

# Automatic segmentation of tumour in MRI brain image using modified GVF model

D.Selvaraj<sup>1</sup>

<sup>1</sup>Research Scholar, Department of Electronics & Communication Engg., Sathyabama University  
Chennai, India

<sup>1</sup>mails2selvaraj@yahoo.com

R.Dhanasekaran<sup>2</sup>

<sup>2</sup>Director, Research  
Syed Ammal Engineering College,  
Ramanathapuram, India

<sup>2</sup>rdhanasekar@yahoo.com

**Abstract**— In this paper, we have proposed an effective brain tumour segmentation technique based on modified Gradient vector flow field model. This method is automatic and does not require human interaction. This proposed method involves 2 stages, preprocessing and segmentation. During preprocessing, the non-brain regions are removed using morphological operators and during segmentation process, the tumour is segmented using modified GVF model. Segmentation results show that the proposed method is robust to noise. The proposed method uses T2 weighted images. The proposed method produced appreciative results.

**Keywords**— GVF, Skull stripping, MRI Image, Morphological Operator, Tumour detection, Brain segmentation

## I. INTRODUCTION

Brain is one of the vital organ of our body. Due to its complexity, it is difficult to distinguish its various components and analyze it. Even though there are several imaging techniques, Magnetic resonance imaging is the commonly used technique for analyzing brain. MRI is a non-invasive technique that can produce very detailed contrast information between the soft tissues. MRI of the brain is an invaluable tool for the doctors in diagnosing various brain diseases and in tumour detection. The MRI of the brain can be divided into 3 regions namely Grey matter (GM), White matter (WM), Cerebrospinal fluid (CSF).

The primary goal of MRI brain image segmentation is to partition the given brain image in to anatomical structures representing Grey matter, White matter, cerebrospinal fluid, skull, scalp and later to detect abnormalities in these tissues. Even though greater number of segmentation methods is available in the literature to segment images according to various criteria such as grey level, texture. Precise segmentation and classification of abnormalities are still a challenging and complicated task because of inherent noise, partial volume effect, different shapes, locations and image intensities of different types of tumour.

Supervised segmentation methods exhibit the problem of repeatability due to inter-observer variance introduced over multiple trials of training. Further, supervised segmentation methods are time consuming and require domain experts. So, these limitations suggest the need for an automatic method for segmentation.

In this paper, a simple automatic segmentation method is presented which can separate the brain tumour from normal

tissues. An initial preprocessing is done based on morphological operators and thresholding technique that we have proposed in our previous research papers [1, 2]. Then, the modified gradient vector flow field model and region based image segmentation techniques are used for refining the result to obtain the final tumour segmentation.

The rest of this paper is organized as follows: section 2 presents the overview of the proposed method. Section 3 gives the concept of GVF, section 4 explains new region growing algorithm based on modified GVF field model. Section 5 presents the detailed experimental results. Lastly, section 6 concludes the paper.

## II. OVERVIEW OF PROPOSED METHOD

The proposed method is composed of 2 major stages as shown in figure 1. In stage1, the input image is preprocessed, i.e., skull is removed using mathematical morphological operators as shown in figure 2. The skull stripped image is further smoothed using 2D Gaussian filter. The smoothed image is shown in figure 3.

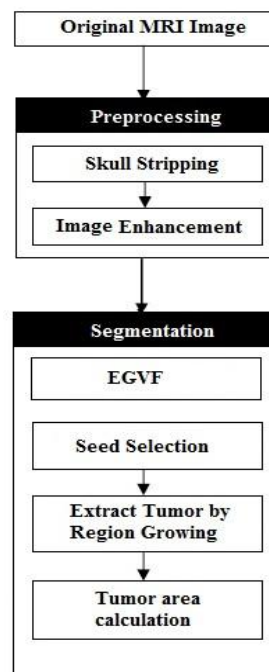


Fig. 1. Proposed Method

A two-dimensional Gaussian function is

$$f(x, y) = A \exp\left(-\left(\frac{(x-x_0)^2}{2\sigma_x^2} + \frac{(y-y_0)^2}{2\sigma_y^2}\right)\right) \quad (1)$$

Here the coefficient  $A$  is the amplitude,  $x_0, y_0$  is the centre and  $\sigma_x, \sigma_y$  are the  $x$  and  $y$  spread parameter. Better image smoothing is implied through larger  $\sigma$ .

In Stage2, an external force field is created around the abnormal region using GVF field model. The force vectors from 8-neighbourhood for each pixel is valued. The pixel having the highest score is considered as seed pixel. Using the seed pixel, a region is grown using region growing algorithm and later the area of tumour is calculated.

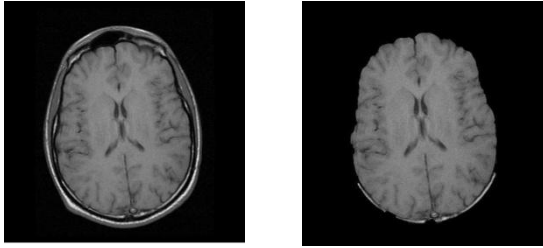


Fig. 2 (a) Input Image (b) Skull Stripped Image

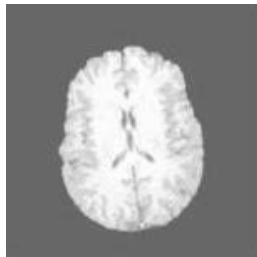


Fig. 3 (a) Smoothened Image

### III. GRADIENT VECTOR FLOW MODEL

Gradient vector flow (GVF) fields are dense vector fields, generated by diffusing the gradient vectors of a gray level or binary edge map, derived from an image [4, 8]. The gradient vector flow field is defined to be vector field. (as shown in figure 4.

$$V(x, y) = [u(x, y), v(x, y)] \quad (2)$$

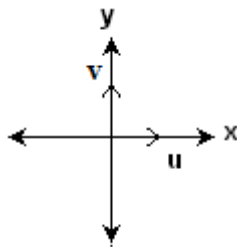


Fig.4. Two-component vector definition for GVF field model

The diffusion process grants to the GVF an increased capture range. Thus, an initial feature point can be guided to a

desired boundary even when it is initialized away from the boundary.

A GVF model as a force field of vectors [5] and they minimized the following energy function to derive the GVF field.

$$E = \iint \mu |\nabla V|^2 + |\nabla f|^2 |V - \nabla f|^2 dx dy \quad (3)$$

Where,  $|\nabla V|^2 = (u_x^2 + u_y^2 + v_x^2 + v_y^2)$ .

The parameter ' $\mu$ ' is a regularization parameter governing the trade off between the first and the second term in the integrand. This parameter should be set according to the amount of noise present in the image

Let a point in 'n' dimensional space  $R^n$  can be defined by  $X = (x^1, x^2, x^3, \dots, x^n)$ . The scalar function at  $X$  is defined by  $f(X) = f(x^1, x^2, x^3, \dots, x^n)$  and the vector function at  $X$  is defined by  $v(X) = (v^1(x^1, x^2, x^3, \dots, x^n), v^2(x^1, x^2, x^3, \dots, x^n), \dots, v^n(x^1, x^2, x^3, \dots, x^n))$ . Assume these functions are defined in a bounded domain  $\Omega \subset R^n$  with  $\partial\Omega$  as its boundary. GVF is defined as the vector function  $v(x)$  in the sobolev space  $W_2^2(\Omega)$  [6] that minimize the following function

$$\int_{\Omega} \mu |\nabla v|^2 + |\nabla f|^2 |v - \nabla f|^2 dx \quad (4)$$

The above equation (4) can be written in its component form as,

$$\int_{\Omega} \mu \sum_{i=1}^n \sum_{j=1}^n \left(\frac{\partial v^i}{\partial x^j}\right)^2 + \sum_{i=1}^n \left(v^i - \frac{\partial f}{\partial x^i}\right)^2 \sum_{i=1}^n \left(\frac{\partial f}{\partial x^i}\right)^2 dx \quad (5)$$

The above equation (5) can be written in simple form as,

$$J = \int_{\Omega} F(x^1, \dots, x^n, v^1, \dots, v^n, \dots, \frac{\partial v^1}{\partial x^1}, \dots, \frac{\partial v^1}{\partial x^n}, \dots, \frac{\partial v^n}{\partial x^1}, \dots, \frac{\partial v^n}{\partial x^n}) dx$$

From calculus of variations [7],  $J$  is stationary if and only if its first variation vanishes i.e.,

$$\delta J = 0 \quad (6)$$

For every permissible variation  $\delta v^i \in W_2^2(\Omega)$ ,  $i=1, 2, \dots, n$ . By applying the laws of variation [8], 'J' can be derived as,

$$\delta J = \delta \int_{\Omega} F \left( x^1, \dots, x^n, v^1, \dots, v^n, \dots, \frac{\partial v^1}{\partial x^1}, \dots, \dots, \frac{\partial v^1}{\partial x^n}, \dots, \frac{\partial v^n}{\partial x^1}, \dots, \frac{\partial v^n}{\partial x^n} \right) dx$$

$$= \int_{\Omega} \left[ \sum_{i=1}^n \frac{\partial F}{\partial v^i} \delta v^i + \sum_{i=1}^n \sum_{j=1}^n \frac{\partial F}{\partial v_j^i} \delta v_j^i \right] dx, \left( v^i \equiv \frac{\partial v^i}{\partial x^j} \right)$$

$$= \sum_{i=1}^n \left[ \int_{\Omega} \frac{\partial F}{\partial v^i} \delta v^i dx + \int_{\Omega} \sum_{j=1}^n \frac{\partial F}{\partial v_j^i} \delta v_j^i dx \right]$$

Using integration by parts, we have

$$\delta J = \sum_{i=1}^n \left[ \int_{\Omega} \frac{\partial F}{\partial v^i} \delta v^i dx - \sum_{j=1}^n \int_{\Omega} \left( \frac{\partial}{\partial x^j} \right) \frac{\partial F}{\partial v_j^i} \delta v^i dx + \int_{\partial\Omega} \eta^j \frac{\partial F}{\partial v_j^i} \delta v^i dS \right]$$

where,  $\eta^j$  is the projection of outward normal unit vector  $\eta$  along  $x^j$  axis at  $\partial\Omega$  and  $dS$  represents the element of area on

the boundary  $\partial\Omega$ . After rearranging the above equation, we get,

$$\delta J = \sum_{i=1}^n \int_{\Omega} \left[ \frac{\partial F}{\partial v^i} - \sum_{j=1}^n \frac{\partial}{\partial x^j} \left( \frac{\partial F}{\partial v^j} \right) \right] \delta v^i dx + \sum_{i=1}^n \sum_{j=1}^n \int_{\partial\Omega} \frac{\partial F}{\partial v^j} \eta^i \delta v^i dS = 0$$

Since variations of  $\delta v^i$ ,  $i=1,2,3,\dots,n$  are independent of each other, it follows that all the coefficients of  $\delta v^i$  in the integrals must each vanish identically in  $\Omega$ , giving n scalar Euler equation.

$$\frac{\partial F}{\partial v^i} - \sum_{j=1}^n \frac{\partial}{\partial x^j} \left( \frac{\partial F}{\partial v^j} \right) = 0 \quad (7)$$

and n boundary conditions

$$\sum_{j=1}^n \left( \frac{\partial F}{\partial v^j} \right) \eta^i = 0 \quad (8)$$

Where,  $i=1, 2, \dots, n$ . Substituting the definition of F in equation (5) and after some algebra, we obtain the Euler equations and boundary conditions for GVF as follows.

$$\mu \sum_{j=1}^n \frac{\partial^2 v^i}{\partial (x^j)^2} - \left( v^i - \frac{\partial f}{\partial x^j} \right) \left( \frac{\partial f}{\partial x^j} \right)^2 = 0 \quad (9)$$

$$\sum_{j=1}^n \frac{\partial v^i}{\partial x^j} \eta^i = 0 \text{ on } \partial\Omega \quad (10)$$

where  $i=1,2, \dots, n$ . equations (8) and (9) can be written in a simple form using a vector notation as,

$$\mu \nabla^2 v - (v - \nabla f) |\nabla f|^2 = 0 \quad (11)$$

The above equation (10) can be written as

$$\mu \nabla^2 u - (u - f_x) (f_x^2 + f_y^2) = 0 \quad (12)$$

$$\mu \nabla^2 v - (v - f_y) (f_x^2 + f_y^2) = 0 \quad (13)$$

where  $\nabla^2$  is the laplacian operator. In homogenous region [ $I(x, y)$  is a constant], the second term in each equation is zero because the gradient of  $f(x, y)$  is zero. Therefore within such region, 'u' and 'v' are determined by the laplacian equation.

Equations 11 and 12 can be solved by treating 'u' and 'v' as function of time stated by Chenyang Xu and J.L Prince, [4] as,

$$u_t(x,y,t) = \mu \nabla^2 u(x,y,t) - [u(x,y,t) - f_x(x, y)] \cdot [f_x(x, y)^2 + f_y(x, y)^2] \quad (14)$$

$$v_t(x,y,t) = \mu \nabla^2 v(x,y,t) - [v(x,y,t) - f_y(x, y)] \cdot [f_y(x, y)^2 + f_x(x, y)^2] \quad (15)$$

The equations 14 and 15 can be rewritten as ,

$$u_t(x,y,t) = \mu \nabla^2 u(x,y,t) - b(x,y)u(x,y,t) + c^1(x,y) \quad (16)$$

$$v_t(x,y,t) = \mu \nabla^2 v(x,y,t) - b(x,y)v(x,y,t) + c^2(x,y) \quad (17)$$

Where,  $b(x,y) = f_x(x,y)^2 + f_y(x,y)^2$

$$c^1(x,y) = b(x,y) f_x(x,y)$$

$$c^2(x,y) = b(x,y) f_y(x,y).$$

To step up the iterative solution, let the indices be i, j and 'n' correspond to x, y and 't' respectively. Spacing between pixels can be  $\Delta x$  and  $\Delta y$  and the time step for each iteration be  $\Delta t$ . Then the required partial derivatives can be approximated as,

$$u_t = 1/\Delta t (u_{i,j}^{n+1} - u_{i,j}^n)$$

$$v_t = 1/\Delta t (v_{i,j}^{n+1} - v_{i,j}^n)$$

Substituting these approximations in to equations (16) and (17) gives the iterative solution to GVF. The value of u and v for each pixel is substituted in to equation (3) to get the energy value E in each iteration. The convergence of iteration can be reached when the energy value is hardly decreased. Each GVF vector will point towards object boundary even if it is far away from them. Models based on GVF field can approach object boundaries even if the initial contour is located far from them. However these models still require human interaction. We modify the existing external force field for use in an automatic seed selection and region growing process.

#### IV. MODIFIED GVF FIELD

A Four component field  $[k(x,y), l(x,y), m(x',y'), n(x',y')]$  is defined first where k, l, m, n represents the amplitudes (i.e., projections) in the x, y, x', y' axes (as shown in figure 5)

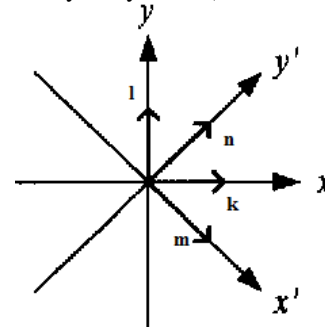


Fig. 5 Four-component vector definition for EGVF field model

Here  $(x, y)$  and  $(x', y')$  form 2 separate Orthogonal co-ordinate Systems with a rotation of  $45^\circ$ . By Extending the GVF field, the force field can be given as

$$V(x, y) = [V_1(x, y), (V_2(x, y))] = [[k, l], [m, n]] \quad (18)$$

$$V_1(x, y) = [k(x, y), l(x, y)]$$

$$V_2(x, y) = [m(x, y), n(x, y)]$$

The equation 18 minimizes the energy function as,

$$E = \iint \mu (|\nabla V_1|^2 + |\nabla f|^2 |V_1 - \nabla f|^2) dx dy + \iint \mu (|\nabla V_2|^2 + |\nabla g|^2 |V_2 - \nabla g|^2) dx' dy' \quad (19)$$

Where,  $\nabla f = (I_x, I_y)$ ,  $\nabla g = (I_{x'}, I_{y'})$  are the gradients of Image I in  $(x, y)$  and  $(x', y')$  co-ordinate Systems. The force vector

field  $V(x, y)$  can be solved from the following Euler equations by applying calculus of variations to the energy function.

$$\mu \nabla^2 k - (k - I_x) |\nabla f|^2 = 0 \quad (20)$$

$$\mu \nabla^2 l - (l - I_y) |\nabla f|^2 = 0 \quad (21)$$

$$\mu \nabla^2 m - (m - I_x) |\nabla g|^2 = 0 \quad (22)$$

$$\mu \nabla^2 n - (n - I_y) |\nabla g|^2 = 0 \quad (23)$$

where,  $\nabla^2$  represents the Laplacian Operator. We can iteratively solve these equations by considering the force vectors  $(k, l, m, n)$ 's as function of time  $n$ . The time step is simply set to 1.

Therefore we get the following iterative equations.

$$k_{n+1} = k_n + \mu \nabla^2 k_n - (k_n - I_x) |\nabla f|^2 \quad (24)$$

$$l_{n+1} = l_n + \mu \nabla^2 l_n - (l_n - I_y) |\nabla f|^2 \quad (25)$$

$$m_{n+1} = m_n + \mu \nabla^2 m_n - (m_n - I_x) |\nabla g|^2 \quad (26)$$

$$n_{n+1} = n_n + \mu \nabla^2 n_n - (n_n - I_y) |\nabla g|^2 \quad (27)$$

The initial conditions are set to  $k_0 = I_x$ ,  $l_0 = I_y$ ,  $m_0 = I_x$ ,  $n_0 = I_y$ . The values of  $k, l, m$  and  $n$  for each pixel  $(x, y)$  are substituted in to Equation (19) to get energy value 'E' in each iteration.

The convergence of iterations can be reached when the energy value is hardly decreased. The motivation of the energy graph is to indicate the level of gradient diffusion. The number of iterations depends up on the image. The overall process is given in the form of flowchart as in figure 5.

After calculating the force vector  $V(x, y)$ 's, they are computed to obtain the signs only as stated by Cheng-Hung Chung[4].

$$\hat{k} = k/|k|, \hat{l} = l/|l|, \hat{m} = m/|m|, \hat{n} = n/|n| \quad (28)$$

The sign value roughly indicates the direction of force on a specific axis and is zero when the force component has zero amplitude. The force will be in the opposite direction when the normalized amplitude in that axis is -1. Consequently, each pixel is considered to connect outwards to 4 of its 8-neighborhood pixels by the strengths  $k, l, m,$  and  $n$ .

### A. SEED SELECTION PROCESS

To search the seeds, we score the status of force vectors from 8-neighborhoods for each pixel. Basically, the score counts the number of neighboring pixels whose force vectors do not point inwards to the considered pixel. For

example Figure (6a) and Figure (6b) have scores 8 and 0, respectively. All pixels have seed selection scores ranging from 0 to 8. Since the force direction generally indicates the gradient directions onwards object boundary, pixels of higher scores will be chosen as the seeds.

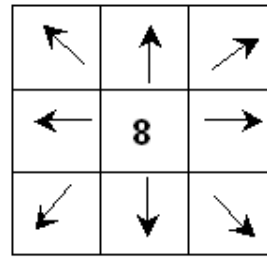


Fig. 6(a). Pixel with 8 score

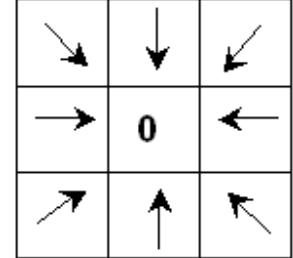


Fig. 6(b). Pixel with 0 score

### B. REGION GROWING PROCESS

The seeds selected in the previous step are utilized to segment the image. The region growing approach is as follows,

- 1) Calculate the gray level difference between the seed pixel and the average of pixels surrounding the seed pixel. Let it be  $\nabla$ . where,  $\nabla = | \text{seed value} - \delta |$ , where  $\delta$  – average value of the surrounding pixels.
- 2) Start by choosing an arbitrary seed pixel and compare it with neighbouring pixel.
- 3) Region is grown from the seed pixel by adding in neighbouring pixels whose value lies within the  $\nabla$  value, increasing the size of the region.

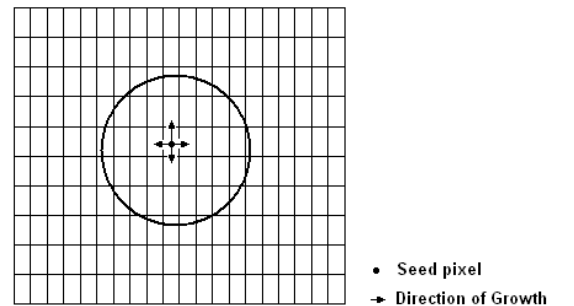


Fig. 7 Start of growing a region

- 4) When the growth of one region stops, we simply choose another seed pixel that does not belong to any other region and start again.
- 5) This whole process is continued until all pixels belong to some region.

### V. EXPERIMENTAL RESULTS

we have presented a technique for segmentation and detection of pathological tissues (tumor) from magnetic resonance (MR) images of brain with the help of modified gradient vector flow field model and region growing. The proposed technique is designed for supporting the tumor detection in brain images with tumor and without tumor. The obtained experimental results shows that GVF model can also

be used in MRI brain image segmentation. The obtained experimental results are shown in figure 8.

The proposed method is implemented in normal brain image and the corresponding skull stripped image and gradient in x and y-axis is shown in figure 8.

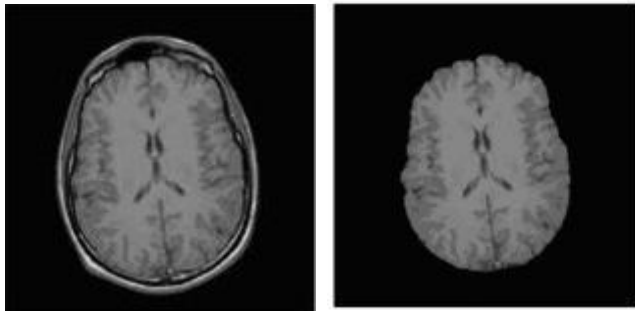


Fig 8(a) Input Image

Fig 8(b) Skull stripped



Fig 8 (c) Gradient in X-axis

Fig 8 (d) Gradient in Y-axis

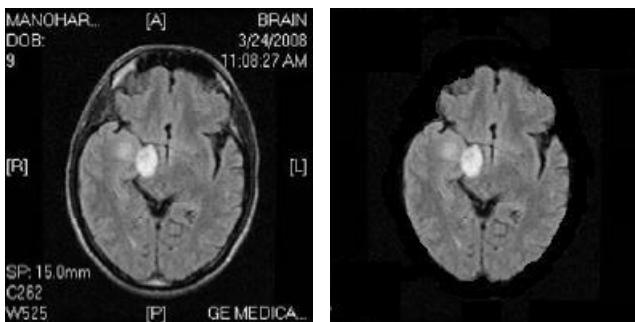


Fig 9(a) Input Image

Fig 9(b) Skull stripped

The proposed method is implemented on abnormal brain image and the obtained results are given in figure 9.

After several iterations, the grey level of the pixels are diffused for scoring to find the seeds. In the figure 10, we can see the arrows are facing outwards i.e., the force vector field is outwards. so, the force moves from the centre of the abnormal region towards the boundary. The image after region growing with the seed is shown in figure 12 a. finally the tumour segmented image is shown in figure 12 b.

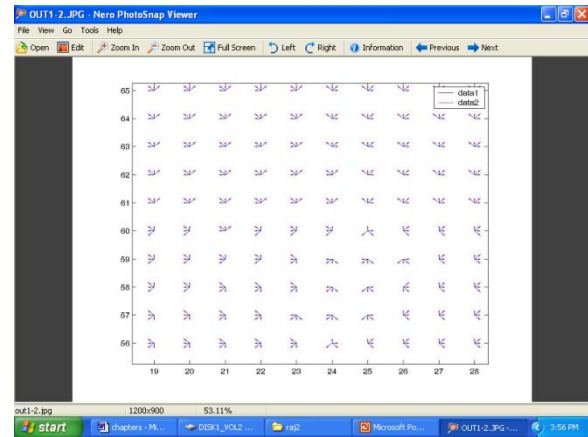


Fig. 11. Energy value curve

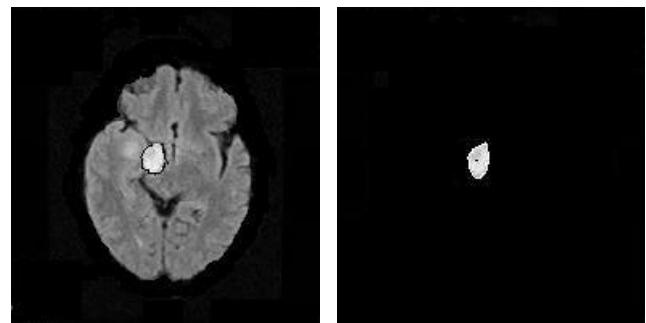


Fig 12 (a) Image after region growing (b) Image after extracting tumour region

The area of an image is the total number of pixels present in the area which can be calculated in the length units by multiplying the number of pixels with the dimension of one pixel. In our proposed method, the size of the input image is 192x4=198. Therefore, the horizontal resolution is 1/192 inch and the vertical resolution is 1/198 inch. The area of single pixel is equal to (1/192)\*(1/198) square inch.

$$A=(1/192)*(1/198)$$

$$\begin{aligned} \text{Area of the tumor} &= A * \text{total number of pixels} \\ &= 2.63 \times 10^{-5} * 380 \\ &= 0.00999 \text{ sq. inch} \end{aligned}$$

## VI. CONCLUSION

The results show that the proposed method can detect the presence of tumor in brain images with tumor and without tumor. The method is unsupervised and can automatically detect the tumor. The area of the tumor is also calculated for various brain images.

## REFERENCES

- [1] Selvaraj, D., Dhanasekaran, R., "Novel approach for segmentation of brain magnetic resonance imaging using intensity based thresholding", 2010 IEEE international conference on communication control and computing technologies, pp 502-507, 7-9 october 2010.
- [2] Selvaraj, D., Dhanasekaran, R., "Segmenting internal brain nuclei in MRI brain image using morphological operators", 2010 International conference on computational intelligence and software engineering, pp 1-4, 10-12 December 2010.

- [3] "Medical Image Processing" from  
[http://en.wikipedia.org/wiki/Medical\\_image\\_processing](http://en.wikipedia.org/wiki/Medical_image_processing)
- [4] Chenyang Xu and J.L Prince, (1998), 'Snakes, shapes and gradient vector flow', IEEE Transactions on image processing, Volume 7, No.3, page 359.
- [5] Chenyang Xu and J.L Prince, (2002), 'Generalized gradient vector flow external forces for active contours', ECCV 2002, LNVS 2352, page 517
- [6] K.E Gustafson, partial differential equations, Newyork, John wiley & sons, 2nd edition.
- [7] R.Courant and D.hilbert, Method of mathemattical physics, Volume 1, Newyork, Interscience.
- [8] R.C.Gonzalez and R.E Woods, Digital image processing, Pearson Education, 2010.
- [9] F.B.Hilderbrand, Methods of applied Mathematics, Englewoods cliffs, PHI 2 nd edition.