An Efficient Accuracy Improved Brain Tumor Segmentation Using CHAN-VESE Contour

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Abstract: Brain segmentation is an important task in medical image processing. Early diagnosis of brain tumor plays an important role in improving treatment possibilities and increases the survival rate of the patients. Manual segmentation of the brain tumors for cancer diagnosis, large amount of MRI images generated in clinical routine is difficult and time consuming task. There is a need for automatic brain tumor image segmentation. The conventional fuzzy c-means (FCM) clustering is the most widely used unsupervised clustering method for brain tumor segmentation on magnetic resonance (MRI) images. This project proposes an efficient FCM algorithm to eliminate the drawback of conventional FCM. The proposed method is to identify thermal information of brain tumors. It can be used to reduce false positive and negative results of segmentation performed in MRI images. In this paper a median filtering technique is used as a preprocessor and segmentation is done by Fuzzy corner metric algorithm. The final process is to extract the tumor cells by chan - vese contour using gradient vector field as external force. The proposed method achieves higher accuracy rate of about 98.6% and it is efficient compared to fuzzy clustering method.

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

I. INTRODUCTION

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

During the past couple of years, there has been tremendous growth in using magnetic resonance imaging (MRI) for diagnostic and treatment purposes. MRI is one of the most common non-invasive medical imaging modality used for the diagnosis and analysis of internal structures, irregularities and abnormalities such as brain tumors. MRI not only provide the detailed functional study of soft tissues and aberrations but also help in understanding the process neurodevelopment in adult brains [1, 2, 3]. In MRI, like other medical imaging modalities, segmentation of brain tumors is a complex and challenging task due to various major reasons such as tumor shape, size and location that vary greatly across patients. The other common reasons, which make segmentation a complicated problem in medical images, are overlapping of tissues, noise, low contrast, textured regions and high spatial resolution which may lead to improper quantification of region of interests [2,7,8]. Since, these segmented approaches practiced by clinicians are manual, time-consuming and expensive; and results in previously discussed limitations, thus, due to these reasons, the automated computational strategies for obtaining the clinical information from medical images are continuously obtaining greater attention.

In recent years, various segmentation strategies (such as deformable model based, statistical and atlas-based) have been proposed in the literature [9-18]. In this study, we propose an iterative brain tumor segmentation approach based on Chan and Vese model to identify and segment tumor from brain MRI images. The significance of our proposed method is that it can easily be modified with the help of assigned iterations to create a robust and independent segmentation framework.

The contribution of this paper is to combine a prior Chan Vese model with some pre-processing techniques along with setting the number of iteration for performing the region of interest (ROI) based segmentation and making the process iterative to guide the contours with the current segmentation. This technique is more flexible than the previously reported methods in a way that it gives users the freedom to determine and set the number of iterations allowing them to get the desired results at respective iteration. In the following sections of this paper, we describe the details of the proposed method and demonstrate the segmentation results when applying it to brain tumor image dataset as acquired by MRI imaging modality. Therefore, in this research we are going to propose a novel diagnostic technique based on based Chan Vese model using iterations detecting and segmenting the tumors from brain MRI images.

The rest of the paper is organized as follows. Section II gives a brief overview of work related to Chan Vese method. Section III describes the proposed methodology in relation to segmentation of brain tumors in MRI images. Section IV presents the experimental results obtained from the proposed method and comparison with existing reported work. The paper is Conclusion in section V respectively.

II. RELATED WORKS

Pradeep et al [1] investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Ioannis S. Gousiasetal et al [2] proposed a framework for accurate intensity-based segmentation of the developing neonatal brain, from the early preterm period to term-equivalent age, into 50 brain regions. Jun Jiang et al [3] proposed a novel automatic tumor segmentation method for MRI images. This method treats tumor segmentation as a classification problem. Additionally, the local independent projection-based classification (LIPC) method is used to classify each voxel into different classes. Syed M et al [4] Proposed a novel patient-independent tumor segmentation scheme by extending the well-known AdaBoost algorithm .The modification of AdaBoost algorithm involves assigning weights to component classifiers based on their ability to classify difficult samples and confidence in such classification.

Marleen de Bruijne et al [5] described a novel method for brain structure segmentation in magnetic resonance images that combines information about a structure's location and appearance. The spatial model is implemented by registering multiple atlas images to the target image and creating a spatial probability map.

AnupBasu et al [6] proposed a new approach that we call the ldquofluid vector flowrdquo (FVF) active contour model to address problems of insufficient capture range and poor convergence for concavities. J. Corso et al [7] presented a method for automatic segmentation of heterogeneous image data that takes a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. Katherine L. Narr et al [8] proposed a hybrid discriminative/generative model for brain anatomical structure segmentation. Bruce Fischl et al [9] improved the performance of an atlas-based whole brain segmentation method by introducing an intensity renormalization procedure that 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

Image segmentation is a fundamental task in image analysis responsible for partitioning an image into multiple sub-regions based on a desired feature. Active contours have been widely used as attractive image segmentation methods because they always produce sub-regions with continuous boundaries, while the kernel-based edge detection methods, e.g. Sobel edge detectors, often produce discontinuous boundaries. The use of level set theory has provided more flexibility and convenience in the implementation of active contours. However, traditional edge-based active contour models have been applicable to only relatively simple images whose sub-regions are uniform without internal edges.

The first process is filtering the brain tumor images by Median Filtering technique, the is mainly to find ROI and convert the images to gray scale images. Second step is segmentation process by using fuzzy corner metric segmentation to suppress the images and finally correlate the image by chan vese active contour. The proposed method uses a fuzzified corner metric based on image intensity to identify the feature makers enclosed by the contour. Proposed work coded in Matlab. Segmenting regions from medical images is an involved process for various reasons.

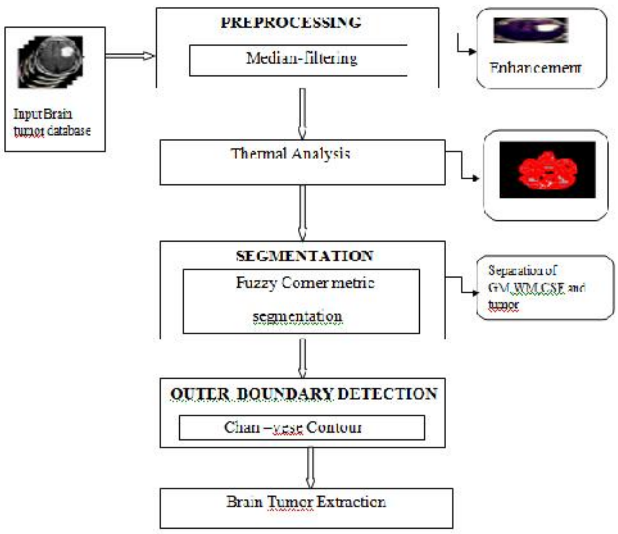


Fig. 1 Proposed Block Diagram

PRE-PROCESSING

It is very difficult to process an image. Before any image is processed ,it is very significant to remove unnecessary items it may hold. After removing unnecessary artifacts, the image can be processed successfully. The initial step of image processing is Image Pre-Processing . Pre-Processing involves processes like conversion to grayscale image,noise removal and image reconstruction. Conversion to grey scale image is the most common pre-processing practice. After the image is converted to grayscale, then remove excess noise using different filtering methods.

Grayscale:

In photography and computing, a grayscale or grayscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Grayscale images are distinct from one-bit black and-white images, which in the context of computer imaging are images with only the two colors, black, and white also called bi-level or binary images. Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the absence of any chromatic variation. Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum e.g. infrared, visible light, ultraviolet, etc, and in such cases they are monochromatic proper when only a given frequency is captured.

Converting Color to Grayscale

Conversion of a color image to grayscale is not unique; different weighting of the color channels effectively represents the effect of shooting black-and-white film with different-colored photographic filters on the cameras. A common strategy is to match the luminance of the grayscale image to the luminance of the colo rimage.

Filtering

An Image filtering is useful for many applications, including smoothing, sharpening, removing noise, and edge detection. A filter is defined by a kernel, which is a small array applied to each pixel and its neighbors within an image. In most applications, the center of the kernel is aligned with the current pixel, and is a square with an odd number 3, 5, 7, etc. of elements in each dimension.

Median filter

The most common technique which used for noise elimination. It is a 'non –linear' filtering technique. This is used to eliminate 'Salt and Pepper noise'. From the grayscale image. Median filter is based on average value of pixels. The advantage of median filter are efficient in reducing Salt and Pepper noise and Speckle noise. Also the edges and boundaries are preserved.

In our proposed work we used median filter for less computation complexity and better smoothing of images. It is better in preserving useful details in the image than the mean filter. Like the mean filter, the median filter considers each pixel in the image and replaces it with the median of the neighborhood pixel values. The median filter has two main advantage over the mean filter:

It is a more robust estimation than the mean. A single unrepresentative pixel in a neighborhood will not affect the median significantly.

It does not create new unrealistic pixel values, since the median must actually be the value of one of the pixels in the neighbourhood.

SEGMENTATION

Segmentation of images is important as large numbers of images are generated during the scan and it is unlikely for clinical experts to manually divide these images in a reasonable time. Image segmentation refers to segregation of given image into multiple non – overlapping regions. Segmentation represents the image into sets of pixels that approximately locate the boundaries or objects in an image and the resulting segments collectively cover the complete image. The segmentation algorithms works on one of the two basic characteristics of image intensity; similarity and discontinuity.

Fuzzy corner metric Segmentation

A fuzzified corner metric , based on image intensity, is proposed to identify the feature markers to been closed by the contour. A concave hull based on α shape, is constructed using the fuzzy corners to give the initial contour. Corners are feature points in an image that are identified by the presence of large variation in intensity around a pixel in all directions. One of the well known corner detector is Harris corner and edge detection method.

Outer boundary detection

All the pixels inside the boundary will be classified into the "object class", while those outside the boundary classified into the "background class". Subsequently a segmented image is formed. To illustrate the principle, we may consider the results . Here the true scene object is circular and is situated in the center of the image. The template object is circular and medium-size. After moving the medium-size template object around entire image and tracing the zero-value GIE points (the white dots), a circular boundary is formed and then the image is segmented.

Active Contours

The method of active contours has become quite popular for a range of applications, mainly image segmentation and motion tracking, through the last decade. This methodology is based upon the use of deformable contours which match to various object shapes and motions. This section provides a theoretical setting of active contours and an indication of existing active contour methods. There are two main approaches in active contours based on the mathematic implementation: snakes and level sets. Snakes explicitly shift predefined snake points based on an energy minimization method, while level set approaches move contours completely as a particular level of a function

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

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

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

IMAGE	SUCCESS RATE	SENSITIVITY	SPECIFICITY
Image 1	97.8993	0.5000	0.5001
Image 2	98.6753	0.5201	0.5210
Image 3	97.9986	0.5220	0.5000
Image 4	98.1207	0.5013	0.5000

Table.1 Segmentation Parameter Analysis

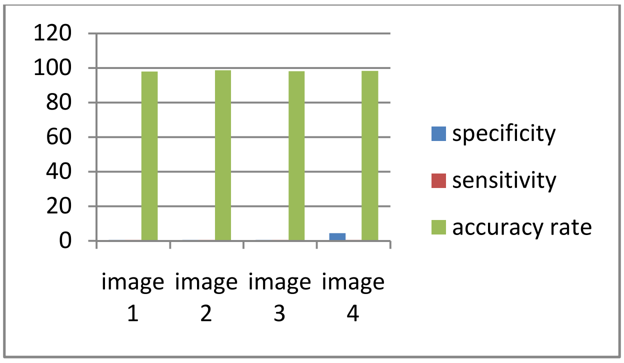
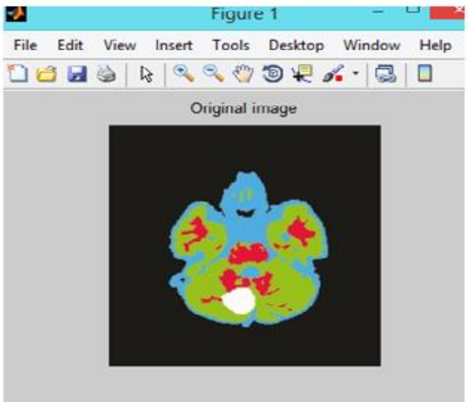


Fig. 2 Graph on Parameter Analysis

IV. SIMULATION RESULTS

In this section, the simulation results are implemented using MATLAB2014 and the comparison results and performance charts are given below:

Input Image



Temperature analysis:

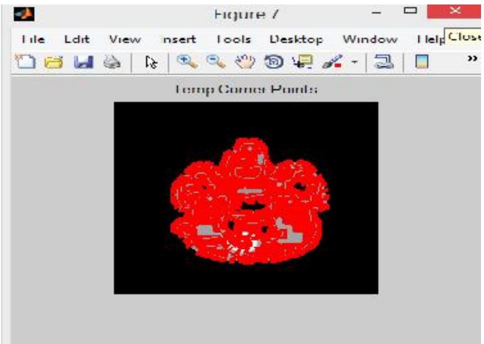


Fig. 3 Thermal Analysis

Corner metric Segmentation:

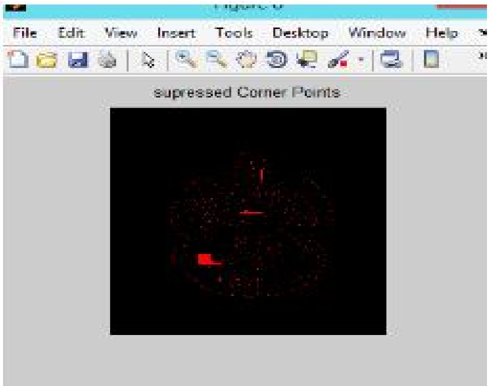


Fig.4 Corner metric Segmentation

Chan –vese Contour:

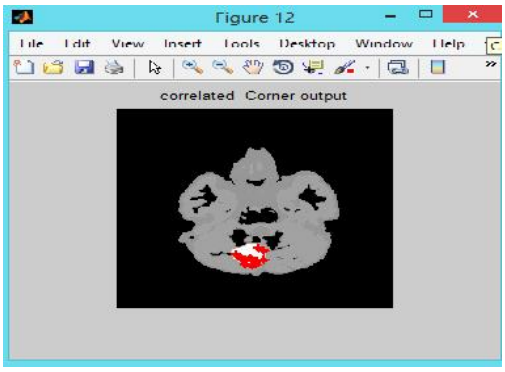


Fig. 5 Chan –vese contour

Detection of Tumor cells:

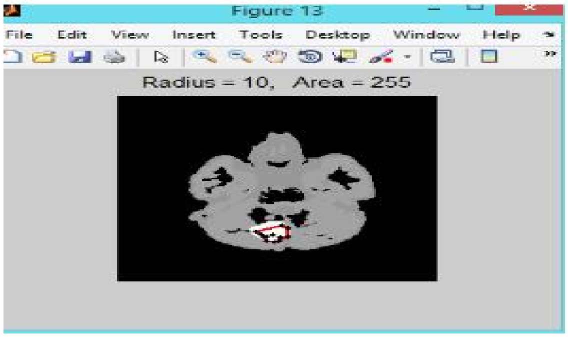
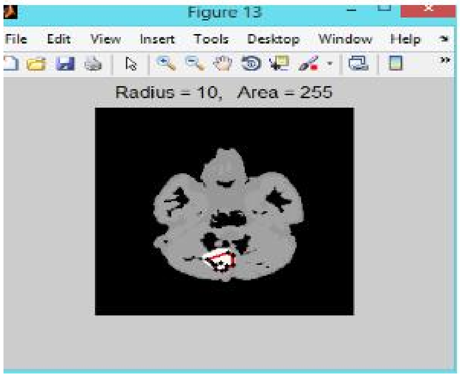


Fig. 6 Extraction of Tumorcells

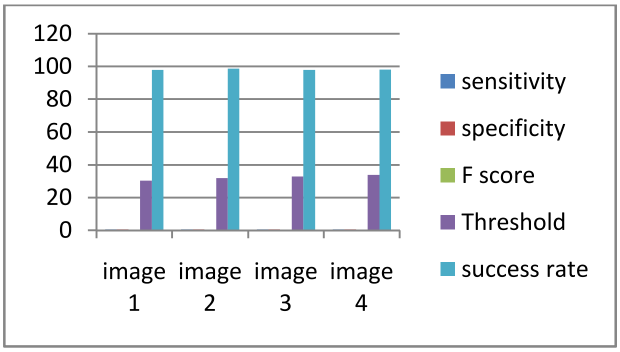
Output Image:



Comparsion Table:

IMAGE	SPECIFICITY	SENSITIVITY	F-SCORE	THRESHOLD	SUCESS 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



V. CONCLUSION

Segmenting regions from medical images is an involved process for various reasons. Deformable contours provide an almost accurate dissection of ROI from background owing to their ability to constrict or expand upon external constraints. There liability of such segmentation can only be guaranteed if the initial contour is close enough to the interest segment. To ensure good results, manual setting has so far been the only viable option which increases the fatigue of clinical users. To facilitate as smooth and less intensive segmentation, a novel method of chanvese contour initialization for ACM is presented in this study. The proposed method uses a fuzzified corner metric based on image intensity to identify the feature markers enclosed by the contour. A concave shape approximating the boundary of these fuzzy corner points is obtained using α hull to give the initial contour for the ACM. The additional computational cost is one order less than the cost of ACM evolution. The proposed technique is form robustly even in the presence of noise.

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