A Threshold Selection Method From Gray-Level Histograms.

Pick a threshold value to separate F/G and B/G in a non parametric & unsupervised way

200	200	200	200	200
200	42	200	42	200
200	200	200	200	200
200	38	200	27	200
200	200	18	200	200

↓ Threshold (50)

255	255	255	255	255
255	0	255	0	255
255	255	255	255	255
255	0	255	0	255
255	255	0	255	255

$$w_0 = Pr(C_0) = \sum_{i=1}^{k} p_i = w(k)$$

$$w_1 = Pr(C_1) = \sum_{i=k+1}^{L} p_i = 1 - w(k)$$

$$\mu_0 = \sum_{i=1}^{k} i\,Pr(i|C_0) = \sum_{i=1}^{k} \frac{i p_i}{w_0} = \frac{\mu(k)}{w(k)}$$

$$\mu_1 = \sum_{i=k+1}^{L} i\,Pr(i|C_1) = \sum_{i=k+1}^{L} \frac{i p_i}{w_1} = \frac{\mu_T - \mu(k)}{1 - w(k)}$$

where $\mu(k) = \sum_{i=1}^{k} i p_i$, $\mu_T = \mu(L) = \sum_{i=1}^{L} i p_i$

claim: $\forall k$, $w_0\mu_0 + w_1\mu_1 = \mu_T$

and $w_0 + w_1 = 1$

$$\sigma_0^2 = \sum_{i=1}^{k} (i-\mu_0)^2 Pr(i|C_0) = \sum_{i=1}^{k} \frac{(i-\mu_0)^2 p_i}{w_0}$$

$$\sigma_1^2 = \sum_{i=k+1}^{L} (i-\mu_1)^2 Pr(i|C_1) = \sum_{i=k+1}^{L} \frac{(i-\mu_1)^2 p_i}{w_1}$$

L Number of gray levels.

n_i Number of pixels at level i.

N Total number of pixels.

p_i $\frac{n_i}{N}$

C_0 Background [1, ..., k]

C_1 Objects / Foreground. [k+1, ..., L]

k separating threshold.

w_0 class probability for B/G

w_1 class probability for F/G

μ_0 class level mean intensity (B/G)

μ_1 class level mean intensity (F/G)

$w(k), \mu(k)$ zeroth and first order cumulative moments of histogram upto k^{th} level.

μ_T Total mean level.

σ_0^2, σ_1^2 Class variances.

σ_w^2 within class variance

σ_B^2 Between class variance

σ_T Total Variance

- Simple, Generic
- Non parametric, unsupervised
- optimal threshold decided by integration (global property) and not by differentiation (local)
- Extension to multithresholding is straightforward.

Measures of class separability

$$\lambda = \frac{\sigma_B^2}{\sigma_w^2} \qquad \kappa = \frac{\sigma_T^2}{\sigma_w^2} \qquad \eta = \frac{\sigma_B^2}{\sigma_T^2}$$

σ_B, σ_w are functions of k. σ_T is not.

σ_w : from second order statistics (class vars)

σ_B : from first order statistics (class means)

∴ η is simplest ⇒ maximize η

pick k to maximize $\eta = \frac{\sigma_B^2}{\sigma_T^2}$ $\propto \sigma_B^2$

$$\sigma_B^2(k^*) = \max_{1 \le k < L} \sigma_B^2(k)$$

Search space S^* can be restricted ~ effective range of histogram

∥ in this case all 3 criteria are equivalent.