

IMAGE RESTORATION

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- Constrained least square filtering

$$\hat{F} = \frac{G}{H} \quad \hat{F} = \left[\frac{H^*}{|H|^2 + \gamma[S_n / S_f]} \right] G \quad \hat{F} = \left[\frac{H^*}{|H|^2 + \gamma|P|^2} \right] G$$

1. Observation
2. Experimentation
3. Mathematical modeling



IMAGE RESTORATION

least square filtering

$$\hat{F} = \frac{G}{H} \quad \hat{F} = \left[\frac{H^*}{|H|^2} \right] G$$

1. Observation
2. Experimentation
3. Mathematical modeling

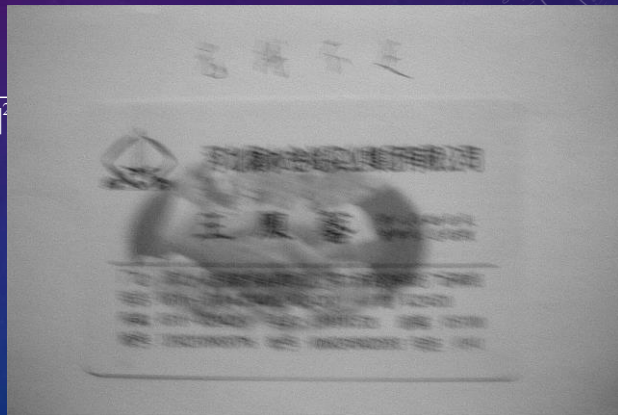


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- Constrained Maximum Likelihood Estimation

$$\hat{F} = \frac{G}{H}$$

1. Observation
2. Experimentation
3. Mathematical modeling

$$H_s = \frac{G_s}{\hat{F}_s}$$

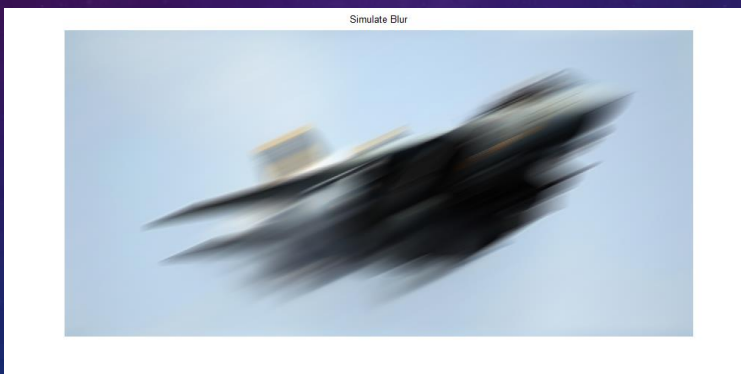
BLUR CAUSED BY UNIFORM LINEAR MOTION

3. Mathematical modeling

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

$$k = 0.0025$$

$$h(x, y) = \frac{1}{V^2 T} \text{rect}(x/VT)$$



BLUR CAUSED BY UNIFORM LINEAR MOTION

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Suppose an image $f(x,y)$ undergoes planar motion and that $x_0(t)$ and $y_0(t)$ are the time-varying components of motion in the x- and y-directions, respectively, T is the duration of the exposure, it follows that :

$$g(x, y) = \int_0^T f[x - x_0(t), y - y_0(t)] dt$$

The FT of g is :

$$\begin{aligned} G(u, v) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \exp[-j2\pi(ux + vy)] dx dy \\ &= \int_0^T \left[\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f[x - x_0(t), y - y_0(t)] \exp[-j2\pi(ux + vy)] dx dy \right] dt \\ &= F(u, v) \int_0^T \exp\{-j2\pi[ux_0(t) + vy_0(t)]\} dt \rightarrow H(u, v) \end{aligned}$$

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

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

$$x_0(t) = at / T$$

$$y_0(t) = bt / T$$



Restoration of Blurred, Noisy Image Using NSR = 0

IMAGE RESTORATION

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- Image degradation
- General image restoration models
- Inverse filtering
- Wiener filtering
- Constrained least squares filtering
- **Geometric image transformation**

GEOMETRIC IMAGE MODIFICATION

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- Image translation, scaling, rotation
- Generalized linear geometrical transformation
- Affine transformation
- Perspective transformation

GEOMETRIC IMAGE MODIFICATION

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- Linear transformations

$$T(\vec{x}) = A\vec{x} \quad R^n \rightarrow R^m$$

- Non-linear transformations

$$R^n \rightarrow R^{n+1}$$

- Affine transformations
- Perspective transformations
- Why matrices
 - Consistent format
 - Easy concatenating

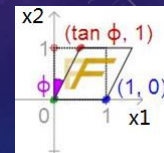
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- Shear parallel to the x1 axis

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & k_2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

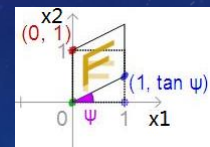
$$y_1 = x_1 + k_2 x_2$$



- Shear parallel to the x2 axis

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ k_1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$y_2 = k_1 x_1 + x_2$$



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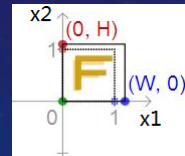
- Scale the x1 axis

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} s_1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad y_1 = s_1 x_1$$

- Scale the x2 axis

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & s_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad y_2 = s_2 x_2$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} s_1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & s_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} s_1 & 0 \\ 0 & s_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



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- Clockwise rotation

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- Counter-clockwise rotation

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

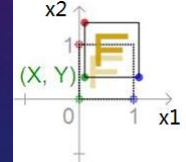


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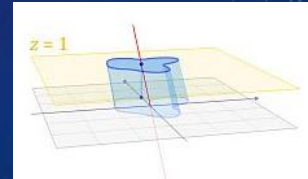
- Translation

$$\begin{aligned} y_1 &= x_1 + b_1 \\ y_2 &= x_2 + b_2 \end{aligned} \quad \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} ? & ? \\ ? & ? \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



- Augmented matrix - homogeneous coordinates

$$\begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} ? & ? & ? \\ ? & ? & ? \\ ? & ? & ? \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \quad \begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & b_1 \\ 0 & 1 & b_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}$$



GEOMETRIC IMAGE MODIFICATION

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- Augmented matrix

$$\begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & b_1 \\ 0 & 1 & b_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \quad \begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & k_2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} s_1 & 0 & 0 \\ 0 & s_2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \quad \begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}$$

GEOMETRIC IMAGE MODIFICATION

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- Affine transformations

- translation+scaling+rotation+reflection+shear+...
- every linear transformation is affine, not every affine transformation is linear

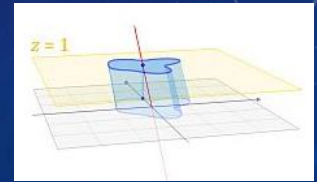
$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- linear transformation followed by a translation

$$\vec{y} = \text{Affine}(\vec{x}) = A\vec{x} + \vec{b} \quad \vec{y} = M\vec{t} = \begin{bmatrix} A & \vec{b} \end{bmatrix} \begin{bmatrix} \vec{x} \\ 1 \end{bmatrix}$$

- Augmented matrix representation

$$\begin{bmatrix} \vec{y} \\ 1 \end{bmatrix} = \begin{bmatrix} A & \vec{b} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \vec{x} \\ 1 \end{bmatrix}$$



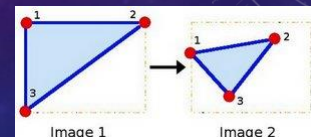
GEOMETRIC IMAGE MODIFICATION

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- Affine transformations properties

- Point line (colinearity) plane
- Ratios of vectors along a line
- parallel lines
- barycenters

$$f\left(\sum_{i \in I} \lambda_i a_i\right) = \sum_{i \in I} \lambda_i f(a_i)$$



- Invertible transformation

$$f: A \rightarrow B \quad \begin{bmatrix} \vec{x} \\ 1 \end{bmatrix} = \begin{bmatrix} A^{-1} & -A^{-1}\vec{b} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \vec{y} \\ 1 \end{bmatrix}$$

$$\{(a_i, \lambda_i)\}_{i \in I} \\ \sum_{i \in I} \lambda_i = 1$$

- all triangles are related to one another by affine transformations

GEOMETRIC IMAGE MODIFICATION

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- Augmented matrix

$$\begin{aligned}
 \begin{bmatrix} y_1 \\ y_2 \\ 1 \end{bmatrix} &= \begin{bmatrix} 1 & 0 & -\Delta x_1 \\ 0 & 1 & -\Delta x_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & \Delta x_1 \\ 0 & 1 & \Delta x_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \\
 &= \begin{bmatrix} 1 & 0 & -\Delta x_1 \\ 0 & 1 & -\Delta x_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos \theta & \sin \theta & \Delta x_1 \cos \theta + \Delta x_2 \sin \theta \\ -\sin \theta & \cos \theta & -\Delta x_1 \sin \theta + \Delta x_2 \cos \theta \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \\
 &= \begin{bmatrix} \cos \theta & \sin \theta & \Delta x_1 \cos \theta + \Delta x_2 \sin \theta - \Delta x_1 \\ -\sin \theta & \cos \theta & -\Delta x_1 \sin \theta + \Delta x_2 \cos \theta - \Delta x_2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}
 \end{aligned}$$

GEOMETRIC IMAGE MODIFICATION



SUMMARY

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- Image degradation
- General image restoration models
- Inverse filtering
- Wiener filtering
- Constrained least squares filtering
- Geometric image modification

IMAGE RESTORATION

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Image inpainting

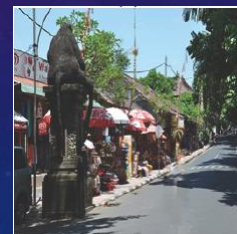
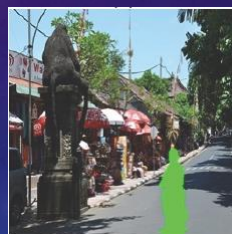
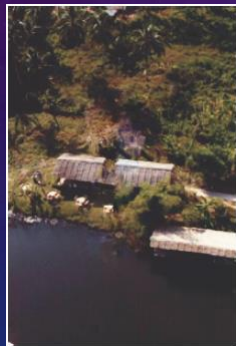


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Image inpainting

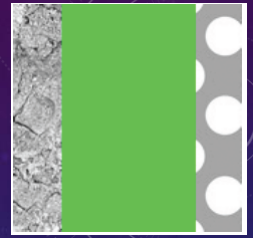
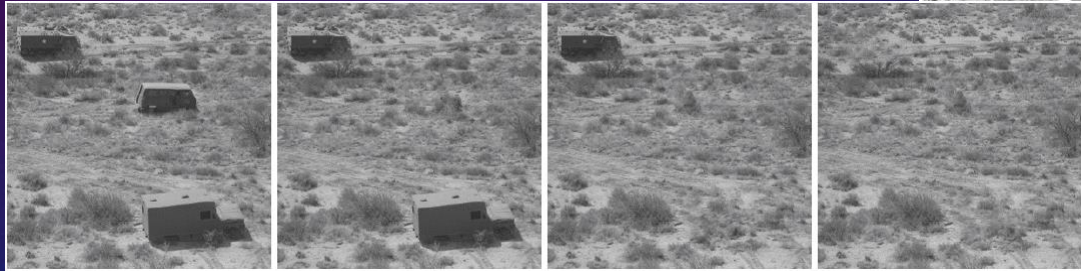


IMAGE RESTORATION

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Image inpainting

Non-local methods in inpainting have gained popularity due to the work of [11], although the authors claim the inspiration from Efros and Leung [3]. Authors of [13] have used graph differential geometry to provide a discrete formulation of image inpainting. Such as bilateral filter, the TV digital inhomogeneous regional means filter. The advantage of choosing graph-based methods can model well the interactions between local or the nonlocal regularization can be derived in the way the connections are made in the graph.

Let I be the Image whose domain is Ω in \mathbb{R}^2 . Let Φ be an embedding that maps each pixel to a square patch. The area of each patch is considered to be d . $\Phi(p)$, $\Phi(q)$ represent square patches around the pixels p , q respectively. They are d -tuples obtained by lexicographically arranging the pixels inside the corresponding patches.

Let $G = (V, E, w)$ be a weighted graph. V and E are the set of vertices and edges respectively. We connect two vertices p, q

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(b) image with missing area

(d) Criminisi method

(e) Non-local mean method

(g) Poisson method