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An Automatic Segmentation Method for Brain Tumor Detection using Chan-Vese Algorithm

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ABSTRACT

Biomedical imaging has become an emerging and interesting field for the radiologistsdue to enhancement in technology to resolve the problems. Brain tumor is one of the most threatening diseases to diagnose because of variations in its size, type and location. So, segmentation plays an efficient role in medical field to get the important information from image and helps in better visualization. In this paper, chan-vese algorithm is performed for the segmentation of brain tumor image. Then, binary mask is applied to detect the actual location of tumor. Various features like FOS, FDTA, and GLDS are extracted to classify the tumor. Tumor is detected by this technique and it provides useful results.

Keywords: Brain tumor, MRI, segmentation, chan-vese algorithm, binary mask, active contour.

1. INTRODUCTION

Image segmentation is the process of dividing or segmenting an image into distinct smaller parts or regions having similar pixel attributes. This is done to identify object or to obtain the useful information from the digital image. Image segmentation can be performed by various ways. Segmentation techniques are contextual or non- contextual. In contextual, spatial relationships are performed between features in an image and it group pixels together on the basis of some global attributes. While in contextual no account for spatial relationships. Existing segmentation techniques are region growing, thresholding, watershed algorithm, morphological operations, k-means clustering, fuzzy c-means clustering, genetic algorithm and chan-vese algorithm. In region growing according to predefined criteria pixels or sub regions are grouped into a larger region. A connected Region of similar pixels from an image is extracted by this method. The segmentation can be done by various thresholding techniques. It can be by using individual thresholds or by a multiple thresholding .The main problem with thresholding is that it considers only intensities not any kind of relationship between the pixels of an image.

The most common image property to threshold is pixel grey level: $g(x, y) = 0$ if $f(x, y) < T$ and $g(x, y) = 1$ if $f(x, y) \geq T$, where T is the threshold. Watershed algorithm is one of the best methods to group pixels of an image on the basis of their intensities. Pixels falling under similar intensities are grouped together. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. K-means clustering is an unsupervisedalgorithm that is used to solve clustering problems. By using the basic knowledge of cluster value image can be easily and simply segmented.Fuzzy c-means is used to represent a system’s behavior by identifying natural grouping of data from a large dataset.This algorithm is based heuristic method. GA has five stages: initialization of population, evaluation of fitness function, selection, crossover, mutation and termination.The Chan-Vese algorithm is an example of a geometric active contour model. Initial segmentation is defined by such models that begin with a contour in the image plane and this contour is evolved according to some evolution equation. The goal is to evolve the contour in such a way that it stops on the boundaries of the foreground region.The Chan-Vese algorithm evolves this contour via a level set method.

Magnetic Resonance Imaging (MRI) is an effective tool which helps in obtaining the internal three dimensional structures of internal parts of human body. It is based on the principle of NMR(Nuclear Magnetic Resonance). In this, strong magnetic fields and radio waves are used to produce the detailed images of the inside of the body. As hydrogen atoms exist naturally in people, so, in clinical and research MRI, hydrogen atoms are most often used to generate useful radio frequency signal that is received by antennas. A magnetic resonance imaging (MRI) scanner uses powerful magnets to polarize and excite hydrogen nuclei (single proton) in human tissue, which produces a signal that can be detected and it is encoded spatially, resulting in images of the body. The MRI machine emits radio frequency (RF) pulse that specifically binds only to hydrogen. The system sends the pulse to that specific area of the body that needs to be examined.

Here are few features which can be extracted for tumor classification. Some of them are Spatial Grey Level Dependence Matrices (SGLDM), Grey Level Difference Statistics (GLDS), First Order Statistics (FOS), Fourier Power Spectrum (FPS), Eractal Dimension Texture Analysis (FDTA) and Surrounding Region Dependence Method (SRDM). Following features are extracted in this paper. Fractal dimension is an important parameter of Fractal geometry that finds significant applications in various fields including image processing.

There are many techniques to measure the texture of an image that includes mean to measure the average intensity of an image, standard deviation to measure the average contrast, smoothness to measure the relative smoothness of intensities in a region, Third Moment to measure the skewness of a histogram, Uniformity to measure the consistency of intensity values and Entropy to measure the randomness. The fractal dimension is an important characteristic of fractals because it has got information about their geometric structure. The topological dimension (defined as d) of an object would not change whatever be the transformation an object undergoes. In the fractal world, the fractal dimension need not be an integer number. The fractal dimension of an object is normally greater than its topological dimension. Eight features are extracted in first order statistics i.e. Mean, Mode, Median, Variance, Skewness, Kurtosis, Energy and Entropy respectively. In the first order statistics, let random variable I represents the gray levels of image region. The first-order histogram P (I) is defined as:

$$P(I) = \frac{\text{number of pixels with gray level I}}{\text{total no. of pixels in the region}}$$

The most frequently used central moments are Variance, Skewness and Kurtosis given byμ_2, μ_3, and μ_4 respectively. The Variance is a measure of the histogram width that measures the deviation of gray levels from the Mean. Skewness is a measure of the degree of histogram asymmetry around the Mean and Kurtosis is a measure of the histogram sharpness.

Grey level difference statistics is another parameter for feature extraction. Homogeneity, contrast, energy, entropy are the features extracted in the GLDS.

Various parameters have calculated in this paper to measure the performance of the proposed algorithm. Few of them are accuracy, Jaccard Index, Mathew’s correlation coefficient (MCC) and sensitivity etc by calculating true false and false negative rate. Accuracy can be defined as closeness of measured value to a standard value. Jaccard Index which is also known as Jaccard Similarity Index is a statistic, used for comparing the similarity and diversity of sample sets. Whereas MCC is calculated on the basis of true positive and negative values. Last but not the least Sensitivity can be defined as proportion of positives that are correctly identified as such.

2. PROPOSED ALGORITHM

Step 1. Read the input MRI brain tumor image.
Step2.Apply chanvese active contour without edges based algorithm.
Step 3. Segmented output image of chanvese algorithm.
Step 4. Extract the mask from segmented image.
Step 5. Select the maximum value in segmented image.
Step 6. Store max value of mask in a variable.
Step 7. Resize scaled image.
Step 8. Select tumor image from largest size portion of image i.e. output image (tumor detected).
Step 9. Extract features.

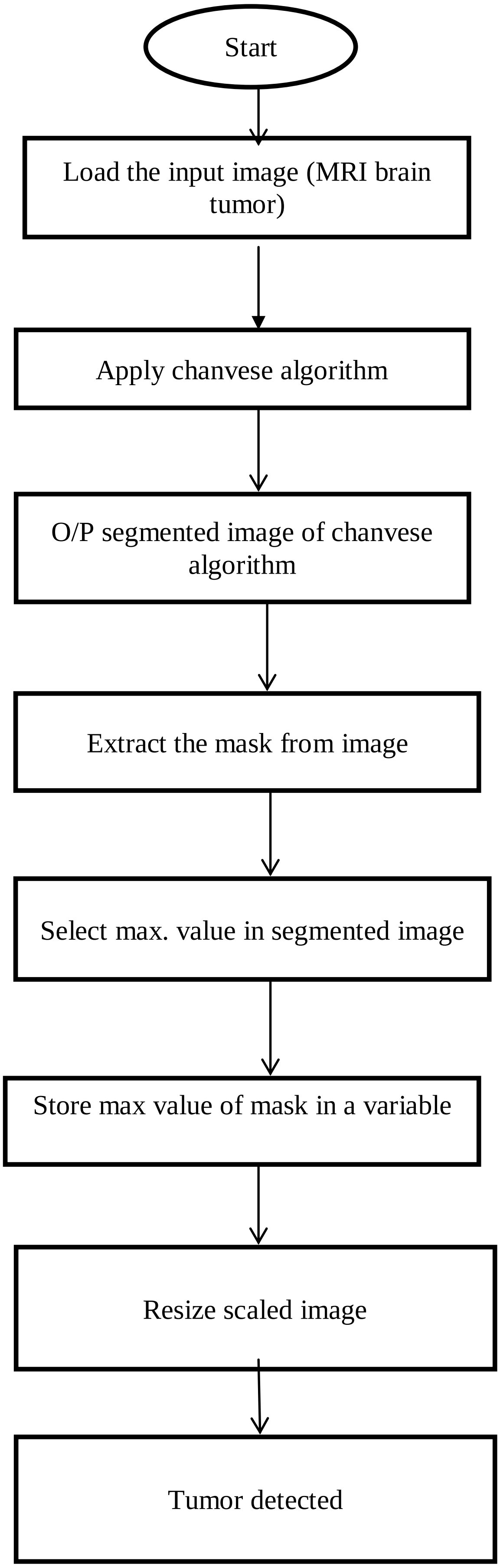
3. PROPOSED METHOD

A. Chan-vese algorithm:- The Chan-Vese algorithm is an example of a geometric active contour model. In this, initial segmentation is defined by such models that begin with a contour in the image plane and this contour is evolved according to some evolution equation. The goal is to evolve the contour in such a way that it stops on the boundaries of the foreground region.The Chan-Vese algorithm evolves this contour via a level set method. In this paper, this methodology is used to segment the tumor area.

B. Binary Mask:- In this paper, binary mask is used to identify the location of the tumor which was done by superimposing it on the segmented image which results from the chan-vese algorithm.

C. Feature extraction:-Feature extraction is done to classify the tumor grade or type. Features based on FDTA, FOS and GLDS are extracted which covers mean, median, variance, skewness, kurtosis, energy and entropy.

4. PROPOSED FLOWCHART



5. RESULT ANALYSIS

In this paper, chan-vese algorithm is applied for the automatic segmentation of brain tumor. After that, binary mask is applied to identify the exact location of tumor. In this proposed methodology “fig 1”. shows the original MRI image, “fig 2”. shows the Input, intial contour and half performed iterations image, “fig 3”. represents the complete iterations performed and global region-based segmentation image, “fig 4”. represents the generated mask image and “fig 5”. shows the tumor detected image

Figure 1. Original MRI image

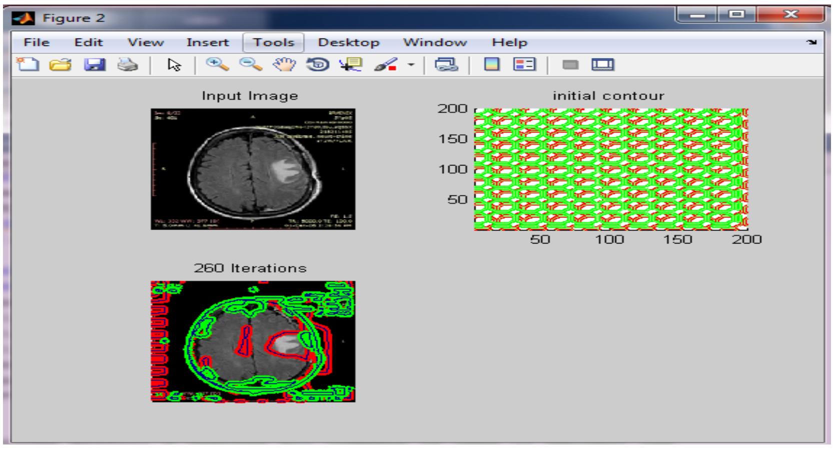


Figure 2. Input, intial contour and half performed iterations image

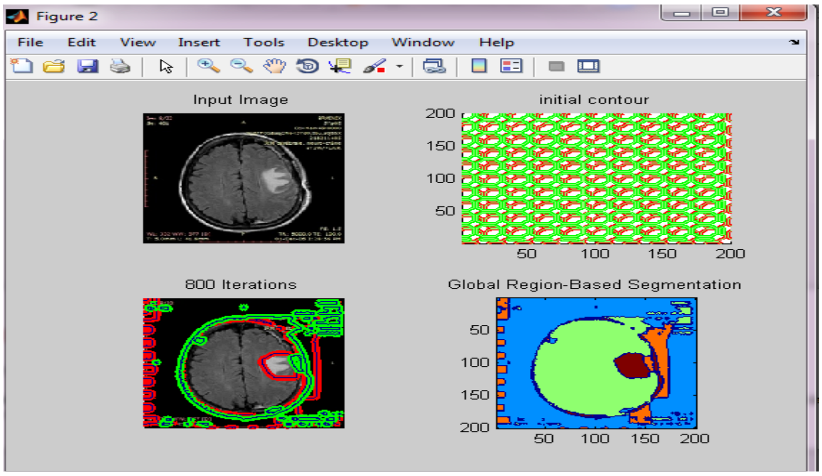


Figure 3. Complete iterations performed and global region-based segmentation image

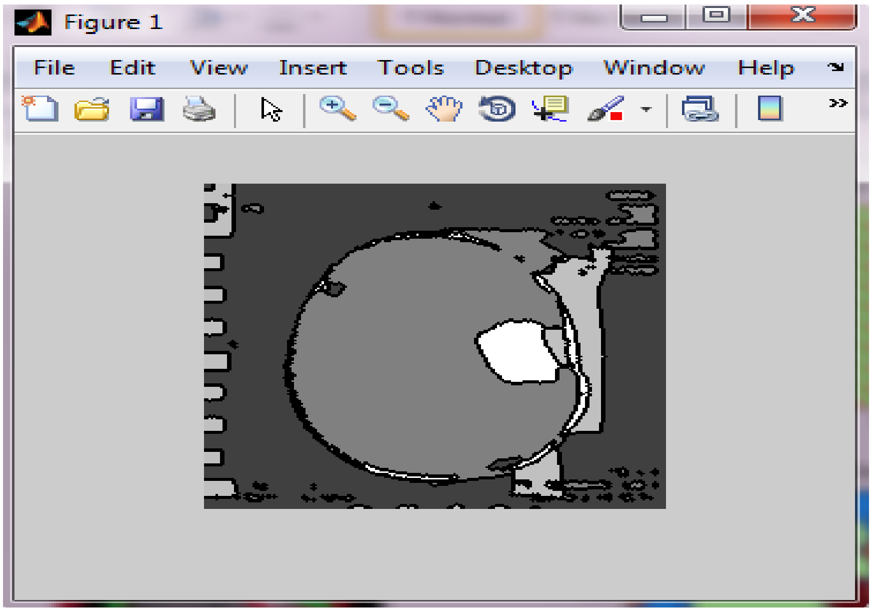


Figure 4. Generated mask image

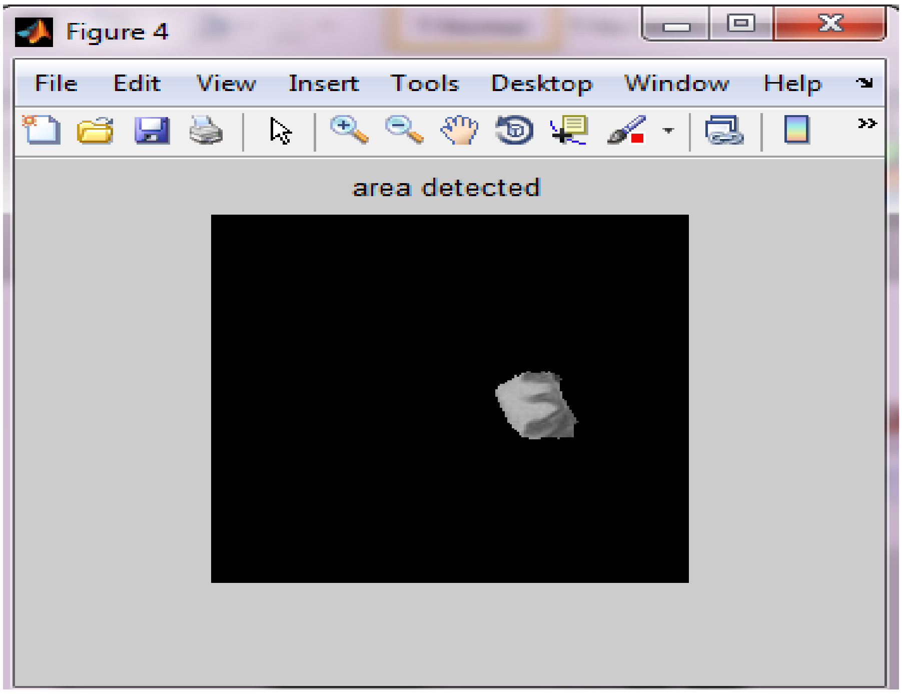


Figure 5. Tumor detected image

CONCLUSION

The proposed system works on the chan-vese algorithm based segmentation. When this technique is applied on various MRI brain tumor images, maximum tumor is detected. The system is tested against various input images and it gives 98.54% accuracy when compared with the neutrosophic sets which is 0.17 % more. Comparison of both neutrosophc sets and chan vese is done by comparing their masks. It provides 100% detection rate on dataset of 20 images. Another parameters calculated are FPR(False positive rate) 0.0101% , Jaccard Index 0.5718%, sensitivity 76.32% respectively. Better feature extraction is done by FDTA (Fractral Dimension Texture Analysis), FOS (First Order Statistics) and GLDS (Grey Level Difference Statistics).

FUTURE SCOPE

In future work, classification of brain tumor grades can be done as tumor belongs to Grade I, Grade II, Grade III and Grade IV. The proposed system doesn't classify the tumor grades, it only extracts the features. In future system can be made which will be able to classify the tumor grades along with the detection of the tumor.

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