**Short Communication**

# Brain Tumor Segmentation using Hierarchical Combination of Fuzzy Logic and Cellular Automata

## Abstract

**Background:** Magnetic resonance (MR) image is one of the most important diagnostic tools for brain tumor detection. Segmentation of glioma tumor region in brain MR images is challenging in medical image processing problems. Precise and reliable segmentation algorithms can be significantly helpful in the diagnosis and treatment planning. **Methods:** In this article, a novel brain tumor segmentation method is introduced as a postsegmentation module, which uses the primary segmentation method's output as input and makes the segmentation performance values better. This approach is a combination of fuzzy logic and cellular automata (CA). **Results:** The BraTS online dataset has been used for implementing the proposed method. In the first step, the intensity of each pixel is fed to a fuzzy system to label each pixel, and at the second step, the label of each pixel is fed to a fuzzy CA to make the performance of segmentation better. This step repeated while the performance saturated. The accuracy of the first step was 85.8%, but the accuracy of segmentation after using fuzzy CA was obtained to 99.8%. **Conclusion:** The practical results have shown that our proposed method could improve the brain tumor segmentation in MR images significantly in comparison with other approaches.

**Keywords:** *Cellular automata, fuzzy, glioma, segmentation*

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## Introduction

Image segmentation plays a vital role in image perception and interpretation in many fields and applications.[1] Moreover, it has a wide range of applications in medical area such as lesion classification, tumor segmentation, and tissue volume estimation.[1] There is a widespread algorithm for image segmentation to detect a pathology or abnormality in a subject.[2] The precise approach for tumor localization can play an essential and undeniable role in diagnosis and treatment planning in brain tumors.[3] Brain tumor contains enhancing tumor, necrotic tumor, and edema.[4]

As glioma is the most common type of brain tumor, most studies of brain tumor segmentation concentrate on this type of brain tumor.[2] There are many reasons for challenges in glioma segmentation. The first reason is the similarity of glioma and gliosis and stroke in magnetic resonance (MR) images,[3] and the second

reason is the appearance of glioma in most locations of the brain with different shapes and sizes. Moreover, there is no sharp boundary between glioma and normal tissue,[4] and there are many types of MR imaging (MRI) data. Hence, using automatic brain tumor segmentation may be applicable for minimizing localization errors. However, there are no unique MRI protocols for heterogeneous tumors.[5]

A wide variety of brain segmentation approaches contain convolutional methods, supervised methods, unsupervised methods, and hybrid methods.[6,7] Convolutional methods include thresholding[8,9] and region growing.[10-13] Thresholding is a simple, fast, and easy to implement method for image segmentation. The main idea of this method is based on converting an image to a binary image, and the threshold would be the decision value for making a pixel zero or one. There is no need for any prior knowledge for global thresholding, but this approach is not appropriate when two classes have different sizes,[14] so a combination of morphological operation

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and the threshold value is introduced, which produces more accurate results.[9,15] In most images, there are more than two regions for segmentation; in these cases, more than one threshold value must be used as a local dynamic threshold.[16] Another approach of convolutional methods is a region growing. This approach is used for segmenting an image whose regions have the same intensity values. The main idea of this approach is that all pixels must be segmented in a region, all pixels of a region must be connected and have some similarity condition, regions must be separated, and two different regions must have different features.[17] This method can be used for images affected by lightning variation. The limitation of this method is the partial volume effect that blurs the border of two tissues.[18] This restriction has been removed by introducing multiple respiratory gas monitoring,[19] and this method has been used for making better results for tumor segmentation in T1 images.[10]

Another method for brain tumor image segmentation is the supervised method. This method uses labeled data to train a decision-making system as a training phase for segmenting unlabeled data as a testing phase.[20] There are many supervised classifiers for brain tumor segmentation like k-nearest neighbor,[21,22] Support vector machine (SVM),[23] random forest,[24,25] artificial neural network (ANN),[26,27] and neuro-fuzzy networks. Unsupervised methods require no data for training, and the number of classes determined automatically by the algorithm. These methods use image-based features such as the intensity of pixels, gradient, and texture of regions.[1] There are many unsupervised methods such as k-means clustering,[28] fuzzy C-means clustering (FCM),[29] parametric active contour models (ACM),[30] and geometric deformable models.[31] The other approach of brain tumor image segmentation is the hybrid technique. Hybrid techniques use two or more methods to provide better results of image segmentation. These techniques use the advantages of used methods to compensate disadvantages of other methods. The are many combinations of methods to make hybrid techniques such as the combination of FCM and SVM[32] and the combination of ACM and ANN.[33] Moreover, there are many studies, which used the cellular automata (CA) as learning and supervised method.[34-37] From comparing of mentioned methods, hybrid methods can present a better precision for brain tumor image segmentation, so in this article, a hybrid method will be presented and compare with other methods.

## Materials and Methods

This article proposes a combination of CA and fuzzy logic as a hybrid method for brain tumor segmentation without any feature extraction. The structure of this combination is shown in Figure 1. This method uses the intensity of each pixel as input. This method consists of two major steps. In the first step, a fuzzy system uses the intensity of each pixels to label them as a tumor or host tissue. In the second
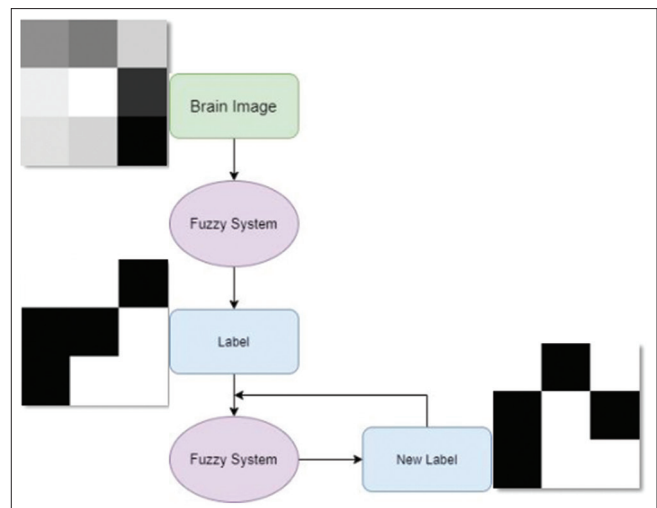


**Figure 1: Diagram of brain tumor image segmentation using the combination of cellular automata and fuzzy system**

step, the label of each pixel and its neighbors will be used by a fuzzy system to improve its label as CA. In this paper, CA uses the current label as input and analyses this by a fuzzy system to make the next and improved label. Hence, considering each labeled image as a frame, each frame will be produced by the last frame. The second step will be performed while the error of labeling is changing. The proposed method will be described as following.

As shown in Figure 1, there are two main sections to image segmentation in this study. At the first section, an image fed to a fuzzy inference system to label its pixels as tumor or host tissue. At this section, the input type is image and the output is label of pixels. Up to this point, the image has been segmented into host or tumor tissue. At the second section, the label feds to a fuzzy system to make improved label. Hence, it works as a CA, which its pixels attributes changes via time passing by considering the attributes of that pixel and its neighbors attributes. Hence, the second section is a CA that uses a fuzzy inference system a transition rules.

### Magnetic resonance imaging brain image dataset

The imaging dataset of this study was obtained from BraTS 2015.[38] This dataset contains Fluid Attenuated Inversion Recovery (FLAIR), T1, T1c, and T2 scans with 1 mm³ resolution. This dataset consists of 220 high-grade gliomas (HGG) and 54 low-grade gliomas (LGG) cases. The multimodal property of this dataset makes it possible to register the tumor into sub-regions, as shown in Figure 2.

As this article aims to segment the whole tumor, the FLAIR scan is used to segmenting the whole tumor.

### Proposed image segmentation algorithm

In this article, for segmenting a pixel as a tumor or host, the interaction between its neighbors is used. This task assigns a label to each pixel as tumor or host, and a label
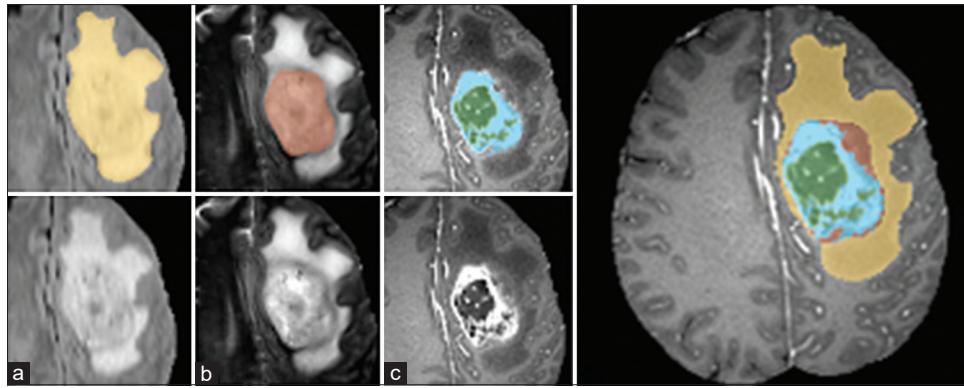
**Figure 2:** Sub-regions of tumor in BraTS. The image was segmented into the whole tumor by FLAIR scan as yellow color on (a). The tumor core is illustrated by red color on the T2 scan (b). Enhancing tumor is showed by blue color, and the necrotic tumor is also shown by green color on T1c scan (c)[38]
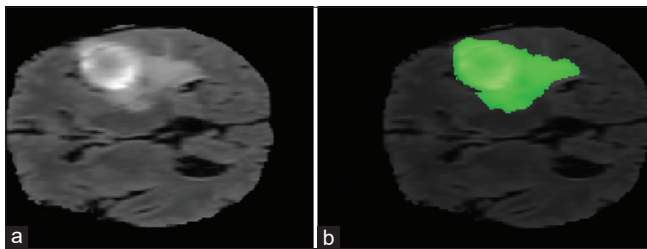


**Figure 3:** (a) FLAIR scan of brain magnetic resonance imaging (b) Tumor segmented brain image by radiologists
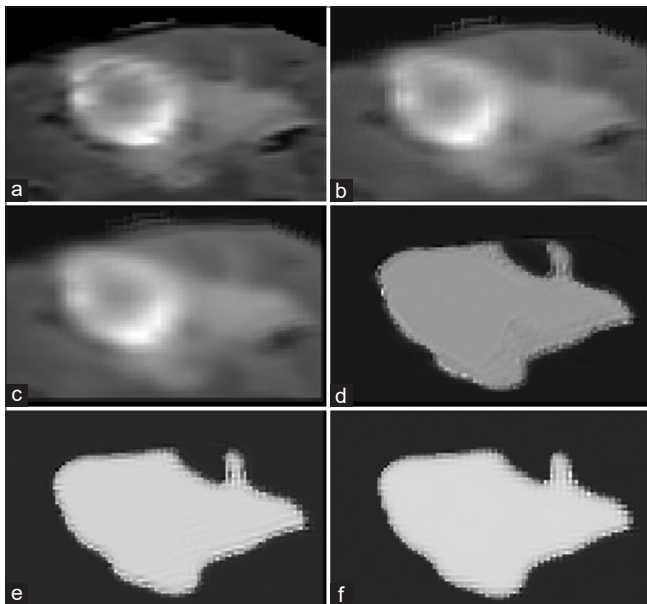


**Figure 4:** (a) Cropped FLAIR scan of Brain Magnetic resonance imaging, (b) Output of first step fuzzy system, (c) output of first-round Fuzzy cellular automata, (d) output of third-round Fuzzy cellular automata (e) output of fifth-round Fuzzy cellular automata (f) output of seventh-round Fuzzy cellular automata

image will be produced, and this label image will be used to make the next label image. Interaction between pixels must be configured as equations or rules. These interactions are configured as a fuzzy system. This fuzzy system uses a label image with Moor neighborhood as input. Sugeno fuzzy system is used with three Gaussian membership functions as fuzzifier and center of gravity as defuzzifier. The proposed algorithm of brain tumor segmentation is described in the following pseudocode in Code 1. The pseudocode finds the best label (tumor or host) for each pixel.

As described in Code 1, the image (FLAIR) and the original label will be used for training a fuzzy system to make a label image. For this aim, the brightness of each pixel and its neighbors will be used as input, and the original label of the pixel will be used as output. With training and simulating the fuzzy system, the label image will be produced, which feeds to another fuzzy system as cells to make better labels. Finally, the improved label image will compare with the original label to computing the error. This procedure will repeat during error change.

## Results

In this article, the proposed algorithm of brain tumor image segmentation is applied on the FLAIR scan, which is available as BraTS 2015 dataset, and tumor segmented brain images by radiologists have been used as the desired output of the method, as illustrated in Figure 3. In this study all 220 HGG and 54 LGG cases have been considered as dataset. This algorithm simulated using MATLAB R2015b version with 3.00 GHz core i5 central processing unit and 4 GB internal Random Access Memory as hardware devices. As it was mentioned, the used data set consists of 220 HGG and 54 LGG, and all these images have been labeled as host, whole tumor, enhancing tumor, and necrotic tumor by different expert radiologists. As this study aims to discriminate host tissue and entire tumor, the FLAIR scan has been used for segmentation.

To analyze the performance of the proposed algorithm and to compare with other approaches, the sensitivity, specificity, and accuracy have been calculated as below:

Where true positive (TP) is the number of TPs, true negative (TN) is the number of TNs, false-positive (FP) is the number of FP and false negative (FN) is the number of FNs.

As it has been mentioned in Code 1, there are two main steps for image segmentation. In the first step, a fuzzy system uses original images and tumor segmented brain images by radiologists to make new labels. In a second step, another fuzzy system uses new labels to make more accurate segmentation [Figure 4]. The second step will be repeated while the accuracy achieves saturation [Figure 5]. As this algorithm is time-consuming, the images will be cropped manually.

As it is obvious from Figures 4 and 5, as the Fuzzy CA round number increases, the value of segmentation accuracy increases too, but the further increase of Fuzzy CA round number results from saturation in segmentation accuracy that causes to exit the second step's loop.

The performance metrics such as sensitivity and specificity can show the validity of a methodology, and the increment of these metrics shows the strength of that methodology. The best accuracy, specificity, and sensitivity of this method are illustrated in Table 1.

## Discussion

As mentioned, the main aim of this study is to increase the performance of a brain tumor image segmentation using a combination of fuzzy logic and CA. To achieve this aim, a simple segmentation method that uses the intensity of each pixel and fuzzy logic was used as a segmentation method which followed by fuzzy CA. The results showed that using Fuzzy CA improves the performance of image segmentation significantly, as illustrated in Figure 5. For more comparison, the performance of the proposed algorithm and other methods is shown in Table 2.

As it is obvious, there is a meaningful increment in all performance values in our proposed method. These results emphasize the fact that fuzzy CA can increase the segmentation performance, and this approach can be used as a postsegmentation module for having better segmentation performance, which uses the output of main segmentation

method results as input and makes the segmentation more precise.

In this article, a new methodology to segment the glioma tumor in brain MR images. There are a few studies which used CA as an image segmentation method. For example, in[36] introduced an approach for brain tumor segmentation by combination of CA and improved tumor-cut algorithm. That study used two paradigms, consisting image transformation and segmentation algorithm to introducing gray-level co-occurrence matrix based CA (GLCM-CA). In GLCM-CA, the CA works as a transformation to getting featured image and efficient tumor-cut algorithm works as segmentation section, but in the current study, our proposed method uses the output of the main segmentation method and makes this more precise and can be used for most other segmentation methods. This article used a fuzzy system as the main segmentation method that used the intensity of each pixel as input the output of this method fed to the fuzzy CA to have better performance values. The results showed that there is a significant increment in performance values in comparison to the other approaches. This study focused on tumor segmentation, but this proposed algorithm can be used to segment other tissues, but its accuracy may be different and for more details, this algorithm must be implemented for other tissues.
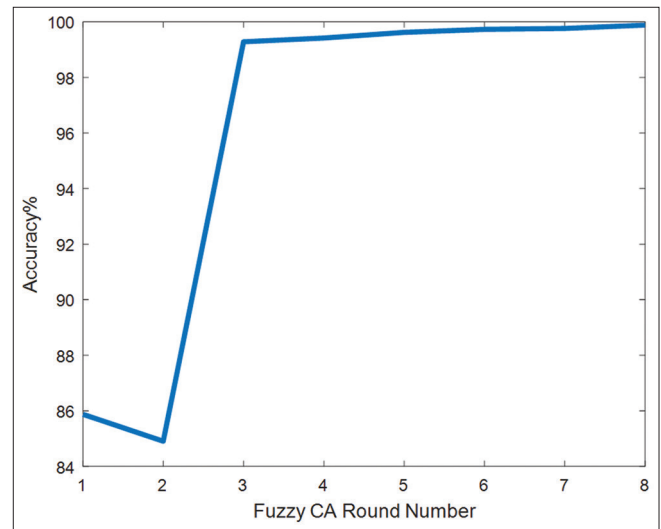


**Figure 5:** Change of segmentation accuracy for the different round of Fuzzy cellular automata

### Table 1: Performance values of the proposed algorithm

| Parameters | Value (%) |
|---|---|
| Sensitivity | 95.15 |
| Specificity | 100 |
| Accuracy | 99.88 |

### Table 2: Comparing the performance of proposed method and other methods

| Authors | Methodology | Sensitivity (%) | Specificity (%) | Accuracy (%) |
|---|---|---|---|---|
| Proposed method | Fuzzy cellular automata | 95.15 | 100 | 99.88 |
| Selvapandian and Manivannan[39] | ANFIS classification | 92.3 | 96.2 | 95.9 |
| Anitha and Raja [40] | CNN classification | 88.8 | 91.6 | 92.1 |
| Pereira *et al*[41] | CNN classification | 87.1 | 89.1 | 92.8 |
| Urban *et al*.[42] | Deep CNN classification | 89.3 | 91.1 | 92.1 |
| Islam *et al*.[43] | Modified AdaBoost | 90.9 | 91.5 | 93.4 |

ANFIS: Adaptive network-based fuzzy inference system, CNN: Convolutional neural network

## Conclusion

In this paper, a new method to improve brain tumor segmentation was introduced. This method uses the combination of cellular and fuzzy logic as a hierarchical approach, without causing overlearning. In this method a basic segmentation method would be considered, then the fuzzy cellular automata would improve the accuracy of segmentation. This method can be applied to different image segmentation algorithms.

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## Conflicts of interest

There are no conflicts of interest.

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