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PII: S1047-3203(17)30100-1
DOI: http://dx.doi.org/10.1016/j.jvcir.2017.04.013
Reference: YJVCI 2003

To appear in: *J. Vis. Commun. Image R.*

Received Date: 14 January 2017
Accepted Date: 28 April 2017

Adaptive stochastic segmentation via energy-convergence for brain tumor in MR images

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Abstract

An adaptive algorithm that formulates an energy based stochastic segmentation with a level set methodology is proposed.The hybrid method uses global and local energies, which are efficient in matching, segmenting and tracing anatomic structures by exploiting constraints computed from the data of the image. The algorithm performs autonomous stochastic segmentation of tumor in Magnetic Resonance Imaging (MRI) by combining region based level sets globally and three established energies (uniform, separation and histogram) in a local framework. The local region is defined by the segmentation boundary which, in the case of level set method, consists of global statistics and local energies of every individual point and the local region is then updated by minimizing (or maximizing) the energies. For analysis, the algorithm is tested on low grade and high grade MR images dataset. The obtained results show that the proposed methodology provides similarity between segmented and truth image up to 89.5% by dice method, and minimum distance of 0.5(mm) by Hausdorff algorithm. This adaptive stochastic segmentation algorithm can also be used to compute segmentation when binary thresholding level is greater than 0.2.

Keywords: Active contours, level set,statistical energies,stochastic segmentation, MR images.

1. Introduction

The brain has a very complex structure and by nature it is tightly bounded within the skull that makes it more complex to diagnose its diseases. The abnormal growth in brain cells creates a cluster known as brain tumor. Diagnosis of a brain tumor is a very intricate process. There are two general classifications of tumors; they could either be benign or malignant [1]. In the case of a benign tumor, the tumorous mass lacks the ability to attack adjacent healthy cells which means that it is unable to metastasize therefore it is termed as non-cancerous.

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Nevertheless, in some cases it can transform into a malignant tumor which is basically a rapid growth of cancerous cells. If this type of tumor is left untreated it can lead to death [2].

Magnetic Resonance Imaging (MRI) employs varying magnetic fields and radio waves to obtain images of any region of interest inside a body. The resultant images have a higher resolution and therefore, can provide much more insight into the tissue abnormalities relative to other non-invasive imaging techniques like X-ray, computed tomography (CT) or Ultrasound. In MR Imaging, every patient must undergo the same image acquisition protocol where they have scans in three axial sequences T1, T2 and Flair consecutively. Longitudinal relaxation (T1) weighted scan provides gray and white matter contrast and uses a gradient echo (GRE) sequence with short echo time (Te) and repetition time (Tr). While, transverse relaxation (T2) scan has a long Te and Tr which makes it preferable for diseases that are related to water accumulation in the brain since radio waves and magnetic field are sensitive to water content. In the case of Fluid Attenuated Inversion Recovery (FLAIR), the reflected signal (noise) from internal fluids is nullified using an inversion-recovery pulse sequence thus providing a clearer image. However, T2-weighted scan sequence is usually preferred in image processing because it provides higher resolution and clarity[3].

MRI aid to identify whether the growth is a primary brain tumor or if it is a secondary cancer that has spread to the brain from another part of the body. Sometimes partial or full tumor removal is the only way of accurate medical diagnosis. The prime task in all this process is to acquire precise locality of the tumor in MR images. Image segmentation here can aid in the identification and isolation of such effected regions. Taking medical image processing into consideration, the hefty query set and the intricacy of the anatomic shapes of interest, it can be noted that the process of image segmentation is challenging where it structures and then recreates an accurate depiction of these structures.

However, manual tumor detection performed by neurosurgeons or radiologists can not only suffer from the subjectivity of visual perception and errors caused by fatigue but it is also a very time consuming task. Due to this, automatic segmentation methods can prove very beneficial as they can be developed to be more precise and mitigate all of the sources of errors.

1.1. Literature Survey

In order to tackle the complex problem of image segmentation, several methods have been proposed by researchers amongst which, the existing level set function technique has been widely accepted. A summary of the significant work on brain tumor segmentation is presented in Table (1).

The level set function can be categorized into two classes: edge and region based. There have been some function models of the two classes presented to solve a variety of problems. One of the approach proposed by Zhu and Yuille in 1996 [8] suggested a region based flow, which is based on competition work. This algorithm combines the snake and region growing approaches. They claimed that it is a multi-band segmentation algorithm for gray level images, color images and texture images. There are numerous benefits of region-based

Table 1: Summary of previous work related to brain tumor Segmentation

Author(year)	Title	Methodology description
Ho, 2002 [4]	"Level-Set Evolution with Region Competition: Automatic 3-D Segmentation of Brain Tumors" [4].	Developed 3D Level set method is based on the region competition framework with smoothness constraints and changeable topology.
Prastawa, 2004 [5]	"A brain tumor segmentation framework based on outliers detection" [5].	A methodology based on three steps,first detects the abnormal region based on intensity parameters, then compute whether regions are composed of both edema and tumor, finally by using spatial geometric properties detect the ROI.
Lee, 2005 [6]	"Segmenting Brain Tumors with Conditional Random Fields and Support Vector Machines" [6].	The Method is based on DRFs (Discriminative random fields) for segmentation and SVM for classification. Discriminative random fields are multidimensional extension of 1-dimensional conditional random fields (CRFs) for lattice-structured data. Discriminative models directly model the posterior probability of the labels given the features.
Wang,2011 [7]	"Automatic MRI brain tumor contour models" [7].	It is a multi - threshold algorithm,by using dilation and erosion operators to obtain an initial contour from the tumor domain image.

methodology such as, vigor against initial curve position and obtuseness to noise of image. However, this method uses the global statistics which are typically noneffective for heterogeneous objects segmentation because segmented objects can not be easily differentiated due to global statistics. Heterogeneous objects are often present in medical images, therefore to accurately perform the segmentation of objects, new energies should be considered that utilize local statistics as well as include the benefits of region-based model. To solve this problem, Chan and Vese introduced active contours without edges in 2001 [9]. This methodology was based on curve evolution, Mumford-Shah function for segmentation and level set techniques. This model does not depend on the gradient of image, therefore the initial curve can be anywhere in the image, but the final contour will always build around the region of interest. Various models have used region-based active contours that were generally used for image regions of constant intensity. Region-based approaches have numerous advantages over edge-based methods. However, region-based techniques employ global statistics and thus are not suitable for segmenting heterogeneous objects. Another adaptable approach for segmentation are the deformable models. It can be categorized into parametric and geometric models. Parametric deformable models permit interaction directly with the model during deformation, therefore it can be used for fast real-time implementation. However, splitting or merging during deformation while implementing model topology can hinder the use of parametric models. Geometric models represent curves as a scalar function centered on the philosophy of energies and the level set method can handle topological changes easily [10]. Recently in 2017, Elisee et al. proposed a localized active contour model with background intensity compensation (LACM-BIC) applied on automatic MR brain tumor segmentation [11]. The author used Hierarchical centroid shape descriptor (HCSD) by applying the k-dimensional tree algorithm for detecting the region of interest which is enclosed in a bounding box and balances the mean intensity distance between an image foreground and background. In the results, they compared the proposed algorithm (LACM-BIC) with local binary fitting (LBF) model, Gaussian distribution fitting (LGDF), Chan-Vase (C-V) and localized MS (LMS) models and also compared the evaluation parameters between the models mentioned above. However, it can be noted, that the different energies and forces that are imperative for convergence, stabilization and optimization of the local boundary were neglected and for accurate analysis of algorithm, comparison of ground truth images and updated methodologies with results to support the proposed methodology.

Although prior models have been popular in medical image analysis, they have some noteworthy drawbacks. There are four major problems related to segmentation of MR images. The first problem is related to noise during the acquisition process that can change the pixel intensity such that region of interest (ROI) recognition becomes indeterminate . Secondly, intensity homogeneity, i.e. a distinct type of tissue can have the same intensity level progressively along the image. This adds complexity in precise detection of the desired boundary. Thirdly, object-region which have heterogeneous measurements can not be segmented with global-energies, since the energies fizzle. The fourth problem is the instability of the contour around the region of interest that corresponds with the speed of each point of contour.

In this paper an active region-based contour model for localization and global set curve evolution adaptive stochastic approach is presented. This helps create an entire region based energy minimization. This algorithm is based on two optimized approaches, level set and region-energy. The algorithm utilizes a single level set as an initial curve to simplify the progression process and improve each point along the curve by local region energies. Four main contributions have been proposed in this research. Firstly, the framework can be used to localize any energy based region. Secondly, a localized active contour is produced to inter-relate with one another to create n-array partitions. Thirdly, the control over stability of the contour around the region of interest using energies and forces of each point. Finally the impact of local radius on a tumor segmentation is analyzed. Therefore, the presented approach showed a capability of reaching maximum accuracy in minimum computation time for the brain tumor segmentation in MRI.

This paper is organized into four sections. Section I provides an introduction and literature survey. Section II highlights the major mathematical techniques. Section III discusses the implementation of the proposed algorithm using MRI brain images. Section IV has evaluation and results in which the performance of the proposed algorithm is evaluated and the results are shown. Section V presents the conclusion. Lastly, in section VI the future work describes the potential enhancement in proposed algorithm.

2. MATHEMATICAL MODELS

The proposed methodology, is a hybrid model of level set and region based energies. Level set is used for initialization of mask and region based energies converge the mask around the desired region.

2.1. Level set

Introduced by Osher and Sethian [12], level set method is a technique used to describe shapes and track affecting interfaces. It produces the track of 3D surface by changing the movement of a planar curve. According to this method, level set boundary is the zero-crossing of the level set function φ which can change front boundary $\gamma(t)$ [10]. Partial differential equations (PDE) are used to determine the implicit level set function φ:

$$\frac{\partial \varphi}{\partial t} = S.|\nabla \varphi| \tag{1}$$

The speed function S is the scalar velocity which is based on the curvature and external parameters like the image gradient which is related to the image data. The gradient operator is denoted by ∇. The algorithm expresses the speed function as $S = S(C)$, in which the local curvature C is given by:

$$C = div(\frac{\nabla \varphi}{|\nabla \varphi|}) = \nabla.\frac{\nabla \varphi}{|\nabla \varphi|}$$

$$= \frac{\varphi_{ii}\varphi_j^2 - 2\varphi_i\varphi_j\varphi_{ij} + \varphi_{jj}\varphi_i^2}{(\varphi^2 i + \varphi_j^2)^{\frac{3}{2}}} \tag{2}$$

The zero level set function ($\varphi = 0$), at time t defines the developed surface. Therefore, the iterative deformation of $\gamma(t)$ is in the normal direction with S. While, at each iteration, $\gamma(t)$ position is calculated by the following equation:

$$\gamma(i,j,t) = \frac{(i,j)}{\varphi(i,j,t)} = 0 \tag{3}$$

The initial function φ is formulated by using the Euclidean distance d among a signed image point of initialγ_0 which is:

$$\varphi_o(i,j) = \pm d(i,j) \tag{4}$$

If the point i lies inside the boundary then the distance d is assigned a negative sign, whereas if the point i lies outside the boundary, it is assigned a positive sign. Then, the region of interest manifests on positions where $\varphi = 0$ [13].

2.2. Region-based Framework

As an alternative of global statistics, every point's local energy along the curve will also contribute with foreground and background for establishing the local regions. Furthermore, to improve these local energies, each point will play an individual role by moving so as to minimize (or maximize) the computed energy in its respective local region. In order to calculate these local energies, the evolving curve is used to segregate the local neighborhoods into local interior and local exterior. Hence, energy optimization is achieved by assigning an appropriate mode to every discrete local region. Therefore, C can be describe as a closed curve, represented as the zero level set of function φ

$$C = \{i|\varphi(i,j,t) = 0\} \tag{5}$$

Heaviside function has the following approximation [14] for C interior

$$H\varphi(i) = \left\{ \begin{array}{cc} 1 & \varphi(i) < -\in \\ 0 & \varphi(i) > \in \\ \frac{1}{2}\{1 + \frac{\varphi}{\in} + \frac{1}{\pi}\sin(\frac{\pi\varphi(i)}{\in}) & otherwise\} \end{array} \right\} \tag{6}$$

and for the exterior C is $(1 - H\varphi(i))$
In order to detect the area just around the mask take the derivative of $H\varphi(i)$. The derivative of the Heaviside function is known as Dirac delta function $\delta\varphi(i)$:

$$\delta\varphi(i) = \left\{ \begin{array}{cc} 1 & \varphi(i) < -\in \\ 0 & \varphi(i) > \in \\ \frac{1}{2}\{1 + \cos(\frac{\pi\varphi(i)}{\in}) & otherwise\} \end{array} \right\} \tag{7}$$

Now introduce second independent variables i and j, that represent every single position of the curve. By establishing a characteristic function $M(i,j)$, as a mask of local region function in terms of a radius parameter r

$$M(i,j) = \left\{ \begin{array}{ccc} 1 & & \parallel i - j \parallel < r \\ 0 & & otherwise \end{array} \right\} \tag{8}$$

When the point j (centered at i) is within a curve of radius $r, M(i,j)$, will be 1 otherwise it will be 0. This interaction produces the interior and exterior regions. Now, the energy function is illustrated in terms of force function F, which is given as follows:

$$E(\varphi) = \int_{\alpha_i} \delta\varphi(i) \int_{\alpha_j} M(i,j).F(I(j).\varphi(j))djdi \tag{9}$$

The force function $F(I(j)$ defines the internal energy measure that represents each point along the contour for a given model. For finding $E(\varphi)$, consider only those points which are near the curve region. Considering equation (9), it is obvious that a wide range of an object is covered by multiplying the Dirac function $\delta\varphi(i)$ in the outer integral over i. This term ensures that the mask will not change the topology by sudden development of latest contours, even though it still allows contours to split and merge. For each point i selected by $\delta\varphi(i)$, and using characteristic function $M(i,j)$ to guarantee that force drives only on local image information about i. Thus the total contribution of the first term in equation (9) is the sum of $F(I(j).\varphi(j))$ values for every $M(i,j)$ neighborhood along the zero level set according to a parameter r (radius). Finally, for curve smoothness, add a parameter λ. which compensates for the removal of arc length of the curve. The final statistical energy is as follows:

$$E(\varphi) = \int_{\alpha_i} \delta\varphi(i) \int_{\alpha_j} M(i,j).F(I(j).\varphi(j))djdi + \lambda \int_{\alpha_i} \delta\varphi(i) \parallel \nabla\varphi(i) \parallel di \tag{10}$$

Variation of energy is given as:

$$\frac{\partial\varphi}{\partial t}(i) = \delta\varphi(i) \int_{\alpha_j} M(i,j).\nabla\varphi(j)F(I(j).\varphi(j))djdi + \lambda\delta\varphi(i)div\left(\frac{\nabla\varphi(i)}{|\nabla\varphi(i)|}\right) \tag{11}$$

Variation can be computed only to ensure that all regional energies can be put into defined region.

2.3. Internal energies

Specifically, there are three internal energies that contribute to localization: the uniform modeling energy, means separation energy, and histogram separation energy.
In this algorithm, segmentation frame is computed, in terms of internal energies. The methodology describe how localization can be improved by these energies while maintaining the stability of the curve. Now briefly present how every individual global energy gives an insightful representation of its response and how

it contributes in a framework. The global mean intensities of the interior and exterior regions are utilized by common methodologies which are represented here as as x and y, respectively [5].

$$x = \frac{\int_{\alpha_j} H\varphi(j).I(j)dj}{\int_{\alpha_j} H\varphi(j)dj} \tag{12}$$

$$y = \frac{\int_{\alpha_j} (1 - H\varphi(j)).I(j)dj}{\int_{\alpha_j} (1 - H\varphi(j))dj} \tag{13}$$

The basis of the internal energy function is the local mean intensities that separate the regions. Now localized versions of the interior mean intensity x_i, and exterior mean intensity y_i, in terms of characteristic function $M(i, j)$ at a point i is given as:

$$x_i = \frac{\int_{\alpha_j} M(i,j).H\varphi(j).I(j)dj}{\int_{\alpha_j} M(i,j).H\varphi(j)dj} \tag{14}$$

$$y_i = \frac{\int_{\alpha_j} M(i,j).(1 - H\varphi(j)).I(j)dj}{\int_{\alpha_j} M(i,j).(1 - H\varphi(j))dj} \tag{15}$$

To formulate local energies at every individual point on the curve, these localized statistics are used, which reduce the instability of every point of the contour.

2.3.1. Uniform Modeling Energy (UM)

Uniform modeling energy is the Chan constant intensity model [9],

$$E_{UM} = \int_{\alpha_j} H\varphi(j)(I(j) - x)^2 + (1 - H\varphi(j))(I(j) - y)^2 dj \tag{16}$$

The foreground (x) and background (y) are constant mean intensities. Therefore the related internal energy force function F, is formed by interchanging the global x and y with their respective local means as x_i and y_i.

$$F_{UM} = \int_{\alpha_j} H\varphi(j)(I(j) - x_i)^2 + (1 - H\varphi(j))(I(j) - y_i)^2 dj \tag{17}$$

It is entirely local energy force. Moreover, to find the implicit level set function φ, take the derivative of equation (17) with respect to $\varphi(j)$.

$$\nabla_{\varphi(j)} F_{UM} = \delta\varphi(j)((I(j) - x_i)^2 - (I(j) - y_i)^2) \tag{18}$$

By substituting above in equation (11), then localized uniform energy model is:

$$\begin{aligned}\frac{\partial\varphi}{\partial t}(i) = \delta\varphi(i) \int_{\alpha_j} M(i,j)\delta\varphi(j).((I(j) - x_i)^2 - (I()j - y_i)^2)dj \\ + \lambda\delta\varphi(i) div\left(\frac{\nabla\varphi(i)}{|\nabla\varphi(i)|}\right)\end{aligned} \tag{19}$$

The uniform energy determines the minimum energy of the exterior and interior regions when they are calculated by global x and y. Next, after the relocation of every point on the curve surface, x_i and y_i is estimated for local interior and exterior of each of those points and the uniform models compute minimum energy locally.

2.3.2. Mean Separation Energy (MS)

Mean separation energy is given as:

$$E_{MS} = \int_{\alpha_j} (x_i - y_i)^2 \tag{20}$$

This energy relies on the fact that both of the background and foreground regions should have extremely distinct mean intensities. The interior and exterior means need to have a large variance in order to update the energy produced so as to move the curve. The force F has been formed by confining the universal energy with the local mean as follows:

$$F_{MS} = (x_i - y_i)^2 \tag{21}$$

By inserting this in equation (11), then get localized region flow

$$\begin{aligned}\frac{\partial\varphi}{\partial t}(i) = \delta\varphi(i)\int_{\alpha_j} M(i,j)\delta\varphi(j).\left(\frac{(I(j)-x_i)^2}{A_x} - \frac{(I(j)-y_i)^2}{A_y}\right)dj \\ +\lambda\delta\varphi(i)div\left(\frac{\nabla\varphi(i)}{|\nabla\varphi(i)|}\right)\end{aligned} \tag{22}$$

Here, A_x and A_y are local interior and exterior regions areas:

$$A_x = \int_{\alpha_j} M(i,j).H\varphi(j)dj \tag{23}$$

$$A_y = \int_{\alpha_j} M(i,j).(1 - H\varphi(j))dj \tag{24}$$

This energy finds very fine edges of the image, when the interior and exterior regions are not constant at every i along the curve. Therefore, it is desired that the local background and foreground means should be different.

2.3.3. Histogram Separation Energy (HS)

Lastly, the proposed algorithm consider a composite energy that is computed from the histograms of the image background and foreground. Its integration into the model is as simple as that of the prior energies. Now consider that $P_x(n)$ and $P_y(n)$ are two intensity histograms using n intensity bins that are calculated from the global external and internal regions of a segmented image. Energy of segmented image, based on minimizing HS statistics reported by Michailovich et al. is given as [15].

$$E_{HS} = \int_n \sqrt{P_x(n) - P_y(n)}dn \tag{25}$$

This will be called HS (histogram separation) energy. It works by separating intensity histograms of external and internal area of the mask, and hence permits outside and inside regions to be varied provided that their intensity profiles are different.
Similarly $P_{(x,i)}(n)$ and $P_{(y,i)}(n)$ signify the intensity histograms in the local image regions $M(i,j)$. Force F is computed by $P_x(n)$ and $P_y(n)$ as:

$$F_{HS} = \int_n \sqrt{P_{x,i}(n) - P_{y,i}(n)}dn \tag{26}$$

For localized version, substitute this in equation (11) and obtain the following:

$$\begin{aligned}\frac{\partial\varphi}{\partial t}(i) = \delta\varphi(i)\int_{\alpha_j}\frac{M(i,j).\delta\varphi(j)}{2}\times\Bigg[F_{HS}\left(\frac{1}{A_x}-\frac{1}{A_y}\right)+\int_n K(n-I(j))\\ \times\left(\frac{1}{A_x}\sqrt{\frac{P_{x,i}(n)}{P_{y,i}(n)}}-\frac{1}{A_y}\sqrt{\frac{P_{y,i}(n)}{P_{x,i}(n)}}\right)\Bigg]dj+\lambda\delta\varphi(i)div\left(\frac{\nabla\varphi(i)}{|\nabla\varphi(i)|}\right)\end{aligned} \tag{27}$$

where K is Gaussian kernel.

3. IMPLEMENTATION

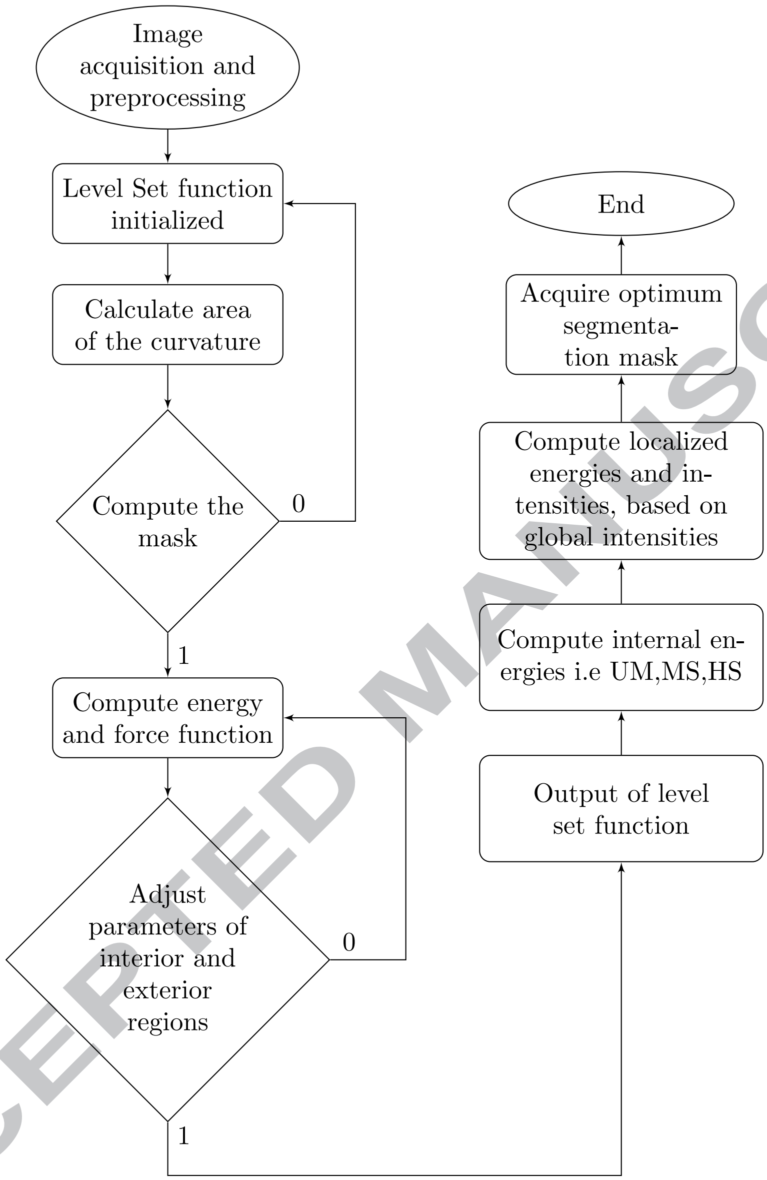
In this algorithm, energies are introduced as a signed distance function φ which allows easy implementation flow in the level set framework. The efficiency, in this methodology, is improved by computing values of zero level set function φ and local region based energies for every point along the surfacing mask. The proposed hybrid method builds the complexity of algorithm and reduces the computation time. In this algorithm, every pixel is dependent on the local region based energies in the narrow band with local exterior and interior statistics. During simulation, local statistical models are stored in the memory for every initialized pixel. Then the statistical representations of every pixel in the mask $M(i,j)$ and its neighborhood are updated globally. Furthermore every individual pixel keeps track of the amount of pixels outside and inside the mask along with the sum of pixel intensities in those regions. Therefore, in order to upgrade this model, values needed to be exchanged between the interior and exterior regions. A global region based method updates the statistics of every m number of pixels in the global region while the related local region based energy flow updates $m.z$ times, where z signifies the number of pixels inside the mask $M(i,j)$.

The process described above is formalized into an algorithm as follows:

Algorithm 1: ASSVEC

Result: Tumor area segmentation in selected image I_{xig}
Data: 3D volume of MRI brain imagesI_x , where $X = [x_1, x_2, x_3, \ldots, x_n]$

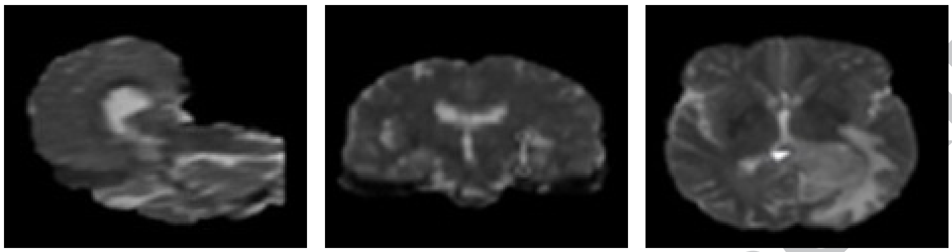
```
Initialization;
For i = k : K (slices)   do
    Acquire 2D slice image I_xi from 3D dataset;
    Convert I_xi to gray scaleI_xig;
    Input radius(r) = a;
    Input weight(w) = b;
      If (r  and  w  ≤  0)   then
         Input again r  and  w ;
      Else
        Initialize level set function φ;
        Compute area of curvature based on image gradient;
        Determine speed function S ;
        Calculate iterative deformation γ(t) ;
        Compute signed distance from mask;
        Update the local mean intensities by using eq.(14)and(15);
        i = i + 1;
        Initial contour built by Level set function;
            For p = 1:T (iterations)   do
              For q = m:M (mask)   do
              Compute uniform energy and force of exterior and interior
              regions by using eq.(19);
              Calculate mean separation energy and force to find very
               fine edge of boundary by using eq.(22);
              Compute histogram energy and force to separate the
               intensities bins of mask by using eq.(27);
              End
              Update the boundary of contour till convergence;
            End
            Stable mask converge around tumor region of interest;
    End
    Compute the Dice index and Hausdorff distance between
     segmented and truth image
```



4. EVALUATION AND RESULTS

Obtaining real brain image data, for research, is a precarious task, because of privacy issues, Hence real data was acquired from BRATS [16].

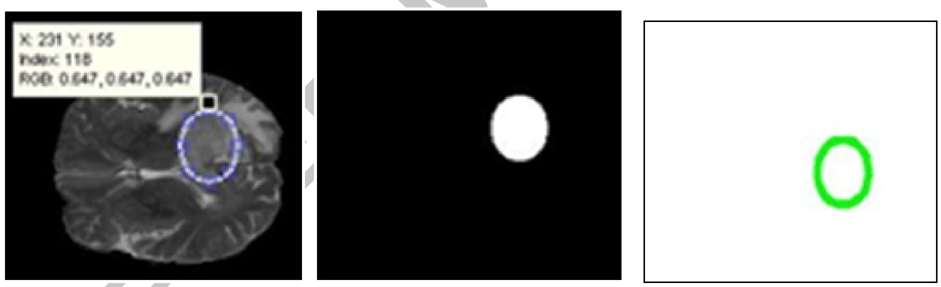
The pathological T2 weighted images are useful for locating the lesioned region in the brain due to higher resolution. For experimentation purposes, the 3D volume dataset was first converted into 2D dataset which comprises of x,y and z slice. Then, these images were converted into pure gray scale intensity images. However since slice z is holistic and has complete information, it is used in the experiment (Fig.1).



(a) (b) (c)

Figure 1: x,y and z slices of T2 weighted image

The initialization of each pixel in the restricted region with internal and external statistics starts the process of adaptive segmentation. An ellipse that relates to a level set initializes the algorithm. The mask changes the topology while the elliptical boundary captures the ROI. As the level set is only updated in the area specified by $\varphi(i)$, it is not likely for new contour to appear in this region Fig.(2).

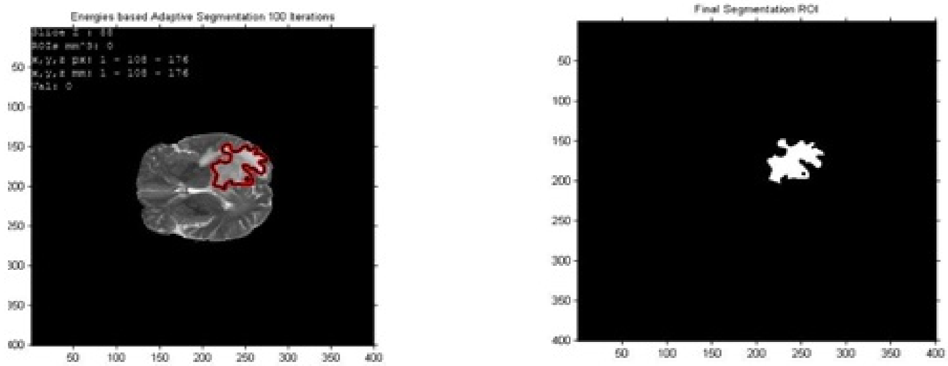


(a) (b) (c)

Figure 2: : Level Set Method (3a) Initialization and segmented region (3b) and (3c) show the ellipse mask capturing the global region of interest (ROI)

In the developed hybrid adaptive segmentation method, the mask is stable even during initialization. It converges in 100-150 iterations and it is so robust that it does not leak during the remaining solution. The proof of such stability is evident from the preliminary tests with different initializations that indicate that the mask can cover the entire tumor even if placed over a small part of tumor Fig.(3).

The corresponding results of the three patients are shown in Fig.(4). Visually, they are satisfying for all the three patients in spite of different tumor shapes. Fig.(5) shows the comparison between ground truth segmented image of tumor and simulated segmented region by the adaptive hybrid method.



(a) (b)

Figure 3: : Hybrid adaptive Segmentation Method (3a) shows behavior of a corresponding Region based energies over the level set mask and sharp changes in intensities within foreground and background, (3b) Final segmented region

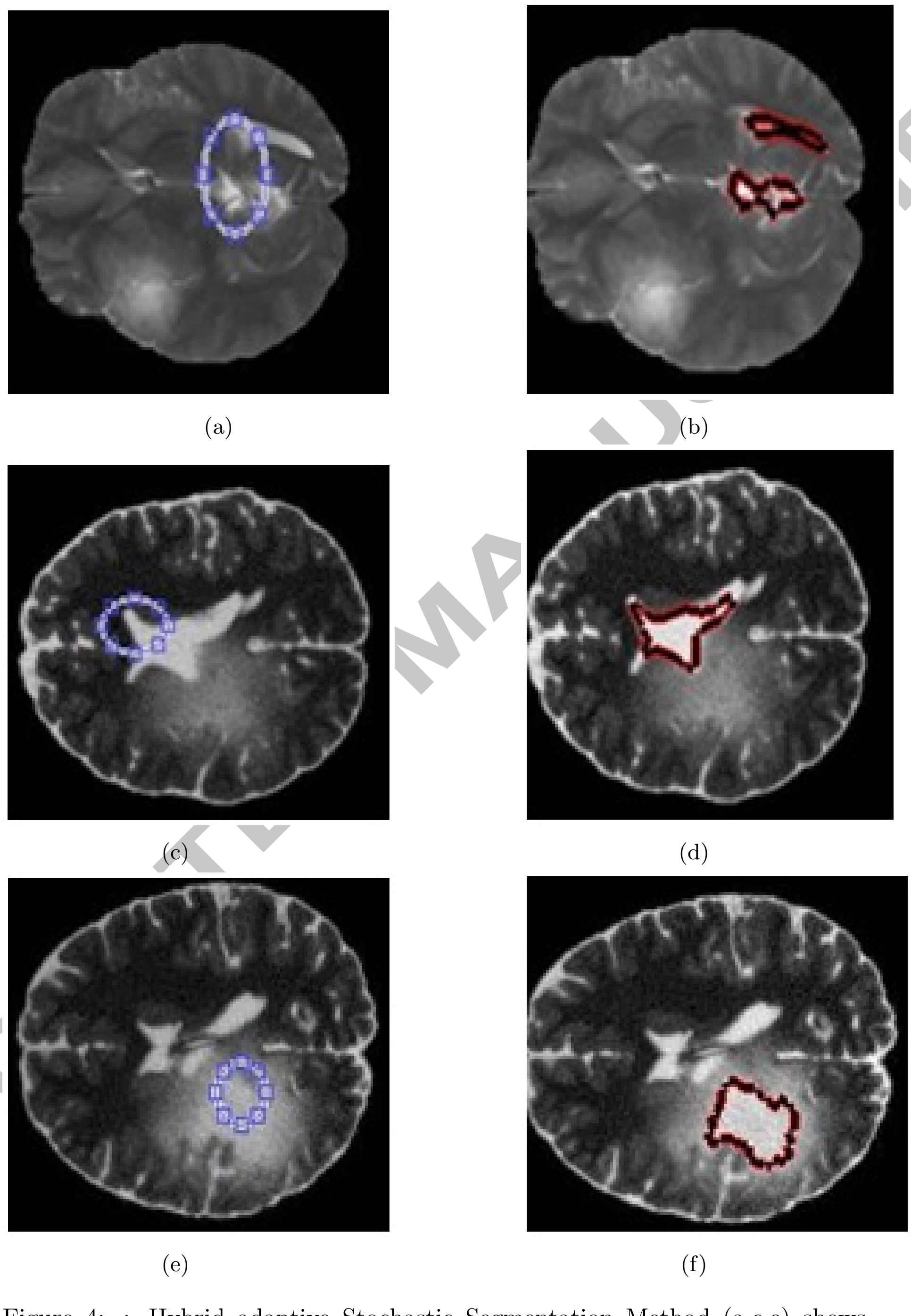
The algorithm calculates the similarity by dice method that is 89.5% and distance 0.5(mm) by Hausdorff algorithm, depending on the contrast, perfusion levels of image and initialization seed of segment algorithm. If image has M binary thresholding levels and M > 0.2 then this adaptive algorithm is likely to compute an M-binary level segmentation more quickly than commonly-used segmentation algorithms.

The suggested algorithm was successfully run on fifteen MRI images. The output of each segmentation was a binary image on the same voxel grid as the original MR Image. The Dice similarity and Hausdorff distance methods were used to show the accuracy of the segmented image.

The Dice similarity coefficient (DSC) was used as a statistical validation metric to evaluate the performance of segmented image and the spatial overlap accuracy of automated probabilistic fractional segmentation of MR images. The Dice coefficient lies in the range [0, 1] and has value 0 if there is no overlap between the two images and 1 if both images are identical.

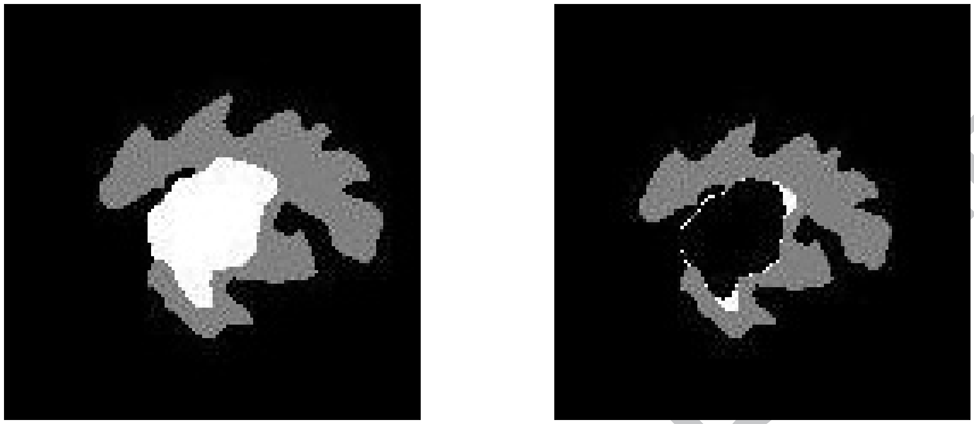
Hausdorff distance computes the shape similarity between segmented image and ground truth image. The function computed the average distance from a point on truth image to the closest point on the segmented image for forward and reverse distances and the output distance was the minimum value from both distances, the lower the distance value, the batter match. That method gives promising results, even in the presence of noise or occlusion. The results for eight tumor datasets are shown in Table (2) .

In this approach, smoothness of contour is optimized by the internal forces while the external forces help guide the contour towards the contour of ROI [17]. The proposed algorithm solved the issue of stability and convergence related to the smoothness of the contour for a segmented object.



(a) (b) (c) (d) (e) (f)

Figure 4: : Hybrid adaptive Stochastic Segmentation Method (a,c,e) shows behavior of a corresponding Region based energies over the level set mask and sharp changes in intensities within foreground and background, (b,d,f) indicate the final segmented region



(a) (b)

Figure 5: Comparison (a) Ground truth segmented image of tumor. (b) Mapped image, black foreground is the segmented region by adaptive method and white background segment is truth region.

Table 2: Comparison with truth image

Dataset	Dice similarity index(%)	Hausdorff distance(mm)
HG0003	72.8	0.767
HG0004	63.8	0.581
HG0005	45.6	0.990
HG0006	77.8	1.16
HG0008	80.3	1.07
HG0022	89.51	1.005
HG0025	75.9	1.25

The stability condition in level set contour is

$$F_{max}\Delta t \leq min(h_i, h_j)$$

Here, F_{max} is the maximum absolute speed of all points on the grid and h_i and h_j are grid spacing in i and j direction. Therefore, for numerical stability the contour can cross only one grid at each time step Δt. This adaptive algorithm, improves the stability by controlling the speed function through internal and external energies and force functions. The speed function guides the dynamics of the mask to slow down and finally reach the steady state [18].

The other problem in formation of contour is convergence, if the iteration does not terminate at the optimal instant, the curve boundary gives an undesirable output. The energies solve this problem with the help of the radius size of the curve. Fig.(6) shows the speed of convergence at different radii.

The results demonstrate that at the largest radius, segmentation curve converges quickly to an incorrect energy value, whereas at an intermediate radius, the segmentation converges smoothly to a correct energy value. Thus proving that the convergence actually depends on the radius, if the radius is too big or too small then energies convergence would fail and the result would be incorrect. The convergence performance comparison of existing algorithms with proposed algorithm is shown in Table (3). In the reference algorithms, the iteration count was chosen based on the image size and the length of the initial contour.

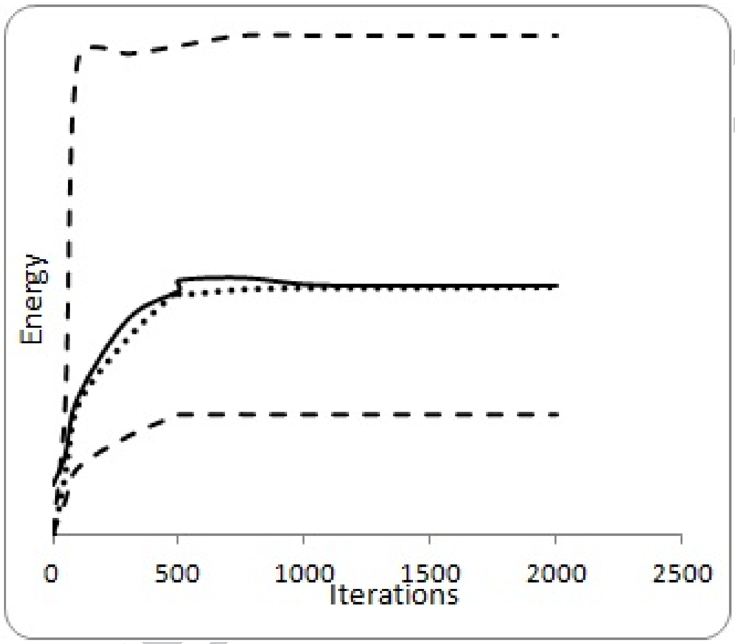


Figure 6: Energies for segmentation at different radii.

Table 3: Comparison of Performance

Ref. to Papers Levelset algorithm	**Papers (old) Converge results**		**Proposed (New) Converge results**	
	Iteration	**Execution time(s)**	**Iteration**	**Execution time(s)**
Malladi et al. (1995) [15]	2000	40	450	15
Mansouri (2002) [19]	1000	35	250	12
Mansouri and Konard(2003) [20]	1000	35	150	14
Chang et al. (2004) [21]	-	-	100	11

One limitation of this proposed method is sensitivity to initialization of contour. In brain MRI images, special care needs to be taken for initialization because of similar intensity structure.

The proposed algorithm not only incorporates the stability and convergence, but also minimizes the computation time with numerical stability of speed function and convergence time [22]. Experiments validate that our approach saves more time than former methods. Therefore the proposed adaptive methodology demonstrates the optimal time-step (Δt) and convergence results (execution time).

5. CONCLUSION

In this paper, simple and intuitive hybrid level set with energies based active contour algorithm has been implemented. The results prove that local energies can interact simultaneously on region of interest for making the segment and they also show significant improvement in accuracy of the segmentation. The proposed method has flexible topology and improved iteration speed and segmentation accuracy. The segmented results are close to the desired object region and real target edges as shown in Fig.(5). This could be helpful for surgeons to detect the boundaries of the tumor in MR images. Finally, this segmentation approach proves that when global region based energies are insufficient, then the combination of localized energies provides the optimum solution for accurate segmentation.

6. FUTURE WORK

As a future work, the contour radius maybe altered automatically which will reduce the need of user intervention. Additionally, the algorithm will also be applicable to 3-D volume of images which may help further improve tumor diagnosis.

References

[1] P. John, et al., Brain tumor classification using wavelet and texture based neural network, International Journal of Scientific & Engineering Research 3 (10) (2012) 1.

[2] S. Charfi, R. Lahmyed, Rangarajan, A novel approach for brain tumor detection using neural network, International Journal of Research in Engineering and Technology 2 (2014) 93–104.

[3] Lubna, Adeel, Comparison of brain tumor mri classification methods using probabilistic features, IASTED International Conference Innsbruck, Austria Biomedical Engineering, (2017).

[4] S. Ho, E. Bullitt, G. Gerig, Level-set evolution with region competition: automatic 3-d segmentation of brain tumors, in: Pattern Recognition, 2002. Proceedings. 16th International Conference on, Vol. 1, IEEE, 2002, pp. 532–535.

[5] M. Prastawa, E. Bullitt, S. Ho, G. Gerig, A brain tumor segmentation framework based on outlier detection, Medical image analysis 8 (3) (2004) 275–283.

[6] C.-H. Lee, M. Schmidt, A. Murtha, A. Bistritz, J. Sander, R. Greiner, Segmenting brain tumors with conditional random fields and support vector machines, in: International Workshop on Computer Vision for Biomedical Image Applications, Springer, 2005, pp. 469–478.

[7] Y. Wang, Z. X. Lin, J. G. Cao, M. Q. Li, Automatic mri brain tumor segmentation system based on localizing active contour models, in: Advanced Materials Research, Vol. 219, Trans Tech Publ, 2011, pp. 1342–1346.

[8] S. C. Zhu, A. Yuille, Region competition: Unifying snakes, region growing, and bayes/mdl for multiband image segmentation, IEEE transactions on pattern analysis and machine intelligence 18 (9) (1996) 884–900.

[9] T. F. Chan, L. A. Vese, Active contours without edges, IEEE Transactions on image processing 10 (2) (2001) 266–277.

[10] T. Zhang, D. Freedman, Tracking objects using density matching and shape priors, in: Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on, IEEE, 2003, pp. 1056–1062.

[11] E. Ilunga-Mbuyamba, J. G. Avina-Cervantes, A. Garcia-Perez, R. de Jesus Romero-Troncoso, H. Aguirre-Ramos, I. Cruz-Aceves, C. Chalopin, Localized active contour model with background intensity compensation applied on automatic mr brain tumor segmentation, Neurocomputing 220 (2017) 84–97.

[12] G. Sapiro, Geometric partial differential equations and image analysis, Cambridge university press, 2006.

[13] S. Osher, R. Fedkiw, Level set methods and dynamic implicit surfaces, vol. 153 of appl, Math. Sci, Springer Verlag.

[14] R. Tsai, S. Osher, et al., Review article: Level set methods and their applications in image science, Communications in Mathematical Sciences 1 (4) (2003) 1–20.

[15] R. Malladi, J. A. Sethian, B. C. Vemuri, Shape modeling with front propagation: A level set approach, IEEE transactions on pattern analysis and machine intelligence 17 (2) (1995) 158–175.

[16] MICCAI, Brats2012 data (http://www2.imm.dtu.dk /projects /BRATS2012 /data.html, accessed date:2015).

[17] M. Valipour, Optimization of neural networks for precipitation analysis in a humid region to detect drought and wet year alarms, Meteorological Applications 23 (1) (2016) 91–100.

[18] M. Valipour, How much meteorological information is necessary to achieve reliable accuracy for rainfall estimations?, Agriculture 6 (4) (2016) 53.

[19] A.-R. Mansouri, Region tracking via level set pdes without motion computation, IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (7) (2002) 947–961.

[20] A.-R. Mansouri, J. Konrad, Multiple motion segmentation with level sets, IEEE Transactions on Image Processing 12 (2) (2003) 201–220.

[21] C.-J. CHANG, J.-W. HSIEH, Y.-S. CHEN, W.-F. HU, Tracking multiple moving objects using a level-set method, International Journal of Pattern Recognition and Artificial Intelligence 18 (02) (2004) 101–125.

[22] C. Yan, Y. Zhang, J. Xu, F. Dai, J. Zhang, Q. Dai, F. Wu, Efficient parallel framework for hevc motion estimation on many-core processors, IEEE Transactions on Circuits and Systems for Video Technology 24 (12) (2014) 2077–2089.

Highlights

- Adaptive stochastic segmentation methodology proposed for tumor detection in MR images.
- Developed frame by using level set function globally and three energies locally.
- Improves each point of curve by optimizing local energies and force functions .
- Solved stability and convergence issues related to curve evolution process.
- Reduced iterations/computation time through internal and external energies/forces.