

# MS LESION DETECTION USING HYBRID METHOD

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**Abstract** - Magnetic Resonance Images are powerful tools to delineate MS lesions in early stage of the diseases. In this paper we introduce a new method that extracts MS lesions in exact shape and size. This extraction can ease evaluation of treatment and other factors by physician. We combine image segmentation method with other image processing techniques to get superior results.

**Keywords** - Magnetic Resonance Image, Segmentation, Entropy, Morphological Operator

## I. INTRODUCTION

Multiple Sclerosis (MS) is characterized pathologically by inflammatory focal demyelination at multiple sites in the central nervous system that recur over time. Magnetic resonance imaging (MRI) attracts great attention for diagnosing MS, visualizing and monitoring of the efficacy of experimental treatment.

The main purpose of this paper is studying of automatic segmentation of MS lesions in MR images.

First, we have been used gray-scale histogram as 1D feature space and have been utilized entropy-based thresholding as a fast and easy global method that select only one optimum threshold for the whole image. In this method, we maximized information contents of object (MS lesion) and background. We have been used three common definitions of entropy for segmentation: Shannon, Tsallis and Renyi

Second, we have been used morphological operation as a post-processing step to retain just MS lesions in result of segmentation.

## II. Materials and Methods

Our MS lesion detection algorithm has two main steps:

- 1- Image segmentation step: in this step we segment MS lesion as an object and differ it from background.
- 2- Post-processing step: in this step we apply image processing operator to result of first step to reserve MS lesion in exact shape and size.

In image segmentation step, we have been used entropy-based thresholding that use gray-scale histogram as a 1D feature. We used global thresholding as a fast and less computational complexity method. The mathematical relation for this type of thresholding is:

$$j(x, y) = \begin{cases} b_0 & i(x, y) \leq t \\ b_1 & i(x, y) > t \end{cases} \quad (1)$$

Where  $i(x, y)$  is original image and  $j(x, y)$  is resultant binary image.  $b_0$  and  $b_1$  are two different gray levels. Determination of  $t$  in above equation is main problem and many methods for that have been proposed. In this paper, we use entropy criterion as a measure to determine threshold value.

Loosely speaking, histogram gives an estimate of the probability of occurrence of gray levels [1]. For an image with  $k$  gray-levels,  $p_i = p_1, p_2, \dots, p_k$  are the probability distribution of the levels. In this segmentation method we have been assumed that have two probability distributions, one for the object and the other for background.

From distribution of  $p_i = p_1, p_2, \dots, p_k$ , we derive two probability distributions, class A and class B that respectively pertain to object and background:

$$P_A : \frac{p_1}{P(A)}, \frac{p_2}{P(A)}, \dots, \frac{p_t}{P(A)} \quad (2)$$

$$P_B : \frac{p_{t+1}}{P(B)}, \frac{p_{t+2}}{P(B)}, \dots, \frac{p_k}{P(B)} \quad (3)$$

Where  $P(A) = \sum_{i=1}^t p_i$  and  $P(B) = \sum_{i=t+1}^k p_i$ . We have also  $P(A) + P(B) = 1$ . The a priori Tsallis entropy for each distribution is defined as [2]:

$$S_T^A(t) = \frac{1 - \sum_{i=1}^t \left( \frac{p_i}{P(A)} \right)^q}{q-1} \quad (4)$$

$$S_T^B(t) = \frac{1 - \sum_{i=t+1}^k \left( \frac{p_i}{P(B)} \right)^q}{q-1} \quad (5)$$

Using pseudo-additive property for Tsallis entropy, we can formulate sum of two entropies as following:

$$S_T(t) = \frac{1 - \sum_{i=1}^t (p_A)^q}{q-1} + \frac{1 - \sum_{i=t+1}^k (p_B)^q}{q-1} \quad (6)$$

$$+ (1-q) \cdot \frac{1 - \sum_{i=1}^t (p_A)^q}{q-1} \cdot \frac{1 - \sum_{i=t+1}^k (p_B)^q}{q-1}$$

We choose the value of  $t$  that maximize the  $S_T(t)$  as optimum threshold value. In this way, we maximize the information measure between object and background:

$t_{opt}^{Tsallis} = \arg \max [S_T^A(t) + S_T^B(t) + (1-q) \cdot S_T^A(t) \cdot S_T^B(t)]$  For Shannon entropy, we can write priori entropies of two classes as below [3]:

$$S_{BG}^A(t) = - \sum_{i=1}^t \left( \frac{p_i}{P(A)} \right) \log_2 \left( \frac{p_i}{P(A)} \right) \quad (7)$$

$$S_{BG}^B(t) = - \sum_{i=t+1}^k \left( \frac{p_i}{P(B)} \right) \log_2 \left( \frac{p_i}{P(B)} \right) \quad (8)$$

And sum of two priori entropies based on additive property for Shannon entropy defined as:

$$S_{BG}(t) = [S_{BG}^A(t) + S_{BG}^B(t)] \quad (9)$$

Threshold that maximize above equation denote optimum threshold value:

$$t_{opt}^{BG} = \arg \max [S_{BG}^A(t) + S_{BG}^B(t)] \quad (10)$$

And finally, Renyi entropies of object and background are defined as below [4]:

$$S_R^A(t) = \frac{1}{1-q} \cdot \log_2 \sum_{i=1}^t \left( \frac{P_i}{P(A)} \right)^q \quad (11)$$

$$S_R^B(t) = \frac{1}{1-q} \cdot \log_2 \sum_{i=t+1}^k \left( \frac{P_i}{P(B)} \right)^q \quad (12)$$

Again optimum threshold value is calculated based on maximizing sum of two entropies:

$$t_{opt}^{Renyi} = \arg \max [S_R^A(t) + S_R^B(t)] \quad (13)$$

In post-processing step we have used morphological operator (closing operator) to delete interference. Then we have been used combination of pixel merging and pixel splitting methods to grow and parse the detected lesion to original size and shape. This merging and splitting have been done based on similarity of neighborhood pixel of original image in pixels coordinate that remain after morphological operation.

Block diagram of above algorithm has been shown in Fig. 1.

### III. RESULTS

Our algorithm has been implemented on a database that contains 23 MR T2 images of MS patient (from The Whole Brain Atlas Project of Harvard University) [6].

A sample MR image from above database that pertains to a patient with MS lesion has been shown in Fig. 2 (a). Result of image segmentation with above three common entropy and entropy-based thresholding method can be seen in Fig. 2 (b-d).

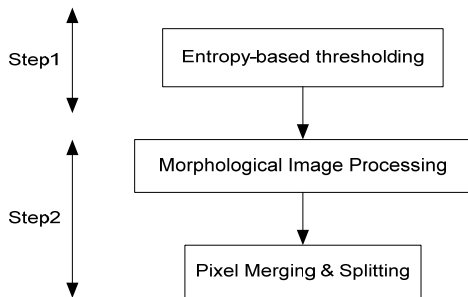


Fig. 1: Block diagram of MS lesion detection

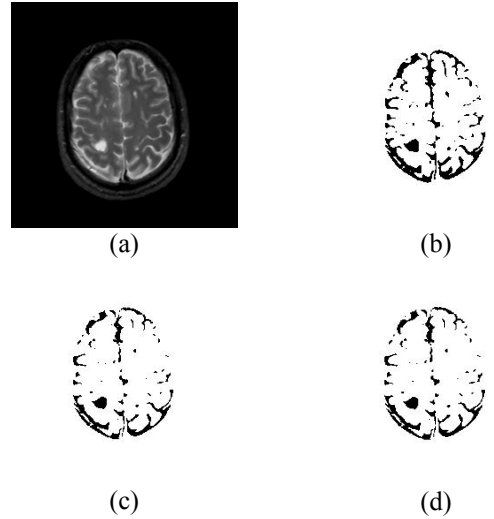


Fig. 2: (a) MR image with MS lesion (b) Shannon entropy-based segmentation result (c) Tsallis entropy-based segmentation result with  $q=0.5$  (d) Renyi entropy-based segmentation result with  $q=0.5$

In Fig. 3 (a-c) we have been applied morphological operator (Closing operator) to binary image that we get from image segmentation step. As can be seen from Fig. 2, the size of detected lesion is different from real size of MS lesion that shown in Fig. 2 (a) so we use pixel merging & splitting step to change the size of detected lesion to exact size. Results of this process that applied to result of Fig. 3 can be seen in Fig. 4.

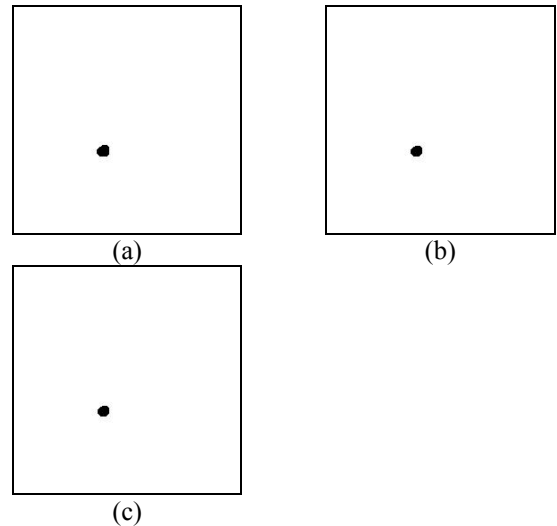


Fig. 3: (a) Closing operator result that applied to Shannon-based segmented image (b) Closing operator result that applied to Tsallis-based segmented image with  $q=0.5$  (c) Closing operator result that applied to Renyi-based segmented image with  $q=0.5$

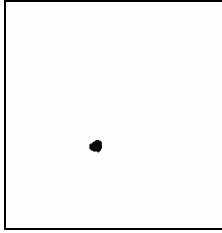


Fig. 4: Result of pixel merging & splitting that applied to morphological results

Result of pixel merging & splitting for all three different image of Fig. 3 was same.

For evaluation of MS detection algorithm we have been used judgement of two expert and measured image quality by the subjective evaluations of a human observer. Result of MS lesion detection for all 23 images of our database analysed in this way and all results assessed suitable.

#### IV. Discussion

After segmentation we get results that were easy to evaluate with physician and after post-processing we extract the MS lesion in exact size and shape. All results were acceptable and useful when have been evaluated by physicians.

Shannon entropy-based thresholding for an image yield to unique result in all condition .But with suitable adjustment of additional parameter ( $q$ ) of Tsallis and Renyi entropy definition we can get superior result in different condition.

Using Tsallis definition in entropy-based thresholding yield superior segmentation results in comparison with two others entropy definition. The main reason for this improvement is due to this fact that Tsallis entropy handles non-additive information that contain in images.

Tsallis and Renyi definitions for same value of  $q$  yield to similar threshold (in most condition). The mathematical proof of this equivalence can be found in reference [5].

In Tsallis and Renyi based thresholding, value of  $0 < q < 1$  (fractional  $q$ ) yield to good threshold value for segmentation step and for  $q > 1$  we didn't get good segmentation result for all images.

#### V. CONCLUSION

We used entropy-based thresholding in combination with image processing technique to detect MS lesion in MR images. We used three common entropy definitions (Shannon, Tsallis & Renyi) for image segmentation purpose and analyzed their effect on final result.

We have shown that Tsallis and Renyi definitions are more suitable in comparison to Shannon definition.

Our results, after segmentation and post-processing, ease the evaluation of MS lesions and expert judgment about treatment.

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