

Segmentation of the Ventricle from CT Scan Brain Image: Active Contour Model

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Abstract

The present paper describes the segmentation of ventricle from CT scan brain images using active contour model along with dilation and erosion to smoothen the border of the ventricle. This work has been implemented in three phases. In the first phase, normalization is applied to gain almost same intensity in similar portion of the images. Then active Contour Model (ACM) is used to segment out the ventricular part from the CT scan brain image in the second phase. Finally, in last phase erosion and dilation is applied on the segmented region to smoothen the border of the ventricle. The area of the ventricle is calculated before and after smoothing the outer region of ventricle using Erosion and dilation followed by interpolating cubic spline curve and then the results are compared. The area of ventricle in each plate of the CT scan brain image plays an important role in examination of the nature of disease suffered by the patient. Hence, this paper enables us to segment out the ventricle and compare the area between Active Contour Model and the proposed method. Almost in all the cases this proposed method gives the satisfactory results in terms of area of the ventricular, which is compared with ground truth. Our proposed method can be effectively use in different applications of medical science also.

Keywords: Ventricle, CT scan Brain, Active Contour Model, Normalization, Erosion, dilation.

1. INTRODUCTION

Brain is one of the complex and magnificent organs in the human body. It gives us awareness of ourselves and of our environment, processing a constant stream of sensory data. It helps in controlling the movement our muscles, secretion of our glands, breathing and internal temperature. Brain can be broadly divided into three main regions namely forebrain, midbrain and hindbrain. Hence, detection of the brain disease in initial level is very essential. Brain comprises of a section called ventricle, which is stuffed with Cerebrospinal fluid (CSF) as described in Fig.1. Amount of CSF controls the shape and size of the ventricle. Alteration in shape and area of ventricle implies that brain is affected by some diseases.

This paper helps us to segment the ventricle from CT scan Brain image using Active Contour Model (ACM) and then calculate the area before and after smoothing the outer border of the ventricle in each image. The area of the ventricle will help to examine the condition of the patient and detect the accurate disease. Identification and proper treatment of the brain disease at an initial stage can save thousands of lives. A variety of techniques are available for segmentation of ventricle from CT Scan Brain Images. Almost all of them are highly rated. In response to the growing demand almost every year, different techniques are put forwarded by different researchers. Still, it is not sufficient to meet the current requirements. Under such situation, we are trying to contribute this piece of work. The aim behind this segmentation is to calculate accurately the area of the ventricle present in each slice of the CT brain image. In the interest to segment out the ventricle part from CT Scan Brain Image, first of all normalization is applied to the CT Scan Brain images to gain same intensity in the similar portions of the image.

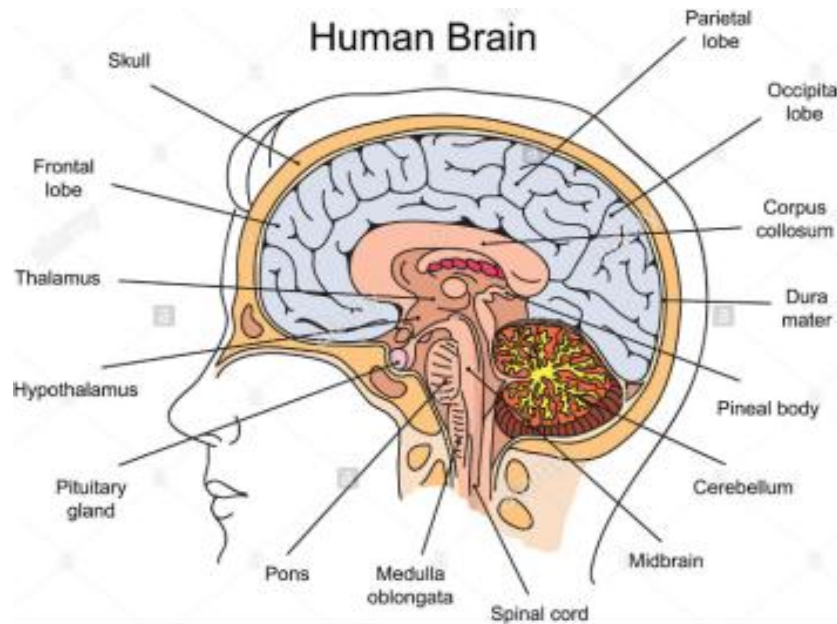


Fig. 1: Structure of Brain: wiki Journal of Medicine by Bruce Blaus

The ventricle is segmented from the image using Active Contour Method. Erosion and dilation is applied to smooth the border of the ventricle and further we draw the periodic interpolation cubic spline curve by selecting few points on the border of the ventricle. This curve helps in turn to calculate the area of ventricle.

The paper is discussed as follows: In section 2 we have enlisted the different existing work as a literature survey. In section 3 we have described our proposed method to overcome the various difficulties as mentioned in section 2. The experimental results of our proposed method along with conclusions are nicely illustrated in section 4 and section 5 respectively

2. LITERATURE SURVEY

Several techniques have been put forwarded by different researchers for the given problem; we are citing few of the interesting work. In 2012, Clangphukhieo B. *et al.*[1] proposed an algorithm to segment out the ventricular part from CT scan brain image. The first step of the algorithm was normalization and then by applying profile of gray level Region of Interest (ROI) was calculated. Then segmentation was based on Bayesian segmentation. The intensity of CT brain images was classified in 3 tissue classes; white matter, grey matter and CSF; and used posterior probability from Baye's Rule to determine CSF areas. Experimental results of this algorithm disclose a low error of 3.14% and a standard deviation of 1.41.

In 2008, John A. Butman *et al.* [11] evaluated ventricle size from serial brain MRI examinations; it segmented the ventricle template using fast marching methods and geodesic active contours, and employed deformable registration for measuring volume of ventricle. They applied 15 series brain MR images, and then compared the results with ground truth from manually segmented images. The mean error in volume estimation was 3.58% with a standard deviation of 3.66%.

In 2003, Naglaa Hassan, Norio Akamatsu [2] have introduced a simple approach for the process of image contrast enhancement using the sigmoid function in spatial domain. In order to achieve this simple contrast enhancement, a novel mask based on using the input value together with the sigmoid function formula in an equation will be used as contrast enhancer. This new contrast enhancer is passed over the target image, operates on each of the pixels, one by one.

In 2014, Shyam Lal and Mahesh Chandra [9] proposed an algorithm for image contrast enhancement that consists of two stages: In the first stage the poor quality of an image is processed by modified sigmoid function. In the second stage the output of the first stage is further processed by contrast limited adaptive histogram equalization to enhance contrast of images. In order to achieve better contrast enhancement of images, a novel mask based on input value together with the modified sigmoid formula that will be used as contrast enhancer in addition to contrast limited adaptive histogram equalization.

In 2016, A. Shenbagarajan, C. Balasubramanian *et al.*[8] formulated an algorithm to analyze the MRI brain images efficiently, where each of the MRI brain images are

classified into normal, non-cancerous brain tumor and cancerous brain tumor. This method comprises of four phases namely pre-processing, segmentation, textural and shape feature extraction and Classification. Segmentation is undertaken by using Active Contour model and classification is done by Artificial Neural Network (ANN) based Levenberg-Marquardt (LM) algorithm. Experimental results revealed that the MRI brain image tumor diagnosis process is accurate, fast and robust.

In the above methods the area of the ventricle is not calculated accurately. Here our aim is to calculate the area of the ventricle before and after using Erosion and dilation and then compare the results.

3. PROPOSED METHOD

Our Brain consists of a part named as ventricle which is filled with cerebrospinal fluid (CSF), a colorless liquid that serves chiefly to maintain uniform pressure within the brain and spinal cord. This fluid is formed continuously by the choroid plexus in the ventricles. In this paper an algorithm will be put forwarded to segment out the ventricle part from the CT brain image using Active Contour Model and then Erosion and dilation will be adopted to smoothen the border of ventricle and at last the area of the ventricle will be determined.

3.1 Intensity of Normalization

Normalization is a technique which helps to achieve same intensity in all the similar portions of the CT scan brain image. It can be mathematically represented as follows-

$$I'(x,y) = \begin{cases} \phi_d + \lambda & \text{if } I(x,y) \leq \phi \\ \phi_d - \lambda & \text{if } I(x,y) \geq \phi \end{cases} \quad (1)$$

$$\text{where } \lambda = \sqrt{\frac{\rho_d (I(x,y) - \phi)^2}{\rho}} \quad (2)$$

Here, $I'(x,y)$ is the normalized intensity; ϕ_d is the average gray value of the desired image; ρ_d is the variance of intensity of the desired image; and ϕ is the average gray value of input images. ρ is the variance of intensity of the input image.

3.2 Active contour model

Active Contour model also provides a powerful technique to segment the heterogeneous images. The primary idea is to evolve a closed curve from the domain of an image. It helps to define the boundaries of shapes in the domain of an image where the approximate shape of the boundary is known. An energy minimizing spine guided by external constraint forces and pulled by image forces towards features. There are several techniques are presented by different researcher but all are

inefficient in solving this problem. Here, we will discuss a class of external force for active contour model that will solve both the problems listed above. This force is termed as gradient vector flow (GVF), which is calculated as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image. The resultant field has a large capture range and forces active contours into concave regions, thereby solving both the problems. The GVF snake addresses two issues over the other snake models; those are poor convergence performance for concave boundaries and poor convergence performance when snake is initialized far from minimum. GVF snake does not require prior knowledge about when to shrink or expand towards the boundary. A snake is a parametric curve which tries to move into a position where its energy is minimized. Kass *et al.* introduced the following energy functional for calculating the snake energy.

$$\begin{aligned} E_{\text{snake}} &= E_{\text{internal}} + E_{\text{image}} + E_{\text{constraint}} \\ &= E_{\text{internal}} + E_{\text{external}}. \end{aligned} \quad (3)$$

The snake energy comprises of three terms. The first term E_{int} represents the internal energy of the snake while the second term E_{img} denotes the image forces, the last term E_{con} gives rise to external constraint forces. The sum of the image forces (E_{img}) and the external constraint forces (E_{con}) is also simply known as the external snake forces, denoted by E_{ext} .

Internal Energy (E_{int}):- The purpose of the internal energy term is to control the deformations made to the snake. It depends on the intrinsic properties of the curve and is the sum of elastic energy and bending energy.

$$\begin{aligned} E_{\text{int}} = E_{\text{elastic}} + E_{\text{bending}} &= \frac{1}{2} \left[(\alpha(s) |V_s|^2 + \beta(s) |V_{ss}|^2) \right] \\ &= \frac{1}{2} \left[(\alpha(s) \left| \frac{dv}{ds} \right|^2 + \beta(s) \left| \frac{d^2v}{ds^2} \right|^2) \right] \end{aligned} \quad (4)$$

Where $\alpha(s)$ and $\beta(s)$ are user defined weights. They are also known as elastic coefficient and coefficient of rigidity of curve or snake respectively which control the internal energy function sensitivity to the amount of stretch and amount of curvature in the snake and also control the number of constraints on the shape of the snake.

External Energy (E_{ext}):- The external energy term is used to control to fit the contour into the image. External energy (E_{ext}) of the contour is consists of energy due to image forces (E_{image}) and energy due to the external constraint forces ($E_{\text{constraint}}$).

The energy due to image force can be defined as follows-

$$E_{\text{image}} = W_{\text{line}} E_{\text{line}} + W_{\text{edge}} E_{\text{edge}} + W_{\text{term}} E_{\text{term}} \quad (5)$$

Where w_{line} represents the weight of the lines, w_{edge} represents weight of the edges and where as w_{term} represents the weight of the termination. In general, if the weight is higher, then it will say that the term have a higher contribution to the image force.

Line function-The line function is the sum of intensities along all lines, i.e. if $I(x,y)$ is represents the intensity of the image at the point (x,y) then

$$E_{\text{line}} = \sum I(x,y) \quad (6)$$

Moreover, sign of w_{line} will determine the line is attracted to either dark or white line. If any noise is present in the image then after elimination of noise, line function is to be calculated.

Edge function- The edge function is based on gradient; it is calculated as under-

$$E_{\text{edge}} = -|\nabla I(x,y)|^2 \quad (7)$$

A snake which is originated far from the experimental object contour may erroneously converge to some local minima. To avoid these local minima scale space continuation is used.

Termination function-

It is used to detect corners and terminations in an image. Let the image be $c(x,y)$.

$$c(x,y) = G_{\delta} * I(x,y), \quad \theta = \tan^{-1} \left(\frac{c_y}{c_x} \right) \quad (8)$$

Let n = unit vector along the direction of gradient

$$= (\cos \theta) i + (\sin \theta) j = (\cos \theta, \sin \theta)$$

Let $n1$ = perpendicular unit vector perpendicular along the

direction of gradient $= (-\sin \theta) i + (\cos \theta) j = (-\sin \theta, \cos \theta)$

$$\therefore E_{\text{term}} = \frac{\partial \theta}{\partial n1} = \left(\frac{\partial \theta}{\partial c} \right) \left(\frac{\partial c}{\partial c_x} \right) + \left(\frac{\partial \theta}{\partial c} \right) \left(-\frac{\partial c}{\partial c_y} \right) \quad (9)$$

since $c = \sqrt{c_x^2 + c_y^2}$

$$\frac{\partial c}{\partial c_x} = \frac{c_x}{\sqrt{c_x^2 + c_y^2}} \text{ and } \frac{\partial c}{\partial c_y} = \frac{c_y}{\sqrt{c_x^2 + c_y^2}}$$

$$\theta = \tan^{-1} \left(\frac{c_y}{c_x} \right)$$

$$\therefore \frac{\partial \theta}{\partial c_x} = \frac{c_x^2}{c_x^2 + c_y^2} \frac{c_{xy} c_x - c_y c_{xx}}{c_x^2}$$

$$\frac{\partial \theta}{\partial c_y} = \frac{c_x^2}{c_x^2 + c_y^2} \frac{c_{yy} c_x - c_{xy} c_y}{c_x^2}$$

$$= \frac{c_x^2}{c_x^2 + c_y^2} \frac{c_{yy} c_x - c_{xy} c_y}{c_x^2} \frac{c_x}{\sqrt{c_x^2 + c_y^2}} +$$

$$(10) \quad E_{\text{term}} = \frac{\partial \theta}{\partial n1} = \left(\frac{\partial \theta}{\partial c} \right) \left(\frac{\partial c}{\partial c_x} \right) + \left(\frac{\partial \theta}{\partial c} \right) \left(-\frac{\partial c}{\partial c_y} \right)$$

$$(11) \quad = \left(-\frac{\partial \theta}{\partial c_y} \right) \left(\frac{\partial c}{\partial c_x} \right) + \left(\frac{\partial \theta}{\partial c_x} \right) \left(-\frac{\partial c}{\partial c_y} \right)$$

$$\begin{aligned}
 & \frac{c_x^2}{c_x^2 + c_y^2} \frac{c_{xy}c_x - c_y c_{xx}}{c_x^2} \frac{c_y}{\sqrt{c_x + c_y}} \\
 &= \frac{c_{yy}c_x^2 - 2c_{xy}c_x c_y + c_{xx}c_y^2}{(c_x^2 + c_y^2)\sqrt{(c_x^2 + c_y^2)}} \\
 &= \frac{c_{yy}c_x^2 - 2c_{xy}c_x c_y + c_{xx}c_y^2}{(c_x^2 + c_y^2)^{3/2}} \tag{12}
 \end{aligned}$$

Note that $c_{xx} = \frac{\partial c_x}{\partial x}$, $c_{yy} = \frac{\partial c_y}{\partial y}$, $c_{xy} = \frac{\partial c_y}{\partial x} = \frac{\partial c_x}{\partial y}$

3.3 Dilation and Erosion-

Dilation operation is applied to enlarge the foreground and shrinks background of a grey scale images. It increases the boundaries of the region while the small holes present in the image become smaller. It increases the brightness of the image. The dilation process is implemented by laying the structuring element B on the image A and sliding it across the image. It can be described in a sequence of steps:

- a) If the origin of the structuring element coincides with a 'white' pixel in the image then there is no change, move to the next pixel.
- b) If the origin of the structuring element coincides with a 'black' in the image then make all pixels black in the image covered by the structuring element.

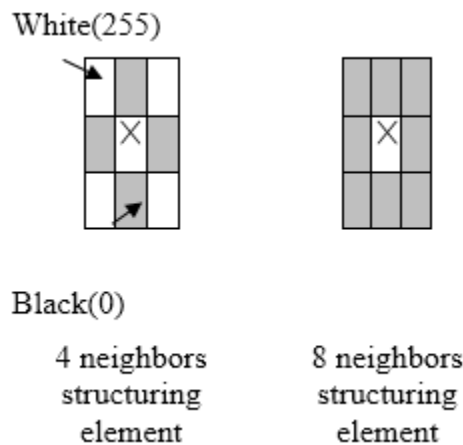


Fig. 2. Shapes of the structuring elements(B)

The dilation of image I by structuring element H is defined by $I \oplus H$. $I \oplus H = \{x + b : x \in I \ \& \ b \in H\}$ If I is a grey scale image and H is symmetric structuring element. The output of dilation is given by a set of translated points such that translate of the reflected structuring element has a non-empty intersection with I. The equation is

based on obtaining the reflection of H about its origin and shifting this reflection by b . This dilation of I by H is the set of all displacements, b such that x and b overlap by at least one element. One of the simplest applications of dilation is for bridging gaps. The structuring element has been used for repairing the gaps. The gaps have been bridged. The erosion operation is applied to grey and as well as binary images to shrink the foreground and enlarge the background. It is used to make an object smaller by removing the outer layer of pixels and also image becomes darker. The erosion process is implemented by sliding the structuring element B on the image A , across the image. It can be described in a sequence of steps:

- a) If the origin of the structuring element coincides with a 'white' pixel in the image then there is no change, move to the next pixel.
- b) If the origin of the structuring element coincides with a 'black' pixel in the image, and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image from 'black' to a 'white'.

This operator takes the image and structuring element as input. The erosion of X by structuring element B is given by $X \ominus B$. $X \ominus B = X - b = \{z: (B + z) \subseteq X\}$. If X is a grey scale shape and B is symmetric structuring element. The output of erosion is the set of translation points where the translated structuring element is contained in the input set X . This equation indicates that the erosion of X by B is the set of all points b such that B , translated by b . One of the simplest uses of erosion is elimination of irrelevant details in terms of size from the grey scale image.

3.4 Cubic Spline Curve

The periodic interpolation cubic spline curve (piecewise smooth) is drawn by selecting few points on the boarder of the ventricle to calculate the area of it. The cubic spline curve is represented by a function whose values are known at a finite number of points, by using cubic polynomials. Let f be a function defined on the interval $[a, b]$, and let

$a = x_0 < x_1 < x_2 \dots < x_{n-1} < x_n = b$ be $n + 1$ distinct points at which the values of the function f are known. The points x_j , $j=0,1,\dots,n$ divide the interval $[a, b]$ into n subintervals, referred to as a partition of $[a, b]$. For every four conjugative points of the partition a cubic spline curve is drawn, hence positional continuity are maintained where s tangential continuity are not maintained. The number of points on the boundary must be one more three times of number of curve. A cubic spline interpolation of f relative to the partition is a function $S: [a, b] \rightarrow \mathbb{R}$ that satisfies the following properties:

- (i) The restriction $S|_{[x_j, x_{j+1}]}: [x_j, x_{j+1}] \rightarrow \mathbb{R}$ of the interpolant S to the interval $[x_j, x_{j+1}]$ coincides with the cubic polynomial

$$S_j(x) = a_j + b_j(x - x_j) + c_j(x - x_j)^2 + d_j(x - x_j)^3,$$

$$j = 0, 1, \dots, n - 1$$

(ii) The function S interpolates f at the point x_0, x_1, \dots, x_n i.e., $S_j(x_j) = f(x_j)$ and $S_j(x_{j+1}) = f(x_{j+1})$ for $j = 0, 1, \dots, n - 1$;

(iii) The function S is continuous, i.e., $S_{j+1}(x_{j+1}) = S_j(x_{j+1})$, $j = 0, 1, \dots, n - 2$;

(iv) The interpolant S satisfies some boundary conditions, i.e., conditions at the ends of the interval $[a, b]$.

4 EXPERIMENTAL RESULTS

In this paper, we have analyzed hundred CT brain scans in Digital Imaging and Communication in medicine (DICOM) format comprising of both healthy and unhealthy datasets. Here we are presenting only four of them, each had the spatial resolution of 512×512 , number of pixels is 262144 and slice thickness is equal to one in Fig 3. These CT brain scans have different amount of CSF, color and as well as contrast of the CT scan brain image. Also, surrounding has some unwanted artifacts. The proposed method is applied in a Matlab 2015 environment, which was installed in processor i5 of the standard machine with 8GB RAM. It gives the satisfactory result for almost all images in terms of area compared with ground truth.

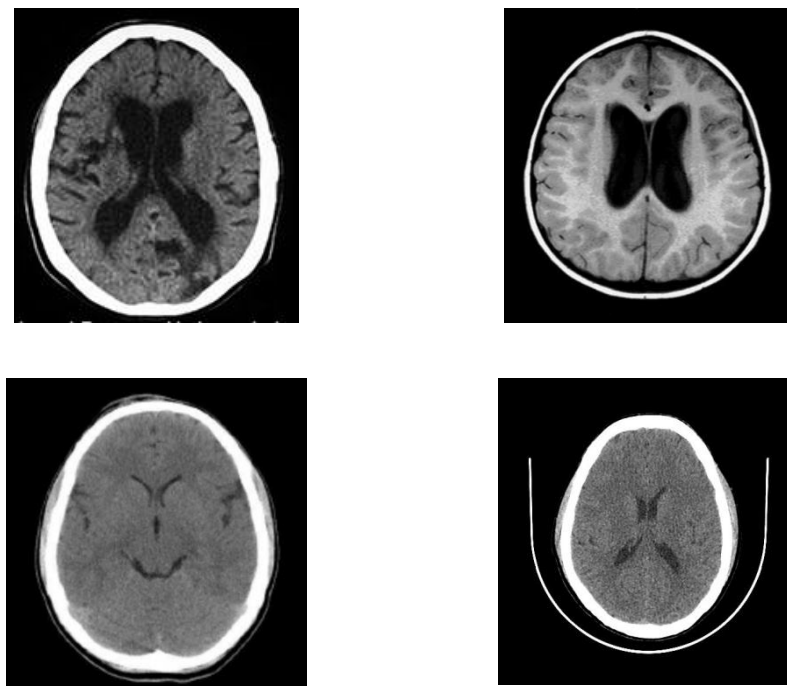
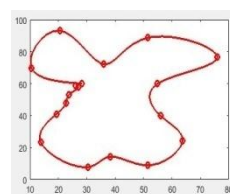
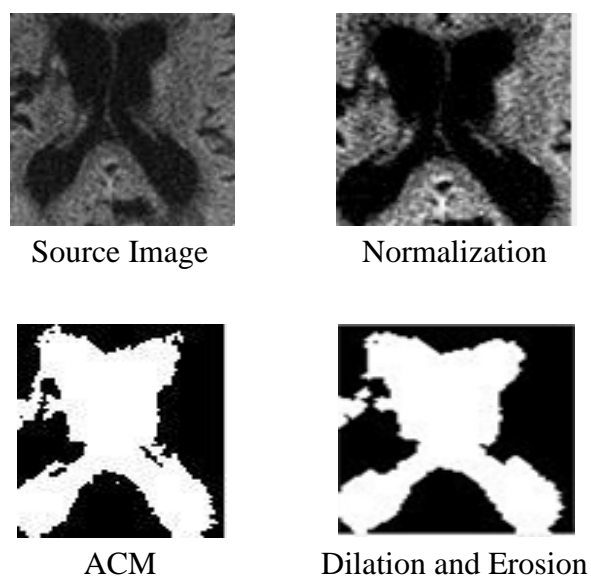


Fig.3. Represents few of the CT brain slices that were analyzed in the dataset.



Cubic spline curve

Fig. 4: Experimental result of our proposed method**Table 1:** Experimental Result of proposed Method for different dataset

| Figure Number | Area calculated after segmentation using ACM (in sq. mm) | Area determined after smoothening and formation of cubic spline curve (in sq. mm) | Area notified by Radiologists (in sq. mm) |
|---------------|--|---|---|
| 1 | 4.0855×10^3 | 3.4381×10^3 | 3.5262×10^3 |
| 2 | 3.0345×10^3 | 2.8632×10^3 | 2.9012×10^3 |
| 3 | 0.5647×10^3 | 0.46572×10^3 | 0.49235×10^3 |
| 4 | 1.3526×10^3 | 1.2879×10^3 | 1.3271×10^3 |

The area calculated after segmentation of first images is 4.0855×10^3 sq. mm whereas the area determined after smoothening and formation of cubic spline curve is 3.4381×10^3 sq. mm, which is almost same as area noticed by the radiologist (3.5262×10^3 sq. mm).

5 CONCLUSIONS

The present paper describes on the segmentation of ventricle from CT scan brain images using active contour model along with erosion and dilation to smoothen the border of the ventricle. The main novelty of the approach is selecting the exact CSF portion of CT scan images using cubic spline drawing on boarder of the ventricle. It is performed by three phases. In the first phase, normalization is applied to gain same intensity in similar portion of the images. In the second phase active Contour Model (ACM) is applied to select the ventricular part from the images, followed by area of the ventricle is evaluated. In the last phase area is interpolated by periodic cubic spline after application of erosion and dilation on the segmented region of ventricle. The experimental result shows the effectiveness of proposed method. In short, the algorithm is very simple and has the ability to construct better quality parameters like area; the addition of conventional approaches to this algorithm makes the algorithm strong, and an excellent contender for the real life implementation;

Some concluding observations from the study are given below.

- The size of the CT scan brain image may be varied, and it may be gray scale and as well as color images,
- It is applicable for low contrast CT scan brain images and as well as bright images also.
- It is automatically select only CSF portion from CT brain image.
- The proposed method evaluate the area of CSF portion.
- It can be applicable for different medical science along with various industrial applications also.
- This proposed method can be used to improve the quality of low contrast images in medical science, satellite imaging, and different industry

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