\infty} g(u) \left[\int_{-\infty}^{\infty} h_o(\tau) R_x(u-\tau) d\tau - R_{xs}(u) \right] du + T_s$$

□ Necessary and sufficient condition:

- Make term in brackets 0 for all u

$$R_{xs}(\tau) = \int_{-\infty}^{\infty} h_o(u) R_x(u-\tau) du$$

□ Note that for linear systems: [equation 48]

□ Since the above is a convolution

$$R_{xs}(\tau) = h_o(u) * R_x(u) = R_{xy}(\tau)$$

□ In terms of PSD

$$P_{xs}(s) = H_o(s) P_x(s) = P_{xy}(s)$$

$$H_o(s) = \frac{P_{xs}(s)}{P_x(s)}$$

Wiener Filter Design

■ To determine

$$H_o(s) = \frac{P_{xs}(s)}{P_x(s)}$$

- Obtain an observation signal sample ($x(t)$)
 - Determine autocorrelation and PSD
- Obtain a signal sampled without noise ($s(t)$)
 - Cross correlate $x(t)$ and $s(t)$; determine PSD
- Implement filter in the frequency domain or take inverse transform to get impulse response

■ If statistics are unknown or can't be measured, assume functional form

- Example: white PSD

Uncorrelated Signal and Noise Case

■ In this case: $\varepsilon\{s(t)n(t)\} = \varepsilon\{s(t)\} \varepsilon\{n(t)\}$

■ Crosscorrelation:

$$R_{xs}(\tau) = \varepsilon\{x(t)s(t+\tau)\} = \varepsilon\{[s(t)+n(t)]s(t+\tau)\}$$

$$R_{xs}(\tau) = \varepsilon\{s(t)s(t+\tau)\} + \varepsilon\{n(t)s(t+\tau)\}$$

$$R_{xs}(\tau) = R_s(\tau) + \varepsilon\{n(t)\} \varepsilon\{s(t+\tau)\} = R_s(\tau) + \int_{-\infty}^{\infty} n(t) dt \int_{-\infty}^{\infty} s(t+\tau) d\tau$$

$$R_{xs}(\tau) = R_s(\tau) + N(0)S(0)$$

■ Autocorrelation:

$$R_x(\tau) = R_s(\tau) + R_n(\tau) + 2N(0)S(0)$$

■ Optimal filter:

$$H_o(s) = \frac{P_s(s) + N(0)S(0)\delta(s)}{P_s(s) + P_n(s) + 2N(0)S(0)\delta(s)}$$

$$H_o(s) = \frac{P_s(s)}{P_s(s) + P_n(s)}$$

Analysis of Optimal MSE

■ Recall: $\text{MSE}_o = R_x(0) - \int_{-\infty}^{\infty} h_o(\tau) R_{xs}(\tau) d\tau$

■ For the uncorrelated case (see previous)

$$R_{xs}(\tau) = R_s(\tau) + N(0)S(0)$$

■ Further assuming zero means

$$\text{MSE}_o = R_x(0) - \int_{-\infty}^{\infty} h_o(\tau) \mathcal{F}^{-1}\{P_s(s)\} d\tau$$

$$\text{MSE}_o = R_x(0) - \int_{-\infty}^{\infty} P_s(s) \int_{-\infty}^{\infty} h_o(\tau) e^{j2\pi s\tau} d\tau ds$$

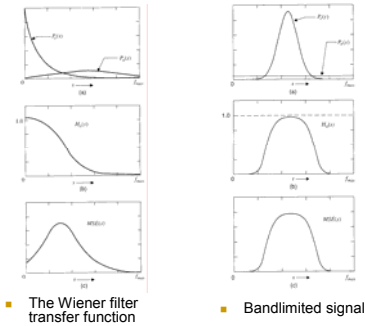
$$\text{MSE}_o = \int_{-\infty}^{\infty} P_s(s) ds - \int_{-\infty}^{\infty} P_s(s) H_o(-s) ds$$

■ Substituting for the optimal filter (even function)

$$\text{MSE}_o = \int_{-\infty}^{\infty} P_s(s) ds - \int_{-\infty}^{\infty} \frac{P_s(s)}{P_s(s) + P_n(s)} ds$$

$$\text{MSE}_o = \int_{-\infty}^{\infty} \frac{P_s(s)P_n(s)}{P_s(s) + P_n(s)} ds = \int_{-\infty}^{\infty} P_n(s) H_o(s) ds$$

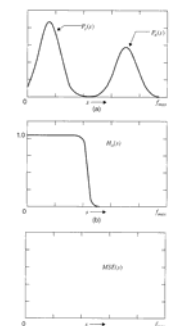
Wiener Filter Examples (I)



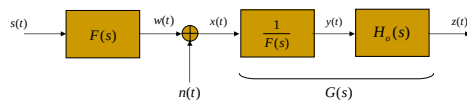
- The Wiener filter transfer function
- Bandlimited signal

Wiener Filter Examples (II)

- Separable signal and noise case
 - MSE is zero



Wiener Deconvolution



- Combine deconvolution (system inversion) and noise filtering
 - Combination of two linear operations
- Spectrum of observed signal: $X(s) = F(s)S(s) + N(s)$
- Input to Wiener filter: $Y(s) = S(s) + \frac{N(s)}{F(s)} = S(s) + K(s)$
- For uncorrelated signal and noise (previous result)

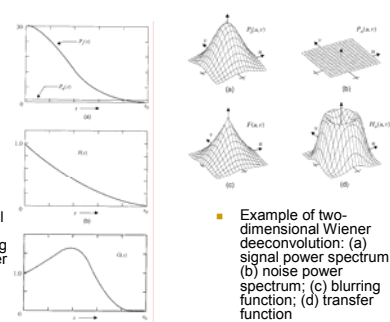
$$H_o(s) = \frac{P_s(s)}{P_s(s) + P_n(s)} = \frac{|S(s)|^2}{|S(s)|^2 + \frac{|N(s)|^2}{|F(s)|^2}}$$

- Wiener (MSE optimal) deconvolution filter:

$$G(s) = \frac{H_o(s)}{F(s)} = \frac{1}{F(s)} \left[\frac{P_s(s)}{P_s(s) + P_n(s)} \right] = \frac{F^*(s)P_s(s)}{|F(s)|^2 P_s(s) + P_n(s)}$$

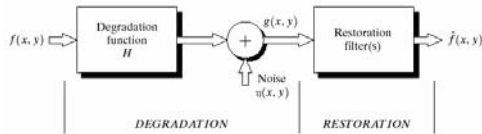
Wiener Deconvolution Examples

- Wiener deconvolution example: (a) signal and noise power spectra; (b) blurring function; (c) Wiener deconvolution transfer function



- Example of two-dimensional Wiener deconvolution: (a) signal power spectrum; (b) noise power spectrum; (c) blurring function; (d) transfer function

Wiener Generalization (I)



■ The two-dimensional Wiener filter:

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

□ Often used approximation:

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

Wiener Generalization (II)

■ Geometric Mean Filter generalization:

$$\hat{F}(u, v) = \left[\frac{H^*(u, v)}{|H(u, v)|^2} \right]^\alpha \left[\frac{H^*(u, v)}{|H(u, v)|^2 + \beta \frac{S_n(u, v)}{S_f(u, v)}} \right]^{1-\alpha} G(u, v)$$

■ Special cases

- $\alpha=1$: inverse filter
- $\alpha=0$: parametric of Wiener filter (standard if $\beta=1$)
- $\alpha=1/2$; $\beta=1$: referred to as the Spectrum equalization filter
 - The product of two quantities raised to the same power
 - Definition of the geometric mean
 - Trade-off between inverse filtering and Wiener filtering controlled by α

Degradation Function Estimation

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

■ In the no (low) noise case

□ Estimation by observation:

$$H_s(u, v) = \frac{G_s(u, v)}{\hat{F}_s(u, v)}$$

□ Estimation by experimentation:

■ Input impulse of strength A

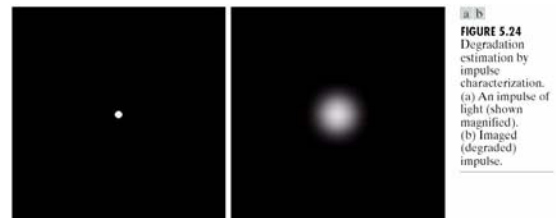
$$H(u, v) = \frac{G(u, v)}{A}$$

□ Estimation by modeling:

■ Example: atmospheric interference

$$H(u, v) = e^{-k(u^2 + v^2)^{1/6}}$$

Estimation by Experiment Example



■ Experimentally determined point spread function (PSF)

Modeling Image Motion

- Systems most often consider motion
 - Camera and/or subject motion
- If T is the exposure duration:
 - $g(x, y) = \int_0^T f[x - x_o(t), y - y_o(t)] dt$
 - Blurred image: $g(x, y)$
 - Planar motion trajectories: $x_o(t)$ and $y_o(t)$
- Fourier transform evaluation yields
 - $G(u, v) = H(u, v)F(u, v)$
 - where
 - $H(u, v) = \int_0^T e^{-j2\pi[u x_o(t) + v y_o(t)]} dt$

Motion Example

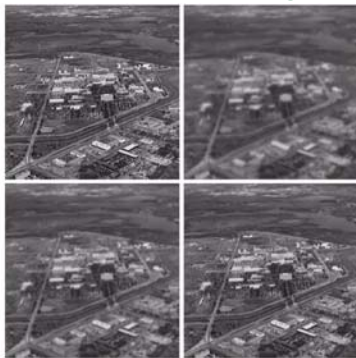


FIGURE 5.26 (a) Original image. (b) Result of blurring using the function in Eq. (5.6-11) with $a = b = 0.1$ and $T = 1$.

- If $x_o(t) = at/T$ and $y_o(t) = 0$
 - $H(u, v) = \int_0^T e^{-j2\pi u a t/T} dt = \int_0^T e^{-j2\pi u a t/T} dt = \frac{T}{\pi u a} \sin(\pi u a) e^{-j\pi u a}$
- Two dimensional linear ($x_o(t) = at/T$ and $y_o(t) = bt/T$) motion
 - $H(u, v) = \frac{T}{\pi(ua + vb)} \sin[\pi(ua + vb)] e^{-j\pi(ua + vb)}$

Atmospheric Turbulence Degradation

FIGURE 5.25 Illustration of the atmospheric turbulence model. (a) Negligible turbulence. (b) Severe turbulence, $k = 0.0025$. (c) Mild turbulence, $k = 0.001$. (d) Low turbulence, $k = 0.00025$. (Original image courtesy of NASA.)



Inverse Filtering Example

FIGURE 5.27 Restoring Fig. 5.25(b) with Eq. (5.7-1). (a) Result of using the full filter. (b) Result with H cut off outside a radius of 40. (c) outside a radius of 70. (d) outside a radius of 85.



- Direct application of
 - $\hat{F}(u, v) = \frac{G(u, v)}{H(u, v)}$
 - Amplifies noise
 - Possible solution:
 - Limit cutoff frequency

Inverse and Wiener Filtering Comparison



FIGURE 5.28 Comparison of inverse- and Wiener filtering. (a) Result of full inverse filtering of Fig. 5.25(b). (b) Radially limited inverse filter result. (c) Wiener filter result.

- Wiener parameter K set experimentally
 - Wiener result much sharper than the band limited inverse filter
 - Full inverse filter results is useless

Motion Blur with Additive Noise Example



FIGURE 5.29 (a) Image corrupted by motion blur and additive noise. (b) Result of inverse filtering. (c) Result of Wiener filtering. (d) Full inverse filter result with noise variance and color of magnitude zero. (e) Same sequence, but noise variance reduced by five orders of magnitude from (c). Note in (b) how the deblurred image is quite unlike the original image.

Mean in Geometric Mean Example

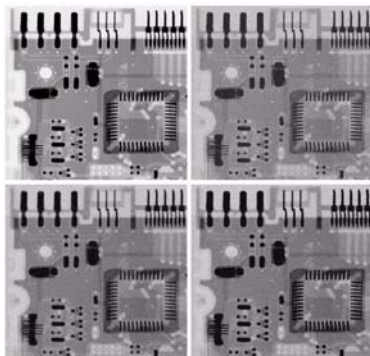


FIGURE 5.7 (a) X-ray image. (b) Image corrupted by additive Gaussian noise. (c) Result of filtering with an arithmetic mean filter of size 3×3 . (d) Result of filtering with a geometric mean filter of the same size. (Original image courtesy of Mr. Joseph E. Pascente, Lxi, Inc.)

Multiple Applications of the Median

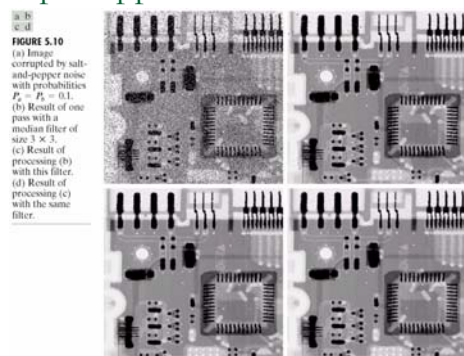


FIGURE 5.10 (a) Image corrupted by salt-and-pepper noise with probabilities $P_s = P_t = 0.1$. (b) Result of one pass with a median filter of size 3×3 . (c) Result of processing (b) with this filter. (d) Result of processing (c) with the same filter.

Mixed Noise Example

- Image corrupted by
 - Uniform noise
 - Uniform and salt and pepper noise
- Filtering methods
 - Arithmetic mean
 - Geometric mean
 - Median
 - Alpha-trimmed mean

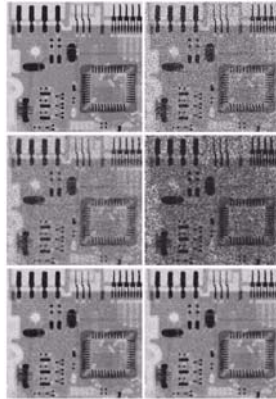


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Mean, Arithmetic Mean, and Adaptive Approach

FIGURE 5.13 (a) Image corrupted by additive Gaussian noise of zero mean and variance 1000. (b) Result of arithmetic mean filtering. (c) Result of geometric mean filtering. (d) Result of adaptive noise reduction filtering. All filters were of size 7×7 .

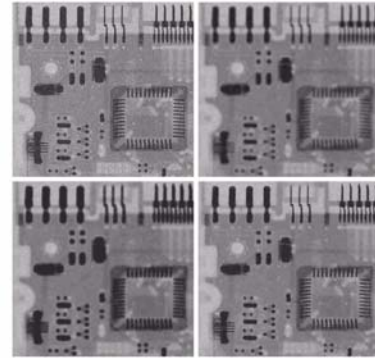


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Median and Adaptive Median

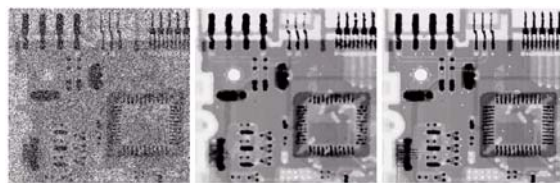


FIGURE 5.14 (a) Image corrupted by salt-and-pepper noise with probabilities $P_s = P_p = 0.25$. (b) Result of filtering with a 7×7 median filter. (c) Result of adaptive median filtering with $S_{max} = 7$.

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Periodic Interference



FIGURE 5.15 From left to right, perspective plots of ideal, Butterworth (of order 1), and Gaussian bandreject filters.

- Band reject filters
 - Straightforward extension from a high/low pass case
 - Ideal, Butterworth, Gaussian

Image Processing
Image Restoration

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Sinusoidal Corruption Example

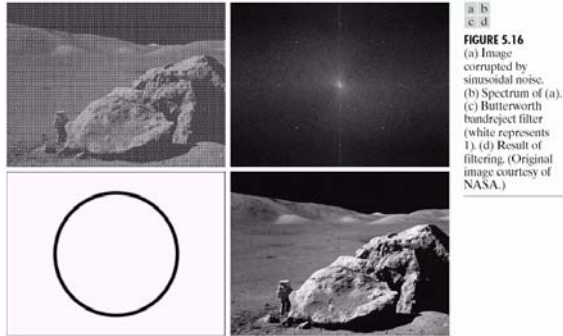


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Periodic Scan Line Interference

- Note horizontal scan line "striping"
 - Vertical spectral comment
- Notch pass filter and spatial interference
- Image with interference rejected

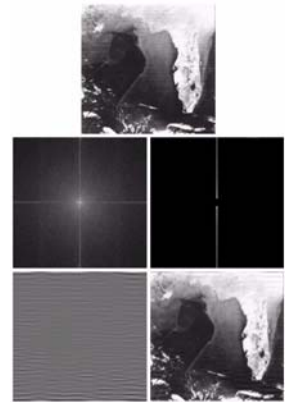


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NASA Image, Spectrum, and Filtering Result



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