

EECS 332 Digital Image Analysis

Histogram Techniques

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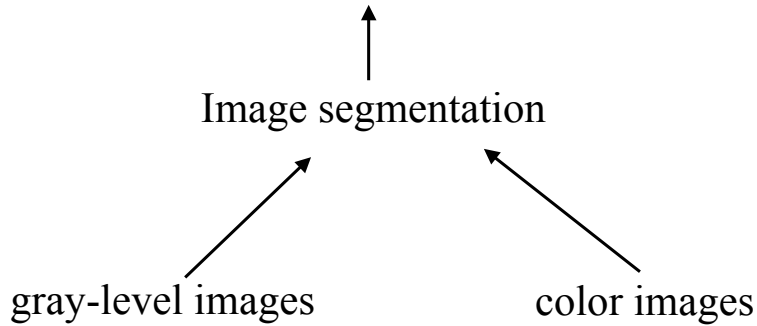
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What we've learnt ...

- Binary image analysis
 - Attributes of a region (area, centroid, orientation)
 - CCL
 - Morphological operators
 - Boundary

Questions

- How do we get those binary images?

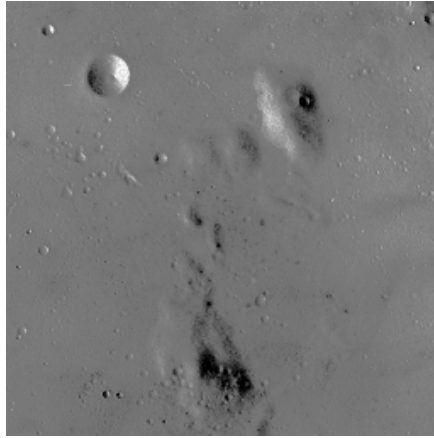


- We'll introduce some basic concepts today.

Outline

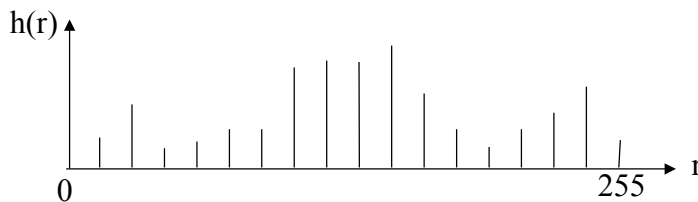
- Histogram
- Histogram equalization
- Fitting
- Lighting correction

Let's view this picture



- Why doesn't this picture look good?
- Can we make it look good? If so, how?

Histogram



- Histogram is a discrete representation of the distribution on the quantized pixel attributes (e.g., pixel intensities).
- Histogram bin
 - # of bins is the levels of quantized attributes
 - The value of each bin is the frequency that the corresponding attribute appears in the image
- E.g. $h(r_k) = n_k$, where
 - r_k is the k -th gray scale of the intensity
 - n_k is the # of pixels with intensity r_k .

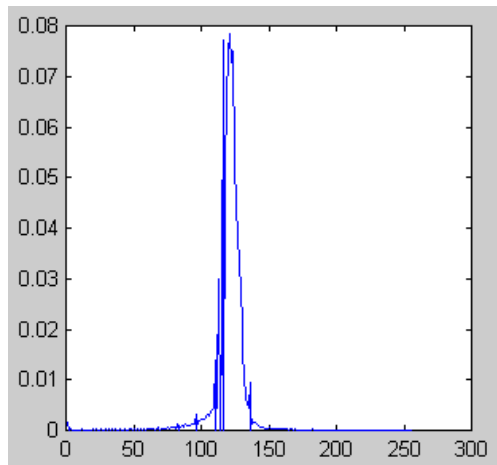
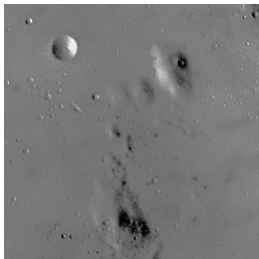
How to construct a histogram

- As easy as ABC ...

```
for r = 1:R
    for c = 1:C
        h(I(r,c)) ++ ;
    end
end
```

Note: This is just conceptual code. You need to consider bin quantization before writing the actual code.

Aha! I know the reason ...

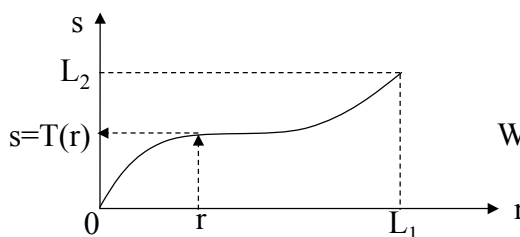


Idea?

- We'd better make the histogram more spread and more even.
- Why?
 - Human vision system can only distinguish about 20 grayscales
- In this particular case, we need to stretch the histogram.
- But, how ... ?

Histogram Equalization

- Problem statement:
 - Input image gray level $r \in [0, L_1]$
 - Output image gray level $s \in [0, L_2]$
 - We need to find a transformation $s = T(r)$
s.t., s tends to be distributed uniformly
 - Requirement: $T(r)$ monotonically non-decreasing



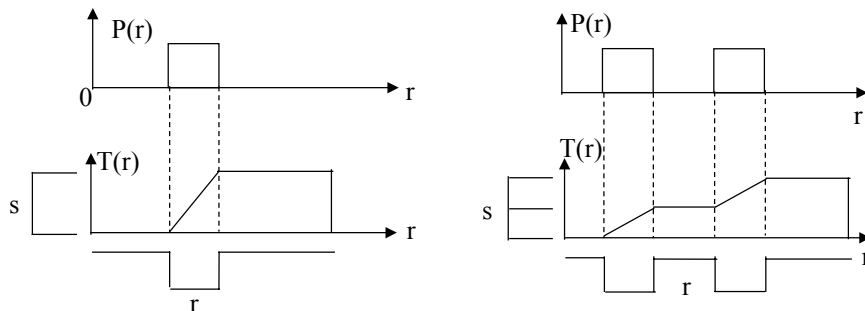
What is the best $T(r)$?

The Solution is simple

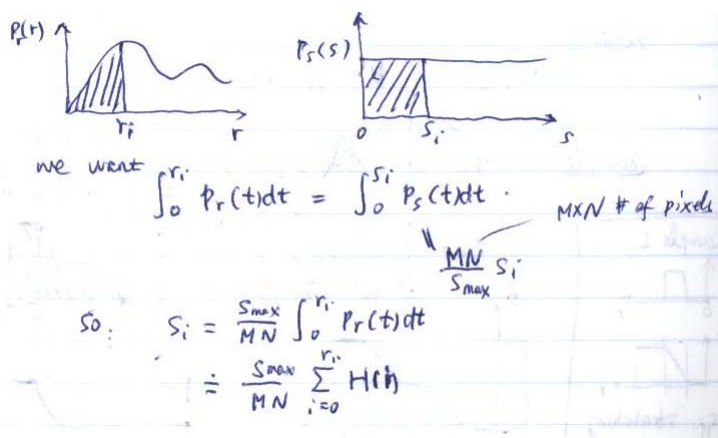
$$T(r_k) = \sum_{j=0}^k P(r_j) \cdot L_2$$

$P(r_j)$: The mass distribution of r_j

Cumulative mass distribution of r_j (or just the normalized cumulative histogram!)



Why does it work?



A formal explanation

gray levels in an image may be viewed as r.v. in the interval $[0,1]$. $r \sim p_r(r)$ where $s = T(r)$
 $s \sim p_s(s)$

probability theory $r \xrightarrow{T(r)} s$

$$p_s(s) = p_r(r) \left| \frac{dr}{ds} \right| = \frac{p_r(r)}{|J|} \quad \text{where} \quad J = \frac{ds}{dr} = \frac{dT(r)}{dr}$$

we choose

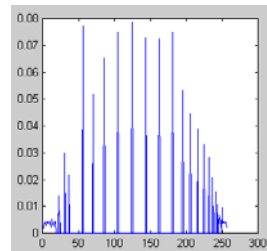
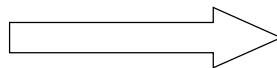
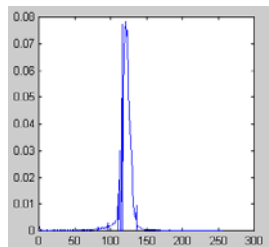
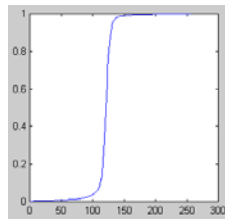
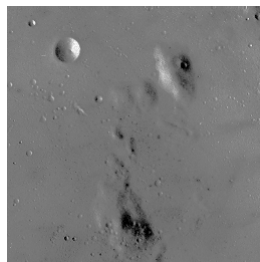
$$s = T(r) = \int_0^r p_r(w) dw$$

$$\text{so} \quad \frac{ds}{dr} = \frac{dT(r)}{dr} = p_r(r)$$

$$\Rightarrow p_s(s) = p_r(r) \cdot \left| \frac{1}{p_r(r)} \right| = 1 \quad 0 \leq s \leq 1.$$

If you have not taken ECE302, skip this.

It works!

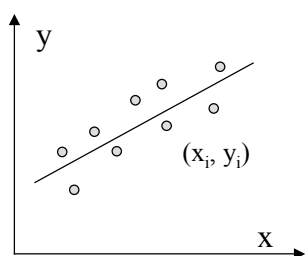


But not perfect



- The lighting is uneven. Some parts are brighter than other parts.
- The shadow also affects the imaging.
- Idea?
 - Seems the lighting is from the upper-right corner
 - Can we correct the lighting by tilting the image?
 - Then, we need to find a tilted 3D plan before compensation.

Line fitting



to find a line $y = ax + b$

s.t.,
$$\sum_{i=1}^N (ax_i + b - y_i)^2 \text{ is minimized}$$

Let's derive on-line!

Note: details can be found in class notes.

Generalized LS fitting

$$\begin{cases} ax_1 + b = y_1 \\ ax_2 + b = y_2 \\ \vdots \\ ax_N + b = y_N \end{cases} \iff \begin{bmatrix} x_1 & 1 \\ x_2 & 2 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$$

$$\iff A = \begin{bmatrix} x_1 & 1 \\ x_2 & 2 \\ \vdots & \vdots \\ x_N & 1 \end{bmatrix}; \quad x = \begin{bmatrix} a \\ b \end{bmatrix}; \quad t = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix}$$

An over-determined linear system. We need to find the least squares solution.

$$Ax = t$$

$$\xrightarrow{\hspace{1cm}} x = (A^T A)^{-1} A^T t \quad \text{Least squares solution}$$

$$A^\dagger = (A^T A)^{-1} A^T$$

Pseudo-inverse

$$x = A^\dagger t$$

Note: is the the same as the last slide?

Plane fitting

$$\begin{cases} a_1 u_1 + a_2 v_1 + a_3 = I(u_1, v_1) \\ a_1 u_2 + a_2 v_2 + a_3 = I(u_2, v_2) \\ \vdots \\ a_1 u_N + a_2 v_N + a_3 = I(u_N, v_N) \end{cases}$$

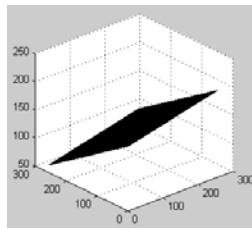
$$\begin{bmatrix} u_1 & v_1 & 1 \\ u_2 & v_2 & 1 \\ \vdots & \vdots & \vdots \\ u_N & v_N & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} I(u_1, v_1) \\ I(u_2, v_2) \\ \vdots \\ I(u_N, v_N) \end{bmatrix}$$

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} u_1 & v_1 & 1 \\ u_2 & v_2 & 1 \\ \vdots & \vdots & \vdots \\ u_N & v_N & 1 \end{bmatrix}^\dagger \begin{bmatrix} I(u_1, v_1) \\ I(u_2, v_2) \\ \vdots \\ I(u_N, v_N) \end{bmatrix}$$

Lighting correction – linear

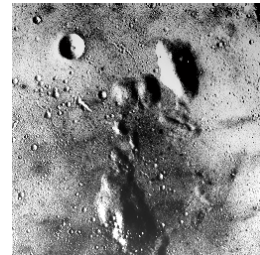


Truncated version

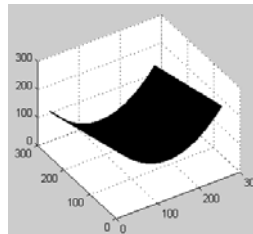


Scaled version

Lighting correction – quadratic



Truncated version



Scaled version