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Effect Of Global Thresholding On Tumor-Bearing Brain Mri Images

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Abstract*: Modern Science has found a special place for the field of Medical Imaging and Bio-medical image processing. With the advent of advanced imaging modalities like Magnetic Resonance Imaging (MRI), Computerised Tomography (CT), Mammography, UltraSonography (USG), it is now possible to look inside into the internal structure of the ailing body. Thus, it helps to diagnose, monitor and track the abnormality, if any. This paper provides us with the results and effects of two standard thresholding techniques applied to tumor-bearing MRI images of brain. The two standard techniques implemented are the basic global thresholding method and the standard Otsu's thresholding method. This paper studies the poor results obtained after applying these two techniques to MRI images of tumor-bearing brain and analyzes the reasons for the same.*

Keywords: image segmentation, MRI, brain tumor, medical imaging, thresholding

Introduction:

Digital Image Processing field consists of implementing various processing operations on digital images using a computer [1]. A digital image is composed of basic units called picture elements. These elements are also called as pixels and each pixel possesses a value along with the element's location information. Applications of image processing include Optical Character Recognition Systems (OCRs), Manufacturing defects detection systems, Digital Forensics, Medical Imaging systems, etc. [2]

The technique of image segmentation sub-divides an image into its constituent objects or regions which may or may not be meaningful and may require further processing to find the meaning or to analyze it. Image segmentation forms a basic step in the analysis of medical images [3].

The rest of the paper is organized as follows: this paper gives a brief literature review about the related work done. We have presented the details about the thresholding techniques used and have given the tested results of those techniques when applied to MRI images of tumor containing brain and have also provided the analysis of the results. We have described two standard global thresholding techniques with which MRI images are tested upon. The paper concludes followed by the acknowledgement and references.

Literature Survey/ Related Work:

The image segmentation techniques to be applied to brain MRI images are thresholding, region-growing, clustering, soft-computing, atlas-based, image/symmetry analysis and other methods [3].Thresholding groups the image pixels in a manner that the gray-level values lying above (or equal to) a threshold value belong to one class and those having value less than the threshold value are placed into the other class. Thresholding can convert an input image to black and white (i. e. binary) image [4].

In cases of breast cancer, thresholding has been used to classify the normal tissue and the tumor tissue [5, 6]. Region-growing has been used to delineate timorous elements in the image [7] .A K-means clustering algorithm was implemented to segment the brain MRI image into classes using a two-level granularity oriented grid based localization which is based on standard local deviation [8]. Discrete Wavelet Transform was used along with K-Means clustering to effectively segment leaves of plants [9]. The method proposed by Dasgupta A. used fuzzy set theory to demarcate the tumor [10]. A hierarchical self-organizing map was used to segment the target area and the results were used for making treatment plan and diagnosis [11]. An atlas-based technique was used to segment brain tumor images for prognosis of tumor progression [12]. An Expectation-maximization method was used along with a glioma growth model to modify the atlas into tumor and edema [13]. Multiple parameters were used to study and analyze physiological and pathological regions and classification was done [14]. Meyer's Watershed algorithm was used with basic noise removal and image morphological functions [15]. A hybrid algorithm that is a combination of thresholding and morphological processing based on a model was used by Moltz JH et al. [16].

Global Thresholding Techniques:

We have tested our images using two of the standard global thresholding techniques:

A. Basic global thresholding

B. Otsu's global thresholding

A. Basic Global Thresholding Algorithm

The basic global thresholding algorithm is based on the concept of computing a global threshold value T, for the entire image, which will be iteratively computed until some criterion is met. The steps of the algorithm as stated in [17] are as follows:

a. Initialize the global threshold value, T.
b. Segment the image using T to produce two groups G1 and G2 such that G1 contains pixels having value greater than T and G2 contains pixels having values less than or equal to T.
c. Compute mean intensities m1 and m2 for groups G1 and G2 respectively.
d. Re-compute new threshold as the average of the two mean intensities

$$T = \frac{(m_1 + m_2)}{2}$$

e. Repeat steps 2 to 4 until the difference between values of T in successive iterations is smaller than a predefined parameter ΔT.

B. Otsu's Thresholding Algorithm

The Otsu's thresholding method is viewed as a statistical decision theory concept. The main goal of this method is to minimize the average error incurred in assigning pixels to classes. The problem solution is based on the probability density function of grey-levels of each class occurring in a given problem. The Otsu's method aims at maximizing the between-class variance. The basic idea is that well-thresholded classes should be distinct with respect to the grey-level values of their pixels, and, conversely, that a threshold giving the best separation between classes in terms of their intensity values would be the optimum i.e. best [18].

The steps of the Otsu's thresholding method as stated in [18] are as follows:

a. Compute the normalized histogram of the input image
b. Compute the cumulative sums P(k) for k=0,1,2,...,L-1
c. Compute the cumulative means m(k) for k=0,1,2,...,L-1
d. Compute the global intensity mean m_G
e. Compute the between-class variance $\sigma_B^2(k)$ for k=0,1,2,...,L-1
f. Obtain Otsu's threshold k* as the value of k for which $\sigma_B^2(k)$ is maximum. If the maximum is not unique, obtain k* by averaging the values of k corresponding to the various maxima detected.
g. Obtain the separability measure, η*, at k=k*.

Results and Discussion:

Our input brain MRI image as shown in Figure 1 was subjected to the standard basic global thresholding algorithm and Otsu's thresholding algorithm. The results in figure 2 show that the tumor portion has completely disappeared from the input image after applying the basic global thresholding method, hence the output is poor. The results in figure 3 show that instead of improving the segmentation results, the entire image components including the tumor portion have become distorted in shape. Thus the Otsu's thresholding method has also given poor results.

It was found out that the grey-level distribution of the image pixels was not sufficiently distinct; hence the use of a single global threshold value was not a good choice to segment the entire image including the tumor itself; also after studying and analyzing the image histogram, it was found out that a clear and a distinct valley separating the modes of the histogram was absent. Thus, it can be concluded that global thresholding technique gives poor results when trying to segment MRI images of tumor-bearing brain [1].

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NOTE: NO CONFLICT OF INTEREST STATEMENT DECLARED

Output Figures:

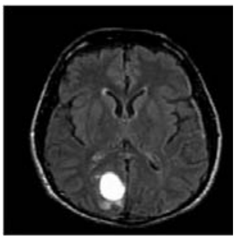

Figure 1: original input MRI image

Figure 2: after applying basic global thresholding

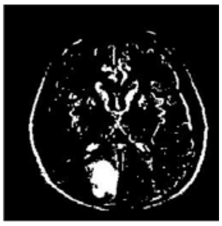

Figure 3: after applying Otsu's global thresholding

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