

MRI Image Segmentation Using Gradient Based Watershed Transform In Level Set Method for a Medical Diagnosis System

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Abstract

Brain image classification is one of the utmost imperative parts of clinical investigative tools. Brain images typically comprise noise, inhomogeneity and sometimes deviation. Therefore, precise segmentation of brain images is a very challenging task. Nevertheless, the process of perfect segmentation of these images is very important and crucial for a spot-on diagnosis by clinical tools. Also, intensity inhomogeneity often arises in real-world images, which presents a substantial challenge in image segmentation. The most extensively used image segmentation algorithms are region-based and usually rely on the homogeneousness of the image intensities in the sections of interest, which often fail to afford precise segmentation results due to the intensity inhomogeneity. This Research presents a more accurate segmentation using Gradient Based watershed transform in level set method for a medical diagnosis system. Experimental results proved that our method validating a much better rate of segmentation accuracy as compare to the traditional approaches, results are also validated in terms of certain Measure properties of image regions like eccentricity, perimeter etc.

Keywords— Medical image Segmentation, Brain Tumor Detection, Pixel Tracking, Gradient based watershed. Level set method, Magnetic resonance imaging.

I. INTRODUCTION

This is well known fact that brain is one the complex organs in human body. The true diagnostic of any neurological disorder depends upon strength and suitability of the method employed for examining the acquired brain data. The area of image segmentation has received major attention due to the sensitivity of the examination task and due to the acute demand for minimizing the risk of regrowth of some of neurological disorder [1]. This area starts with the critical study of the existing methods and on the basis of gaps found in these methods, it creates an opportunity for introducing best suited new state-of-the-art automatic or semi-automatic brain MR image segmentation method(s).

Generally, the segmentation methods are divided into two broad classes, i.e. semi-automatic methods and fully automatic methods. Regarding fully automatic methods, the question that up to how much extent this method eliminates the involvement of the operator / expert still remains to be answered. For example if it is an Artificial Neural Network based method the training and testing data are prepared by human expert, if it's a clustering based approach then the selection of number of clusters depends upon expert. Finally, when it comes to verification and validation of the results produced by any of the chosen automatic image segmentation method, then the elimination of human expert becomes impossible.

In our experiments, the data consist of magnetic resonance imaging (MRI) images of healthy brain

and a magnetic resonance imaging (MRI) image of a brain with a tumor (frontal meningioma).

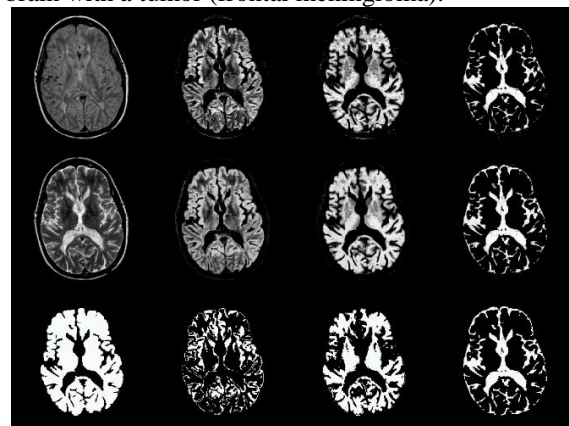


Figure 1. Slices from a standardized FSE PD, T2 study pair (left images of rows 1 and 2), the corresponding slices from the scenes depicting the fuzzy affinity relations for the GM, WM, and CSF objects (first row), the same slices from the scenes depicting the connectedness values (second row), and the hard (binary) segmented objects (third row). Binary mask for brain parenchyma is shown in the bottom left image.

Now, how precisely the verification of the results has been carried out, how much accurate the training and the testing data sets were prepared and how much accurate the number of clusters in clustering based approaches were chosen depends upon the

professional strength of the expert. Indeed, this quality of MRI data examination varies from expert to expert.

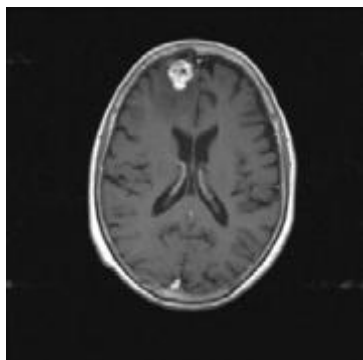


Figure 2. Image magnetic resonance imaging of the brain suffers from a frontal meningioma

As a result of discussion above regarding data examinations, the chances for some percentage of undesired variation in the results cannot be completely ruled out. According to Warfield and Kikinis's [2] investigation, 15% variability in the results was found when the MRI dataset was examined by five different experts. In another study, Kaus *et al* [3] also reached to the conclusion that from 15% to 22% variation was there when MRI dataset was investigated by different experts. In reality, this much variation is un-affordable for the patients suffering from neurological disorders.

On the other hand, the performance of automatic segmentation methods is also not that much encouraging. The results produced by using these methods were investigated by taking into considerations manually prepared ground truth by a human expert. It was found that these results vary from 82% to 94%. In addition to it, it was also observed that, some of these methods are computationally expensive either in terms of resources utilization or in terms of execution time [4][5][6].

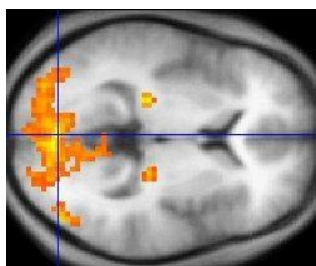


Figure 3. An MRI scan showing regions of activation in orange, including the primary visual cortex.

In medical imaging there is a massive amount of information, but it is not possible to access or make use of this information if it is efficiently organized to extract the semantics. To retrieve semantic image, is a hard problem. In image retrieval and pattern recognition community, each image is mapped into a

set of numerical or symbolic attributes called features, and then to find a mapping from feature space to image classes. Image classification and image retrieval share fundamentally the same goal if there is given a semantically well-defined image set. Dividing the images which is based on their semantic classes and finding semantically similar images also share the same similarity measurement and performance evaluation standards.

A. Image Segmentation System and process

An image retrieval framework consisting of three stages; *feature extraction*, *feature selection* and *image retrieval*. Medical image segmentation [7] is the method of labeling each voxel in a medical image dataset to state its anatomical structure. The labels that result from this method have a wide variety of applications in medical research. Segmentation is a very common method so it is difficult to list most of the segmented areas, but a general list would consist of at least the following; the brain, heart, knee, jaw, spine, pelvis, liver, prostate, and the blood vessels. The input to a segmentation process is grayscale digital medical image, (like CT or MRI scan). The desired output restrains the labels that classify the input grayscale voxels. The use of segmentation is to give preeminent information than that which exists in the original medical images only. The set of labels that is produced through segmentation is also called a label map, which briefly tells its function as a voxel by voxel guide to the original imagery. Frequently used to improve visualization of medical image and allow quantitative measurements of image structures, segmentation are also important in building anatomical atlases, researching shapes of anatomical structures, and tracking anatomical changes over time.

A few data mining techniques are also used for segmenting medical image. Data mining is the method of discovering meaningful global patterns and relationships that lie hidden within very huge databases containing vast amount of data. Similar type of data is classified by using classification or clustering method, which is the elementary task of segmentation and pattern matching. Various techniques like neural networks, Bayesian networks, decision tree and rule-based algorithms are used to get the desired data mining outcomes in segmentation.

Magnetic Resonance Imaging (MRI) is noninvasive procedure and can be used safely for brain imaging as often as necessary. MRI images are used to produce accurate and detailed pictures of organs from different angles to diagnose any abnormalities. There are two types of MRI high field for producing high quality images and low field MRI for smallest diagnosis condition. MRI images allow the physician to visualize even hair line cracks and

tears in injuries to ligaments, muscles and other soft tissues. MRI is based on the principle of absorption and emission of energy in radio free range of electron magnetic spectrum. Magnetic resonance imaging (MRI) is excellent for showing abnormalities of the brain such as stroke, hemorrhage, tumor multiple sclerosis or lesions.

The study of brain disorders requires accurate tissue segmentation of brain MRI images. For large database manual delineation of WM, GM and CSF in brain MRI images by a human expert is too time-consuming. Doctors use the scheme to automated segment the region of WM, GM and CSF. If the image have some type of disorder then it automatically detect that region. The tissues are segmented by using neuro fuzzy techniques into WM, GM, CSF and tumor region [8]. And from these regions, calculate some statistical features like energy, entropy, contrast, inverse difference moment, mean, standard deviation, average gray scale value of region, area of region are computed and can store the values in a database [8] and given by Keith A. Johnson and J. Alex Becker [9].

B. Structure of Assessment

The edifice steps of this paper is as follows. The Introductory Section ends with a brief introduction of MRI image segmentation and its necessity in the field of medical imaging. The part A in introduction shows a brief explanation about principle and issues in developing an object tracker.

In Section II, we explain a General review of traditional methods and techniques involve in medical MRI image segmentation.

In section III we address the proposed work flow and used methodology for the medical image segmentation.

Section IV Illustrate the results and validation parameters from the proposed segmentation technique.

Section V explains conclusion and discussion regarding the proposed research work and problem scenario.

II. GENERAL REVIEW OF EXISTING METHODS FOR MEDICAL IMAGE SEGMENTATION

Segmentation is the process of partitioning an image to several segments. The main difficulties in segmentation are:

- Noise
- The bias field (the presence of smoothly varying intensities inside tissues)
- The partial-volume effect (a voxel contributes in multiple tissue types)

A. Existing de-noising methods

In spite of the presence of substantial number of state-of-the-art methods of de-noising but accurate removal of noise from MRI image is a challenge. Methods such as use of standard filters to more advanced filters, nonlinear filtering methods, anisotropic nonlinear diffusion filtering, a Markov random field (MRF) models, wavelet models, non-local means models (NL-means) and analytically correction schemes.

These methods are almost same in terms of computation cost, de-noising, quality of de-noising and boundary preserving. So, de-noising is still an open issue and de-noising methods needs improvement. On the other hand, nonlinear filters preserve edges but degrade fine structures, like,

- ✓ Markov random field method (MRF) [10]
- ✓ Wavelet-based methods [11, 12, 13]
- ✓ Analytical correction method [14, 15]

B. Image segmentation methods

Techniques such as *thresholding*, the *region growing*, *statistical models*, *active control models* and *clustering* have been used for image segmentation. Because of the complex intensity distribution in medical images, thresholding becomes a difficult task and often fails. [16]. in the region growing method, thresholding is combined with connectivity [17].

Fuzzy C-means is a popular method for medical image segmentation but it only considers image intensity thereby producing unsatisfactory results in noisy images. [18]. A bunch of algorithms are proposed to make FCM robust against noise and in homogeneity but it's still not perfect [18] [17] [19] [20] [21] [22].

Accurate estimation of the *probability density function* (PDF) is essential in *probabilistic classification* [23]. Non-parametric approach does not make any assumption in obtaining the parameters of PDF thereby making it accurate but expensive [24]. In parametric approaches, a function is assumed to be a PDF function. It is easy to implement but sometimes lacks accuracy and does not match real data distribution [23].

Learning vector quantization (LVQ) is a supervised competitive learning technique that obtains decision boundaries in input space based on training data [32].

Self-organizing maps (SOM) is an unsupervised clustering network that maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units [32]. The input data is organized into several patterns according to a similarity factor like Euclidean distance and each pattern assigns to a neuron. Each neuron has a weight that depends on the pattern assigned to that neuron [47].

Watershed transform is a gradient-based segmentation technique where different gradient values are considered as different heights. A hole is made in each local minimum and immersed in water, the water will rise until local maximums. When two body of water meet, a dam is built between them. The water rises gradually until all points in the map are immersed. The image gets segmented by the dams. The dams are called watersheds and the segmented regions are called catchments basins [33] [34]. Its fast implementation method is proposed by [35] and [36]. The over segmentation problem still exists in this method [33] [34].

The *region growing* starts with a seed, which is selected in the centre of the tumor region. During the region growing phase, pixels in the neighbor of seed are added to region based on homogeneity criteria thereby resulting in a connected region.

The *active control model* is a framework for delineating an object outline from a noisy image and is based on a curve, $X(s) = [x(s), y(s)]$, defined in the image domain where s in range of $[0, 1]$ is an arc length. It deforms in a way that minimizes an energy function. The internal energy and is used to control the tension and rigidity of the deforming curve. The external energy is used to guide the deforming curve toward the target. [37] used Gaussian Gradient Force to compute external force.

A *Markov random field*, Markov network or undirected graphical model is a set of random variables having a Markov property described by an undirected graph. It is a statistical model used to model spatial relations that exist in the neighbour of pixels [38].

In graph cut based approaches, the problem of image segmentation is considered as a graph partitioning problem and global criterion that measures both total dissimilarity among the different groups and the total similarity inside then is used. An efficient method based on generalized Eigen value.

The main challenge lies in segmentation of brain with anatomical deviation like tumor with different shape, size, location and intensities. The tumor not only changes the part of brain which tumor exists but also sometimes it influences shape and intensities of other structures of the brain. Thus the existence of such anatomical deviation makes use of prior information about intensity and spatial distribution challenging.

III. MRI IMAGE SEGMENTATION USING GRADIENT BASED WATERSHED TRANSFORM IN LEVEL SET METHOD

This research work proposed a brain MRI image segmentation technique based on 2 level gradient watershed transform using level-set method. The study of automatic brain tumor segmentation represents an interesting research problem in machine

learning and pattern recognition. However, developing highly accurate automatic methods remains a challenging problem. This is because humans must use high-level visual processing and must incorporate specialized domain knowledge to perform this task, which makes developing fully automatic methods extremely challenging.

Unlike the standard level set methods, the tumor and non-tumor region information is embedded in the level set speed function to automatically extract the 2D tumor surface. The first approach called the block 1 process uses the *level set segmentation* as a deformable model and defines its speed function based on intensity thresholding so that no explicit knowledge about the density functions of the tumor and non-tumor regions are required. The threshold is updated iteratively throughout the level set growing process. The second approach which is called as block 2 consist of *two level gradient based watershed segmentation*. We had also used some morphological operators along with watershed transform in order to extract a sharp segmented region.

Basically, the level set method (LSM) is a numerical technique for tracking interfaces and shapes. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize these objects (this is called the Eulerian approach).

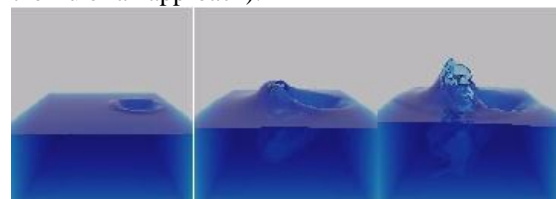


Figure 4: An illustration of the level set method

The figure 4 illustrates several important implementation details about the level set method. In the upper-left corner we see a shape; that is, a bounded region with a well-behaved boundary. Below it, the red surface is the graph of a level set function φ determining this shape, and the flat blue region represents the $x - y$ plane. The boundary of the shape is then the zero level set of φ , while the shape itself is the set of points in the plane for which φ is positive (interior of the shape) or zero (at the boundary).

In the top row we see the shape changing its topology by splitting in two. It would be quite hard to describe this transformation numerically by parameterizing the boundary of the shape and following its evolution. One would need an algorithm able to detect the moment the shape splits in two, and then construct parameterizations for the two newly obtained curves.

On the other hand, if we look at the bottom row, we see that the level set function merely translated downward. This is an example of when it can be much easier to work with a shape through its level set function than with the shape directly, where using the shape directly would need to consider and handle all the possible deformations the shape might undergo. Thus, in two dimensions, the level set method amounts to representing a closed curve Γ (such as the shape boundary in our example) using an auxiliary function φ , called the level set function. Γ is represented as the zero level set of φ by

$$\Gamma = \{(x, y) | \varphi(x, y) = 0\},$$

And the level set method manipulates Γ implicitly, through the function φ . φ is assumed to take positive values inside the region delimited by the curve Γ and negative values outside.

If the curve Γ moves in the normal direction with a speed v , then the level set function φ satisfies the level set equation

$$\frac{\partial \varphi}{\partial t} = v |\nabla \varphi|.$$

Here, $|\cdot|$ is the Euclidean norm (denoted customarily by single bars in PDEs), and t is time. This is a partial differential equation, in particular a Hamilton–Jacobi equation, and can be solved numerically, for example by using finite differences on a Cartesian grid.

The initial segmentation block in our proposed track high intensity pixels after thresholding the original MRI input image, figure below shows the structure of first block.

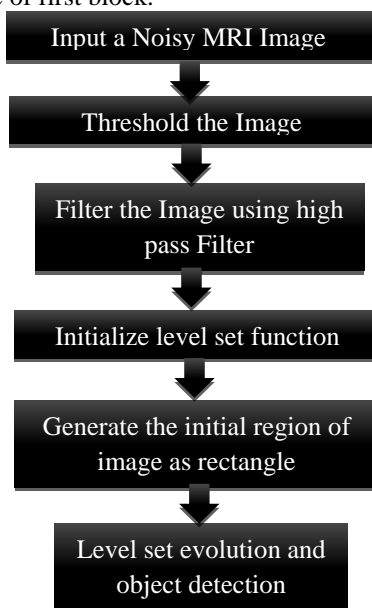


Figure 5. Structure of Level set method used in our proposed methodology as an initial block of segmentation.

In our segmentation process, for using watershed segmentation different methods are used. Two basic principle methods are given below: 1) the computed local minima of the image gradient are chosen as a marker. In this method an over segmentation occurs. After choosing marker region merging is done as a second step; 2) Watershed transformation using markers utilizes the specifically defined marker positions. These positions are either defined explicitly by a user or they can be determined automatically by using morphological tools. After converting the image in the binary format, some morphological operations are applied on the converted binary image. The purpose of the morphological operators is to separate the tumor part of the image. Now only the tumor portion of the image is visible, shown as white color. This portion has the highest intensity than other regions of the image.

A watershed line is defined as the line separating two catchment's basins, as shown in Figure 6. The rain that falls on either side of the watershed line will flow into the same lake of water. The image gradient can be viewed as terrain. The homogeneous regions in the image usually have low gradient values which represent valleys, while edge represents the peaks having high gradient values.

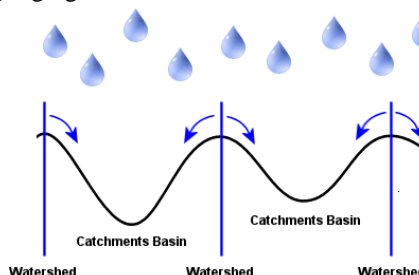


Figure 6. Watershed line with catchment basins.

The watershed transform detects intensity valleys in the image and the image is enhanced by highlighting the intensity valleys. The enhanced image is used to convert the objects of interest into intensity valleys. We detect all intensity valleys below a particular threshold with output as a binary image. Then imposed minimum function will modify the image to contain only valleys. The imposed minimum function will also change a valley's pixel values to zero. All regions containing an imposed minimum will be detected by the watershed transform. The exact workflow for the final segmentation block in proposed approach is shown in figure 7.

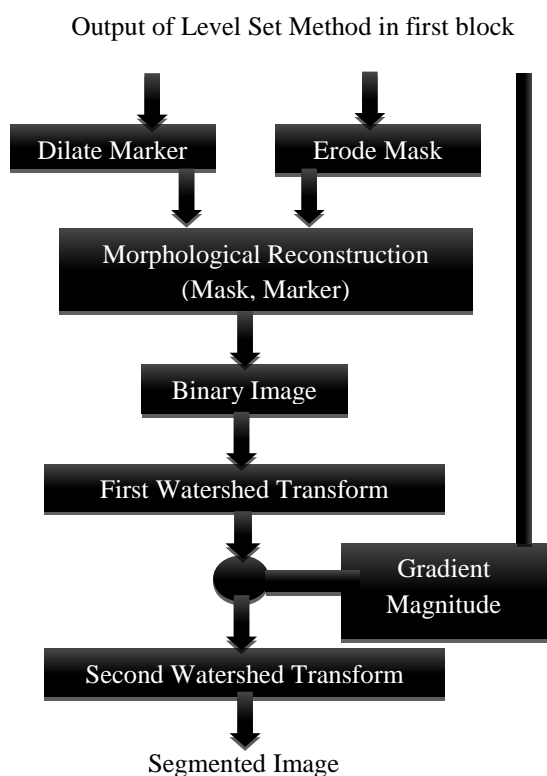


Figure 7. Employment of gradient based watershed transform on the output of level set segmentation used in our proposed methodology as a final block of segmentation.

The segmentation of the imposed minima image is accomplished with the watershed function in MATLAB. Watershed function returns a label matrix containing non-negative numbers that correspond to watershed regions. Pixels that do not fall into any watershed region are given a value of zero. The label matrix is to convert it to a color image. In the colored version of the image, each labeled region is displayed in a different color and the pixels that separate the region are white. We specify a polygonal region of interest of the objects in binary image. Total area is a scalar whose value corresponds roughly to the total number of pixels in the image.

Basic approaches for watershed segmentation

- The first one starts with finding a *downstream* path from each pixel of the image to a local minimum of image surface altitude.
- A catchment basin is then defined as the set of pixels for which their respective downstream paths all end up in the same altitude minimum.
- While the downstream paths are easy to determine for continuous altitude surfaces by calculating the local gradients, no rules exist to define the downstream paths uniquely for digital surfaces.

- The second approach is essentially dual to the first one; instead of identifying the downstream paths, the catchment basins fill from the bottom.
- Imagine that there is a hole in each local minimum, and that the topographic surface is immersed in water - water starts filling all catchment basins, minima of which are under the water level. If two catchment basins would merge as a result of further immersion, a dam is built all the way to the highest surface altitude and the dam represents the watershed line.
- An efficient algorithm is based on *sorting* the pixels in increasing order of their gray values, followed by a *flooding* step consisting of a fast breadth-first scanning of all pixels in the order of their gray-levels.
- During the sorting step, a brightness histogram is computed. Simultaneously, a list of pointers to pixels of gray-level h is created and associated with each histogram gray-level to enable direct access to all pixels of any gray-level.
- Information about the image pixel sorting is used extensively in the flooding step.

IV. ANALYSIS OF RESULTS AND VALIDATION OF APPROACH

In order to test the performance of the proposed segmentation method, a brain MRI is segmented in this research work. Figure below gives original MRI image representation.

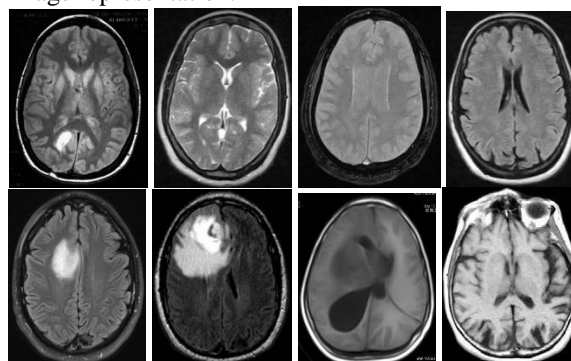


Figure 8. Example Medical resonance imaging data samples taken from the internet database, these samples are captured from various angles throughout the brain area.

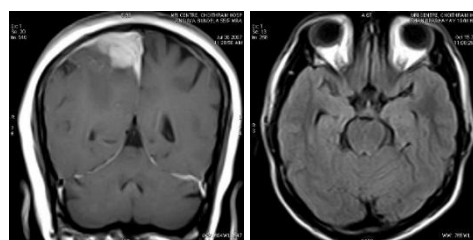


Figure 9. Some original dataset also considered which is taken from a local hospital in order to justify results from the proposed segmentation approach.

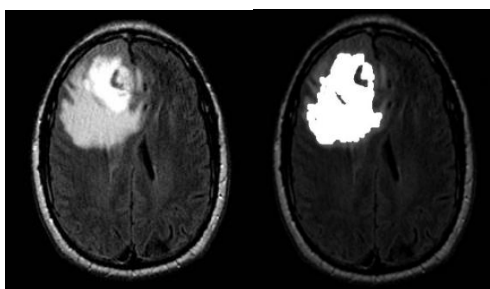


Figure 10. It shows the thresholding operation on original input magnetic resonance imaging data, this thresholding was performed based on intensity of image pixels.

After the Application of Level Set Method in the selected thresholded region of MRI image, the region of interest from the boundary regions start converging. The segmented portion further extracted by passing it through a bank of Morphological operators and watershed transform. The level set method (LSM) is a numerical technique for tracking interfaces and shapes. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize these objects (this is called the Eulerian approach). Also, the level set method makes it very easy to follow shapes that change topology, for example when a shape splits in two, develops holes, or the reverse of these operations. All these make the level set method a great tool for modeling time-varying objects, like inflation of an airbag, or a drop of oil floating in water.

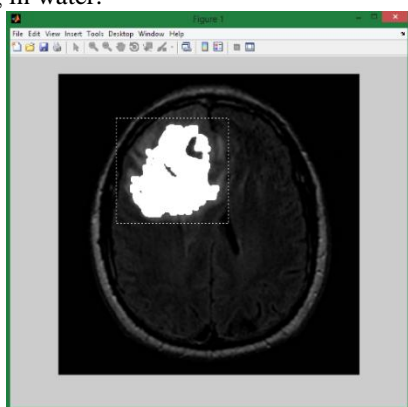


Figure 11. Before applying level set operation on thresholded data, we have to select a region on which we have to apply the level set segmentation (Whole area can also be considered if computation cost is not an issue in segmentation process)



Figure 12. Initialization of Level-set method, it start converging initially from the center of selected pre-processed region (in figure it shown by a red circle)

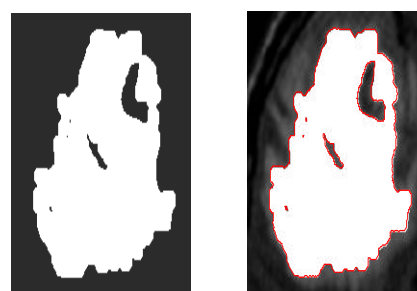


Figure 13. Segmentation of region of interest boundaries after application of level set method in a loop of 5 iterations (As we seen earlier that level-set method starts from center of selected region and continue to run till it found the difference pixel boundaries as shown by the red edges)

For a segmentation purpose, the gradient magnitude (i.e., the length of the gradient vectors) is interpreted as elevation information. Local minima of the *gradient* of the image may be chosen as markers, in this case an over-segmentation is produced and a second step involves region merging. Also, this watershed transformation makes use of specific marker positions which have been either explicitly defined by the user or determined automatically with morphological operators or other ways.



Figure 14. Application of Gradient Magnitude Vector (For a segmentation purpose, the gradient magnitude (i.e., the length of the gradient vectors) is interpreted as elevation information.)

based Watershed transformation on the region extracted from level-set method, basically the filled region in the figure above shows the watershed of a relief correspond to the limits of the adjacent catchment basins of the drops of water.



Figure 15. Extracted Final Output of tumorous region in 2D from medical data (for thresholded image shown in figure 6), after extracting the desired region, we make a difference boundary around the region extracted.

Various Geometrical Parameters considered for result analysis in our work are

- Area
- Eccentricity
- Perimeter
- Major Axis Length
- Minor Axis Length

The tabular results for following mentioned parameters are shown at last of this research paper and compared with [41], also the calculation of such parameters can be explained in terms of image as:

- 'Area' — Scalar; the actual number of pixels in the region. (This value might differ slightly from the value returned by bwarea, which weights different patterns of pixels differently.)
- 'Eccentricity' — Scalar that specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment.) This property is supported only for 2-D input label matrices.
- 'Perimeter' — Scalar; the distance around the boundary of the region. regionprops computes the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region.

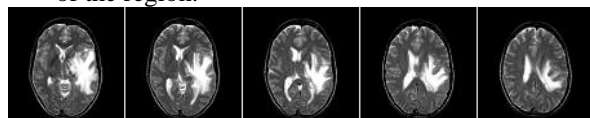


Figure 16. Different Image used for the validation of Various Geometrical Parameters considered for result analysis in proposed work

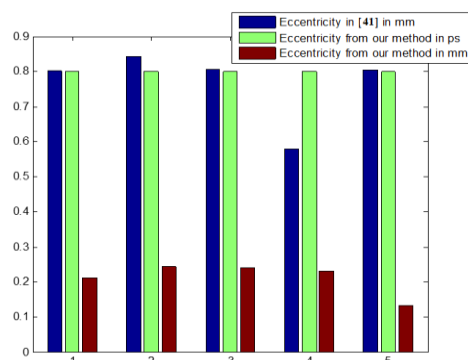


Figure 17. The figure above shows the bar plot comparison of Eccentricity calculated from segmented region by [41] and using our proposed methodology in pixel square and also in millimeter

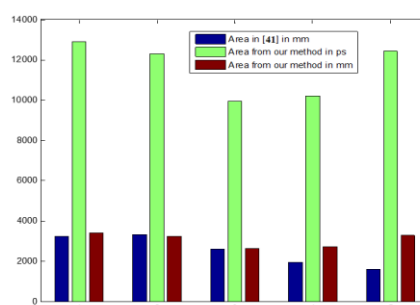


Figure 18. The figure above shows the bar plot comparison of Area calculated from segmented region by [41] and using our proposed methodology in pixel square and also in millimeter

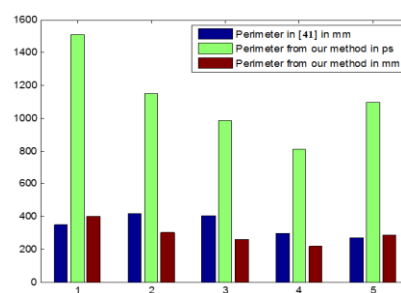


Figure 19. The figure above shows the bar plot comparison of Perimeter calculated from segmented region by [41] and using our proposed methodology in pixel square and also in millimeter

V. CONCLUSION & DISCUSSION

Computer-aided segmentation is a key step for finding application in computer aided diagnosis, clinical studies and treatment planning. This research article explain an extended review of existing and methodology culmination with a new methodology which is better and more accurate as compare to the traditional approaches.

The results show that Gradient based Watershed transform in level set method can successfully segment a tumor provided the parameters are set properly in MATLAB R2013B (8.2.0.701). Our

Hybrid approach algorithm performance is better for the cases where the intensity level difference amongst the tumor and non-tumor regions is higher. It can also segment non homogenous tumors providing the non-homogeneity is within the tumor section. This work proves that methods aimed at general purpose segmentation tools in medical imaging can be used for automatic segmentation of brain tumors.

The quality of the segmentation was similar to manual segmentation and will speed up segmentation in operative imaging. Among the classification methods investigated, the level set method and watershed transform is marked out best out of all others. The user interface in the main application must be extended to allow activation of the segmentation and to collect initialization points from a pointing device and transfer them to the segmentation module.

Finally the main program must receive the segmented image and present the image as an opaque area. It has only one limitation that the method is semi-automatic. Different geometric and Statical parameters also considered during result analysis for more detailed analysis.

Further work can be carried out to make this method automatic so that it can compute the dimensions of the segmented tumor automatically. We plan to work with the research 3-D sagittal MP-RAGE volumes, to determine good diffusion filter parameters so that a single threshold can be found for the brain, as our algorithm currently fails to include all the cortical regions of the brain for these images. We also plan to extend the principles generated for automatic brain segmentation to the problem of lung segmentation for use in studies of lung diseases such as cystic fibrosis and emphysema, where the volume of the lungs is needed. A reliable consistent method for outlining the lungs is required for MR chest images. Early results with MR images are promising, and will be continued.

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