Segmentation of Brain Tumor using Contourlet Transform and Chan-Vese Active Contour Model Approach

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Abstract:

The brain tumor segmentation acts as a major task in the field of medical image processing. The detection of cancer in manual manner with the large MR images is very tedious, as it requires more time. Thus, in order to overcome the drawbacks of the manual segmentation of the brain tumor, automatic brain tumor segmentation is needed. This paper presents an automatic segmentation of brain tumor using Contourlet transform and Chan-Vese active contour model. The Contourlet transform captures edges and smooth contour at any orientation and it also filters the noise in image in a better way. The Contourlet transform with its extra feature of directionality gives images of high resolution. Chan-Vese active contour models are region based segmentation models and they use optimal piecewise smooth approximation function for the segmentation. These models are very accurate as compared to the traditional segmentation techniques.

Keywords-Segmentation;Chan-Vese Active Contour Models; Contourlet Transform; Magnetic Resonance Imaging.

I. INTRODUCTION:

A group of tissue that are prearranged with the creation of irregular cells is known as Brain tumor and in recent years, it acts as a major reason for the death of many people. There are various kinds of cancers, among which brain tumor is the serious disease that requires immediate detection and effective treatment to save the patient's life [1]. Due to the formation of the tumor cells, the detection of these cells is very tedious and needed to be compared with the MRI treatment.

Segmentation of a given medical image is an important and significant stage for the analysis of medical images. Also, this is the first and most significant step in most of the medical applications. Especially, for the analysis of the human brain, segmentation is the common tool applied to visualize the anatomical structures of the brain. Analysing changes of pathological regions, surgery planning and image guided interventions requires segmentation procedure [2]. In the literature, various types of segmentation approaches with different accuracy have been reported from past three decades [3].Enormous amount of growth in visualizing brain damage and exploring anatomy of brain provides huge amount of information with an increasingly larger level of quality. Due to huge amount of database, it becomes the tedious and complex problem to analyse these database by the radiologists who have to extract prominent data manually. Sometimes, the manual analysis is prone to error and often time consuming process. To overcome the issues of brain data analysis, an inventions of computer based techniques for the betterment of diagnosis and treatment planning. Hence the proposed work presents a novel methods for the segmentation of brain tumors and to classify tumor type so that possible diseases can be identified.The entire success or failure of the disease detection entirely depending on the accuracy of the segmentation. In recent years many segmentation techniques have been developed for medical image applications [4]. The segmentation method to be used is chosen on the application and the modality of the image used. In recent years Segmentation of the tumour in the MR images of the brain is well thought-out as the active research topic.

II. RELATED WORK:

Automatic detection and segmentation of brain tumors in MRI images is a very challenging task due to occurrence of high degree of gray-level similarity in the image.Numbers of algorithms were proposed to make segmentation process robust against noise and in homogeneity but it's still not perfect. To overcome the mentioned problems, Deformable active contour models were introduced [5]. Deformable models are widely discussed and used in the field of medical image segmentation.Deformable models works on the basis of object boundaries and the features considered with respect to image boundaries are namely the shape, texture, smoothness and internal and external forces on the object [6]. All these factors results the segmentation of desired object boundaries. The closed contours and object shapes in the image can be utilized to mark the boundaries of an object. This process of identifying the boundary of an object is a closed curvature or plane that is initially positioned close to the preferred edge and later permitted to experience an iterative reduction progression.

Nguyen Mong Hien et al. [7] have proposed a new brain MRI image segmentation strategy based on wavelet transform and K-means clustering. This method proposed a technique that improves the accuracy of the brain tumor segmentation. In the first stage, this technique uses wavelet transform to denoising of MR image and in the next stage, brain MR image is segmented by k-means clustering algorithm. Experimental results show that the proposed strategy can effectively improve the segmentation accuracy of the noisy MR image of the brain but the complete removal of noise is difficult using wavelet transform due to its limited directionality.

Lata Ayesha Akter and Goo-Rak Kwon [8] have presented the technique that integrates the Contourlet transform and Canny edge detector for the segmentation of brain tumor.In this technique, they have used a new transformation called Contourlet Transform which is integrated with canny edge detector. Before applying Canny edge detector for segmentation, Contourlet transform is applied. The results indicates that using canny edge detector after enhancing the image by Contourlet transform along with an enhancement function, the brain MR image can be segmented. But using the Canny edge detector, the accuracy of segmentation is very poor. To overcome this drawback, Deformable models are widely used segmentation methods for the brain tumor segmentation.

Zhang et al. [9] have introduced a deformable model based segmentation algorithm by incorporating the Chan-Vese model for solving the Brain MR Image segmentation issues. Using this technique and integrating themultiphase Chan-Vese framework by including both theshape as well as statistical information of the image pairs intothe energy functions, they were able to characterize the tumors. However, this method outperforms in the presence of noise in the MR images.

Muhammad Zawish et al [10] have demonstrated variation methods for accurately segmenting the tumors from brainMR image database. This method is based on Chan-Vese activecontour models without edges. In this technique, a force shrinks thecontour and another force expands

the contour. These two forces getbalanced when the contour reaches the tumor boundary and thus allow to find the contour of the object resulting inits precise segmentation. The efficiency of the algorithm has beentested and verified on various brain MR images. But this method gives poor performance for the image with inhomogeneity in nature.
Kimmi Verma et al. [11] have introduced a novel 3-D based geometric transform invariantfor translatory, rotatory and scaling invariant technique for the segmentation of brain tumors in MR images. The technique provides computationally efficient aid infinding features like shape of the tumor, location of it and texture todiagnose from the given MR images. But to improvise the accuracy of the segmentation, pre-processing steps that involves removal of noise, enhancement of imagesare required.
M. Venkata Ramana et al. [12] have presented a new technique enhanced Curveletstransform based artificial
neural network for brain tumor segmentation. Wavelets are not good for images withdifferent orientations or smooth curves. Ridgelets could handleimages with line singularities but could not handle images withcurves. Curvelets transform can overcome this problem besidesrepresenting images with different scales and different angles.Curvelets transform with enhancements can support for the detection of brain tumor. Thus in this method enhanced Curvelets transform is used to have better segmentation accuracy.
EliseeIlunga et al. [13] have presented the technique known as Localized Region-based Active Contour Model (LRACM). In this method, the automatic selection of LRACM based on image content and its application on brain tumor segmentation is introduced. Thereby, a framework to select one of three LRACM, i.e., Local Gaussian Distribution Fitting (LGDF), localized Chan-Vese and Localized Active Contour Model. Using this method, visual features are extracted toselect the method that may process a given input MR image. The experimental results indicates that the proposed method is capable to select the suitable LRACM to handle a specific image. Hence, the selection framework achieves better segmentation accuracy.

III. PROPOSED METHODOLOGY:

The proposed methodology is aniterative brain tumor segmentation approach based on Chan-Vese active contour model to identify and segment tumor from brain MR images. The significance of the proposed technique is that it caneasily be modified with the help of assigned iterations to createa robust and independent segmentation framework.The main objective of the proposed methodology is to combine a prior Chan Vesemodel with pre-processing method using Contourlet transform before segmenting the brain tumor from MR image. By settingthe number of iteration for performing the region of interest based segmentation and making the process iterative todirect the contours with the current segmentation.
Thistechnique is more flexible than the existed techniques in a way that it gives users the freedom to determineand set the number of iterations allowing them to get thedesired results at respective iteration. The following block diagram illustrates the proposed segmentation process.

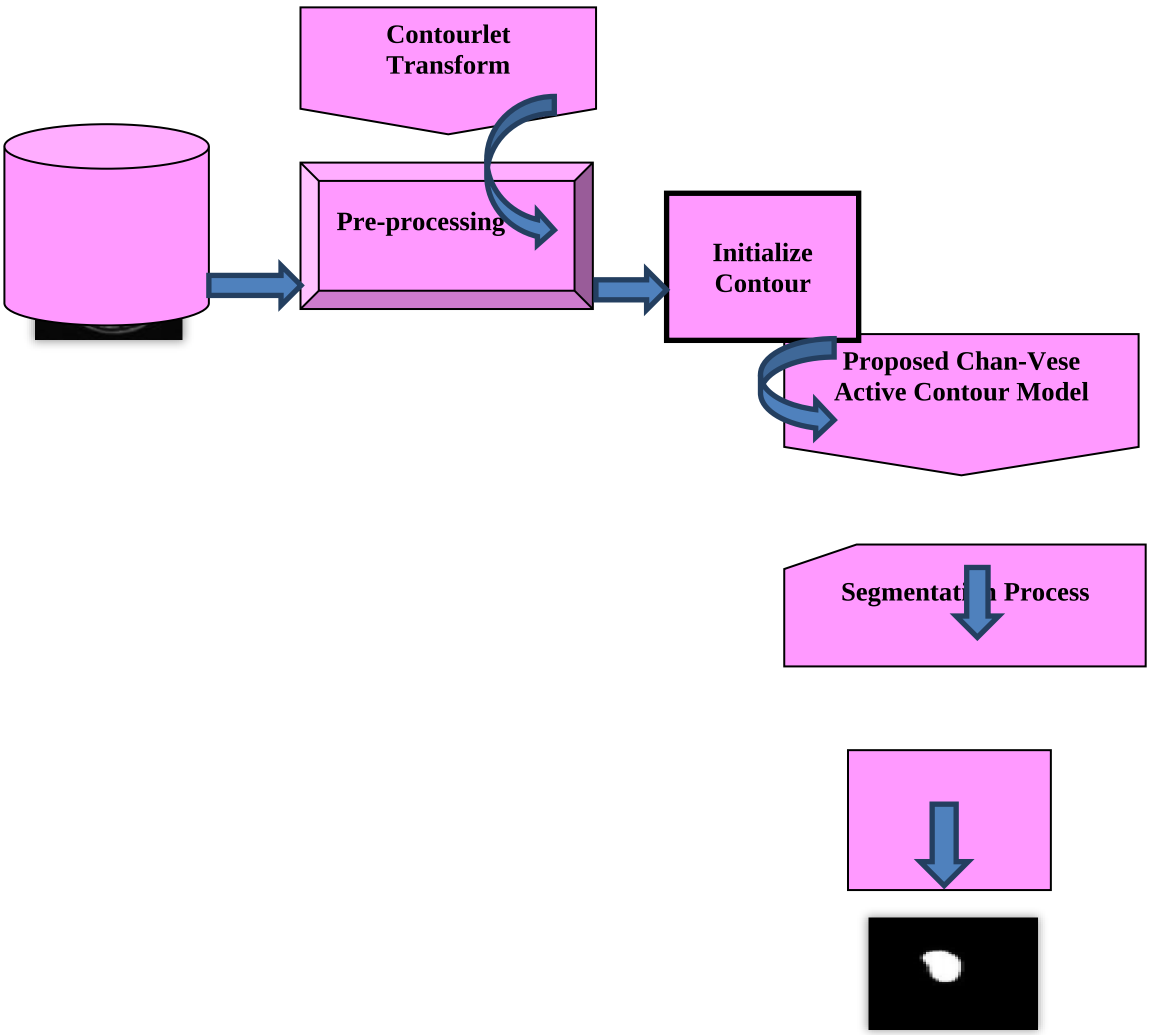


Fig. 1. Block diagram of the proposed segmentation model used for the segmentation of brain tumor from MR image.

A. Pre-processing by Contourlet Transform:

To achieve the best possible target to segment the tumor, it is necessary that medical image should be distinct, sharp and noise free. Though MRI scanners technologies for medical image are improving tremendously now a day's, which gives images of high resolution and quality but noise is still a major issue of many images.
Contourlet Transform proposed by Do and Vetterli [14] captures edges and smooth contour at any orientation. It also filters the noise in image in a better way. The Contourlet transform with its extra feature of directionality achieves better results than the discrete wavelet transform and yields new potentials in removing speckle noise and preserving the edge well without the effort to set a threshold.

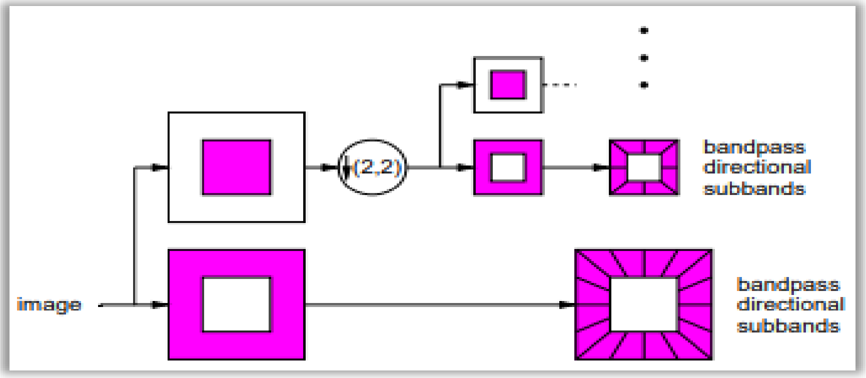


Fig. 2 Block diagram of the Contourlettransform depicting the DFBs [14].

A Laplacian pyramid (LP) is first used to capture point discontinuities, then followed by a directional filter bank (DFB) to link point discontinuity into linear structure. First stage is low pass decomposition and second stage is DFB decomposition.The original image is decomposed toa lowpass image and a bandpass image by LP decomposing. Each bandpass imageis further decomposed by DFB. Repeating the same steps upon the lowpass image,the multiscale and multi-direction decomposition of the image will be obtained. For frequency partition of the Contourlet-transform where the four scales are divided into four-four, eight, and eight directional scales, respectively.The resulting frequency division is shown in figure 3.The Contourlet construction provides a space-domainmultiresolution scheme that offers flexible refinementsfor the spatial resolution and the angular resolution.

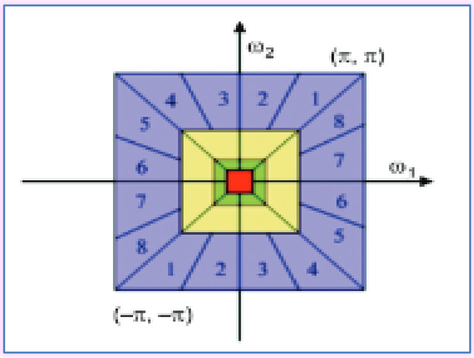


Fig. 3 Frequency division of the Contourlet transform.

B. Chan-Vese Active Contour Model:

Chan-Vese active contour model [15] is a powerful and flexible method which isable to segment many types of images, including some that would be quite difficultto segment in means of "classical" segmentation i.e. using thresholding or gradientbased methods.This model is based on the Mumford-Shah functional [16] for segmentation, and isused widely in the medical imaging field, especially for the segmentation of thebrain, heart and trachea.The model is based on an energy minimization problem, which can be reformulatedin the level set formulation, leading to an easier way to solve the problem.
Let Ω be the open set $\mathbb{R}^2$, with $\partial\Omega$ is its boundary. The main concept of the Chan-Vese active contour model is to search for a particular partition of a given image $I(x)$ into two regions, one representing the objects to be detected and the other representing the background. For the

given image $I(x)$, they proposed to minimize the following energy functional.

Let $I:\Omega \rightarrow ¡^2$ be an input image and let C be a closed curve; the energy functional is expressed as,

$$E_{CV}(\phi, c_1, c_2) = \lambda_1 \int_{\Omega} \left| I(x) - c_1 \right|^2 H_{\varepsilon}(\phi(x))dx + \lambda_2 \int_{\Omega} \left| I(x) - c_2 \right|^2 (1 - H_{\varepsilon}(\phi(x)))dx + \mu Length(C) + \mathrm{v}\, Area(in(C))$$

(1)

where, $\mu \geq 0$, $v \geq 0$, λ_1 and $\lambda_2 > 0$ are fixed parameters. The Euclidean length term is used to regularize the contour. c_1 and c_2 are two constants that approximate the image intensities inside and outside of the contour C respectively. Observing the terms in equation 4, we can say that the evolution of the curve is influenced by two terms; the curvature regularizes the curve and makes it smooth during evolution and the region termaffects the motion of the curve. Minimizing the above energy functional by using the steepest gradient descent method and representing the contour C with zero level set as,

$$C = \{(x \in \Omega)\phi(x) = 0\} \qquad (2)$$

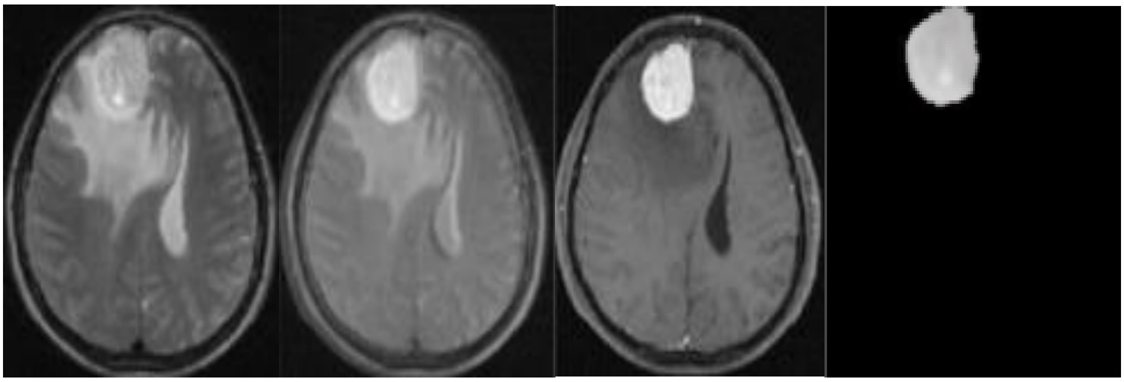
Then the curve evolution function is given by,

$$\frac{\partial \phi}{\partial t} = (-\lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2 + \mu div(\frac{\nabla \phi}{|\nabla \phi|}) - v)\delta_{\varepsilon}(\phi) \quad (3)$$

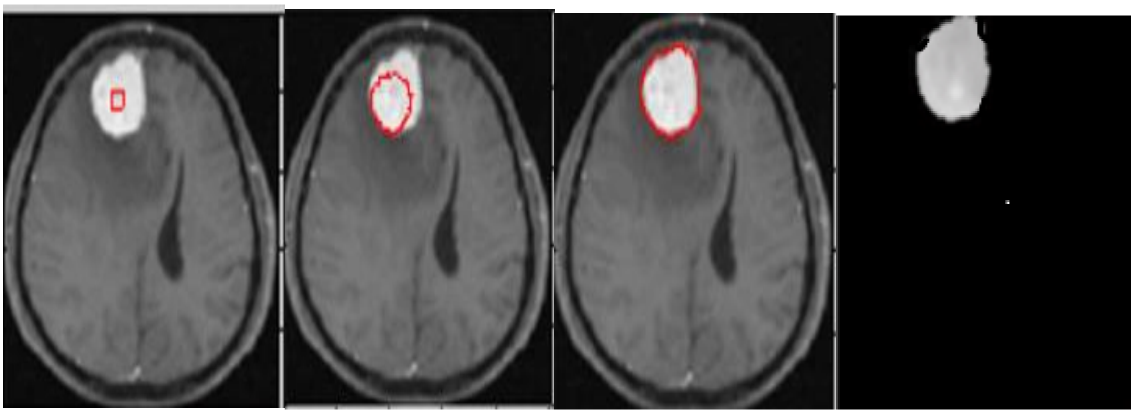
The proposed segmentation framework consists of four steps namely; Pre-processing, initialization contour into the image, setting the iterations values and finally applying the Chan-Vese active contour algorithm as depicted in the figure1. In the proposed Chan-Vese active contour model, a new region-based signed pressure force function is introduced and which efficiently stop the contours at weak or blurred edges. The external and internal boundaries are automatically detected with the initial contour initialized in the image. Based on the iterations settings, the contour converges to the desired tumor boundary. In this technique, a force shrinks the contour and another force expands the contour. To determine the contour of the interested object, the two forces should be balanced. This balancing of two forces results in the precise segmentation of the tumors in the brain MR images.

III. EXPERIMENTAL RESULTS:

The experiment is conducted using real image data set contains the MR images of brain, imaged on a 1.5 Tesla MRI scanner to obtain T1 weighted and T2 weighted images. Each MR image has the size of 256 X256. The test dataset consists of tumors of different shapes, locations, sizes and intensity. The data set is obtained from the brain web database. The database consists of several anonymous patients' brain tumor as well as the standard segmentation results. In this paper, the qualitative analysis of the given MR images have been carried out to visualize the segmentation results. The results are obtained using MATLAB software. The following diagrams demonstrates the brain tumour segmentation process.



(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 4 Segmentation process of the proposed methodology: (a) Original image, (b) Filtered image, (c) Enhanced image, (d) Ground truth of the original image, (e) Initial position of the contour, (f) Contour evolution after 200 iteration, (g) Tumour boundary detection at 300 iterations and (h) Final segmented tumour.

The original MR image having tumour is filtered using Gaussian filter and pre-processed by applying Contourlet transform as shown in figure 4(c). After enhancing, the features are highlighted and the contour is initialized in the image as shown in figure 4(e). By increasing the number of iterations, the desired tumour boundary can be obtained as depicted in figure (g). Finally, the segmented tumour can be separated by applying banalization process as in figure 4(h). The combination of Contourlet transform and Chan-Vese active contour model gives better convergence as compared to the other deformable models.

IV. CONCLUSIONS:

In this paper, Contourlet based Chan-Vesesegmentation method is presented and tested using brain MR image having tumor history. The application of Contourlet transform enhances the important features and makes the contour to converge towards the tumor boundary accurately. This reduces the computational complexity and segmentation results can be obtained with a faster rate. The experimental results indicates that, the proposed methodology is robust and up-to-date method forsegmenting brain tumors from MRI images. It is more flexible number ofiteration is incorporated for performing the region ofinterest(ROI) based segmentation. This

technique would be helpful for radiologists and medicalexperts as it can be applied for brain tumor segmentation in MR images as itproduces promising segmentation results.

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