JURTEKSI (Jurnal Teknologi dan Sistem Informasi) ISSN 2407-1811 (Print)
Vol. X No 4, September 2024, hlm. 749 – 756 ISSN 2550-0201 (Online)
DOI: http://dx.doi.org/10.33330/jurteksi.v10i4.3470
Available online at http://jurnal.stmikroyal.ac.id/index.php/jurteksi

DEEP LEARNING FOR CALCULATING BRAIN TUMOR VOLUME IN 3D MRI IMAGES USING HYBRID ACTIVE CONTOUR SEGMENTATION METHOD

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Abstract: Brain cancer is a serious medical condition that requires intensive and meticulous care. One of the critical steps in identifying brain cancer is the accurate measurement of tumor volume. Magnetic Resonance Imaging (MRI) is one of the most important diagnostic tools used in the medical field for brain visualization. In this discussion, we will explain how the Active Contour method can be used to calculate brain tumor volume in MRI images and how 3D visualization can assist doctors in making better diagnoses and treatment decisions. The Active Contour method, also known as the “Snake,” is an image processing technique used to identify the contours or edges of objects in images. This method works by defining an initial curve around the desired object and then iteratively shifting the curve to match the actual contour of the object in the image. In this study, the Active Contour method will be applied to brain MRI images to identify tumor edges. This research represents an important step in improving the care of brain cancer patients, enabling more accurate diagnoses and more effective treatments

Keywords: active contour; brain cancer diagnosis; 3D visualization; tumor volume

Abstrak: Kanker otak merupakan kondisi medis yang bersifat serius dimana memerlukan perawatan yang intensif dan teliti. Salah satu langkah penting dalam mengidentifikasi kanker otak adalah dengan mengukur volume tumor secara akurat. Citra Magnetic Resonance Imaging (MRI) adalah salah satu alat diagnostik yang paling penting dalam bidang medis yang digunakan untuk visualisasi otak. Dalam pembahasan ini, akan dijelaskan bagaimana metode Active Contour dapat digunakan untuk menghitung volume tumor otak pada citra MRI dan bagaimana visualisasi 3D dapat membantu dokter dalam diagnosis dan perawatan yang lebih baik. Metode Active Contour, juga dikenal sebagai “Snake,” yaitu teknik pengolahan citra yang digunakan untuk mengidentifikasi kontur atau tepi objek dalam citra. Metode ini bekerja dengan mendefinisikan suatu kurva awal di sekitar objek yang diinginkan dan kemudian menggeser kurva tersebut secara iteratif untuk menyesuaikan dengan kontur objek yang sesungguhnya dalam citra. Dalam penelitian ini, metode Active Contour akan diterapkan pada citra MRI otak untuk mengidentifikasi tepi tumor. Penelitian ini merupakan langkah penting dalam meningkatkan perawatan pasien yang terkena kanker otak dan memungkinkan diagnosis yang lebih tepat dan perawatan yang lebih efektif.

Kata kunci: active contour; diagnosis tumor otak; visualisasi 3D; volume tumor

INTRODUCTION

A brain tumor is an abnormal mass of cells growing in the human brain, which has limited space for expansion due to the skull. Unlike other tumors in the human body, a growing brain tumor can press on vital areas of the brain, resulting in a significant number of deaths. This research is based on the importance of detecting and treating brain tumors accurately and efficiently. Brain tumors, which are one of the most common types of tumors, especially in men, can be malignant or benign. Although not always life-threatening, proper treatment is crucial to prevent further complications. One of the primary methods for detecting brain tumors is through Magnetic Resonance Imaging (MRI), which provides clear images of the brain's soft tissues. However, this process is often time-consuming and involves a great deal of subjectivity from experts [1].

Brain tumors are one of the most frequently occurring tumor types, particularly in men. In the United States, they make up 85-90% of all tumors found in the central nervous system. The disease affects about 6.6 individuals per 100,000 annually, with a death rate of 4.7 per 100,000 each year. [2]. Brain tumors can be detected through various methods, one of which is Magnetic Resonance Imaging (MRI), known for providing clear images of soft tissues. Although brain tumors can be either benign or malignant and are not always life-threatening, prompt and appropriate treatment is essential to avoid further complications. Treatment often involves using high-dose radiation to destroy tumor cells.

This treatment is called radiotherapy. Because it involves high radiation doses, careful planning is required. The system responsible for this is the Treatment Planning System (TPS). The initial step in TPS is delineation, which focuses on capturing a clearer image of the tumor and determining the target volume in 3D. [3]. The imaging process is typically conducted by medical physicists or doctors and can often be time-consuming and subjective. Automating the procedure would be more efficient. This is achievable with the development of digital image processing, which enables extracting more information from image analysis. As a result, digital image processing can be utilized in the imaging of target volumes.

Overall, the Active Contour Hybrid method in calculating tumor volume, compared to machine learning-based methods, lies in its accuracy in segmentation, tolerance to noise, independence from training data, and flexibility in contour adjustment and configuration. On the other hand, machine learning tends to require larger training data and struggles to handle variations in complex tumor shapes without additional significant adjustments or configurations [4].

The stages include image segmentation (contouring), 3D image reconstruction, and target volume calculation [5]. Other researchers used cubic spline interpolation and constrained the interpolated values to obtain the reconstructed slices. The final tumor was then visualized as a 3D isosurface. The system's accuracy was calculated by removing the original slices from the series, interpolating them, and then comparing the two images [6].

A different researcher carried out a study on target volume delineation using active contour methods. This research focused solely on representing the CTV. The findings demonstrated high accuracy and validated that the active contour algorithm can effectively identify the CTV. [7]. The brain tumor is determined by

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brain image segmentation using various techniques based on magnetic resonance imaging (MRI) [8]. Building on prior research, this study conducts the segmentation of brain tumor target volumes in MRI images using the active contour method. The process involves determining the GTV, CTV, PTV, and OAR on axial head images. The segmentation results are then reconstructed and displayed in 3D. The calculation and visualization of the target volumes are part of the Treatment Planning System (TPS), which serves as a guideline for treatment [9].

METHOD

Image segmentation is an important aspect in the field of image processing and computer vision. This segmentation is widely used in various fields, including industrial automation, medical image analysis, intelligent monitoring, and traffic management [10]. Active contours are a segmentation method that uses a closed curve model that can expand or contract. To achieve the research objectives, the researchers have outlined the research steps according to the following diagram.

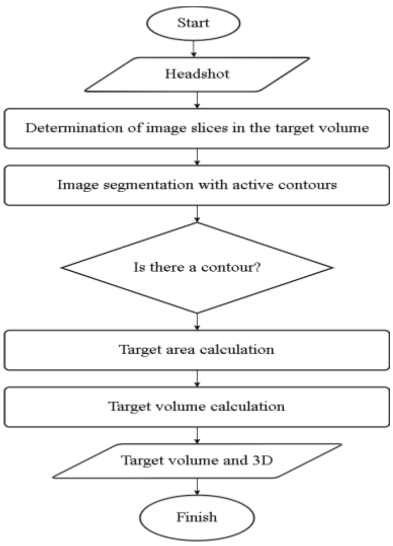

Image 1. Research Steps

Acquisition of Brain MRI Images. The first step is to collect brain MRI images from relevant patients. The MRI images must be of high quality and should cover the area containing the tumor. Tumor Segmentation with the Active Contour Method. After acquiring the MRI images, the next step is to segment the tumor using the Active Contour method. In this stage, the researcher will initialize the initial curve to process the curve around the tumor and move it until it fits the tumor's edges.

Tumor Volume Calculation once the segmentation is complete, the tumor volume can be calculated by counting the number of pixels within the segmented region. The tumor volume can be measured in cubic millimeters (mm^3). 3D Visualization. The result of the tumor volume calculation can be visualized in 3D to provide a clearer representation. The Research Steps for Calculating Brain Tumor Volume Using Hybrid Active Contour Segmentation:

Step 1: Loading MRI Images

First, it is necessary to load the MRI image containing a brain tumor in the appropriate format. Use the imread function or dicomread if the image is in DICOM format. Loading the MRI image.

```
image = imread('brain_mri_image.jpg');
```

Step 2: Image Preprocessing

Perform preprocessing steps on the MRI images, such as contrast enhancement or noise removal if necessary. An example of contrast enhancement

```
image = imadjust(image);
```

Step 3: Initializing Active Contour

Initialize the initial contour for the Active Contour method. It can use initial points or an initial mask for initialization.

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An example of initializing with initial points.

initial_contour = [x1, y1; x2, y2; x3, y3; ...];

Step 4: Applying the Active Contour Method

Use the active contour function in MATLAB to apply the Active Contour method to an MRI image. Applying the Active Contour method

final_contour = activecontour(image, initial_contour, num_iterations);

Step 5: Calculating Volume

After the tumor contour is generated, we can calculate the volume using the voxel volume formula or measure the volume in relevant units based on the image resolution. % Calculating volume in specific units pixel_size = 0.1; % Replace with the pixel size according to the image reolution

volume = sum(sum (final_contour))* pixel_size;

Step 6: Visualization of Results

Finally, visualize the segmentation results and the generated contour. Image visualization with contour:

```
figure; imshow(image, []);
hold on;
plot(final_contour(:, 1), final_contour(:, 2), 'r', 'LineWidth', 2);
title('Segmentasi Tumor Otak dengan Active Contour');
hold off;
```

$$X = \sum_{P=0}^{255}\sum_{q=0}^{255}[S(0) + S] \qquad (1)$$

Description:

X : total pixels in the image, including black and white pixels.

p and q : coordinates of pixels in the image, where **p** represents the width and **q** represents the height of the image.

256 x 256 : resolution of the image, indicating that the image has 256 pixels in width and height.

S(0) : represents black pixels in the image (usually with a value of 0).

S(1) : represents white pixels in the image (usually with a value of 1)

This formula adds up all the pixels in an image with a resolution of 256x256, and classifies them as black or white.

Image pixels=width (p) x heigh (q) = 256 x 256. The variable I, s (0) and s (1) are image, black and white pixels respectively. The total number of white pixel (wp) in image (X) has expressed by:

$$X = \sum_{P=0}^{255}\sum_{q=0}^{255}[S] \qquad (2)$$

Description:

In this formula, only white pixels S(1) are summed, so this formul calculates the total number of white pixels (wp) in the image.

wp is the total number of white pixels that usually represent an identified object or area, such as a tumor in a medical image.

Here, wp = number of white pixels and the value of 1 pixel = 0.264mm. Then, area of tumor computation has illustrated as:

$$T_{area} = \left[\left(\sqrt{\text{wp}}\right)*0.264\right]\text{mm}^2 \qquad (3)$$

Description:

T_area : The calculated area (e.g., tumor area).

Wp : The number of white pixels representing the tumor in the image.

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0.264 mm : The physical size of 1 pixel in millimeters (1 pixel is equal to 0.264 mm in the real world).

Wp : The square root of the number of white pixels is used to calculate the length dimension of the tumor area, since 2D images are calculated in units of length times width.

RESULTS AND DISCUSSION

Citra Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) has become one of the most important diagnostic tools in modern medicine. This technology allows medical professionals to view the internal structures of the human body with a high level of detail, aiding in the detection, diagnosis, and treatment of various health conditions. We will discuss how MRI image processing is used to detect multiple sclerosis (MS), brain tumors, and joint injuries, as well as its impact on enhancing medical practice.

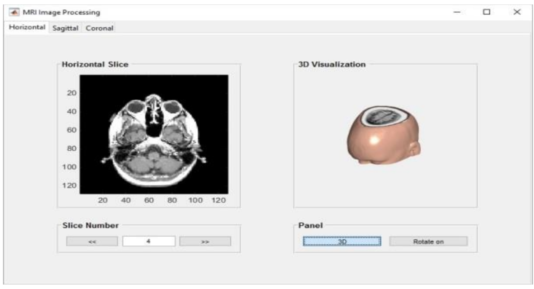

Image 2. Export Citra MRI Ke 3D

Segmentasi and Ekstraksi Fitur

Fractal texture algorithm analysis has been divided into two distinct stages, such as (i) reference image decomposition thresholding and (ii) texture feature extraction. This technique is applied to each region of the image recursively until the total number of thresholds is found. The total number of thresholds is determined by the end-user. In this work, the threshold size is initialized as the two aforementioned stages. The image decomposition thresholding is mathematically expressed by the following equation.

$$I_d(p,q) = \begin{cases} 1, & \text{if } t_{lower} < I_g(p,q) \leq t_{upper} \\ 0, & \text{otherwise} \end{cases}$$

Where $tlower$ and $tupper$ represent the lower and upper threshold values. From the decomposition process of each segmented image, features such as the average fractal dimension, area, boundary, and additional shape features like solidity, perimeter, and center of mass are extracted. The feature vector extracted from the unknown test image data is used for further classification using a known training set.

Tumor Cell Calculation

Abnormal brain images that have been identified are transferred to the next phase, which involves opening areas to eliminate small objects from the binary image. From this extracted tumor region, the number of affected cells is determined using binarization methods. The resulting binary image consists of two values: white pixels (1) and black pixels (0). To begin with, the number of zero (0) and non-zero (1) pixels in an image (X) can be computed using this equation.

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Table 1. Dataset of accuracy Percentage for Each Interpolated Slice

No	Original Shape (2D)	Interpretasi Biner	Akurasi Matlab	Volume
1	83.4	88.9	92.2	30.1082 cc
2	89.4	90.7	93.9	30.1082 cc
3	90.4	91.4	94.5	30.1082 cc
4	91.3	92.0	95.6	30.1082 cc
5	89.8	92.3	95.8	30.1082 cc
…..	…….	……	…….	……………
26	90.6	93.1	96.3	30.1082 cc
27	85.7	89.9	92.7	30.1082 cc
mean ±variance	89.97	92.45	95.31	30.1082 cc

Description:
1 cc = 1 ml = 1 cm³. So, 1 cc = 1 cm³ = 1 x 1.000 mm³ = 1.000 mm³
30.1082 cc = 30108.2 mm³.

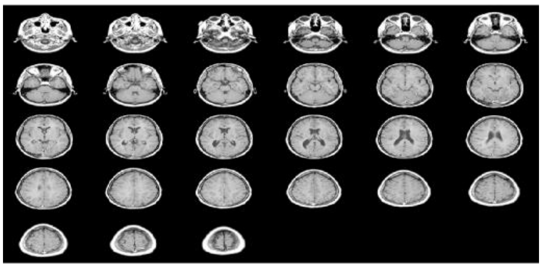

Image 3. MRI 2D

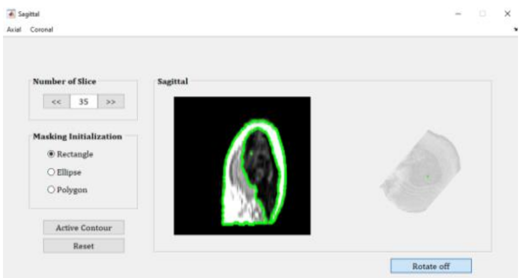

Image 4. Image Sagital Rectangle

The image above represents the conversion from 2D to 3D. The sagittal view of an image represents a cross-section from front to back along this plane. It is commonly used in MRI or CT scans. This option refers to the initialization method of masking, where the user can select a rectangular area to begin the active contour segmentation process.

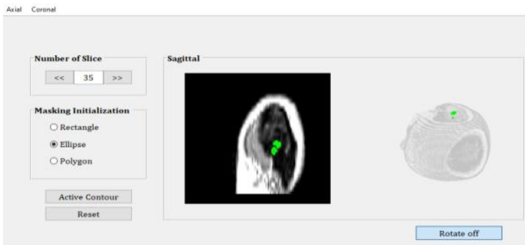

Image 5. Image Sagital Ellipse

The image above represents the conversion from a 2D image to a 3D model to smooth or delimit parts of the object in the 2D image. By using an elliptical shape to define the area to be segmented in the 2D image, it helps capture objects that are roughly oval or round. On the right side, there is an image of the 3D reconstruction result from the 2D slices. This 3D reconstruction aids in understanding the structure of the body or object in three dimensions, allowing for more detailed visualization of the object from various angles.

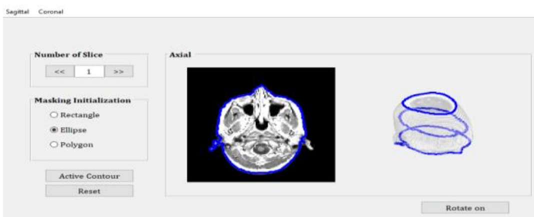

Image 6. Axial Ellipse

The axial view shows a horizontal cross-section from top to bottom. the axi-

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al view displays the top part of the head and is used in MRI or CT scans to show parts of the brain, skull, or other head structures. On the right, there is a 3D model of the axial slice. The image above represents the result of reconstructing 2D images into a 3D shape. The blue line surrounding the 3D model indicates the area that was outlined by the ellipse in the 2D image and then converted into the 3D model.

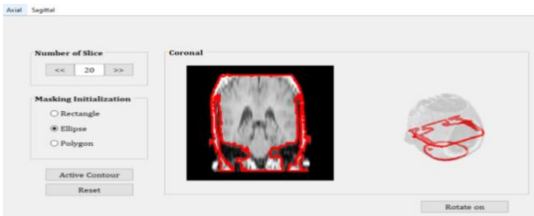

Image 7. Coronal Image with Ellipse V2

The coronal view is a cross-section of the body taken from front to back. The coronal view is used to view brain structures from the front to the back. On the right, the 3D model generated from the coronal slice is displayed. The red line on the 3D model shows the boundary projection resulting from the masking ellipse on the 2D image.

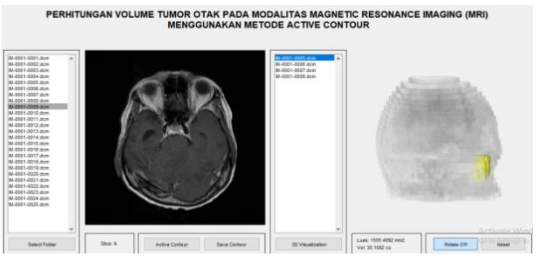

Image 8. 3D Image Result

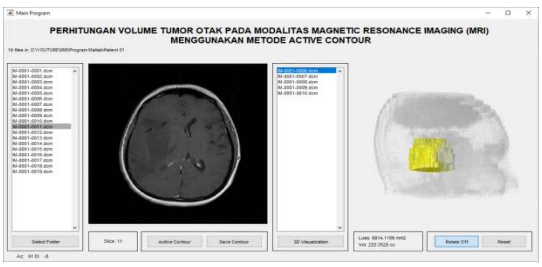

Image 9. 3D Results of Brain Tumor Disease Side View

Explanation:

Left panel (DICOM file list): This is a list of MRI files in DICOM (*.dcm) format. Each file contains a 2D slice image from the brain scan at various slices.

Middle panel (2D Image): The middle image shows one of the slices from the patient's brain MRI. At the bottom, the label Slice: 9 is displayed, indicating slice number 9 from the series of MRI images.

Right panel (3D Visualization): This image shows a 3D representation of the brain tumor volume that has been generated through segmentation using the active contour method. The yellow section in the 3D image represents the tumor area identified from the 2D images.

In the area and Volume information section in the bottom right corner, details about the area (Area: 1505.4092 mm²) and tumor volume (Vol: 30.1082 cc) are provided, calculated based on the segmentation results from the MRI images.

CONCLUSION

In this research, the active contour method will be presented for 3D reconstruction of brain tumors using a series of parallel MRI slices. The proposed model demonstrates higher efficiency, achieving an average precision of 89.97% on original image tests, 92.45% on binary interpretation, an average accuracy of 95.031% in MATLAB, and an average tumor volume measurement of 30,108.2 mm³. Based on test results from the application system using MATLAB, the right panel displays a 3D visualization of the brain tumor volume generated through segmentation using the active contour method, with the yellow section indicating the identified tumor area. Information on the area size (1505.4092 mm²) and tumor volume (30.1082 cc), visible in the bottom right corner, is calculated based on the segmentation results. By generating a 3D output to detect brain tumors with active contours, patients, medical personnel, and researchers can obtain clear information about brain tumors through active contour visualization.

ACKNOWLEGMENTS

We express our deepest gratitude to the Directorate of Research and Technology, Ministry of Education, Culture, Research, and Technology for the research funding support provided through the Beginner Lecturer Research (PDP) scheme in the 2024 fiscal year.

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