DIGITAL IMAGE PROCESSING PRESENTATION

presented to:-

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Image Degradation

- The act of **loss of quality** of an image. In event of image degradation, an image gets blurry and loses its quality to much extent.

Linear, Position-Invariant Degradation

- The image corrupted by additive **noise** and by a **degradation function** can be **modeled** as:

$$g(x, y) = H[f(x, y)] + \eta(x, y)$$

- Assuming further that the **noise** term is **zero**:

$$\eta(x, y) = 0 \text{ so that } g(x, y) = H[f(x, y)].$$

- The degradation function is **linear** when:

$$H[af_1(x, y) + bf_2(x, y)] = aH[f_1(x, y)] + bH[f_2(x, y)]$$

where **a** and **b** are arbitrary **scalars** and **f1(x,y)** and **f2(x,y)** are two arbitrary input **images**.

Linear, Position-Invariant Degradation (cont..)

- The degradation function is **position-invariant** when:

$$H[f(x-\alpha, y-\beta)] = g(x-\alpha, y-\beta)$$

For any $f(x,y)$and any $\alpha\ and\ \beta$. This definition indicates that the **response** at any point in the image **depends** only on the **value** of the input at that point, **not** on its **position**.

Estimating The Degradation Function

- There are three principal ways to **estimate** the **degradation function H(u,v)** for use in **image restoration**:
- (1) **Observation**
- (2) **Experimentation**
- (3) **Mathematical modeling**

Estimating By Image Observation

- Based on the assumption that the image was degraded by a linear, position-invariant process.
- Estimate **H(u,v)** by gathering **information from the image itself**.
- **Identify** a portion of the image that is visually **unblurred k(x,y)** (**sub image**). **Let** the **observed image** be **g(x,y).**
- The **degradation function** can be **estimated** by applying an **inverse Fourier transform** to the **ratio of** the **Fourier transform of** the **observed image and** the **sub image**.

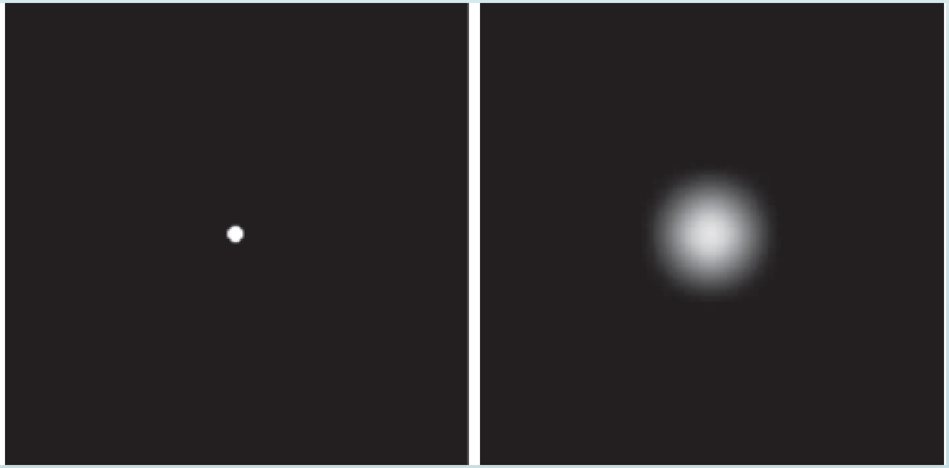
$$H(U,V) = \frac{G(U,V)}{K(U,V)}$$

- Used in specific circumstances such as restoring an old photograph of historical value.

Estimating By Experimentation

- If equipment similar to one used to acquire degraded image is available:
  - Find **system settings** reproducing the most **similar degradation** as possible.
  - Obtain an **impulse response of the degradation** by **imaging an impulse** (dot of light) using the **same system settings**. (a linear, space-invariant system is characterized completely by its impulse response)
- Since that the **Fourier transform of an impulse** is a **constant** (**A**), the **degradation function** can be **estimated** by applying an **inverse Fourier transform** to the **ratio** of the **Fourier transform of** the **observed image g(x,y) and** the **impulse function**.

$$H(U,V) = \frac{G(U,V)}{A}$$



a b

FIGURE 5.24 Estimating a degradation by impulse characterization. (a) An impulse of light (shown magnified). (b) Imaged (degraded) impulse.

Estimating By Modeling

- A **model** is a **set of equations** that **approximate** the real **system**. Using the constructed models, the degradation function can be approximated.
- Scenario **1: Complete knowledge about** the **blur** available.
  - Retrieve the original image by applying an **inverse filter**.
- Scenario **2:** There is only a **partial knowledge** of the blurring function available.
  - **Wiener Filter** is used in this case.
- Scenario **3:** There is **no knowledge** about the blurring function (**Blind Restoration**).
  - **Blind restoration techniques** are used in this scenario.

Estimating By Modeling (cont..)

- This shows an example of a image affected by turbulence in the atmosphere
- The equation below is a simple model to approximate the degradation:

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

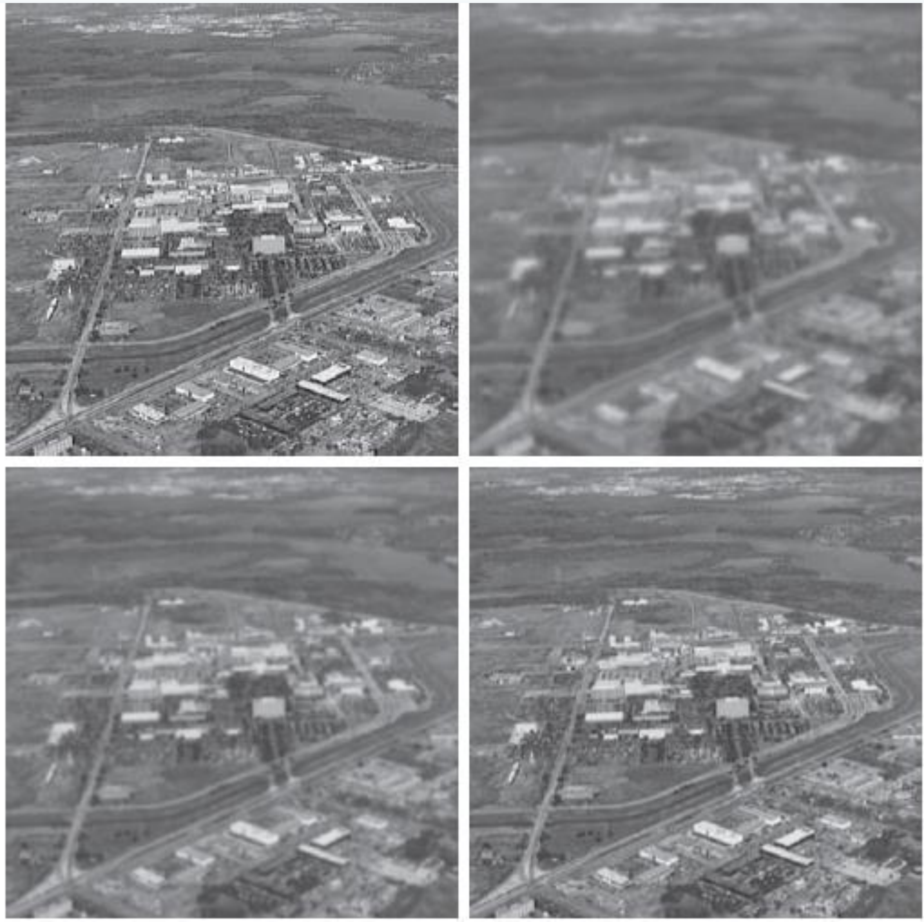


FIGURE 5.25 Modeling turbulence. (a) No visible turbulence. (b) Severe turbulence, $k = 0.0025$. (c) Mild turbulence, $k = 0.001$. (d) Low turbulence, $k = 0.00025$. All images are of size 480×480 pixels. (Original image courtesy of NASA.)

Inverse Filtering

- Inverse Filtering is the process of receiving the input of a system from its output.
- Direct Inverse Filtering is the simplest approach to restore the original image once the degradation function is known.
- $\hat{F}(u, v) = G(u, v)/H(u, v)$.
- Where $G(u, v) = F(u, v).H(u, v) + N(u, v)$.
- And $\hat{F}(u,v) = F(u,v) + N(u,v)/H(u,v)$.
  - $\hat{F}$(u, v) -> Fourier transform of the restored image.
  - G(u, v) -> Fourier transform of the degraded image.
  - H(u, v) -> Estimated or derived or known degradation function.

Inverse Filtering(cont..)

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

If the degradation H(u, v) has zero or very small values, then the ratio N/H could easily dominate our estimation of F (noise tend to infinity).

Therefor inverse filtering is not used in its original form and we have to go for wiener filtering.

Inverse Filtering(cont..)

The image can be restored if the term N/H is zero or very small value.

We can't reconstruct the image due to noise, even if we know the degradation function.

➔ $N(u, v)/H(u, v)$.

One approach to get around the zero or small-value problem is to **limit the filter frequencies to value near the origin** where H is large in general.

Inverse Filtering(cont..)

- The result when applying degradation function on an image and restore the original image.

Inverse Filtering(cont..)

- The result when adding gaussian noise to blurred image with degradation function and restore the original image.

Minimum Mean Square Error (Wiener) Filtering

- Very sensitive to noise.
- Uses statistical properties about signal and noise to improve image restoration.
- Considers image and noise as random process.
- Objective:

  minimize mean square error between restored image and original uncorrupted image.

$$e^2 = E\left\{(f - \hat{f})^2\right\}$$

Minimum Mean Square Error (Wiener) Filtering(cont..)

- Estimated image :

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

- H(u, v): degradation function.
- $|H(u,v)|^2$ = H(u, v) H*(u, v)
- Sη = $|N(u,v)|^2$: power spectrum of the noise.
- Sf= $|F(u,v)|^2$: power spectrum of the original image.

Minimum Mean Square Error (Wiener) Filtering(cont..)

- When noise is zero:

  N(u ,v) = 0, so ➔ Sη = $|N(u\ ,v)|^2 = 0.$

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

  inverse filtering

- When Sη(u, v) and/or Sf(u, v) is unknown:

  $$\frac{1}{H(u,v)} \cdot \frac{|H(u\ ,v)|^2}{|H(u\ ,v)|^2 + K}$$

  Where K is chosen manually to obtain the best filter.

Minimum Mean Square Error (Wiener) Filtering(cont..)

- The result when adding gaussian noise to blurred image with degradation function and restore the original image.

Minimum Mean Square Error (Wiener) Filtering(cont..)

- **Problems with wiener filtering:**
  - The problem of having to know the degradation function H.
  - The power spectra of the undegraded image and noise must be known also.
  - The performance of wiener filter depends on the correct estimation of the K.
  - Can't handle rotational motion bluer.
  - wiener filter performs poorly if both, signal and noise are non-stationary.

Comparison between inverse and wiener Filtering

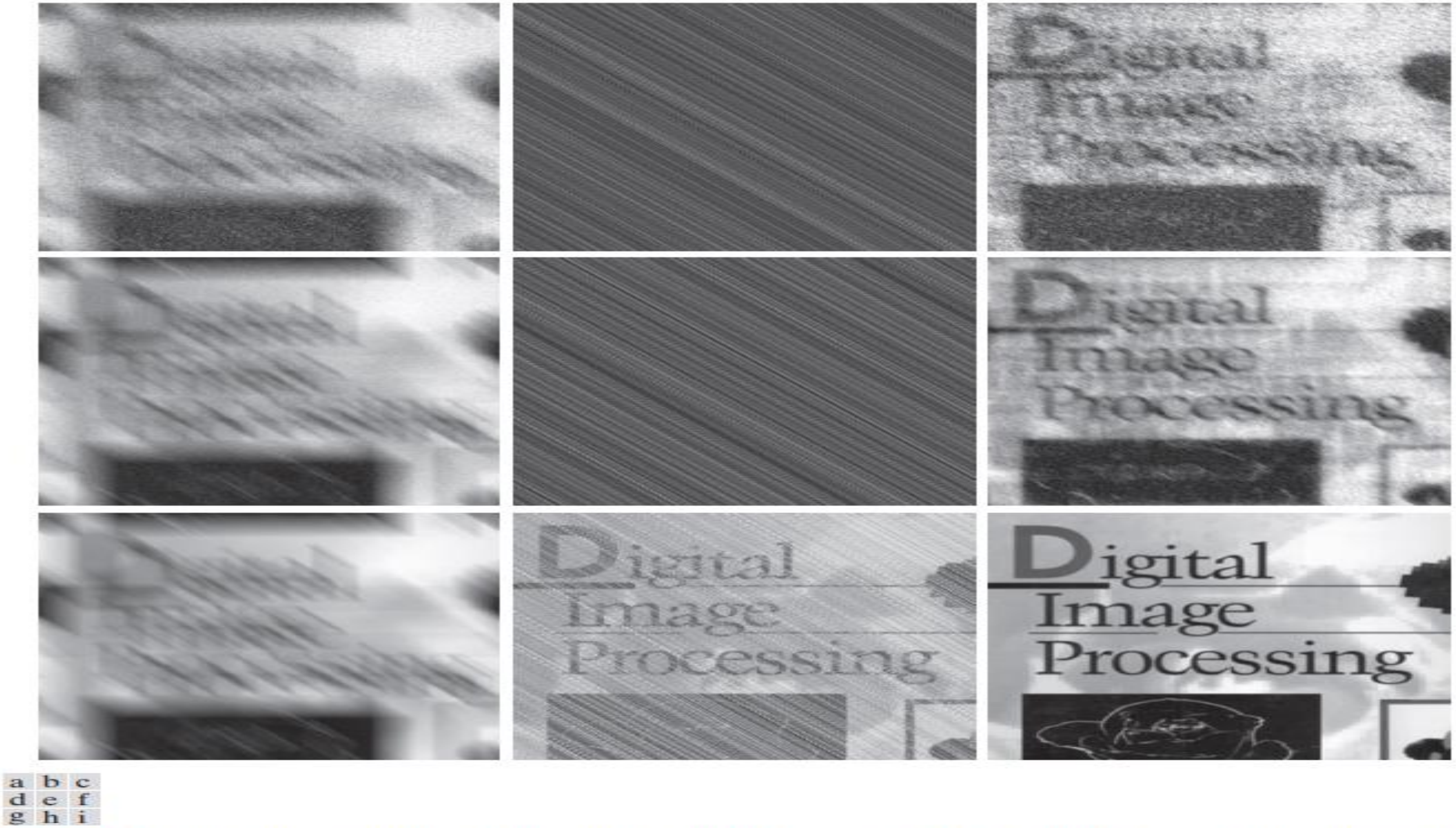


FIGURE 5.29 (a) 8-bit image corrupted by motion blur and additive noise. (b) Result of inverse filtering. (c) Result of Wiener filtering. (d)–(f) Same sequence, but with noise variance one order of magnitude less. (g)–(i) Same sequence, but noise variance reduced by five orders of magnitude from (a). Note in (h) how the deblurred image is quite visible through a "curtain" of noise.

Constrained least squares filtering

- CLSF requires knowledge of only the mean and variance of the noise.
- The CLSF algorithm yields an optimal result for each image to which it is applied.
- Degradation model written in a vector-matrix form:

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

$$\Downarrow$$

$$\mathbf{g} = \mathbf{Hf} + \boldsymbol{\eta}$$

- Where g , f , η size = MN × 1.
- H size = MN × MN.

Constrained least squares filtering (cont..)

- The key advantage of formulating the restoration problem in matrix form is that it facilitates derivation of restoration algorithms.
- objective is to find the minimum of a criterion function, C, defined as

$$C = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left[\nabla^2 f(x, y) \right]^2$$

- subject to the constraint:

$$\left\| \mathbf{g} - \mathbf{H}\hat{\mathbf{f}} \right\|^2 = \left\| \boldsymbol{\eta} \right\|^2$$

Constrained least squares filtering (cont..)

- The frequency domain solution to this optimization problem is:

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

- Where P(u, v) is the Fourier transform of the function P(x ,y)

$$p(x,y) = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Constrained least squares filtering (cont..)

- The result when adding gaussian noise to blurred image with degradation function and restore the original image with CLSF.

Comparison of deblurring by Wiener and constrained least squares filtering.

FIGURE 5.30 Results of constrained least squares filtering. Compare (a), (b), and (c) with the Wiener filtering results in Figs. 5.29(c), (f), and (i), respectively.

Thank you.