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An Efficient Fuzzy Technique for Detection of Brain Tumor

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Abstract

In this epoch Medical Image segmentation is one of the most challenging problems in the research field of MRI scan image classification and analysis. The importance of image segmentation is to identify various features of the image that are used for analyzing, interpreting and understanding of images. Image segmentation for MRI of brain is highly essential due to accurate detection of brain tumor. This paper presents an efficient image segmentation technique that can be used for detection of tumor in the Brain. This innovative method consists of three steps. First is Image enhancement to improve the quality of the tumor image by eliminating noise and to normalize the image. Second is fuzzy logic which produce optimal threshold to avoid the fuzziness in the image and makes good regions regarding Image and tumor part of the Image. Third is novel OTSU technique applied for separating the tumor regions in the MRI. This method has produced better results than traditional extended OTSU method.

Key Words: Fuzziness, Segmentation, OTSU, Weight, crisp set, Tumor

1. Introduction

Medical images are produced rapidly recent years. Almost every day, huge medical visual data are produced from X-ray, Computed Tomography (CT) scanner, Magnetic Resonance Imaging (MRI) scanner and so on. The images, if processed appropriately can provide very useful information to assist doctors in diagnosis. Image segmentation is the process of partitioning a digital image into sets of pixels. Image segmentation is important for classification and analysis. Manual brain segmentation probably is more accurate than fully automated segmentation ever likely to achieve. However, the major drawbacks of manual image segmentation are time consuming and subjectivity of human segmentation [1]. Therefore, it is significant to develop a reliable automated segmentation to overcome the drawbacks of manual segmentation. The challenges for automatic segmentation of the MRI head images have given rise to many different approaches. The techniques of segmentation developed so far include statistical pattern recognition techniques [2,3,4], morphological processing with thresholding [5,6], clustering algorithm[7] and active contour[8,9]. In this paper, we segment the intracranial area into 2 clusters which are abnormal regions, CSF and brain matter.in this paper a novel fuzzy OTSU method is used for brain tumor detection.

2.OTSU Method

Otsu thresholding proposed a criterion for maximizing the between-class variance of pixel intensity to perform picture thresholding [10,11,12]. Basic OTSU Thresholding technique involves segmenting or decomposing the entire image into regions of some similar properties like pixels of same intensities for further analysis. Hence using this method the image can be separated into dark and light regions. This is called as Thresholding the image. The separated regions are called assigned class labels where the intensity levels of each pixel in one region will be greater than the Threshold value and the intensity levels of pixels in the second region will be less than the Threshold value. The high frequency components in the resultant image are enriched whereas the low frequency background structure was removed. A global threshold value applied on the reconstructed image acquired for each MRI image and a binary image providing all the probable points of brain tumor formed. The threshold value is automatically obtained from the grey level histogram with the application of a peak detection method A significant technique for image segmentation that attempts to recognize and extract a target from its background with the aid of the distribution of gray levels or texture in image objects is referred to as Thresholding [13]. The statistics of the one-dimensional (1D) histogram of gray levels and on the two-dimensional (2D) co-occurrence matrix of an image form the basis of a majority of the thresholding techniques. Precisely, the discriminate criterion chooses the optimal threshold in order to maximize the separability of the resultant classes in gray levels. The procedure makes use of only the zeroth- and the first-order cumulative moments of the gray-level histogram and hence is trouble-free[14]. It is possible to extend the method to multithreshold problems in an uncomplicated manner.

2.1. Methodology

An image is a 2D grayscale intensity function, and contains pixels with gray levels from 1 to L.

The probability of gray level in an image is:

$P_i = f_i/N$=> (number of pixels with gray level/total number of pixels) (1)

In the case of bi-level thresholding of an image; the pixels are divided into two classes, C_F with gray levels [1, 2….t] and C_B with gray levels [t+1….L].

Then, the gray level probability distributions for the two classes are

$C_F = p_1/w_F(t),\ldots.p_t/w_F(t)$

$C_B = p_{t+1}/w_B(t),\ p_{t+2}/w_B(t),\ldots,p_L/w_B(t)$ (2)

Where $w_F\ (t) = \Sigma\ p_i$ (where i = 1, 2, 3..., t) and $w_B\ (t) = \Sigma\ p_i$ (where i = t+1, t+2...L)

Also, the means for classes and are

$\mu_F = \Sigma\ ip_i/w_F\ (t)$ (where i = 1, 2, 3..., t) and

$\mu_B = \Sigma\ ip_i/w_B\ (t)$ (where i = t+1, t+2... L) (3)

Let μ_T be the mean intensity for the whole image. It is easy to show that $w_F\ \mu_F + w_B\ \mu_B = \mu_T$ and also

$w_F + w_B = 1$ Otsu defined the between-class variance of the threshold image as

$\sigma_B^2 = w_F\ (\mu_F - \mu_T)^2 + w_B\ (\mu_B - \mu_T)^2$ (4)

Likewise the above formula can be extended for use in case of multiple thresholds extension and Proposed method for basic OTSU method.

3. EXTENDED OTSU METHOD

The above OTSU method is simple and easier. However it fails if the Histogram is unimodal or close to unimodal. Hence an extension to the basic OTSU method will be implemented by selecting an optimal threshold. In this extended method the gray level distribution will be described using the average variance instead of average mean which is normally used in the basic OTSU method. Here $\mu_F(t)$ and $\mu_B(t)$ can be regarded as the objects center gray and the background's center gray respectively, μ_T is the whole image center. This method makes sure that $(\mu_F - \mu_B)^2$ is as bigger as it can get and gray distribution can be described not only by gray mean, but also by gray variance. The average variance will be used here to replace average mean in the basic OTSU method. The image variance reflects image uniformity; the variance is small inside of the objects and background. But the variance of edge and its neighborhood changes acutely. Hence it is reasonable to use average variance instead of the foreground and the background means in OTSU method.

$$t^*=\mathrm{ArgMax}[w_F(\sigma_1^2(t)-\sigma_T^2(t))^2+w_B(\sigma_2^2(t)-\sigma_T^2(t))^2 \qquad (5)$$

$$\sigma_1^2(t)=1/w_F(t)\,\Sigma(i-\mu_F(t))^2p(i)(\text{where } i=1,2,\ldots t)$$

$$\sigma_2^2(t)=1/w_B(t)\Sigma(i-\mu_B(t))^2p(i)(\text{where } i=t+1,t+2,\ldots m-1)$$

$$\sigma_T^2(t) = \Sigma(i-\mu_T(t))^2p(i) \ (\text{where } i=t+1,t+2,\ldots L)$$

This method represents well adaptability and certain anti-noise abilities; it will not be although this method has some difficulties processing images with unimodal distribution.

4. NOVEL FUZZY OTSU METHOD

Step1: Features are based on the grey-level histograms from selected regions of the brain. The distances to the brain images normalized from 0 to 255 are utilized in the construction of the regions. Histogram modeling techniques alter an image in order to ensure that the histogram is of the desired shape. This is beneficial for the elongation of low levels of brain tumor images with the narrow histograms. Histogram equalization is a conventional histogram modeling methodology. According to the information theory, the uniform distribution attains maximum entropy, which encloses the most information. Thus, the tumor information needs to be maximized in order to redistribute the gray-levels and achieve at the most uniform histogram .The next is fuzzy logic which produce optimal threshold to avoid the fuzziness in the image and makes good regions regarding image and tumor part of the image.

Step2: Fuzzy set theory assigns a membership degree to all elements among the universe of discourse according to their potential to fit in some class. The membership degree can be expressed by a mathematical function $\mu_A(x_i)$ that assigns, to each element in the set, a membership degree between 0 and 1.Let be the universe (finite and not empty) of discourse and x_i is an element of A. Fuzzy set **A** in **X** is defined

as

$$A = \{(x_i ,\mu_A (x_i)) \ x_i \in X \} \qquad (6)$$

The S –function is used for modeling the membership degrees. This type of function is suitable to represent the set of bright pixels and is defined as

$$\mu_{AS}(x) = s(x, a, b, c)$$

$$= \begin{cases} 0, & x \leq a \\ 2\left\{\dfrac{(x-a)}{(c-a)}\right\}^2, & a \leq x \leq b \\ 1-2\left\{\dfrac{(x-c)}{(c-a)}\right\}^2, & b \leq x \leq c \\ 1, & x \geq c \end{cases}$$

$$\text{Where } \ b = (1/2)(a+c) \qquad (7)$$

The S–function show in the Fig2 can be controlled through parameters **a** and **c**. Parameter **b** is called the cross over point where .The higher the gray level of a pixel (closer to white), the higher membership value and vice versa.

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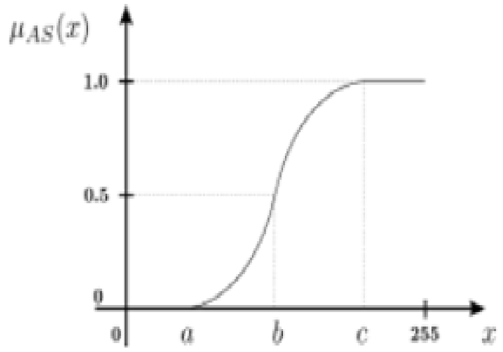

Fig 2: Typical shape of the S-function function

Measures of Fuzziness are **a** reasonable approach to estimate the average ambiguity in fuzzy sets is measuring its fuzziness. The fuzziness of a crisp set should be zero, as there is no ambiguity about whether an element belongs to this t or not if the set is maximally ambiguous and its fuzziness should be maximum. Degrees of membership near 0 or 1 indicate lower fuzziness, as the ambiguity decreases. Kaufmann in introduced an index of fuzziness (IF) comparing a fuzzy set with its nearest crisp set. A fuzzy set **A*** is called crisp set of **A** if the following conditions are satisfied:

Step3: The optimal threshold value exists at the valley of the two peaks or at the bottom rim of a single peak. The valley in the histogram that separates the object from the background, its probability of occurrence is small in gray level histogram. Because of the optical threshold should near the cross where the object and the background intersect. The probability of occurrence at the threshold value should divide into two parts. Its first half belongs to background and second half belongs to object. Then we apply a new weight N_W to the OTSU method.

$$t=(P1*X1+P2*X2)* N_W \quad (8)$$

Where $X1=(\sigma_1^2(o)- \sigma_T^2(t))^2$

$X2= (\sigma_2^2(t)- \sigma_T^2(t))^2$

$N_{W=}(1-P_T(t)/2)$

Using this method we can make sure that the result threshold value resides at the valley or at the bottom of the right rim of single peak. It's also maximizes group variance and ensures that both the variance of the object and that of the background keep away from the variance of the whole image. Smaller the p(t)/2, larger will be the weight.

5. EXPERIMENTAL RESULTS

In order to verify the effectiveness of the proposed method, a set of images of different kinds are tested. Experimental results illustrate that the system is capable for detecting tumors for the interpretation of radiologists in their daily practice besides enhancing their diagnostic performance. The performance evaluation of two methods has been described based on table of values and graph shown. From the Extended OTSU method we can infer that the values plotted in graph1 are too high and ambiguous values among some of brain tumors images, hence we cannot clearly differentiate among the normal, moderate or severely tumor affected brain. From the Novel Method we can infer that the values plotted in graph1 are neither too low nor too high .Further comparing the plotted values in graph1 against each of the images in table1 it is evident that the values clearly reflect the levels of severity of the tumor. Images m5,m8 have low severity, m2,m6,m7,m9 have high severity and m1 and m4 have moderate. M3,This is due to the fact that the values for Extended OTSU method from table1 are either too low or too high. In the proposed method the defects can be extracted more precisely even in the presence of noise. The steady line of proposed method in the graph shows that the proposed method can work well in the presence of noise.

ISSN 22773061

7. OUT PUT IMAGES

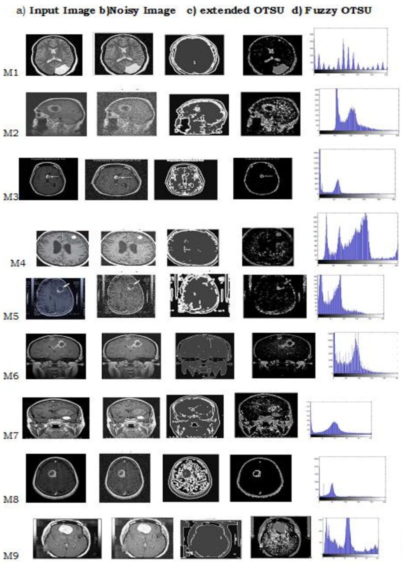

Image	EOTSU	NFOTSU
m1	0.327	0.068
m2	0.317	0.083
m3	0.008	0.015
m4	0.373	0.036
m5	0.418	0.014
m6	0.248	0.072
m7	0.297	0.091
m8	0.294	0.019
m9	0.273	0.073

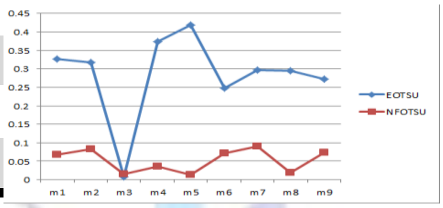

Fig3.1) Tumor images 2) Histograms 3)Table1 4) Grapgh1

6. Conclusion and Future Extensions:

The proposed Novel fuzzy OSTU method can detect the tumors in the images effectively even with Gaussian noise or Salt and Pepper noise of 40%. However This method has two limitations 1)It does not work for Speckle noise and Poisson noise and 2)The values of a and c of s-curve are to be manually defined. In future the work can be progressed to overcome those problems by selecting S-curve parameters automatically and by extending to speckle and poison noise removal.

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