



國立高雄第一科技大學
National Kaohsiung First University of Science and Technology

Histogram Equalization

Author: Shih-Shinh Huang

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Outline

- Image Histogram
- Equalization Algorithm
- Theorem and Proof



Image Histogram

- Definition

- The histogram of a digital image is a discrete function $p(r_k)$ with gray values r_0, r_1, \dots, r_{L-1} .

$$p(r_k) = \frac{n_k}{n}$$

- n_k : number of pixels with gray value r_k :
- n : total number of pixels in the image

Image Histogram

- Definition

- **Example:** A 10x10 image I_{in} with gray values with gray values $r_0 = 0, r_1 = 1, \dots, r_7 = 7$

0	6	5	3	4	1	1	3	4	1
3	2	3	4	3	2	3	4	3	2
2	1	0	3	4	2	2	0	4	2
1	0	5	6	1	2	5	6	7	2
6	3	4	6	1	1	4	6	7	1
3	1	5	2	1	3	0	2	1	3
2	1	2	0	4	2	2	3	4	2
1	0	5	6	7	2	5	6	7	2
1	3	4	1	7	0	4	0	7	1
3	1	5	2	1	3	5	2	1	0

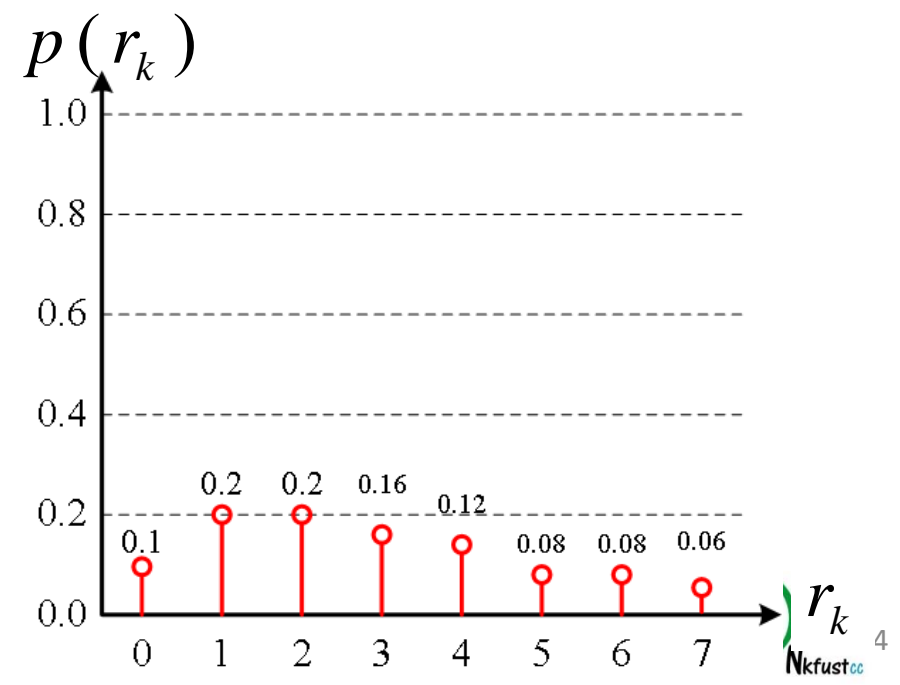


Image Histogram

- Typical Histograms
 - Histogram provides a global description of the image appearance

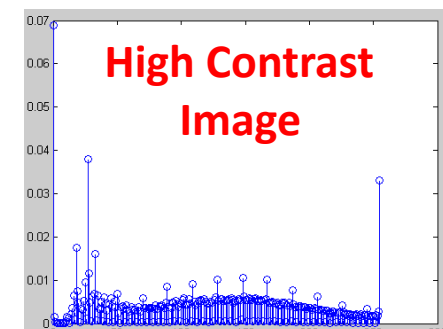
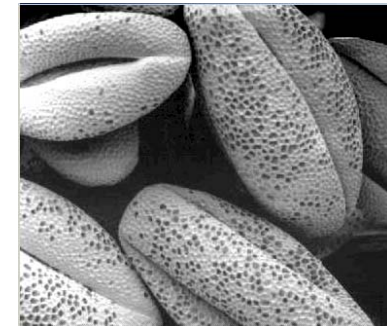
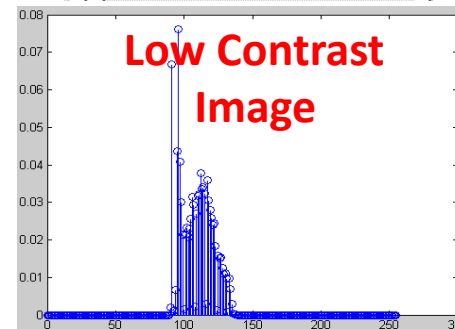
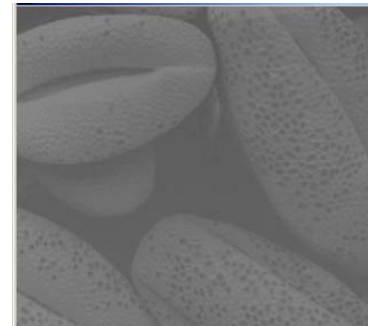
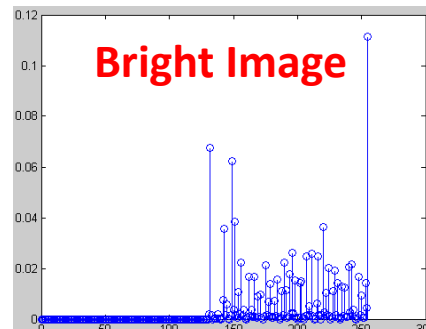
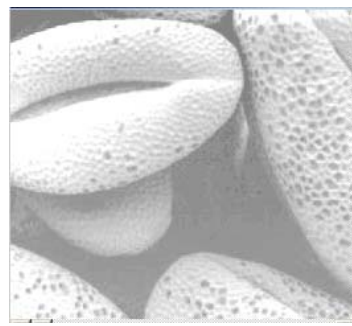
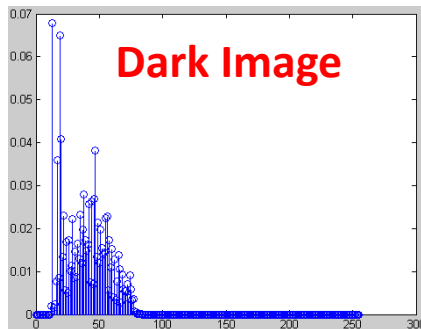
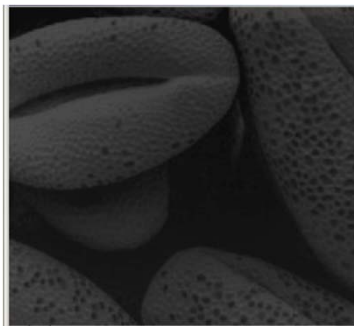
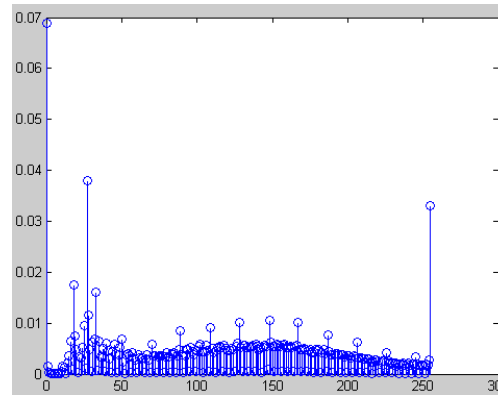
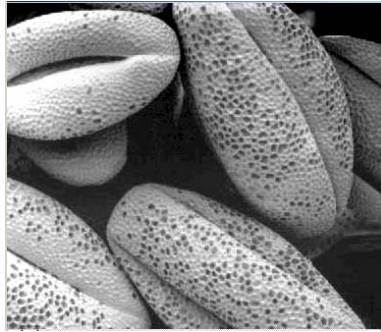


Image Histogram

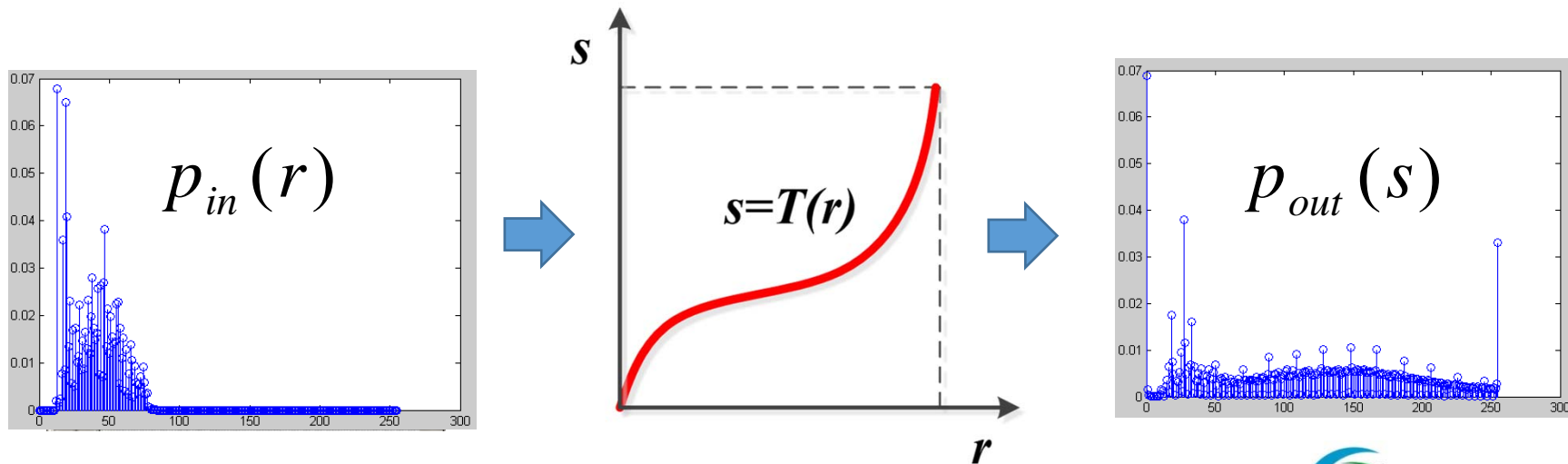
- Typical Histograms



- The histogram of the high contrast image is more uniformly distributed in all gray values.
- Histogram equalization is an algorithm to transfer the original histogram to a more flat one.

Equalization Algorithm

- Formal Description
 - Design a transformation $s = T(r)$ to **equalize** the distribution of the original image I_{in} .



Equalization Algorithm

- Design of $s = T(r)$

Maximal Intensity

Cumulative Distribution
Function

$$s_k = T(r_k) = (L-1) \times \sum_{j=0}^k p_{in}(r_j)$$

$$s_0 = T(r_0 = 0) = (L-1) \times \sum_{j=0}^{k=0} p_{in}(r_j)$$

$$s_1 = T(r_1 = 1) = (L-1) \times \left(\sum_{j=0}^{k=1} p_{in}(r_0) p_{in}(r_j) p_{in}(r_1) \right)$$

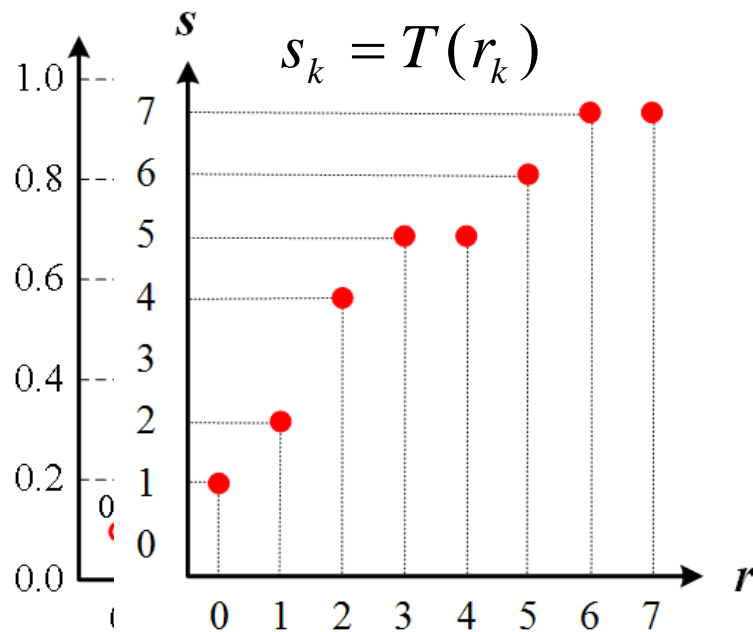
⋮
⋮



Equalization Algorithm

- Design of $s = T(r)$

$$s_k = T(r_k) = (L-1) \times \sum_{j=0}^k p_{in}(r_j)$$



$$s_0 = T(r_0 = 0) = 7 \times (0.1) = 0.7 \rightarrow 1$$

$$s_1 = T(r_1 = 1) = 7 \times (0.1 + 0.2) = 2.1 \rightarrow 2$$

⋮

$$s_7 = T(r_7 = 7) = 7 \times (0.1 + \dots + 0.06) = 7$$

=1



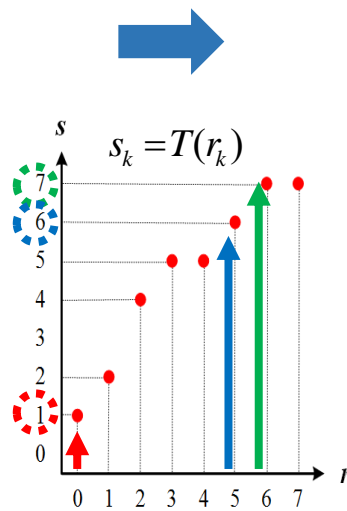
Equalization Algorithm

- Image Transformation

$$I_{out}(x, y) = T(I_{in}(x, y))$$

0	6	5	3	4	1	1	3	4	1
3	2	3	4	3	2	3	4	3	2
2	1	0	3	4	2	2	0	4	2
1	0	5	6	1	2	5	6	7	2
6	3	4	6	1	1	4	6	7	1
3	1	5	2	1	3	0	2	1	3
2	1	2	0	4	2	2	3	4	2
1	0	5	6	7	2	5	6	7	2
1	5	4	1	7	0	4	0	7	1
5	1	5	2	1	5	5	2	1	0

I_{in}

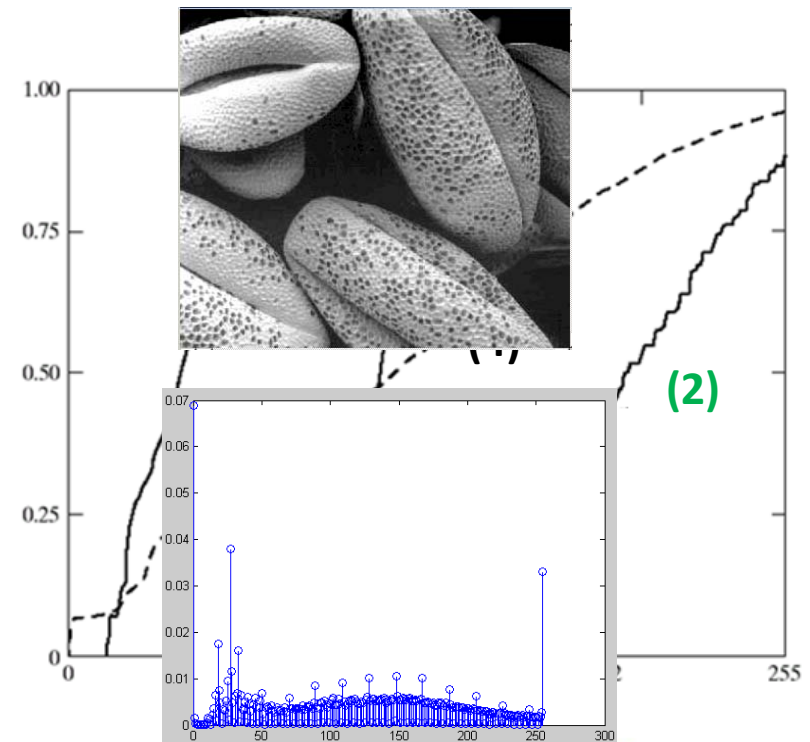
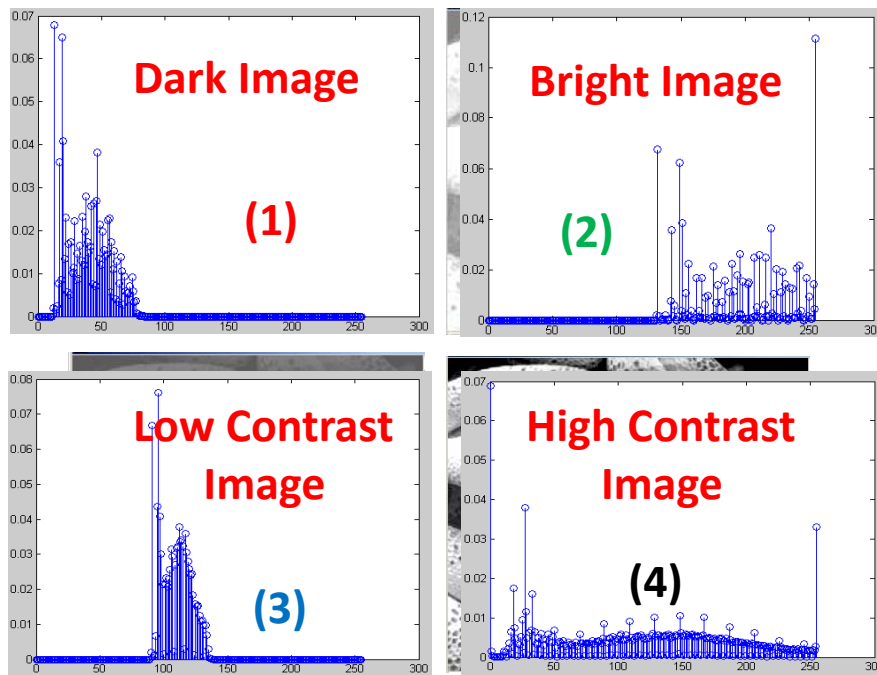


1	7	6	5	5	2	2	5	5	2
5	4	5	5	5	4	5	5	5	4
4	2	1	5	5	4	4	1	5	4
2	1	6	7	2	4	6	7	7	4
7	5	5	7	2	2	5	7	7	2
5	2	6	4	2	5	1	4	2	5
4	2	4	1	5	4	4	5	5	4
2	1	6	7	7	4	6	7	7	4
2	5	5	2	7	1	5	1	7	2
5	2	6	4	2	5	6	4	2	1

I_{out}

Equalization Algorithm

- Examples





Equalization Algorithm

- Pseudo Code
 - **Step 1:** Compute the histogram of input image

$$p(r_k) = \frac{n_k}{n}$$

- **Step 2:** Compute the transformation function

$$s_k = T(r_k) = (L - 1) \times \sum_{j=0}^k p_{in}(r_j)$$

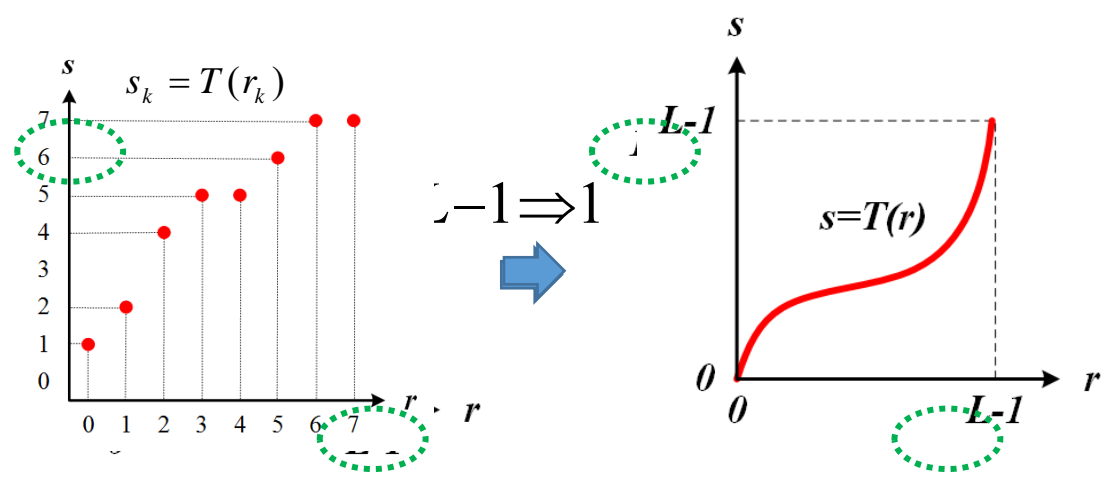
- **Step 3:** Transform the value of each pixel by

$$I_{out}(x, y) = T(I_{in}(x, y))$$



Theorem and Proof

- Assumptions
 - $T(r)$ is a **monotonically increasing continuous** function without loss of generality
 - $T(r)$ is a function mapping from $[0,1]$ to $[0,1]$



Theorem and Proof

- Proposition

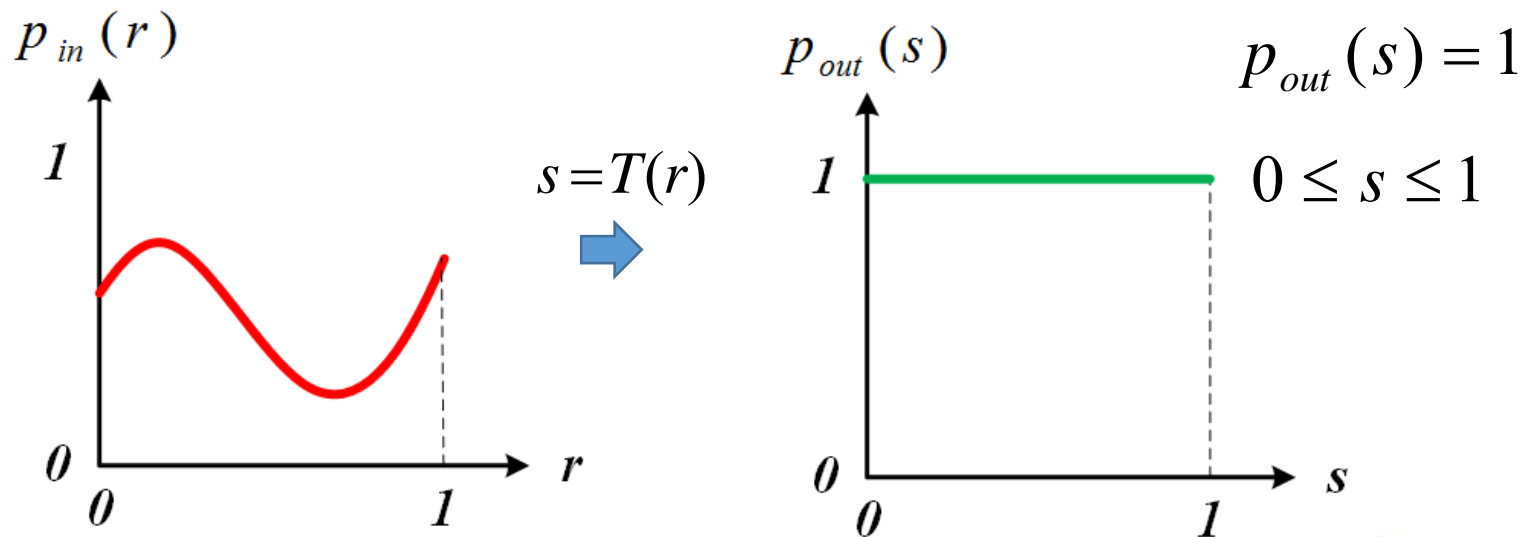
- Let $p_{in}(r)$ denote the probability density of the Gray values in the input image.
- Let $p_{out}(s)$ be the probability density of $p_{in}(r)$ after transformation $s = T(r)$

$$\text{Discrete: } s_k = T(r_k) = \left(\sum_{j=0}^k p_{in}(r_j) \right) \left(\sum_{j=0}^k p_{in}(r_j) \right)$$

$$\text{Continuous: } s = T(r) = \int_0^r p_{in}(w) dw \quad 0 \leq r \leq 1$$

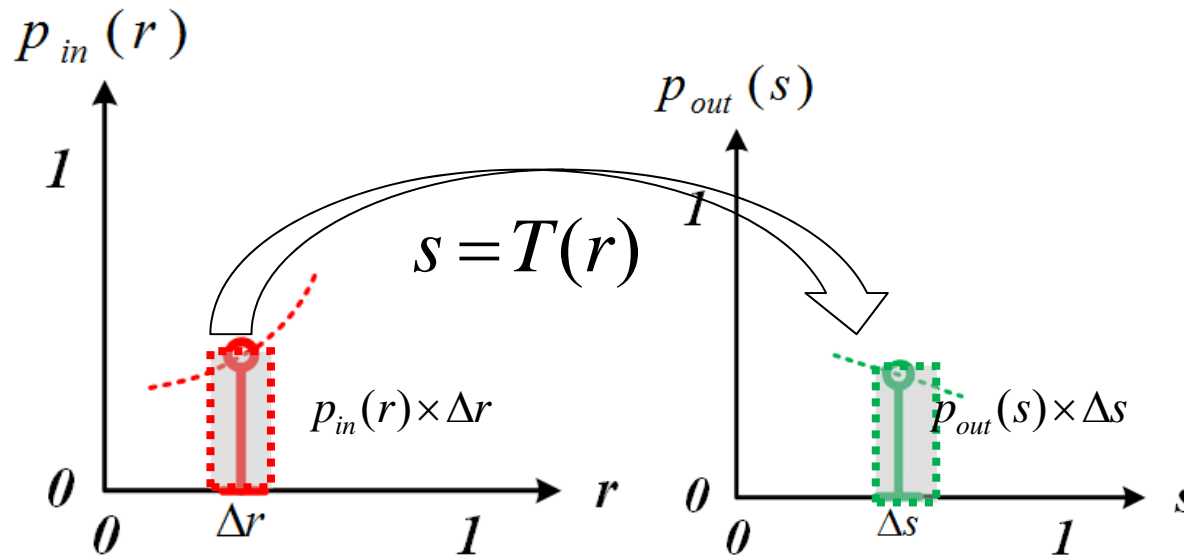
Theorem and Proof

- Proposition $s = T(r) = \int_0^r p_{in}(w)dw$
- **Prove:** $p_{out}(s)$ is uniformly distributed in $[0,1]$



Theorem and Proof

- Proof
 - Use the fundamental theorem of calculus



$$p_{out}(s) \times \Delta s = p_{in}(r) \times \Delta r$$



$$p_{out}(s) \times ds = p_{in}(r) \times dr$$



$$p_{out}(s) = p_{in}(r) \frac{dr}{ds}$$

Theorem and Proof

- Proof

- Derive $p_{out}(s)$ using $s = T(r) = \int_0^r p_{in}(w)dw$

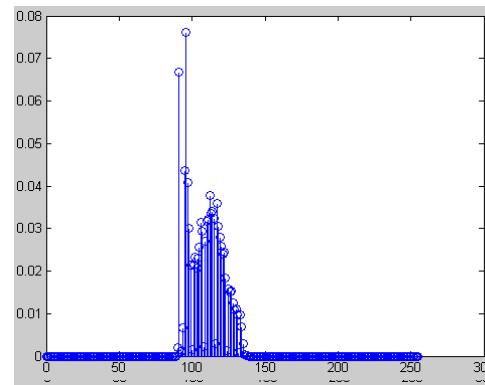
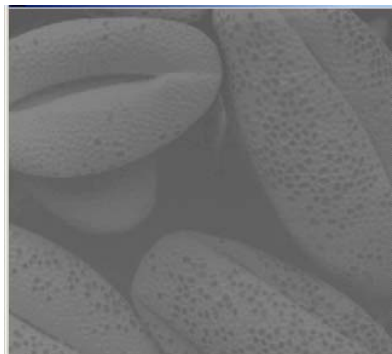
$$p_{out}(s) = p_{in}(r) \frac{dr}{ds} = p_{in}(r) \left(\frac{ds}{dr} \right)^{-1}$$

$$= p_{in}(r) \left(\frac{d \int_0^r p_{in}(w)dw}{dr} \right)^{-1} = p_{in}(r) (p_{in}(r))^{-1} = 1$$

➔ $p_{out}(s) = 1$ **Uniformly Distributed**

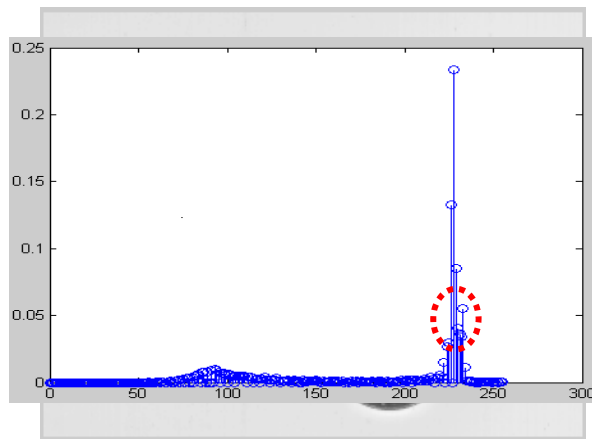
Theorem and Proof

- Discussion
 - The output probability density $p_{out}(s)=1$ is uniform regardless of the input
 - The histogram of output image is only approximately uniform since it is in the **discrete** case.

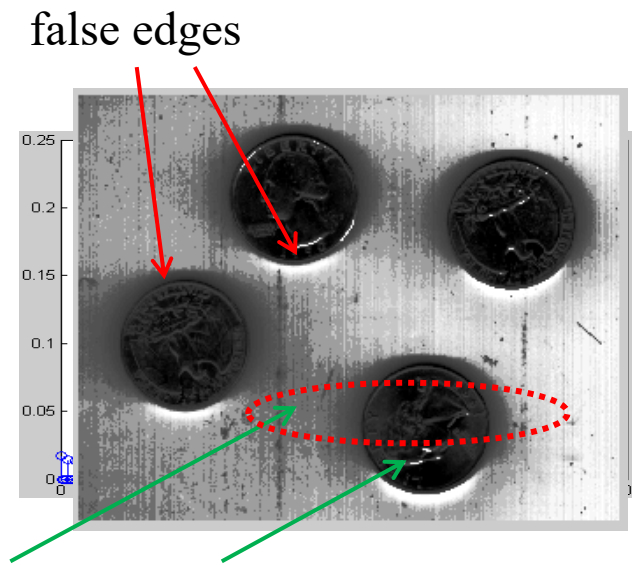


Theorem and Proof

- Discussion
 - This algorithm usually **but not always** results in an enhanced image.



Histogram Equalization



“graininess” and “patchiness”

