A Hybrid Segmentation Model based on Watershed and Gradient Vector Flow for the Detection of Brain Tumor

D. Jayadevappa[1], S. Srinivas Kumar[2], and D. S. Murty[3]

[1]Research Scholar, ML Department, MSRIT, Bangalore, India
[2]Professor & Head, ECE Department, JNTU, Kakinada, A.P, India
[3]Professor & Head, ECE Department, GVPCE, Vishakapatnam, A.P, India
jayadev_latha@rediffmail.com, {samay_ssk2, dsmurty41}@yahoo.com

Abstract

Medical Image segmentation deals with segmentation of tumor in CT and MR images for improved quality in medical diagnosis. Geometric Vector Flow (GVF) enhances the concave object extraction capability. However, it suffers from high computational requirement and sensitiveness to noise. This paper intends to combine watershed algorithm with GVF snake model to reduce the computational complexity, to improve the insensitiveness to noise, and capture range. Specifically, the image will be segmented firstly through watershed algorithm and then the edges produced will be the initial contour of GVF model. This enhances the tumor boundaries and tuning the regulating parameters of the GVF snake mode by coupling the smoothness of the edge map obtained due to watershed algorithm. The proposed method is compared with recent hybrid segmentation algorithm based on watershed and balloon snake. Superiority of the proposed work is observed in terms of capture range, concave object extraction capability, sensitivity to noise, computational complexity, and segmentation accuracy.

Keywords: *Image segmentation, Watershed transform, and Gradient Vector Flow*

1. Introduction

Automated detection of tumors [1] [2], in different images is motivated by the necessity of high accuracy requirements in medical diagnosis. Image segmentation technique [3] plays crucial role in medical imaging by facilitating the delineation of regions of interest. There are numerous techniques in medical image segmentation [4] depending on the region of interest. Thresholding [5] is the most basic one**;** it is based on separating pixels in different classes depending on their gray level. In medical imaging, several variations of this approach incorporating local intensities [6] or connectivity [7] are proposed. In this case, the gray level between tumor and muscles is very close, so this technique is difficult to apply. Classifiers often use features in order to train for regions of interest recognition. But, in this case, the great variability in shape and gray level of tumors is very difficult to characterize. Clustering techniques, viz., K-means [8] are interesting methods classifying pixels in an extracted features space but they are sensitive to noise therefore, this method is not directly adapted to noisy MR images. Recently, Deformable models [9] and Watershed transform methods [10] are efficient for medical image segmentation.

2. Related work

Important issues concerning fundamental aspects of image segmentation methods viz., initialization, convergence, ability to handle topological changes, stopping criteria and over-segmentation, must be taken into account. Segmentation by Deformable models [11] uses image forces and external constraints to guide the evolution. Former versions [12] [13] of this method require the initialization to be done close to the boundaries of the objects, to guarantee proper convergence. Modeling the contours in the level set framework [14] easily solves the topological problem, but do not address the initialization and convergence issues. Gradient Vector Flow [15] [16] largely solves the poor convergence by making use of the amplification of image gradient to increase the snake capture range but should contain the medial axis of the object. Watershed transform [17] treats the image as a 3D surface, starts the region growing from the surface minima. However it may lead to a strong over-segmentation [18][19][20] if proper image smoothing is not provided. The marker controlled watershed transform [21][22][23] overcomes the over-segmentation problem up to some extent. However, highly specialized filters are required to extract the markers. To overcome these shortcomings, recently hybrid models are proposed.

Kiran et al. [24] proposed watersnakes, make snakes unsupervised and prevent the snake from getting trapped into local minima but, traditional snakes could not be initialized far away from the target edges, so they cannot drive watershed lines resulting over-segmentation. In [25] a snake zone is defined around the object boundaries where the corresponding watershed points are the object boundary and energy minimization is carried out using dynamic programming, but this does not guaranty automatic initialization, resulting poor convergence. Dagher et al. [26] succeeded to tackle the problem of over-segmentation while preventing under-segmentation by introducing water-balloons, it combines both watershed and balloon snake to ensure automatic initialization of snakes and parameter optimization, but this hybrid model suffers with poor capture range for the image with overlapping tissues and its inability to extract concave objects. Further, the use of this technique in real applications is limited due to high computational time.

In this paper, a new hybrid model for segmentation of brain tumors from MR images is proposed. It is aimed to increase the capture range to the image border and to improve the concave object extraction capability. This proposed method substantially reduces the above mentioned problem of convergence in noisy images and computational complexity. The proposed method is compared with recent hybrid segmentation algorithm [26] based on watershed and balloon snake. Superiority of the proposed work is observed in terms of capture range, concave object extraction capability, sensitivity to noise, computational complexity and segmentation accuracy.

This paper is organized as follows: the definitions of the watershed with markers and GVF snakes are summarized in section 3. The new hybrid model is proposed in detail in section 4. Experimental results of the new model are presented in section 4. Concluding remarks are given in section 6.

3. Background

3.1 Watershed transform

Assume that the image f is an element of the space $C(D)$ of a connected domain D then the topographical distance between points p and q in D is,

$$T_f(p,q) = \inf_\gamma \int \left\| \nabla f(\gamma(s)) \right\| ds \quad (1)$$

where, '$\inf_\gamma$' is over all paths (smooth curve) inside D, based on this Roerdink et al. [27] defines the watershed as follows.
Let $f \in C(D)$ have a minima $\{m_k\}_{k \in I}$, for some index set I. The catchment basin $CB(m_i)$ of a minimum m_i is defined as the set of points $C \in D$, which are topographically closer to m_i than to any other regional minimum m_j.

$$CB(m_i) = \{x \in D \mid \forall_j \in I \setminus \{i\} : f(m_i) + T_f(x, m_i) < f(m_j) + T_f(x, m_j)\} \quad (2)$$

The watershed of f is the set of points which do not belong to any catchment basin;

$$W_{shed}(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right) \quad (3)$$

Let W be some label, $W \in I$. The watershed transform of f is a mapping of $\lambda : D \to I \cup \{W\}$ such that $\lambda(p) = i$ if $p \in CB(m_i)$ and $\lambda(p) = W$ if $p \in W_{shed}(f)$. So the watershed transform of f assigns labels to the points D, such that (i) different catchment basins are uniquely labelled, and (ii) a special label W is assigned to all points of the watershed of f.

The watershed transform is the method of choice for image segmentation in the field of mathematical morphology [28][29] has proven to be a powerful and fast technique for both contour detection and region-based segmentation. However, recent progress allows a regularization of the watershed lines with an energy-based watershed algorithm (water snakes) [25]. The proposed work is based on GVF snake which easily allow a regularization of the watersheds.

The advantage of the watershed transform is that, it produces closed and adjacent contours including all image edges. However, often the watershed produces a severe over-segmentation also. Some solutions of the over-segmentation are addressed in [18]. The marker-controlled watershed segmentation has been shown to be a robust and flexible method for segmentation of objects with closed contours, where the boundaries are expressed as ridges [25]. Markers are placed inside an object of interest; internal markers associate with objects of interest, and external markers associate with the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors.

3.2 Gradient Vector Flow

Active contour [30] is an energy minimizing spline, its energy depends on its shape and location within the image.
An energy function $E(c)$ can be defined on the contour as

$$E(c) = E_{\text{int}} + E_{ext} \quad (4)$$

where, E_{int} and E_{ext} denote the internal and external energies respectively. The internal energy function determines the regularity, i.e., smooth shape, of the contour. A common choice for the internal energy is a quadratic functional given by

$$E_{\text{int}} = \int_0^1 \alpha \left| c'(s) \right|^2 + \beta \left| c''(s) \right|^2 ds \quad (5)$$

Here, α controls the tension of the contour, and β controls the rigidity of the contour. The external energy term that determines the criteria of contour evolution depending on the image $I(x, y)$, and can be defined as

$$E_{ext} = \int_0^1 E_{img}\left(c(s)\right) ds \quad (6)$$

$E_{img}(x, y)$, denotes a scalar function defined on the image plane, so that local minimum of E_{img} attracts the snakes to edges. Solving the problem of snakes is to find the contour that minimizes the total energy term E using Greedy algorithm [31] with the given set of weights α and β . Initialization of object boundary is the limitation to use this model for segmentation, which can be overcome by other models.

GVF snake [15][16] has been defined as an external force to push the snake into objects concavity.

It is a 2D vector field $V(s) = \left[u(s), v(s)\right]$, which minimizes the following energy functional

$$E = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + \left|\nabla f\right|^2 \left|V - \nabla f\right|^2 dxdy \quad (7)$$

where, u_x , u_y , v_x , and, v_y are the spatial derivatives of the field, μ is the regularization parameter, which should be set according to the amount of noise of the image and ∇f is the gradient of the edge map which is defined as the negative external force i.e. $f = -E_{ext}$. The behavior of the GVF approach that is able to converge to boundary concavity can be explained from the Euler equations used to find the GVF field.

These Euler equations are:

$$\mu \nabla^2 u - \left(u - f_x\right)\left(f_x^2 + f_y^2\right) = 0 \quad (8a)$$

$$\mu \nabla^2 v - \left(v - f_y\right)\left(f_x^2 + f_y^2\right) = 0 \quad (8b)$$

where, ∇^2 is the Laplacian operator. Compared to the balloon force, the GVF approach is proven to converge relatively faster. This is caused by the external force employed by the GVF that make the capture range of the active contours bigger. Since the GVF uses the classical formulation, its basic principle is to diffuse the edge information from the object boundary to the rest of the image. The generation of GVF is iterative and computationally intensive.

4. The proposed hybrid model

The algorithm proposed in this paper belongs to the category of hybrid techniques, since it results from the integration of edge and region-based techniques through the morphological watershed transform. This algorithm delivers accurately localized and closed object contours while it requires a small number of input parameters (Markers and GVF parameters optimization). Initially, the noise corrupting the image is reduced by a noise reduction technique that preserves edges remarkably well, while reducing the noise quite effectively. At the second stage, this noise suppression allows a more accurate calculation of the image gradient and reduction of the number of the detected false edges [32]. Then, the gradient magnitude is input to the watershed detection algorithm, which produces an initial image tessellation into a large number of primitive regions [17].

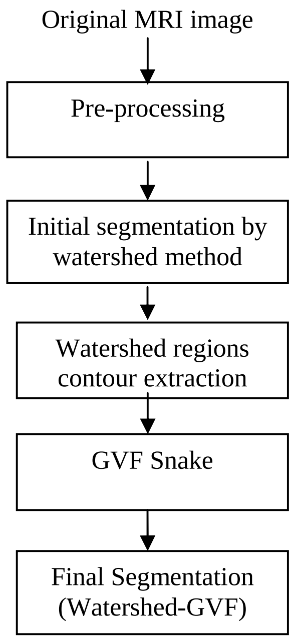


Figure1. Flow diagram of the proposed segmentation algorithm (hybrid model)

This initial over-segmentation is due to the high sensitivity of the watershed algorithm to the gradient image intensity variations, and, consequently, depends on the performance of the noise reduction algorithm.

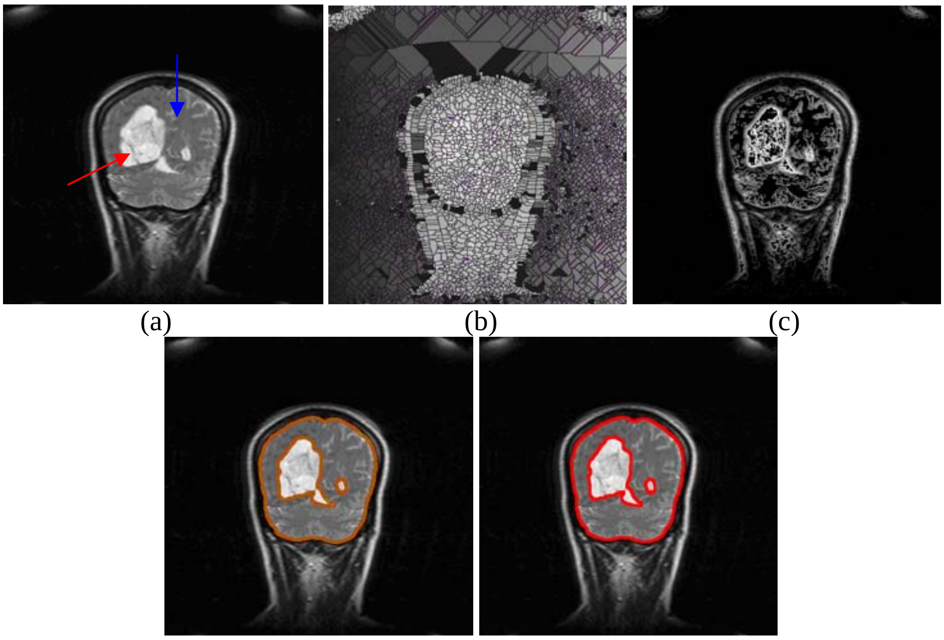
Over-segmentation is further reduced by markers, i.e., gradient magnitudes prior to the application of the watershed transform. The output of the watershed transform is the starting point of a bottom-up hierarchical merging approach. Figure (1), illustrates the proposed hybrid segmentation algorithm. This method consists of different modules. Before carrying out segmentation, the MR image [33] must undergo a preprocessing step to avoid the over-segmentation. The second module is the Watershed transform based on the concept of marker controller, deals with the immersion principles, applied to a topographic image representation to extract watershed region contours. Those contours will constitute the initial GVF snakes that will deform to capture the target edges. The last part combines the Watershed and GVF to segment tumor from brain MR image, i.e., coupling the smoothness of the edge map to the initial size of the GVF snake by automatic initialization of contour in order to preserve a limited number of suspect areas. GVF snakes have a large capture range so correct snake deformation can be achieved even if the contour of the watershed region is far away from the target edges. So, GVF snake is most suitable to drive the watershed contours towards tumor boundaries. Currently, development of an efficient detection model that assists the radiologist has thus become very interesting for a better diagnostic.

4.1. Advantages of the proposed model

The proposed method has the following advantages:

- Efficient edge preserving smoothing guided by GVF.
- Ability to automatically detect all image minima and to make the regions grow inside the respective zones, of influence; a property inherited from the watershed transform.
- Ability to automatically stop the growing process whenever two users labeled regions get into contact; a characteristics difficult to implement using Level set.
- Ability to change the image topology by using a simple merging mechanism, thus reducing over-segmentation
- Relatively low sensitiveness to noise
- Execution time directly proportional to the image size.

5. Experimental Results and Discussion



(a) (b) (c)

(d) (e)

Figure 2. Segmentation using proposed hybrid model. (a) Original image, (b) Traditional watershed segmentation (c) Gradient image, (d) Watershed regions and (e) Final segmentation.

In this section, the experimental results of the proposed model compared to both GVF snakes and Water- balloons are shown. In the experiments below, the proposed method is tested with data sets of MRI slice of brain of size 512 x 512 pixels attained of tumors pathology. The performance of the proposed model is evaluated in terms of capture range, concave object extraction capability and computational time to achieve better segmentation accuracy and reproducibility. The proposed segmentation strategy is presented in Figure.2. Fig. 2(a), 2(b), and 2(c) corresponds to original MR image having brain tumor, traditional watershed, and gradient image respectively. Watershed regions, after applying marker - controlled watershed algorithms are shown in fig. 2(d). The final segmentation combining watershed and GVF is as shown in fig. 2(e). The red and blue arrows in the fig. 2(a) correspond to the tumor area and non tumor area respectively.

5.1 Performance of the proposed model in the presence of noise

Performance of each method can be observed if they are applied to a set of images having characteristics such as irregular illumination, occlusions, noisy or smoothed regions, sharp or diffuse edges. So, the robustness of the proposed model is tested with noisy images. Original MR images with Gaussian noise, speckle noise, and salt and pepper noise are given in Fig. 3(a), (b), and (c) respectively. The capture range of the proposed segmentation model in the presence of various types of noise is observed in Fig. 3(d), (e), and (f) respectively.

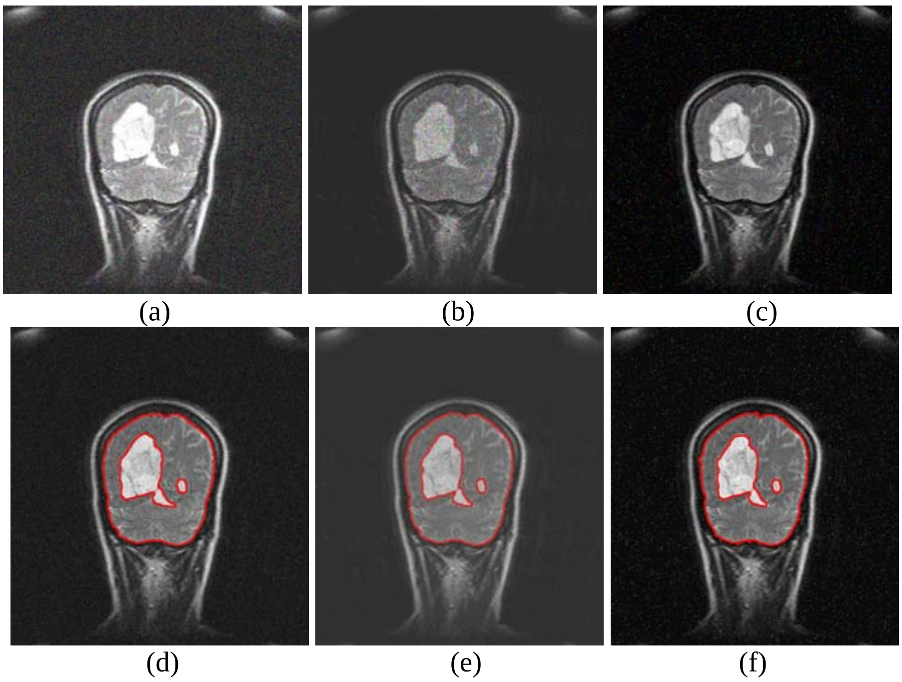


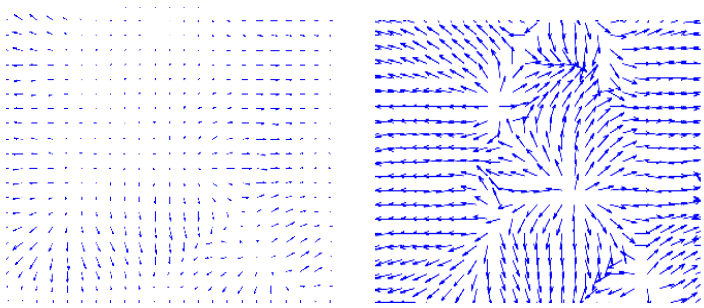
Figure 3. Segmentation results of the proposed method in the presence of various types of noise. (a) MR image with Gaussian noise ($\sigma = 0.2$) (b) MR image with Speckle noise ($\sigma = 0.2$) and (c) MR image with Salt & pepper noise ($\sigma = 0.2$), (d) Segmentation with Gaussian noise, (e) Segmentation with speckle noise and (f) Segmentation with salt & pepper noise.

5.2. Comparison with the other methods

The comparison given in this section shows the difference of the proposed approach with the GVF approach of Xu and Prince [16] and with the Water-balloon approach [26]. The superiority of this work is compared in terms of capture range, sensitivity to noise, concave object extraction capability, computational complexity and segmentation accuracy.

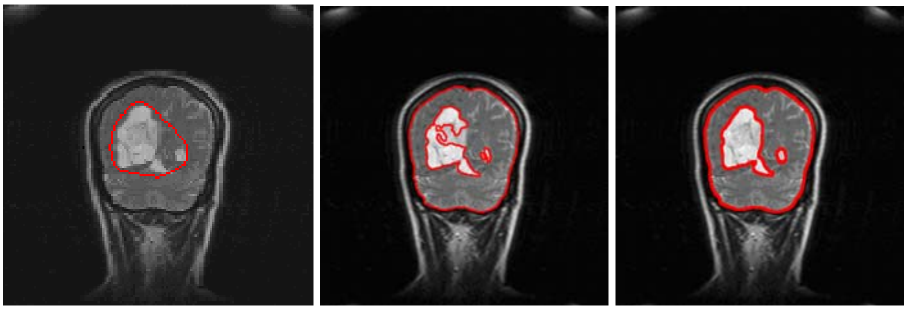
5.2.1 Capture range

The external force of traditional snake [30] defined by the gradient of a Gaussian filtered image is used in water-balloons [26] as shown in fig. 4(a). This causes the contour to have a very limited capture range. If an object in the image has an edge which shows a blurred concavity then the traditional snake will have a problem in tracing the edge at this part. A conventional procedure is to increase the σ value of the Gaussian filter. However, the edge of the object will also be blurred and cannot be traced accurately. To overcome this problem GVF snake is proposed [16].



(a) (b)

Figure 4. Image forces. (a) Traditional potential force in balloon snake and (b) Force in GVF snake.

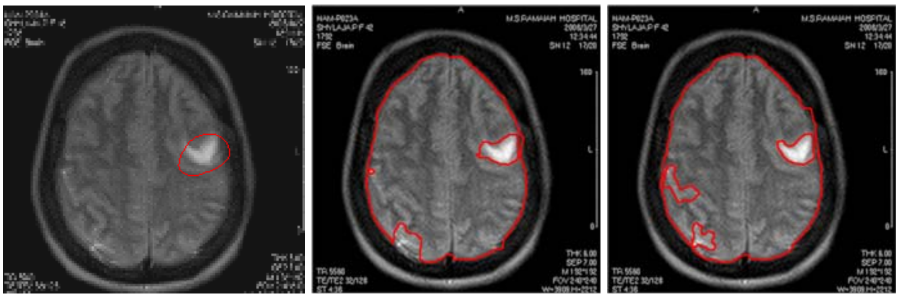


(a) (b) (c)

Figure 5. Comparative results of the proposed method with respect to capture range. (a) GVF method, (b) Water-balloon method and (c) Proposed method.

This method makes use of the normalized GVF as the static external force of the snake (Eq.7) to increase the snake capture range and evolution speed. Fig 4(b) shows the external force of the GVF. However, the generation of GVF snake is a computationally intensive process and extensive iterations are required. As mentioned before, this drawback is overcome by combining watershed transform and GVF snake. Therefore, the combination of watershed and GVF snake provides excellent capture range. We compare the capture ranges of GVF snake, water-balloon model with the proposed hybrid method with an image size of 512 x 512 pixels. The results of GVF snake, water-balloon and the proposed models are shown in figs. 5(a) - (c) respectively. The results show that the proposed hybrid model moves smoothly towards the object boundary and captures the tumor accurately but both GVF snake and water-balloon fails. As shown in fig. 5(a), GVF without watershed blocks the contour moving towards the object resulting poor convergence. In fig. 5(b), the capture range of the water-balloon method is better than the GVF method because, the watershed is combined with the balloon snake. However, it is observed that still the contour leaks through the low contrast edges. Whereas, in the proposed method, the contour survives with both weak and strong edges resulting better convergence to the object boundary.

5.2.2 Concave object extraction capability



(a) (b) (c)

Figure 6. Comparative results with respect to concave object extraction capability. (a) GVF method, (b) Water-balloon method and (c) Proposed method.

In this section, the concave object extraction capability of GVF, Water-balloon and the proposed model is compared using the MR image having the concave shape object boundary. The results are demonstrated in figure 6. It is observed that GVF snake alone cannot converge to the concave tumor boundary, in contrast both water-balloon and the proposed methods move onto the concave region successfully and extract the object correctly but there is a contour leakage in case of water-balloon method. The result in fig. 6(c) shows that, the proposed model exactly converges to the concave object boundary and hence it accurately segments the tumor in the given MR image.

5.2.3 Sensitivity to noise

The proposed method is compared with GVF snake and water-balloon methods and the experimental results shows that, the proposed approach is insensitive to noise.

Fig. 7, illustrates the segmentation of the tumor from MR image added with Gaussian noise ($\sigma = 0.2$), speckle noise ($\sigma = 0.2$), and salt & pepper noise ($\sigma = 0.2$). In fig. 7(a)-(c), it is observed that, GVF snakes often converge to the local minimum in the presence of noise, but they do not converge to the object boundary.). In fig. 7(d)-(f), water-balloon method significantly increased the capture range towards the target but its contour unable to extract watershed regions near the weak edges, resulting poor object boundary extraction. In this situation the proposed model shown in Fig. 7(g)-(i), is most suitable to segment the tumors in the presence of various types of noise as mentioned earlier.

5.2.4 Computational complexity

In this work, MATLAB 7.1 version is used on dual core Pentium–IV processor with 1GB RAM in implementing various segmentation methods. As far the computational complexity is concerned, it is observed that, the proposed method reduces the computation time compared to GVF and Water-balloon methods. In case of GVF snake, computation time is involved in both generating the external forces, and evolution of the contour to reach the desired object boundary. It is also observed that, the capture range of GVF snake can be improved by increasing the number of iterations of GVF. However, this will increase the computational time significantly and even it is high for concave object extraction.

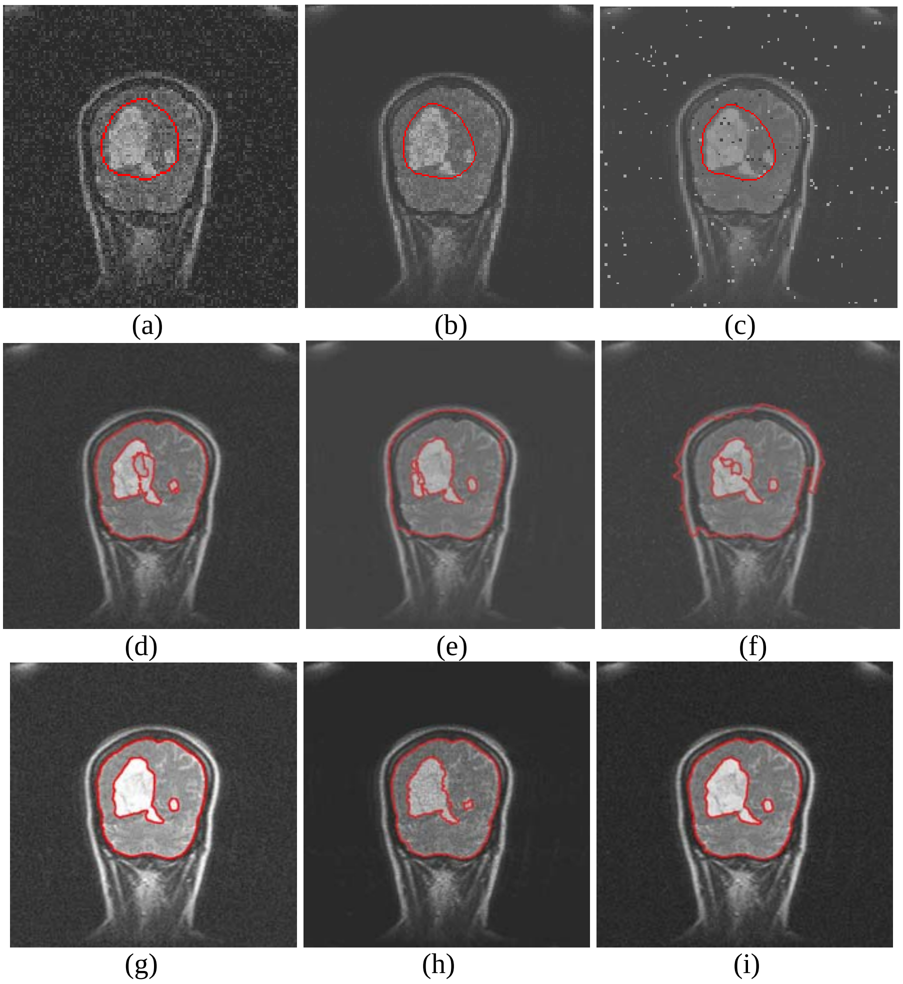


Figure 7. Segmentation results in the presence of Gaussian noise, speckle noise, and salt & pepper noise respectively. (a)-(c) GVF method (d)-(f) Water-balloon method and (g)-(i) Proposed method.

In case of water-balloon, watershed regions will constitute the initial snake that will deform to capture the object edges. Since traditional snake suffers with poor capture range, so as to increase the number of iterations to converge, resulting increased computational time.
In the proposed method, marker controlled watershed is directly applied on the gradient image to segment watershed regions; this significantly reduces the computational time compared to earlier methods. Table 1, and Fig. 8 summarizes the computational time involved in various methods to capture the tumor in original image, image with concave object boundary, and noisy image (Gaussian noise of $\sigma = 0.2$).

5.2.5 Segmentation accuracy

The proposed method is evaluated with another performance parameter called segmentation accuracy. The percentage of segmentation accuracy can be defined as,

$$\%\ \text{Segmentation accuracy} = \frac{\text{Number of correctly classified pixels for segmented area}}{\text{Total number of pixels}}$$

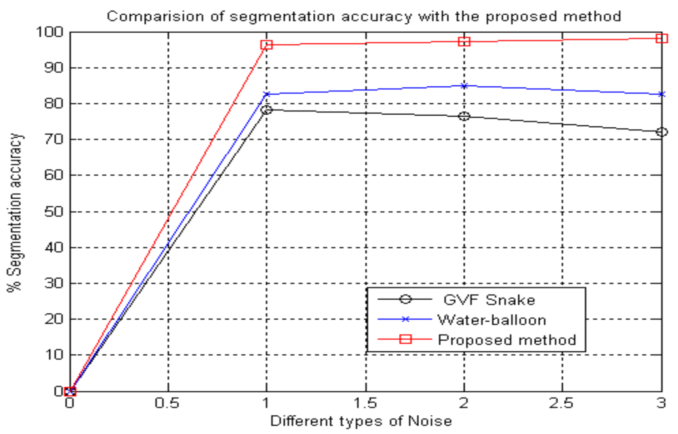


Figure 9. Segmentation accuracy of GVF, water-balloon and the proposed method in the presence of Gaussien noise, Speckle noise and Salt & pepper noise.

Table 1. Comparison of computational time with the proposed model.

SL. No.	Type of images	Computation time		
		GVF	Water-balloon	Proposed method
1	Original image	220s	75s	28s
2	Image with Concave object	285s	70s	32s
3	Noisy image (Gaussian noise $\sigma = 0.2$)	300s	82s	35s

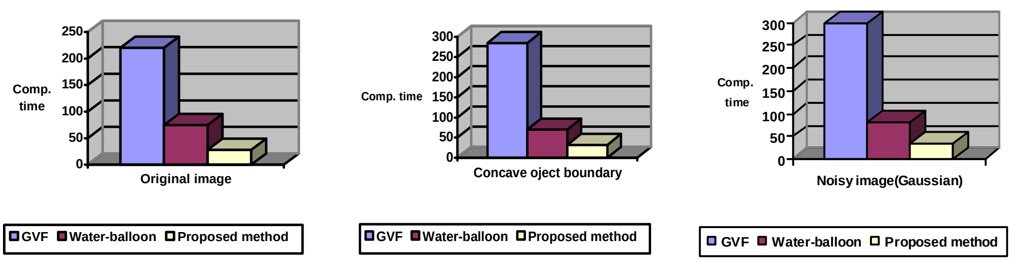


Figure 8. Comparison of the computational time involved in various methods. (a) Time involved for original image, (b) Time involved for image with concave object and (c) Time involved for image added with Gaussian noise ($\sigma = 0.2$).

The performance of the proposed method is also tested with Gaussian noise, Speckle noise and salt & pepper noise. The graph shown in fig. 9, illustrates the segmentation accuracy. It is observed that, the proposed method has better segmentation accuracy compared to GVF and water-balloon methods in the presence of noise.

6. Conclusions and future work

In this paper, hybrid segmentation model combined with GVF snake and marker controlled watershed is introduced to segment the brain tumor. Real MR images are used for the validation of the proposed framework. This method is tested with different images including noisy gray level images. The computation requirement of the whole scheme is very low and gives better capture range.

In comparison with GVF snake and water-balloon methods, the proposed method gives robust contour that converges to boundaries of tumors of different sizes in very noisy images The experimental results show that the algorithm is able to speed up the process considerably while capturing the desired object boundary compared to other methods. Nevertheless, this is a generic segmentation technique working on all kinds of tumors in any gray level modality. Future work includes by treating the image as a 3D time-dependent surface and selectively deforming this surface based on variational approaches in conjunction with the anisotropic filter. This effectively removes most of the non-significant image extrema, which will remove the added parameter and allow the technique to be used with less tuning and interaction by the user.

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Authors

D Jayadevappa was born in Kabbur, Karnataka, India in 1970. He received his B.E degree in Instrumentation Technology from Siddaganga Institute of Technology, Tumkur, Bangalore University in 1994, M.Tech degree from Jayachamarajendra College of Engineering, Mysore, Visveswaraya Technological University in 2000 with specialization in Bio-Medical Instrumentation and presently pursuing Ph.D degree from JNTU college of Engineering, Kakinada, A.P, India.

He is currently working as an Assistant Professor in the department of Medical Electronics, M. S. Ramaiah Institute of Technology, Bangalore. He has 13 years of teaching and industrial experience and is the Member of IAENG, IETE, and ISTE. His areas of interests are Digital Image Processing and Bio-Medical Signal Processing.

S. Srinivas Kumar was born in Kakinada, AP, India in 1962. He graduated from Nagarjuna University in 1985. He received M.Tech degree from Jawaharlal Nehru Technological University, AP, India in 1987 & received Ph.D. from E& ECE Department, IIT, Karagpur in 2003. Currently he is Professor and Head of ECE Department, JNTU College of Engineering, Kakinada, AP, India. He has twenty one years of experience in teaching undergraduate and post-graduate students and guided number of post-graduate theses. He has published 25 research papers in National and International journals. Two research scholars have submitted their thesis under his guidance. Presently, he is guiding three Ph. D students in the area of Image processing. His research interests are in the areas of digital image processing, computer vision, and application of artificial neural networks and fuzzy logic to engineering problems.

D. S Murty received B.E degree in ECE from Andhra University in 1980, M.Tech from IIT, Kharagpur in 1982, and the Ph.D degree from Birla institute of Technology, Ranchi in 1994. Currently working as professor & Head ECE department, at GVPCE, Vishakhapatnam. He has 20 years of Industrial experience at SAIL, Ranchi in R & D section. He has 24 Research publications at national and global levels. He was the Innovator of 'Operator Strategy Mode' economical automatic system for improving productivity of Merchant Mill & automatic skidding detection system for Rolling Mills. He has two patents in international level (US 6,496,120 B1, Dec, 17, 2002).