3D Model Visualization for Brain Tumour using MRI Images

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Abstract. The inaccurate prediction of tumour is because of the 2D images do not present the complete natural tumour representation as in 3D visualization. In order to construct the 3D model, the contour of 2D MRI images must be merged together. In this work, the edge detection of brain tumour on 2D images is done using the Geodesic Active Contour (GAC) model based on Additive Operator Splitting (AOS), then 3D model is visualized using Image Manifold (IM) and Volume Estimation (VE) methods. The comparison of performance for both methods is calculated. In conclusion, the execution time for VE method is higher than IM method since more images are used in VE method to calculate the volume of the tumour accurately. In terms of iteration number, Volume Estimation has a higher number of iterations, but for error and root mean square error, both methods have roughly the same value.

1. Introduction

2D MRI images can be used to construct 3D model image by using specific methods, hence the important information of the tumour growth, feature and property can be obtained from the visualization of 3D model image. This is very important especially for the purpose of diagnosis and treatments process. There is significant potential of 3D visualization that still unexplored and not have been developed completely, thus 3D visualization turn out to be an important area of researcher to offer any new tool, devices, procedures, or propose a precise diagnosis and recommends a better treatments approach.

The Additive Operator Splitting (AOS) scheme idea is to decompose a multi-dimensional problem into one dimensional in order to solve it efficiently. The average of one-dimensional solutions approximates the final multi-dimensional solution. Some of the advantages of the AOS scheme are aside (from having a good rotational invariance), it also can be easily implemented in arbitrary dimensions and unveil a memory requirement and computational complexity. This scheme also claimed as, are at least ten times more efficient compared to the explicit scheme [1]. The fast algorithms based on the semi-implicit AOS scheme for the geometric and geodesic active contour model is presented in [2]. The findings revealed that the AOS-based iteration is nearly twice and in some cases three times as expensive as an explicit iteration. A significant speedup is also obtained when they implement the AOS-based on implicit active contour models. The AOS method is employed in the Geodesic Active Contour method.
for image segmentation using the microscopic cell image by [3]. Their finding concludes that AOS scheme is not only successfully improves the efficiency, but also reduced the iteration times and CPU time comparing to the explicit scheme. Their experiment also proves the AOS scheme is suitable for applications such as medical image processing since the scheme significantly increase a convergence speed up.

In [4], they rearrange the governing equation for the subjective surface flow in an AOS implementation and using the Fast-Marching algorithm in conditioning the viewpoint surface in order to conduct a devised new initialization paradigm, thus obtaining a near real-time solution to the shape completion problem in 2D and 3D. The comparison is also made on several examples of real 3D medical images between the proposed algorithm with the original method and the results show a remarkable improvement. [5] introduced an amplification of the ML (Manifold Learning), called Tangent Bundle ML (TBML). This proposed technique requires the original points of the Data Manifold and the tangent spaces to provide a possibility of accurate reconstruction for low-dimensional representations of manifold-valued data. Besides, a new solution for the Manifold Learning which is a geometrically motivated Grassman and Stiefel Eigenmaps method is also presented. [6] proposed algorithms for biomedical video denoising using real-valued side information. They demonstrate real-world use of their proposed algorithms on echocardiography data and associated electrocardiogram (ECG) signals. [17] provided the construction of 3D images from various medical data which trained by computer tomography and magnetic resonance imaging. The proposed approach is a 3D model reconstruction from medical images using the detailed initial information from the generated DICOM files.

Data from MRI images are in the form of volumetric matrices and there are two possibilities to use the data for visualization, which are use the volumetric data directly or use the conversion from volumetric to geometric data. Algorithms to perform the conversion are divided into two groups, spatial and sliced based conversion where the first group uses active contour for three-dimensional data, and such algorithms use the minimization of the surface energy [7 - 9]. The full utilization of the input data is one of the significant advantages of these algorithms, but the complexity of computing as well as high memory utilization is the major drawback [10]. Meanwhile, the detection of shapes in 2D space using 2D algorithms, and the creation of the edges for every slice before they are combined into single solid using another algorithm fall in the second group of the proposed algorithms. Propositions of contour-solid conversion algorithms are presented in [11 - 14].

2. Materials and Methods

The basic steps of the 3D visualization are roughly the same, as shown in figure 1. The input is a 2D MRI medical images, which then were converted to the nearly raw raster data (nrrd) data format. nrrd is a library and file format designed to support scientific visualization and image processing involving n-dimensional raster data. Two-dimensional filtering is used to reduce the image noise, including improving the signal to noise ratio. Then, image interpolation method is used to estimate image value at a location between the image pixels. Nearest neighbour, bilinear, and bicubic interpolation are some interpolation methods which are widely used. Then, three-dimensional filtering will smooth the 3D image before the segmentation, classification, and registration in order to enhance a region of interest. Lastly, choose the suitable 3D rendering and 3D reconstruction depends to the different requirements of 3D visualization and system capability [15].
In the previous work, GAC-AOS method have been applied to perform edge detection on every MRI image. The details on this work have been described by [16]. The summary of processes involved on edge detection are demonstrated as in figure 2:

- Select the image
- Crop the selected tumour area
- Perform edge detection using GAC-AOS method

![Image](image_url)

(a) Original Image  
(b) Cropped Image  
(c) Final Contour

**Figure 1.** 3D visualization steps.

**Figure 2.** The process of edge detection on the brain tumour for front, side, and top view images.

After the segmentation is done, volume estimation is used to calculate the volume of the tumour using the following equation (1) based on [17]:

$$V = \sum_{i=1}^{n} v_i$$  \hspace{1cm} (1)

where
\( n \) is the number of slices where the tumour is detected
\( v_i \) is the volume of the tumor area between the segments of image slice, calculated based on the truncated pyramid volume formula. The segments are approximated with rectangles as in (2).

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v_i = \frac{1}{3}H(S_1 + \sqrt{S_1S_2} + S_2)
\]

where
\( H \) is the distance between the 2D slices,
\( S_1 \) is the area of tumour zone in slice \( i \),
\( S_2 \) is the area of tumour zone in slice \( i + 1 \).

For Image Manifold (IM) technique, a 3D Slicer software is used. 3D Slicer is an open source software application which is extensible and has been widely used by many researchers especially for medical visualization and image computing. Slicer is a top of some independent projects that focused separately on image visualization, surgical navigation including graphical user interface. Some of the advantages of 3D slicer besides its extensibility from other open source and commercial software tools and workstations are the breadth of functionality, portability across platforms as well as non-restrictive software license. These main features differentiate Slicer from the other tools that focus to cover similar parts of functionality [18]. The steps to construct 3D model using 3D Slicer are as follows:

Step 1: Loading data
1.1 Choose File → Add Data → brain.nrrd (check Centered if applicable) and click Apply.
1.2 Result: the data is loaded and will be displayed in the three windows (directional).

Step 2: Creating volume
2.1 Choose Volumes module → volume name: 3D and click Apply.
2.2 Result: the volume created.

Step 3: Creating Models
3.1 Editor module → Creating the volume choose Master Volume (depends on Slicer version).
3.2 In Edit Selected Label Map window choose Level number and colour.
3.3 Click Threshold → choose range (on the right you can see what areas are within this range) → click Apply.
3.4 Click Make Model → choose Name → check Smooth Model (if applicable).
3.5 Result: The model is built with the pre-chosen colour.

Figure 3 shows the 3D model visualization using image manifold (IM) and volume estimation (VE) methods. The numerical results of figure 3 are shown in table 1 and table 2.
3. Results and Discussion
The comparison results between the IM method and VE method are shown in table 1 and table 2. VE method has the biggest number of iteration due to the size of the tumour. As for maximum error and root mean square error (RMSE), both methods have nearly the same value. From table 2, we can conclude that the volume of the brain tumor in both methods are roughly the same. These results proved that both methods have a good agreement in volume calculation. In terms of execution time, Volume Estimation method is faster compared to Image Manifold method in constructing the 3D model of the brain tumor.

Table 1. Comparison of the error between IM and VE methods for edge detection.

| Item                  | IM method       | VE method       |
|-----------------------|-----------------|-----------------|
| No. of iteration      | Min: 500        | Min: 500        |
|                       | Max: 650        | Max: 800        |
| Maximum error         | 2.55828e-004    | 2.50109e-004    |
| RMSE                  | 3.25902e-006    | 3.78996e-006    |
| Execution time (to converge) | 567.621563 seconds | 753.463601 seconds |

Table 2. Comparison of the volume and time execution between IM and VE methods.

| Item          | IM method       | VE method       |
|---------------|-----------------|-----------------|
| Volume        | 1.953.648 mm$^3$ | 1.567.432 mm$^3$ |
| Volume of tumour | 122.103 mm$^3$  | 97.964.5 mm$^3$ |
| Execution Time | 16 seconds      | 0.053827 seconds |

4. Conclusion
The volumetric image estimation from a 2D MRI medical image and extended to the 3D volume image model is essential for accurate evaluation of the 3D medical images. The three phases which are the integration of mathematical modelling, simulation for visualizing 3D medical image model and estimating the volume of tumour growth is appropriate to determine the tumour zone, thus can provide revised evidence-based on tumour histology, location, growth as well as the treatment effect.

5. References
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