A Semantic approach for segmentation of brain MR Images Using Adaptive CFM

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Abstract : MRI images play a vital role in clinical and research applications that requires segmentation as an important task .This requires classification of different intensity classes for pathological representations of biological tissues. Intensity in Brain MRI images plays a vital role since it is the main feature to classify the grade of the Glioma. We propose a region-based active contour model based on Charged Fluid Model that sketches upon intensity information in limited regions at a manageable scale, in order to overcome the difficulties caused by intensity inhomogeneities. A drawback of the basic Charged Fluid Model is the initial placement of the contour, which often fails to provide accurate segmentation results due to the intensity inhomogeneity. In this paper, we propose an extended CFM for brain MRI image segmentation by region based approach, which is able to deal with intensity in homogeneities in the input MRI image. Later incorporation of semantics is done in the region merging stage. Performance evaluation is done with the existing Watershed segmentation and our method is found to be more efficient in grouping the regions and identifying the grade of the Glioma with respect to the radiologist opinion since the approach is semantic.

Keywords: Charged Fluid Method, Bias field, Magnetic Resonance Images, Semantic Image segmentation and Intensity inhomogeneities.

I. INTRODUCTION

Medical imaging is the method or process used to create the images of human body for clinical purposes or medical science. Medical imaging is a state-of-the-art technology used to see 2D and 3D images of the living body. Magnetic resonance imaging (MRI) is a highly developed medical imaging technique that provides more information about the human soft tissue anatomy. The advantages when compared with other imaging techniques enable it to provide three-dimensional data that highlights the high contrast between soft tissues. However, the amount of data is enough for manual analysis/interpretation, and this has been one of the highest obstacles in the effective use of MRI. Our work concentrates on Glioma detection in Brain MRI. Gliomas are the most common primary malignant brain tumors. The World Health Organization (WHO) classifies them, from the least to the most aggressive, into four grades [16]:

- Grade I–pilocytic astrocytoma
- Grade II–diffused astrocytomas
- Grade III–anaplastic astrocytomas
- Grade IV–glioblastomas

In interpretation of MRI scan, we learn about three different types of images, T1, T2 and Photon density images that are the output of different magnetisation percentage of input MRI. The high-fat-content tissues look bright in T1-weighted images and high-water-content tissues look dark. The reverse is true for T2-weighted images. Normally all the diseases are characterized by amount of water content in tissues, T2-weighted images are generally used for pathological investigations and T1-weighted images are dealing with details of anatomy and pathology, if contrast enhancement is applied. In proton-weighted images, bright areas indicate high-proton-density tissues namely cerebrospinal fluid, and dark areas indicate cortical bone denoted by low-proton-density. Proton-density images give details of anatomy and certain pathological information.[17]Hence a combined analysis and segmentation approach is required for differentiating the three input images(T1,T2&p) for grading the Gliomas.Our approach is highly useful because, it deals with hyper intense and hypo intense areas.

All tumor analysis such as Breast cancer, Lung cancer, Bone marrow cancer etc. have pathological information or test for ruling the prognosis and diagnosis. But brain tumor is the only case where the basic therapeutic choice starts with MRI analysis and pathological information need to be extracted from MRI alone without any gene tests. Segmenting of MRI images for identification of tumors and their class need to be done in a systematic way. Semantics plays a vital role here because all the analysis are done solely by the radiologist. In informatics point of view the analysis done are epistemic rather than ontological. Hence we propose ontology assisted semantic grouping of segmented regions for better pathological information [15].

Segmenting the region of interest is the difficult task in the MRI analysis. To achieve this, in literature various algorithms have been proposed. But, these segmenting algorithms differ from one submission to another. To serves for all applications there is no specific algorithm is presented. Various segmentation algorithms such as threshold, region and statistics based, deformable models based, atlas guided technique and knowledge based approaches are available. Along with these, deformable models are the most traditional models due to their ability to recover the shape of biological structures most accurately in various image segmentation applications. These models are broadly classified into parametric and geometric models [3]. A moving equation should be defined to make the initial contours to the composition boundaries based on which these algorithms are viewed as a modeling of a curve progression. There are different algorithms proposed in these deformable models amongst which Charged Fluid Model (CFM) is much accurate [8]. But there are some limitations existing in this algorithm like, typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to present exact segmentation results due to the intensity inhomogeneity [9].

The characteristics of the sources creating intensity inhomogeneities are not easily identified; deterministic methods cannot be designed to account for the inhomogeneities in MR images. Intensity inhomogeneity frequently occurs in real-world images due to different factors, such as spatial variations in elucidation and imperfections of imaging devices, which complicates lots of problems in image processing and computer vision. Image segmentation is not easy for images with intensity in homogeneities because of the existence of overlapping between the different ranges of the intensities in the regions to segment. This makes it not possible to recognize these regions based on the pixel intensity. Those widely used image segmentation algorithms usually rely on intensity homogeneity, and therefore are not appropriate to images with intensity inhomogeneities. In common, intensity inhomogeneity has been a challenging difficulty in image segmentation.

In the field of medical image segmentation lots of algorithms have been proposed such as Watershed transform, deformable models etc. Watershed transform is a common technique for image segmentation and is used in many fields of image processing mainly in medical image segmentation. However, if the watershed transform is applied directly to image segmentation, there is a problem of over-segmentation. This is caused by insignificant structures or noise and the number of segments will be very high.

Among the deformable models Charged Fluid Model (CFM) is much efficient. A drawback of many deformable models is the initial placement of the contour. There are some restrictions existing in this algorithm that the regions of interest rely on the homogeneity of the image intensities. Due to the intensity inhomogeneity the existing approaches fail to provide correct segmentation results. In this paper, we propose an extended CFM for brain MRI image segmentation by region based approach, which is able to deal with intensity inhomogeneities in the segmentation. This method has the ability to estimate the bias field and segment the image. The estimated bias field is used later for correcting the inhomogeneity in intensities.

The paper is organized as follows: Section 2 describes about the related works section 3 describes about the problem of intensity inhomogenities, charge fluid model and bias correction. Section 4 explains the incorporation of semantics Section 5 explains the experimental results of the proposed method and the evaluation and finally, section 6 concludes the paper.

II. RELATED WORK

Chunming Li, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas and John C. Gore have presented a deviation level set structure for segmentation and bias correction of images with intensity in homogeneities [3].

Yongyue Zhang, Michael Brady, and Stephen Smith have proposed a novel hidden Markov random field (HMRF) model, which is a stochastic process generated by a MRF whose state succession cannot be observed straight but which can be ultimately estimated through observations and an exact and robust segmentation can be achieved. [4]. Herng-Hua Chang, Daniel J. Valentino, Gary R. Duckwiler and Arthur W. Toga developed a new deformable model, the charged fluid model (CFM), that uses the simulation of a charged fluid to segment anatomic structures in magnetic resonance (MR) images of the brain and they demonstrated the performance of the new algorithm in the segmentation of anatomic structures on simulated and real brain MR images of unusual subjects [2].

V. Caselles, R. Kimmel, and G. Sapiro presented a novel scheme for the revealing of object boundaries, that technique was based on active contours evolving in time according to inherent geometric measures of the image. That proposed approach was based on the relation between active contours and the computation of geodesics or minimal distance curves [10].

M. Duraisamy and S. Duraisamy have presented an efficient CNN based segmentation method with lungs and brain MRI images. That approach hit the aim with the help of the following major steps, which contain the pre-processing of the brain and lung images and segmentation using cellular neural network [2]. Herng-Hua Chang and Daniel J. Valentino introduced the concept of using the simulation of a charged fluid to execute image segmentation and that algorithm was used to segment noisy and inhomogeneous objects with pointed corners and cusps in monochrome images. They calculated the electric potential of the simulated system using the finite-size particle (FSP) method implemented via the fast Fourier transform (FFT) algorithm [10].

Jagath C. Rajapakse and Frithjof Kruggel proposed a statistical model to segment clinical magnetic resonance (MR) images in the occurrence of noise and intensity inhomogeneities. They presented the results with simulated and hand-segmented images to match up to performance of the algorithm with further statistical methods [10].

Xiang Li, Lihong Li, Hongbing Lu, Dongqing Chen, and Zengrong Liang presented a new fuzzy segmentation algorithm to improve the noise performance of the AFCM algorithm and that algorithm achieve exact segmentation in the presence of inhomogeneity effect and high noise levels by incorporating the spatial neighborhood information into the objective function [7]. Zhen Ma, Joao Manuel R. S. Tavares and R. M. Natal Jorge classified the current algorithms into three categories and review their features. From their discussions we can see that each type has its appropriate application fields [5].

III. BIAS FIELD ESTIMATION AND CFM SEGMENTATION

A. Charged Fluid Model

To investigate and analyze the biological models physics-based probabilistic systems were being used. In charged fluid models, each fluid element has its own charge and the value is calculated by interpolating the charges of the enclosed particles. Now, assume that a system of charged particles is initialized inside a region of interest (ROI) in an image. The particles will continue advancing apparent until they encounter a balancing inner force related to features in the image [8]. However, it is confused to arrange and direct the particles toward the boundary of interest such that the final contour corresponding to the particle positions can exactly and properly represents the ROI.

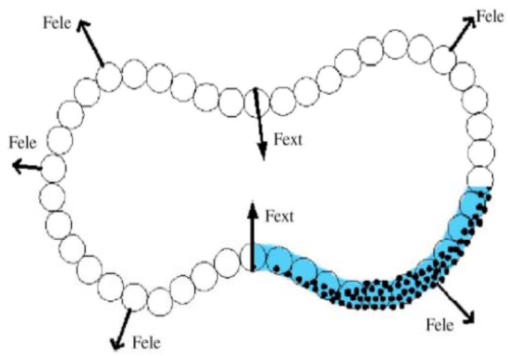

Fig. 1 Concept of a charged fluid

A charged fluid theoretically consists of charged elements i.e., the large circles, each of which exerts a repelling electric force on the others. The fluid elements, as if they were consisted of different amounts of charged particles like solid dots, are connected to one another by 8-connectivity when they advance. The charged fluid, behaving like a liquid, can be influenced by internal electric forces Fele of revulsion as well as external forces Fext from the image data. As there are few drawbacks in the CFM model stated in like there should be a valuable technique which can automatically segment the image, in this paper we propose an extended CFM for brain MRI image segmentation by region based approach, which is able to deal with intensity inhomogeneities in the segmentation.

B. Bias Estimation

In order to deal with intensity inhomogeneities in image segmentation, a method based on real-world image model that describes the composition with intensity inhomogeneity is proposed. In this paper, we reflect on the following multiplicative model of intensity inhomogeneity. From the physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image i can be modeled as

$$i = bT + n \quad \text{--} \qquad (1)$$

where T is the true image, b is the factor that accounts for the intensity inhomogeneity, and n is additive noise. The component is referred to as a bias field. The true image T measures an intrinsic physical property of the objects being imaged, which is therefore assumed to be piecewise (approximately) constant. The bias field is assumed to be slowly changeable. The additive noise n can be assumed to be zero-mean Gaussian noise.

In this paper, we consider the image i as a function $i: \Omega \to \Re$ defined on a continuous domain Ω. The assumptions about the true image T and the bias field b can be affirmed more specifically as follows:

(A) The bias field b is slowly varying, which implies that b can be well estimated by a constant in a region of each point in the image domain.

(B) The true image T approximately takes n distinct constant Values $c_1, \ldots, c_n$ in disjoint regions $\Omega_1, \ldots, \Omega_n$, respectively, Where $\{\Omega_i\}_{i=1}^{n}$ forms a partition of the image domain, i.e. $\Omega = \cup_{i=1}^{n} \Omega_i$ and $\Omega_i \cap \Omega_j = \emptyset$ for $i \neq j$ based on the model in (7) and the assumptions A and B, we propose a method to estimate the regions $\{\Omega_i\}_{i=1}^{n}$, the constants $\{c_i\}_{i=1}^{n}$, and the bias field b . The obtained estimates of them are denoted by $\{\widehat{\Omega}_i\}_{i=1}^{n}$, the constants $\{\hat{c}_i\}_{i=1}^{n}$, and the bias field $\hat{b}$, respectively. The obtained bias field b should be slowly varying and the regions $\widehat{\Omega}_1, \ldots, \widehat{\Omega}_n$ should satisfy certain regularity property to avoid spurious segmentation results caused by image noise. We define a criterion for looking such evaluations based on the above image model and assumptions (A) and (B). This criterion will be defined in terms of the regions Ω_i , constants c_i , and function b , as energy in a variational framework, which is minimized for finding the optimal regions $\{\widehat{\Omega}_i\}_{i=1}^{n}$, constants $\{\hat{c}_i\}_{i=1}^{n}$, and bias field $\hat{b}$. As a result, image segmentation and bias field estimation are simultaneously accomplished.

Our energy $\in$ in (5) is expressed in terms of the regions $\Omega_1, \ldots, \Omega_n$. It is difficult to derive a solution to the energy minimization problem from this expression of $\in$. The energy $\in$ is formulated by representing the disjoint regions $\Omega_1, \ldots, \Omega_n$ and the energy minimization can be solved by using well-established variational methods [6].

The equation to find out the energy for the image is derived in paper (1). This is defined by

$$F(\emptyset.c,b) = \in(\emptyset,c,b) + vL(\emptyset) + \mu R_p(\emptyset) \quad \text{--} \qquad (2)$$

Where the energy is $\in(\emptyset,c,b)$, with $L(\emptyset)$ and $R_p(\emptyset)$ being the regularization terms as defined below.

$$\in(\emptyset,c,b) = \int \sum_{i=1}^{n} e_i(X) M_i(\emptyset(X)) d_X \quad \text{--} \qquad (3)$$

The energy term $L(\emptyset)$ is defined by

$$L(\emptyset) = \int |\nabla H(\emptyset)| dX \quad \text{--} \qquad (4)$$

that calculates the arc length of the zero level contour of $\emptyset$ and therefore serves to smooth the contour by correcting its arc length [5]. The energy term $R_p(\emptyset)$ is defined by

$$R_p(\emptyset) = \int p(|\nabla\emptyset|) dX \quad \text{--} \qquad (5)$$

with a potential (energy density) function $p: [0, \infty] \to \Re$ such that $p(s) \geq p(1)$ for all $s = 1$, i.e. is a minimum point of p .

By minimizing this energy, we achieve the result of image segmentation given by the level set function $\emptyset$ and the estimation of the bias field. The energy minimization is achieved by an iterative process: in each iteration, we minimize the energy $F(\emptyset.c,b)$ with respect to each of its variables $\emptyset$, c, and b , given the other two updated in previous iteration. We provide the solution to the energy minimization with respect to b as follows.

Energy Minimization With Respect to: For fixed $\emptyset$ and , the optimal b that minimizes the energy $\in(\emptyset,c,b)$, denoted by, is given by

$$\hat{b} = \frac{IT^{(1)} * K}{T^{(2)} * K} \quad \text{--} \qquad (6)$$

Where $T^{(1)} = \sum_{i=1}^{n} c_i u_i$ and $T^{(2)} = \sum_{i=1}^{n} c_i^2 u_i$. Note that the convolutions with a kernel function K confirms the slowly varying property of the derived optimal estimator $\hat{b}$ of the bias field.

IV. EXTENDED CFM SEGMENTATION

In charged fluid models, setting the initial contours could fail due to the intensity inhomogeneity. In this paper we propose a region based approach for dealing the intensity inhomogeneities i.e., extended CFM for brain MRI image segmentation. Our method is able to segment the image and estimate the bias field and is used for intensity inhomogeneity correction. So, energy minimization is achieved by using this approach through getting the bias field $\hat{b}$ .The advantage of using the region based approach is that, we can set the accurate initial contours without impact of intensity inhomogeneities. The segmentation of the medical image involves the following three algorithms which are demonstrated below and the numbers specified in the brackets refer to the equations derived in the reference paper [9].

***Algorithm 1*. Charged fluid [9]**

1. parameter setting of b in Eq. (6)
2. image potential computation using Eq. (15)*

3. **repeat (i)**

(a) uniform charge distribution over fluid elements

(b) **repeat (j)**

Algorithm 2

(c) **until(j)** electrostatic equilibrium is achieved based on Eq. (14)*

(d) 1-pixel-wide front construction

(e) **Algorithm 3**

(f) mean potential computation and charge normalization using Eq. (9)*

4. **until(i)** no deformation in the charged fluid shape

5. subpixel precision calculation, if desired

***Algorithm 2.* Charge distribution procedure[9]**

1. forward FFT computation of the charge array based on Eq. (6)*
2. inverse FFT computation of the potential array based on Eq. (7)*
3. electric field computation using Eq. (11)*
4. advance distance computation using Eq. (13)*
5. charge interpolation using the SUDS.

***Algorithm 3*. Front deformation procedure**

1. effective field computation using Eq. (16)*
2. 2-pixel-wide interface localization

*indicates the equations and figures used from reference paper [9].

V. REGION MERGING

The segmented image has clusters of data that are heterogeneous, the clustered information has to be grouped to make them enable for classification, and here we propose a semantic approach for grouping the neighbours. The non-semantic and semantic portion for clustering is given below.

a)Non-Semantic Criteria:

T_1 and T_2 are preset thresholds.

1. Merge region I,j as long as they have one weak separating edge until no two regions pass this test.

2.Merge regions i,j where $s(i,j) \leq T_2\ Where$

$$S(i,j) = \frac{c_1+\alpha_{ij}}{c_2+\alpha_{ij}} \quad -- \qquad (7)$$

Where c_1 and c_2 are constants,

$$\alpha ij = \frac{(area_i)^{\frac{1}{2}}+(area_j)^{\frac{1}{2}}}{perimeter_i\ .\ permeter_j} \quad -- \qquad (8)$$

Until no two regions pass this test.

b) Semantic Criteria:

3. Let B_{ij} be the boundary between R_I and R_j . Evaluate each B_{ij} with a Bayesian decision function that measures the (conditional) probability that B_{ij} separates two region R_i and R_j of the same interpretation. Merge R_i and R_j this conditional probability is less than some threshold. Repeat steps 3 until no regions pass the threshold test.

4. Evaluate the interpretation of each region R_i with a Bayesian decision function that measures the (conditional) probability that an interpretation is the correct one for that region. Assign the interpretation to the region with the highest confidence of correct interpretation. Update the conditional probabilities for different interpretations of neighbors. Repeat the entire process until all regions have interpretation assignments.

The semantic portion of the above algorithm has the goal of maximizing an evaluation function measuring the probability of a correct interpretation (labeled partition), given the measurements on the boundaries and region of the partition. The interpretation assignment is done with the reference Tumor Ontology [13] as shown below.

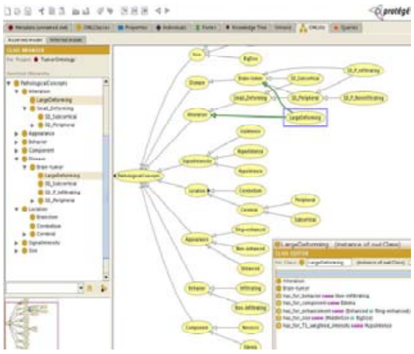

Fig 2. Concepts of the Brain Tumor Ontology (FMA)

VI. PERFORMANCE EVALUATION

The experimentation of the proposed algorithm has been implemented on various intensity inhomogeneity images of brain MRI. The algorithms have been implemented in a system with CPU of Core i5 Processor 2.4GHz using MATLAB 12.0.

The results of using the MRI brain images in Semantic CFM with the judgment using the wavelet approaches for the intensity estimation and segmentation is analyzed.

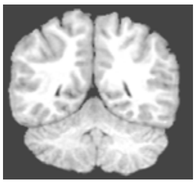

Fig 3. Intensity Brain MRI

Fig 4. Bias estimated image

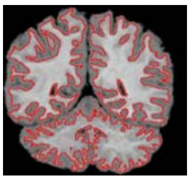

Fig 5. Resultant CFM segmentation-Intensity Corrected

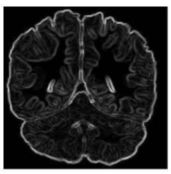

Fig 6. Gradient magnitude of input image

Fig 7. Watershed output Segmentation: HI- Contrast image

Fig.3 shows images reveal observable intensity inhomogeneities. The bias corrected image segmentation result images and are shown Fig 4 and Fig 5 correspondingly. It can be seen that the intensities within each brain MRI images become quite consistent in the bias corrected images. The most accuracy of the image quality in terms of intensity homogeneity can be also established by comparing the bias corrected images.

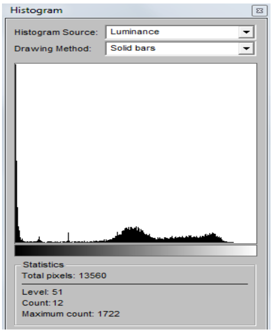

Fig 8. Histogram of SCFM

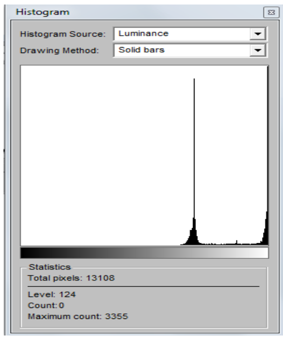

Fig 9. Histogram of Watershed

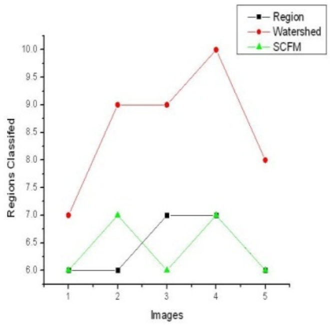

Fig 10. Images vs Region classified

Performance evaluation with respect to region analysis is done between the Semantic CFM segmentation, Radiologist opinion and Watershed Segmentation. Our proposed method shows meaningful regions as close to the radiologist opinion whereas Watershed even when combined with semantics slows down in performance since that does not deals with intensity inhomogeneities.

VII. CONCLUSION

Intensity plays a vital role in Brain MRI imaging to identify the grade of the Glioma since pathological report is unavailable in case of brain tumor. Hence our approach concentrates in presenting an Extended CFM work for segmentation with semantics and bias correction of images with intensity inhomogeneities. The work is based on a generally accepted model of images with intensity inhomogeneities and a derived local intensity bias filed property of the input MRI. Segmentation and bias field estimation are performed by minimizing the proposed energy function. Since meaningful interpretation of information present in the MRI input is essential, we have proposed a coactive semantic segmentation approach for further region analysis. Our method is much more robust to initialization than the wavelet based approaches.

This approach is for meaningful clustering of the pathological data in the brain MRI. The future work is to find all the innermost pathological information and thereby designing a new classifier to enable grading the Glioma efficiently.

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