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Segmentation of Brain Tumor from MRI Image using Gradient Vector Flow

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Abstract : Brain tumor scans are one of the complex segmentation problems. It is not at all easy to extract the tumor affected regions from the surrounding pixels which makes it a really difficult aspect for computer aided diagnosis systems. A new vector field analysis of the GVF images for the detection of tumor boundaries has been proposed by the author. The boundary and non-boundary points has been identified using the vector entropy analysis algorithm of GVF vectors. The output of the proposed algorithm has been compared with other existing segmentation methods on the basis of three parameters-sensitivity, specificity and accuracy. Experimental result shows that our proposed scheme outperforms previous schemes based on other approach.
Keywords : Brain tumor segmentation, vector field analysis, gradient vector flow.

1. INTRODUCTION

The main cause of Brain tumor is the uncontrolled growth of cancer cells inside Brain. There are basically two types of Brain tumors *i.e*. primary brain tumors and metastatic brain tumors. The first one starts in the brain and keep inside in the brain whereas the second one starts from other part of body as cancer and then reaches to the brain as tumor.

The National Brain Tumor Foundation (NBTF) for research in United States observes that over 29000 people were identifies as primary Brain tumor patients and almost 13000 died due to that in U.S.

Brain tumor segmentation has been identified as one of the most complicated problem in the field of Bio- medical image processing because of its different shape and size. Different boundary detection algorithms has been developed over the years for correctly identifying these parameters *i.e*. amplitude thresholding[2], texture segmentation [3], template matching[4], and region-growing segmentation[5]. Another segmentation technique is Fuzzy *c*-means clustering[1][6]. In this approach segmentation can be achieved by dividing gray values in groups. However conventional FCM is sensitive to noise. Another famous approach for segmentation of the image is called the snakes or active contours [7]. Snakes or active contours are paths defined within an image plane itself which can be controlled by the internal forces of the paths and external forces by the image. Two types of contours are explained here; parametric active contours [8] and geometric active contours [9].

It is defined as a curve that gently develops in the image such that it relates with the boundary of the identified object. In medical image processing the active contours or snakes has been successfully utilized for the detection of object boundaries. But, the snake suffers with certain restrictions. It has to be necessarily defined close to the identified object [10]. Because of that lot of researchers are using modified snakes such as balloon snakes[11], T-snakes[12], and multi-direction snakes[13]. Whereas, Gradient Vector Flow (GVF) [14] replaces a GVF field of the edges of an image by enlarging the bigger gradients far from the identified boundary. At the end, a new gradient vector field has been developed. The image internal force is redefined to maximize the capture range and minimize the to the noise sensitivity.

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Due to the appearance of 3-D MRI data and very minute difference between tissue cell and tumor cell, the segmentation of these data has become a challenging problem. The demand is to segment the boundary pixels of similar property and merge into continuous structure.

In this article, a new vector field analysis of the GVF images for the identification ofbrain tumor object boundaries has been proposed. The method defined as vector entropy analysis (VEA)[15]-[16] is motivated by the discrete orientation force field analysis (DOFFA)[17]. The VEA analysis has been used to identify the points laying withboundary and without boundary.

2. LITERATURE REVIEW

This section is divided into two subparts. First part contains the brief introduction of MRI technology and second part briefs few pre-existing segmentation techniques.

A. Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) plays a very important role in clinical diagnosis. For example, one major application of MRI images is to detect brain tumor. Automatic brain tumor detection has been emerged as a challenging problem in the field of medicine [18]-[20].

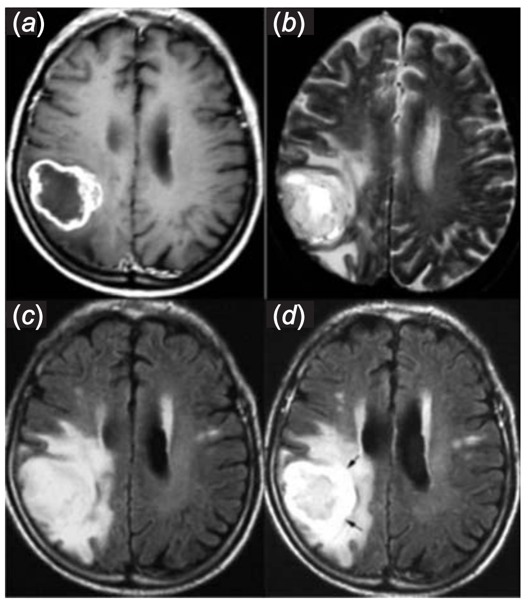


Figure 1. Four imaging modalities: (*a*) T1-weighted MRI; (*b*) T2-weighted MRI; (*c*) FLAIR; and (d) FLAIR with contrast enhancement

In medical processes, the distinct methods such as T1-weighted MRI, T2-weighted MRI, FLAIR MRI and many more are used for the diagnosis of the tumor cells [21].

B. Segmentation Techniques

There are various methods available these days for the segmentation of the brain tumor tissues which are mainly classified in three types one is manual, second is semi-automatic and another is fully automatic [22].

1. **Threshold Based Method :** Threshold based method is a very easy and successful method of segmentation which is again classified into two categories such as global thresholding [24] and local thresholding [25]. In global thresholding onethreshold value is calculated for thresholding of whole image whereas in local thresholding different thresholds have been calculated using local features from different regions across the image.
2. **Region Based Method :** The region based methods [5] merge the different regions if they follow the predefined similar predicate. Region growing and watershed segmentation[26] are two well-known approaches in this category.

3. **Clustering :** Clustering [1],[6] is a method of bunching a set of objects belong to a similar class(using some similarity function). There are different types of clustering algorithms available such as Probabilistic Clustering, Hierarchical Clustering, Overlapping Clustering and Exclusive Clustering.

In conclusion, the good results of brain tumor segmentation by using these methods are hard to achieve. In most situations, these methods were used as a preprocessing step in the segmentation of brain tumor. Therefore, more advanced automatic methods were proposed to accord with the requirements of clinical doctors.

3. GRADIENT VECTOR FLOW

Gradient vector flow (GVF) field was came into picture by Xu and Prince in 1998 [15]as a new external force to solve two important issues in parametric active contour model proposed by Kass et al. on 1987; the small capture ranges of the external forces and problems of moving into boundary indentation.

The traditional deformable active contour model [27]-[28] is a curve $A(K) = [\ a(k), b(k)\ ]$, $k \in [0,1]$ that travels inside the image to decrease to the energy function minimum level. The curve effectively converts the shape of the primary contour by internal and external forces. The smoothing of contour is achieved by internal forces and the curve approaches the demanded boundary. The object contour will be got when the energy function is minimized. The energy is

$$E = \int 1012\, [\alpha\, |\, A'(K)\, |^2 + \beta |A''(K)|^2] + E_{ex}(A(K))\, dk \qquad (1)$$

Where, $A'(K)$ and $A''(K)$ are first and second derivatives of $A(K)$ with respect to k. The parameter γmanages the strain of the curve, δ manages its rigidity and E_{ex} is the external energy calculated from the image. The snake has to follow the Euler equation so that the energy function can be decreased to a minimum level.

$$\gamma A''(K) - \delta A''''(K) - \nabla E_{ex} = 0 \qquad (2)$$

We have defined the snake as a function of time t so that it can function dynamically, *i.e.*

$$A_t(K, t) = \gamma A''(K, t) - \delta A''''(K) - \nabla E_{ex} \qquad (3)$$

When the solution $A(K, t)$ is controlled, the term $A_t(K, t)$ reaches to zero

$$E_{ex}^{1}(a, b) = -|\nabla I(a, b)| \qquad (4)$$

$$E_{ex}^{2}(a, b) = -|\nabla [G\sigma(a, b) * I(xa, b)]| \qquad (5)$$

$$E_{ex}^{3}(xa, b) = I(a, b) \qquad (6)$$

$$E_{ex}^{4}(a, b) = G\sigma(a, b) * I(a, b) \qquad (7)$$

Where, $G\sigma(a, b)$ is a 2-D Gaussian functions with zero mean and standard deviation (σ).

$*$ = linear convolution symbol and

∇ = gradient operator.

These forces suffer with problem of small capture range and limited convergence around boundary. These problems have been overruled by Xu et al., as they proposed Gradient vector flow snake which utilizes the balanced force condition as aninitial point of snake. It defines a new static external force field called GVF field

$$F_{ex} = V(a, b) = [u(a, b), v(a, b)] \qquad (8)$$

here, u and v are the grey level changes on a-axis and b-axis of the image respectively. To get the F_{ex} following energy function has to be minimized:

$$\in = \iint \mu\, (u_a^{\,2} + u_b^{\,2} + v_a^{\,2} + v_b^{\,2}) + |\nabla f|^2\, |v - \nabla f|^2\, da db \qquad (9)$$

where, u_a, u_b, v_a, v_b are derivative of a-axis and b-axis respectively. $f(a, b)$ is the edge map like canny; which is carried out from image $I(a, b)$.The following equation can be used from [29].

$$f(a, b) = -E_{ex}^{i}(a, b) \tag{10}$$

where i = 1, 2, 3, 4. μ is a regularization parameter balancing the first term and the second term in the formula. Enhanced Possibilistic Fuzzy C-Means method is used to initialize the deformable contour and then it has been placed to final tumor boundary.

4. PROPOSED METHOD

The GVF snake starts by computing the forces in the image plain also called as GVF forces used to move the snake to the boundaries of the desired areas and it can be computed by simply using diffusion equations with gradient component and image edge map.

As the GVF snake is obtained from diffusion operations, it expands the capture range and it also pulls the contour points to the desired boundary.

A. Algorithm

The algorithm follows below mentioned sex steps :

1. The gray level edge map can be obtained bu simply applying the ∇ operator to the original image as mentioned in equation (4) and (5).
2. The vector field can be obtained by applying GVF on gray level edge map using equation (8)
3. Divide the whole image into small window of certain size lets say nxn..
4. Analyse the vectors of every sub image. Apply VEA with a specific window size at each pixel:
   (*a*) Select a window size.
   (*b*) Calculate entropy of the vectors in everyspecific window by

$$E(A) = \sum_{i=1}^{n} p(ai) \log (p(ai)) \tag{11}$$

   where A is angle of vector and $p(ai)$ is the probability of angle of every vector in the window.

$$E(A) = \text{angle of vectors entropy.}$$

   (*c*) Determine the ratio of the entropy of angle of vectors.

$$\text{Ratio} = \frac{E_A(A)}{E_B(B)} \tag{12}$$

   where EB (B) = angle of vectors entropy before flipped and E_A (A) = angle of vectors entropy after being flipped.
5. The ratio categorizes each window as the boundary or non-boundary. The classifier is given by

$$S(W, p) = \begin{cases} \text{Boundary} & \text{Ratio} < \Delta_1 \\ \text{Non boundary} & \text{Ratio} > \Delta_2 \end{cases}$$

   where W is the window mapped around the pixel and Δ_1 and Δ_2 are the thresholds generated by the clustering procedure.
6. The gray level edge map is then converted to binary image.

5. RESULT & CONCLUSION

The proposed system has been tested on limited dataset of brain MRI images having brain tumor which is available publicly. It is a kind of latest algorithm for contours which concentrate on force field and also on implementation of snake.

The outputs of the proposed system are shown in [Figure 2] which also contains image with initial contour, external energy, snake movement and external force field. These outputs are then compared with existing algorithms using three parameters sensitivity, specificity and accuracy as shown in [Table 1].

Sensitivity defines the probability of a sample having tumor. Specificity defines the probability of a sample not having tumor. Accuracy defines how accurate the results are.

$$\text{Sensivity} = \frac{TP}{TP + FN},$$

$$\text{Specificity} = \frac{TN}{TN + FP},$$

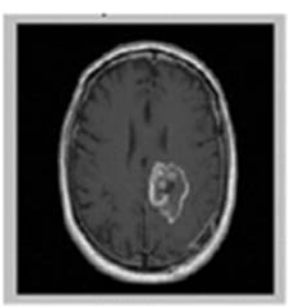
$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \text{ where,}$$

TP : True Positive,
N : True Negative,
FN : False Negative,
FP : False Positive

This comparison proved that it is better in detecting the brain tumor in brain MRI image.

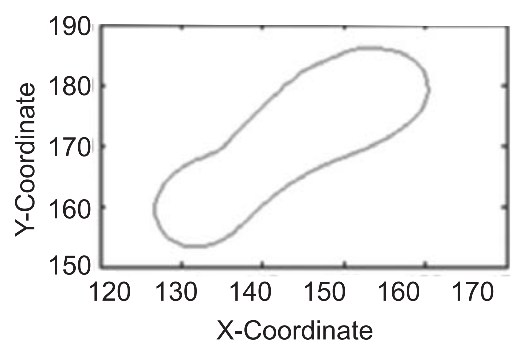
Table 1
Comparison Table of Different Methods

Critreia	*Thresholding*	*Region growing*	*GVF*
Sensitivity	1.0	0.8	1.0
Specificity	0.6	0.7	0.8
Accuracy	0.6	0.8	0.9

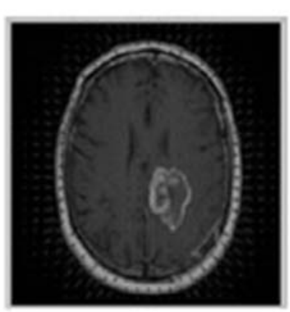


i(*a*)

i(*b*)



i(*c*)



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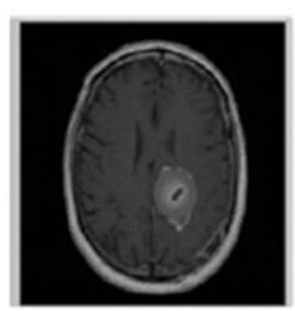

i(*e*)

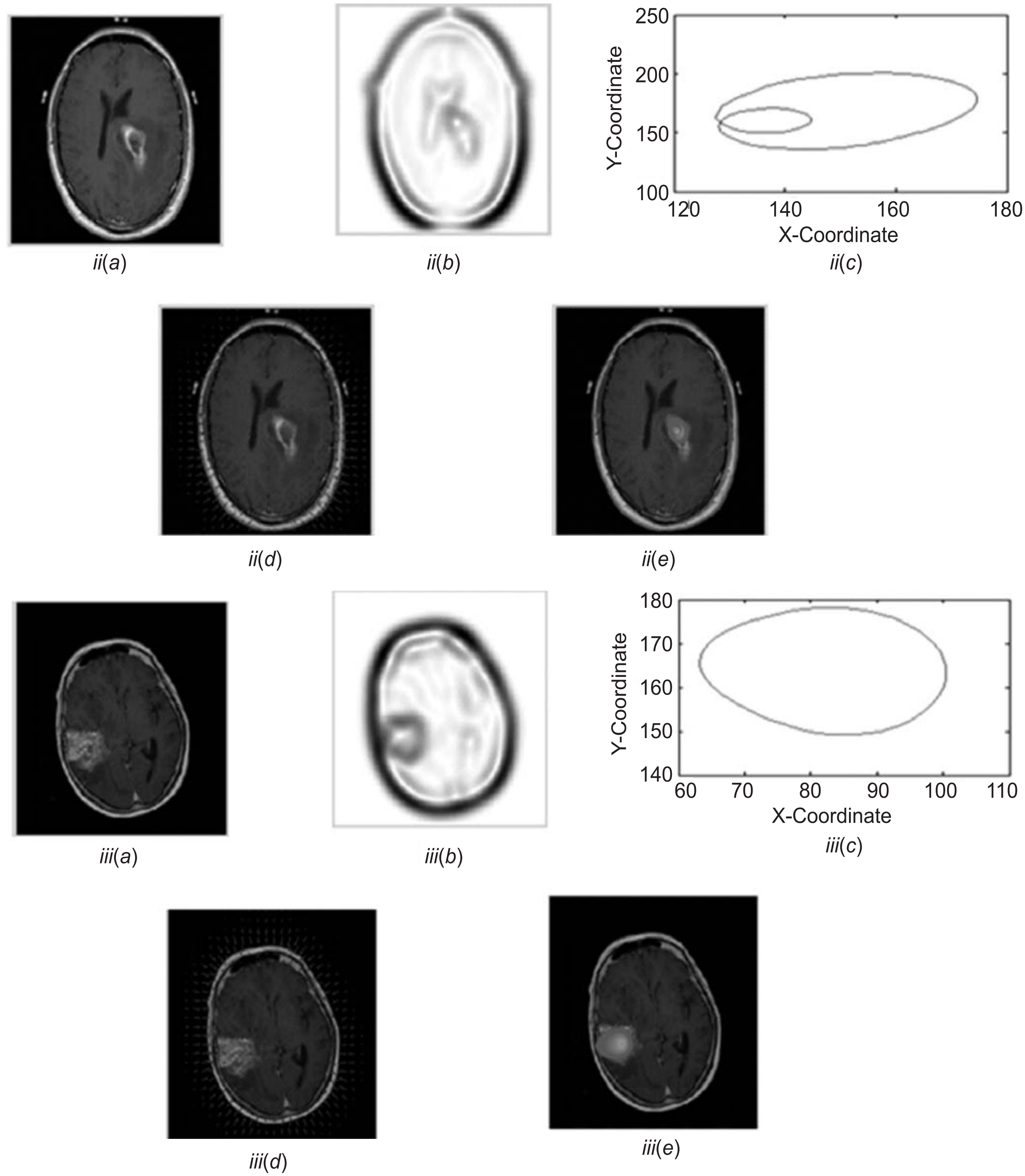

Figure : (*i*)-(*iii*)(*a*) Image with initial contour; (*b*) External energy; (*c*) Snake movement; (*d*) External force field; (*e*) Output

6. FUTURE WORK

One of the important future aspect of tumor segmentation is to identify the type of the tumor and also the growth of the tumor can also be monitored using graphs obtained by the study of the MRI images of the affected people. It can also be used to separate the three brain tissues viz. White Matter(WM), Grey Matter (GM) and Cerebrospinal Fluid (CSF).

7. REFERENCES

1. T. Logeswari and M. Karnan, "An Improved Implementation of Brain Tumor Detection Using Soft Computing," Communication Software and Networks, 2010. ICCSN '10. Second International Conference on, Singapore, 2010, pp. 147-151.
2. J. S. Lee and I. Jurkevich, "Segmentation of SAR images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 27, no. 6, pp. 674-680, Nov 1989.
3. Matalas, S. Roberts and H. Hatzakis, "A set of multiresolution texture features suitable for unsupervised image segmentation," European Signal Processing Conference, 1996. EUSIPCO 1996. 8th, Trieste, Italy, 1996, pp. 1-4.
4. Y. C. Zeng, "Pattern recognition using rotation-invariant filter-driven template matching," 2011 18th IEEE International Conference on Image Processing, Brussels, 2011, pp. 2389-2392.
5. K. S. Angel Viji and J. Jayakumari, "Modified texture based region growing segmentation of MR brain images," Information & Communication Technologies (ICT), 2013 IEEE Conference on, JeJu Island, 2013, pp. 691-695.
6. Sathya A, Senthil S, Samuel A. ”Segmentation of breast MRI using effective Fuzzy C-Means method based on Support Vector Machine”, Information and Communication Technologies (WICT),2012: 67-72.
7. Dancea O, Tsatos O, Gordan M, et al. ”Adaptive fuzzy c-means through support vector regression for segmentation of calcite deposits on concrete dam walls”, Automation Quality and Testing Robotics, 2010, 3: 1-6.
8. M. Kass, A. Witkin, and D. Terzopoulos, “Snakes: Active contour models,” International Journal of Computer Vision, vol. 1, no. 4, pp. 321-331, 1988.
9. Z. Hou and C. Han, “Forse field analysis snake: An improved parametric active contour model,” Pattern Recogint. Lett., vol. 26, no. 5, pp.513-526,2005.
10. V. Caselles, F. Catte , T. coll, and F. Dibos, “A geometric model of active contours,”NumerMath.,vol. 66, pp 1-31, 1993.
11. P.C. Yuen, G.C. Feng and J.P. Zhou, “A contour detection method : Initialization and contour model”, Pattern Recognition Letter Volume 20, Issue 2, February 1999 Pages 141-148
12. L. D. Cohen, “On active contour models and balloons,” Computer Vision, Graphics, and Image Processing. Image Understanding, vol. 53, no. 2, pp. 211-218, 1991.
13. T. Mcinerney and D. Terzopoulos, “T-snakes: Topology adaptive snakes,” Medical Image Analysis, vol. 4, pp. 73-91, 2000.
14. J. Tang, “A multi-direction gvf snake for the segmentation of skin cancer images,” Pattern Recognition., vol. 42, pp. 1172-1179, 2009.
15. C. Xu and J. L. Prince, “Gradient vector flow: a new external force for snakes,” in Proceedings of the International IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 66-71, 1997.
16. SirikanChucherd “Edge Detection of medical image processing uding vector field analysis,” 2014 11th International Joint Conference on Computer Science and Software Engineering(JCSSE).
17. S. Churcherd and A. Roodtook, “Edge enhancement using vector analysis for low contrast medical images processing,”International Conference in Information and communication Technology for Embedded System , January 2014.
18. Z. Hou and C. Han, “Forse field analysis snake: An improved parametric active contour model,” Pattern Recognit. Lett., vol. 26, no. 5, pp. 513-526, 2005.
19. Ahmed Faisal, SharminParveen, ShahriarBadsha and Hasan Sarwar, “An Improved Image Denoising and Segmentation Approach for Detecting Tumor from 2-D MRI Brain Images”, International Conference on Advanced Computer Science Applications and Technologies, pp. 452-457, 2012.
20. Tao Xu and Mrinal Mandal, “Automatic Brain Tumor Extraction from T1-weighted Coronal MRI Using Fast Bounding Box and Dynamic Snake”, Proceedings of the 34th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 2012, pp. 444-447, 2012.
21. S.M. Ali, LoayKadomAbood and Rabab SaadoonAbdoon, “Brain Tumor Extraction in MRI images using Clustering and Morphological Operations Techniques”, International Journal of Geographical Information System Applications and Remote Sensing, Vol. 4, No. 1, 2013.
22. A. Drevelegas and N. Papanikolaou, Imaging modalities in brain tumors, in Imaging of Brain Tumors with Histological Correlations. Springer, 2011, pp. 13-33.

23. S. H. Shaikh, A. Maiti and N. Chaki, "Image binarization using iterative partitioning: A global thresholding approach," Recent Trends in Information Systems (ReTIS), 2011 International Conference on, Kolkata, 2011, pp. 281-286.

24. Qian-Ru Wei, Da-Zheng Feng and Ming-Dong Yuan, "Automatic local thresholding algorithm for SAR image edge detection," Radar Conference 2013, IET International, Xi'an, 2013, pp. 1-5.

25. R. Rajesh, N. Senthilkumaran, J. Satheeshkumar, B. S. Priya, C. Thilagavathy and K. Priya, "On the type-1 and type-2 fuzziness measures for thresholding MRI brain images," Fuzzy Systems (FUZZ), 2011 IEEE International Conference on, Taipei, 2011, pp. 992-995.

26, C. Vijayakumar and D. C. Gharpure, Development ofimage-processing software for automatic segmentationof brain tumors in mri images, Journal of MedicalPhysics/Association of Medical Physicists of India, vol. 36,no. 3, p. 147, 2011.

27. M. Letteboer, W. Niessen, P. Willems, E. B. Dam,and M. Viergever, Interactive multi-scale watershedsegmentation of tumors in mr brain images, in Proc. of theIMIVA Workshop of MICCAI, Citeseer, 2001.

28. T. McInerney and D. Terzopoulos, Deformable models in medical image analysis: A survey, Medical Image Analysis,vol. 1, no. 2, pp. 91-108, 1996.

29. Chenyang Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," in IEEE Transactions on Image Processing, vol. 7, no. 3, pp. 359-369, Mar 1998.