

OTSU THRESHOLDING

Consider a histogram and its zeroth and first moments, p_0 and p_1 :

A histogram is represented by its counts, $c(i)$ for each graylevel from $i=0$ to 255 (for an 8-bit histogram).

If we normalize the counts by the total pixels in the image or count total of the histogram, CT , we have $p(i)=c(i)/CT$, where,

$$1 = \sum_{i=0}^{255} p(i)$$

Thus $p(i)$ is a fraction and represents a “probability” whose sum is unity.

Now the zeroth and first histogram moments are:

$$p_0 = \sum_{i=0}^{255} p(i) \quad \text{and} \quad p_1 = \sum_{i=0}^{255} i * p(i)$$

In IM, the histograms have only non-empty bins, thus we change this to:

$$1 = \sum_{i=0}^{lastbin} p(i) \quad \text{and} \quad p_0 = \sum_{i=0}^{lastbin} p(i) \quad \text{and} \quad p_1 = \sum_{i=0}^{lastbin} p(i) * g(i)$$

where i = bin number from 0 to $lastbin = (numbins - 1)$

In the Otsu thresholding method, one seeks to maximize the Between Class Variance of the foreground (bright) data and background (dark) data. That is the data above and below

some threshold T. The equation describing the Between Class Variance is:

$$(1) \text{BCV} = N_b \cdot (M_b - M)^2 + N_a \cdot (M_a - M)^2$$

Where

N_b and N_a are the cumulated normalized counts below the threshold and the cumulated normalized counts above the threshold, respectively.

M_b and M_a are the mean graylevel values from the cumulated bins below the threshold and from the cumulated bin above the threshold, respectively.

M is the mean graylevel from the image or complete histogram.

Thus,

$$(2) \quad N_b = p_{0b} = \sum_{i=0}^T p(i) \quad \text{and} \quad N_a = p_{0a} = \sum_{i=T+1}^{\text{lastbin}} p(i)$$

$$(3) \quad G_b = p_{1b} = \sum_{i=0}^T p(i) * g(i) \quad \text{and} \quad G_a = p_{1a} = \sum_{i=T+1}^{\text{lastbin}} p(i) * g(i)$$

where G_b and G_a are normalize cumulated graylevels below and above the threshold, respectively.

$$(4) \quad M_b = \frac{P_{1b}}{P_{0b}} = \frac{G_b}{N_b} \quad \text{and} \quad M_a = \frac{P_{1a}}{P_{0a}} = \frac{G_a}{N_a}$$

The reason that we have to divide by N_b and N_a to get M_b and M_a is that the means are computed by the sums divided by ONLY those pixels in each class. But the N_b , N_a , G_b and G_a are sums divided by the total count. Thus to factor out the total counts and have result that are divide by only

the counts in the class we need to divide G_b by N_b and G_a by N_a .

The mean of the image (mean of complete histogram) can then be expressed as:

$$(5) M = N_b * M_b + N_a * M_a$$

Also

$$(6) 1 = N_b + N_a$$

Now we would like to express BCV from equation (1) in a more efficient formula.

So if we substitute equation (5) into equation (1) and simplify (with a bit of effort), we get

$$(7) BCV = N_a * N_b * (M_a - M_b)^2$$

This basically says that BCV is the difference between the means of the two classes and thus we are attempting to find the threshold that maximizes the separation of these two means.

Equation (7) can be made more efficient by substituting equation (4) to cast this using G_b and G_a instead of M_a and M_b , thus avoiding the extra divides. We therefore get

$$(8) BCV = (G_a * N_b - G_b * N_a)^2 / (N_a * N_b)$$

However, we can alternately simplify equation (7) to completely avoid M_b and therefore the need for the second set of cumulative moments, G_a and N_a . We do this by first expressing equation (5) as

$$(9) M_a = (M - N_b * M_b) / N_a$$

Now, if we substitute equation (9) into equation (1) and simplify (with a bit of effort), we get

$$(10) \text{BCV} = (M - M_b)^2 * N_b / (1 - N_b)$$

where we also have used $N_a = (1 - N_b)$ from equation (6).

But we can take this even further. If we substitute into equation (10), $M_b = G_b / N_b$ from equation (4) and simplify, we get

$$(11) \text{BCV} = (N_b * M - G_b)^2 / (N_b * (1 - N_b))$$

This is the most efficient way to express BCV as it only needs the one set of below threshold cumulative arrays, N_b and G_b along with the global mean.