

# **Brain tumor Simple Linear Iterative Clustering Segmentation using Chan -vese Contour**

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**ABSTRACT:** Brain tumor prediction is a significant task in medical image handling. Early diagnosis of brain tumor assumes a significant job in improving treatment possibilities and expands the survival rate of the patients. Manual segmentation of the brain tumors for cancer growth analysis, enormous measure of MRI images produced in clinical routine is troublesome and time consuming task. In this paper, to recognize thermal data of brain tumors, the proposed basic linear iterative clustering is given a chain vese contour strategy. In this paper, a median filtering strategy is utilized as a preprocessor and segmentation is finished by Fuzzy corner metric algorithm. To diminish the computational complexity and to build the computing time Simple Linear Iterative Clustering is used. The last process is to remove the tumor cells by chan - vese contour utilizing angle vector field as outside force. The proposed strategy accomplishes higher

precision rate of about 98.6% and it is efficient

compared with past fuzzy clustering technique.

**Keywords-** Fuzzy c-means, thermal information, median filtering fuzzy corner metric, chan vese contour.

## **I INTRODUCTION**

Medical image investigation plays a most important role in biomedical sciences which is used for studying, analyzing and deciphering the problems. These problems are analysed from medical imaging datasets as acquired by various medical imaging modalities (such as MRI, X-Ray, CT-scan and ultrasound) through various quantitative and computational methods. These techniques helped a clinicians and medical experts to extract the important biological data from images that is useful for clinical decision-making, particularly neurosciences research and developing potential therapeutic strategies.

Past couple of years, there has been tremendous growth in using magnetic resonance imaging (MRI) for diagnostic and treatment process. MRI is a common non-invasive medical imaging modality which can be used for the diagnosis and analysis of internal structures, abnormalities and irregularities i.e., brain tumor.

MRI is also used to help in understanding the process neurodevelopment in adult brains. The segmentation of brain tumor is a most challenging process due to many reasons such as shape, size and location that vary greatly across tumor patients to patients. Some of other common major reasons are low contrast, overlapping of tissues, textured regions, high spatial resolution and noises which may lead to improper quantification of region of interests.

By considering these problems lot of approaches are practiced by clinicians are manual, time-consuming and expensive; and results in previously discussed limitations. In recent years, many more segmentation has been proposed in the literature [1-10]. In this paper, an iterative brain tumor segmentation approach based on Simple Linear Iterative Clustering using Chan and Vese model to identify and segment tumor from brain MRI images. This method can be easily modified with the support of assigned iterations to improve a robustness and independence in segmentation system.

Therefore, in this research the rest of the paper is organized as follows. Section II gives a brief overview of work related to brain tumor segmentations. Section III illustrated the preliminaries which are in relation to proposed method. Section IV described the proposed segmentation of brain tumors in MRI images and the section V described the experimental results obtained from the proposed method with corresponding image outputs. Section VI explained performance of proposed and compared with existing work. Conclusion are outlined in section VII and the references are named respectively.

## **II RELATED WORKS**

In this section, the work is related to the brain tumor using MRI images which is done before with various method is discussed with references.

Pradeep et al [1] investigated the use of intensity normalization as a pre-processing step, which is not usual in CNN-based segmentation methods, and also proved together with data augmentation to be very effective for brain tumor segmentation in MRI images.

Gousias et al [2] proposed a segmentation algorithm that is modelled the intensities across the whole brain by introducing a structural hierarchy and anatomical constraints.

Jun Jiang et al [3] proposed an automatic tumor segmentation method for MRI images which treated tumor segmentation as a classification problem. In addition, the local independent projection-based classification is used to classify every voxel into various classes.

Syed M et al [4] proposed a patient-independent tumor segmentation scheme by using AdaBoost algorithm. The AdaBoost algorithm involved assigning weights to component classifiers based on their ability to segment the difficult samples and confidence.

Marleen et al [5] described a spatial model is implemented by registering multiple atlas images to the target image and creating a spatial probability map. The structures are modeled by a Gaussian scale-space classifier.

AnupBasu et al [6] proposed that the fluid vector flow (FVF) active contour model to address problems of insufficient capture range and poor convergence for concavities.

J. Corso et al [7] presented an automatic segmentation of heterogeneous image data which is taken a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches.

Narr et al [8] proposed a hybrid discriminative/generative model for brain anatomical structure segmentation.

Bruce Fischl et al [9] proposed an atlas-based whole brain segmentation method by introducing an intensity renormalization procedure which is improved the performances. So that it automatically adjusts the prior atlas intensity model to new input data.

Sterr et al [10] proposed a robust segmentation technique based on an extension to the traditional fuzzy c-means (FCM) clustering algorithm.

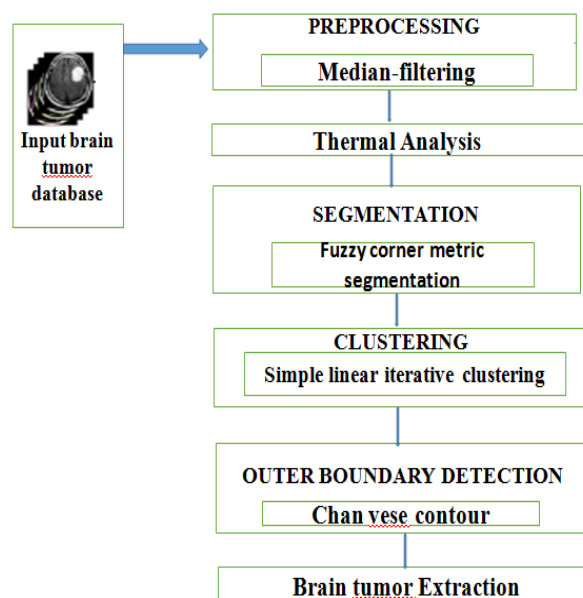
### III PROPOSED METHODOLOGY

In this section, the proposed topology of this paper is discussed. This method is similar to the preliminaries where the segmentation algorithm is modified with a addition of new clustering technique. In this proposed method, the segmentation is done by fuzzy corner metric algorithm and the clustering is done with the simple linear iterative clustering (SLIC). These SLIC is improved by integrating texture features.

The proposed framework for an iterative brain tumor detection based on chan-veese contour is shown in fig.2. First, a histogram reconstruction model is used to reconstruct the input image, which is further enhanced by gamma transformation. Next, the local tri-directional pattern descriptor is used to extract texture features of the image; this is followed by an

improved SLIC superpixel segmentation. As per the work flow of fig.1, this section is explained as below.

The first process of tumor detection is collecting the input datasets of tumor affected MRI sample images and then given into the system.



**Fig. 1 Proposed Block Diagram**

#### PRE-PROCESSING

##### 3.1 Pre-processing

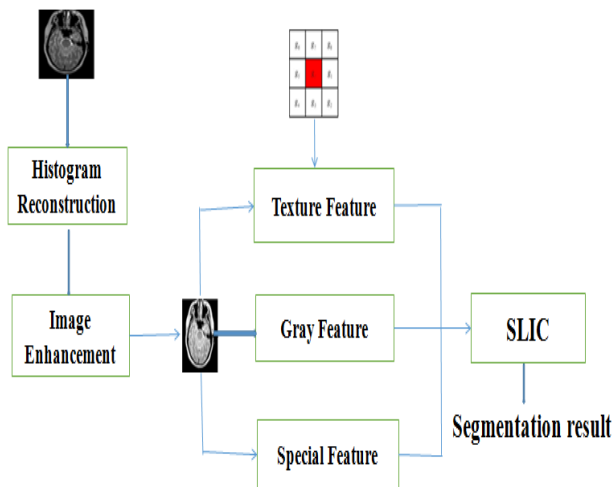
Next step of pre-processing is carried with several processes. The very first step of pre-processing is to convert the gray matter to RGB and white matter. It is used to remove the noise level using Median Filtering technique. This technique is mainly used to find ROI and convert the images to gray scale images.

##### 3.2 Segmentation

Next process is a segmentation which is carried out with the fuzzy corner metric segmentation. The fuzzy corner metric is discussed clearly in the section III and it is used to suppress the images of abnormal tissues and then detect the tumor cells.

### 3.3 Clustering

Next the Clustering is applied to the image, it is the process of collection of objects similarities between an objects belonging to other clusters. For a perfect clustering, a simple linear iterative clustering (SLIC) is proposed which is explained below in detail.



**Fig.2 Proposed framework**

#### 3.3.1 Proposed Simple linear iterative clustering (SLIC)

The proposed SLIC is an efficient superpixel generation algorithm. The proposed SLIC is the process of clustering the pixels according to the colour similarity and spatial distance of the pixels. It is an iterative clustering process which has all pixels belonging to one class will be used to update the clustering center,

and these misclassified pixels will have an impact on the update process. The proposed SLIC algorithm consists of a k-means clustering to reduce the search range in it. On comparing, SLIC algorithm is more efficient in storage, fast in computing time, fitness to edge and low in computational complexity which improved the performance of image segmentation. The SLIC algorithm is suitable for segmentation of medical images for obtaining accuracy.

### 3.4 Boundary detection

This is the final step for the brain tumor detection which is used to correlate the detected tumor cells within the boundary by using the active and chan-veese contour model. Therefore, the tumor affected portion of the brain will be detected with the high accuracy, sensitivity, and specificity.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

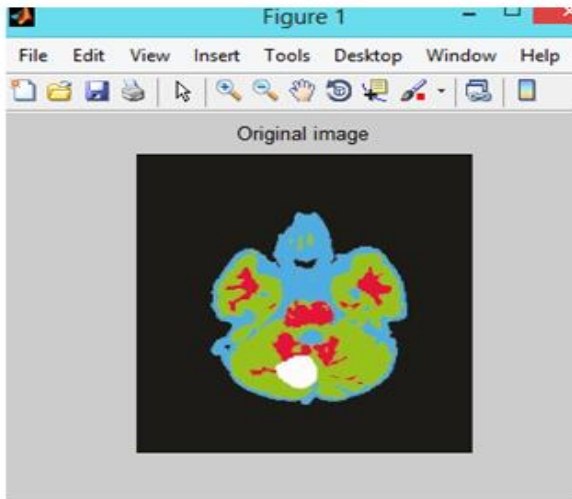
$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

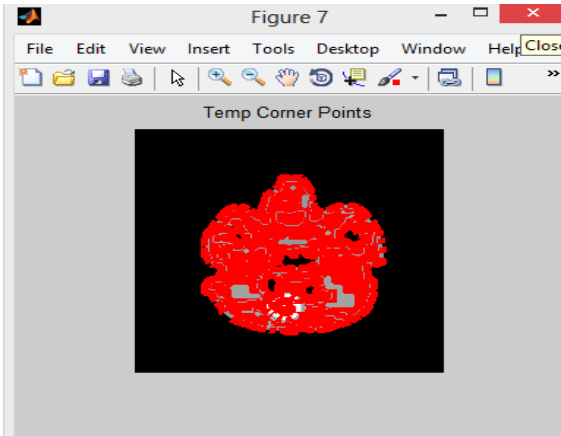
## IV SIMULATION RESULTS

The experimental results showed for the proposed approach to detect the tumor is implemented in the MATLAB software where the results obtain a good accuracy and reduces false positive and false negative using proposed methodology

### Input Image

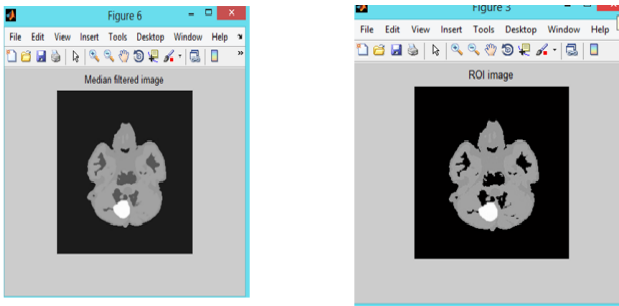


**Temperature analysis:**



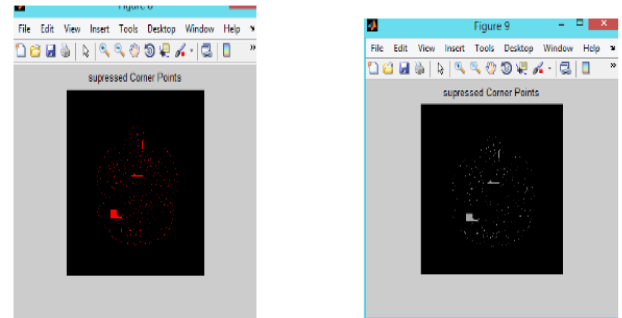
**Fig. 5 Thermal Analysis**

**Median Filtering:**



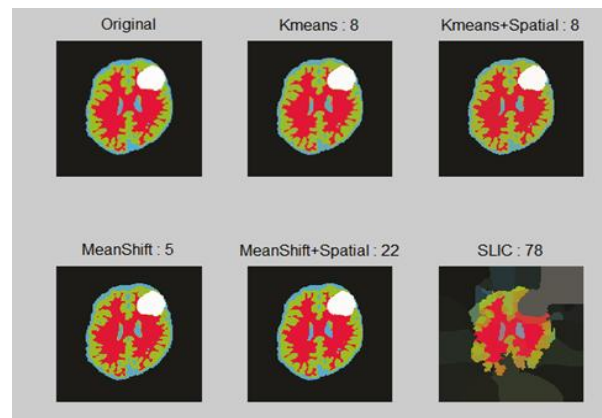
**Fig. 6 Median Filtering**

**Corner metric Segmentation:**



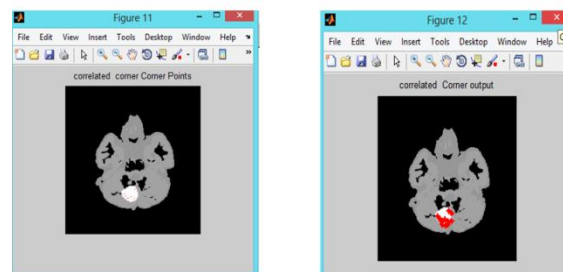
**Fig.7 Corner metric Segmentation**

**Simple Linear Iterative Clustering:**



**Fig.8 SLIC**

**Chan-veese contour:**



**Fig. 9 Chan vese contour**

Output Image:

V CONCLUSION

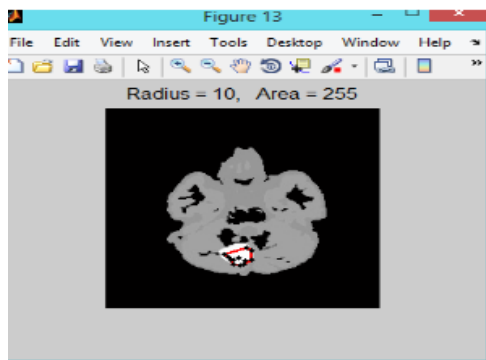
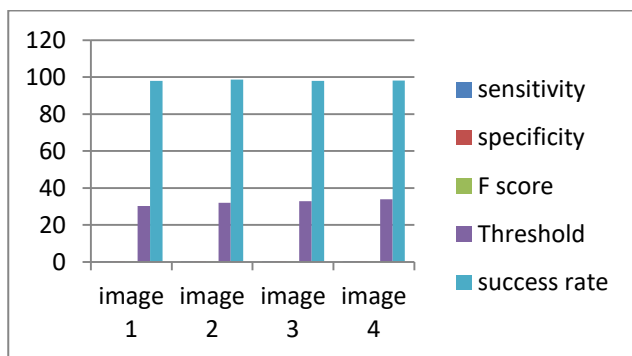


Fig. 6 Extraction of Tumorcells

Comparsion Table:

IMAGE	SPECIFICITY	SENSITIVITY	F-SCORE	THRESHOLD	SUCCESS RATE
Image 1	.5000	0.5001	0.2958	30.1745	97.8993
Image 2	0.5201	0.5210	0.2780	32.0257	98.6753
Image 3	0.5220	0.5000	0.2889	32.9213	97.9986
Image 4	0.5301	0.5000	0.2732	33.8990	98.1207

Comparsion Graph



In this approach, a simple linear interactive clustering (SLIC) with chan-veese contour has been proposed for enhancing brain tumor segmentation in MRI images. In pre-processing, the median filtering technique is used for measuring area and to remove noises in tumor cells. True positive and negative results were identified by Fuzzy corner metric segmentation algorithm based on image intensity. Simple Linear Iterative Clustering algorithm segmented the superpixels with less computational power. Tumor cells are detected within the boundary condition Chan – veese contour was used. The parameter analysis has been done by calculating the parameters Specificity, Sensitivity and accuracy level. The proposed method achieved about 98.6% accuracy rate compared to fuzzy clustering method. It is very useful towards the creation of a new MRI imaging sequence of future studies.

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