Brain Extraction on T2-weighted Magnetic Resonance Imaging using Image Processing Techniques

Prerana Bajracharya
College of Arts and Sciences
Georgia State University
Atlanta, USA
pbajracharya@student.gsu.edu

***Abstract*—Magnetic Resonance Imaging (MRI) is a powerful medical imaging technique that provides detailed visualization of internal body structures, including the brain. By utilizing a combination of strong magnetic fields and radio waves, MRI captures high-resolution images without exposing patients to ionizing radiation. Brain extraction, or skull stripping, is an essential step in T2-weighted MRI analysis, as it accurately isolates the brain region from non-brain structures. In this paper, an approach for brain extraction is proposed using image processing techniques. Our method incorporates Otsu's thresholding, morphological operations (erosion and dilation), and the extraction of the largest connected component. The performance of the approach is evaluated on T2-weighted MRI images. Although the method successfully extracts the brain, further improvements are needed to enhance its accuracy and robustness. The proposed approach offers an alternative to computationally intensive AI-driven algorithms and provides efficient brain identification and extraction in T2-weighted MRI.**

***Index Terms*—MRI, T2w, Brain Extraction, Morphological Operators**

I. Introduction

Magnetic Resonance Imaging (MRI) is a powerful medical imaging technique that provides detailed visualization of internal body structures, including the brain. By utilizing a combination of strong magnetic fields and radio waves, MRI captures high-resolution images without exposing patients to ionizing radiation. MRI is widely used in the field of medicine due to its non-invasive nature and its ability to produce images with excellent soft tissue contrast. There are different types of MRI scans available, including T1-weighted, T2-weighted, and diffusion-weighted imaging, each highlighting different tissue properties.T2-weighted MRI sequences provide detailed information about various brain structures and pathological conditions. However, T2-weighted images often suffer from lower tissue contrast and increased susceptibility to artifacts compared to other MRI sequences.

Brain extraction, also known as skull stripping, plays a crucial role in T2 imaging analysis by accurately isolating the brain region from non-brain structures. It removes the skull, scalp, and other surrounding tissues, allowing for a focused examination of the brain itself. By extracting the brain, the impact of artifacts, partial volume effects, and variations in tissue intensities outside the brain can be minimized.

Brain extraction in T2 images has several important applications in the medical field. It facilitates accurate volumetric measurements, cortical thickness analysis, and quantitative assessment of brain structures. Furthermore, brain extraction helps improve the registration of T2 images to standard brain atlases, enabling precise localization of abnormalities, such as tumors, lesions, or neurodegenerative changes. It also assists in studying the relationship between brain structure and function, aiding in the identification and characterization of various neurological disorders.

The literature extensively documents the advancements in computational methodologies for identifying brain regions, which offer valuable support to radiologists in their analyses. However, the manual analysis of brain regions is known to be time-consuming, resulting in diagnostic delays, hindered prognosis, and delayed initiation of early interventions. While existing algorithms primarily emphasize brain extraction and processing through software tools, some approaches incorporate Artificial Intelligence (AI) algorithms for improved accuracy. Nevertheless, this AI-driven approach often entails a computationally intensive process, which may pose significant challenges and potential limitations for certain applications.

In an effort to overcome such limitations, our research endeavors exclusively focus on the utilization of digital image processing (DIP) techniques for the identification and extraction of the brain. By employing DIP methodologies, the aim is to alleviate the computational burden associated with AI algorithms and provide an alternative approach that ensures efficient brain identification and extraction.

The approach in this paper includes thresholding using Otsu's method, Morphological operations and Lagest Connected Component Extraction.

II. Reviews of Related Works

Some of the popular techniques for brain extraction from T2 MRI include:

Freesurfer: Freesurfer is a widely used software suite for neuroimaging analysis. It includes a brain extraction tool called ”recon-all” that combines intensity-based segmentation, surface deformation, and atlas registration techniques to accurately extract the brain.

Brain Extraction Tool (BET): BET is a widely used brain extraction technique developed as part of the FMRIB Software Library (FSL). It utilizes a deformable surface model and thresholding to estimate the brain boundary based on intensity and spatial information. [1]

Statistical Parametric Mapping (SPM): SPM is a popular software package for analyzing neuroimaging data. It offers a brain extraction method called ”New Segment” that incorporates intensity-based tissue classification algorithms to segment brain tissues and separate them from non-brain structures.

ANTs (Advanced Normalization Tools): ANTs is an open-source image registration and segmentation toolkit. It provides robust brain extraction algorithms such as ”antsBrainExtraction” that employ template-based registration and intensity-based segmentation to extract the brain region. [2]

These techniques can be implemented using various software packages and libraries, and their effectiveness may vary depending on the specific characteristics of the T2 MRI images and the desired application. It is important to evaluate and validate the results of brain extraction techniques to ensure accuracy and reliability for subsequent analysis.

III. Background

A. Morphological operators

Morphological operators are image-processing techniques that modify the shape, size, or structure of objects in an image based on their spatial properties. These operators are commonly used in tasks such as image segmentation, noise removal, and feature extraction. Morphological operators are nonlinear operators with monotone contrast-invariant and translation-invariant properties (M´arquez-neilaet al., 2013). The most basic morphological operations are dilation and erosion defined as:

Erosion: Erosion is the fundamental morphological operator that shrinks the boundaries of objects in an image. It achieves this by comparing the structuring element with the image, pixel by pixel. If all the pixels in the structuring element match the corresponding pixels in the image, the center pixel is set to 1; otherwise, it is set to 0. This operation erodes away the pixels at the object boundaries, resulting in the objects appearing smaller and thinner.’

With A and B as sets in Z^2 , the erosion of A by B, denoted $A \ominus B$, is defined as

$$A \ominus B = \{z | (B)_z \subseteq A\}$$

where A is a set of foreground pixels, B is a structuring element, and the z’s are foreground values (1’s). Z represents the two-dimensional integer grid or lattice, commonly referred to as Z^2 which is the image.

Dilation: Opening is a sequence of erosion followed by dilation. It is useful for removing small objects or noise while preserving larger structures. Opening starts by applying erosion, which removes small objects and smoothes the image. Then, dilation is applied, which restores the size of the remaining objects, effectively removing the noise.

With A and B as sets in Z^2 , the dilation of A by B, denoted as $A \oplus B$, is defined as

$$A \oplus B = \{z | (\widehat{B})_z \cap A \neq \phi\}$$

This equation is based on reflecting B about its origin and translating the reflection by z, as in erosion. The dilation of A by B then is the set of all displacements, z, such that the foreground elements of $\widehat{B}$ overlap at least one element of A. [3]

B. Otsu’s Thresholding Method

Otsu’s thresholding method is a widely used image thresholding technique that automatically determines an optimal threshold value to separate an image into foreground and background regions. It is based on the assumption that the image contains two classes of pixels, typically foreground and background, with distinct intensity distributions.

The main idea behind Otsu’s method is to find a threshold that minimizes the intra-class variance, or equivalently maximizes the inter-class variance. The threshold separates the pixels into two groups, where the sum of variances within each group is minimized, indicating a clear separation between foreground and background.

C. Largest Connected Component

The concept of the largest connected component pertains to binary images, where pixels are classified as either foreground or background. [6] In this context, the largest connected component refers to the most extensive region or cluster of connected foreground pixels within the image. It represents the cluster that encompasses the maximum number of connected foreground pixels.

The identification and analysis of the largest connected component carry significance in several applications involving binary images. This measure enables the isolation and focused examination of the primary object or region of interest present in the image, thereby disregarding smaller isolated objects or noise.

In the field of medical imaging, the identification of the largest connected component aids in the extraction and isolation of essential organs or structures from an image. Likewise, in computer vision and object detection tasks, it facilitates the recognition of the primary object within an image or the segmentation of distinct objects based on their connectivity.

IV. Proposed method

The flowchart in FIg. 1. show the flow of the program. The image is first thresholded using Otsu’s Method. The next step is Erosion which filters noise and also disconnects any unwanted structure attached to the brain. The LLC separates out the the largest component in the image. Finally, Dilation is used to retain if the components of brain were filtered by erosion.

The details of each step is as follows:

A. Image Acquisition

1) Acquire 3D Brain Image: The 3D images are obtained using the free-access OpenNEURO dataset [5], which contains dataset via multiple modalities (fmri, T1w, T2w, DTI, susceptibility-weighted image, angiography). For the purpose of this approach T2w and T1w images were used. The OpenNEURO dataset contains Full-brain volumetric images (384x384x274) in NIfTI format. A simple batch file was run to read all files from their repository.

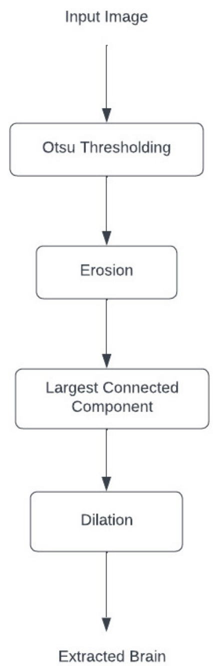

Fig. 1. Example of a figure caption.

B. Otsu Threshold Algorithm

Image binarization (Fig. 2) is carried out with the Otsu threshold algorithm, in order to facilitate the detection of the brain components using morphological operators. The value of standard deviation(σ) was used as 3.

C. Erosion

Erosion (Fig. 3) is applied to the output of Otsu threshold algorithm. The Structuring Element used was sphere with the radius of 8.

D. Largest Connected Component

The brain is the largest connected component (LCC) in the middle axial slices of a MRI scan. LCC is performing operations on a binary mask, which is a binary image where certain pixels are labeled as foreground (typically represented by white pixels) and the rest as background (typically represented by black pixels). It performs labeling of connected components, calculates the size of each component, identifies the label of the largest component, and creates a mask that isolates the voxels belonging to the largest component. Fig. 3 shows the output og the step.

E. Dilation

Dilation (Fig. 3) is applied to the output of LCC. The Structuring Element used was sphere with the radius of 10.

V. Results

In this section, we present the evaluation of the extracted brain image.

A. Brain Extraction

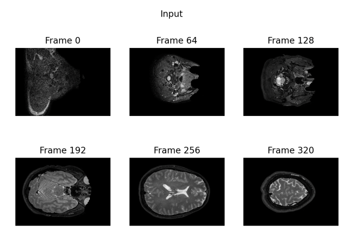

Fig. 2. Sliced Input Image

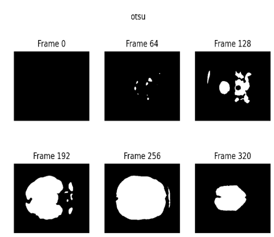

Fig. 3. Sliced Image after Otsu Thresholding

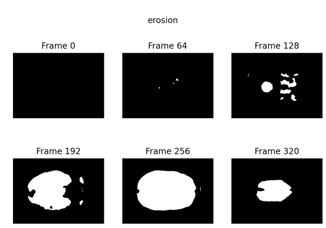

Fig. 4. Sliced Image after Erosion

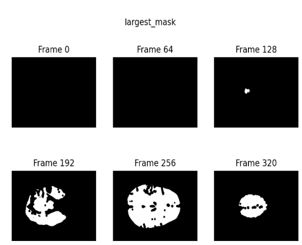

Fig. 5. Sliced Image after LLC

The approach was also tested in T1w images and it successfully extracted the brain.

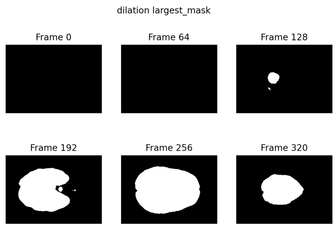

Fig. 6. Sliced Image after Dilation

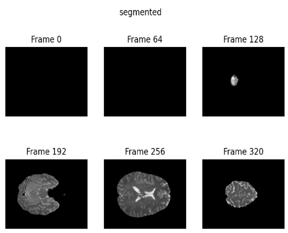

Fig. 7. Sliced Final Image

B. Metrics

For the comparison, the output from the brain extraction from freesurfer was compared. In order to assess the similarity between the segmented brain and freesurfer output, Dice similarity coefficient Dice [4], Sensitivity (SE) and Specificity (SP) were computed.

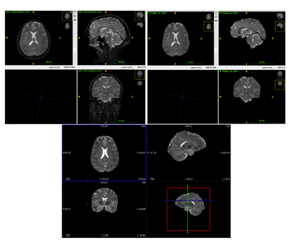

Fig. 8. Top Left: Input Brain Image, Top Right: Proposed Approach Output, Bottom: Freesurfer Output

$$Dice = \frac{2TP}{2TP + FP + FN}$$

$$SE = \frac{TP}{TP + FN}$$

$$SP = \frac{TN}{TN + FP}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP, FP, FN and TNdenote true positive, false positive, false negative and true negative, respectively.

VI. Conclusion

The approach successfully extracted Brain from both T1w and T2w images. However, the metrics show that there is still room for improvements. Current comparison is only done in freesurfer generated images. This in compared to output from other approaches to further gauge of the output.

The main drawbacks of these methods are that they often depend on many parameters such as size and shape of the structural element for morphological operation. These parameters are fixed by empirical experimentation; the value on these parameters directly influences the final output of these methods.

Future works could be to improve the performance with different parameters in larger and different dataset.

TABLE I
Comparison Metrics

Output Category	**Metrics**			
	Dice	***SE***	***SP***	***Accuracy***
Proposed Approach	54.6%	99.84%	78.84%	68.06%

References

[1] S. M. Smith, "Fast robust automated brain extraction," Human Brain Mapping, vol. 17, pp. 143–155, Nov. 2002.

[2] Avants, B. B., Epstein, C. L., Grossman, M., & Gee, J. C. (2009). Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain. Medical Image Analysis, 12(1), 26-41. DOI: 10.1016/j.media.2007.06.004

[3] Gonzalez, R. C., & Woods, R. E. (Richard E. (n.d.). Digital image processing.

[4] Dice, L.R. (1945), Measures of the Amount of Ecologic Association Between Species. Ecology, 26: 297-302. https://doi.org/10.2307/1932409

[5] Michael Hanke and Florian J. Baumgartner and Pierre Ibe and Falko R. Kaule and Stefan Pollmann and Oliver Speck and Wolf Zinke and Jorg Stadler (2018). Forrest Gump. OpenNeuro. [Dataset] doi: 10.18112/openneuro.ds000113.v1.3.0

[6] Latin, I. ; Transactions, A. (2022). Brain Extraction in Multiple T1-Weighted Magnetic Resonance Imaging slices using Digital Image Processing Techniques (Vol. 20, Issue 5).