2018 Computer Vision

Image Enhancement and Restoration

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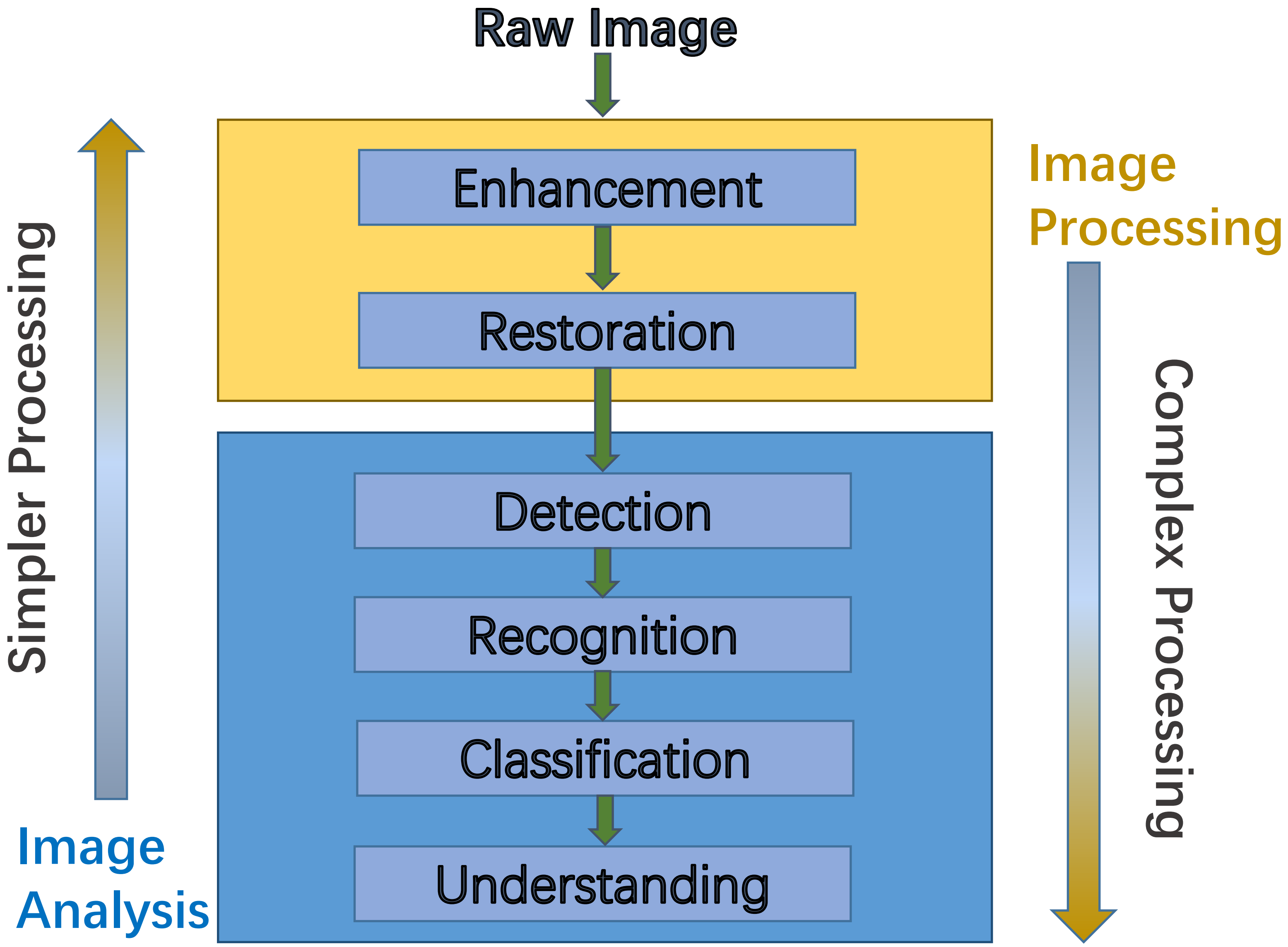
Things which we see are not by themselves what we see…
It remains completely unknown to us what the objects may be by themselves and apart from the receptivity of our senses. We know nothing but our manner of perceiving them.

Immanuel Kant

https://wenku.baidu.com/view/ca74a7ca0c22590102029d78.html?from=search

Structure of a Vision System



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Overview

- **Introduction to image enhancement**

  The concept of image enhancement

  The traditional methods of image enhancement

- **Introduction to image restoration**

  The concept of image restoration

  The traditional methods of image restoration

Overview

- **Image Dehazing**

    The concept of haze and atmospheric scattering model

    Some methods of image dehazing

- **Super-Resolution Image Reconstruction**

    The concept of SR

    Some methods of SR

- **Underwater Image Enhancement and Restoration**

    The concept of image restoration

    Some methods of underwater image enhancement and restoration

01

Introduction to Image Enhancement

Image Enhancement

- Goal: improve the 'visual quality' of the image

    for human viewing

    for subsequent processing

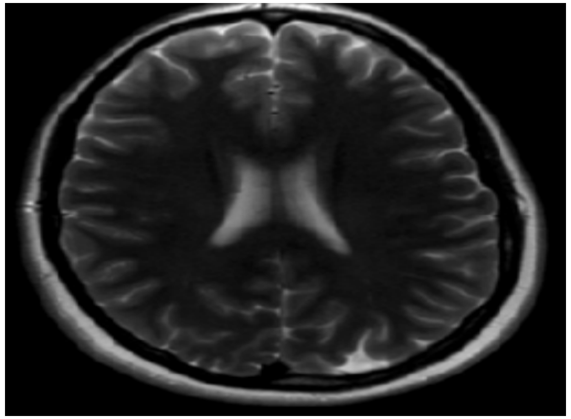
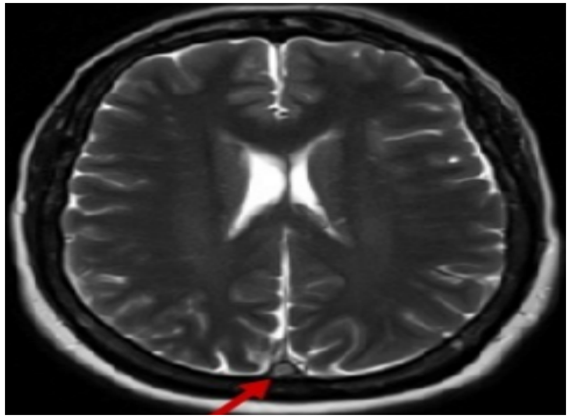
- No general theory of 'visual quality'

    General assumption: if it looks better, it is better

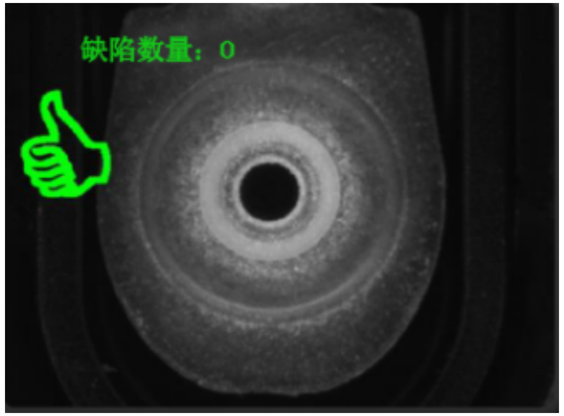
    Often not a good assumption

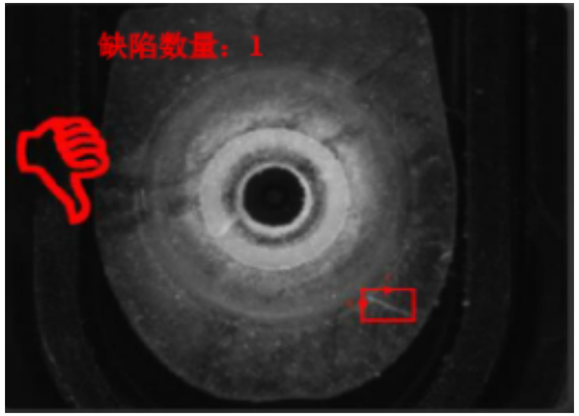
Application Field


Aeronautics and astronautics

Biomedical





Industrial production

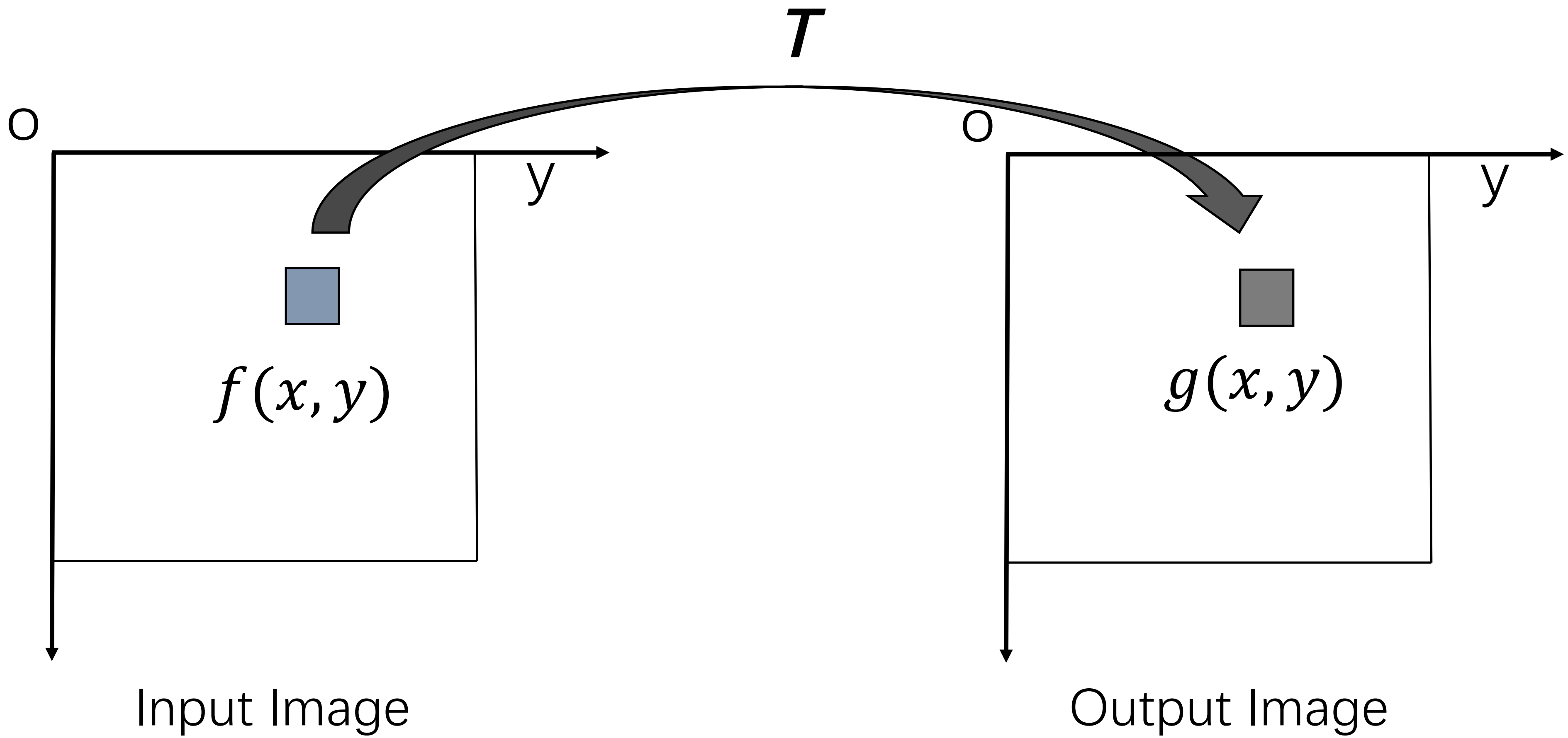

Public safety

Image Enhancement Methods

- Image enhancement
  - Spatial domain
    - Point operation
      - Gray-level transformation
      - Histogram modification
    - Local operation
      - Smoothing
      - Sharpen
  - Frequency domain
    - High-pass filtering
    - Low-pass filtering
    - Homomorphic filtering

Spatial domain method

- Point operation



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Spatial domain method

- Point operation

$$g(x, y) = T[f(x, y)]$$

$f(x, y)$ ------ *Original image*

T ------ *Space conversion function*

$g(x, y)$ ------ *Processed image*

Image Enhancement Methods

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    - Homomorphic filtering

Spatial domain method

- Point operation

Gray-level transformation

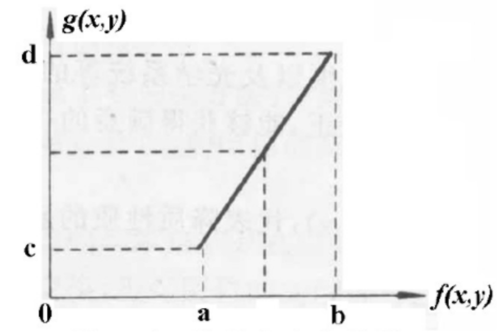
- Linear transformation
- Nonlinear transformation

Spatial domain method

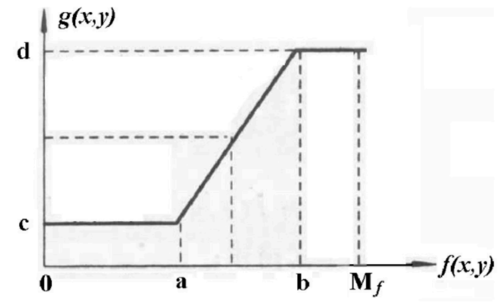
- Point operation

Linear transformation

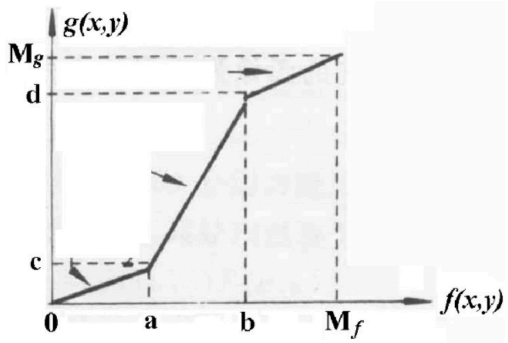
$$g(x,y) = \frac{d-c}{b-a}[f(x,y)-a]+c$$



$$g(x,y) = \begin{cases} c & 0 < f(x,y) < a \\ \dfrac{d-c}{b-a}[f(x,y)-a]+c & \mathrm{a} \le f(x,y) \le b \\ d & \mathrm{b} < f(x,y) \le M_f \end{cases}$$



$$g(x,y) = \begin{cases} \dfrac{c}{a} f(x,y) & 0 < f(x,y) < a \\ \dfrac{d-c}{b-a}[f(x,y)-a]+c & \mathrm{a} \le f(x,y) \le b \\ \dfrac{M_{g-d}}{M_{f-b}}[f(x,y-b)]+d & \mathrm{b} \le f(x,y) \le M_f \end{cases}$$



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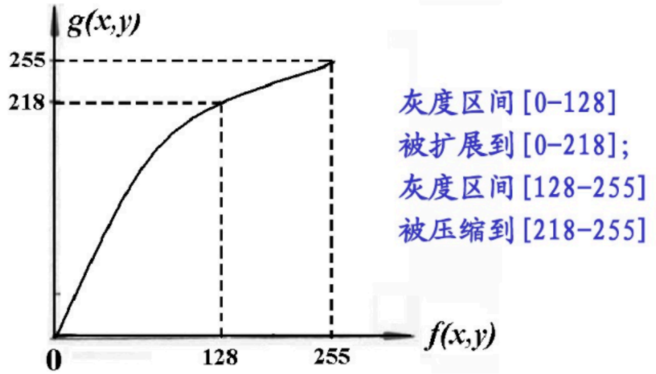
Spatial domain method

- Point operation

Nonlinear transformation

Logarithmic transformation

$$g(x,y) = a + \frac{\ln[f(x,y)+1]}{b \cdot lnc}$$



Exponential transformation

$$g(x,y) = b^{c[f(x,y)-a]} - 1$$

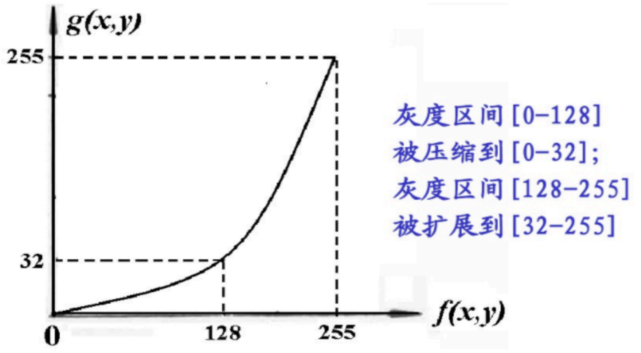


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Image Enhancement Methods

- Image enhancement
  - Spatial domain
    - Point operation
      - Gray-level transformation
      - Histogram modification
    - Local operation
      - Smoothing
      - Sharpen
  - Frequency domain
    - High-pass filtering
    - Low-pass filtering
    - Homomorphic filtering

Spatial domain method

- Point operation

Histogram

The histogram of a digital image with gray levels from 0 to L-1 is a discrete function $p(r) = n_r/N$, where:

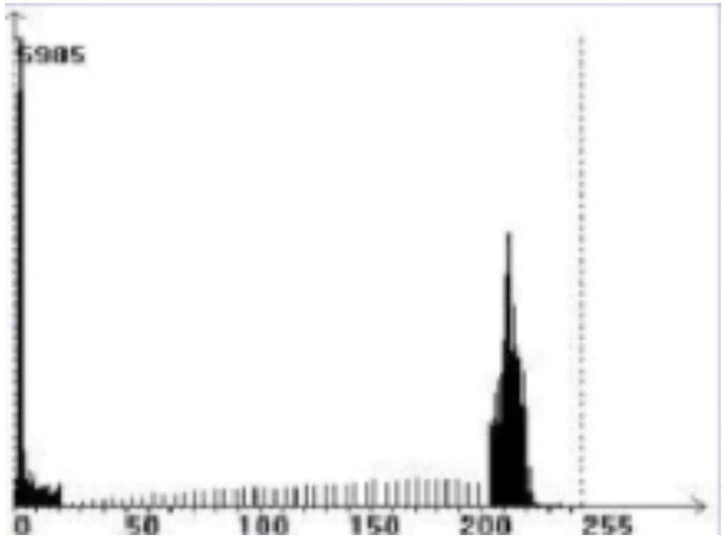
- r is the gray level , 0,1,2,⋯, L-1
- n_r is the number of pixels in the image with that gray level
- N is the total number of pixels in the image

Spatial domain method

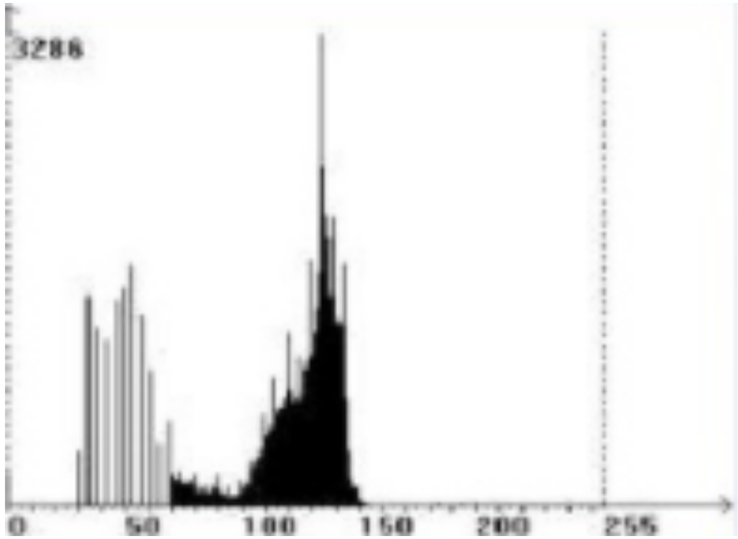
- Point operation

Histogram

Grayscale histograms reflect the gray distribution of an image



(a)



(b)

https://wenku.baidu.com/view/f439eed50b4e767f5bcfce3d.html

Spatial domain method

- Point operation

Histogram modification — Histogram equalization / Histogram specification

$$S = T(r)$$

r ------ Gray level of original image

T ------ Gray transformation function

S ------ Gray level of output image

Spatial domain method

- Point operation

Histogram equalization

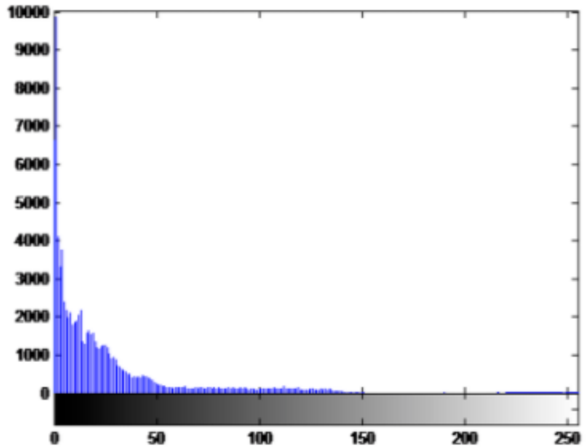
The goal is to modify the gray levels of an image so that
the histogram of the modified image is flat.

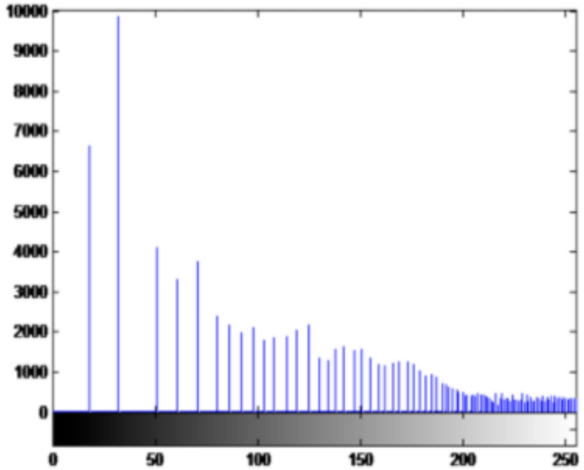
- Expand pixels in peaks over a wider range of gray-levels.
- “Squeeze” low plains pixels into a narrower range of gray levels.

Spatial domain method

- Point operation

  Histogram equalization





Spatial domain method

- Point operation

Histogram specification

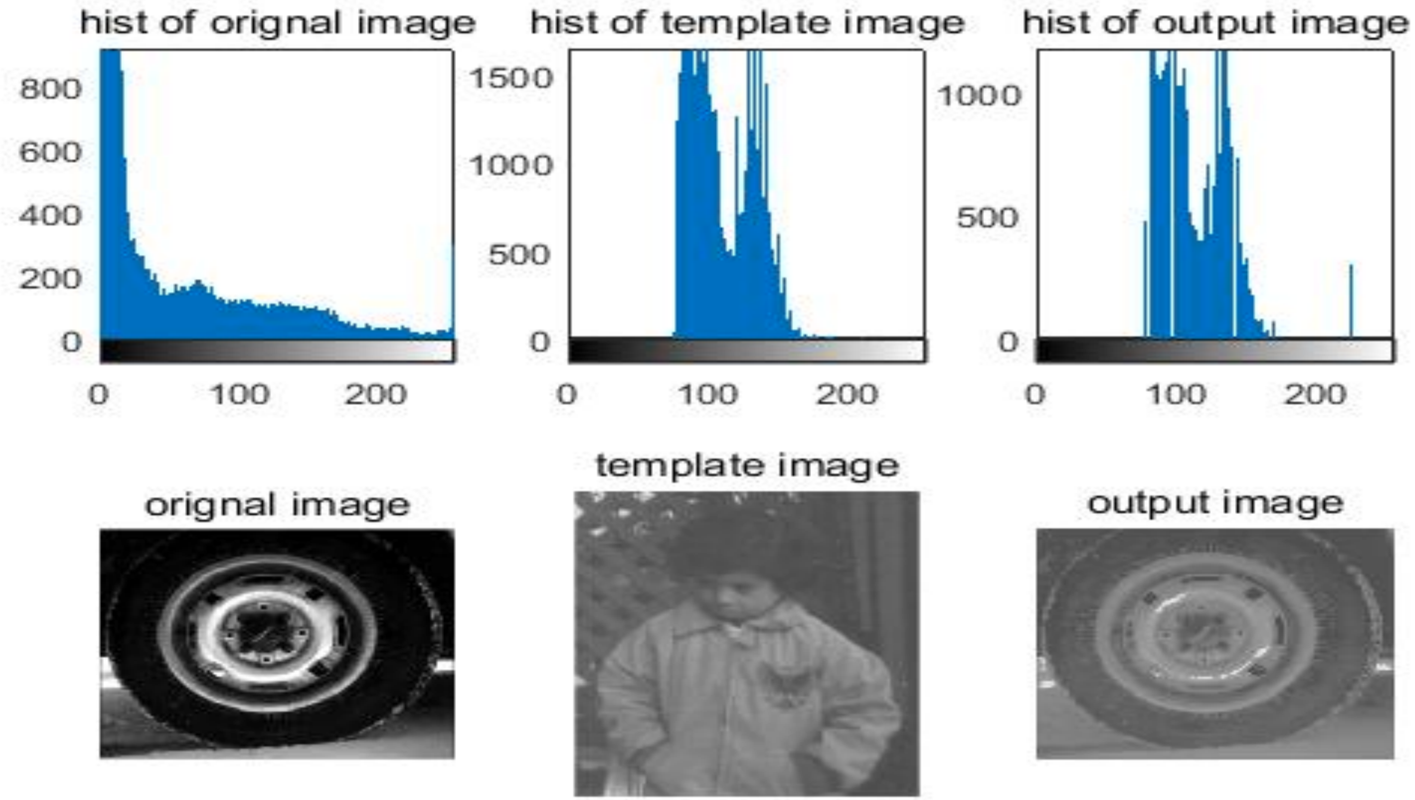
The method used to generate a processed image that has a specified histogram.

- Equalize the histogram of the input image
- Equalize the specified histogram
- Relate the two equalized histograms

Spatial domain method

- Point operation

Histogram specification



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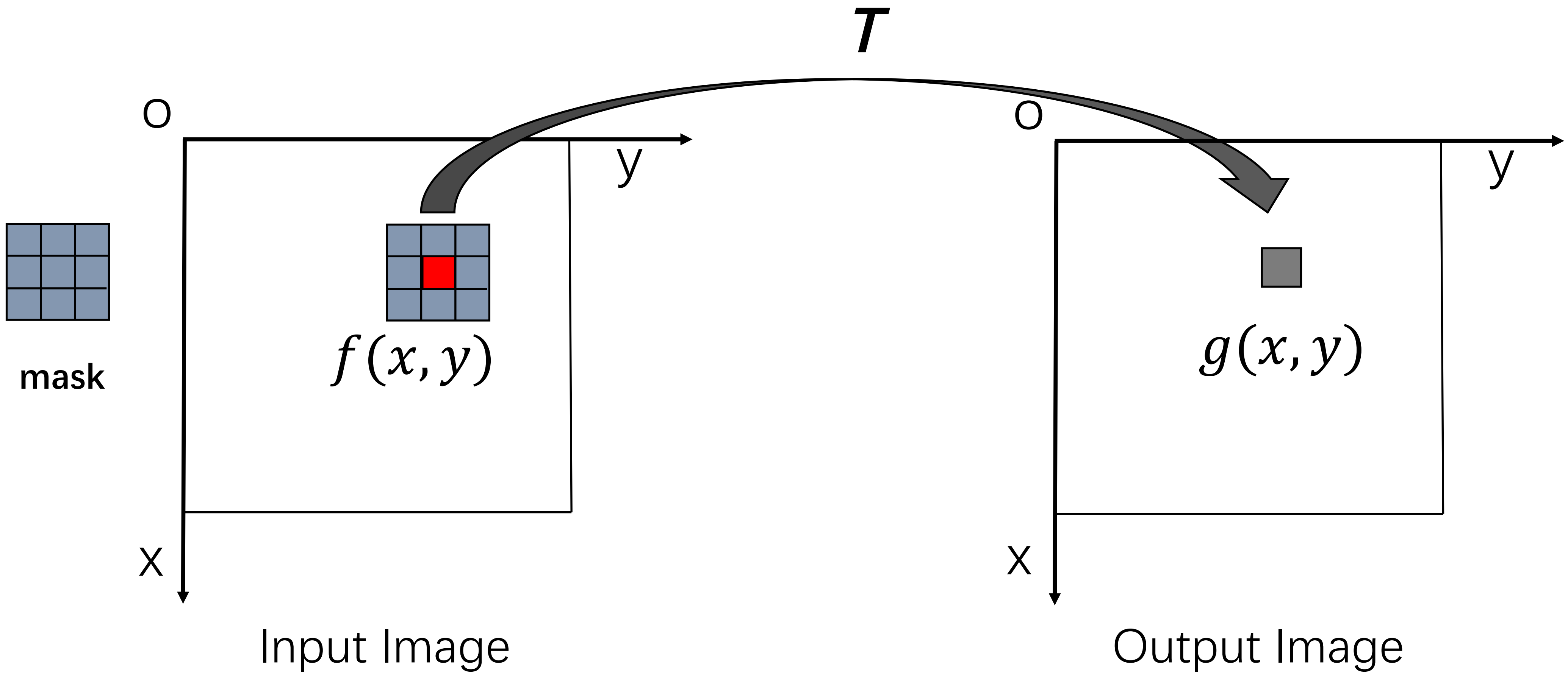
Spatial domain method

- Local operation



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Spatial domain method

- Local operation

Smoothing

Smooth (average, blur) an image without disturbing

- sharpness or
- position

of the edges

Spatial domain method

- Local operation

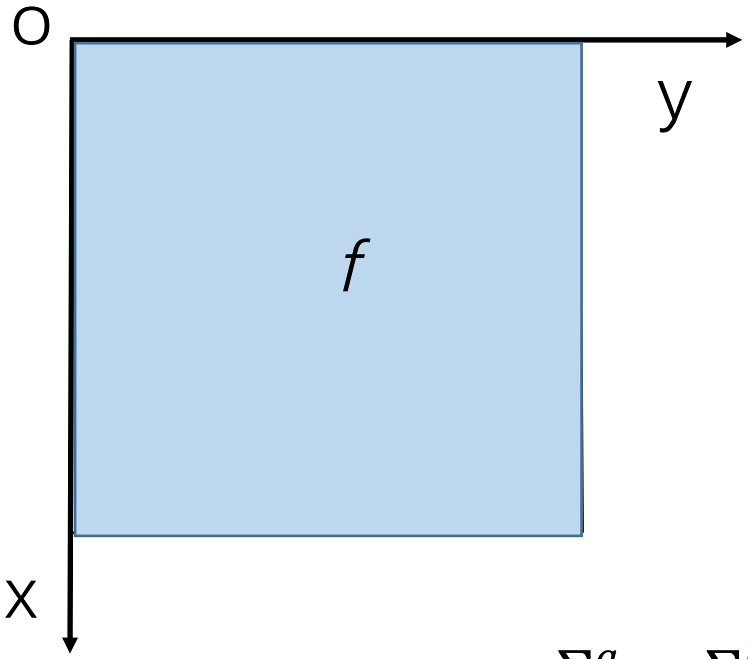
  Smoothing

Smoothing space filters
- Average filter
- Order-static filter
  - Maximum filter
  - Median filter
  - Minimum filter

Spatial domain method

- Local operation

Average filter



$$\frac{1}{9}\times\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$$\frac{1}{16}\times\begin{bmatrix}1 & 2 & 1\\ 2 & 4 & 2\\ 1 & 2 & 1\end{bmatrix}$$

$$g(x,y)=\frac{\sum_{s=-a}^{a}\sum_{t=-b}^{b}w(s,t)f(x+s,y+t)}{\sum_{s=-a}^{a}\sum_{t=-b}^{b}w(s,t)}$$

Spatial domain method

- Local operation

Average filter

Raw Image

Result

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Spatial domain method

- Local operation

Smoothing

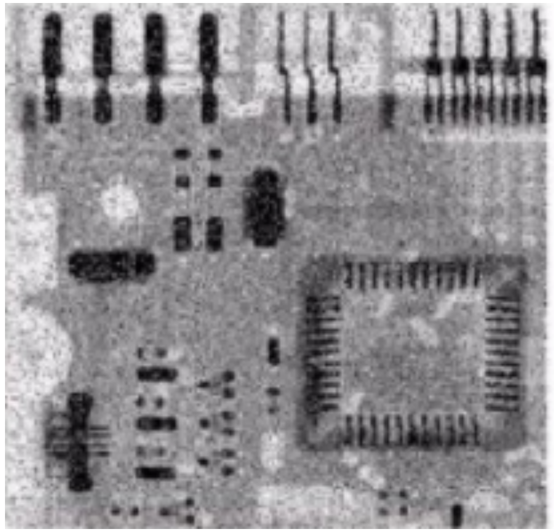
- Smoothing space filters
  - Average filter
  - Order-static filter
    - Maximum filter
    - Median filter
    - Minimum filter

Spatial domain method

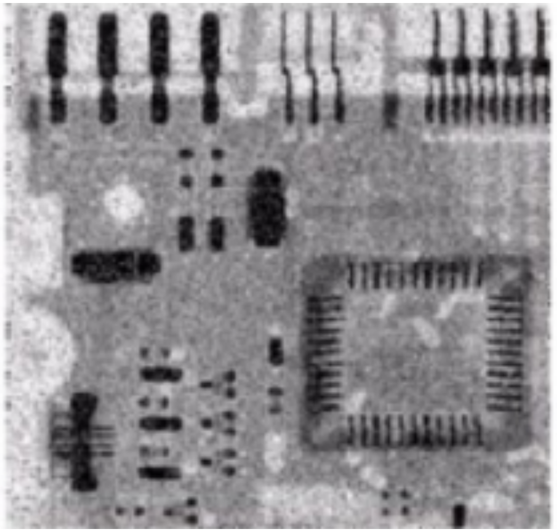
- Local operation

Median filter

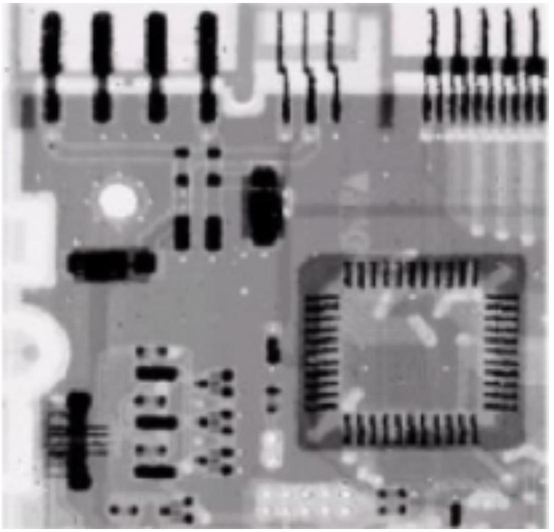
Replace pixel by the median value of its neighbor.



Raw Image



3×3 Average filter



3×3 Median filter

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Image Enhancement Methods

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Spatial domain method

- Local operation

Sharpen

Enhance detail features in a blurred image without increasing noise.

Sharpen space filters

Gradient operators

Laplacian operators

Spatial domain method

- Local operation

  Gradient operators

Roberts operators

$G_x =$

1.	0
0	-1

$G_y =$

0.	1
-1	0

$$G_x = 1 * f(x,y) + 0 * f(x+1,y) + 0 * f(x,y+1) + (-1) * f(x+1,y+1) = f(x,y) - f(x+1,y+1)$$

$$G_y = 0 * f(x,y) + 1 * f(x+1,y) + (-1) * f(x,y+1) + 0 * f(x+1,y+1) = f(x+1,y) - f(x,y+1)$$

$$G(x,y) = |G_x| + \left|G_y\right| = |f(x,y) - f(x+1,y+1)| + |f(x+1) - f(x,y+1)|$$

Sobel operators

$S_x =$

-1	0	1
-2	0.	2
-1	0	1

$S_y =$

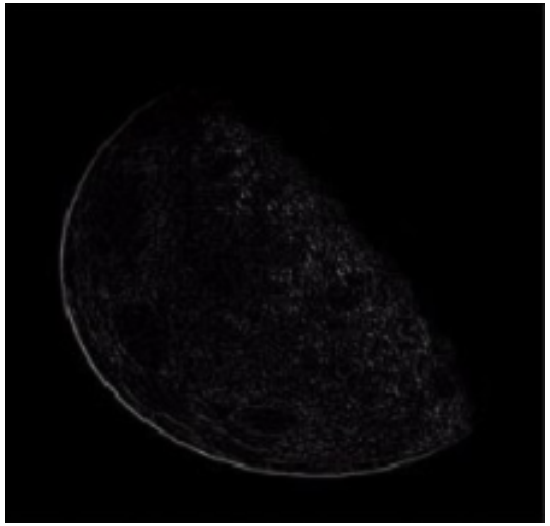
1	2	1
0	0.	0
-1	-2	-1

Spatial domain method

- Local operation

  Gradient operators

+



=

$f(x, y)$ $G(\cdot)$ $g(x, y)$

Spatial domain method

- Local operation

Laplacian operators

0	1	0
1	-4	1
0	1	0

1	1	1
1	-8	1
1	1	1

0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1

Raw image

Result

https://wenku.baidu.com/view/a804a638854769eae009581b6bd97f192379bf5d?pn=NaN

Image Enhancement Methods

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Frequency domain method

Spatial domain ⟶ Frequency domain ⟶ Spatial domain

(transfer function)

$$f(x,y) \xrightarrow{DFT} F(u,v) \xrightarrow{H(u,v)} G(u,v) \xrightarrow{IDFT} g(x,y)$$

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

Frequency domain method

Low-pass filtering : Smooth image and remove noise

High-pass filtering : Sharpen image remove blur and show the edge

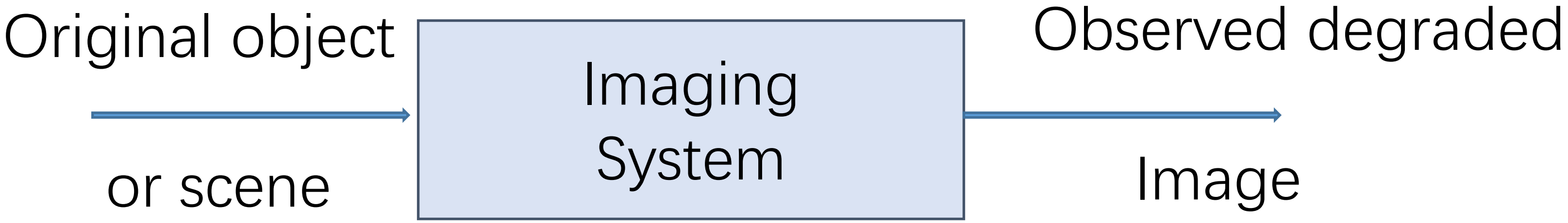
Homomorphic filtering : detail enhancement and contrast enhancement

02

Introduction to Image Restoration

Image Restoration

- This is the second stage in the processing of digital images.
- The observed image is assumed to be a degraded version of an original or "perfect" image.

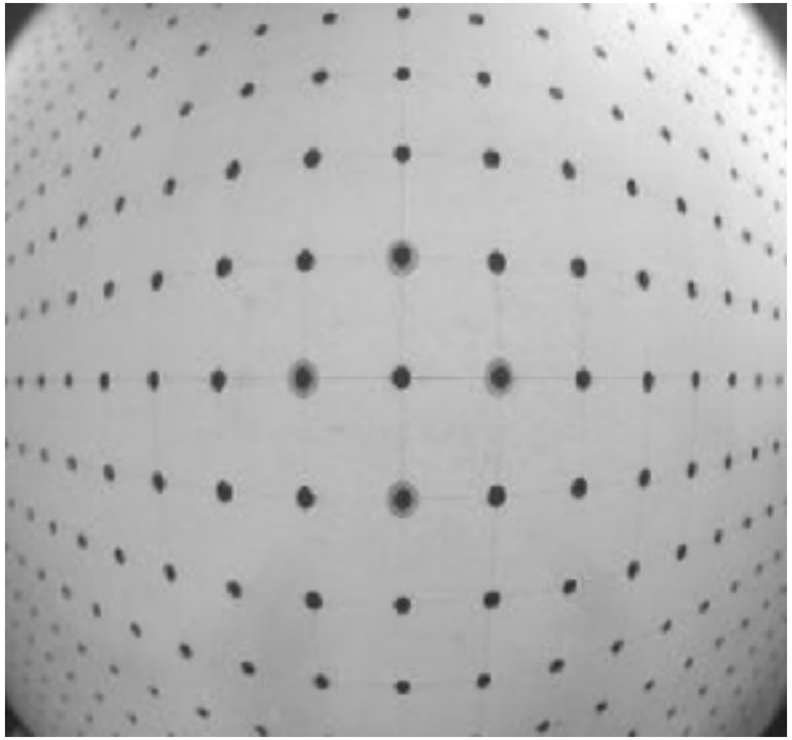


Degradations: blur, noise, etc.

Image Restoration

- Geometric distortion

(a)



(b)

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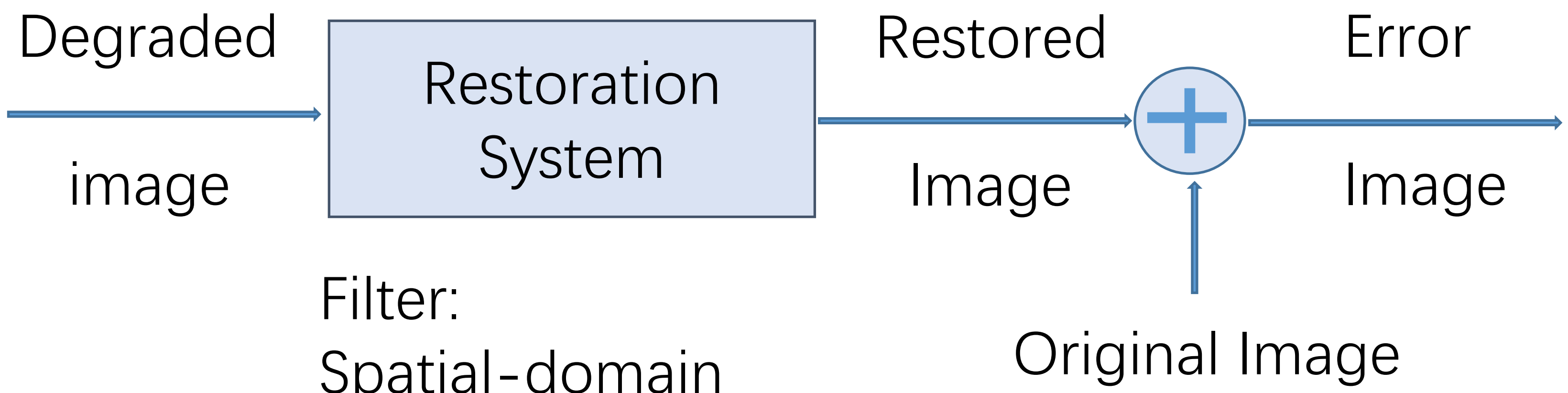
Image Restoration

- Blur

https://wenku.baidu.com/view/a34c9dc116fc700aba68fc3f.html

Image Restoration

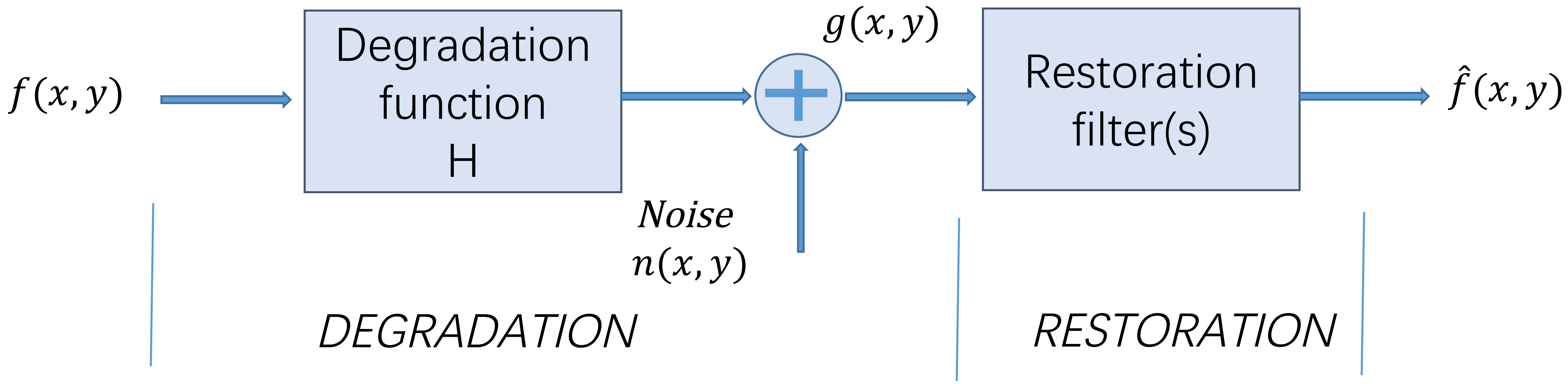
- Goal: Obtain a restored image such that the error between the original and the restored image is minimum in some sense.



Filter:
Spatial-domain
Frequency-domain
Nonlinear

Image Restoration

- Model of the image degradation/restoration process



Spatial domain $g(x,y) = h(x,y) * f(x,y) + n(x,y)$

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

Image Restoration

- Image restoration
  - Algebraic restoration
    - Constrained least squares filtering
    - … …
  - Filtering restoration
    - Inverse filtering restoration
    - Wiener filtering restoration
    - … …
  - Geometric restoration

Image Restoration

- Filtering restoration

  Inverse filtering restoration

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

Without considering noise : $$\hat{F}(u,v) = \frac{G(u,v)}{H(u,v)}$$

Transfer function : $$H_1(u,v) = \frac{1}{H(u,v)} = \frac{\hat{F}(u,v)}{G(u,v)}$$

Consider noise : $$\hat{F}(u,v) = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

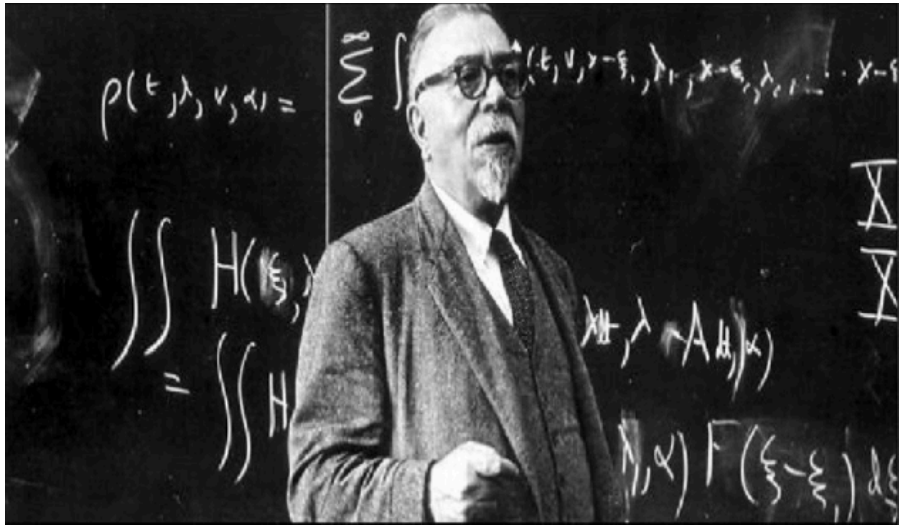
Image Restoration

- Filtering restoration

  Wiener filtering restoration

  Consider the (desired) image and noise as random fields

  Produce a linear estimate from the observed image to minimize MSE



Norbert Wiener

https://wenku.baidu.com/view/a34c9dc116fc700aba68fc3f.html

Image Restoration

- Filtering restoration

Wiener filtering restoration

Minimize MSE between the original and restored

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

Transfer function

$$\frac{\hat{F}(u,v)}{G(u,v)} = \frac{1}{H(u,v)} \cdot \frac{|H(u,v)|^2}{|H(u,v)|^2 + s\,\dfrac{P_n(u,v)}{P_f(u,v)}}$$

Result

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

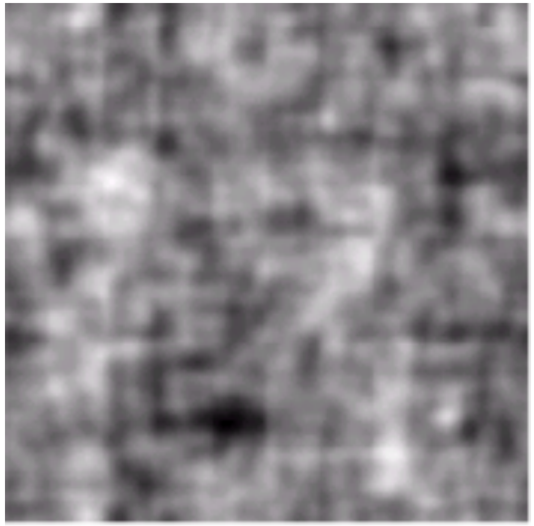
Image Restoration

- Filtering restoration

  Wiener filtering restoration

(a)

(b)



(c)

(d)

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Image Restoration

- Geometric restoration

  Space transformation

  Gray-level difference

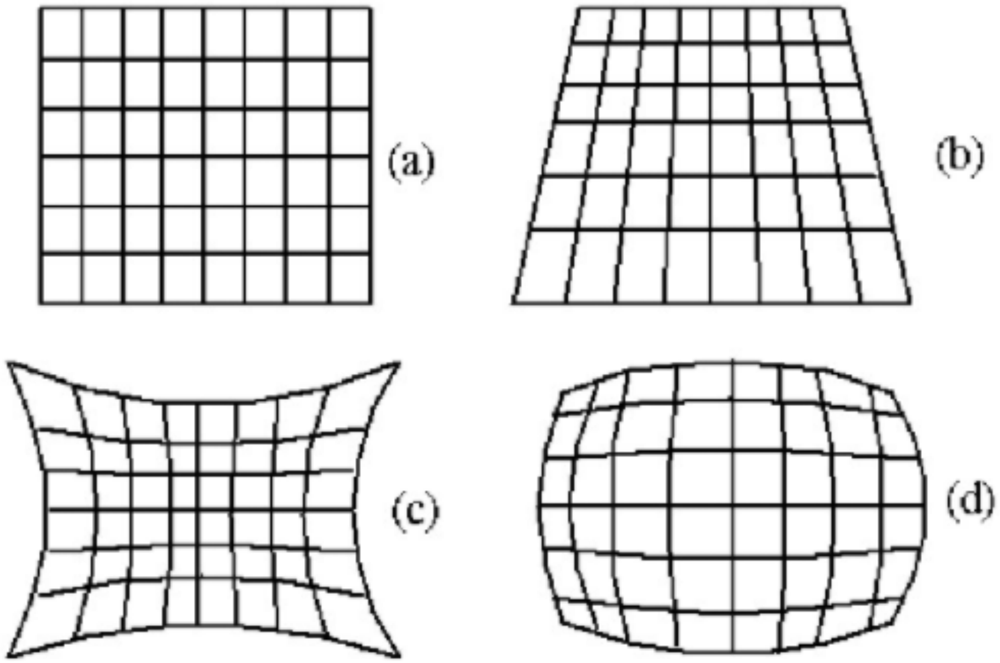

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Image Restoration

- Geometric restoration

Space transformation

This is a spatial transformation, i.e., from one coordinate system to another.

- Let $f(x, y)$ be defined over the co-ordinate system (x, y)
- Let $g(x', y')$ be a geometrically transformed image defined over the co-ordinate system (x', y')
- Then we have

$$x' = h_1(x, y)$$

$$y' = h_2(x, y)$$

Image Restoration

- Geometric restoration

Space transformation

Known $h_1(x, y)$ and $h_2(x, y)$

Direct method

The pixel co-ordinates of degraded image $(x', y') \longrightarrow (x, y)$

Indirect method

The integer coordinates of a hypothetical corrected image (x, y)

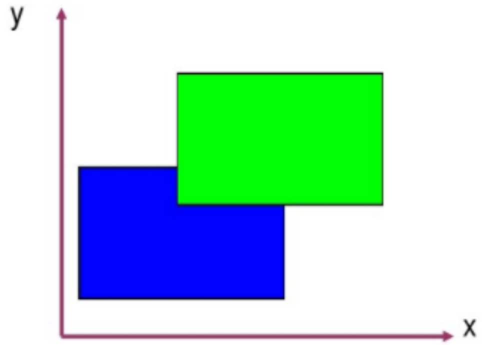
$\longrightarrow (x', y')$

Image Restoration

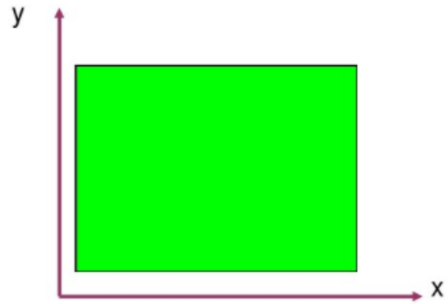
- Geometric restoration

  Space transformation

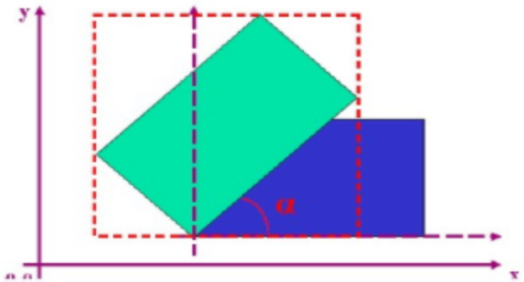
(a)
$$\begin{cases} x' = x + tx \\ y' = y + ty \end{cases}$$



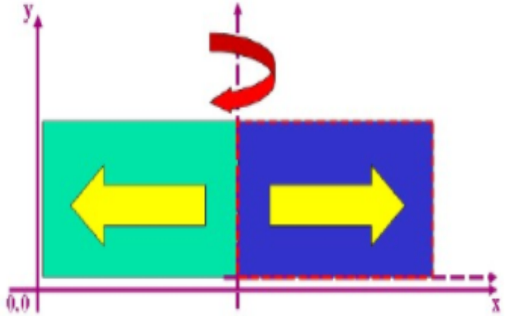
(b)
$$\begin{cases} x' = cx \\ y' = dy \end{cases}$$



(c)
$$\begin{cases} x' = x\cos\alpha - y\sin\alpha \\ y' = x\sin\alpha + y\cos\alpha \end{cases}$$



(d)
$$\begin{cases} x' = -x \\ y' = y \end{cases}$$



(e)
$$\begin{cases} x' = x \\ y' = -y \end{cases}$$

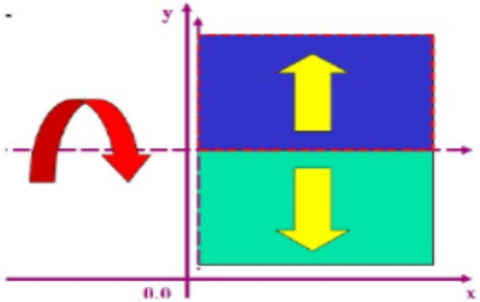


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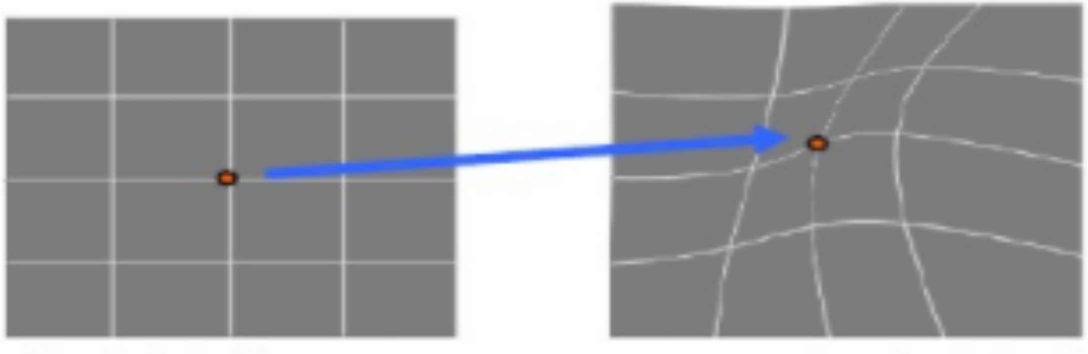
Image Restoration

- Geometric restoration

Space transformation

Unknown $h_1(x, y)$ and $h_2(x, y)$

$$x' = \sum_{i=0}^{n}\sum_{j=0}^{n-i} a_{ij}x^i y^j \qquad y' = \sum_{i=0}^{n}\sum_{j=0}^{n-i} b_{ij}x^i y^j$$



(a) (b)

https://wenku.baidu.com/view/ac7b512171fe910ef12df8b2.html?rec_flag=default&mark_pay_doc=2&mark_rec_page=1&mark_rec_position=1&mark_rec=view_r_1&clear_uda_param=1

Image Restoration

- Geometric restoration

Space transformation

Unknown $h_1(x,y)$ and $h_2(x,y)$

$$\begin{cases} x' = ax + by + c \\ y' = dx + ey + f \end{cases}$$

Distorted image (x_1', y_1'), (x_2', y_2'), (x_3', y_3')

Undistorted image (x_1, y_1), (x_2, y_2), (x_3, y_3)

$$x_1' = ax_1 + by_1 + c \qquad y_1' = dx_1 + ey_1 + f$$
$$x_2' = ax_2 + by_2 + c \qquad y_2' = dx_2 + ey_2 + f$$
$$x_3' = ax_3 + by_3 + c \qquad y_3' = dx_3 + ey_3 + f$$

Image Restoration

- Geometric restoration

Gray-level difference

$$\begin{cases} x' = ax + by + c \\ y' = dx + ey + f \end{cases}$$

The pixel value of a non integer is judged by the pixel values around its integer coordinates.

- Nearest neighbor interpolation
- Bilinear interpolation

Image Restoration

- Geometric restoration

Gray-level difference

- Nearest neighbor interpolation

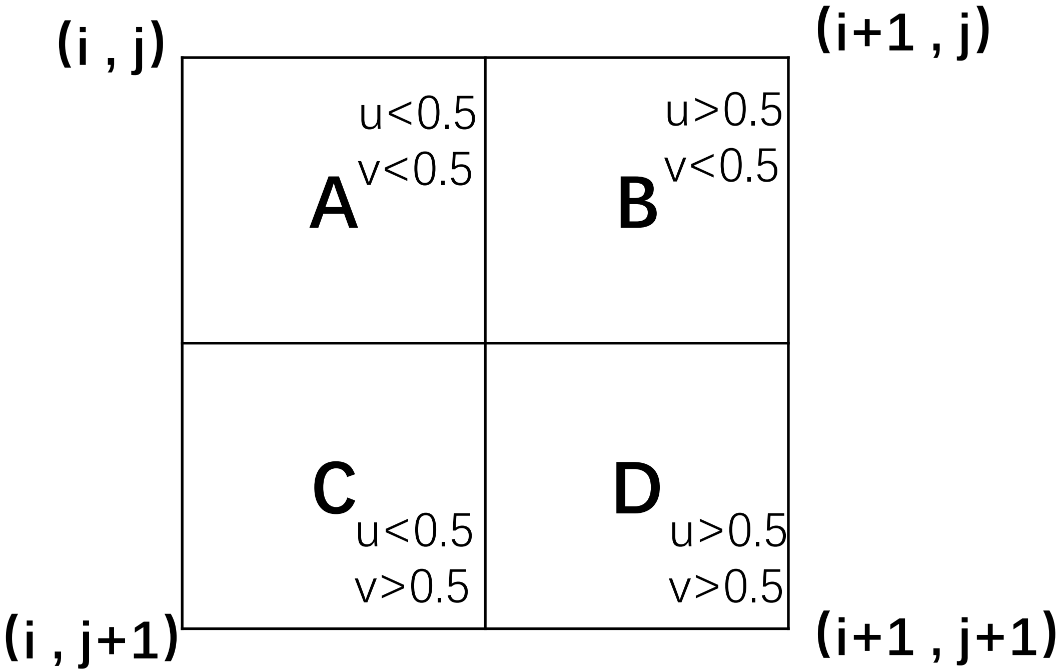


Image Restoration

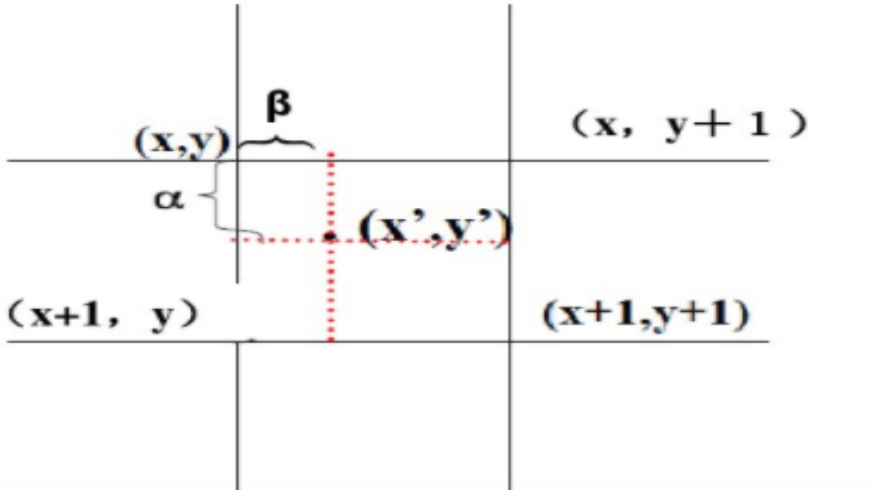
- Geometric restoration

Gray-level difference

- Bilinear interpolation

$$f(x',y') = (1-\alpha)(1-\beta)f(x,y) + (1-\alpha)\beta f(x,y+1)$$

$$+\alpha(1-\beta)f(x+1,y) + \alpha\beta f(x+1,\ \ y+1)$$



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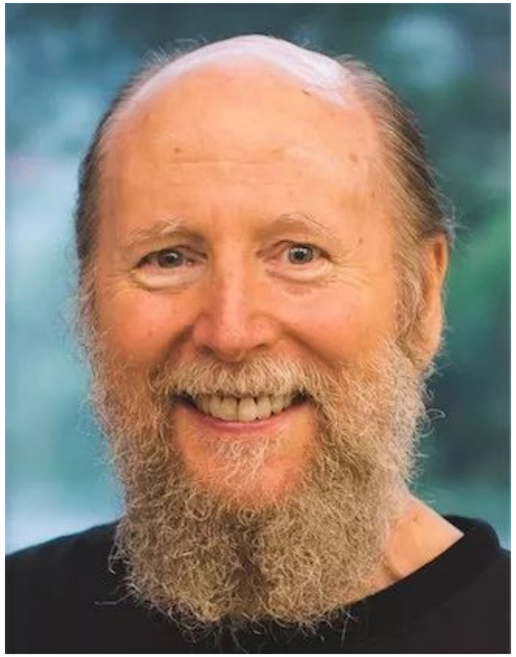
Reinforcement Learning

《Reinforcement Learning: An Introduction》

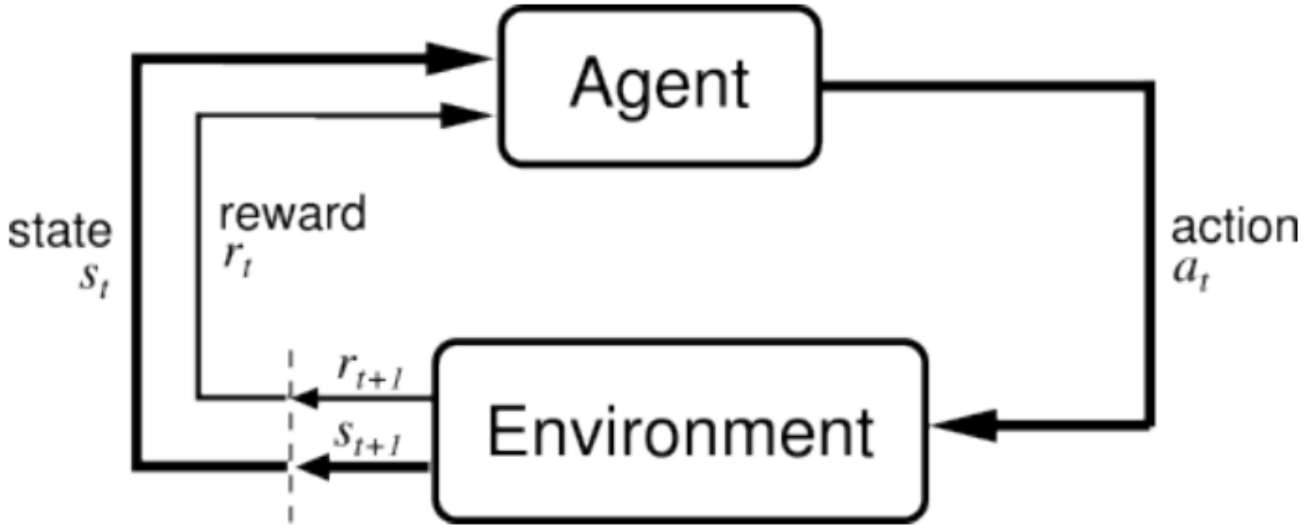
Richard S. Sutton and Andrew G. Barto



https://www.zhihu.com/question/50461146

Reinforcement Learning

"Reinforcement learning problems involve learning what to do—how to map situations to actions—so as to maximize a numerical reward signal."



《Reinforcement Learning: An Introduction》Richard S. Sutton and Andrew G. Barto

http://www.cis.upenn.edu/~cis519/fall2015/lectures/14_ReinforcementLearning.pdf

Reinforcement Learning

- Formally this is a Markov decision process (MDP)

S： a set of states

A： a set of actions

P_{sa}： state transition distributions

$$\sum_{s'} P_{sa}(S) = 1 \ , \qquad P_{sa}(s') \geq 0$$

R ：the reward function

$$S_0 \xrightarrow{a_0} S_1 \xrightarrow{a_1} S_2 \xrightarrow{a_2} S_3 \xrightarrow{a_3} \cdots$$

Crafting a Toolchain for Image Restoration by Deep Reinforcement Learning

Ke Yu   Chao Dong   Liang Lin   Chen Change Loy

Image Restoration

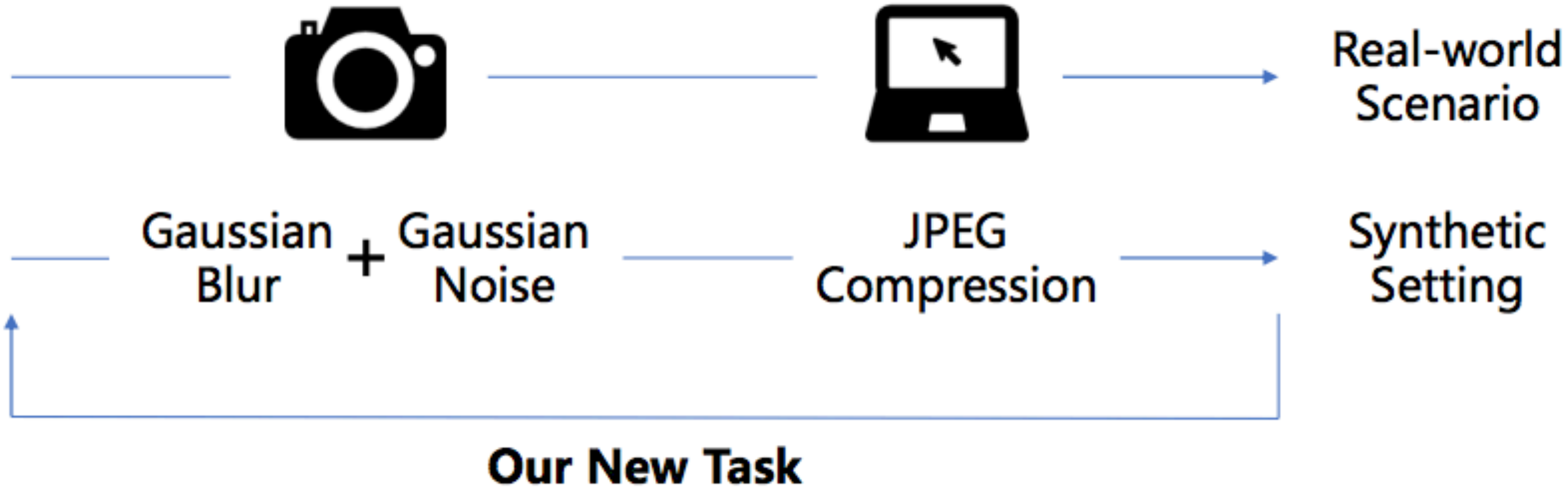
- There are many individual tasks
  - Denoising
  - Debluring
  - JPEG Deblocking
  - Super-Resolution
  - …
- Towards more complicated distortions
  - Address multiple levels of degradation in one task [1,2]
  - Address multiple individual tasks [3]

[1] J. Kim, J. Kwon Lee, and K. Mu Lee. Accurate image super-resolution using very deep convolutional networks. In CVPR, 2016.
[2] Y. Tai, J. Yang, X. Liu, and C. Xu. Memnet: A persistent memory network for image restoration. In ICCV, 2017.
[3] K. Zhang,W. Zuo, Y. Chen, D. Meng, and L. Zhang. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. TIP, 2

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Image Restoration – A New Setting

- Consider **multiple distortions simultaneously**
  - Real-world: Image capture and storage
  - Synthetic: Gaussian blur, Gaussian noise and JPEG compression



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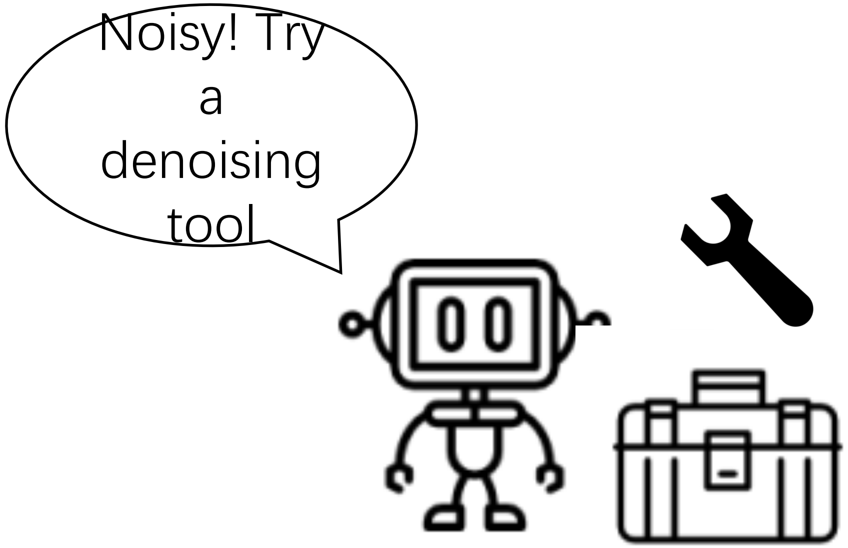
Motivation

- Can we use a single CNN to address multiple distortions
  - Inefficient: Require a huge network to handle all the possibilities
  - Inflexible: All kinds of distorted images are processed with the same structure
- Find a more **efficient** and **flexible** approach!
  - Process different distortion in a different way

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Method – Decision Making

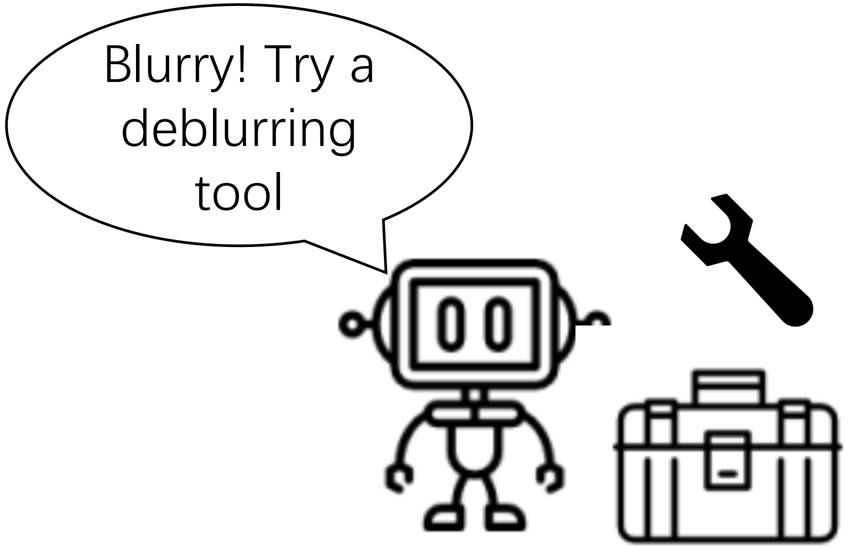
- Progressively restore the image quality
- Treat image restoration as a **decision making** process



http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Method – Decision Making

- Progressively restore the image quality
- Treat image restoration as a **decision making** process



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Method – Decision Making

- Progressively restore the image quality
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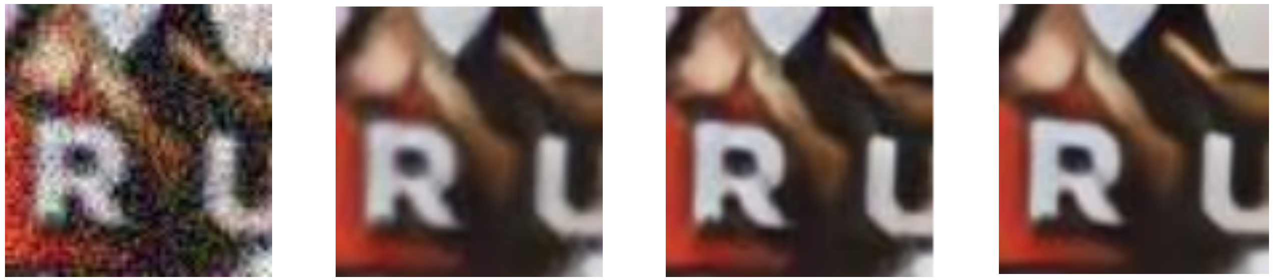
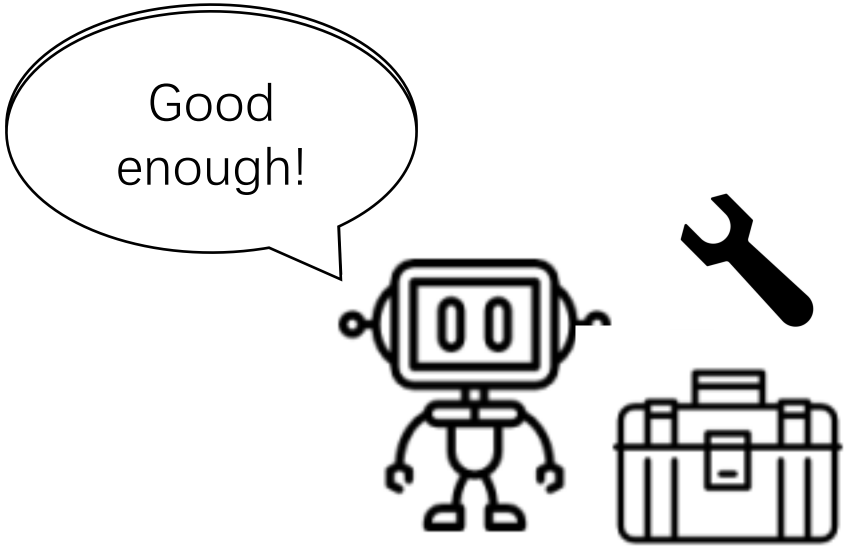
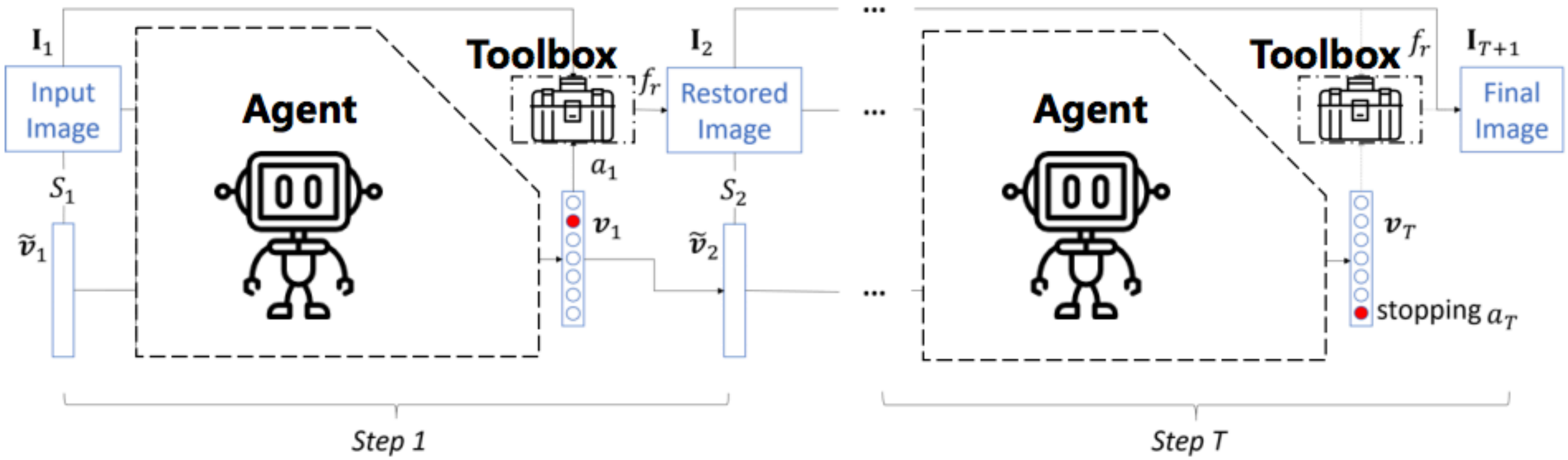




Method – Overview

- Our framework requires a **toolbox** and an **agent**



http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Method – Toolbox

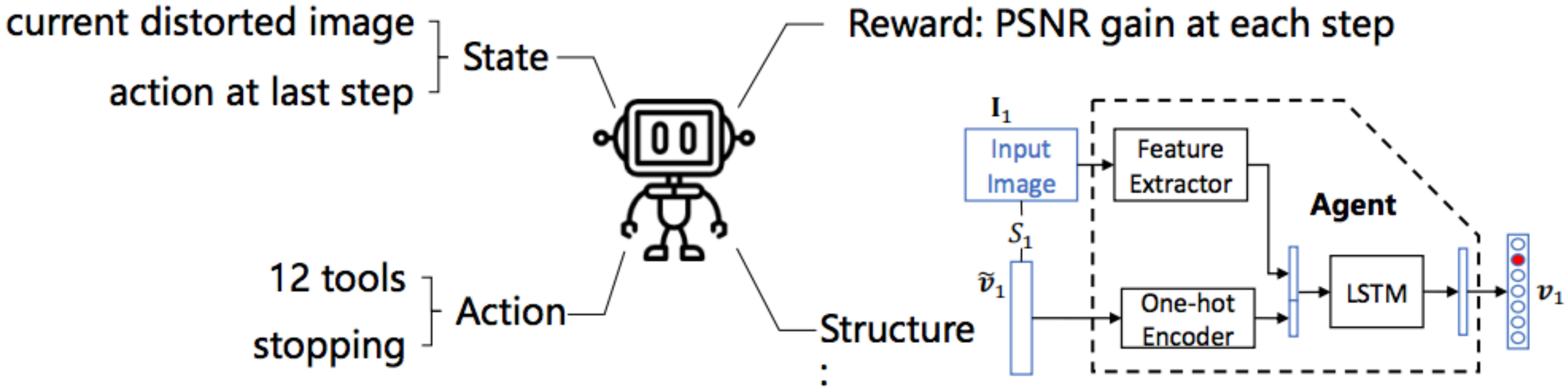
- We design 12 tools, each of which addresses a simple task
  - 3-layer CNN [1]
  - 8-layer CNN

Distortion Type (Parameters)	Distortion Level Interval	CNN Depth
Gaussian Blur (σ)	[0, 1.25], [1.25, 2.5]	3
	[2.5, 3.75], [3.75, 5]	8
Gaussian Noise (σ)	[0, 12.5], [12.5, 25]	3
	[25, 37.5], [37.5, 50]	8
JPEG Compression (Q)	[60, 100], [35, 60]	3
	[20, 35], [10, 20]	8

[1] C. Dong, C. C. Loy, K. He, and X. Tang. Image super-resolution using deep convolutional networks. TPAMI, 38(2):295–307, 2016.

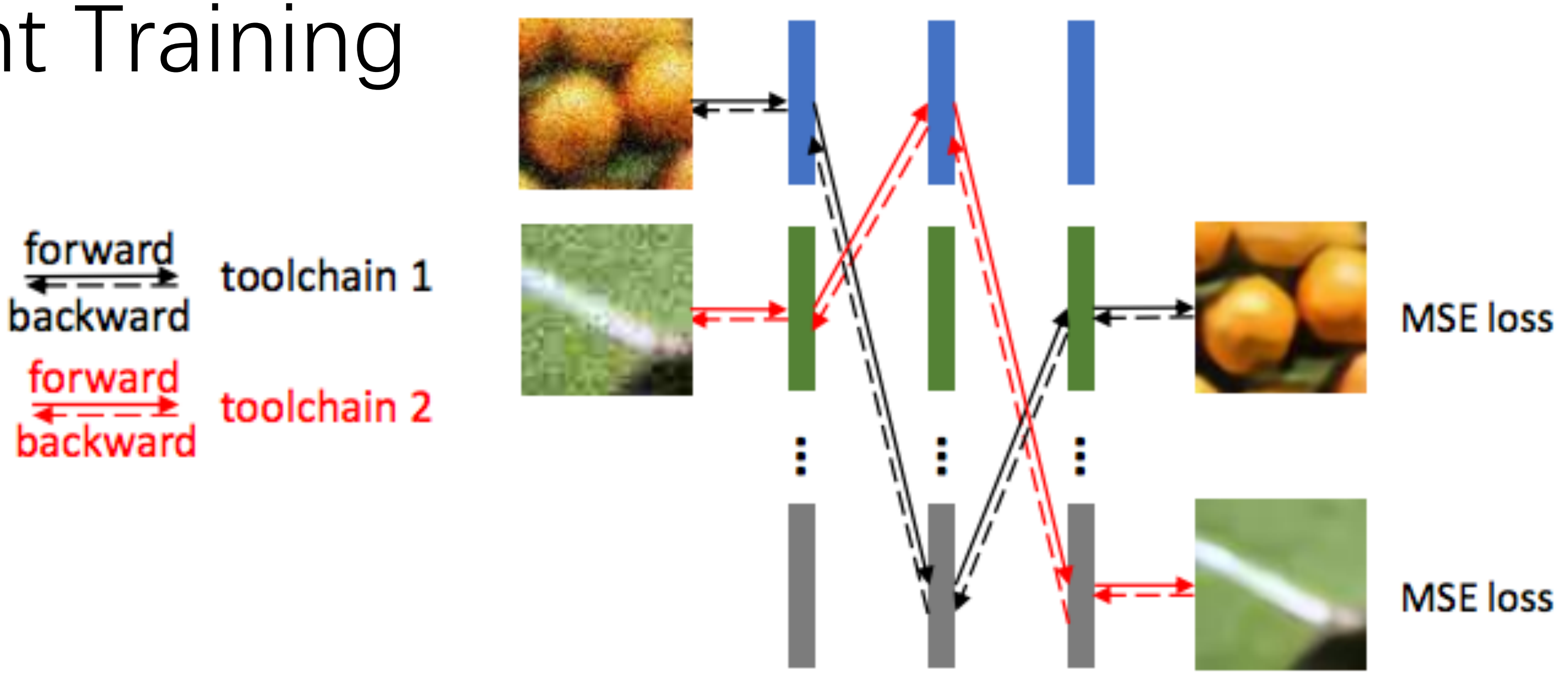
Method – Agent

- Use **reinforcement learning** to address tool selection



Method – Joint Training

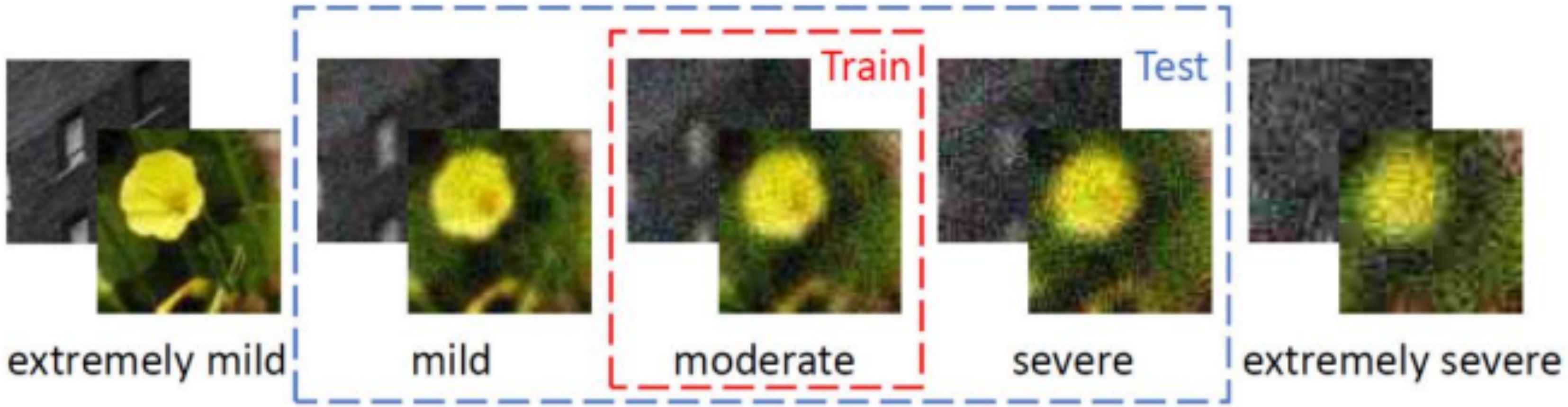
- Challenge of 'Middle State'
  - Intermediate results after several steps of processing
  - None of the tools has seen these intermediate results
- Joint Training



http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Experimental Results

- Dataset: DIV2K [1]



- Comparison with generic models for image restoratio
  - VDSR [2]
  - DnCNN [3]

[1] E. Agustsson and R. Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In CVPR Workshop, 2017.

[2] J. Kim, J. Kwon Lee, and K. Mu Lee. Accurate image super-resolution using very deep convolutional networks. In CVPR, 2016.

[3] K. Zhang,W. Zuo, Y. Chen, D. Meng, and L. Zhang. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. TIP, 2

Experimental Results

- Quantitative results on DIV2K

Test Set	Mild (unseen)		Moderate		Severe (unseen)	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
DnCNN	28.03	**0.6503**	26.42	0.5554	24.99	0.4658
VDSR	**28.04**	0.6496	26.40	0.5544	24.90	0.4629
VDSR-s	27.69	0.6383	25.99	0.5399	24.50	0.4505
RL-Restore	28.04	0.6498	**26.45**	**0.5587**	**25.20**	**0.4777**

Competitive performanc

Better generality

Test Set	Mild	Moderate	Severe
DnCNN	**28.03**	26.42	24.99
RL-Restore + BN	28.02	**26.48**	**25.29**

- Runtime Analyses

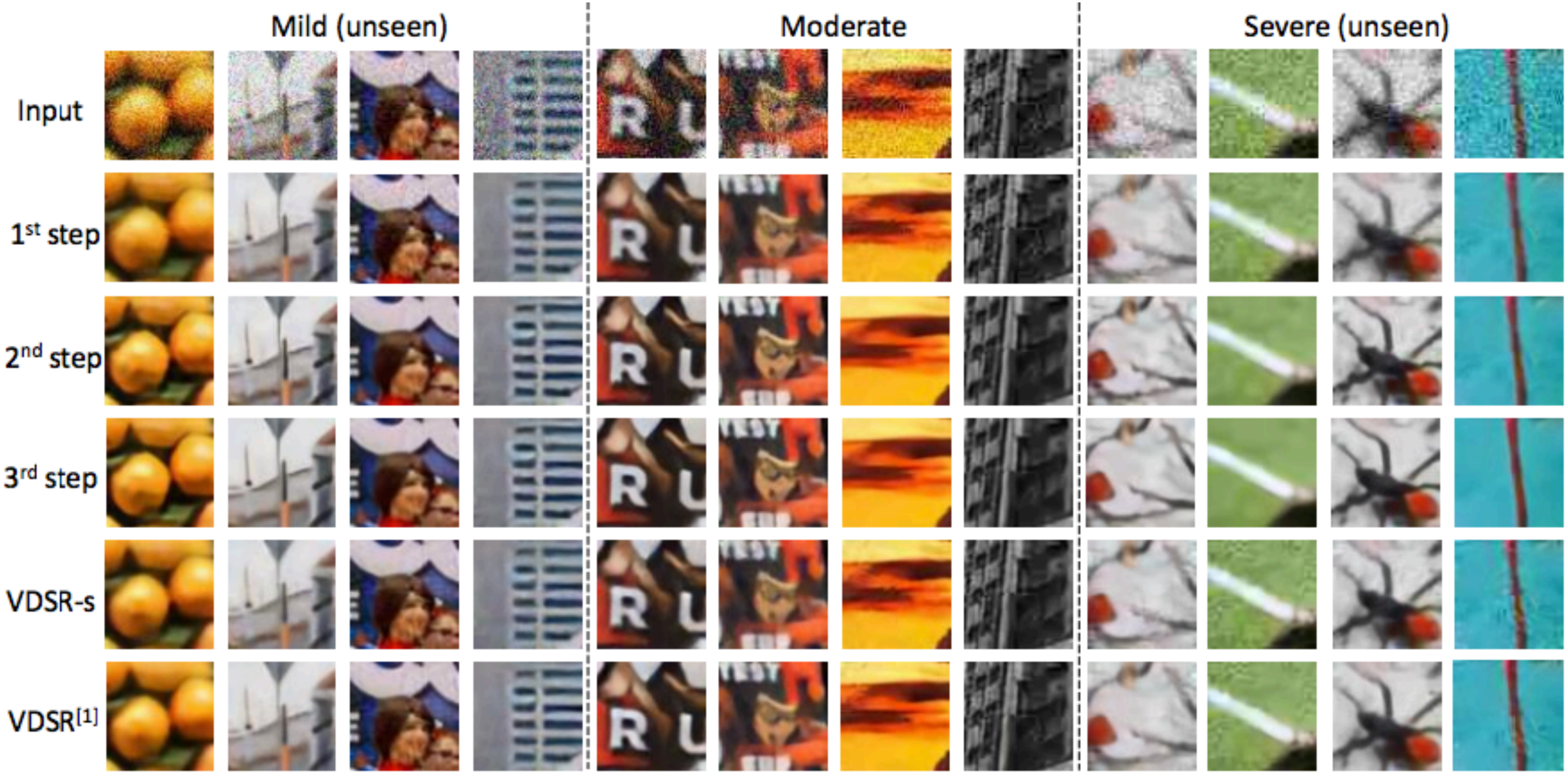
Model	DnCNN	VDSR	VDSR-s	*RL-Restore*
Time	0.0280	0.0238	0.0144	**0.0128**

More efficient

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Experimental Results

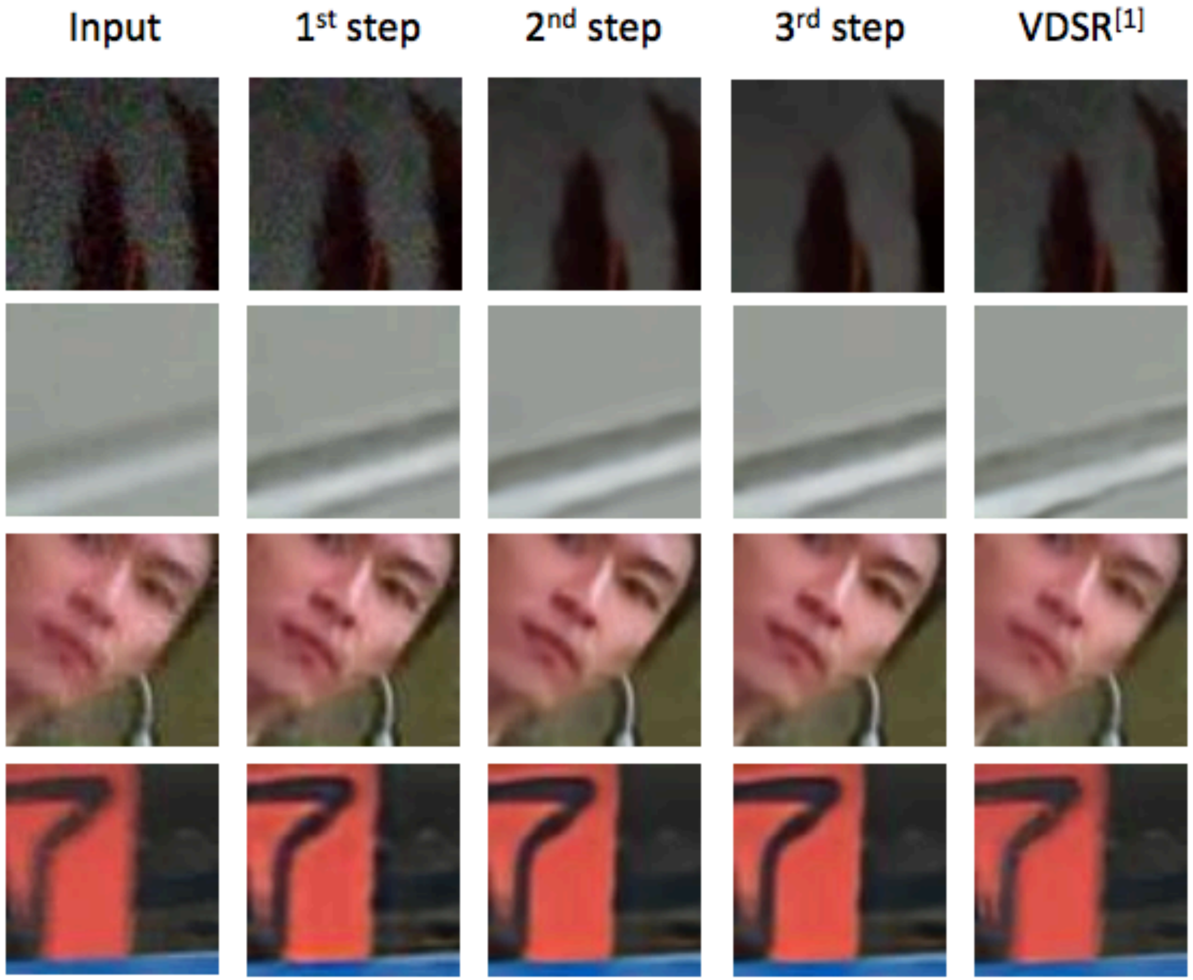
- Quantitative results on DIV2K



http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Experimental Results

- Quantitative results on real-world images



[1] J. Kim, J. Kwon Lee, and K. Mu Lee. Accurate image super-resolution using very deep convolutional networks. In CVPR, 2016.

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Experimental Results

- Ablation Study

Test Set	Mild (unseen)		Moderate		Severe (unseen)	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
+Joint	**28.04**	**0.6498**	**26.45**	**0.5587**	**25.20**	**0.4777**
+Noise	27.78	0.6372	26.20	0.5441	24.97	0.4643
Original	27.52	0.6027	25.91	0.5119	24.81	0.4490

Joint training

Test Set	Mild (unseen)		Moderate		Severe (unseen)	
Metric	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
w/ Stopping	**27.78**	**0.6372**	**26.20**	**0.5441**	**24.97**	**0.4643**
w/o Stopping	27.61	0.6284	26.08	0.5351	24.85	0.4589

Stopping action

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf

Conclusion

- Contributions
  - Address image restoration in a reinforcement learning framework
  - Propose joint learning to cope with middle process state
  - Dynamically formed toolchain performs competitively against human-designed networks with less computational complexity
- Future work
  - Incorporate more tools (trained with GAN loss)
  - Handle spatial-variant distortions

http://ice.dlut.edu.cn/valse2018/ppt/2018ValseDChao.pdf