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Separation from Brain Magnetic Resonance images (MRI) using Multistage Thresholding Technique

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ABSTRACT

Image separation is a significant task concerned in dissimilar areas from image dispensation to picture examination. One of the simplest methods for image segmentation is thresholding. However, many thresholding methods are based on a bi-level thresholding process. These methods can be extended to form multi-level thresholding. Still, they become computationally expensive since a large number of iterations would be necessary for computing the most select threshold values. To conquer this difficulty, a new process based on a Shrinking Search Space (3S) algorithm is proposed in this paper. The method is applied on statistical bi-level thresholding approaches including Entropy, Cross-entropy, Covariance, and Divergent Based Thresholding (DBT), to attain multi-level thresholding and used for separation from brain MRI images. The paper demonstrates that the collision of the proposed 3S method on the DBT method is more important than the other bi-level thresholding approaches. Comparing the results of using the proposed approach against those of the Fuzzy C-Means (FCM) clustering method demonstrates a better segmentation performance by improving the comparison index from 0.58 in FCM to 0.68 in the 3S method. Also, this method has a lower calculation impediment of around 0.37s with admiration to 157s dispensation time in FCM. In addition, the FCM approach does not always guarantee the convergence, whilst the 3S method always converges to the optimal result.

Keywords: *Medical image processing; Magnetic resonance imaging; Separation; Thresholding; Brain images.*

I. INTRODUCTION

A significant constituent of Computer-Aided Detection (CAD) systems based on Magnetic Resonance Imaging (MRI) is separation. There are two ways of separation that are physical and mechanical separation. Automatic separation is categorized into a number of groups: standard methods such as thresholding, region growing, and edge-based methods; soft computing methods such as neural networks and fuzzy clustering methods; arithmetic methods such as Expectation-Maximization (EM) and Markov Random Fields (MRF) methods; model-based methods, and rule-based methods.

Thresholding is one of the majority extensively used approaches in image segmentation, and also one of the simplest approaches. Image thresholding is the course of classifying grey image values into two or more levels. This method has been used on T1-weighted MRI images to part brain tissues such as a skull, Gray Matter (GM), White Matter (WM), and Cerebro Spinal Fluid (CSF). Most of the existing thresholding methods are bi-level, which use two levels to categorize the image into background and thing segments. However, MRI images have many dissimilar parts which make these methods non-applicable. Thus, the loss of information from the image may occur, and the examination system may deceive physicians in their irrefutable assignment.

Consequently, an optimum multi-level thresholding algorithm is necessary to find each thresholding level to ensure that all significant information from MRI images is retained. Fuzzy C-means (FCM) is an early multi-level thresholding method. In this method, a cluster is assigned to each tissue class in MRI segmentation. The data in each cluster should be compared based on a resemblance principle.

This resemblance principle may be a geometrical distance such as Euclidian distance between each data and a centre point which is the delegate of each cluster. This type of clustering is known as distance-based clustering. Thus, the goal of clustering is giving labels to each data, where each label identifies a cluster. Because of the reputation of the FCM method, we use it as a benchmark to evaluate the efficacy of the 3S multi-level thresholding technique planned in this paper.

In this work, first, a region rising method is applied to the brain MRI Images to eliminate the skull province. To fully part the skull, some morphological operations are used. Then, the proposed 3S multi-thresholding approach is applied to the resulting image to segment dissimilar brain tissues.

II. BACKGROUND

Because a great number of multi-level thresholding systems are imitative from bi-level ones, the assessment bi-level methods, and then exhibit how to use these methods in the thresholding system. According to the research reported in the circumstances, the two-stage thresholding methods are categorized into six groups including histogram contour information, dimension space clustering, histogram entropy information, image attribute information, spatial information, and local characteristic. In this paper, we have evaluated dissimilar approaches in the kind of histogram entropy class. These methods include Entropy method, Covariance method, different Based Thresholding method (DBT), and the Cross-Entropy method, which are investigated here.

Let L be grey levels [1, 2,…,L] in a given image, with the possibility distributions denote by pi. Now, presume that the pixels are separated into two classes, C0 and C1 (Background and Object or vice versa), where C0 denotes pixels with levels [1, 2, T], and C1 denotes pixels with levels [T+1,…, L], where T is the necessary threshold value. Assume that the zero-order increasing instant or in other word, the chance of quantity of classes C0 and C1 are w0 and w1, correspondingly. Likewise, the first order cumulative moment or the mean values of classes C0 and C1 are given by μ0 and μ1, respectively. Also, the mean value of the entire image is given by μT. In the same way, the second-order increasing moments or the variance values of classes C0 and C1 are given by μ0 and μ1, correspondingly. After this brief introduction to notations, we start to discuss some bi-level thresholding techniques.

The Covariance (Otsu) method: In this method, the covariance between two classes C0 and C1 are maximized. This value is equal to:

$$\sigma_B^2 = w_0(\mu_0 - \mu_T)^2 + w_1(\mu_1 - \mu_T)^2 \tag{1}$$

The optimal threshold T is designed by maximizing the covariance of the two classes. An exhaustive search optimization method is required to optimize the task.

The Entropy (Kapur) method: In this method, two possibility distributions are derived from grey-level possibility distributions. One is defined for separate values 1 to T, and the other for values T+1 to L. The total entropy φ(f) is the sum of the entropies connected with each allocation. That is,

$$\phi(t) = \ln(w_0) + \frac{H_t}{w_0} + \ln(w_1) + \frac{H_T - H_t}{w_1} \tag{2}$$

Where, Ht and HT are the entropies of class C0 and whole image, correspondingly; thus, the entropy of class C1 is HT - Ht. It is essential to obtain the greatest information between the entity and the situation distributions in the image. The separate value T which maximizes φ(f) is chosen as the threshold value.

The Cross-Entropy (Al-Attas) method: This process obtains the optimum threshold that minimizes the minimum cross-entropy using gamma allocation. The loyalty task of threshold selection which minimizes the cross-entropy of the image is found to be,

$$\eta(t) = -m_{1B}(t)\log\left(\frac{m_{1B}(t)}{m_{0B}(t)}\right) - m_{1O}(t)\log\left(\frac{m_{1O}(t)}{m_{0O}(t)}\right) \tag{3}$$

Where $m_{0B}(t)$ and $m_{0o}(t)$ are the zero-order cumulative moments of the background and object, and $m_{1B}(t)$ and $m_{1o}(t)$ are the first order cumulative moments of the background and object, respectively.

The DBT (Chowdhury) method: In this method, the total average information for discerning class C0 versus class C1, and discriminating information for class C1 versus class C0 can be deliberate by the logarithm of the likelihood ratios. Therefore, the total standard information for discriminating class C0 from class C1 is the departure function,

$$J(C_0, C_1) = \frac{1}{w_0}\ln\frac{w_1}{w_0} + \frac{1}{w_1}\ln\frac{w_0}{w_1} \tag{4}$$

Where w0 and w1 are the probability of incidence classes C0 and C1, correspondingly, and t is necessary to reduce this purpose to get a threshold T, which distinguishes the object from the environment.

III. PROPOSED 3S MULTI-THRESHOLDING METHOD

The proposed method uses a bi-level thresholding method as the core of the 3S multi-thresholding method. The flowchart diagram clarification in (Figure 1) shows the method of the proposed method as well as the pre-processing steps in this research work. Based on the flowchart in (Figure 1), the Region of Interest is originating first, which is a rectangular section that our image fits in. Then, the IC removal is performed via a region growing method followed by some morphological operations. Lastly, to realize the multi-level thresholding, a bi-level thresholding based on the mentioned numerical methods are performed.

After implementing one bi-level thresholding technique and sentence the best threshold, the two most optimal classes C0 (higher grey levels class) and C1 (lower grey levels class) are eminent. The class C0 is saved and left as an optimum class, and then the algorithm continues with lower grey values in class C1 to treat it as the unique image.

As a result, the first iteration gives the first optimal class in a high range of grey values. Then the same bi-level thresholding technique is applied on the remained class C1, to subdivide it again into two new classes C1 (higher grey levels class) and C2 (lower grey levels class). Therefore, the second iteration fixes the second class C1. This process is frequent on C2 and the succeeding results until it reaches the grey value zero in the histogram.

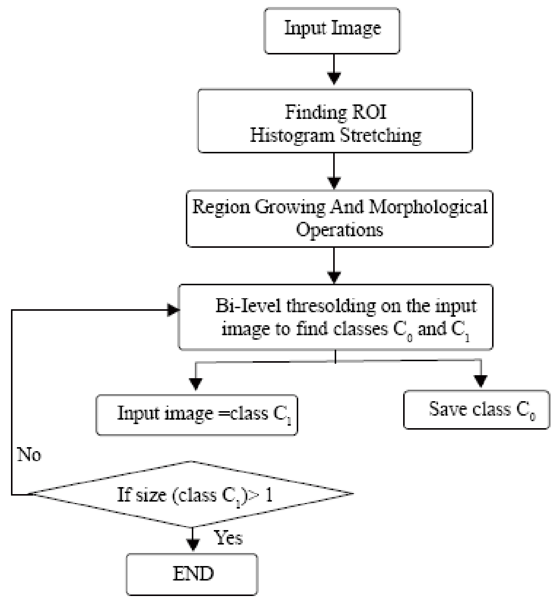

Figure 1: The flow chart of the proposed 3S system.

As illustrated, finding the optimal class of higher grey values in all iterations is essential. However, this is not the only case for each thresholding technique. In thresholding techniques where a costing task has to be maximized, this connection from high-to-low grey values is used, but for the thresholding techniques which are dealing with minimizing a cost occupation, a society from low-to-high grey values is done, i.e. the most optimal class that is close to lower ancient values is found first. The portion of histogram below this value is thrown out, and then the method continues with the remained portion.

In this method, the histogram portion of the image is stored in a variable for finding the best threshold value, and then this changeable is used in the search method. In each stage, after finding the threshold value, the part of this variable with indexes higher than a threshold value is thrown out, and the remained portion is stored in the same inconsistent. This system continues to reach the first point of the histogram.

IV. EXPERIMENTAL RESULTS

We have experienced our 3D T1-weighted MRI images of Brain Web simulated brain from the MIDAS database with dissimilar noise levels and attainment times, to section brain tissues. This algorithm has been executed on a COMPAQ PC Pentium4 (1.6 GHz) with 512MB RAM. The algorithms mentioned above have been tested on these MRI images. Figure 2a shows an axial brain MRI image after pre-processing, which is just a simple contrast stretching method. The graph in Figure 2b shows the histogram of the grey level image.

Figure 3a explains the consequence of region rising algorithm on the picture shown in Figure 2a, which includes the skull of the brain. As it was stated earlier, to make an absolute IC mask, it is needed to do some morphological operations on this result to fill up the gaps and eliminate thin bridges. Figure 3b shows the resulting mask. Figure 3d is the result of applying this mask on the input image shown in Figure 3c. Then, the four dissimilar calculation two-stage thresholding methods are common with the 3S method and applied on the image displayed in Figure 3d. Also, the FCM method is functional in this image.

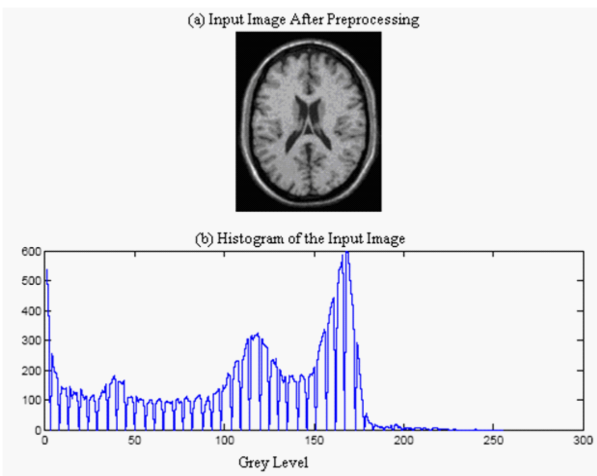

Figure 2: (a) Grayscale image. (b) Histogram of the greyscale image.

The next methods have produced a lower number of thresholds but in dissimilar situations. Also, the 3-cluster FCM has predictable three main peaks in the histogram. The difference between the DBT method and the FCM method is that DBT has measured thresholds for superior grey values. This is useful since advanced grey values have a lower possibility and according to information assumption, these values have higher significance, and they have to be measured as dissimilar objects.

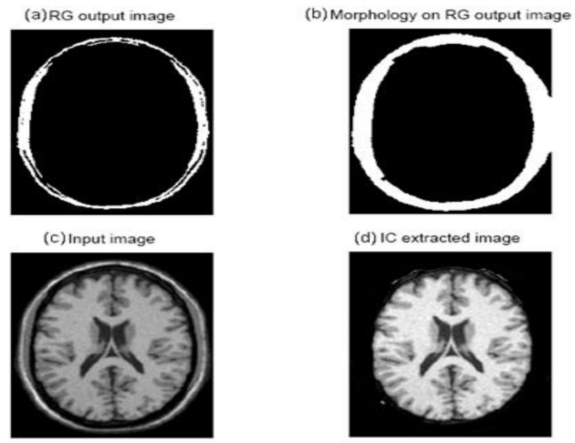

Figure 3: (a) IC extracted image using a region growing algorithm. (b) Applying morphological operation on the main facade to eliminate the non-skull pixels. (c) Input image. (d) The result of applying the mask in (b) on the input in (c).

CONCLUSION

We have used a new multi-stage thresholding method based on a Shrinking Search Space (3S) method on brain magnetic resonance images. The compensation of this method with admiration to other multi-stage thresholding algorithms and the FCM method are: 1) the eminence of segmentation compared to other methods is high; 2) the search difficulty is very low compared to the extensive searches in other algorithms; thus, the calculation time is much lower than that of the FCM method; 3) in obtainable algorithms, the numeral of thresholds must be resolute earlier, but the 3S algorithm repeatedly finds the optimal threshold number, such that it covers all objects with different grey levels. Consequently, the 3S technique restrains from producing redundant thresholds; i.e. it removes the redundancy in the number of thresholds that exists in older methods.

Based on the results mentioned above, the 3S+DBT method has the better ability for segmentation of brain MRI images than the other three methods. This method is constructed based on the maximum likelihood function, which is basic in the Bayesian algorithm for many pattern appreciation techniques. There are intermittent misclassifications by the FCM method due to its intermittent non-converging nature. Thus, the 3S method could be a deputy for the FCM method in many separation applications in terms of both superiority and calculation difficulty.

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