Detection of Brain Tumor using GVF and Watershed Segmentation

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Abstract- the segmentation of brain tumor on MRI image is complicated and it is very important in medical field. If the segmentation done by expert it will be time consuming to overcome this problem researcher provided an alternative method for this. This is less time consuming in this paper a semi-automatic method is used for brain tumor segmentation by MRI images. This process involves preprocessing in which the contrast enhancement is done first and followed by sobel edge detection and GVF computation[2]. Snakes or active contours are used to mark internal and external marking on MRI image. Adding the prior knowledge model is helpful and iterative watershed is done in MATLAB.

Keywords – Sobel, Iterative Watershed, GVF (Gradient vector flow).

I. INTRODUCTION

According to human physiology when cells get old it will disappear and new cells are formed if this process goes wrong it means old cells do not disappear and new cells are produced unnecessarily therefore unexpected growth of brain cells causes tumour. If patient suffering from this and if this not

Treated properly it could cause heavy brain damage, which may lead to death. For proper diagnosis and treatment doctor should know location and size of tumour is necessary for treatment like surgery ,radio therapy and chemo therapy ,doctor should know the changes taking place in tumour size now MRI image technique is effective than other .

MRI scanning is safety it won't damage to the body in any manner than other radio techniques like CT, PET are used.

The old method of MRI images was very difficult and time consuming method and the result depend on the experience of skilled person. Therefore a semi-automatic technique for the segmentation of brain tumor is implemented There are two existing techniques are Intelligent based and non intelligent based The main intension of the image segmentation is to segment an image into many regions which are Helpful for performing particular and useful task so it is widely being used.

One challenge in brain tumor detection is making the internal and external boundary around the tumor. But with the help of GVF we can achieve this and iterative watershed segmentation is done

India's population is 1,065,071,550 in that population tumour containing peoples are around 80,124. The rest of the paper is organized as follows: Section II explains about the methods and materials. Section III for dedicated to the proposed approach. The experimental results are presented in the section IV. Finally we have conclusions Section in the last.

II.METHODS AND MATERIALS

A. Pre-processing

Pre processing is very important in image processing and also in segmentation .MRI images have nose in it which will remove and enhancing is done, edge detection is done by sobel operator.

B. Sobel operator

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig .2.1: Sobel operator

The sobel operator have 3*3 kernel operator as in figure 2.4 This can be done by simply rotate it to 90degree [7] The arrangement of the operator is shown in the figure it have the 3*3 matrix the first row have the negative value mid row have zero value and last row have positive value this is related to the 90degree by doing this now in 1st column consists of positive value mid column zero value and last column negative value.
By using these kernels there will respond to the maximally edge which is running the vertically and horizontally to the grid of the pixels respectively or relatively. There kernels will applied separately to input image to separate the gradient measurements to each their orientation we call it Gx and *Gy*

$$|G| = \sqrt{(Gx^2) + (Gy^2)} \qquad (1.b)$$

Typically, an approximate magnitude is computed using,

$$|G| = |Gx| + |Gy| \qquad (2.b)$$

Which is much faster to compute.
The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$\theta = \arctan(Gy/Gx) \qquad (3.B)$$

C. GRADIENT VECTOR FLOW

The gradient vector flow field is defined to be the vector field v(x, y) = [u(x, y), v(x, y)] that minimizes the energy functional

$$\varepsilon = \iint \mu\ (u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2\ |v-\nabla f|^2\ dx\ dy \qquad (1)$$

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

$$v_t(x, y, t) = \mu\ \nabla^2 v(x, y, t) - [v(x, y, t) - fy(x,y)].[f_x(x,y)^2+f_y(x,y)^2] \qquad (3)$$

$$u_t = (1/\Delta t) * (u_{i,j}^{n+1} - u_{i,j}^{n}) \qquad (4)$$
$$v_t = (1/\Delta t) * (v_{i,j}^{n+1} - v_{i,j}^{n}) \qquad (5)$$

$$\nabla^2 u = (1/\Delta x\Delta y) * (u_{i+1,j} + u_{i,j+1} + u_{i-1,j} + u_{i,j-1} - 4u_{i,j}) \qquad (6)$$
$$\nabla^2 v = (1/\Delta x\Delta y) * (v_{i+1,j} + v_{i,j+1} + v_{i-1,j} + v_{i,j-1} - 4v_{i,j}) \qquad (a)$$

Substituting these approximations into (a) gives iterative solution to GVF as follows:

$$u_{i,j}^{n+1} = (1- b_{i,j}\ \Delta t)\ u^n_{i,j} + r\ (u^n_{i+1,j} + u^n_{i,j+1} + u^n_{i-1,j} + u^n_{i,j-1} - 4\, u^n_{i,j}) + c^1_{i,j}\ \Delta t \qquad (7)$$

$$v_{i,j}^{n+1} = (1 - b_{i,j}\Delta t)\, v^{n}_{i,j} + r\,(v^{n}_{i+1,j} + v^{n}_{i,j+1} + v^{n}_{i-1,j} + v^{n}_{i,j-1} - 4v^{n}_{i,j}) + c^{2}_{i,j}\,\Delta t \quad (8)$$

Where

$$r = \frac{\mu\Delta t}{\Delta x\Delta y}$$

Convergence of the above iterative process is guaranteed by a standard result in the theory of numerical methods. Provided that b, c1 and c2 are bounded, equations are stable whenever the Courant–Friedrichs–Lewy step-size restriction
$r \leq 1/4$ is maintained. Since normally Δx, Δy and μ are fixed, using the definition of r in equation, it is found that the following restriction on the time-step Δt must be maintained in order to guarantee convergence of GVF

$$\Delta t \leq \frac{\Delta x\Delta y}{4\mu}$$

THE ITERATIVE WATERSHED

There are two levels of iterative watershed process one is level 1 and second is level 2.

LEVEL 1

Usually the image contains the noise and fussy area with tumour probability between 0 and 1 in order to do this we will use the watershed techniques

- In the figure 1 we can easily see red lines where the tumour is present
- between the green and red lines tumour may be present
- outside the green line no tumour

LEVEL 2

The algorithm can be used 2 times by adding the previous markers we get the inside and outside the concentric regions which will decrease the like hood.

III. PROPOSED METHOD

In this paper, a new approach is presented for brain Tumor segmentation on MRI images which is semi-automatic and does not need any user interaction in segmentation. Fig. shows the block diagram of the proposed algorithm.

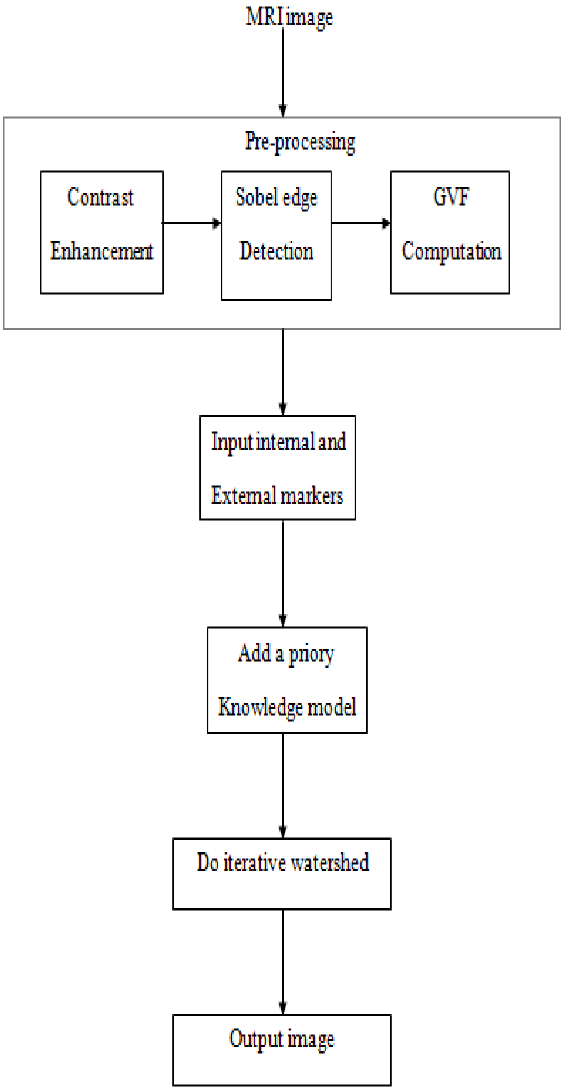
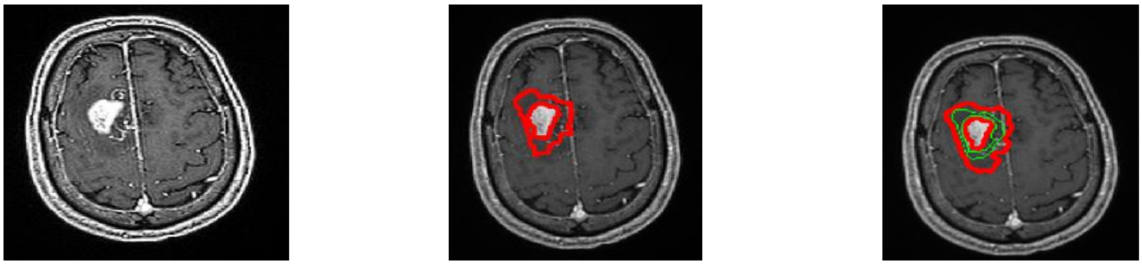


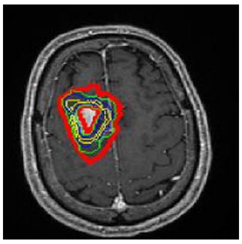
Fig 3. Proposed algorithm

IV. EXPERIMENTAL RESULTS

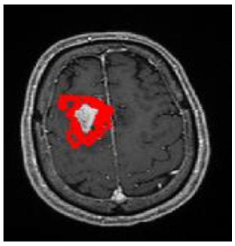
MRI image is used as input in which internal and external characterizing is done the output can be get. Here the iterative watershed technique is used, it have two calm. Clam 1 and clam 2 the inconclusiveness is a part of segmentation so in this paper fuzzy area around the tumor is probability between one and zero so this technique is used.



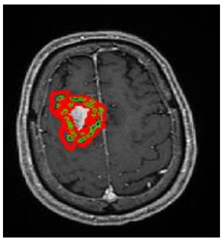
(a) (b) (c)



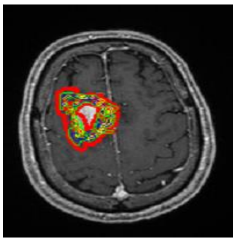
(d)



(e)



(f)



(g)

Fig 4. (a) Input MRI (b) First watershed using GVF (c) Iterative watershed: Level 1 (d) Iterative watershed: Level 2 (e) Iterative watershed using GVF (f) Iterative watershed: level 1 (g) Output obtained by computing the finest segmentation

First give the input image as in fig (4.a) which is of MRI. In fig (4.) the first watershed technique is shown in which we have to do first both the internal and external marking of the tumor manually with the help of GVF. In fig (4.3) the first iterative watershed level 1 is shown similarly in fig (4.4) the second iterative watershed level 2 is shown with the help of iterative watershed level 1 and iterative watershed level 1 the final iterative watershed is shown in fig (4.5). By using the knowledge model and the final iterative watershed obtained in fig (4.5) we can get better results for iterative watershed in fig (4.6) the final output is obtained by computing the finest segmentation as input of fig (4.6) which is shown in fig (4.7)

V. CONCLUSION

The segmentation of brain tumor on MRI image is complicated and it is very important in medical field. If the segmentation done by expert it will be time consuming to overcome this problem researcher provided an alternative method for this. This is less time consuming in this paper a semi-automatic method is used for brain tumor segmentation by MRI images.

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