The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

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INTRODUCTION TO COMPUTER VISION

Atlas Wang
Assistant Professor, The University of Texas at Austin

Visual Informatics Group@UT Austin
https://vita-group.github.io/

Visual Degradation

Data Acquisition

Degradation before Data Acquisition

- Heavy Rain/Snow
- Underwater
- Low Light
- Haze/Sandstorm

Degradation in Data Acquisition

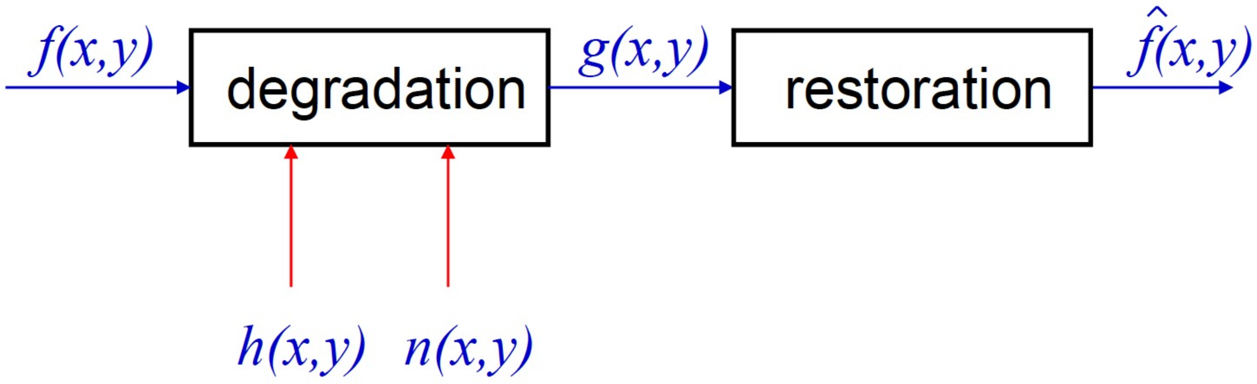
- Downsample
- Motion Blur
- System Noise
- Optical Distortion

Degradation after Data Acquisition

- Scratches
- Watermark
- Mildew
- Compression Loss

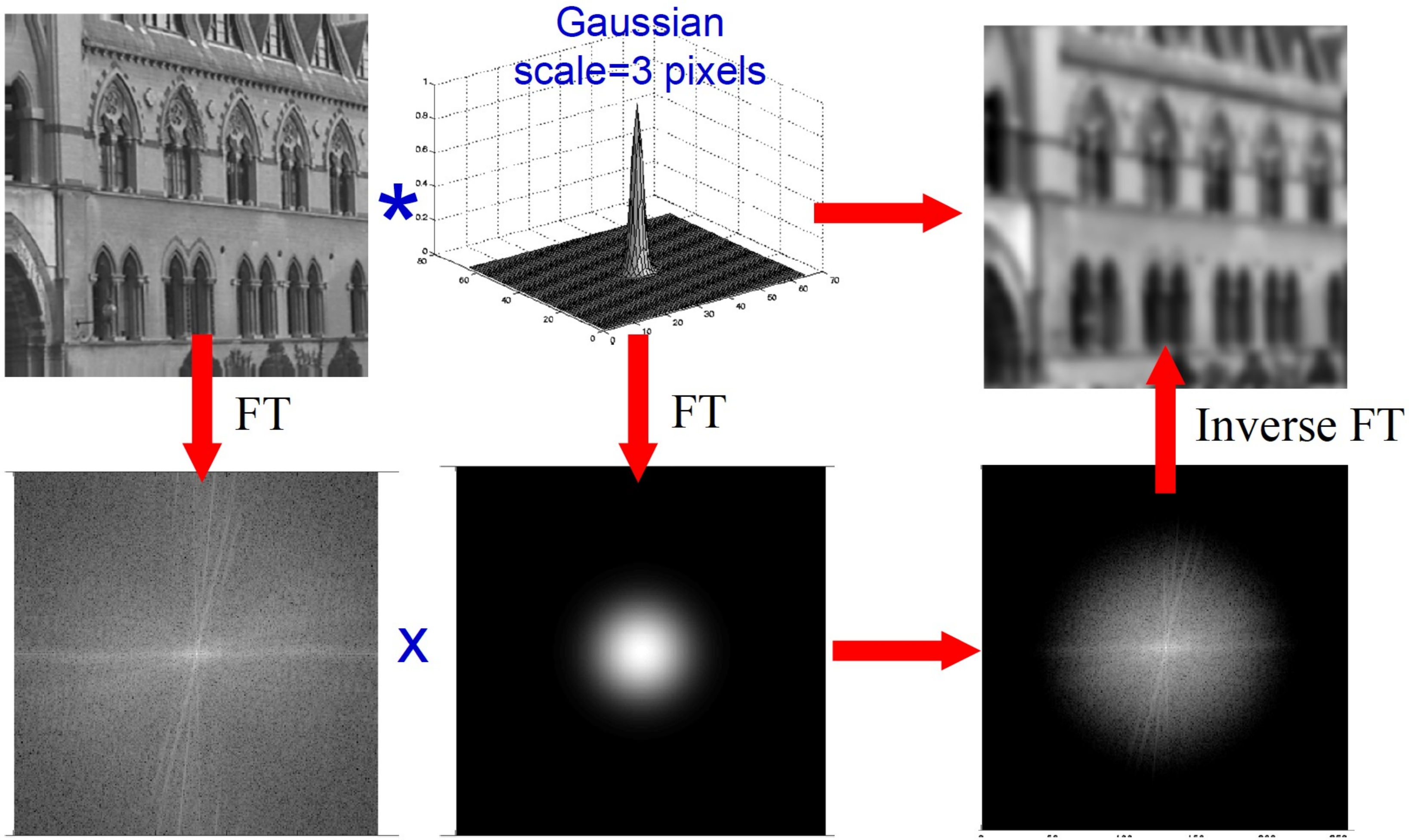
Image Degradation Model

- $f(x,y)$ – image before degradation, 'true image'
- $g(x,y)$ – image after degradation, 'observed image'
- $h(x,y)$ – degradation filter
- $\hat{f}(x,y)$ – estimate of $f(x,y)$ computed from $g(x,y)$
- $n(x,y)$ – additive noise



$$g(x,y) = h(x,y) * f(x,y) + n(x,y) \Leftrightarrow \quad G(u,v) = H(u,v)\, F(u,v) + N(u,v)$$

Example: Image Blur



Blurring acts as a low pass filter and attenuates higher spatial frequencies

Goal of Image Enhancement Diversified

- From traditional signal processing (reconstruction) viewpoint
  - Full-reference metrics: PSNR, SSIM, etc.

- … to human perception (subjective quality)-based
  - No-reference metrics (e.g., NIQE), and human study

- … And to task-oriented, “end utility”-based
  - Typical examples: dehazing, deraining, (extreme) light, underwater …
  - **Representative datasets: RESIDE** dehazing (TIP’18), **MPID** deraining (CVPR’19)
  - **CVPR UG2+ Challenge:** http://www.ug2challenge.org

Discussion: Patch-Based v.s. Image-Level

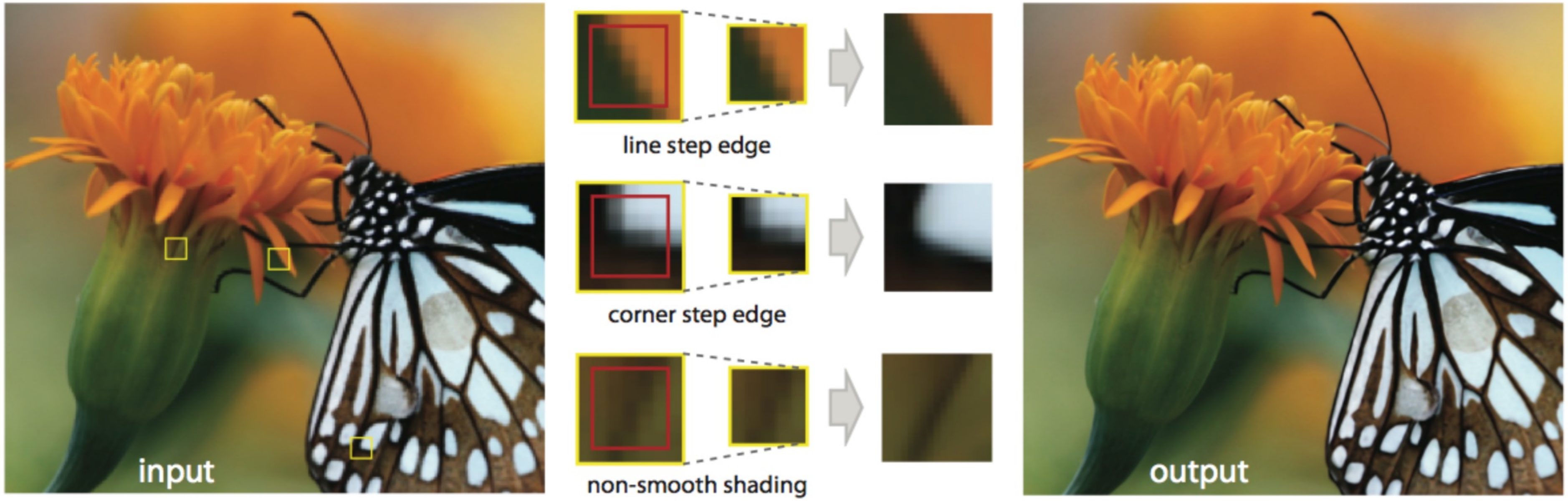
- The term “**patch**-**based**” may be vague because it can refer to any algorithm that works with small **image patches**.
  - BM3D image denoising, sparse coding for image super-resolution, image compression algorithms such as JPEG…

- Traditional image processing works on patches
  - Efficiency (esp. when model learning capacity is limited)
  - A lot of natural image statistics and similarities to exploit

- Deep learning image processing works on whole images
  - Mostly obtain better results as they are more “global-view”
  - But often ignore some useful prior knowledge on patch-level

Discussion: Self v.s. External Similarity

- Natural images contain abundant **self-similarities**.
  - For every patch in a natural image, we can probably find many similar patches in the same image.
  - Nonlocal patch-based methods exploit this self-similarity by finding/collecting similar patches and processing them jointly.
  - Cross-scale self-similarity (*Example Below*)



Learning to Enhance Images

- Data-driven training of “end-to-end” models (usually assuming “pairs”)
- Prior/physical information can still be helpful

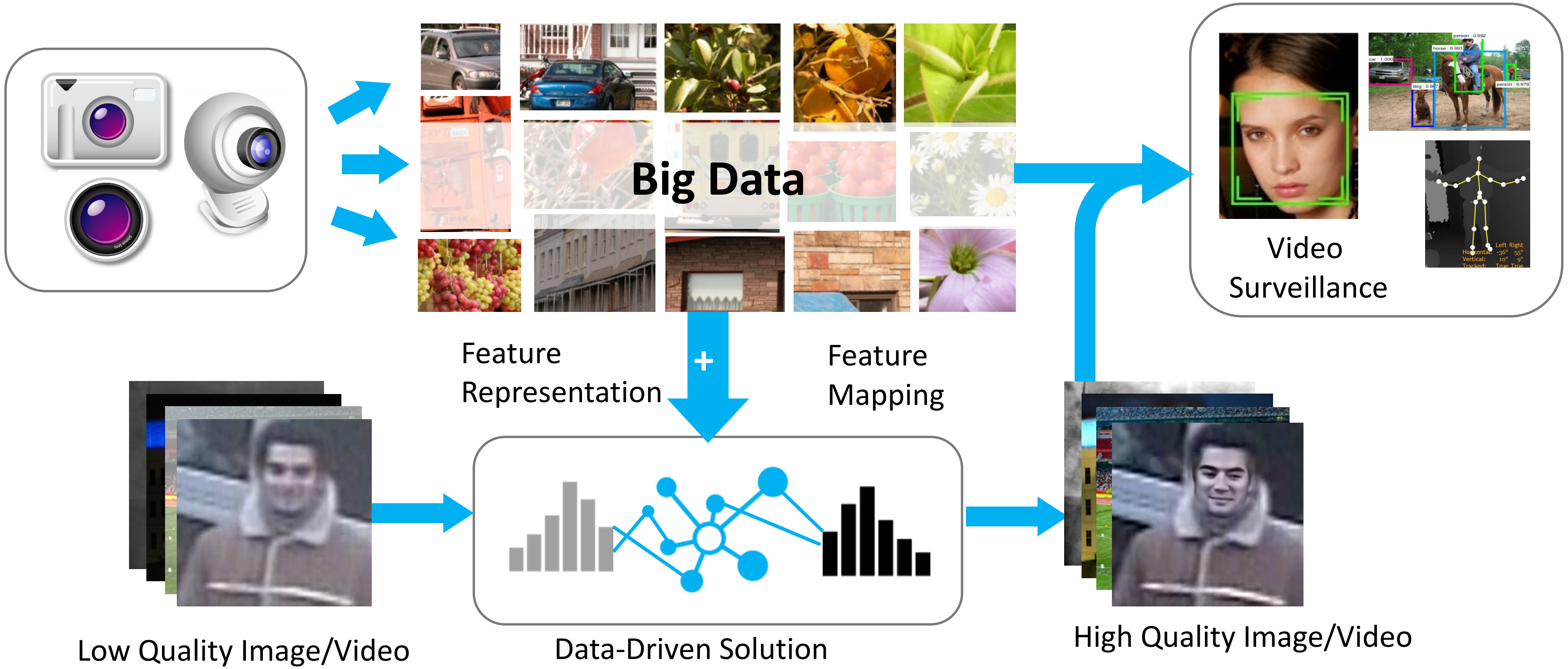


Image Denoising

- Simplest Low-Level Vision Problem

  - Noisy Measurement: $y = x + e$

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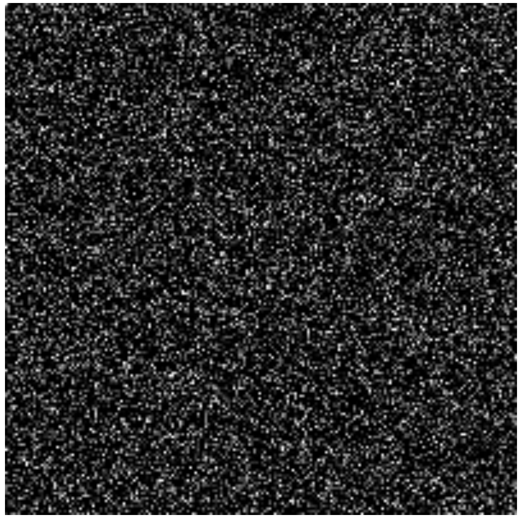


Image Denoising

- Simplest Low-Level Vision Problem

  - Estimate the clean image: $\hat{\boldsymbol{x}} = f(y)$

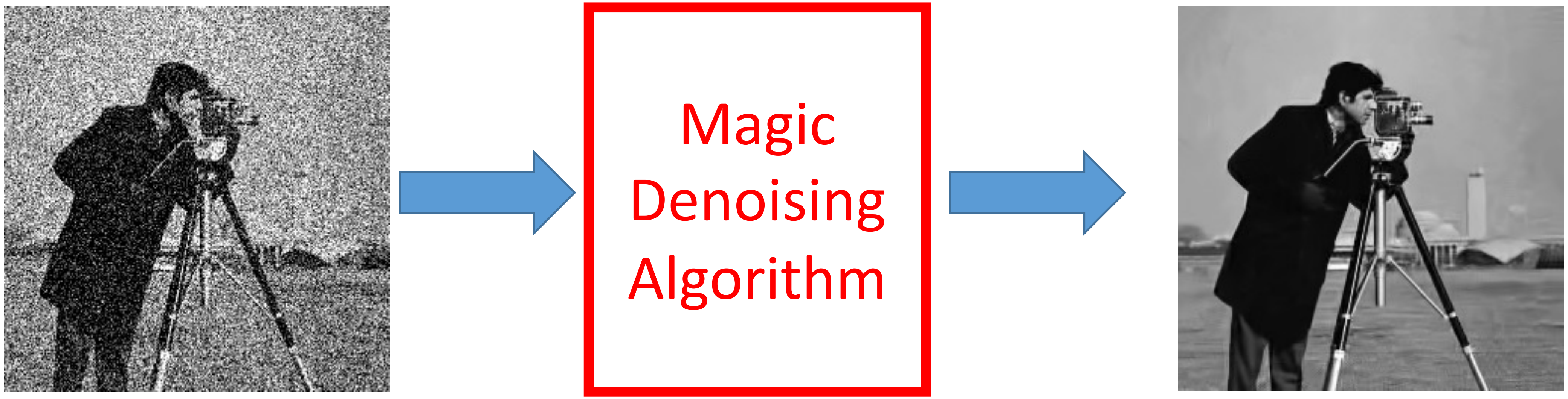


Image Denoising – Conventional Methods

- Collaborative Filtering
  - Non-local Mean, BM3D, etc

Classical Image Denoising: BM3D

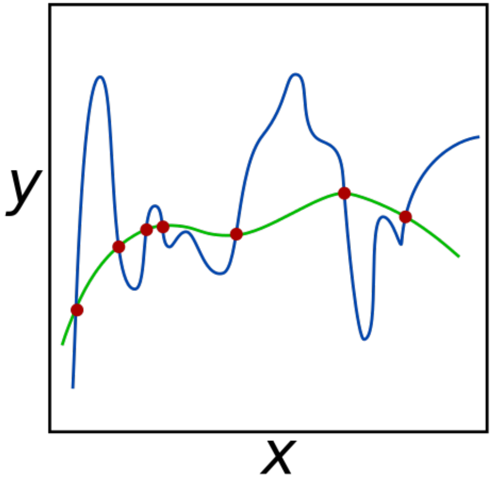
- BM3D = *Block-Matching and 3D filtering*, suggested first in 2007.
- Given a 2D square-block, finds all 2D similar blocks and “group” them together as a 3D array, then performs a *collaborative filtering* (method that the authors designed) of the group to obtain a noise-free 2D estimation.
- Averaging overlapping pixels estimations.
- Gives state of the art results.

Based on: K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. *Image denoising by sparse 3-D transform-domain collaborative filtering*. IEEE Transactions on Image Processing, 16(8):2080–2095, 2007.

Patch-based + Self-Similarity + Domain Expertise

Image Denoising – Conventional Methods

- Collaborative Filtering
  - Non-local Mean, BM3D, etc
- Piece-wise Smooth
  - Total Variation, Tikhonov Regularization, etc



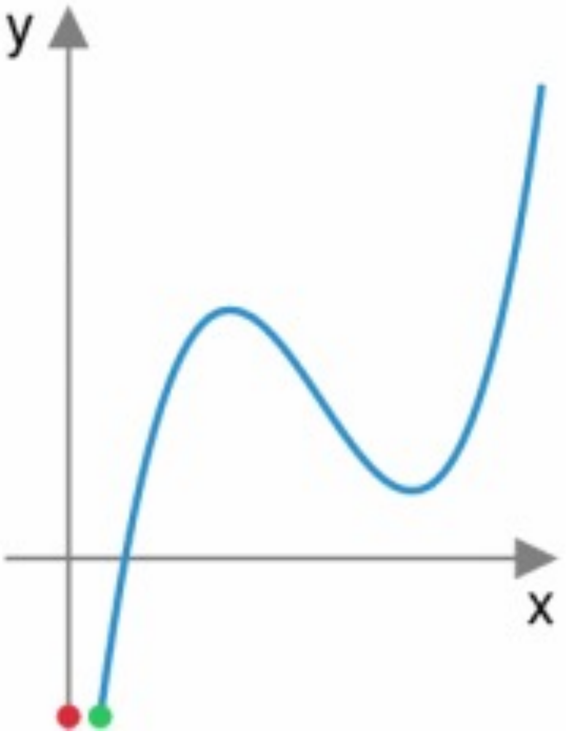
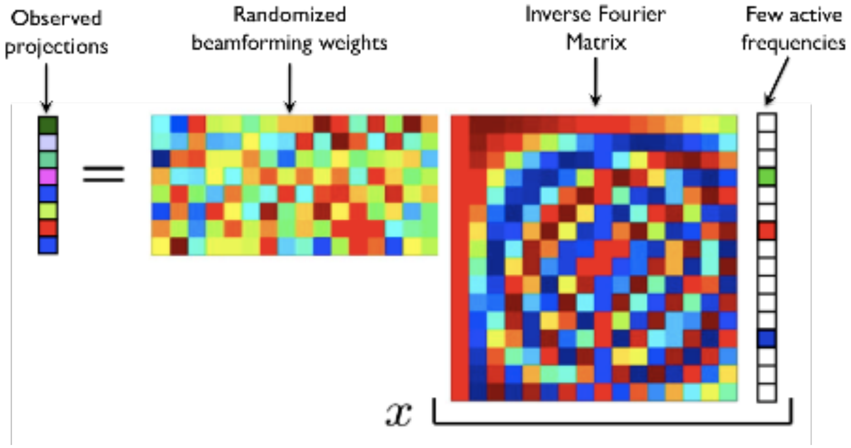
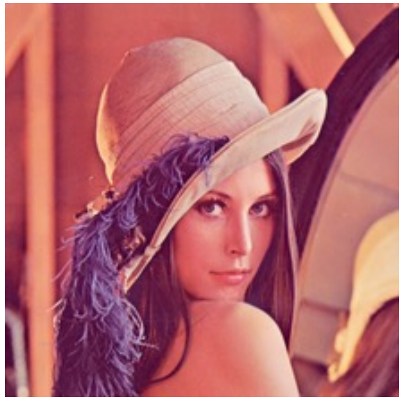
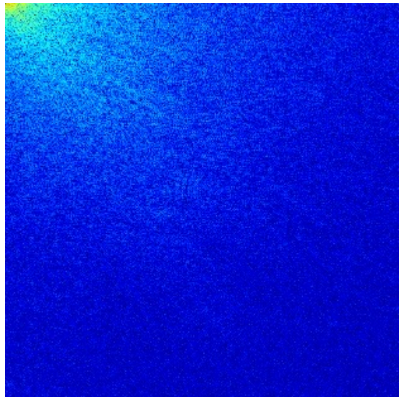


Image Denoising – Conventional Methods

- Collaborative Filtering
  - Non-local Mean, BM3D, etc
- Piece-wise Smooth
  - Total Variation, Tikhonov Regularization, etc
- Sparsity
  - Discrete Cosine Transform (DCT), Wavelets, etc
  - Dictionary Learning: KSVD, OMP, Lasso, etc
  - Analysis KSVD, Transform Learning, etc







It is all about good "prior"

Conventional

- Shallow Model
  - Equivalently one free layer

Deep Learning

- Deep Model
  - Multiple free layers

Conventional

- Shallow Model
  - One free layer
- **Unsupervised**
  - **No training corpus needed**
  - **Data efficient**

Deep Learning

- Deep Model
  - Multiple free layers

- **Supervised**
  - **Training corpus needed**
  - **Data inefficient**

?

Conventional

- Shallow Model
  - One free layer
- Unsupervised
  - No training corpus needed
  - Data efficient
- **Inverse Problem**
  - **Assumption & Understanding of the Data**
  - **Regularizer & structures of the Model**
  - **Flexible**

Deep Learning

- Deep Model
  - Multiple free layers
- Supervised
  - Training corpus needed
  - Data inefficient
- **Inverse Problem**
  - **Little assumption**
  - **Almost free model**
  - **Few work until recent**

Image Deblurring

- Blurred Measurement: $y = M \otimes \boldsymbol{x}$

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$\otimes$

$$M = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

Image Deblurring

- Estimate the stable image: $\hat{\boldsymbol{x}} = f(y)$

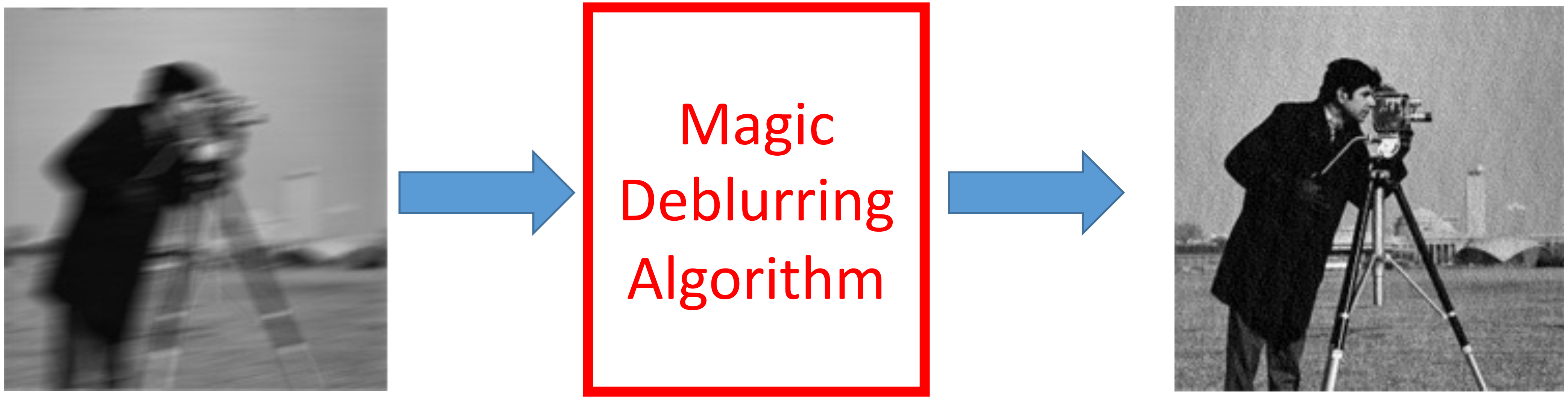


Image Deblurring

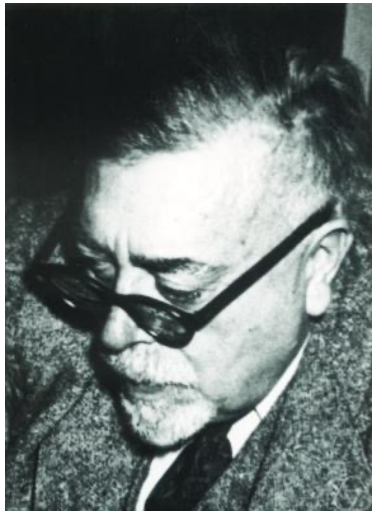
- Non-blind Image Deblurring
  - Suppose you know the blurring kernel, $\boldsymbol{M}$.
  - $\widehat{\boldsymbol{x}} = f(y, M)$
  - All training data need to have consistent $\boldsymbol{M}$, as the testing data

Image Deblurring

- Non-blind Image Deblurring
  - Suppose you know the blurring kernel, $\boldsymbol{M}$.
  - $\hat{\boldsymbol{x}} = f(y, M)$
  - All training data need to have consistent $\boldsymbol{M}$, as the testing data
- Blind Image Deblurring – More challenging yet practical problem
  - Estimate both the image, and the blurring kernel
  - $\{\hat{\boldsymbol{x}}, M\} = f(y)$

Wiener Filtering

Norbert Wiener
(1894-1964)
"Father of cybernetics"



Restoration with a Wiener filter

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

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

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

$$W(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K(u,v)}$$

where

$$K(u,v) = S_\eta(u,v)/S_f(u,v)$$

$S_f(u,v) = |F(u,v)|^2$ power spectral density of $f(x,y)$

$S_\eta(u,v) = |N(u,v)|^2$ power spectral density of $\eta(x,y)$

Limitation: Assuming known stationary signal and noise spectra, and additive noise

$$g(x,y) \rightarrow \boxed{\text{F.T.}} \xrightarrow{G(u,v)} \boxed{\text{Wiener filter}} \xrightarrow{\hat{F}(u,v)} \boxed{\text{I.F.T.}} \xrightarrow{\hat{f}(x,y)}$$

Example: Motion Deblurring by Wiener Filtering

blur = 20 pixels

$$W(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + K(u,v)}$$

1. Compute the FT of the blurred image
2. Multiply the FT by the Wiener filter
3. Compute the inverse FT

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

Maximum a posteriori (MAP) Estimation

- original *f(x,y)*
- motion blur
- additive intensity noise

For an image with n pixels, write this process as

$$\hat{\mathbf{g}} = \mathtt{A}\mathbf{f} + \mathbf{n}$$

where $\hat{\mathbf{g}}$ and $\mathbf{f}$ are n-vectors, and $\mathtt{A}$ is an $n \times n$ matrix.

- Estimate *f(x,y)* by optimizing a cost function:

$$\hat{\mathbf{f}} = \arg\min_{\mathbf{f}} \underbrace{(\overset{\text{observed image}}{\mathbf{g}} - \overset{\text{generated image}}{\mathtt{A}\mathbf{f}})^2}_{\text{Likelihood/ loss function}} + \underbrace{\lambda p(\mathbf{f})}_{\text{prior/ regularization}}$$

Example

$$p(f) = (\nabla \mathbf{f})^2$$

to suppress high frequency noise

Blind Deblurring?

- Estimate *f(x,y)* and *h(x,y)* by optimizing a cost function:

$$\min_{\mathbf{f},\mathbf{h}} \underbrace{(\underset{\substack{\text{observed}\\\text{image}}}{\mathbf{g}} - \overbrace{\mathtt{A}(\mathbf{h})\,\mathbf{f}}^{\substack{\text{generated}\\\text{image}}})^2}_{\substack{\text{Likelihood/}\\\text{loss function}}} + \lambda \underbrace{p_f(\mathbf{f})}_{\substack{\text{image}\\\text{prior}}} + \mu \underbrace{p_h(\mathbf{h})}_{\substack{\text{blur}\\\text{prior}}}$$

Blind Deblurring

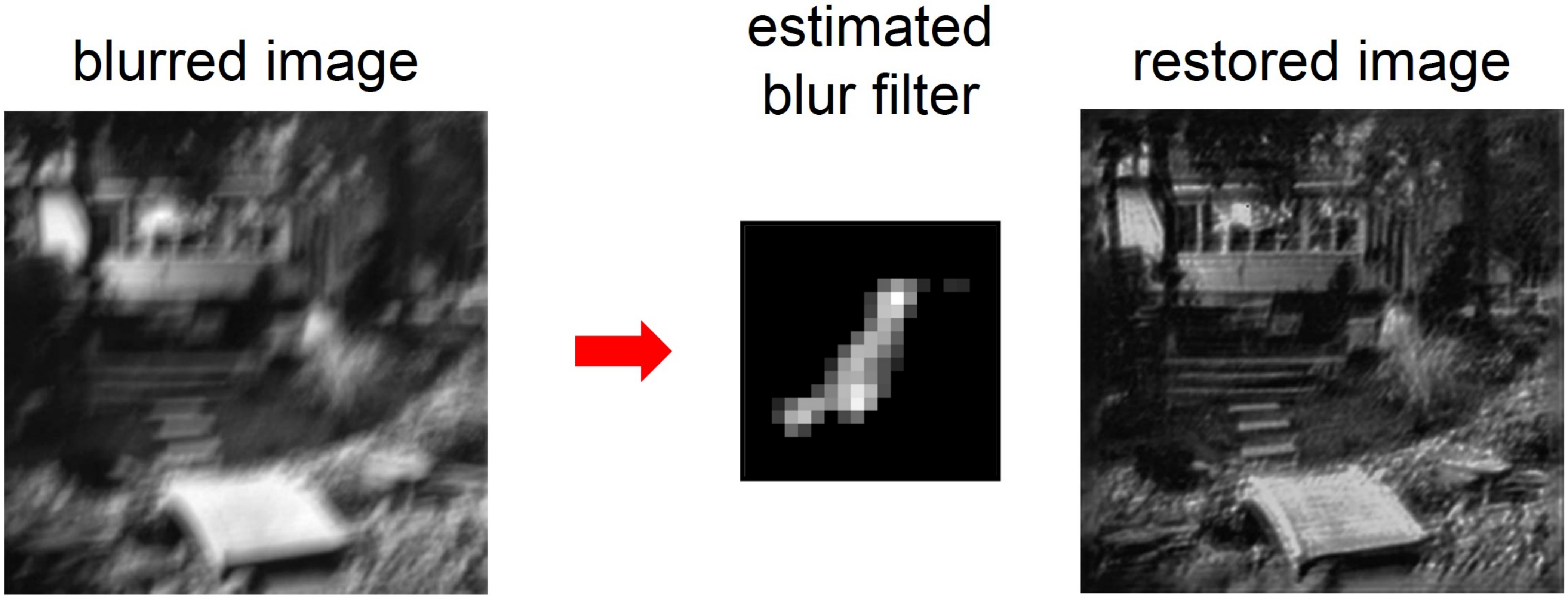


Image Super-Resolution

- Low-Resolution Measurement: $y = D * M \otimes \boldsymbol{x}$

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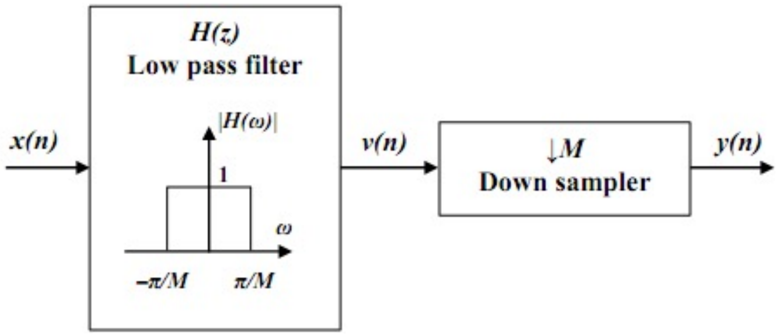


Image Super-Resolution

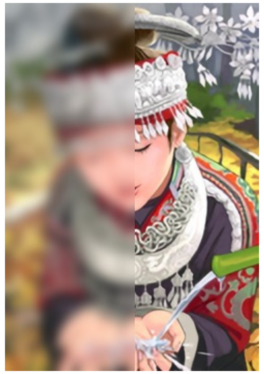
- Estimate the stable image: $\hat{\boldsymbol{x}} = f(y)$

Many More Tasks in the Real World!

Underwater Enhancement

Dehazing

Inpainting



Super Resolution

Rain Removal

Denoising

Low Light Enhancement

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