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Hemangioma Neoplasm in Spinal Cord Dissection on RAG Spurious Purgation

Dr.D.Satheesh Kumar , Dr.P.Ezhilarasu

Abstract— This paper proposes a new framework to image segmentation on spinal cord tumor hemangioma, which combines edge- and region-based in formation with spectral techniques through the morphological algorithm of watersheds for the benign vascular tumors may occur in any tissue in the body. A pre-processing step is used to reduce the spatial resolution without losing important image information. The Hemangioma is swelling Neoplasm that occurs in spinal cord lined in blood vessels for segmentation and Hemangiomas are connected to the circulatory system. The appearance depends on location. If they are on the surface of the skin, they are reminiscent of a ripe strawberry . The segmentation of spinal cord neoplasm involves eliminating the edema and necrosis regions through Region Similarity Graph with spurious tisuses elimination. The proposed technique is applied on different MR images for both visual evaluations and quantitative. The experimental results clearly demonstrate the effectiveness of the proposed approach to produce simpler segmentations and to compare favourably with state-of-the-art methods.

Keywords—: Hemangioma, Region Similarity Graph,image segmentation, MRI, Tumor.

I. INTRODUCTION

Radiologists examine the patient physically by using Computed Tomography (CT scan) and Magnetic Resonance Imaging (MRI). A hemangioma is a benign, and usually a self-involuting tumor, (swelling or growth) of the endothelial cells that line blood vessels and is characterised by increased number of normal or abnormal vessels filled with blood. A hemangioma is a benign, and usually a self-involuting tumor, (swelling or growth) of the endothelial cells that line blood vessels and is characterised by increased number of normal or abnormal vessels filled with blood. It usually appears during the first weeks of life. It usually appears during the first weeks of life and generally resolves by age 10. In more severe cases hemangiomas may leave residual tissue damageMRI images showed the brain structures, tumor's size and location. From the MRI images the information such as tumors location provided radiologists, an easy way to diagnose the tumor and plan the surgical approach for its removal.

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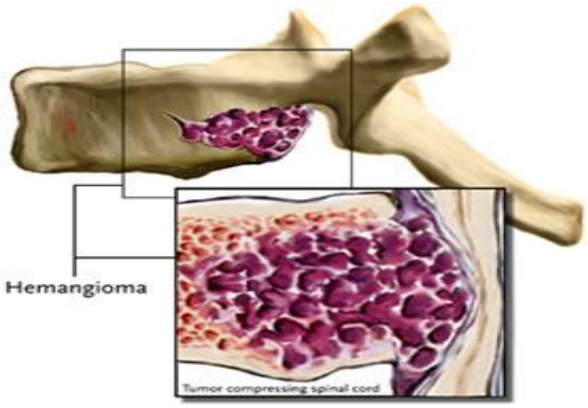

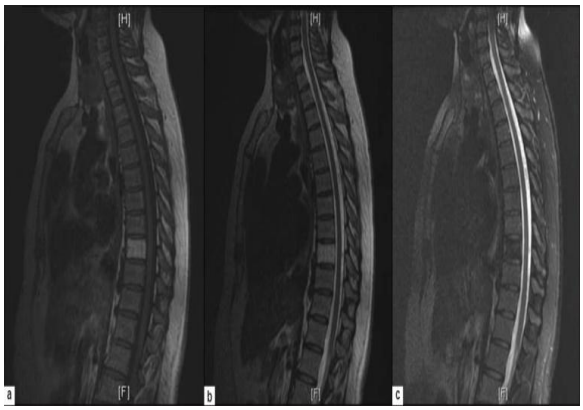

Fig 1.1 Hemangioma in the spinal Cord Regions

This image processing consist of image enhancement using histogram equalization, edge detection and segmentation process to take patterns of brain tumors, so the process of making computer aided diagnosis for brain tumor grading will be easier. The terminology used to define, describe and categorize vascular anomalies, abnormal lumps made up of blood vessels, has changed. The term hemangioma was originally used to describe any vascular tumor-like structure, whether it was present at or around birth or appeared later in life. Mulliken et al. categorized these conditions into two families: a family of self-involuting tumors, growing lesions that eventually disappear, and another family of malformations, enlarged or abnormal vessels present at birth and essentially permanent. The importance of this distinction is that it makes it possible for early-in-life differentiation between lesions that will resolve versus those that are permanent.

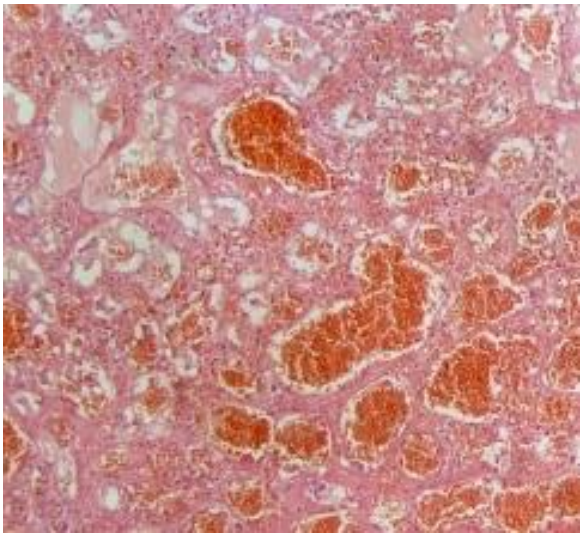

Fig 1.2 Pathaology of Hemangioma affected cells

II. LITERATURE SURVEY

The process of separation of image areas based on different attribute such as texture, grey value range etc is known as Image segmentation. The main objective in image processing applications is extraction of important image features from image data which will eventually lead to automatic computerized description, interpretation and analysis of the scene. Segmentation by the medical experts manually from the magnetic resonance images of the brain tumour is very much time-consuming task, tiresome, susceptible to error,. Several segmentation methods had been proposed by the digital image processing community, many of which are ad - hoc [6]. Four of the most common methods are:

1) amplitude thresholding,
2) texture segmentation
3) template matching, and
4) region-growing segmentation.

This is very much important for detecting necrotic tissues, edema and tumors. Various algorithms for segmentation had been suggested by several authors. Siyal et al described a new method on "Fuzzy C-means for segmentation purpose" [7]. Phillips, W.E et al described "Application of fuzzy C-Means Segmentation Technique for tissue Differentiation in MR Images of a hemorrhagic Glioblastoma Multiforme"[15]. S. Murugavalli1 et al, proposed "A high speed parallel fuzzy c-mean algorithm for brain tumor segmentation" [14]. S. Murugavalli1, proposed "An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Neuro Fuzzy Technique" [13], Vaidyanathan M et al described "Comparison of Supervised MRI Segmentation methods for Tumor Volume Determination during Therapy"[12]. Jayaram K et al described "Fuzzy Connectedness and Image Segmentation"[11].Kannan et aln describe "Segmentation of MRI Using New Unsupervised Fuzzy C mean Algorithm"[10] Ruspini, E Described "Numerical methods for fuzzy clustering"[9]. Dunn, J.C., described "A fuzzy relative of the ISODATA process and its use in detecting compact, well Separated clusters"[6]. Bezdek, J.C., described "Cluster validity with fuzzy sets"[8]. Some other methods such as Learning vector quantization, Watershed, Hybrid SOM or graph cut based approach had also been proposed in different literatures. Zhang et al. [2], suggest employing the Hidden Markov Random Field (HMRF) model for segmenting Brain MRI by using Expectation-Maximization algorithm. The study shows that HMRF can be merged with other techniques with ease. For instance, to achieve three-dimensional and fully automated approach for brain MRI segmentation, the bias field correction algorithm proposed by Guillemaud & Brady (1997) can be easily incorporated into the technique suggested by them. The proposed technique acts as a general method that can be applied to a range of image segmentation problems with improved results. HMRF model is quite flexible for image modeling as it carries the ability to encode both the statistical and spatial properties of an image. HMRF model with Gaussian Emission Distribution is referred as GHMRF that produces images with controllable spatial structure — smaller the standard deviation, the transparent the spatial structure. The expectation maximization algorithm not only offers a proficient method for parameter estimation, but also provides a comprehensive framework for unsupervised classification. In short, the HMRF-EM method can plausibly overcome almost all the drawbacks associated with FM-EM method. The experimental results show that HMRF-EM produced promising results even with high level of noise, low image quality and large number of classes, as compared to RM-EM method. The major limitation in their work is that preliminary estimations based on threshold are purely heuristic. It does not generate perfect results in case of high invariability of brain MRI, particularly in terms of contrast between brain tissues and intensity ranges. And in case of poorly defined image, EM procedure is very likely to produce inaccurate segmentation. Apart from this, the whole algorithm is a bit slower than the original FM-EM model, due to the involvement of additional MRF-MAP classification, EM fitting procedure and bias field correction. However, it can obtain slightly good speed by utilizing ICM deterministic method. Marroquin et al. [4] highlight the significance of 3D segmentation of brain MR scans. It uses separate parametric models for the intensity of each class. The brain Atlas is employed with a robust registration procedure to find non-rigid transformation to map the standard brain to the specimen to be segmented. This transformation is further used to segment brain from non-brain tissues, computing prior probabilities and finding automatic initialization and finally applying MPM-MAP algorithm to find out optimal segmentation. Major findings from the study show that the MPM-MAP algorithm is comparatively robust than EM in terms of errors while estimating the posterior marginal. For optimal segmentation, the MPM-MAP algorithm involves only the solution of linear systems and is therefore computationally efficient.

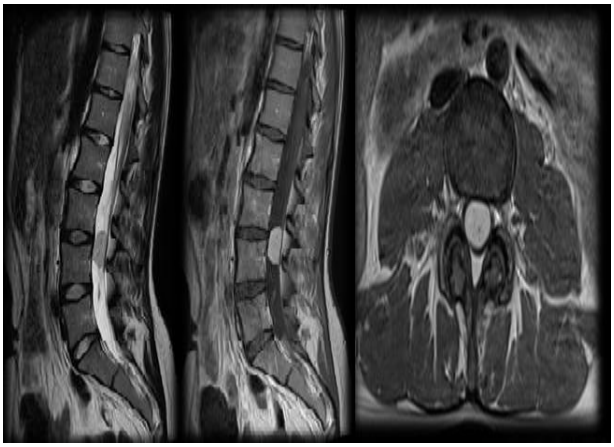

Fig 2.1 Hemangioma Neoplasm in Spine Regions

III. METHODOLOGY

A. EXISTING METHOD

In Image segmentation is one of the largest domains in image analysis, and aims at identifying regions that have a specific meaning within images. Another definition of image segmentation is the identification of regions that are uniform with respect to some parameter, such as image intensity or texture. While the latter definition is often used for technical reasons, the former definition should be preferred from an application point of view. Although the effort made in the computer vision community there is no algorithm that is known to be optimum in image segmentation. Much research is being done to discover new methods building up on previous ideas.

B. DISADVANTAGES

A Spectral methods are promising approaches to perceptual grouping or image segmentation that take into account global image properties as well as local spatial relationships. They treat image segmentation as a graph partitioning problem. These methods use the eigenvectors and the eigenvalues of a matrix representation of a graph derived from the pairwise similarities, as measure by one or more cues to partition an image into disjoint regions. One important issue of these approaches is the size of the corresponding similarity matrix.

C. PROPOSED METHOD

The algorithm described in this paper can be well classified into the category of hybrid techniques, since it combines the edge-based, region-based and the mor phological techniques together through the spectral based clustering approach. We propose that our method can be considered as an image segmentation framework within which existing image segmentation algorithms that produce over-segmentation may be used in the pre liminary segmentation step.This new approach overcomes some limitations usually associated with spectral clustering approaches.) An array of regions where each region is represented by a linked-list of pixels which correspond to the pixels that belong to the region. This dual representation of a partitioned image allows for a efficient implementation. The label map grants us immediate access to the label of every pixel in the image. The array of lists gives us immediate access to the set of pixels that belong to each region. Using this representation two different regions can be merged into one by iterating through the corresponding linked-lists and updating the label map.

The proposed methodology has four major stages. First, we reduce image noise, as a pre-processing stage, using an anisotropic filter. Next, we create an over segmented image based on the gradient image and watershed transform. In the third stage, the over segmented image will be the input for the image Region Similarity Graph (RSG) construction. Finally, we apply a spectral approach on the RSG. This framework integrates edges and region-based segmentation with spectral-based clustering as depicted in Figure 1.

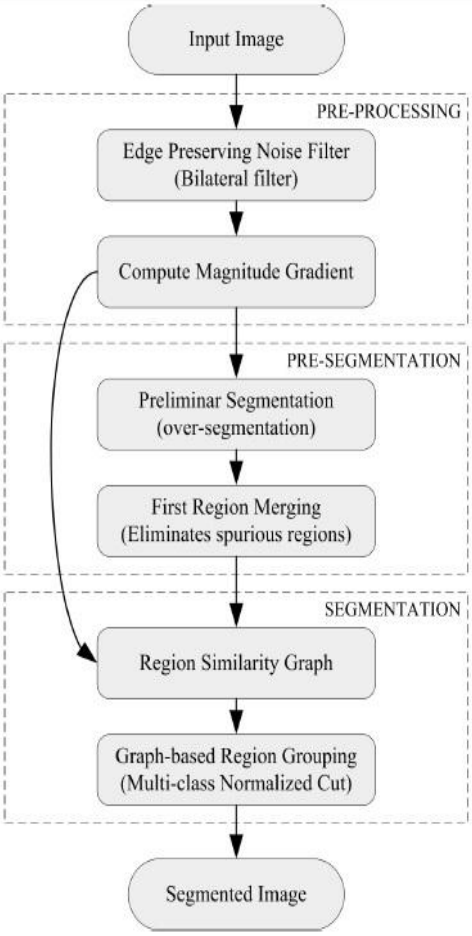

Figure 3.1 Block diagram of the proposed method (WNCUT).

D. ADVANTAGES

- The combination of watershed and spectral methods solves the weaknesses of each method by using the watershed to provide small prototype regions from which
- similarity matrix can be obtained.
- Rather than cluster ing single points we will cluster micro-regions, confident that the underlying primitive regions are reliable.

- Using this representation two different regions can be merged into one by iterating through the corresponding linked-lists and updating the label map. Even more, we can easily obtainthe centroid and the mean value of the new region.

IV. SPINAL CORD DISSECTION ON RAG SPURIOUS PURGATION

In an earlier work [13], we designed a segmentation method by combining conditional random fields (CRF) with a cost-sensitive SVM, which allowed us to incorporate spatial information in the segmentation process. In this paper, incorporation of a spatial information is achieved through seed points that are selected via SVM. These seed points allow us to accurately localize desired regions, proposed method has higher specificity and sensitivity rates compared to [13] due to the use of a (seeded) spatial algorithm in our segmentation scheme. The programming language used with MATLAB is usually referred to as MATLAB.

List of Modules

1. Region similarity graph
2. Pairwise similarity
3. Intensity distance
4. centroid of pixels

REGION SIMILARITY GRAPH

Spectral methods use the eigenvectors and eigenval ues of a matrix derived from the pairwise similarities of features. This effect is achieved by creating a fully connected graph. Based on the graph construction, there are two main groups of methods for image segmentation: region-based methods where each node repre sents a set of connected pixels, and pixel-based methods where each node corresponds to a pixel of the image.

The RSG structure is an undirected weighted graph where the set of nodes corresponds to the atomic regions. For each pair of regions, the set of links represent relationships and the link weights W represent similarity measures between the regions.

Some characteristics of the RSG model that yield to relevant advantages with regard to the region adjacency graph model are:

i) the RSG allows the existence of links between pairs of non-adjacent regions.

ii) it is defined once and it does not need any dynamic updating when merging regions.

PAIRWISE SIMILARITY

In the RSG model nodes are represented by the centroid of each micro-region. Links together with their associated weights are defined using the spatial similarity between nodes, their connectivity and the strength of intervening contours between region centroids. The resulting graph is a structure where region nodes represent complete image regions.

For each pair of nodes, node similarity is inversely correlated with the maximum contour energy encountered along the line connecting the centroids of the regions. If there are strong contours along a line connecting two centroids, these atomic regions probably belong to different segments and should be labelled as dissimilar. Let i and j be two atomic regions and the orientation energy OE $*$ between them, then the intervening contours contribution to the link weight is given by:

$$\omega_{ic}(i,j) = \exp\left[-\frac{\max_{t\in line(i,j)}\left\|OE * (\overline{x_i} - \overline{x_j})\right\|^2}{\sigma_{ic}^2}\right]$$

INTENSITY DISTANCE

The intensity distance between nodes contributes for the link weight according to the following function:

$$\omega_I(i,j) = \exp\left(-\frac{\left(I_{\overline{x_i}} - I_{\overline{x_j}}\right)^2}{\sigma_I^2}\right)$$

These cues are combined in a final link weight similarity function, with the values σic and σI selected in order to maximize the dynamic range of W: $W(i,j) = \omega_{ic}(i,j).\omega_I(i,j)$

CENTROID OF PIXELS

For each region ri , spatial location xi is computed as centroid of their pixels. Two dynamic data structures are used through which it is very convenient to add or remove regions:

1) A label map in which each pixel value corresponds to the label of the region that this pixel belongs to;

2) An array of regions where each region is represented by a linked-list of pixels which correspond to the pixels that belong to the region. This dual representation of a partitioned image allows for a efficient implementation. The label map grants us immediate access to the label of every pixel in the image.

The array of lists gives us immediate access to the set of pixels that belong to each region. Using this representation two different regions can be merged into one by iterating through the corresponding linked-lists and updating the label map. Even more, we can easily obtain the centroid and the mean value of the new region.

V.EXPERIMENT RESULT

The programming language used with MATLAB is usually referred to as MATLAB script or M-script. After becoming familiar with the basic syntax of the M-script, a number of useful utilities are available to you that allow you to make extended uses of MATLAB. You can, for example, write programs that involve simulation. You can also create graphics, web pages, and GUI applications. When you develop

programs using MATLAB, you can output the results to a number of media, including graphics files, HTML pages, PDF files, and Word documents. You can also connect up MATLAB with other applications, such as Excel or LabView to make extended uses of it. Since it is programmed in part using Java, you can modify it in the background using Java.The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential. The experiment was carried out in 3T- and 7Tweighted clinical brain MR images. Fig. 5.1 shows three 3Tweighted clinical brain MR images that were used in [5], together with the estimated bias fields and segmentation results. It is clear from this figure that in spite of the quite obvious bias field and noise in these images, the proposed algorithm can estimate the bias field and achieves satisfactory segmentation results. initialize the centroids with k-means clustering.

SCREENSHOTS

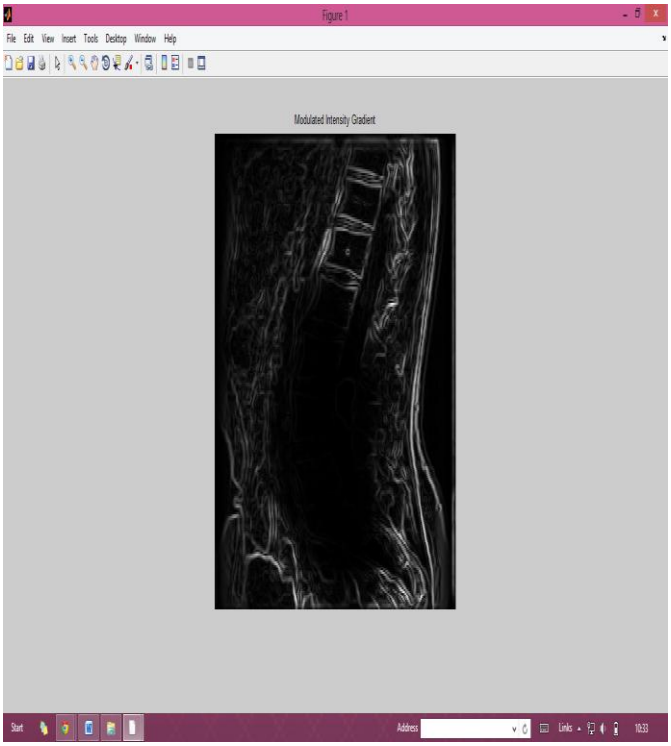

Fig 5.1 Modulated Intensity Gradient Regions

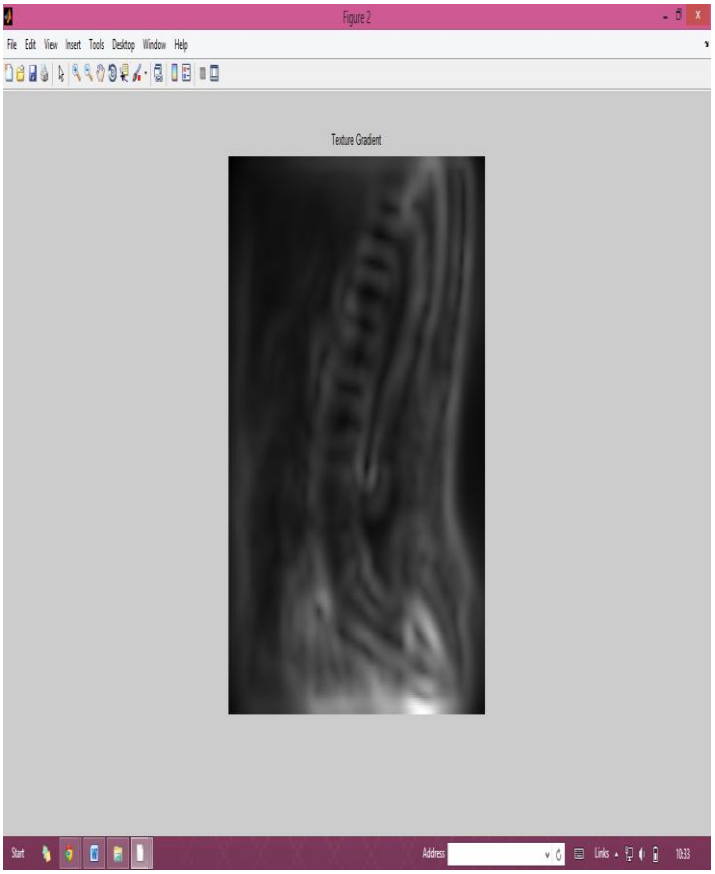

Fig 5.2 Texture Gradient Regions in Spinal Cord

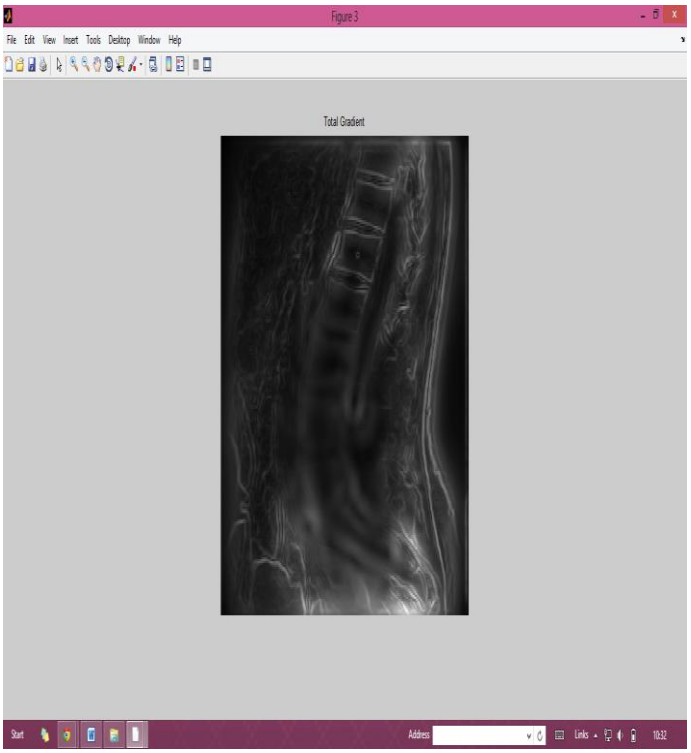

Fig 5.3 Total Gradient Regions in Spinal Cord

Fig 5.4 Segmented Lesions in Spinal Cord

VI. CONCLUSION

This framework to image segmentation on spinal cord tumor hemangioma, which combines edge- and region-based in formation with spectral techniques through the morphological algorithm of watersheds for the benign vascular tumors may occur in any tissue in the body [16], and [17]. Computational applications frames the proposed an image segmentation method which combines edge- and region-based in- formation with spectral techniques through the morphological algorithm of watersheds. An initial partitioning of the image into primitive regions is set by applying a rainfalling watershed simulation on the image gradient magnitude. This step presents a new approach to overcome the problems with flat regions. This initial partition is the input to a computationally efficient graph partition process that produces the final segmentation. The latter process uses a region similarity graph representation of the image regions. The real time execution time in the test cases is less than 12 seconds in almost all the cases and thus can be said to be good as per the current industry standard ad is also very less as compared to manual process. So, based on the above discussion it can be claimed to be a noble segmentation approach in its family of unsupervised clustering approach. This is future scope for 3 – D modelling and volume analysis of brain and tumour and classification of tumour based on this segmentation approach. This work can be implemented using Finite Automata [18], [19], and [20].

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