# Visuelle Perzeption für Mensch-Maschine Schnittstellen

Vorlesung, WS 2013 / 2014

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# Basics:
# Image Preprocessing

WS 2013/14

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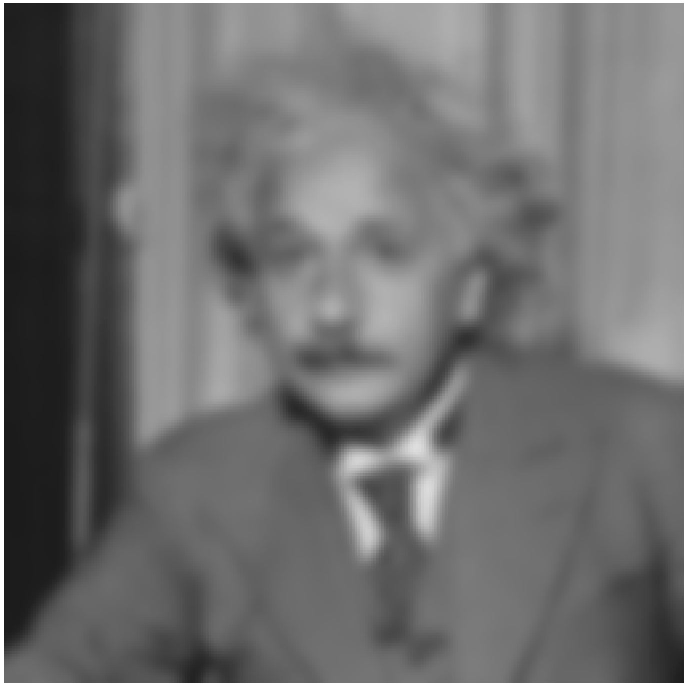
# Linear Image Restoration

# Blur



out-of-focus blur

motion blur

Question 1: How do you know they are blurred?
I’ve not shown you the originals!

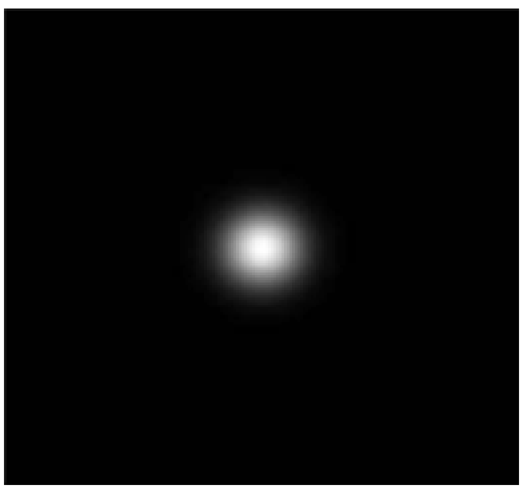
Question 2: How do I deblur an image?

# Linear Blur Model

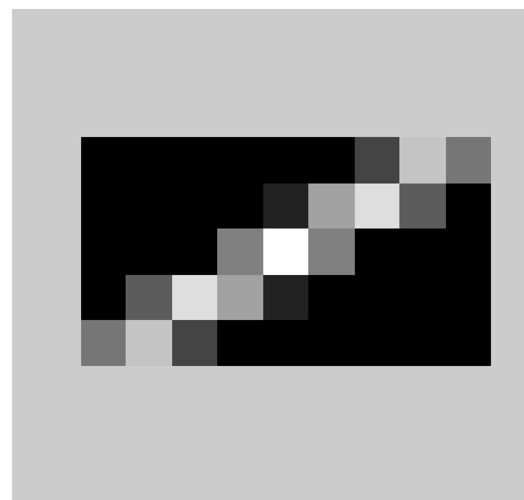
- **Spatial domain**

$$x(m,n) \longrightarrow \boxed{h(m,n)} \longrightarrow y(m,n)$$

blurring filter



Gaussian blur



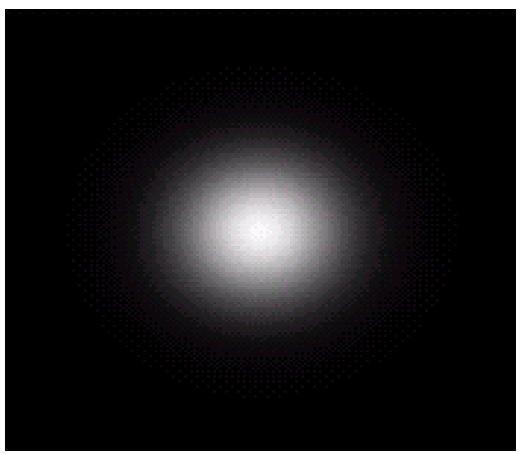
motion blur

# Linear Blur Model

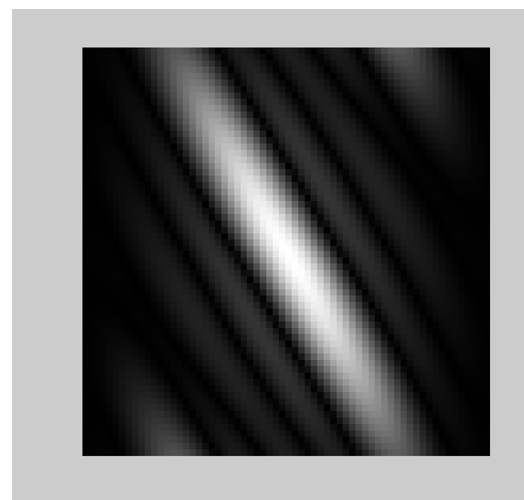
- **Frequency (2D-DFT) domain**

$$X(u,v) \longrightarrow \boxed{H(u,v)} \longrightarrow Y(u,v)$$

blurring filter

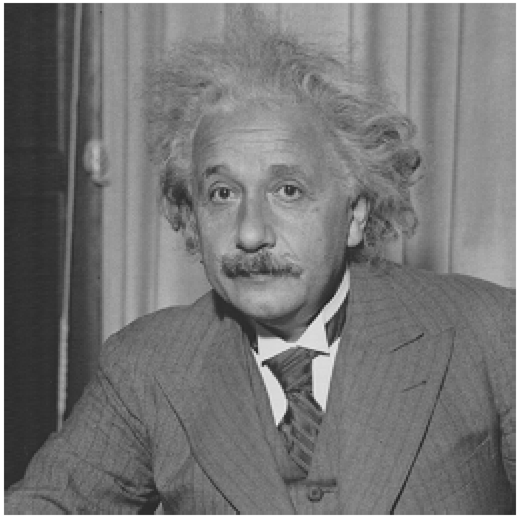


Gaussian blur

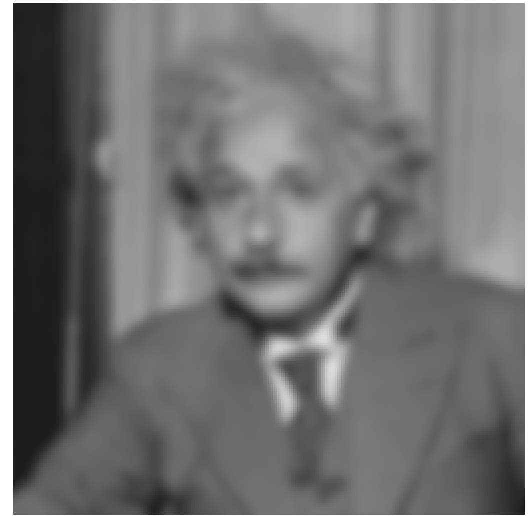


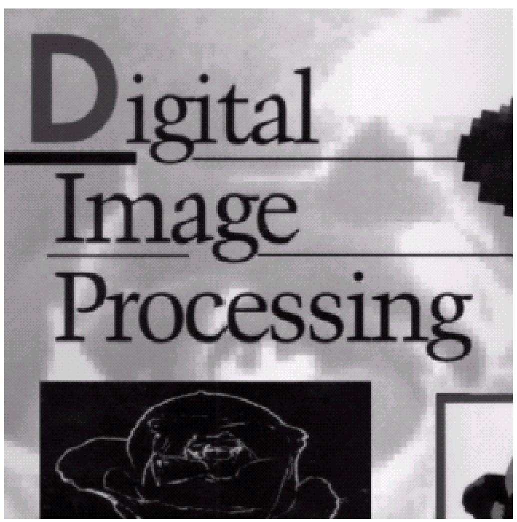
motion blur

# Blurring Effect

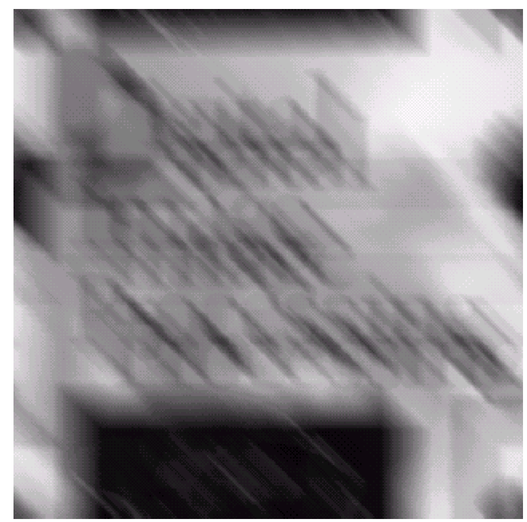


Gaussian blur






motion blur



From [Gonzalez & Woods]

# Image Restoration: Deblurring/Deconvolution

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$$x(m,n) \longrightarrow \boxed{h(m,n)} \longrightarrow y(m,n) \longrightarrow \boxed{g(m,n)} \longrightarrow \hat{x}(m,n)$$

blurring filter

deblurring/deconvolution filter

- **Non-blind deblurring/deconvolution**

Given: observation $y(m,n)$ and blurring function $h(m,n)$

Design: $g(m,n)$, such that the **distortion** between $x(m,n)$ and $\hat{x}(m,n)$ is minimized

- **Blind deblurring/deconvolution**

Given: observation $y(m,n)$

Design: $g(m,n)$, such that the **distortion** between $x(m,n)$ and $\hat{x}(m,n)$ is minimized

# Deblurring: Inverse Filtering

$$x(m,n) \longrightarrow \boxed{h(m,n)} \longrightarrow y(m,n) \longrightarrow \boxed{g(m,n)} \longrightarrow \hat{x}(m,n)$$

blurring filter

inverse filter

$$X(u,v)\,H(u,v) = Y(u,v)$$

$$G(u,v) = \frac{1}{H(u,v)}$$

$$X(u,v) = \frac{Y(u,v)}{H(u,v)} = \frac{1}{H(u,v)}\,Y(u,v)$$

**Exact recovery!**

# Deblurring: Pseudo-Inverse Filtering

$$x(m,n) \longrightarrow \boxed{h(m,n)} \longrightarrow y(m,n) \longrightarrow \boxed{g(m,n)} \longrightarrow \hat{x}(m,n)$$

blurring filter

deblur filter

**Inverse filter:** $G(u,v) = \dfrac{1}{H(u,v)}$

What if at some $(u,v)$, $H(u,v)$ is 0 (or very close to 0) ?

**Pseudo-inverse filter:**

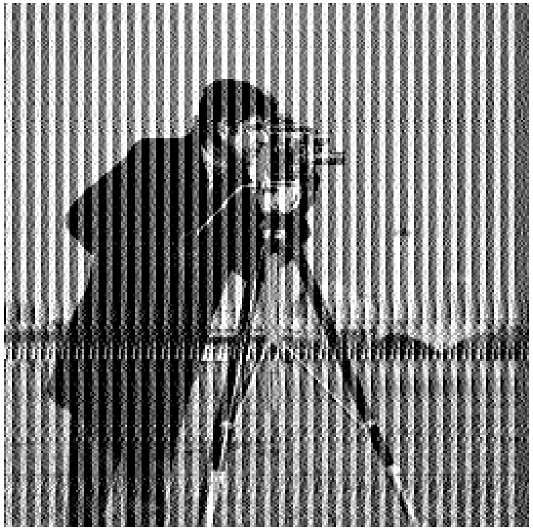
$$G(u,v) = \begin{cases} \dfrac{1}{H(u,v)} & |H(u,v)| > \delta \\ 0 & |H(u,v)| \le \delta \end{cases}$$

small threshold

# Inverse and Pseudo-Inverse Filtering

blurred image

$$G(u,v) = \frac{1}{H(u,v)}$$



$$G(u,v) = \begin{cases} \dfrac{1}{H(u,v)} & |H(u,v)| > \delta \\ 0 & |H(u,v)| \le \delta \end{cases}$$

$\delta = 0.1$

# More Realistic Distortion Model

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additive white Gaussian noise

$w(m,n)$

$$x(m,n) \longrightarrow \boxed{h(m,n)} \longrightarrow + \longrightarrow y(m,n) \longrightarrow \boxed{g(m,n)} \longrightarrow \hat{x}(m,n)$$

blurring filter

deblur filter

$$Y(u,v) = X(u,v)\,H(u,v) + W(u,v)$$

- **What happens when an inverse filter is applied?**

$$\hat{X}(u,v) = Y(u,v)G(u,v) = \frac{X(u,v)H(u,v)+W(u,v)}{H(u,v)}$$

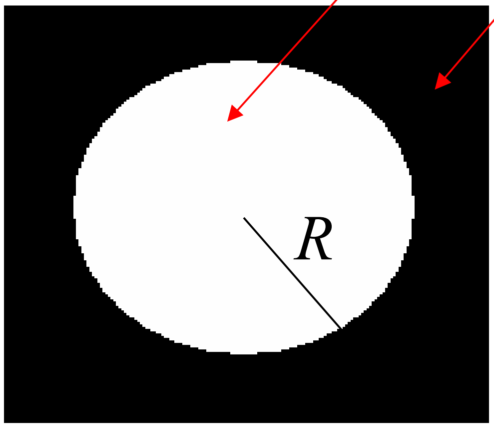
$$= X(u,v) + \frac{W(u,v)}{H(u,v)}$$

close to zero at high frequencies

# Radially Limited Inverse Filtering

**Radially limited inverse filter:**

$$G(u,v)=\begin{cases}\dfrac{1}{H(u,v)} & \sqrt{u^2+v^2}\le R\\ 0 & \sqrt{u^2+v^2}>R\end{cases}$$



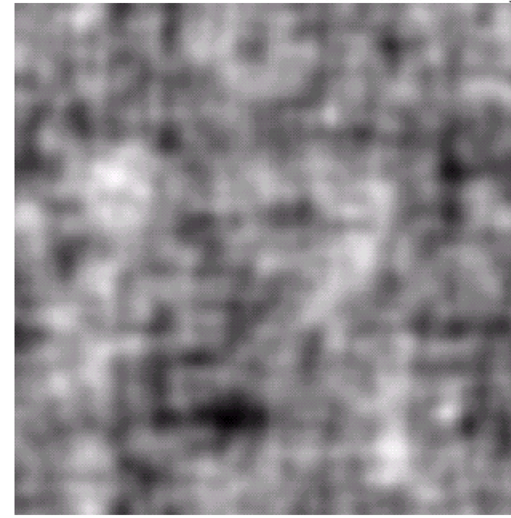

- **Motivation**
  - Energy of image signals is concentrated at low frequencies
  - Energy of noise uniformly is distributed over all frequencies
  - Inverse filtering of image signal dominated regions only

# Radially Limited Inverse Filtering

Image size: 480x480

Original

Blurred

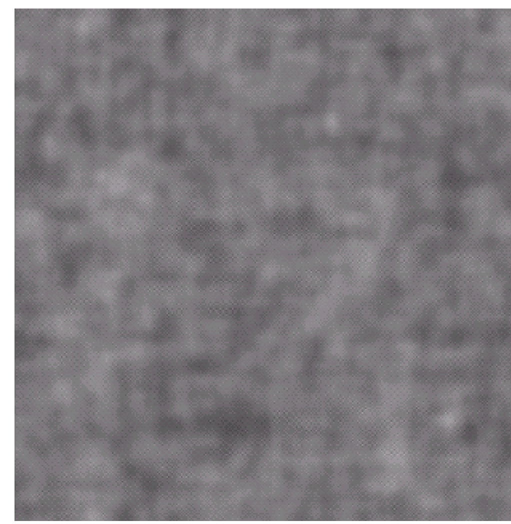


Inverse filtered

Radially limited inverse filtering:

$R = 40$

$R = 70$



$R = 85$

From [Gonzalez & Woods]

# Estimating the degradation function

- Three principle ways:
  - observation
  - experimentation
  - mathematical modeling
- The process of restoring an image by using a degradation function that has to be estimated in some way sometimes is called **blind deconvolution**,
- due to the fact that the true degradation function is seldom known completely.



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# Estimation by image observation



- Look at a small section of the image *gs(x, y)* containing simple structures and strong signal content.
- We can construct an unblurred image $\hat{s}(x, y)$ of the same size and characteristics as the observed subimage.
- Assuming that the effect of noise is negligible because of our choice of a strong-signal area, it follows that

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

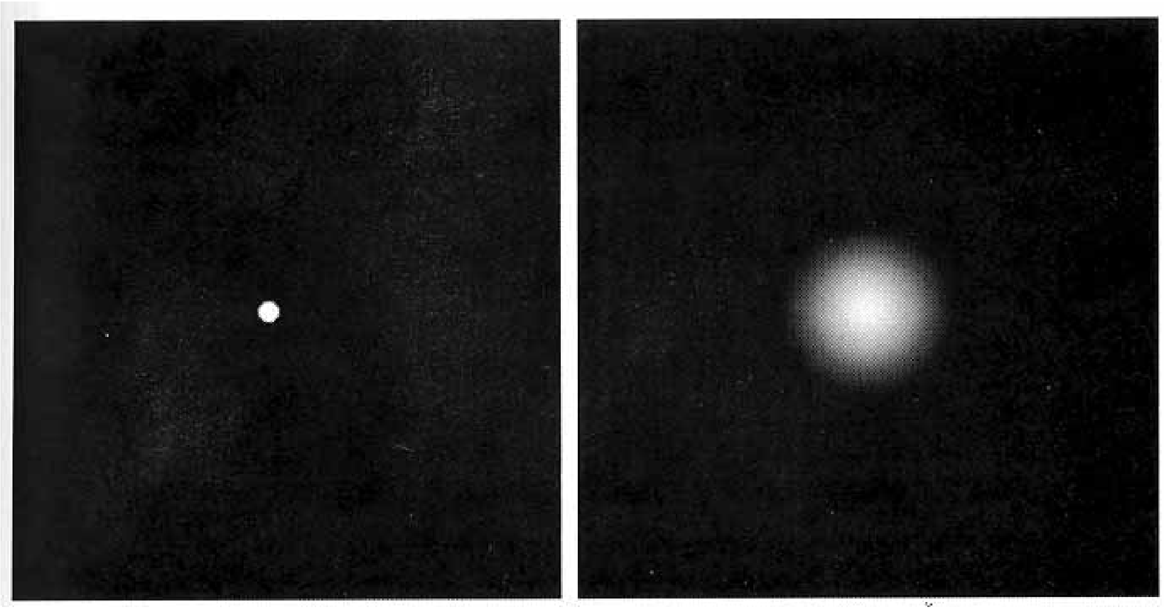
- Assuming position invariance we then deduce *H(u, v),* e.g. *H* could be a smoothed circular version of *Hs*.

# Estimation by experimentation

- If equipment similar to the equipment used to acquire the degraded image is available, it is possible in principle to obtain an accurate estimate of the degradation:
  - An image as similar as possible to the degraded image is taken with the equipment.
  - Am impulse is simulated by a bright dot of light.
  - As the Fourier transform of an impulse is a constant, it follows that

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

# Estimation by experimentation



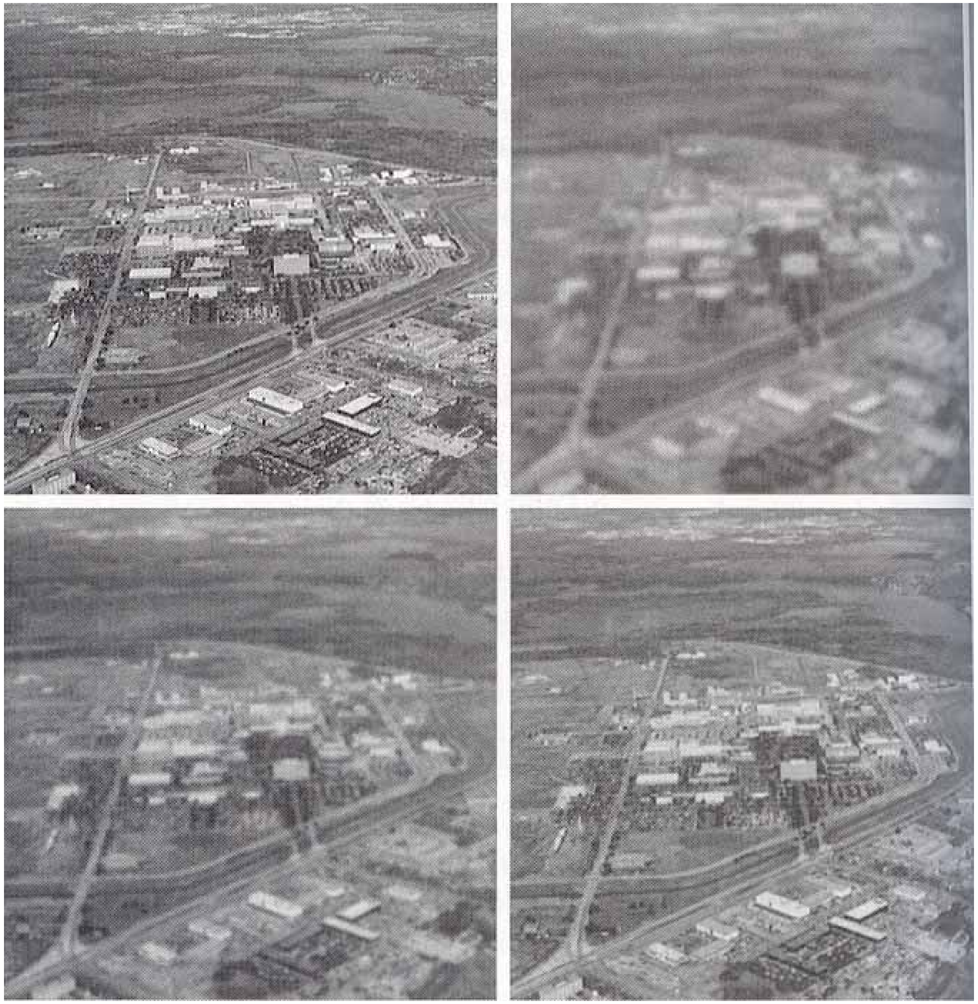
# Estimation by modeling

- A degradation model based on the physical characteristics of atmospheric turbulence:

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

  where *k* is a constant depending on the nature of the turbulence.
- Shape of the Gaussian low pass filter
- Another approach is to derive a mathematical model starting from basic principles of the phenomenon, e.g. uniform linear motion between the image and the sensor during image acquisition.

# Estimation by modeling



$k$=0.0025

$k$=0.001

$k$=0.00025

# Modeling linear motion as a degradation function

- Assume shuter opening and closing takes place instantaniously. Let xo(t) and yo(t) be the time varying x an y motion……
- We can model the process by writing the degraded image g(x,y) and then try to infer the degradation function h(x,y).

Modeling linear motion as an image degradation

Assume "shutter" opening and closing takes place instantaneously

Let $x_0(t)$, $y_0(t)$ be the time varying x & y motions

For a period T of exposure

$$\underbrace{g(x,y)}_{\text{blurred image}} = \int_0^T \underbrace{f}_{\text{moving image}}[x - x_0(t), y - y_0(t)]\, dt$$

Fourier transforming

$$G(u,v) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} g(x,y)\, e^{-j2\pi(ux+vy)}\, dx\, dy$$

$$G(u,v) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \int_0^T f[x - x_0(t), y - y_0(t)]\, dt\; e^{-j2\pi(ux+vy)}\, dx\, dy$$

$$G(u,v) = \int_0^T \left[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f[x - x_0(t), y - y_0(t)]\, e^{-j2\pi(ux+vy)}\, dx\, dy\right] dt$$

$$G(u,v) = \int_0^T F(u,v)\, \underbrace{e^{-j2\pi[u x_0(t) + v y_0(t)]}}_{\text{phase shift due to shift of } f(x,y)}\, dt$$

$$G(u,v) = F(u,v) \underbrace{\int_0^T e^{-j2\pi[u x_0(t) + v y_0(t)]}\, dt}_{\text{call this } H(u,v)}$$

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

For simple linear motion $x_0(t) = \frac{at}{T}$, $y_0(t) = 0$

we can derive

$$H(u,v) = \int_0^T e^{-j2\pi u x_0(t)} dt$$

$$H(u,v) = \int_0^T e^{-j2\pi \frac{ua t}{T}} dt$$

$$H(u,v) = \frac{T}{\pi u a} \sin(\pi u a) e^{-j\pi u a}$$

If we allow $y_0 = \frac{bt}{T}$ as well the degradation function becomes

$$H(u,v) = \frac{T}{\pi(ua+vb)} \sin\left[\pi(ua+vb)\right] e^{-j\pi(ua+vb)}$$

# Algebraic approach to restoration

- We now formulate the image restoration problems in a linear algebraic framework.
- We are seeking an estimate of **f**, denoted by $\hat{\mathbf{f}}$, which minimizes a predefined criterion of performance.
- Here: least-squares criterion functions.

# Wiener filtering

- Making use of concepts found previously allows us to write

$$\hat{F}(u,v) = \left[ \frac{H^*(u,v)}{\left|H(u,v)\right|^2 + g\left[S_h(u,v)/S_f(u,v)\right]} \right] Y(u,v) \tag{1}$$

$$= \left[ \frac{1}{H(u,v)} \frac{\left|H(u,v)\right|^2}{\left|H(u,v)\right|^2 + g\left[S_h(u,v)/S_f(u,v)\right]} \right] Y(u,v)$$

where $|H(u, v)|2=H^*(u, v)H(u, v)$ and we have assumed that $M=N$.

# Wiener filtering (contd.)

- When $\gamma$=1, the term inside the brackets reduces to the so-called Wiener filter, after N. Wiener [1942].
- It does not have the same problem as the inverse filter with zeros in the degradation function.
- If $\gamma$ is variable we refer to the **parametric Wiener filter**.
- If the noise is zero, the noise power spectrum vanishes and the Wiener filter reduces to the inverse filter.
- By setting $\gamma$=1, we can no longer say in general that Eq. (1) yields an optimal solution in the sense of Least squares, because $\gamma$ must be adjusted to satisfy the constraint.
- However, the solution obtained is optimal in the sense that it minimizes $E\{(f-\hat{f})2\}$.

# Wiener filtering (contd.)

- When $S\eta(u, v)$ and $Sf(u, v)$ are not known it is sometimes useful to approximate Eq. (1) by

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

where $K$ is a constant.

# Wiener (Least Square) Filtering

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**Wiener filter:** $G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K}$

$$K = \frac{\sigma_W^2}{\sigma_X^2}$$

noise power

signal power

- Optimal in the least MSE sense, i.e.

$G(u, v)$ is the best possible linear filter that minimizes

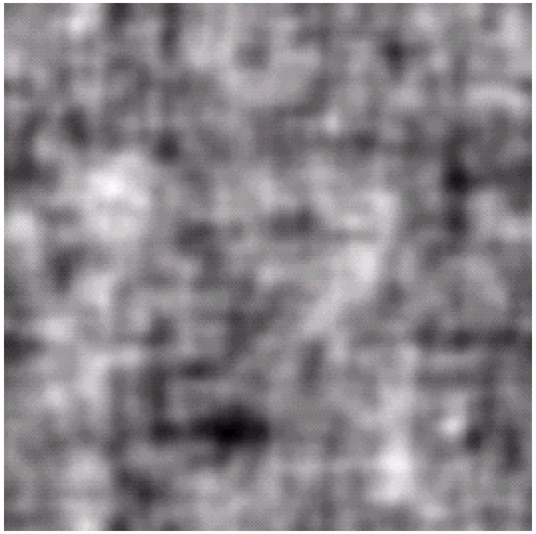
$$error\ energy = E\left\{\left|\hat{X}(u,v) - X(u,v)\right|^2\right\}$$

- Have to estimate signal and noise power

# Weiner Filtering

Blurred image

Inverse filtering



Radially limited inverse filtering
$R = 70$

Weiner filtering



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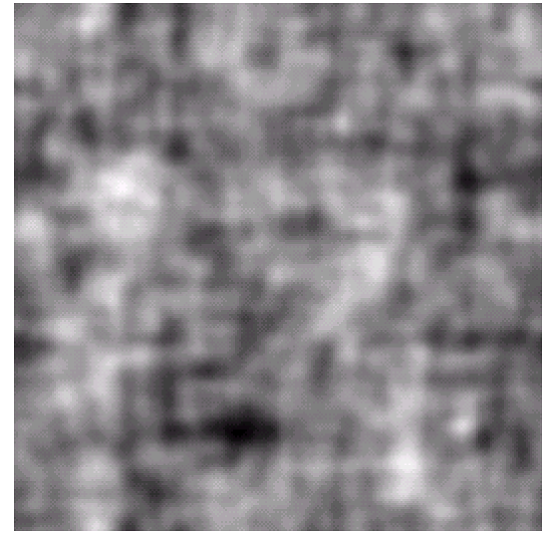
# Weiner Filtering

Blurred image

Inverse filtering



Radially limited inverse filtering
$R = 70$

Weiner filtering

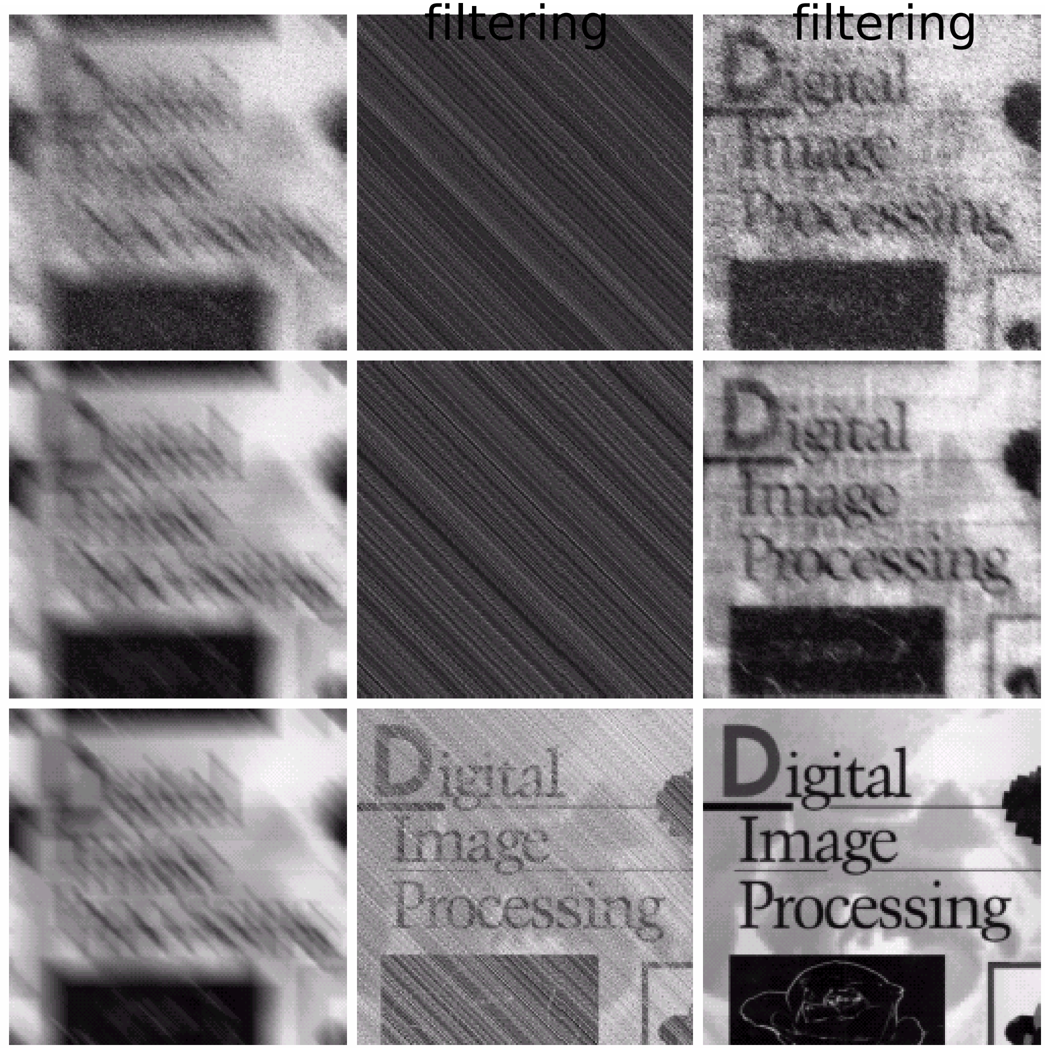
# Inverse vs. Weiner Filtering

distorted | inverse filtering | Wiener filtering

motion blur + noise

less noise

less noise




From [Gonzalez & Woods]

# Summary of Linear Image Restoration Filters

**Inverse filter:**

$$G(u,v) = \frac{1}{H(u,v)}$$

**Pseudo-inverse filter:**

$$G(u,v) = \begin{cases} \dfrac{1}{H(u,v)} & |H(u,v)| > \delta \\ 0 & |H(u,v)| \le \delta \end{cases}$$

**Radially limited inverse filter:**

$$G(u,v) = \begin{cases} \dfrac{1}{H(u,v)} & \sqrt{u^2+v^2} \le R \\ 0 & \sqrt{u^2+v^2} > R \end{cases}$$

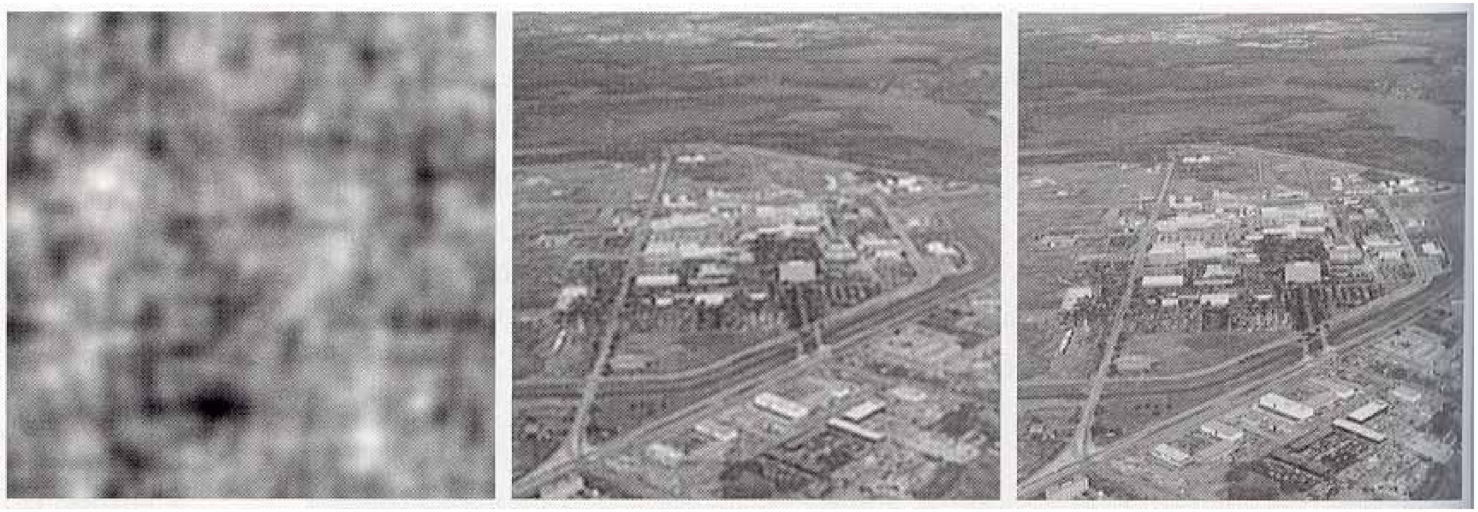
**Wiener filter:**

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K}$$ where $K = \dfrac{\sigma_W^2}{\sigma_X^2}$

**Wiener denoising filter:**

$$G(u,v) = \frac{\sigma_X^2}{\sigma_X^2 + \sigma_W^2}$$

# Example of Wiener filtering I



result of
full inverse filtering

radially limited
inverse filter result

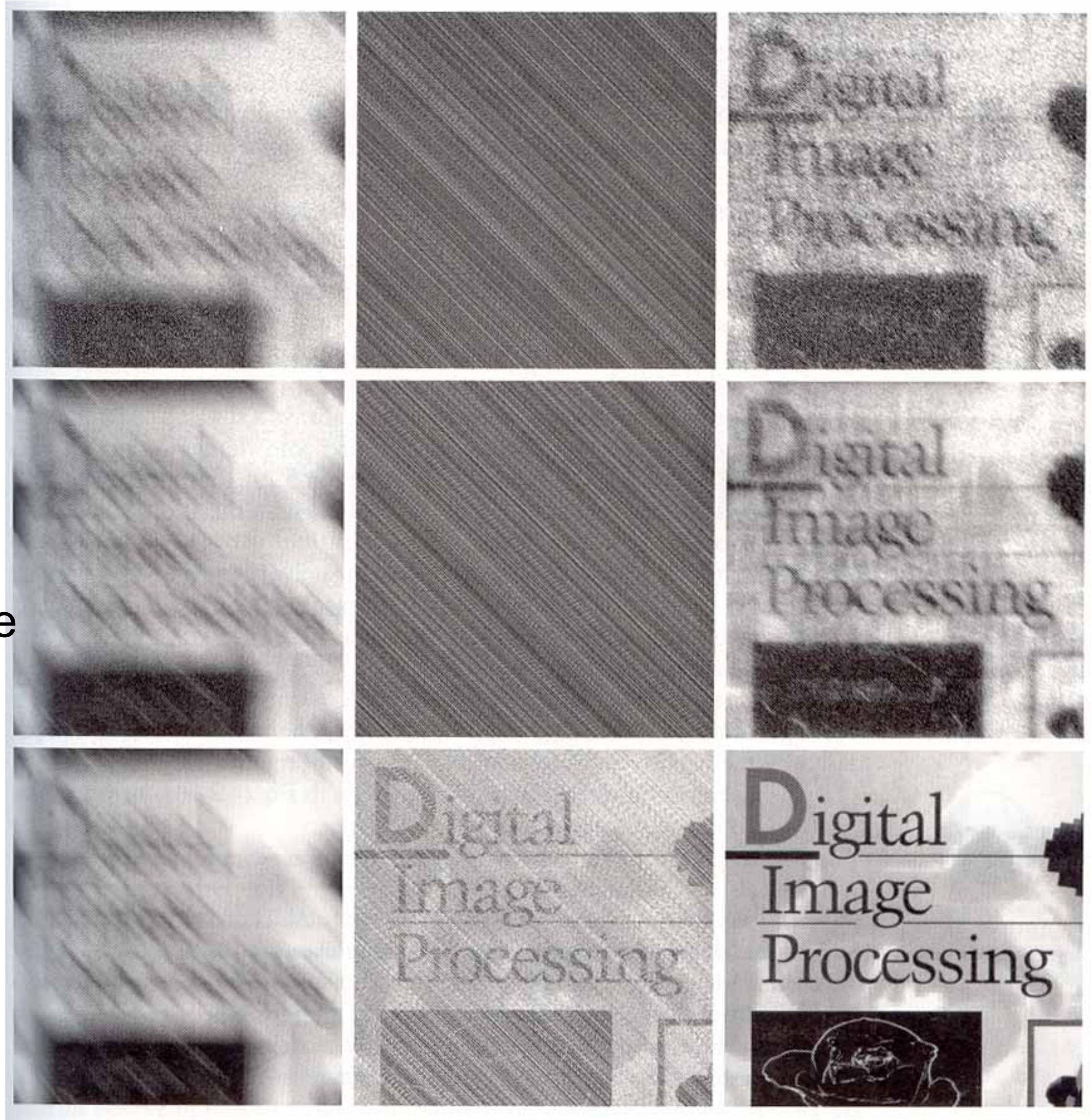
Wiener
filter result

# Example of Wiener filtering II

motion blur
plus
strong noise

motion blur
plus
reduced noise

motion blur
plus
weak noise




corrupted image   inverse filtering   Wiener filtering



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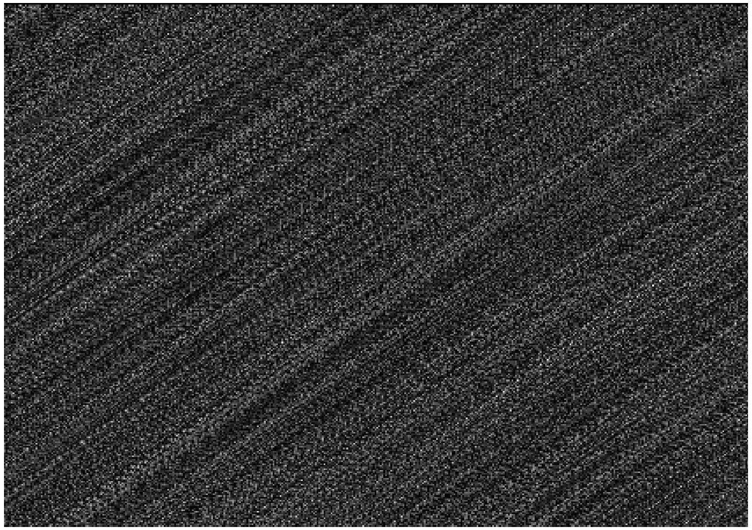
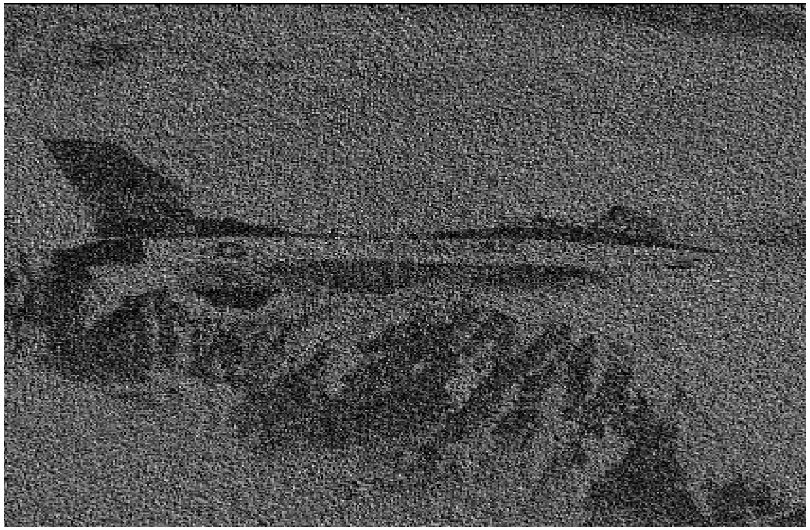
# Restoration results using Wiener filtering

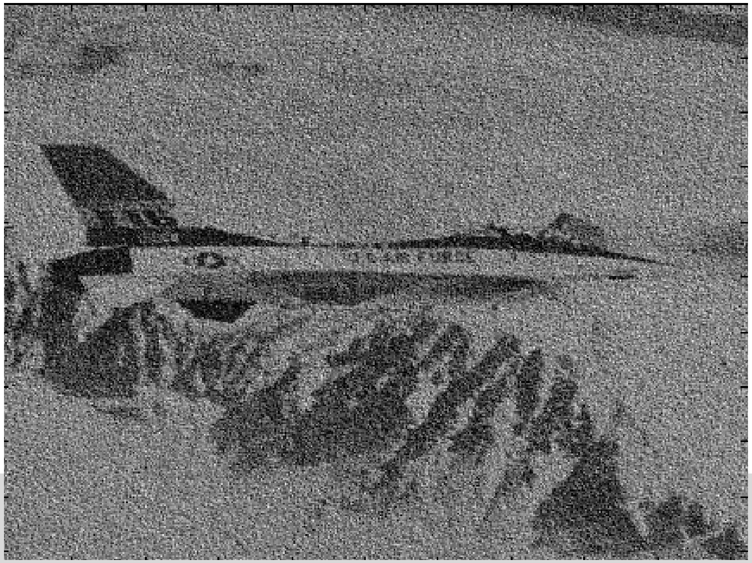
Degraded:30dB. Restored using Wiener, K=0



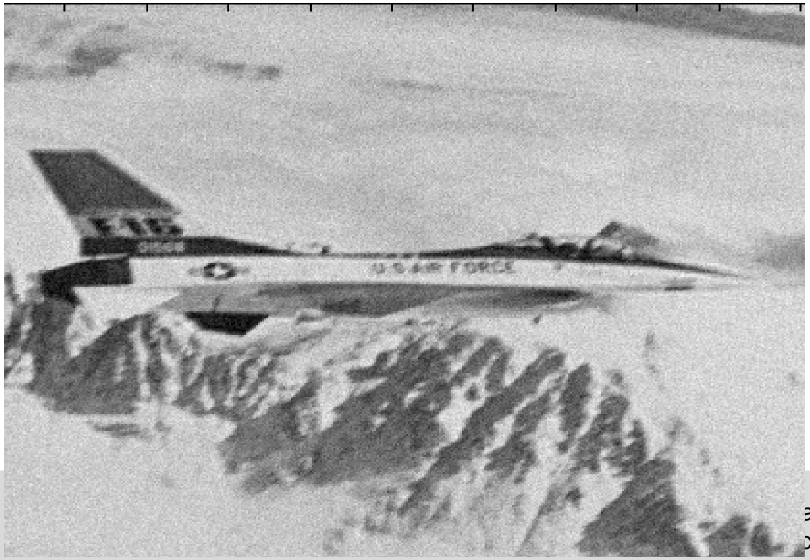
Degraded:30dB. Restored using Wiener, K=0.0001

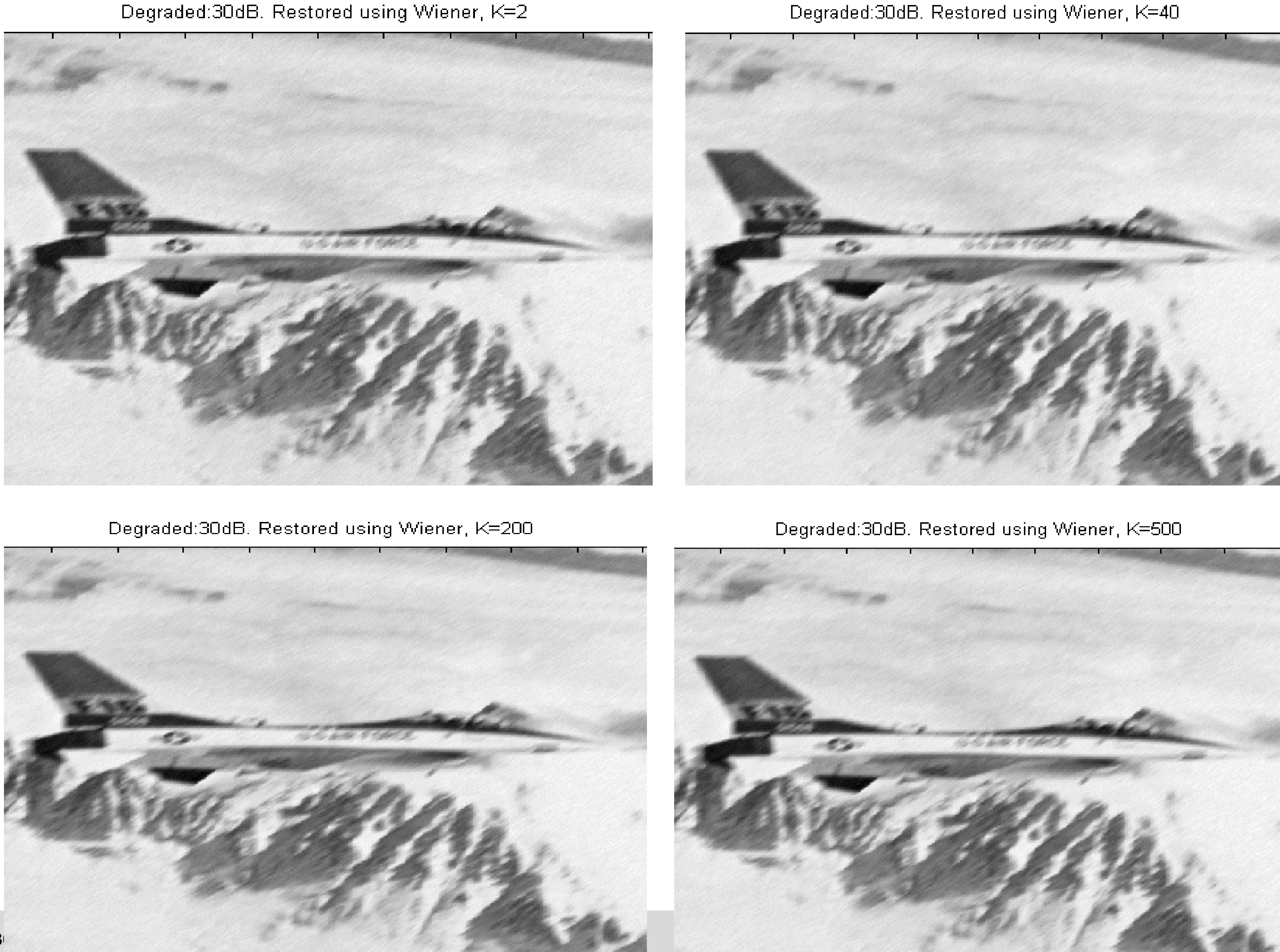


Degraded:30dB. Restored using Wiener, K=0.001



Degraded:30dB. Restored using Wiener, K=0.1




Degraded:30dB. Restored using Wiener, K=2
Degraded:30dB. Restored using Wiener, K=40
Degraded:30dB. Restored using Wiener, K=200
Degraded:30dB. Restored using Wiener, K=500

# Experiments on Real Video Data

# Experiments on Real Video Data

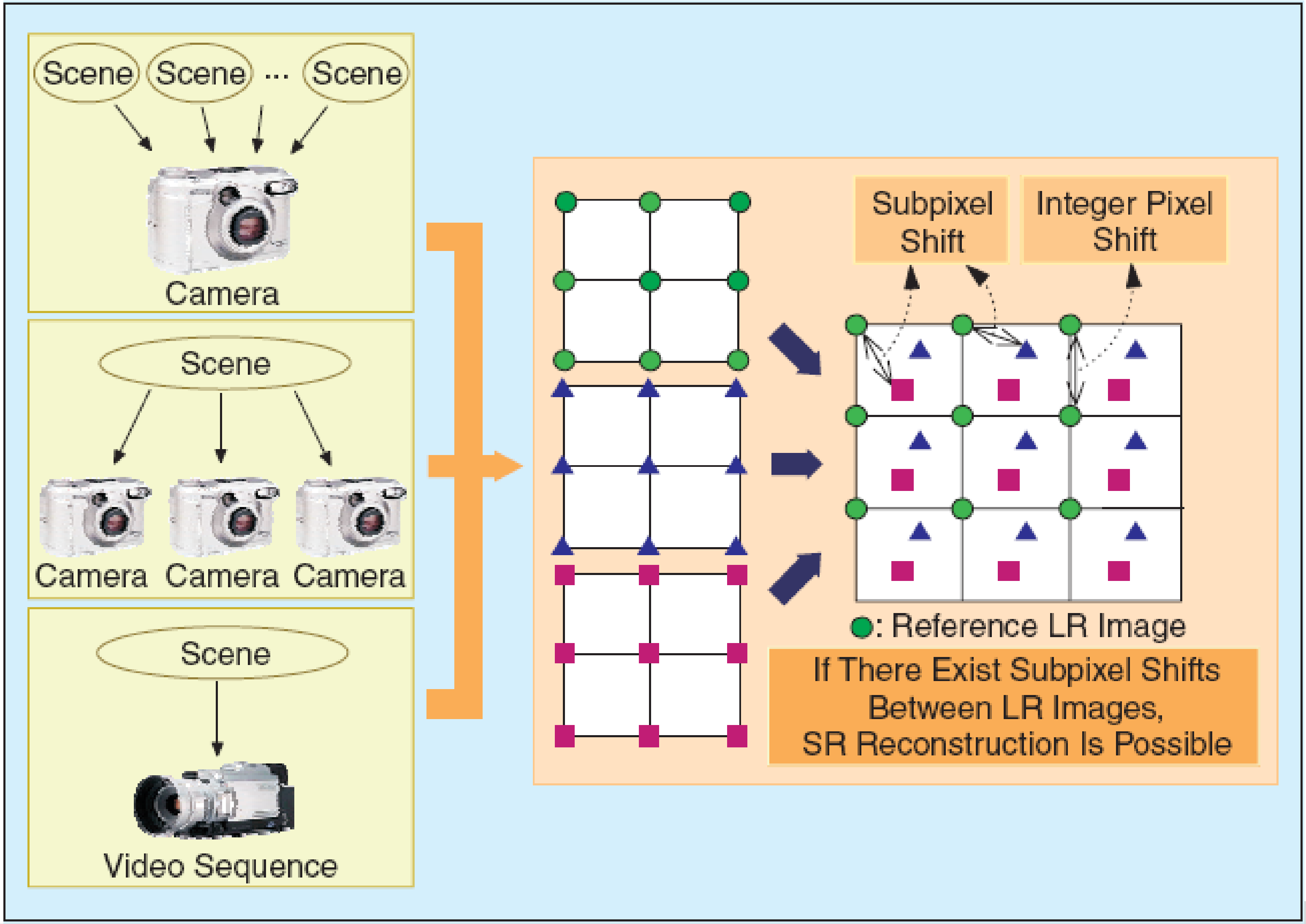
The PSF changes continuously (nonstationary blur), different sampling region get different PSF and results. It is **Current Work**!

# Advanced Image Restoration

- **Adaptive Processing**
  - Spatial adaptive
  - Frequency adaptive
- **Nonlinear Processing**
  - Thresholding, coring …
  - Iterative restoration
- **Advanced Transformation / Modeling**
  - Advanced image transforms, e.g., wavelet …
  - Statistical image modeling
- **Blind Deblurring / Deconvolution**

# Super-resolution image reconstruction

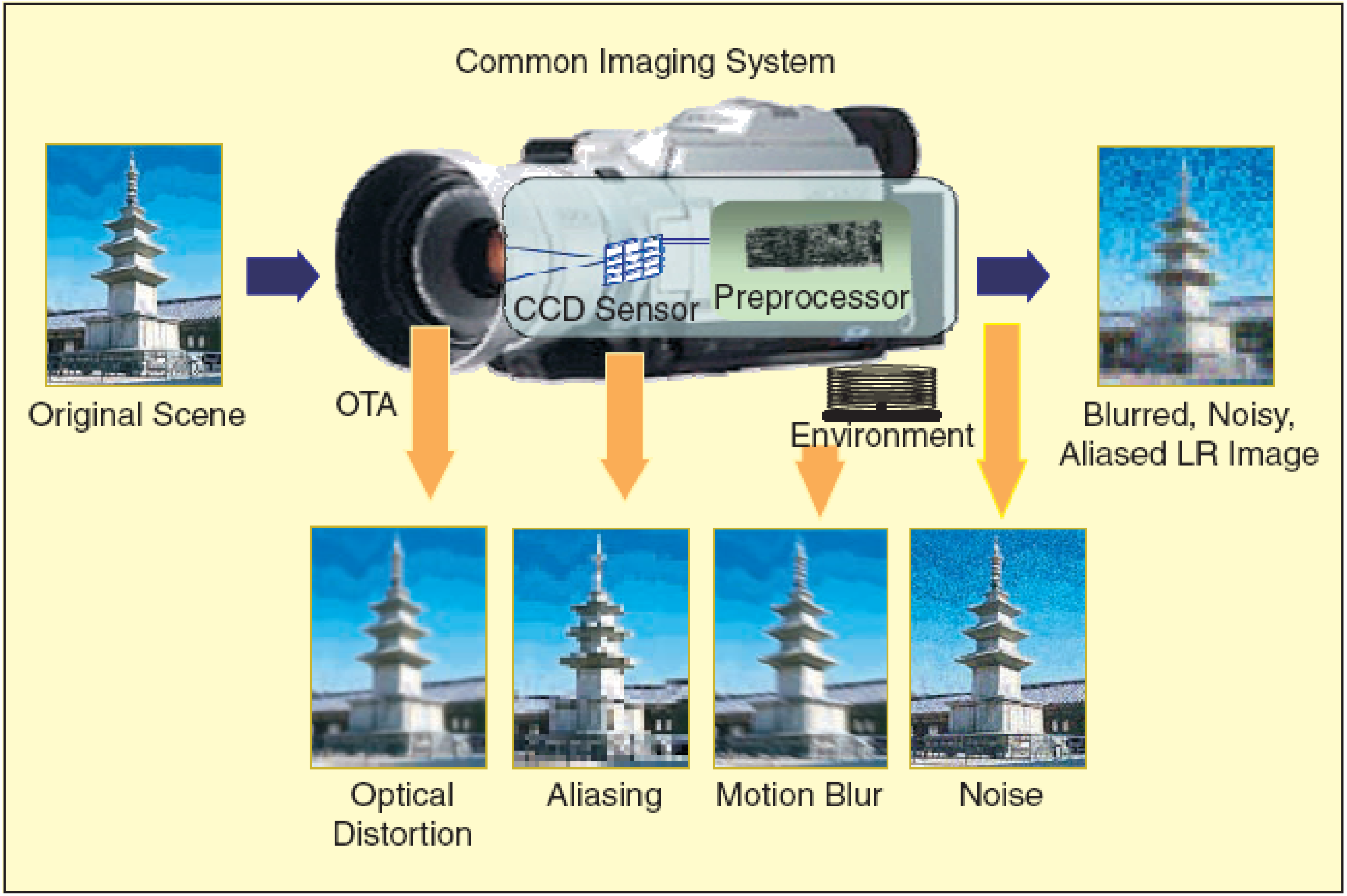
# Basic premise for super resolution



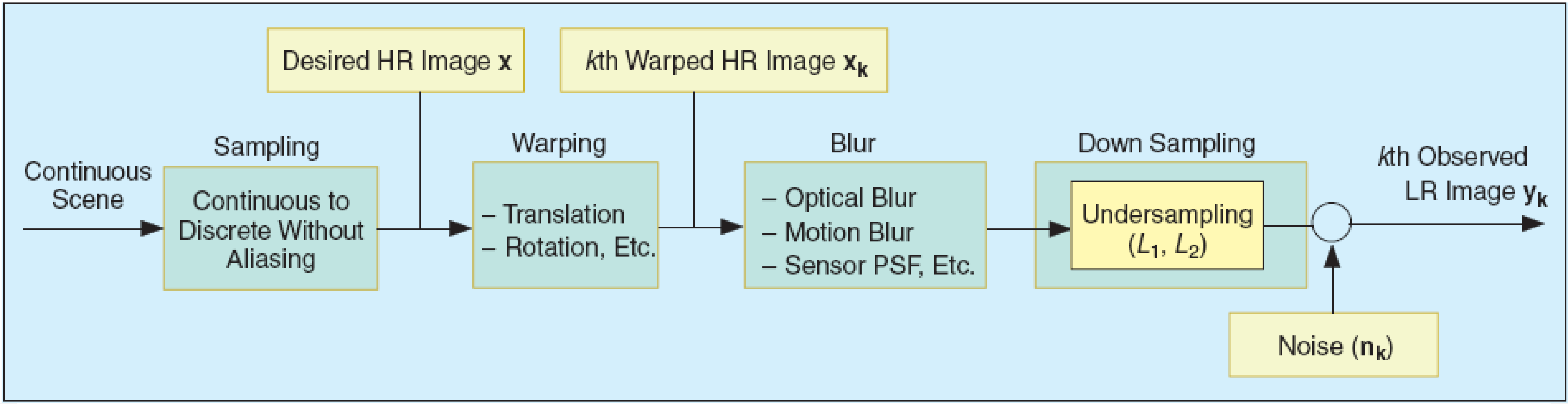
# Basic premises

- Aliasing (undersamping)
- Multiple images
- Motion (etc.) between images

# Common image acquisition system



# Observation model

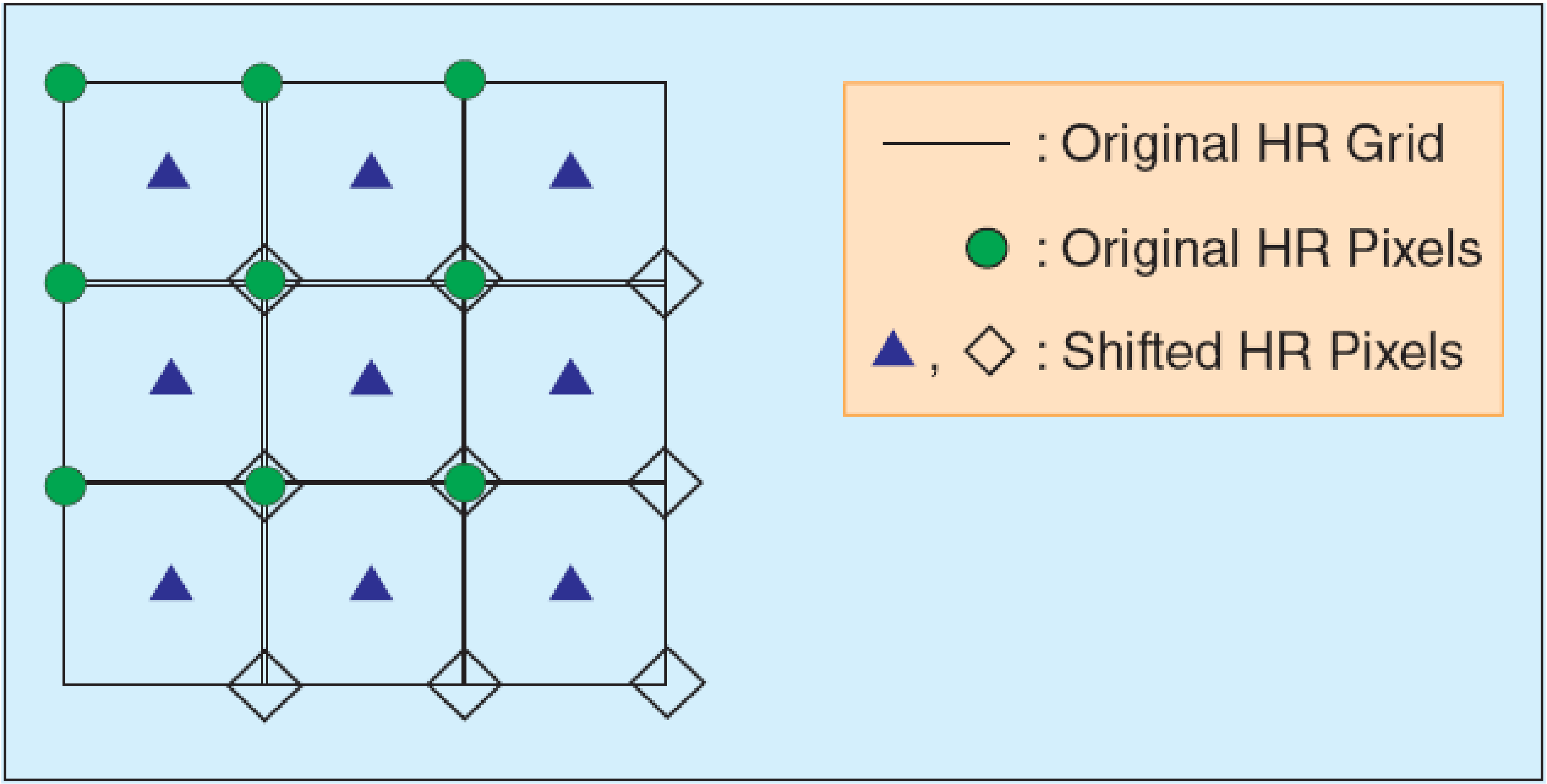


# Observation model

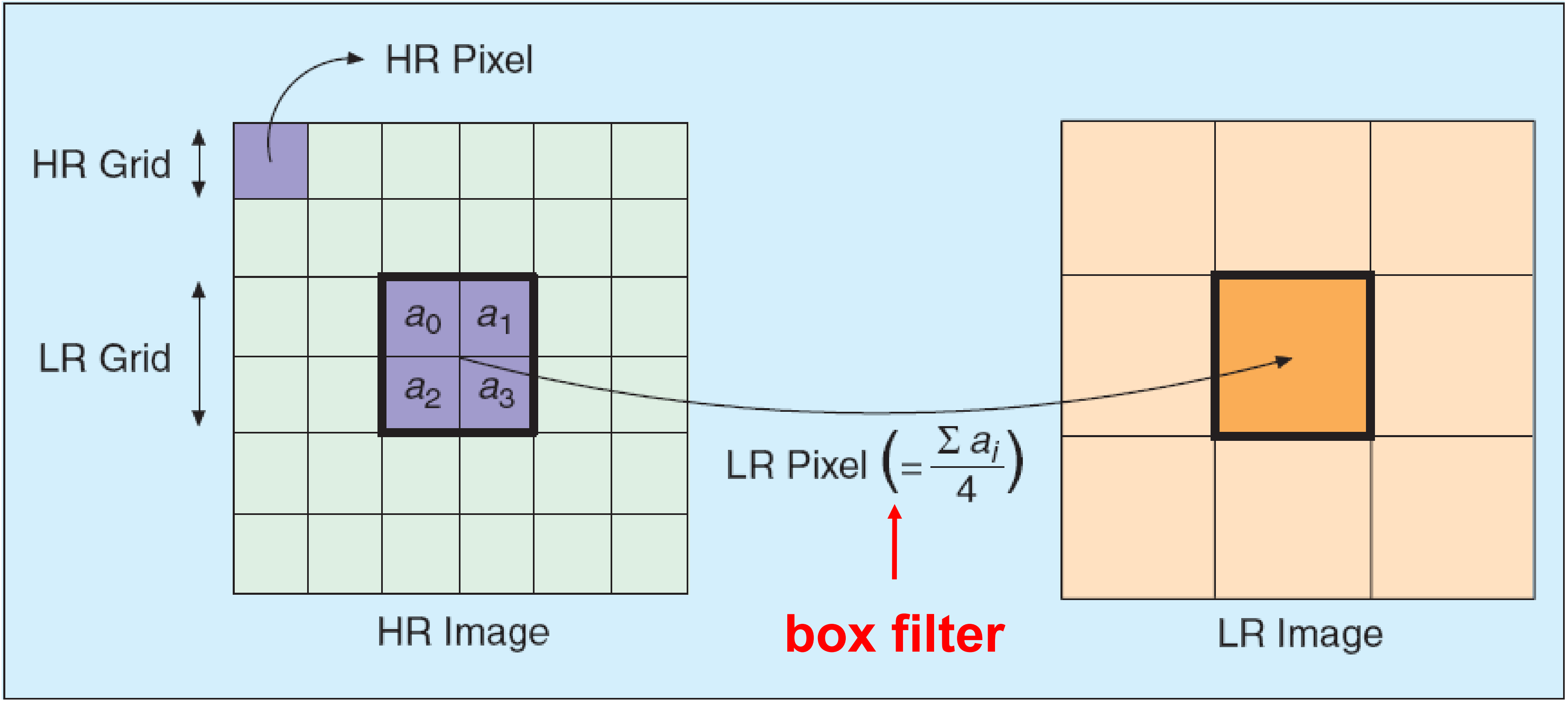
$$\mathbf{y}_k = \mathbf{D}\mathbf{B}_k\mathbf{M}_k\mathbf{x} + \mathbf{n}_k \quad \mathit{for}\ 1 \leq k \leq p$$

- **x** is the high-resolution (HR) image
- **y**k are the low-resolution (LR) images
- **M**k is a (block circulant) warp matrix representing motion.
- **B**k is a (block circulant) blur matrix.
- **D** is a (block circulant; attention: dimension is number of pixels in LR image x number of pixels in HR image) subsampling matrix.
- **n**k is a noise vector.
- **Motion** has to be estimated for each frame.

# Interpolation in HR sensor grid



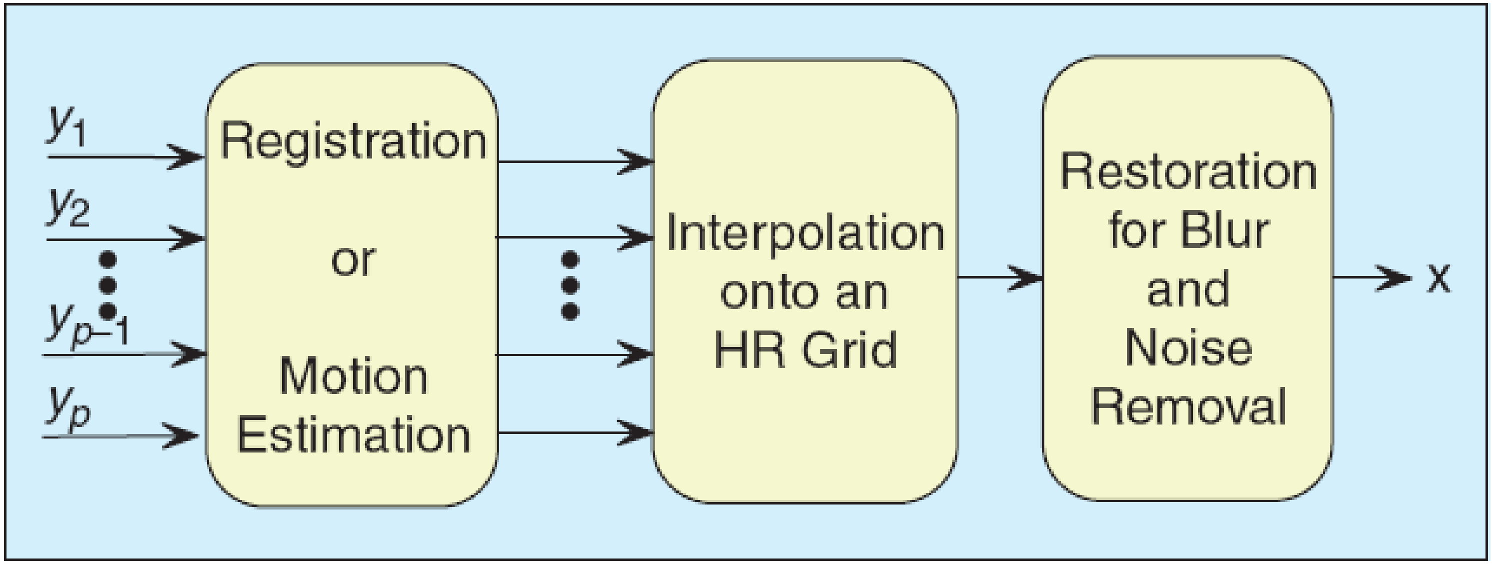
# Low-resolution sensor PSF



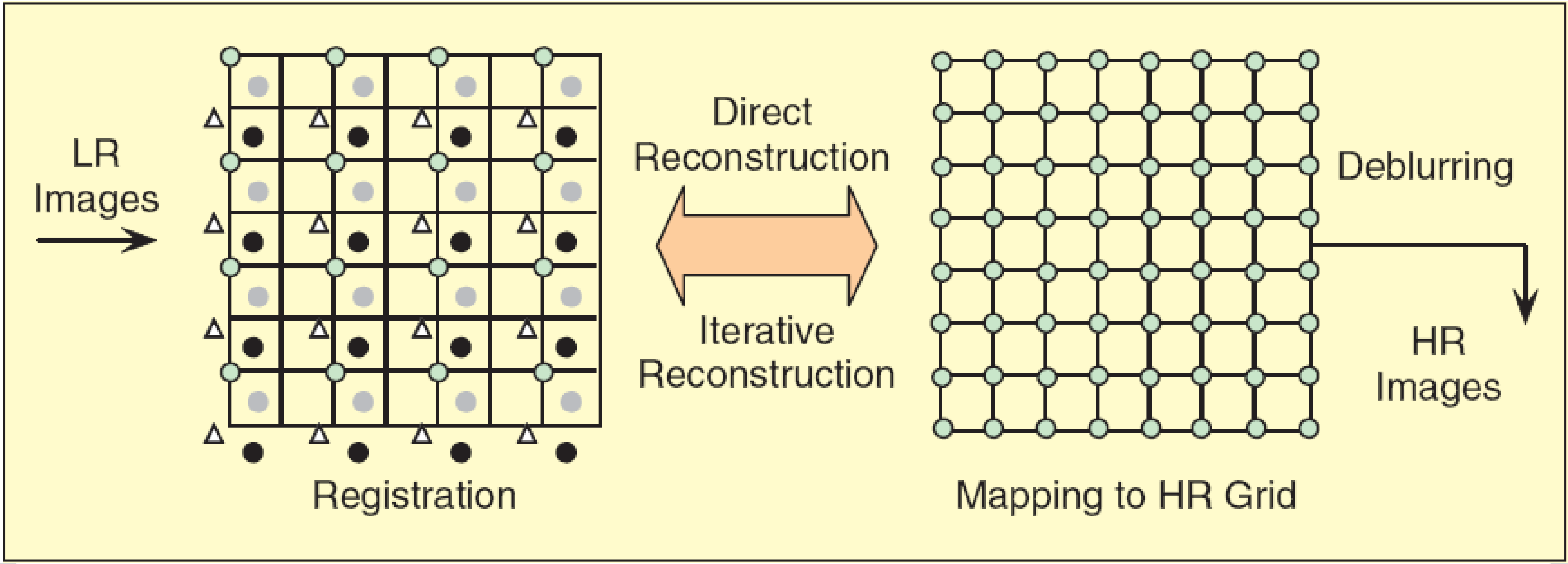

- Although the blurring acts more or less as an anti-aliasing filter, in SR image reconstruction, it is assumed that aliasing is always present in LR images.

# Scheme for super-resolution image reconstruction

- The aim of the SR image reconstruction is to estimate the HR image **x** from the LR images **y***k* for *k*=1, … *p*.



# Registration-interpolation-based reconstruction



# Example

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a) nearest neighbour interpolation from one LR image

b) bilinear interpolation from one LR image

c) nonuniformly interpolated from four LR images

d) deblurred image from c) using Wiener filter

# Reference


- S. C. Park, M. K. Park, M. G. Kang: Super-Resolution Image Reconstruction: A Technical Overview. IEEE Signal Processing Magazine, May 2003.