

The Image Histogram

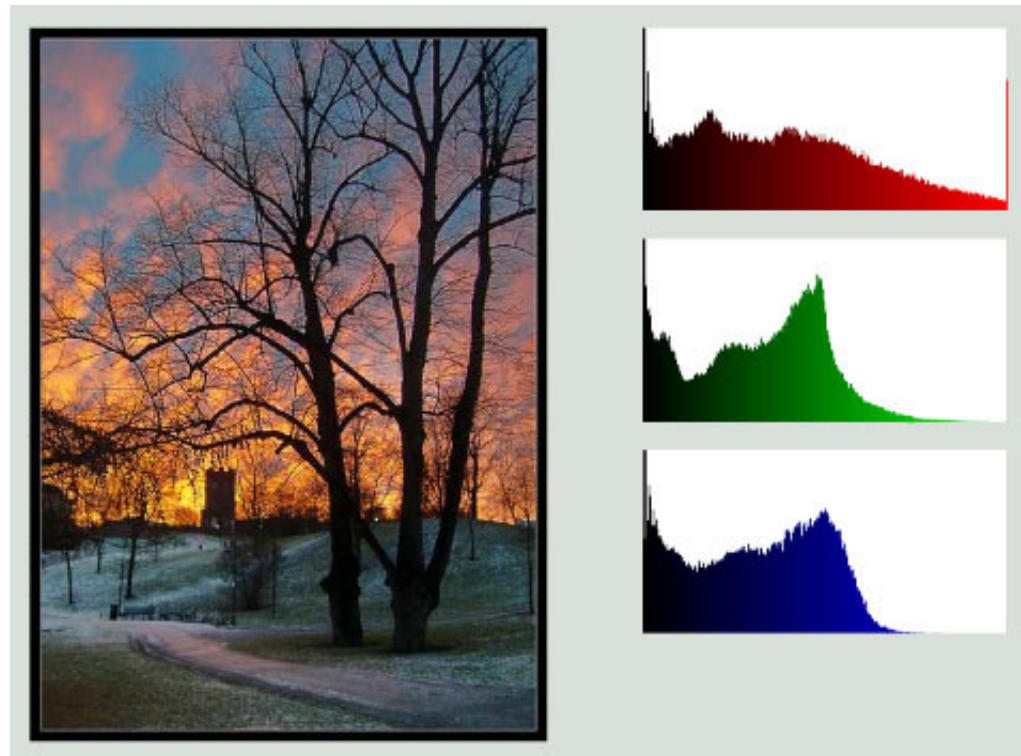
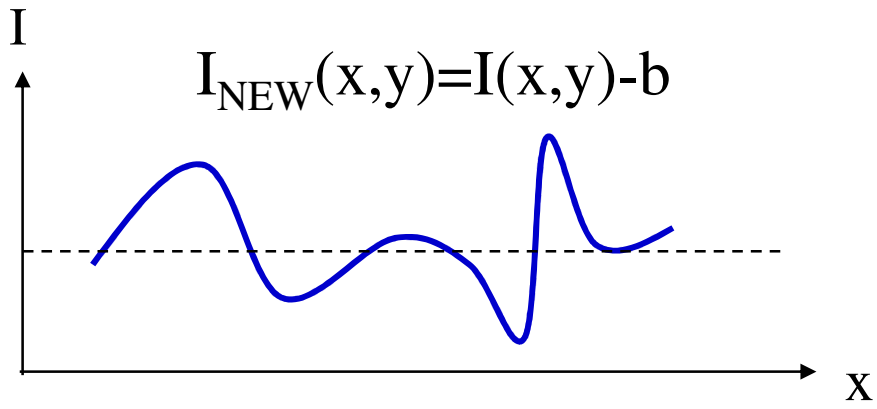
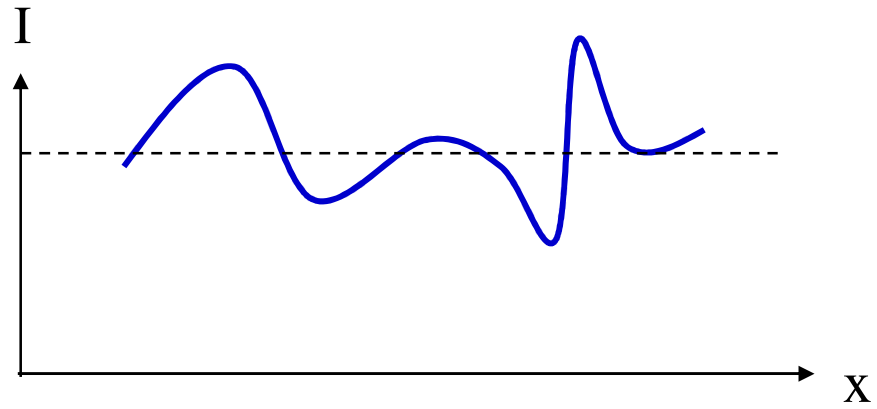


Image Characteristics



Image Mean

$$I_{av} = \frac{\sum_i \sum_j I(i, j)}{\sum_i \sum_j 1}$$

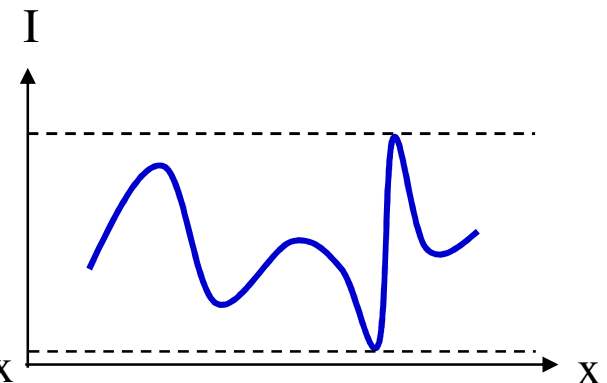
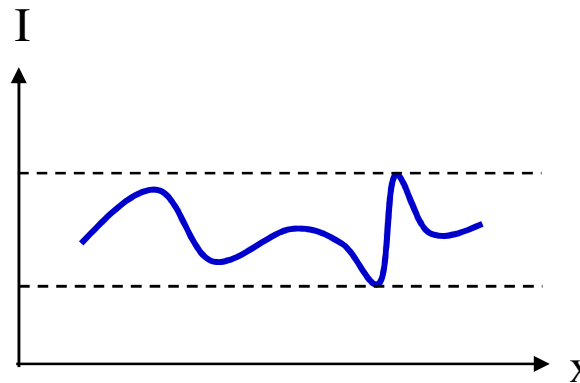




Changing the image mean

Image Contrast

- The contrast definition of the entire image is ambiguous
- In general it is said that the image contrast is high if the image gray-levels fill the entire range



Low contrast



High contrast

Global Contrast

Global Contrast – Definition 1

$$\max\{ I(x, y) \} - \min\{ I(x, y) \}$$

Global Contrast – Definition 2

$$\text{var}\{ I(x, y) \} = \text{mean}\{ (I(x, y) - I_{av})^2 \}$$

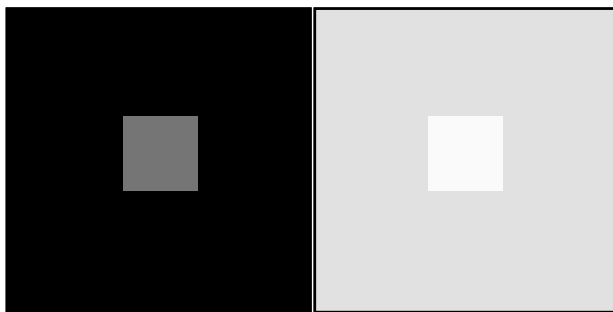
Global Contrast – Definition 3

$$\text{std}\{ I(x, y) \} = \sqrt{\text{var}\{ I(x, y) \}}$$

Local Image Contrast

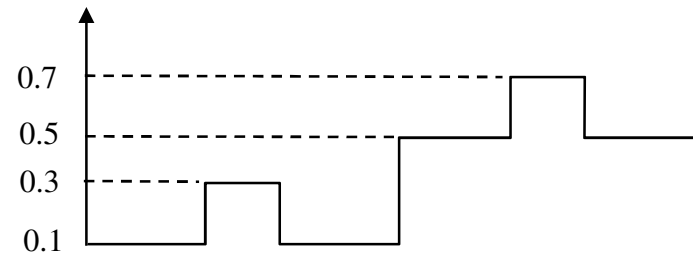
- The **local contrast** at an image point denotes the (relative) difference between the intensity of the point and the intensity of its neighborhood:

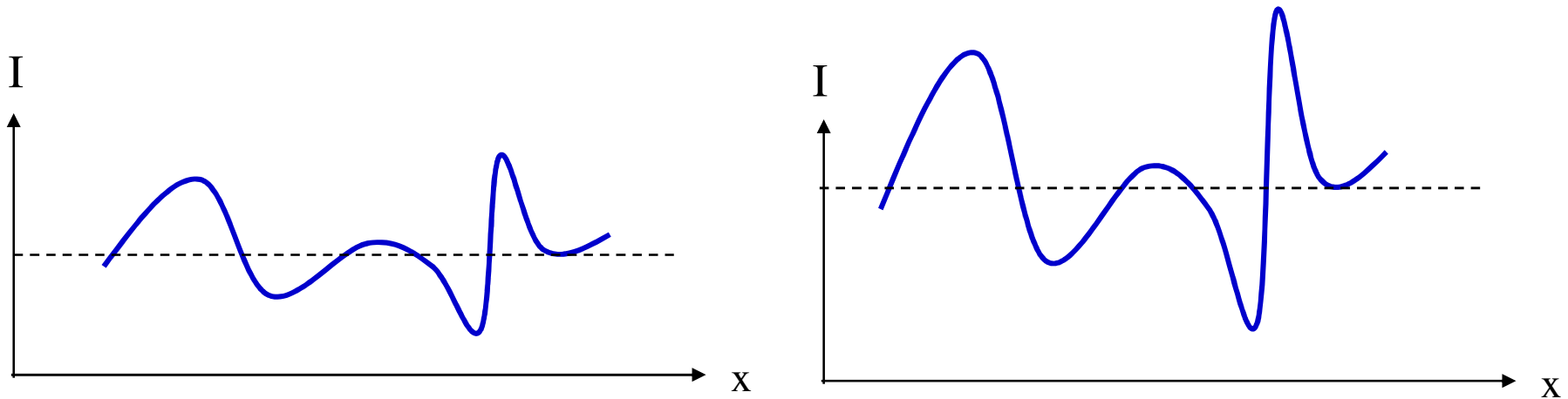
$$C = \left| \frac{I_p - I_n}{I_n} \right|$$



$$C = \left| \frac{0.3 - 0.1}{0.1} \right| = 2$$

$$C = \left| \frac{0.7 - 0.5}{0.5} \right| = 0.4$$





$$I_{\text{NEW}}(x,y) = \alpha \cdot I(x,y)$$



$\alpha=1$
(+ β)



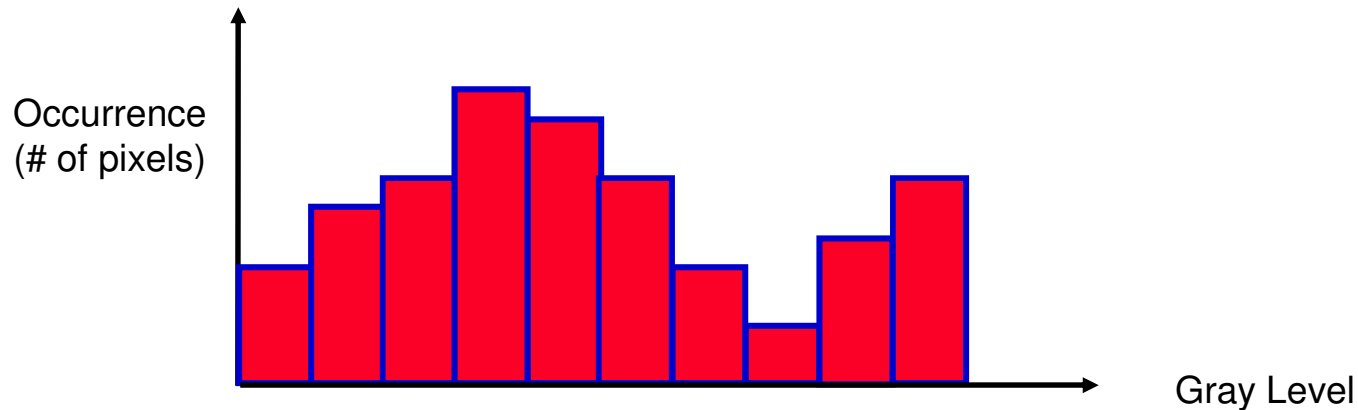
$\alpha=0.8$
(+ β)



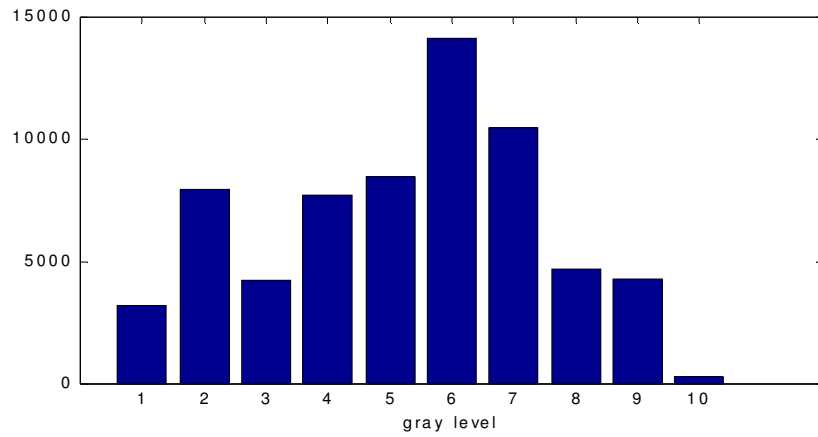
$\alpha=1.1$
(+ β)

Q: How can we maximize the image contrast using linear operation on the image values? $I_{\text{NEW}}(x,y) = \alpha \cdot I(x,y) + \beta$

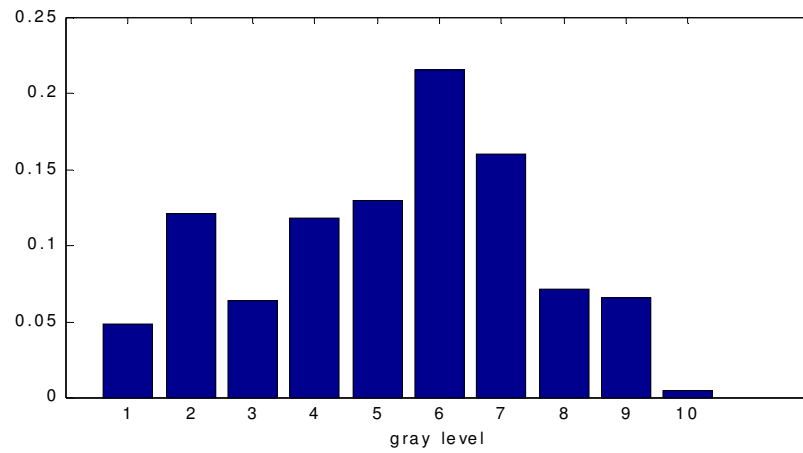
The Image Histogram



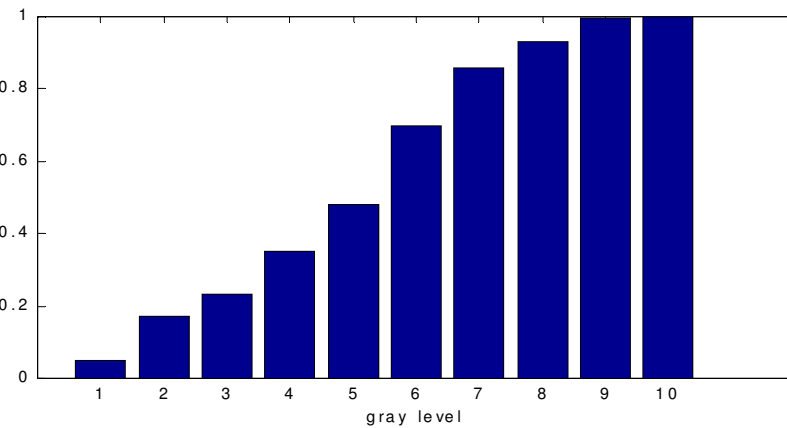
- $H(k)$ specifies the # of pixels with gray-value k
- Let N be the number of pixels: $N = \sum_k H(k)$
- $P(k) = H(k)/N$ defines the normalized histogram
- $C(k) = \sum_{i=1}^k H(i)$ defines the accumulated histogram



Histogram

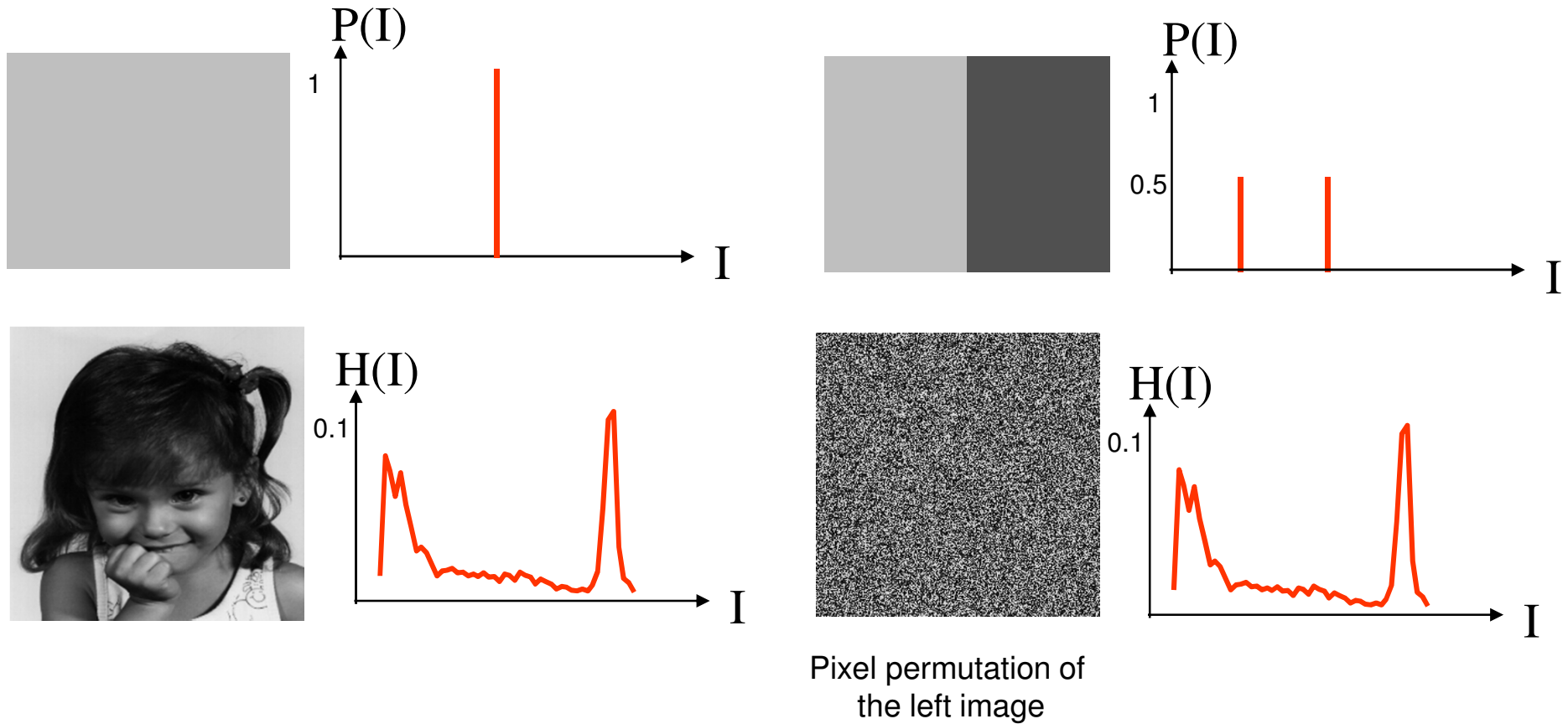


Normalized Histogram



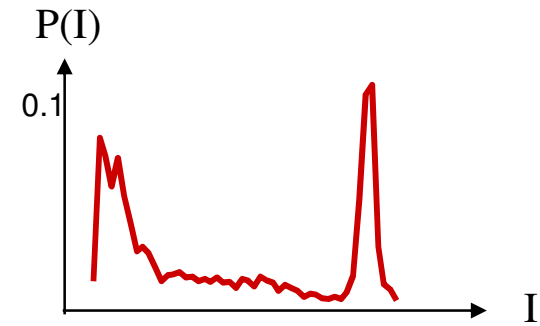
Accumulated Histogram

Examples

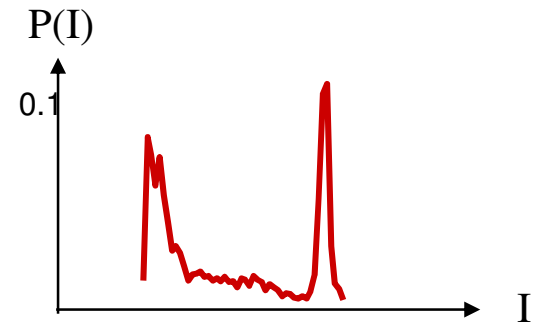


The image histogram does not fully represent the image

Original image



Decreasing contrast



Increasing average

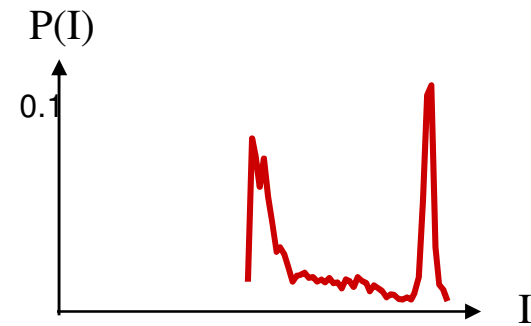


Image Statistics

- The image mean: $E\{I\} = \frac{1}{N} \sum_{i,j} I(i, j) = \frac{1}{N} \sum_k k H(k) = \sum_k k P(k)$

- The image s.t.d. : $\sigma(I) = \sqrt{E\{(I - E\{I\})^2\}} = \sqrt{E(I^2) - E^2(I)}$

where $E\{I^2\} = \sum_k k^2 P(k)$

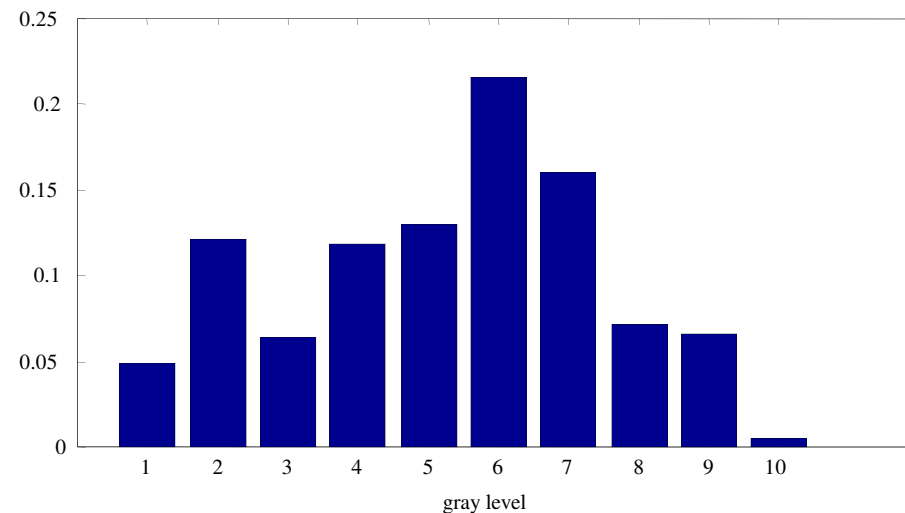
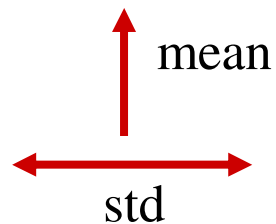
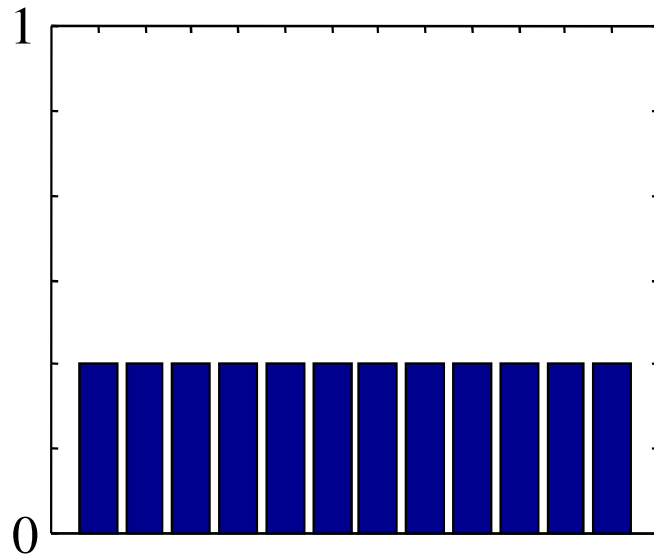


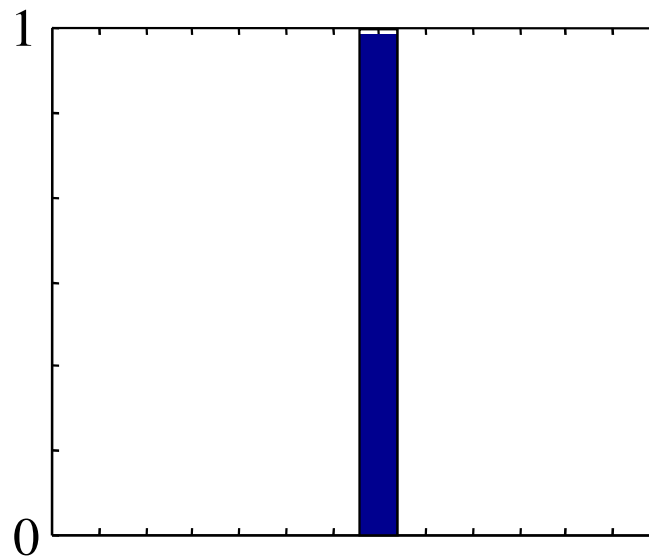
Image Entropy

$$Entropy(I) = -\sum_k P(k) \log P(k)$$

- The image entropy specifies the uncertainty in the image values.
- Measures the averaged amount of information required to encode the image values.

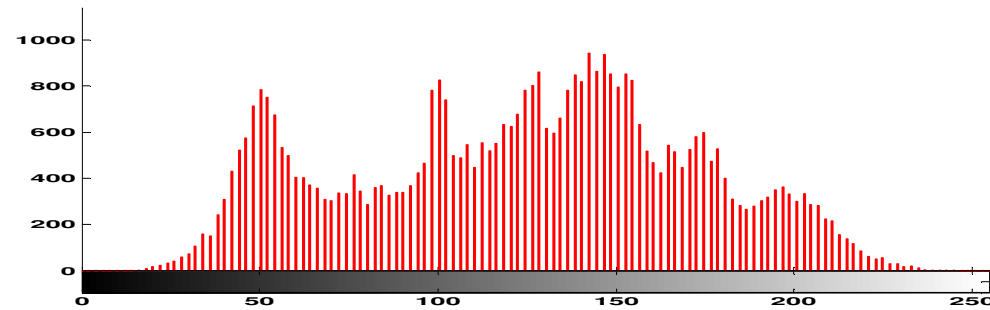


Max Entropy

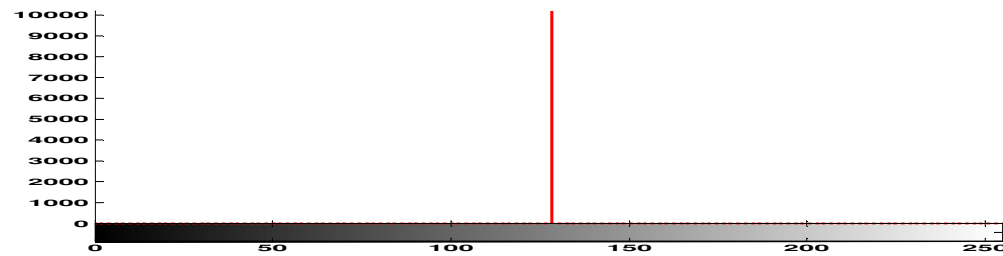


Min Entropy

- An infrequent event provides more information than a frequent event
- Entropy is a measure of histogram dispersion



entropy=7.4635



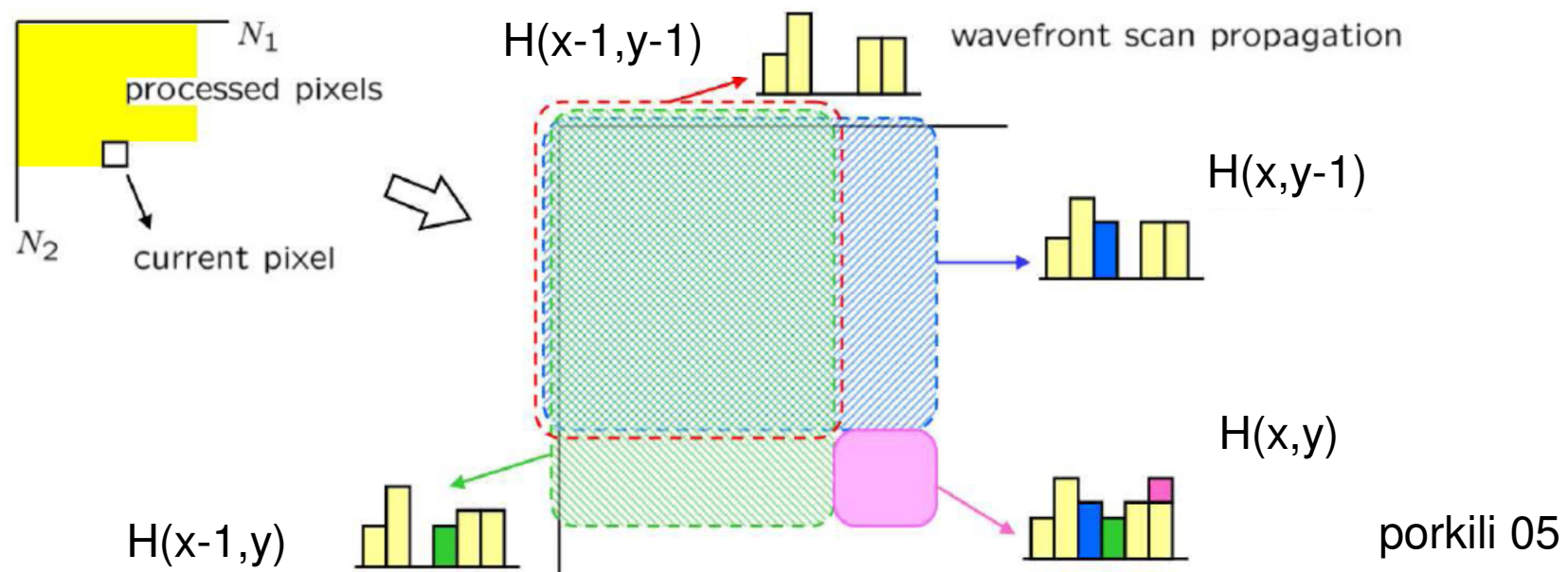
entropy=0

Adaptive Histogram

- In many cases histograms are needed for local areas in an image
- Examples:
 - Pattern detection
 - adaptive enhancement
 - adaptive thresholding
 - tracking



Implementation: Integral Histogram

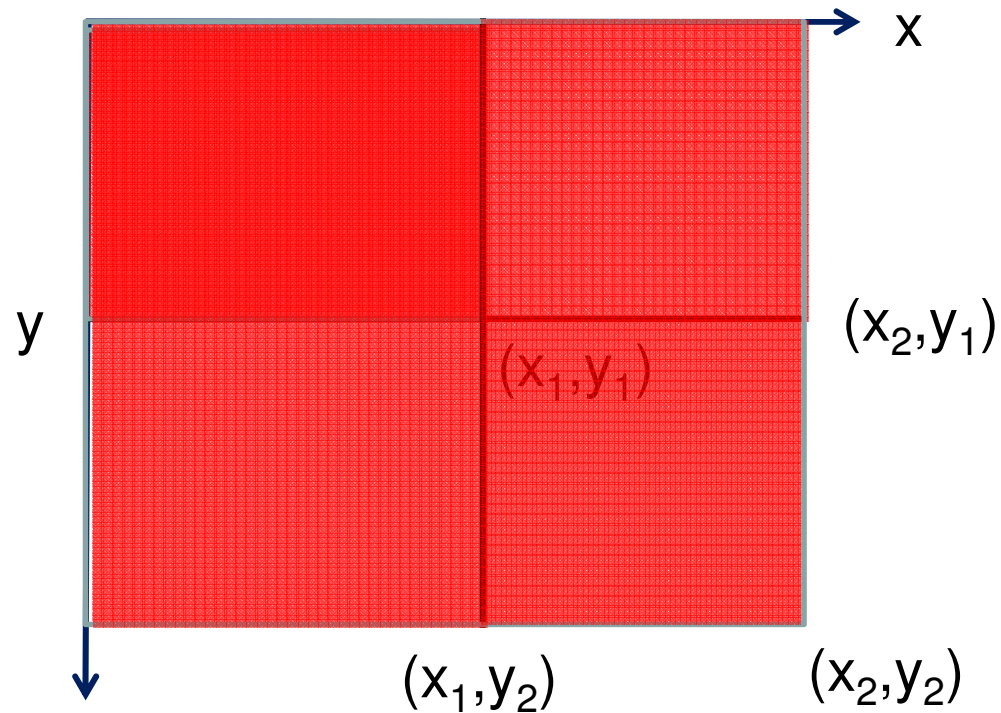


porkili 05

- **Integral histogram:** $H(x, y)$ represent the histogram of a window whose right-bottom corner is (x, y)
- Construct by scan order:

$$H(x, y) = H(x, y-1) + H(x-1, y) - H(x-1, y-1)$$

- Using integral histogram we can calculate local histograms of any window $H(x_1:x_2, y_1:y_2)$



$$H(x_1:x_2, y_1:y_2) = H(x_2, y_2) + H(x_1, y_1) - H(x_1, y_2) - H(x_2, y_1)$$

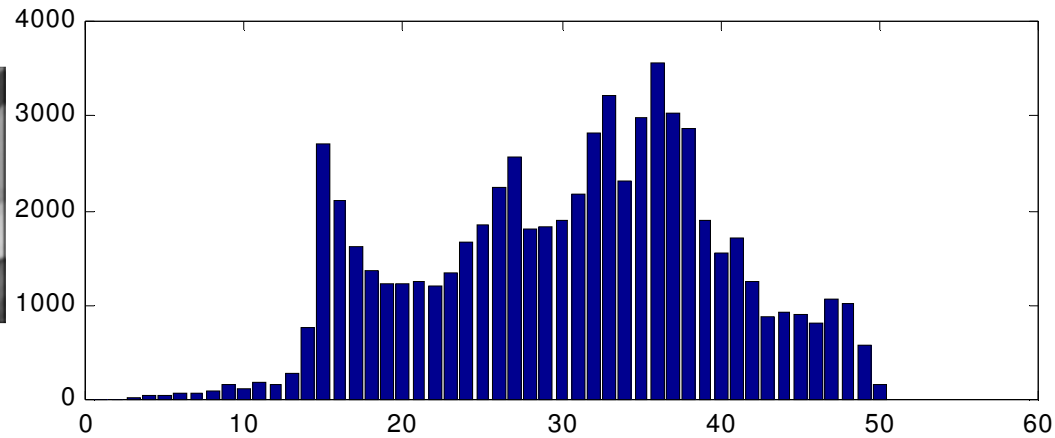
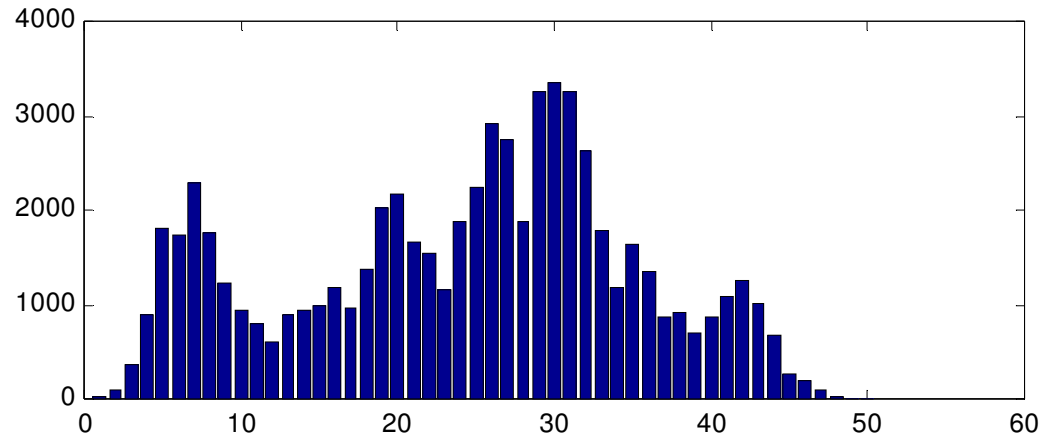
Histogram Usage

- Digitizing parameters
- Measuring image properties:
 - Average
 - Variance
 - Entropy
 - Contrast
 - Area (for a given gray-level range)
- Threshold selection
- Image distance
- Image Enhancement
 - Histogram equalization
 - Histogram stretching
 - Histogram matching

Example: Auto-Focus

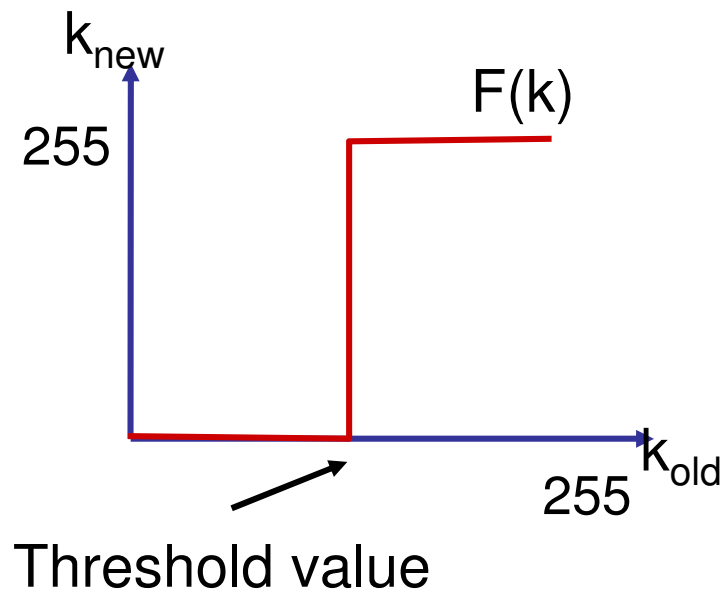
- In some optical equipment (e.g. slide projectors) inappropriate lens position creates a blurred (“out-of-focus”) image
- We would like to automatically adjust the lens
- How can we measure the amount of blurring?





- Image mean is not affected by blurring
- Image s.t.d. (entropy) is decreased by blurring
- Algorithm: Adjust lens according the changes in the histogram s.t.d.

Thresholding

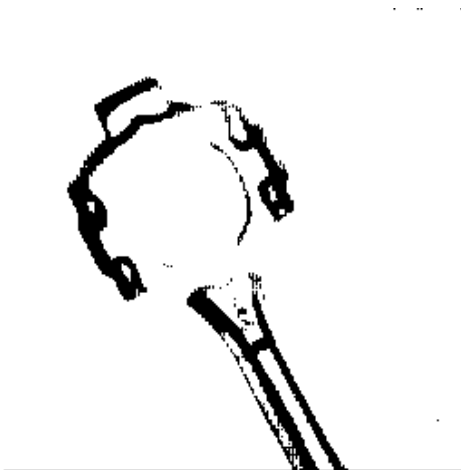
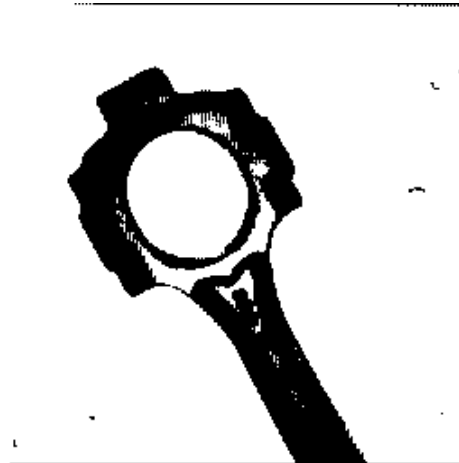


Threshold Selection

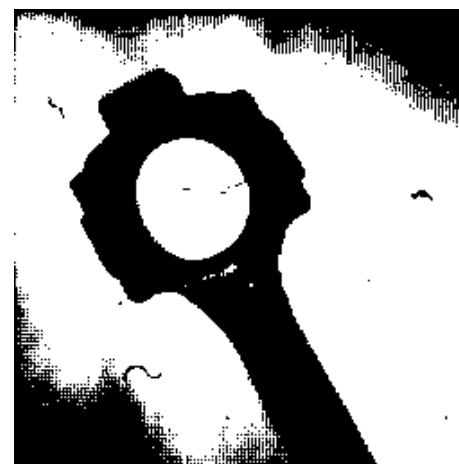
Original Image



Binary Image



Threshold too low



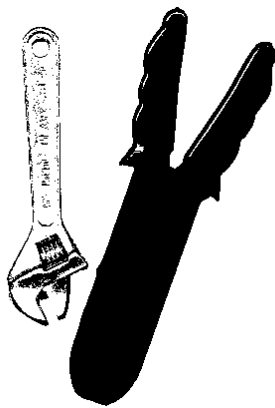
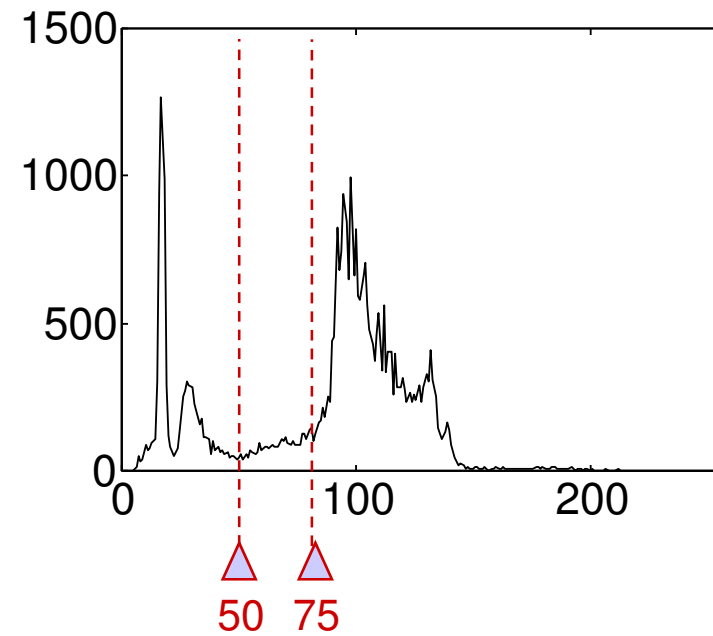
Threshold too high

Segmentation using Thresholding

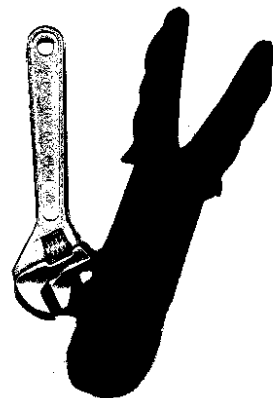
Original



Histogram



Threshold = 50



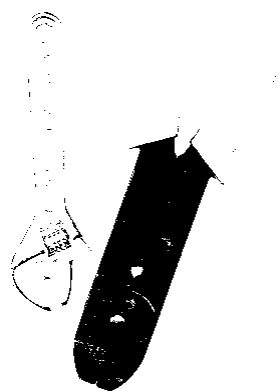
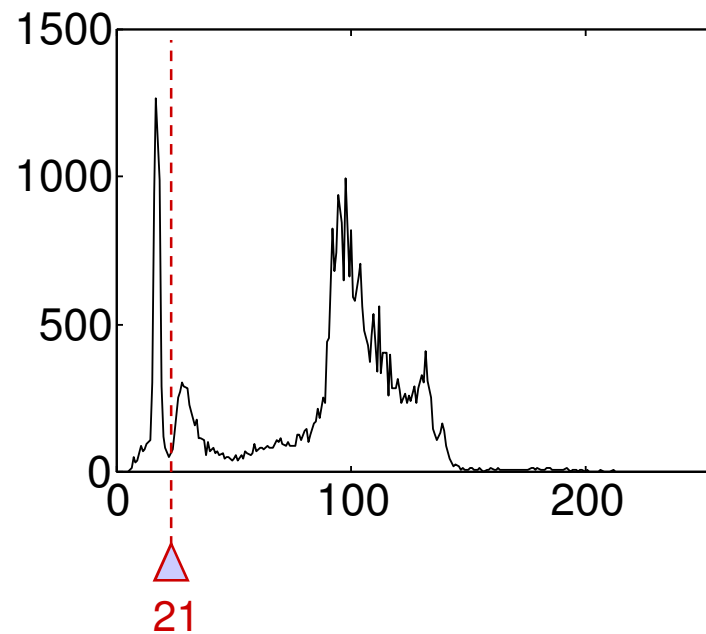
Threshold = 75

Segmentation using Thresholding

Original



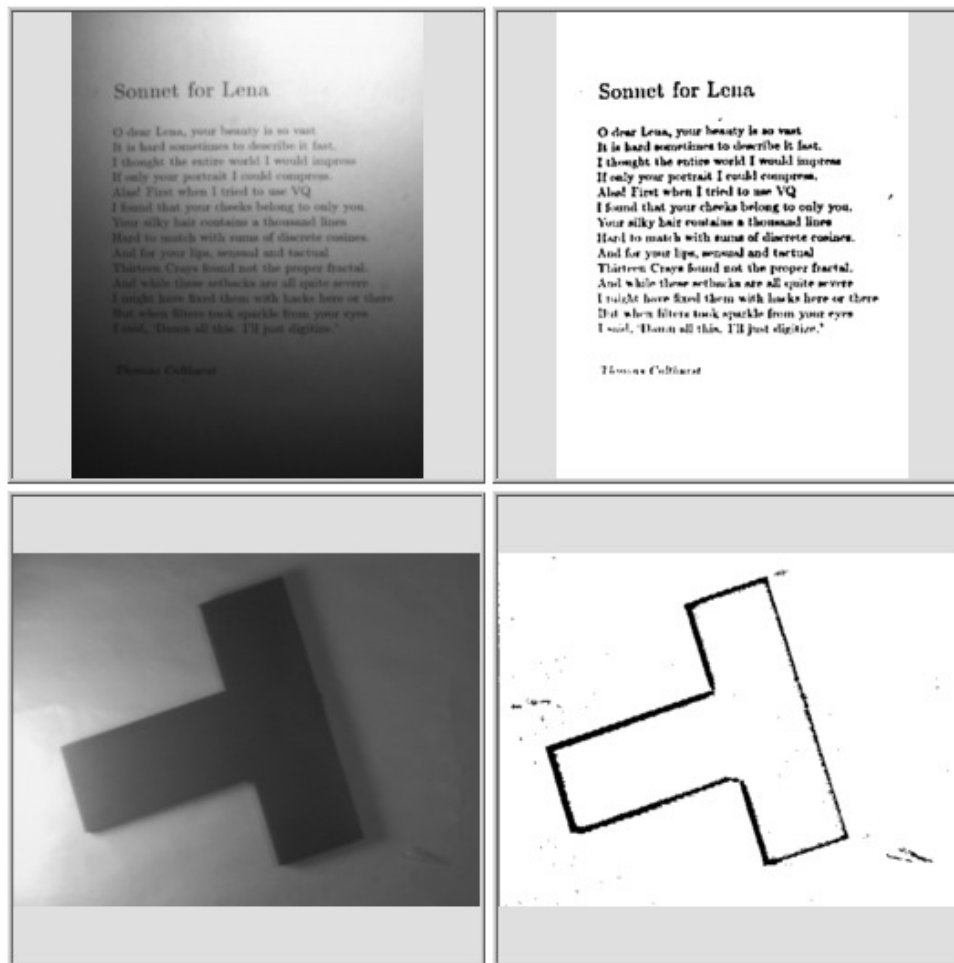
Histogram



Threshold = 21

Adaptive Thresholding

- Thresholding is space variant.
- How can we choose the local threshold values?



Histogram based image distance

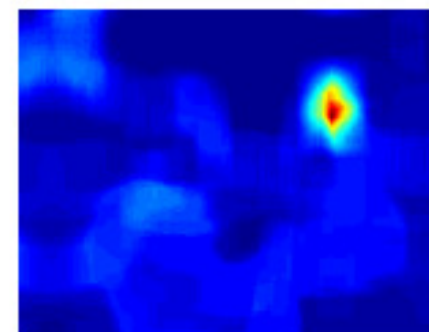
- **Problem:** Given two images A and B whose (normalized) histogram are P_A and P_B define the distance $D(A,B)$ between the images.
- Example Usage:
 - Tracking
 - Image retrieval
 - Registration
 - Detection
 - Many more ...



input



target

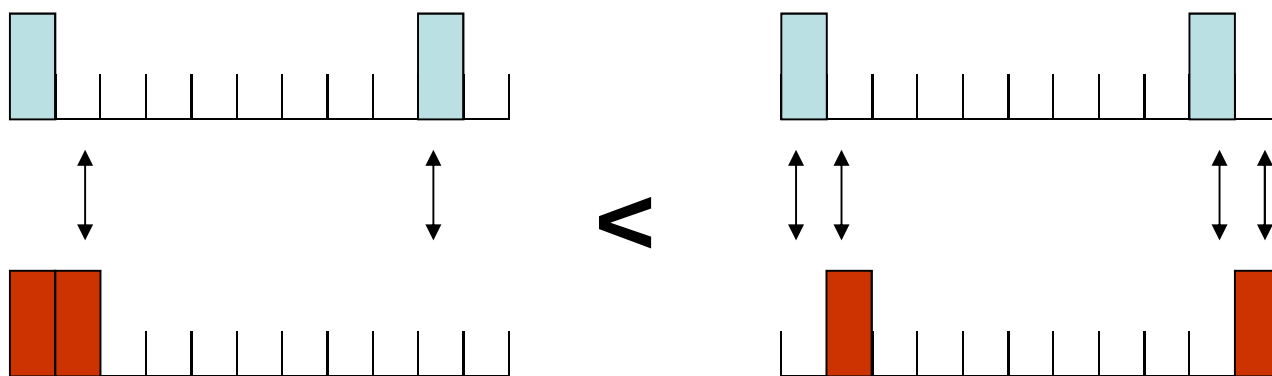


similarity

Option 1: Minkowski Distance

$$D_p(A, B) = \left[\sum_k |P_A(k) - P_B(k)|^p \right]^{1/p}$$

- **Problem:** distance may not reflect the perceived dissimilarity:



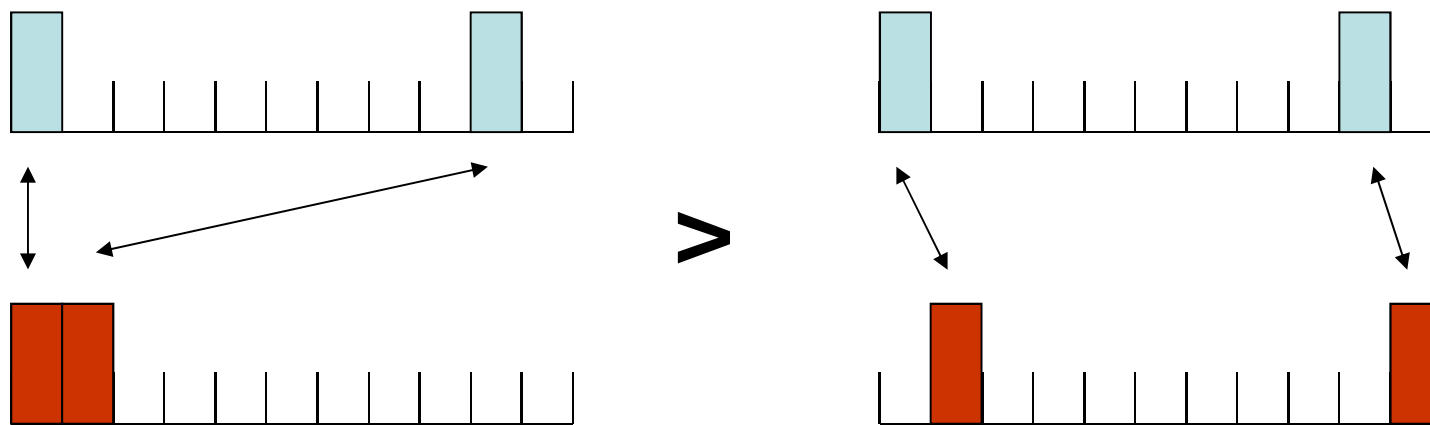
Option 2: Kullback-Leibler (KL) Distance

$$D_{KL}(A \parallel B) = \sum_k P_A(k) \log \frac{P_A(k)}{P_B(k)}$$

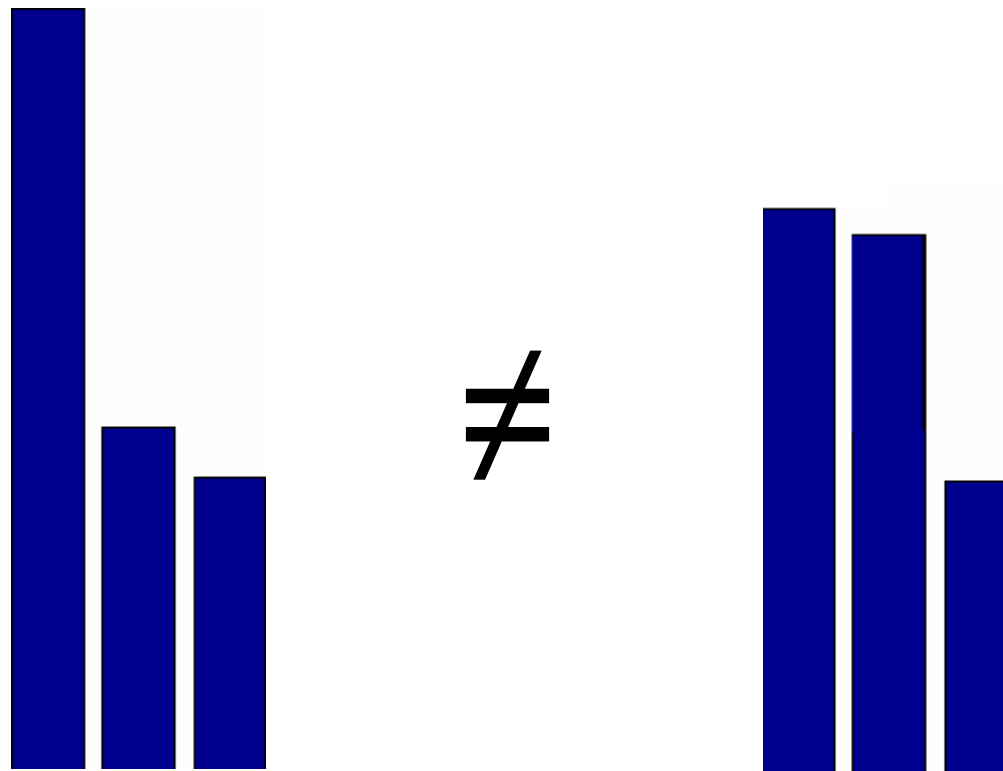
- Measures the amount of added information needed to encode image A based on the histogram of image B.
- Non-symmetric: $D_{KL}(A \parallel B) \neq D_{KL}(B \parallel A)$
- Suffers from the same drawback of the Minkowski distance.

Option 3: The Earth Mover Distance (EMD)

- Suggested by Rubner & Tomasi 98
- Defines as the minimum amount of “work” needed to transform histogram H_A towards H_B
- The term d_{ij} defines the “ground distance” between gray-levels i and j .
- The term $F=\{f_{ij}\}$ is an admissible flow from $H_A(i)$ to $H_B(j)$

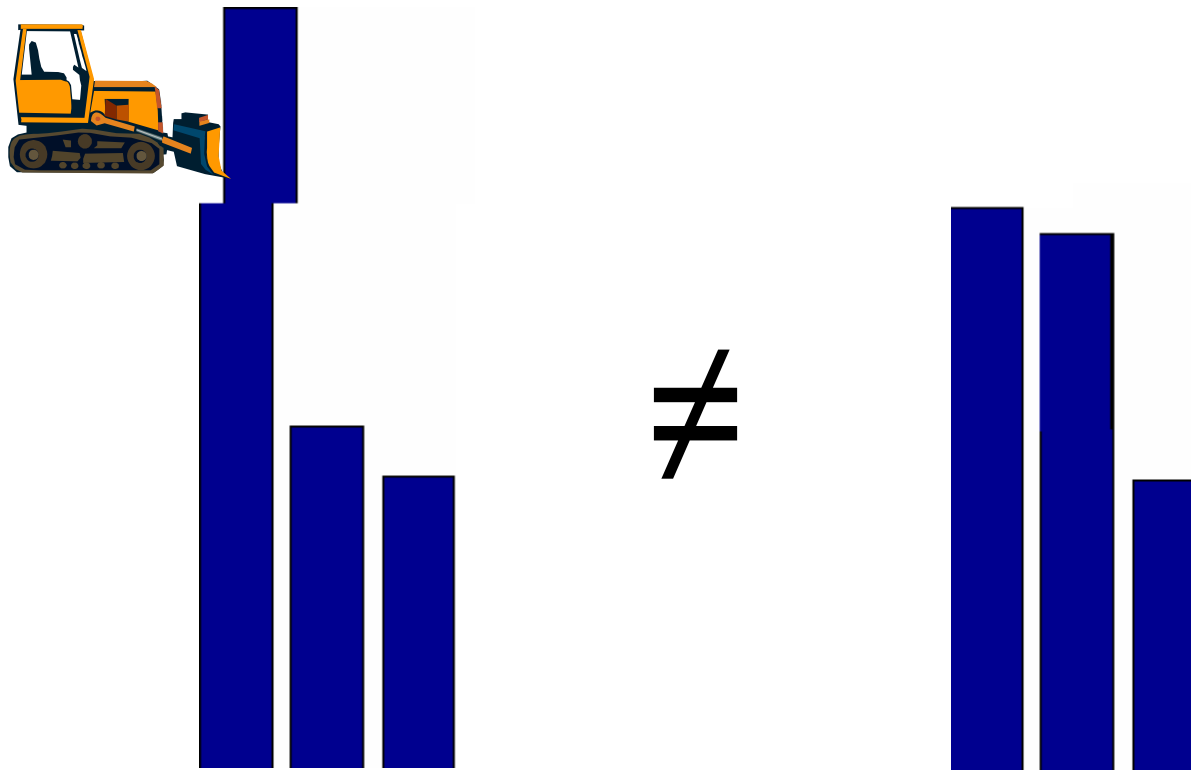


Option 3: The Earth Mover Distance (EMD)



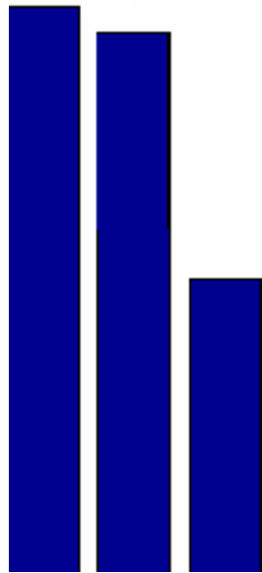
From: Pete Barnum

Option 3: The Earth Mover Distance (EMD)

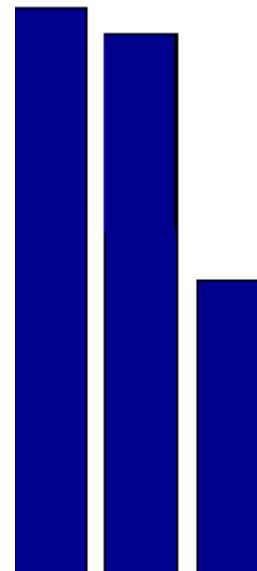


From: Pete Barnum

Option 3: The Earth Mover Distance (EMD)

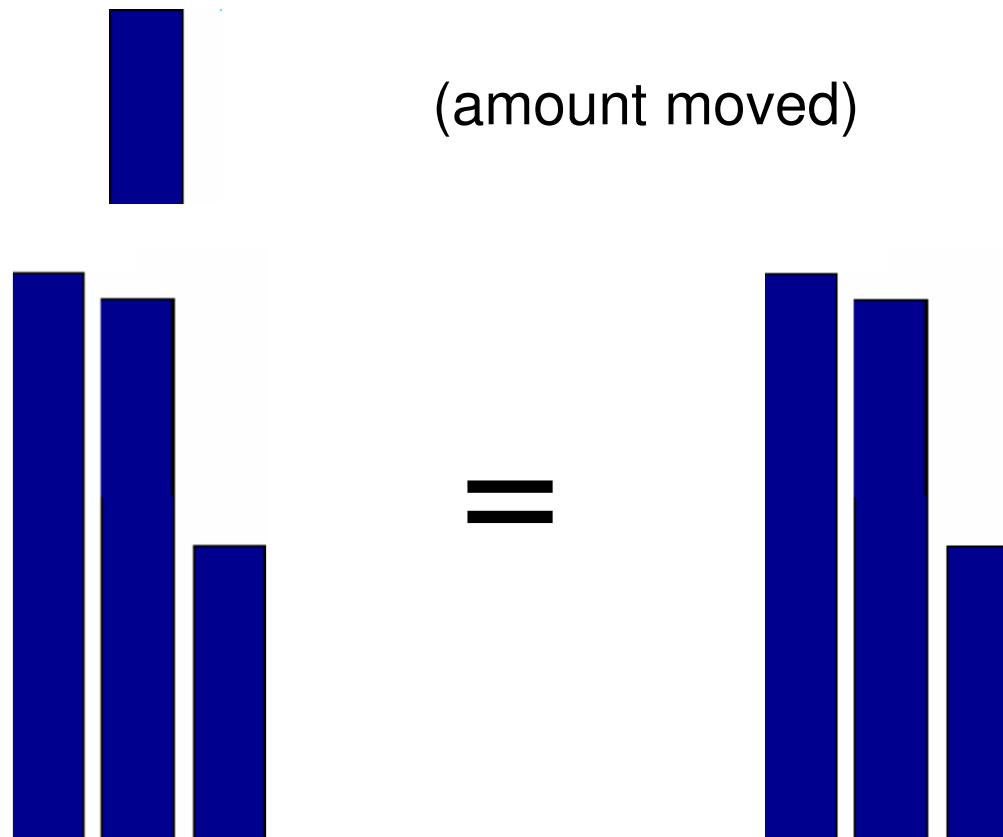


=

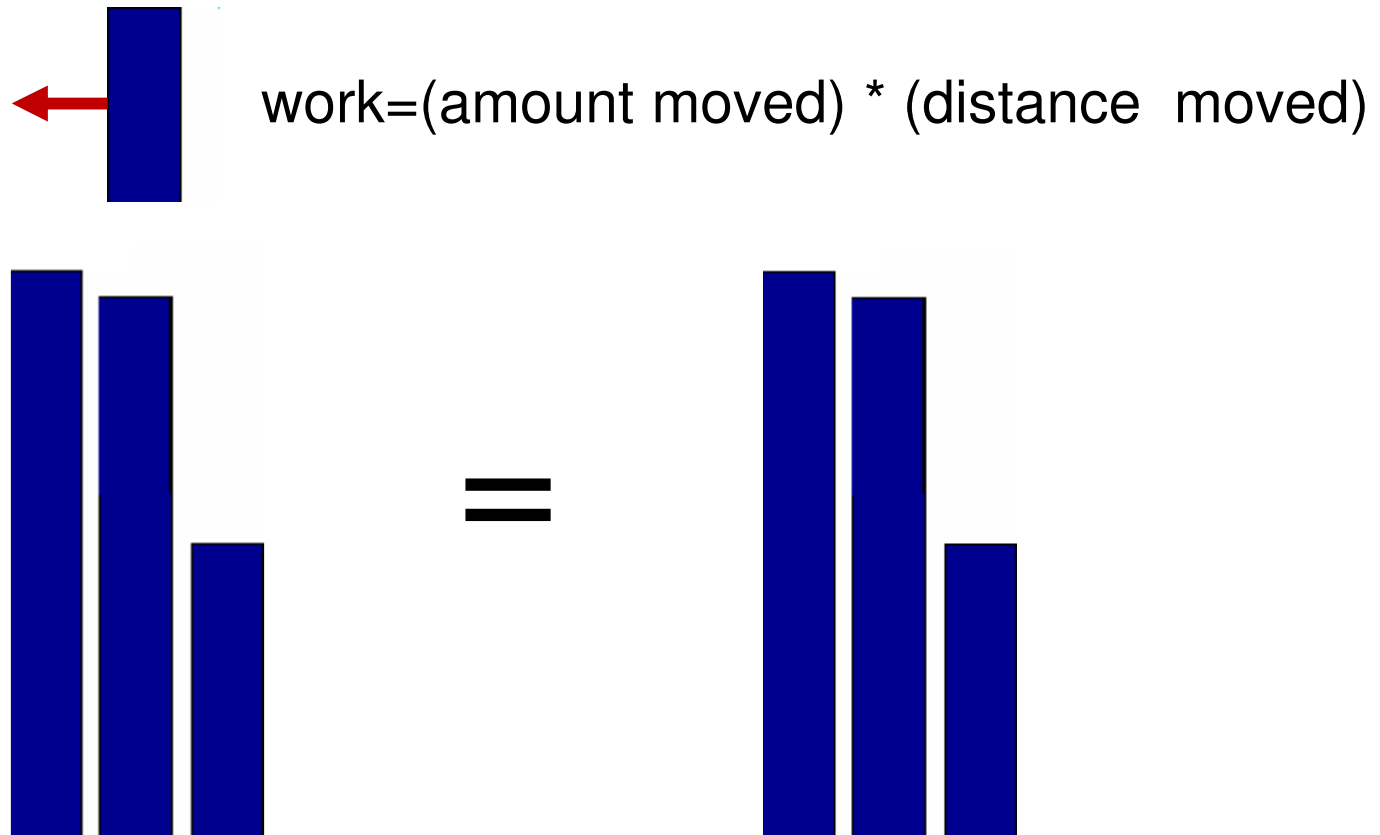


From: Pete Barnum

Option 3: The Earth Mover Distance (EMD)



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$$D_{EMD}(A, B) = \min_F \sum_i \sum_j f_{ij} \cdot d_{ij}$$

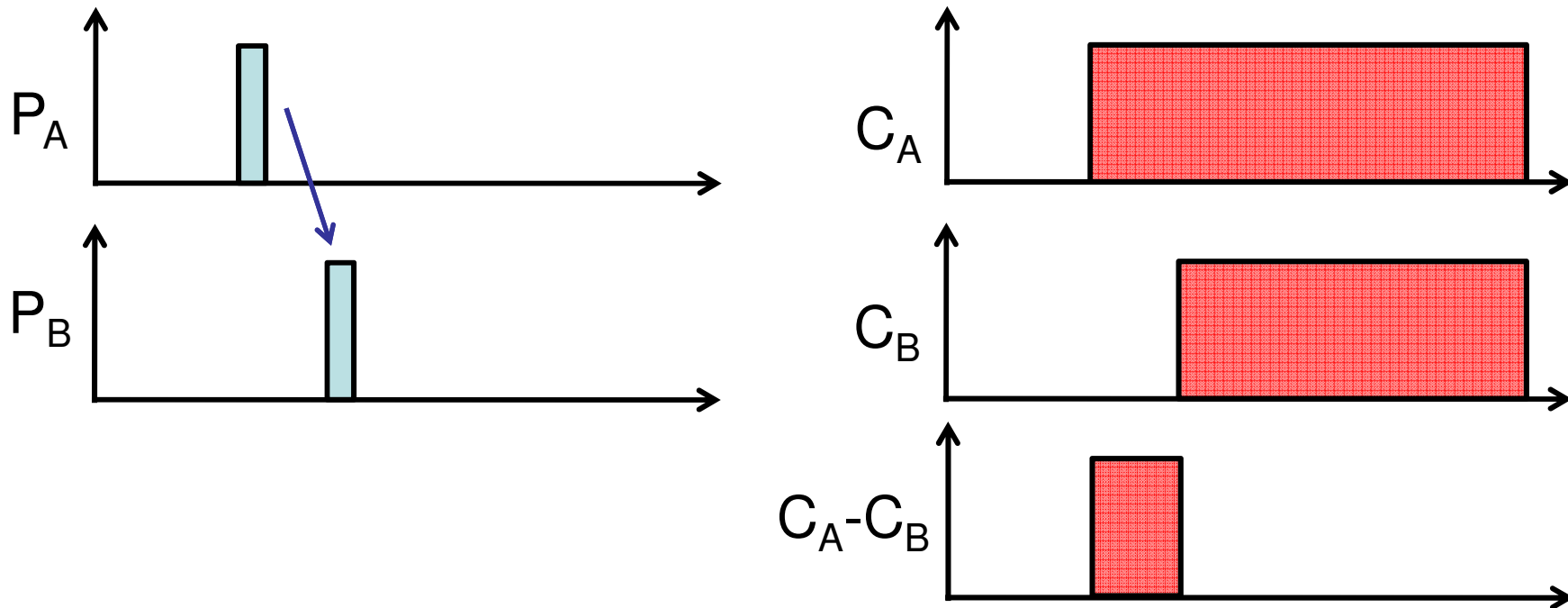
$$s.t. \quad f_{ij} \geq 0 ; \quad P_B(k) = \sum_i f_{ik} ; \quad P_A(k) \geq \sum_i f_{ki}$$

- Constraints:
 - Move earth only from A to B
 - After move P_A will be equal to P_B
 - Cannot send more “earth” than there is
- Can be solved using Linear Programming
- Can be applied in high dim. histograms (color).

Special case: EMD in 1D

- Define C_A and C_B as the accumulated histograms of image A and B respectively:

$$D_{EMD}(A, B) = \sum_k |C_A(k) - C_B(k)|$$



Special case: EMD in 3D

The screenshot shows a Microsoft Internet Explorer browser window displaying a web application titled "IRS Demo". The address bar shows the URL `http://vision.stanford.edu/~rubner/demo/index.html`. The application interface is divided into several sections:

- Query Section:** Features a color wheel on the left and a 4x4 grid of colored squares on the right. A "Reset" button is located below the grid.
- Search Options:** Includes a "Number of images to return:" dropdown set to "20", and buttons for "Query by color", "Random query", and "Use image#".
- Display Options:** Includes a "Display MDS" button and a checkbox for "Auto MDS".
- Last signature:** A horizontal bar with a blue segment and a black-and-white checkered pattern.
- Performance Metrics:** Displays "Query CPU time: 0.72 seconds", "Query CPU time: 0.68 seconds", and "MDS CPU time: 0.07 seconds, MDS stress: 0.000".
- Image Retrieval Results:** A large area on the right showing a cluster of small image thumbnails. Below this, a row of eight larger image thumbnails is displayed, each with a number, an EMD score, and a filename:

Rank	EMD Score	Filename
1)	9.4	93002.jpg
2)	10.5	34091.jpg
3)	11.9	39094.jpg
4)	12.1	19047.jpg
5)	12.1	34074.jpg
6)	12.3	135081.jpg
7)	12.5	135044.jpg
8)	13.1	34086.jpg