A New iterative triclass thresholding technique for Image Segmentation

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Abstract: We present a new method in image segmentation that is based on Otsu’s method but iteratively searches for sub regions of the image for segmentation, instead of treating the full image as a whole region for processing. The iterative method starts with Otsu’s threshold and computes the mean values of the two classes as separated by the threshold. Based on the Otsu’s threshold and the two mean values, the method separates the image into three classes instead of two as the standard Otsu’s method does. The first two classes are determined as the foreground and background and they will not be processed further. The third class is denoted as a to-be-determined (TBD) region that is processed at next iteration. At the succeeding iteration, Otsu’s method is applied on the TBD region to calculate a new threshold and two class means and the TBD region is again separated into three classes, namely, foreground, background, and a new TBD region, which by definition is smaller than the previous TBD regions. Then, the new TBD region is processed in the similar manner. The process stops when the Otsu’s thresholds calculated between two iterations is less than a preset threshold. Then, all the intermediate foreground and background regions are, respectively, combined to create the final segmentation result. Tests on synthetic and real images showed that the new iterative method can achieve better performance than the standard Otsu’s method in many challenging cases, such as identifying weak objects and revealing fine structures of complex objects while the added computational cost is minimal.

Keywords: color image, otsu’s method, segmentation, thresholding, triclass segmentation

I. INTRODUCTION

In image processing, segmentation is often the first step to pre-process images to extract objects of interest for further analysis. Segmentation techniques can be generally categorized into two frameworks, edge-based [1]–[2] and region based [3] approaches. As a segmentation technique, Otsu’s method is widely used in pattern recognition, document binarization, and computer vision. In many cases Otsu’s method is used as a pre-processing technique to segment an image for further processing such as feature analysis and quantification. Otsu’s method searches for a threshold that minimizes the intra-class variances of the segmented image and can achieve good results when the histogram of the original image has two distinct peaks, one belongs to the background, and the other belongs to the foreground or the signal. The Otsu’s threshold is found by searching across the whole range of the pixel values of the image until the intra-class variances reach their minimum. As it is defined, the threshold determined by Otsu’s method is more profoundly determined by the class that has the larger variance, be it the background or the foreground. As such, Otsu’s method may create suboptimal results when the histogram of the image has more than two peaks or if one of the classes has a large variance. Over the years, researchers have proposed many methods to improve the standard Otsu’s method. For example, Cheriet et al. proposed a recursive approach based on Otsu’s technique to focus on the brightest homogeneous object in an image [4]. A quad-tree approach was developed to segment images by combining a centroid clustering and boundary estimation methods but the approach only works under the assumption that the histogram consists of Gaussian distributions only. In the authors added a weight term to force the resultant threshold value resides at the valley of the two peaks or at the bottom rim of a single peak. The standard bi-level thresholding technique has been extended to multilevel thresholding in [5]. In the standard Otsu’s method 1D histogram is used for binization and methods have been proposed to expand the histogram to two dimensions (2D) by considering gray levels and average, albeit the 2D implementation is more computational intensive. Theoretically, it has been shown in that the objective function of Otsu’s method is equivalent to that of K-means method in multilevel thresholding [9]. In terms of speeding up computations, a fast search implementation of the threshold was proposed by Reddi et al.
In this paper, we present a new iterative method that is based on Otsu’s method but differs from the standard application of the method in an important way. At the first iteration, we apply Otsu’s method on an image to obtain the Otsu’s threshold and the means of two classes separated by the threshold as the standard application does. Then, instead of classifying the image into two classes separated by the Otsu’s threshold, our method separates the image into three classes based on the two class means derived. The three classes are defined as the foreground with pixel values are greater than the larger mean, the background with pixel values are less than the smaller mean, and more importantly, a third class we call the “to-be-determined” (TBD) region with pixel values fall between the two class means. Then at the next iteration, the method keeps the previous foreground and background regions unchanged and re-applies Otsu’s method on the TBD region only to, again, separate it into three classes in the similar manner. When the iteration stops after meeting a preset criterion, the last TBD region is then separated into two classes, foreground and background, instead of three regions. The final foreground is the logical union of all the previously determined foreground regions and the final background is determined similarly. The new method is almost parameter free except for the stopping rule for the iterative process and has minimal added computational load. We tested the new iterative method on synthetic and real images and found that it can achieve superior performance in segmenting images such as zebra fish and nuclei images acquired by microscopes. Results show that the new method can segment weak objects or fine structures that are typically missed by the standard Otsu’s method.

II. IMAGE SEGMENTATION

Image segmentation refers to the process of partitioning a digital image into multiple segments i.e. set of pixels, pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture, so as to locate and identify objects and boundaries in an image. Practical application of image segmentation range from filtering of noisy images, medical applications (Locate tumors and other pathologies, Measure tissue volumes, Computer guided surgery, Diagnosis, Treatment planning, study of anatomical structure), Locate objects in satellite images (roads, forests, etc.), Face Recognition, Finger print Recognition, etc. Many segmentation methods have been proposed in the literature. The choice of a segmentation technique over another and the level of segmentation are decided by the particular type of image and characteristics of the problem being considered.

Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

Detecting Discontinuities

It means to partition an image based on abrupt changes in intensity, this includes image segmentation algorithms like edge detection.

Detecting Similarities

It means to partition an image into regions that are similar according to a set of predefined criterion; this includes image segmentation algorithms like thresholding, region growing, region splitting and merging.

Segmentation Based on Edge Detection

This method attempts to resolve image segmentation by detecting the edges or pixels between different regions that have rapid transition in intensity and linked to form closed object boundaries. The result is a binary image. Based on theory there are two main edge based segmentation methods- gray histogram and gradient based method.

Thresholding Method

Image segmentation by thresholding is a simple but powerful approach for segmenting images having light objects on dark background. Thresholding technique is based on image space regions i.e. on characteristics of image. Thresholding operation convert a multilevel image into a binary image i.e., it choose a proper threshold T, to divide image pixels into several regions and separate objects from background. Any pixel \((x, y)\) is considered as a part of object if its intensity is greater than or equal to threshold value i.e., \(f(x, y) \geq T\), else pixel belong to background. As per the selection of thresholding value, two types of thresholding methods are in existence, global and local thresholding. When T is constant, the approach is called global thresholding otherwise it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven. In local thresholding, multiple thresholds are used to compensate for uneven illumination. Threshold selection is typically done interactively however; it is possible to derive automatic threshold selection algorithms.

A. Histogram shape

Based methods, where, for example, the peaks, valleys and curvatures of the smoothed histogram are analyzed.

B. Clustering

Based methods, where the gray-level samples are clustered in two parts as background and foreground (object), or alternately are modeled as a mixture of two Gaussians.

C. Entropy

Based methods result in algorithms that use the entropy of the foreground and background regions, the cross-entropy between the original and binarized image, etc.
D. Object Attribute

Based methods search a measure of similarity between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc.

E. Spatial

Based methods use higher-order probability distribution and/or correlation between pixels.

F. Local

Based methods adapt the threshold value on each pixel to the local image characteristics. In these methods, a different T is selected for each pixel in the image.

Region Based Segmentation Methods

Compared to edge detection method, segmentation algorithms based on region are relatively simple and more immune to noise. Edge based methods partition an image based on rapid changes in intensity near edges whereas region based methods, partition an image into regions that are similar according to a set of predefined criteria.

III. METHODS

A. Otsu’s Method

Otsu’s method searches the histogram of an image to find a threshold that binarizes the image into two classes, the background with a mean of μ₀ and the foreground with a mean of μ₁, as shown in the top of Fig. 1. Without loss of generality, here we assume that the foreground is brighter than the background, i.e., μ₁ > μ₀. The calculation of threshold T is as follows:

\[
T = \arg \min_T \sigma^2_0(T)
\]

Where \( \sigma^2_0(T) = q_0(T)\sigma^2_0(T) + q_1(T)\sigma^2_1(T) \)

The subscript 0 and 1 denote the two classes, background and foreground, respectively, and \( q_i \) and \( \sigma_i, i = [0, 1] \) are the estimated class probabilities and class variances, respectively.

These quantities are calculated as

\[
q_0 = \sum_{i=1}^{T} p(i) \quad q_1 = \sum_{i=T+1}^{K} p(i)
\]

and the individual class variances are given as

\[
\sigma^2_0(T) = \sum_{i=1}^{T} (i - \mu_0(T))^2 p(i)/q_0(T) \]

\[
\sigma^2_1(T) = \sum_{i=T+1}^{K} (i - \mu_1(T))^2 p(i)/q_1(T)
\]

Where we assume that the pixel values of the image are from 0 to K. So from the above equations we can see that T is function of the pixel values of both the foreground and the background. If the signal intensity changes, it may affect T in such a way that the segmentation result may become less optimal.

Fig.1: Top, Otsu’s method binarizes an image to two classes based on threshold T by minimizing the within-class variance. Bottom, in our iterative method we classify the histogram into three classes, namely the foreground region with pixel values greater than μ₁ (shown in yellow), the background region with pixel values less than μ₀ (shown in blue), and the third region, called TBD, in red. The superscript denotes the number of iteration in our new algorithm.

Fig.2: Experiments on a zebra fish microscopic image. (a) A raw zebra fish embryo image acquired by a bright-field microscope. Its spinal cord is pointed by the arrow. (b) The result given by Otsu’s method.

Fig 3: (a) A test image showing a zebra fish embryo acquired by a bright field microscope. The arrow points to pericardial edema.2 (b) the result given by the standard Otsu’s method.

In Fig. 2(a) shows an original image of zebra fish consisting of multiple objects in gray scale. The segmentation result of the standard Otsu’s method is shown in Fig. 2(b), from which we can observe that most objects are correctly segmented or marked. Similarly in Fig. 3(a) shows an original image of zebra fish embryo consisting of multiple objects in gray scale. The segmentation result of the standard Otsu’s method is shown in Fig. 3(b), from which we can observe that most objects are correctly segmented or marked. Then we purposely added a strong object to the original image to increase the overall signal intensity in the
foreground and tested how Otsu’s method performs in this case. Some weak objects are actually missed now by Otsu’s method. The reason is that the increased signal intensity resulted in raised \( T \) in segmentation, causing the method to miss weak objects. As shown above, there are cases that Otsu’s method does not produce satisfactory results even when the foreground has a high signal intensity, i.e., a higher signal-to-background ratio (SBR). In other words, the performance of Otsu’s method is not a function of SBR only. To understand quantitatively what factor also determines the performance of Otsu’s method and therefore allows us to design a better approach, we introduce the notion of “distance ratio” which we define as the ratio of the distance in mean between the foreground and background to the full pixel range of an image.

B. Iterative Method

The idea of dividing an image’s histogram iteratively into three classes. For an image \( u \), at the first iteration, Otsu’s method is applied to find a threshold \( T^{[1]} \) where the superscript denotes the number of iteration. We then find and denote the means of the two classes separated by \( T^{[1]} \) as \( \mu_0^{[1]} \) and \( \mu_1^{[1]} \) for the background and foreground, respectively. Then we classify regions whose pixel values are greater than \( \mu_1^{[1]} \) as foreground \( F^{[1]} \) and regions whose pixel values are less than \( \mu_0^{[1]} \) as background \( B^{[1]} \). For the remaining pixels \( u(x, y) \) such that \( \mu_0^{[1]} \), we denote them as the TBD class. So our iterative process assumes that the pixels that are greater than the mean of the “tentatively” determined foreground are the true foreground.

\[
U = F^{[1]} \cup B^{[1]} \cup _{[1]}
\]

(7)

Where \( U \) is the logical union operation. At the second iteration, we apply Otsu’s method to find threshold \( T^{[2]} \) on region \( _{[1]} \) only. We then calculate the two classes means in \( _{[1]} \) separated by \( T^{[2]} \) as \( \mu_0^{[2]} \) and \( \mu_1^{[2]} \). Similarly, the second iteration will generate a new \( F^{[2]} \), \( B^{[2]} \), and \( _{[2]} \) such that

\[
_{[1]} = \mu_{[2]}^{[2]} \cup \mu_{[2]}^{[2]} \cup _{[2]}
\]

(8)

Where \( F^{[2]} \) is defined as the region in \( _{[1]} \) with pixel values greater than \( \mu_1^{[1]} \), \( B^{[2]} \) as the region in \( _{[1]} \) with pixel values less than \( \mu_0^{[1]} \), and \( _{[2]} \) are the new TBD region. The iteration stops when the difference between two consecutive thresholds \( |T^{[n+1]} - T^{[n]}| \) is less than a preset threshold. At the last iteration \( [n + 1] \), \( _{[n]} \) is separated into two instead of three classes, i.e., foreground \( F^{[n+1]} \) is defined as the region of \( _{[n]} \) that is greater than \( T^{[n+1]} \) instead of \( \mu_1^{[n]} \) and background \( B^{[n+1]} \) is defined as the regions with pixel value less than \( T^{[n+1]} \). The innovation of the new method is to iteratively define the TBD regions to gain a high distance ratio, which will result in better segmentation by applying Otsu’s method.

To examine how the iterative three-class method performs, we first tested it on the previous image of Fig. 5(a)-(b) The results created by the proposed method on iteration one to four, respectively. In the final result, the spinal cord of the zebra fish embryo, pointed by the red arrow, is fully segmented by our method. We note the two results are almost identical in segmenting the original objects.
Fig.5: (a)–(d) the results created by the proposed method on iteration one to four, respectively. In the final result, the spinal cord of the zebra fish embryo, pointed by the red arrow, is fully segmented by our method.

Fig 6: (a) The result of the first iteration of the new method. (b) The result of the fourth iteration, which detects the spherical boundary of the pericardial edema (pointed by the arrow) while it is missed by the standard Otsu’s method.

In addition to the above test cases, we applied the new iterative method on real microscopic images. For the first type of images we applied the new method on in vivo zebra fish images acquired by a bright-field microscope. Fig. 2(a) shows a raw image of a zebra fish embryo. Because zebra fish embryos are transparent we can directly observe many anatomic structures without fixing and staining. For example the spinal cord of result the embryo is visible in Fig. 2 (a). The segmentation result of Otsu’s method is shown in Fig. 2(b). Though the standard Otsu’s method can segment the major structure of the embryo it misses detailed anatomic structure such as the spinal cord. For comparison, Fig. 5 (a)–(d) show the results generated by the new method at iteration one to four, respectively. We can observe that some detailed structures are gradually segmented. In particularly, the new algorithm is able to accurately segment the spinal cord (pointed by the arrow) at iteration four, as shown in Fig. 5(d).

As the second example, we tested the iterative method on zebra fish images obtained in a different experiment where zebra fish embryos developed pericardial edema. An original image is shown in Fig. 3(a) and its standard Otsu’s result is shown in Fig. 3(b), which does not segment the half spherical boundary of the edema. The results of applying the iterative method are shown in Fig. 6(a) and (b) for the first and fourth iterations. From the result of the fourth iteration we can observe that the algorithm is able to segment the half spherical boundary of the pericardial edema. In Fig. 10 we plot the histograms of Figs. 6(a) and their iterative thresholds given by the new method. In both examples, the thresholds decrease monotonically as the method proceeds to segment fine structures of the zebra fish objects. We can observe that the histograms of the two examples are approximately bi-modal, yet Otsu’s method can only segment the large structures in both cases. In comparison, the new method is able to segment fine structures as the thresholds are gradually reduced to approach the background level but remain in the range of the true signals.

IV. CONCLUSION

As Otsu’s method is widely used as a pre-processing step to segment images for further processing, it is important to achieve a high accuracy. But it misses out weak objects.

In this paper, we proposed to take advantage of Otsu’s threshold by classifying images into three tentative classes instead of two permanent classes in an iterative manner. The three classes are designated as the true foreground and background, and a third TBD region that is to be further processed at the next iteration. The iteration stops until the change in thresholds of two consecutive iterations is less than a threshold.

The performance of the new algorithm is evaluated on both synthetic and real microscopic images. Results demonstrate that the proposed algorithm can achieve superior performance in segmenting weak objects and fine details. The new method is also almost parameter-free except for the preset threshold to terminate the iterative process. The added computational cost is minimal as the process usually stops in a few iterations and each iteration only processes a monotonically shrinking TBD region.

REFERENCES


AUTHOR’S BIOGRAPHIES

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