A Threshold Selection Method from Gray-level Histograms

Siva Naik(23EE65R04)
Signal Processing System Design Lab(EE69205)
Signal Processing and Machine Learning
Electrical Engineering
Indian Institute of Technology Kharagpur

***Abstract*—This paper introduces a nonparametric and unsupervised method for automated image segmentation by selecting optimal threshold values. The method aims to enhance the separability of image classes based on gray levels, maximizing discriminant criterion. This approach relies on the zeroth- and first-order cumulative moments of the gray-level histogram, ensuring simplicity and practicality. One notable feature of this method is its suitability for multi threshold problems, making it adaptable to diverse applications. To validate its effectiveness, the paper includes experimental results that demonstrate the method's robustness and utility in real-world scenarios.**

keywords: Nonparametric,discriminant criterion, unsupervised.

I. Introduction

It is important in image processing selecting the appropriate gray level threshold is a critical task for isolating objects from their backgrounds. Various techniques have been proposed for this purpose. In an ideal scenario, the image histogram exhibits a distinct and well-defined valley between two peaks, representing the objects and the background, making it straightforward to select a threshold at the lowest point of this valley. However, in most real-world images, this valley can be challenging to identify precisely. This difficulty arises when the valley is broad, noisy, or when the two peaks are significantly different in height, sometimes rendering the valley indistinct.

To address these challenges, several techniques have been developed. They include methods like valley sharpening, which focuses on histogram regions with large derivative values (e.g., Laplacian or gradient), and the difference histogram approach, which selects the threshold based on the gray level with the most substantial difference. These methods incorporate information from neighboring pixels or edges in the original image to improve the suitability of the histogram for thresholding.

Another category of methods directly manipulates the gray-level histogram using parametric techniques. For instance, they attempt to approximate the histogram as a sum of Gaussian distributions through least squares fitting and apply statistical decision procedures. However, these methods often involve intricate and occasionally unstable calculations, and, in many cases, the Gaussian distributions do not accurately represent the underlying data modes.

A. Formulation

Let the pixels of a given image be represented in L gray levels [1,2,3......L]. The no of pixels at level i is denoted by n_i and the total number of pixels by N=n1+n2....nL. . Now to segment the image pixels into two classes S0 and S1 (background and objects) by a threshold level T. S0 denotes pixels with levels [1,2,3,...,T] and S1 denotes pixels with levels [T+1.......,L]. . We formulate probabilities of class occurrence and the mean of S0,S1 class given by

$$w_o = Pr(S_o) = \sum_{i=1}^{T} P_i = (k) \tag{1}$$

$$w_1 = Pr(S_1) = \sum_{i=1}^{T} P_i = (1 - w_0) \tag{2}$$

Mean of both the classes is given by

$$u_0 = \frac{\sum_{i=0}^{T-1} i \cdot n_i}{\sum_{i=0}^{T-1} n_i} \tag{3}$$

$$u_1 = \frac{\sum_{i=T}^{L-1} i \cdot n_i}{\sum_{i=T}^{L-1} n_i} \tag{4}$$

The variance of both classes is given by

$$\sigma_0^2 = \frac{\sum_{i=0}^{T-1} (i - u_0)^2 \cdot n_i}{\sum_{i=0}^{T-1} n_i} \tag{5}$$

$$\sigma_1^2 = \frac{\sum_{i=T}^{L-1} (i - u_0)^2 \cdot n_i}{\sum_{i=T}^{L-1} n_i} \tag{6}$$

in order to evaluate the threshold (at level T) we shall introduce the following discriminant criterion measure[measure of class seperability].

Optimal threshold value to segment S0 and S1 is given by

$$J(\theta) = \frac{\sigma_B(\theta)}{\sigma_w(\theta)} \tag{7}$$

where

$$\sigma_B(\theta) = (u_0 - u_1)^2 \tag{8}$$

where

$$\sigma_w(\theta) = (\sigma_0^2 - \sigma_1^2)$$

(9)

From equation (7) we can say that with in class variance should be larger, it can be achieved by taking

$$T = \arg\max J(\theta) \tag{10}$$

B. Fast Implementation of Otsu's

We calculate only "between class variance" which is quicker to calculate with first order moment. The threshold with the maximum between class variance also has the minimum within calss variance. so it can be used for finding the best threshold and therefore due being simpler is much better approach to use.

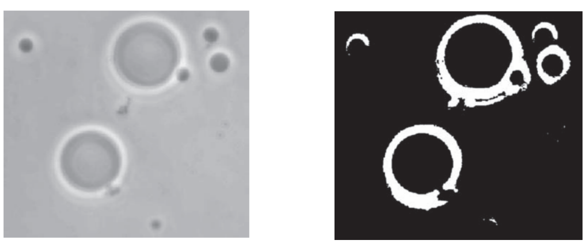
The formula for between calss variance,

$$\sigma_B^2 = w_0(u_0 - u_T)^2 + w_1(u_1 - u_T)^2 \tag{11}$$

$$\sigma_B^2 = w_0 \cdot w_1(u_1 - u_0)^2 \tag{12}$$

Here we are not finding out variance of the calsses, Hence segmenting the image becomes easier and less computaion.

II. EXPERIMENTAL RESULTS



(a) input image (b) segmented image

Fig. 1: Example input image demonstrates Otsu thresholding seperates back ground and foreground of the image

(a) input image (b) segmented image

Fig. 2: Example input image with noise demonstrates Otsu thresholding seperates back ground and foreground of the image

III. CONCLUSION

The nonparametric and unsupervised method for automatic threshold selection for picture segmentation, based on the discriminant criterion and the utilization of zeroth- and first-order cumulative moments of the gray-level histogram, offers a straightforward and effective approach for image processing. The primary objective of maximizing the separability of the resultant classes in gray levels is achieved with a simple and efficient procedure. Furthermore, the method can be easily extended to address multithreshold problems.

IV. ACKNOWLEDGEMENT

I would like to express my deepest gratitude to Dr. Debdoot Sheet for their invaluable support and guidance throughout the project. Their expertise and mentorship have been instrumental in shaping the outcome of this endeavor. Finally, I am grateful for the unwavering support of my family and friends, whose encouragement and understanding have been a source of strength throughout this journey.

V. REFERENCES

[1] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," in IEEE Transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62-66, Jan. 1979, doi: 10.1109/TSMC.1979.4310076.

[2] Chen Yu, Chen Dian-ren, Li Yang and Chen Lei, "Otsu's thresholding method based on gray level-gradient two-dimensional histogram," 2010 2nd International Asia Conference on Informatics in Control, Automation and Robotics (CAR 2010), Wuhan, 2010, pp. 282-285, doi: 10.1109/CAR.2010.5456687.