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Brain Tumor Detection and Extraction using Type-2 Fuzzy with Morphology

Dillip Ranjan Nayak[1], Neelamadhab Padhy[2] and Basanta Kumar Swain[3]

[1]Research scholar School of Computer Science & Engineering Gandhi Institute of Engineering & Technology, University Gunupur (Odisha), India.
Assistant Professor, Department of Computer Science & Engineering, Govt. College of Engineering Kalahandi, Bhawanipatna (Odisha), India.
[2]Associate Professor, School of Computer Science & Engineering, Gandhi Institute of Engineering &Technology, University Gunupur (Odisha), India.
[3]Assistant Professor, Department of Computer Science & Engineering, Govt. College of Engineering Kalahandi, Bhawanipatna (Odisha), India.

(Corresponding author: Dillip Ranjan Nayak)
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ABSTRACT: Segmentation is the key process for the detection of the brain tumor. Different kinds of thresholding methods are used by researchers in segmentation process in order to detect the brain tumors. This research paper tackles detection of brain tumor by avoiding any threshold mechanism over the MRI scan images for detection and extraction of brain tumor in patients. The proposed method for tumor detection is based on Type-2 fuzzy and morphological operators which help to alleviate the herculean task of exact location identification of brain tumor. First, we have applied Hamacher T co-norm(S norm) with triangular function for initial enhancement and followed by INT function to enhance the tumor position for finding the exact location. Finally, Erode operation is applied to get the more accurate location of tumor position from medical point of view. The proposed method has produced the clear picture as well as identified the exact location of brain tumor despite of vagueness in the original images.

Keywords: Brain Tumor, Clustering. Morphological Operators, MRI, Segmentation, Type-2 fuzzy, Thresholding.

Abbreviations: *MRI,* magnetic resource imaging.

I. INTRODUCTION

A brain tumor is a kind of inner cell growth inside the brain. Brain tumors appear in different sizes and shapes. Hence, early detection of brain tumor and diagnosis is a difficult process. It is observed that Magnetic Resonance Imaging (MRI) with fuzzy is a significant technique for locating tumor position.

Fuzzy Image segmentation [1] and watershed segmentation [2] are mainly used to locate the boundaries of brain tumor. An image can be partitioned into multiple regions by adopting the image segmentation process. Several researchers suggested various algorithms for image segmentation of the brain images [3-7]. It is hard to detect the exact location of tumor and volume of the tumor due to the presence of vagueness in brain tissue.

Moreover, the brain tumor cells are high intensity in nature due to the presence of portentous fluid. Therefore, fuzzy function is the appropriate technique for classification of tumors. Now a day, there are many fuzzy computing methodologies which are used for classifying MR images [8-10]. Fuzzy clustering [11] and segmentation using Neural network [12] are also used to detect tumors from MR images. Intensity adjustment is also applied to detect and segment brain tumor [13]. Mainly, Type-1 fuzzy technique is used In fuzzy thresholding and fuzzy clustering scenario. But, finding exact thresholding point or clustering point is a difficult task in Type-1 fuzzy techniques. It is also found in the research that Type-1 fuzzy algorithms are demanding high computational time due to the uncertainty of information. However, our proposed Type-2 fuzzy sets with morphology helps to detect the exact brain tumor by combining the advantages of rough set and fuzzy set [14]. In this research article we have observed that, Type-2 fuzzy sets yielded improved performance as it can cope with high degree of uncertainties which is not possible in Type-1 fuzzy algorithm. It is also seen that Type-2 fuzzy set produces pretty good real-time response in brain tumor detection and extraction.

Type-2 fuzzy set is an extension of two dimensional type-1 fuzzy set into the three dimensional. Type-2 fuzzy sets are highly used to get the true membership function for a fuzzy condition [15] in uncertainty scenario. The main motto of this research work is to get the information about the tumor using Hamacher T co-norm [16, 17] with fuzzy morphological operations.

Authors have presented this research article in different sections as follows: Section II describes about material and methods adopted in the current work. Results are discussed in Section III. Section IV and Section V depict about conclusion and future work respectively.

II. MATERIALS AND METHODS

The uncertainties are mathematically modeled using Type-2 fuzzy sets. The basic theory of Type-2 fuzzy sets was introduced by Zadeh [18]. Image can be enhanced using Type-2 fuzzy set [19]. The truncated Type-2 fuzzy set and triangular Type-2 fuzzy logic are mostly used in getting brain tumor detection [20, 21]. Type-1 fuzzy set defined as A= {(x, $\mu_A(x)$|x ϵ X} where $\mu_A(x)$: X ∈ [0, 1] with the membership function on an element *x varies* as 0≤ $\mu_A(x) \leq 1$. Chaira [16] defined the value of membership function of the Type-2 fuzzy set is A_{TYPE2}={x, $\mu_A(x)$|x ϵ X};$\mu_A(x)$ ϵ type 2 membership function. Type-2 fuzzy set contains two types of membership functions which are upper membership function and lower membership function. Both the membership functions mathematically represented as:

$$\mu^{UP} = [\mu(x)^{\alpha}] \quad , \tag{1}$$

$$\mu^{low} = [\mu(x)^{1/\alpha}] \quad , \tag{2}$$

where α ϵ [0, 1]. Type-2 fuzzy set can be represented more appropriately as A_{TYPE2}={x, $\mu_U(x), \mu_L(x)$|x ϵ X} where $\mu_L(x) < \mu(x) < \mu_U(x), \mu \epsilon [0,1]$

The morphological operations are consisting of set theory and set operations. So, fuzzy set theory can be easily applied to the mathematical morphology operations. In this research paper, authors have applied dilation and erosion as morphological operations. dilation is used to add pixels to boundaries of objects in an image and erosion removes pixels from object boundaries. Then dilation is an increasing transformation function which is defined as

$$B \oplus M = \cup_{x \epsilon B} M(x), \tag{3}$$

whereas, erosion is represented as a decreasing transformation function which is defined as

$$B \ominus M = \{x | M(x) \subseteq B\} \tag{4}$$

In the similar fashion, opening and closing operations using image B *and* structuring element *M* are defined as

$$B \circ M = ((B \ominus M) \oplus M). \tag{5}$$

and $B \bullet M = ((B \oplus M) \ominus M)$. (6)

Pre-processing is applied for MRI images for removing noise as well as for enhancement. The algorithm is consisting of three stages. In first step we fuzzify the MRI images using triangular membership function. Then Type2 function is defined by Hamacher, an algebraic T norm and T conform which has no min or max operators is used for enhancement. In the second stage INT operation is used for enhancing the brain tumor images. INT operation decreases the pixel values which are less than 0.5 and increases the values which are greater than 0.5. At the end, morphological operations are applied to get exact position of tumor. In this research work, we have used INT operation to increase the contrast of the image [22]. We have also integrated the morphological functions like reconstruction and erode function for separating the tumor region from the brain. Our proposed algorithm is presented below:

1 MRI images of brain are passed as input.

2. Conversion of input the images into gray scale images G.

3. Fuzzify the gray scale image as, G1= $\frac{d-mn}{mx-mn}$, (7)

where d = double (image)

mn = minimum (minimum (image)),

mx = maximum (maximum (image))

4. Set alpha=0.5 which is middle value in between [0, 1].

5. Determination of average image gray scale value (λ) from image G1 i.e. Step 3.

6. Find μ^{UP} =G1. ^alpha and μ^{low} =G1. ^ (1/alpha).

7. Calculate the Hamacher T-co-norm of membership function which is mathematically written as Eqn. 8

$$\mu^{Type2} = \frac{\mu^{up} + \mu^{low} + (\lambda-2)\mu^{up}.\mu^{low}}{1-(1-\lambda)\mu^{up}.\mu^{low}} \tag{8}$$

where λ = image average.

8. Enhancement of image by applying the intensifier operation to modify the membership values as Eqn. 9.

$$\mu_{mn} = \begin{cases} 2 \cdot [\mu^{type2}]^2 & 0 \le \mu_{mn} \le 0.5 \\ 1 - 2 \cdot [1 - \mu^{type2}]^2 & 0.5 \le \mu_{mn} \le 1 \end{cases} \tag{9}$$

9. Perform reconstruction function and clearing function over the enhanced image (Step 8) to avoid noise.

10. Exposure of Erode operation over smooth images (Step 9) to get clearer picture of tumor.

III. RESULTS AND DISCUSSION

The experimental results are carried out by using four different sizes of brain images with different types of brain tumors. These brain tumor images are taken from FPGA Implementation of Brain Tumor Detection and Advanced Magnetic Resonance Imaging of the Physical Processes in Human Glioblastoma sites [23, 24].These images do not contain a clear vision in its ridges and valley structures with brain features. Figure 1 has size 230 × 230. Fig. 5 shows an image of a brain with size of 210 × 210. Fig. 9 has brain image size 120 × 120 with low visible features and Figure 13 has a brain tumor just like small hole with size 210 × 210.

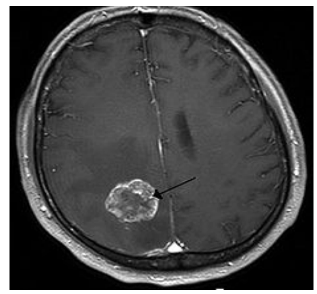

Fig. 1. Original brain1 image.

Fig. 2 shows the enhanced result by applying Type 2 and INT operator over original image i.e Fig. 1.

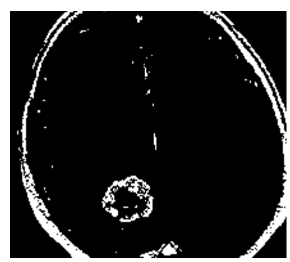

Fig. 2. Enhanced brain1 image.

It is observed that clear structure of tumor is not visible in Fig. 2. We have applied reconstruction operation and clearing function over Fig. 2 in order to get the clear visibility of tumor. The result is shown in Fig. 3.

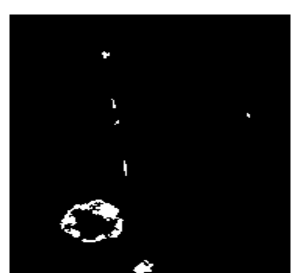

Fig. 3. Clearer tumor picture of brain1 image.

It is further observed in Fig. 3 that it contains streaks in the results near to the location of tumor. We have applied erode operation over Fig. 3. The resultant of erode operation is shown in Fig. 4.

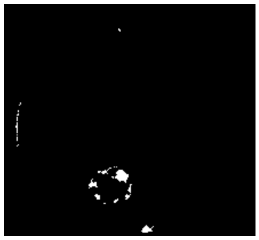

Fig. 4. Erode brain1 image.

Fig. 4 represents the exact location as well as clearer image of brain tumor. We have followed the same algorithm over another image and the results are depicted in Fig. 5 to 8.

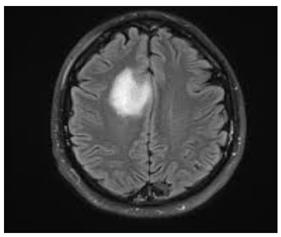

Fig. 5. Original brain2 image.

Fig. 5 is first enhanced by Type 2 and INT operator to get Fig. 6.

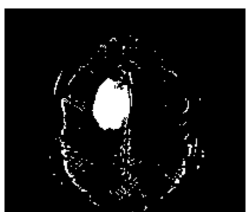

Fig. 6. Enhanced brain2 image.

Fig. 7 is resultant of Reconstruction operation and clearing function over Fig. 6.

Fig. 7. Clearer tumor picture of brain2 image.

Fig. 8 repesents the exact and clear image of turmor after applying erode operation.

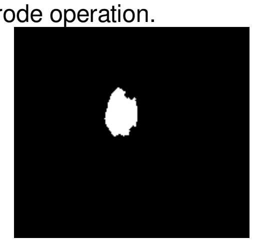

Fig. 8. Erode brain2.

We have tested the algorithm over many other brain image for brain tumor detection and extraction using our proposed algorithm. The results are shown in two sets of images ranging from Fig. 9 to 12 and Fig. 13 to 16. Fig. 9 shows an image of brain3 which does not say about the location and clarity of tumor.

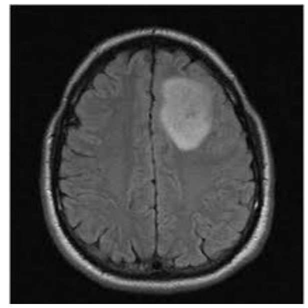

Fig. 9. Original brain 3 image.

We have applied the image enhancement and result is shown Fig. 10 which is based on enhanced-fuzzy morphological method with increasing darkness.

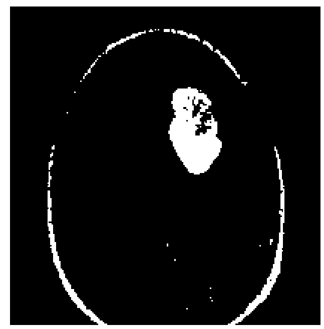

Fig. 10. Enhanced brain3 image.

We have applied reconstruction operation and clearing function over Fig. 10. The result is shown in Fig. 11.

Fig. 11. Clearer tumor picture of brain3 image.

Finally, erode function is applied over Fig. 11 to get the exact location and clear image of tumor which is shown in Fig. 12.

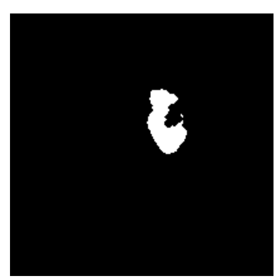

Fig. 12. Erode brain3 image.

Fig. 13 shows an image of a brain4 which is small in size and contains significant uncertainty. Fig. 11 shows the results of fuzzy method with slightly clearer and less boundary mark areas. Fig. 12 shows better result of Type-2 fuzzy morphological method with no boundary mark areas than the original image

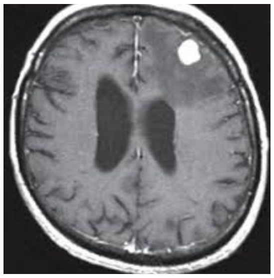

Fig. 13. Original brain 4 image.

Fig. 14 shows the results of enhancement-fuzzy method that has clear tumor area.

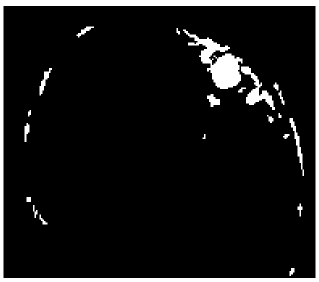

Fig. 14. Enhanced brain 4 image.

Fig. 15 is the representation of clear tumor picture which is obtained by using reconstruction operation and clearing function.

Fig. 15. Clearer tumor picture of brain4 image.

The exact location and more clarity picture of tumor is finally obtained by using erode operation which is shown in Fig. 16.

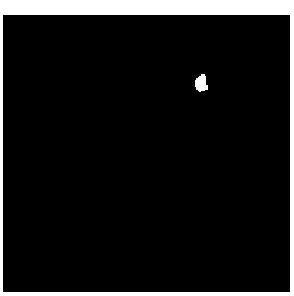

Fig. 16. Erode brain4 image.

IV. CONCLUSION

In this research paper, we have applied Type-2 fuzzy set with morphology for detection of brain tumor. The proposed fuzzy segmentation method was experimented with MRI scanned brain images of human for detecting exact position of tumor in the brain. The central idea of this research article called Type-2 fuzzy sets with morphological operations is applied over many sets of brain images. The proposed method yielded pretty good results over traditional techniques by detecting brain tumor with exact location and clear picture of tumor in spite of vagueness in original images.

V. FUTURE SCOPE

In future we will focus over Pythagorean fuzzy sets for detection and extraction of brain tumor that will handle the uncertainty in highly uncertain environment.

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Conflict of Interest. The authors have no affiliations with or involvement in any organization or entity with any financial interest or other equity interest; and expert testimony or patent-licensing arrangements, or non-financial interest in the subject matter or materials discussed in this manuscript.

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