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An Efficient Segmentation for Medical Images Based On Iterative Tri Class Thresholding Technique

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Abstract: A New technique in picture division that is in view of Otsu's system however iteratively looks for sub districts of the picture for division, as opposed to regarding the full picture in general locale for preparing. The iterative technique begins with Otsu's limit and processes the mean estimations of the two classes as differentiated by the edge. In light of the Otsu's edge and the two mean values, the strategy differentiates the picture into three classes rather than two as the standard Otsu's technique does. The initial two classes are dead set as the frontal area and foundation and they won't be handled further. The second rate class is indicated as a to-be-resolved (TBD) district that is handled at next cycle. At the succeeding emphasis, Otsu's technique is connected on the TBD area to ascertain another edge and two class implies and the TBD locale is again divided into three classes, namely, forefront, foundation, and another TBD district, which by definition is s maller than the past TBD locales. At that point, the new TBD locale is prepared in the comparative way. The methodology stops when the Otsu's limits computed between two emphases is not as much as a preset edge. At that point, all the halfway forefront and foundation locales are, separately, joined to make the last division result. Tests on engineered and genuine pictures demonstrated that the new iterative technique can accomplish preferable execution over the standard Otsu's strategy in numerous testing.

Keywords: Binarization, Otsu's Method, Segmentation, Threshold, Triclass Segmentation.

I. INTRODUCTION

In image processing, division is frequently the first venture to preprocess pictures to concentrate objects of enthusiasm for further investigation. Division systems can be by and large classified into two structures, edge-based [1]–[3] and locale based [4]–[6] approaches. As a division system, Otsu's technique is generally utilized as a part of example distinguishment [7]–[9], document binarization, and PC vision. By and large Otsu's system issued a preprocessing strategy to fragment a picture for further transforming, for example, highlight investigation and evaluation. Otsu's system hunt down a limit that minimizes the intra-class changes of the fragmented picture and can attain to great results when the histogram of the first picture has two particular tops, one has a place with the foundation, and alternate fits in with the closer view or the signal. The Otsu's threshold is found via looking over the entire scope of the pixel estimations of the picture until the intra-class differences achieve their base. As it is characterized, the limit dictated by Otsu's system is all the more significantly controlled by the class that has the bigger fluctuation, be it the foundation or the closer view.

In that capacity, Otsu's technique may make problematic results when the histogram of the picture has more than two crests or if one of the classes has a vast fluctuation. Throughout the years, specialists have proposed numerous techniques to enhance the standard Otsu's system. For instance, Cheriet et al. proposed a recursive methodology in view of Otsu's method to concentrate on the brightest homogeneous protest in a picture. A quad-tree methodology was created to fragment pictures by joining a centroid bunching and limit estimation routines yet the methodology just works under the suspicion that the histogram comprises of Gaussian circulations just. In [11], the creators addenda weight term to constrain the resultant limit worth dwells at the valley of the two crests or at the base edge of a solitary top. The standard bi-level thresholding procedures has been stretched out to multilevel thresholding. In the standard Otsu's method1D histogram is utilized for binarization and routines have been proposed to grow the histogram to two measurements (2D) by considering dim levels and normal, yet the 2Dimplementationis more computational escalated. Hypothetically, it has been indicated that the target capacity of Otsu's strategy is identical to that of K-means system in multilevel thresholding. As far as accelerating computations.

In this paper, we exhibit another iterative technique that is in view of Otsu's system yet differs from the standard utilization of the strategy imperative way. At the first emphasis, we apply Otsu's technique on a picture to acquire the Otsu's edge and the method for two classes differentiated by the limit as the standard application does. At that point, as opposed to arranging the picture into two classes divided by the Otsu's threshold, our strategy divides the picture into three classes as the forefront with pixel qualities are more noteworthy than the bigger mean, the foundation with pixel qualities are not exactly the littler mean, and all the more critically, a second rate class we call the "to-be-determined"(TBD) locale with pixel qualities fall between the two class implies. At that point at the following cycle, the strategy keeps the past closer view and foundation districts unaltered and re-applies Otsu's system on the TBD district just to, once more, separate it into three classes in the comparable way. At the point when the emphasis stops in the wake of meeting a preset rule, the last TBD district is then differentiated into two classes, closer view and foundation, rather than three areas. The last closer view is the consistent union of all the already decided forefront locales and the last foundation is resolved likewise. The new technique is very nearly parameter free aside from the halting principle for the iterative process and has insignificant included computational burden. We tried the new iterative technique on engineered and genuine pictures and observed that it can accomplish predominant execution in fragmenting pictures, for example, zebrafish and cores pictures procured by magnifying instruments. Results demonstrate that the new system can section frail protests or fine structures that are ordinarily missed by the standard Otsu's strategy.

II. OTSU'S METHOD

In computer vision and image processing, Otsu's method is used to automatically perform clustering-based image thresholding, or, the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal.[2] The extension of the original method to multi-level thresholding is referred to as the Multi Otsu method. In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2(t) = w_1(t)\sigma_i^2(t) + w_2\sigma_i^2(t) \quad \textbf{(1)}$$

Weights $\omega_i$are the probabilities of the two classes separated by a threshold $t$and $\sigma_i^2(t)$variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing inter-class variance:

$$\sigma_w^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)] \quad \textbf{(2)}$$

which is expressed in terms of class probabilities $w_1$and class means μ_1.The class probability $w_1(t)$is computed from the histogram as t:

$$w_1(t) = \sum_0^t P(i) \quad \textbf{(3)}$$

While the class mean $\mu_1(t)$is:

$$\mu_1(t) = \left[\sum_0^t P(i)\, x(i)\right] / w_1 \quad \textbf{(4)}$$

Where $x(i)$is the value at the center of the i_{th} histogram bin. Similarly, you can compute $w_2(t)$and $\mu_2(t)$on the right-hand side of the histogram for bins greater than t. The class probabilities and class means can be computed iteratively. This idea yields an effective algorithm.

III. IMAGE SEGMENTATION

Segmentation is often considered to be the first step in image analysis. The purpose is to subdivide an image into meaningful non-overlapping regions, which would be used for further analysis. It is hoped that the regions obtained correspond to the physical parts or objects of a scene (3-D) represented by the image (2-D). In general, autonomous segmentation is one of the most difficult tasks in digital image processing.

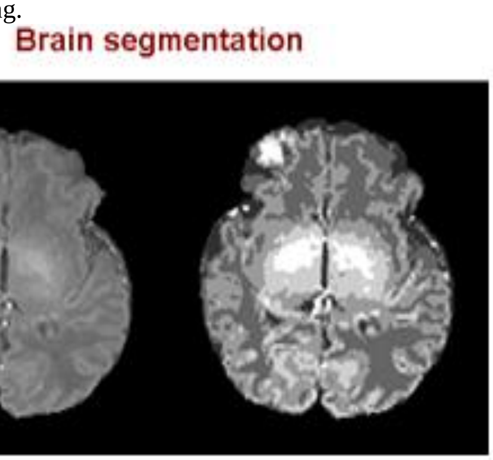

Fig.1. Examples of segmentation.

All the image segmentation methods assume that: The intensity values are different in different regions, and, Within each region, which represents the corresponding object in a scene, the intensity values are similar. Proposed brain tumor segmentation using discriminative random field (DRF) method. In [2], Lee et al. exploited a set of multiscale image-based and alignment-based features for segmentation. However, the proposed framework does not allow training and testing the proposed models across different patients. Corso et al. [3] discussed conditional random field (CRF) based hybrid discriminative-generative model for segmentation and labeling of brain tumor tissues in MRI. The CRF model employs cascade of boosted discriminative classifier where each classifier uses a set of about one thousand features. Wels et al. [5] used intensity, intensity gradient, and Haar-like features in a Markov random field (MRF) method that combines probabilistic boosting trees and graph cuts for tumor segmentation. Overall, these methods of incorporating spatial dependencies in classification using DRF/CRF/MRF demand very careful tumor characterization for convergence.

IV.TRI CLASS SEGMENTATION

The idea of dividing an image's histogram iteratively into three classes is illustrated at the bottom of Fig. 1. 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 μ[1] 0 and μ[1] 1 for the background and foreground, respectively. Then we classify regions whose pixel values are greater than μ[1] 1 as foreground F[1] and regions whose pixel values are less than μ[1]0 as background B[1]. For the remaining pixels u(x, y) such that μ[1]0≤ u(x, y) ≤ μ[1]1 we denote them as the TBD class _[1]. So our iterative process assumes that the pixels that are greater than the mean of the “tentatively” determined foreground are the true foreground. Similarly, pixels with values less than μ0 are for certain the background. But the pixels in the TBD class, which are the ones that typically cause misclassifications in the standard Otsu’s method, are not decided at once and will be further processed. Fig. 3. A synthetic example to demonstrate the iterative performance of the new iterative tri-class method on Fig. 2(c). (a)–(d) show the results obtained after the first to the fourth iterations, respectively. As the iteration proceeds, more foreground objects are correctly segmented, especially near the bottom of the image.

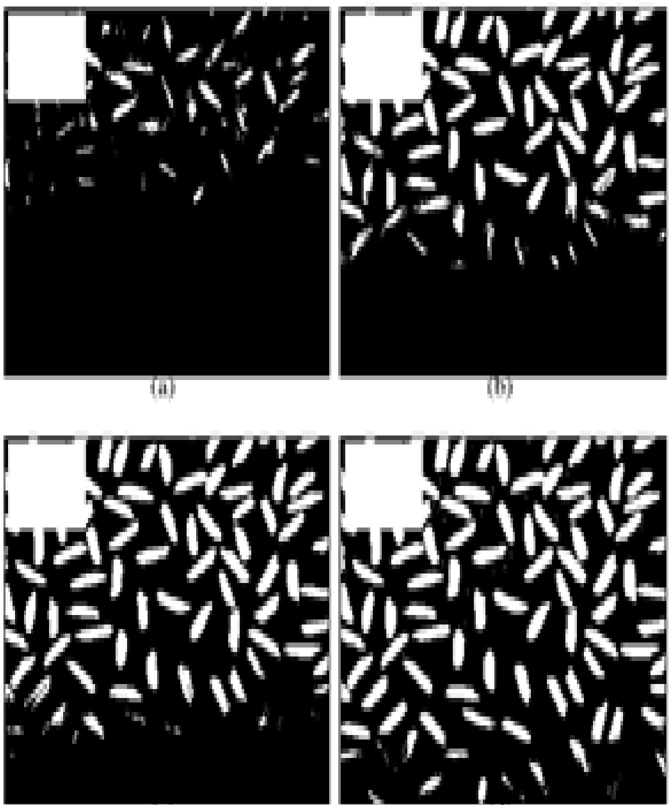

Fig.2. A synthetic example to demonstrate the iterative performance of the new iterative tri-class method on Fig. 2(c). (a)–(d) show the results obtained after the first to the fourth iterations, respectively. As the iteration proceeds, more foreground objects are correctly segmented, especially near the bottom of the image.

V. EXPERIMENTAL RESULTS

The experiential results of proposed system we applied the new iterative method on real microscopic images. for the first type of images we applied the new method on in Brain tumor images acquired by a bright-field scan images . as show the fig.3: it is experimental results of brain tumor image. The results of applying the iterative method are shown in Fig.(d) to (g) 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.

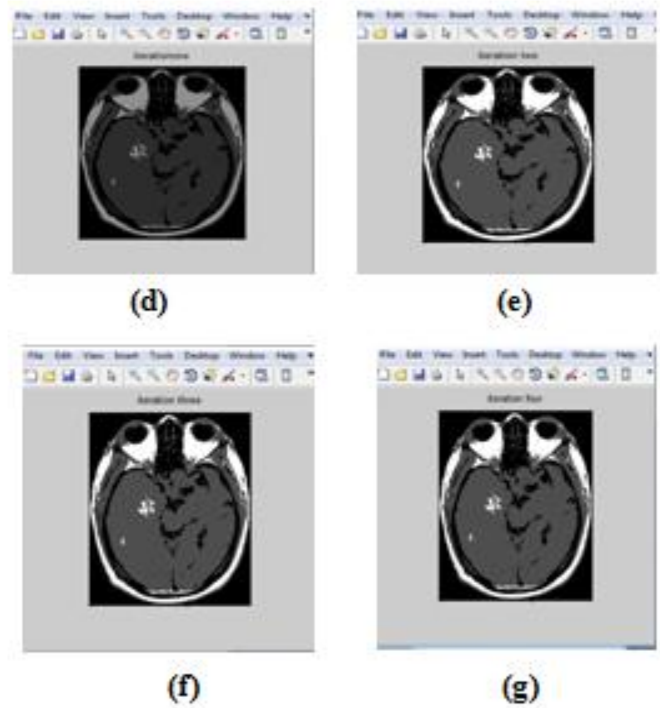

Fig. 3. (d) A first iteration a Brain image acquired by a bright field scan images . (e) Second iteration image . (f) The result of the Third iteration of the new method. (g) The result of the fourth iteration

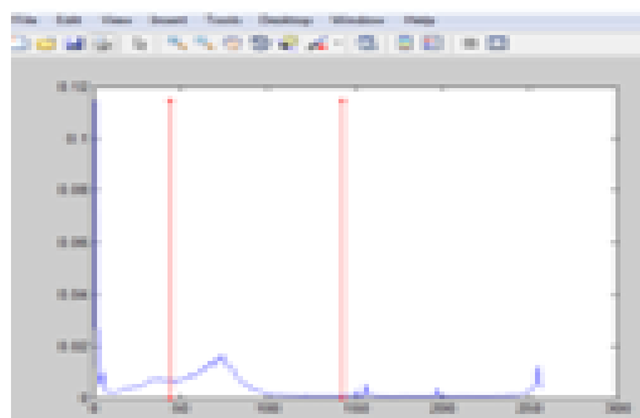

Fig.4. Histogram of brain image.

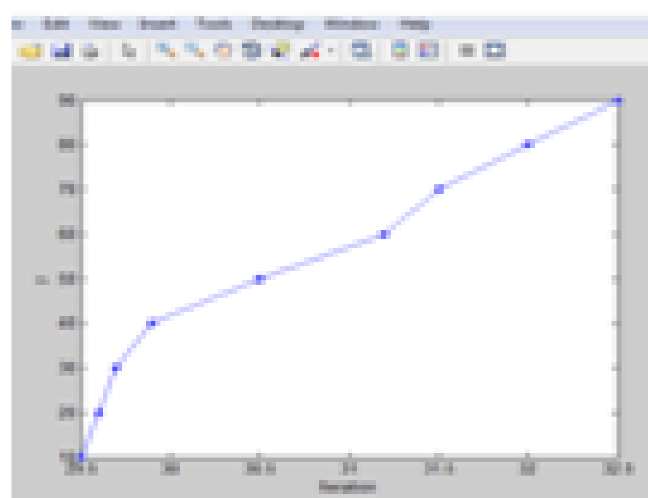

Fig.5. Distance ration of proposed system.

As show the fig.5 is distance ratio of proposed system From the figure we observe that despite very low distance ratios at the first iterations for both figs.4 and 5, the ratios quickly increase from iteration two, suggesting that the TBD regions at each iteration provide favorable inputs for Otsu's method to process. The above examples on both synthetic and real images demonstrate that the new method achieves superior performance in segmenting single or multiple objects, even in very challenging cases. Performance evaluation of proposed system. In this calculate standard deviation and peak signal to noise ratio, mean and intensity.

TABLE I: Performance Evaluation of Proposed System

Intensity	PSNRV	MEANR	S DTR
44-143	16.1290	3.7792e+03	0.5996

V. 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. However, since Otsu's threshold is biased towards the class with a large variance, it tends to miss weak objects or fine details in images. For example in biomedical images, nuclei and axons may be imaged with very different intensities due to uneven staining or imperfect lightening conditions, raising difficulty for algorithms like Otsu's method to successfully segment them. Without a robust segmentation results, more sophisticated processing such as tracking and feature analysis become highly challenging. 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. At each iteration, the tri-class approach keeps regions that are determined to be foreground and background unchanged and focuses on the third TBD region An advantage of Otsu's method is that it is parameter-free, making it widely used in practice. Similarly, the proposed method is almost parameter-free except the determination of the stopping rule of the iteration process. Testing results show that the new method can achieve better performance in challenging cases. We note that there are many segmentation methods, but many of them require careful selection of parameters to achieve satisfactory performance. From this perspective, a parameter-free method may be well suited in many applications.

VI. REFERENCES

[1] L. Herta and R. W. Schafer, "Multilevel threshold using edge matching,"Comput. Vis., Graph., Image Process., vol. 44, no. 3, pp. 279–295, Mar. 1988.

[2] R. Kohler, "A segmentation system based on thresholding," Comput. Graph. Image Process., vol. 15, no. 4, pp. 319–338, Apr. 1981.

[3] X. Xu, "A method based on rank-ordered filter to detect edges in cellular image," Pattern Recognit. Lett., vol. 30, no. 6, pp. 634–640, Jun. 2009.

[4] S. Baukharouba, J. M. Rebordao, and P. L. Wendel, "An amplitude segmentation method based on the distribution function of an image," Comput. Vis., Graph., Image Process., vol. 29, no. 1, pp. 47–59, Jan. 1985.

[5] M. J. Carlotto, "Histogram analysis using scale-space approach," IEEE Trans. Pattern Anal. Mach. Intell., vol. 9, no. 1, pp. 121–129, Jan. 1987.

[6] J. Kittler and J. Illingworth, "Minimum error threshold," Pattern Recognit., vol. 19, no. 1, pp. 41–47, Jan. 1986.

[7] P. Sirisha, C. N. Raju, and R. P. K. Reddy, "An efficient fuzzy technique for detection of brain tumor," Int. J. Comput. Technol., vol. 8, no. 2, pp. 813–819, 2013.

[8] C. H. Bindu and K. S. Prasad, "An efficient medical image segmentation using conventional OTSU method," Int. J. Adv. Sci. Technol., vol. 38, pp. 67–74, Jan. 2012.

[9] P. Gupta, V. Malik, and M. Gandhi, "Implementation of multilevel threshold method for digital images used in medical image processing," Int. J., vol. 2, no. 2, Feb. 2012.

[10] R. Farrahi Moghaddam and M. Cheriet, "AdOtsu: An adaptive and parameterless generalization of Otsu's method for document image binarization," Pattern Recognit., vol. 45, no. 6, pp. 2419–2431, 2012.

[11] Y. Zhang and L. Wu, "Fast document image binarization based on an improved adaptive Otsu's method and destination word accumulation," J. Comput. Inf. Syst., vol. 7, no. 6, pp. 1886–1892, 2011.

[12] O. Nina, B. Morse, and W. Barrett, "A recursive Otsu thresholding method for scanned document binarization," in Proc. IEEE WACV, Jan. 2011, pp. 307–314.